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Precipitable water vapor, temperature and humidity retrieval using AMSU-A, MHS and HIRS

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ABSTRACT: A multiple linear regression method and a neural network method are performed to retrieve the Precipitable Water Vapor, surface temperature and relative humidity using microwave (AMSU-A, MHS) and infrared (HIRS) ATOVS sounders. Each method is performed using microwave, infrared, and mixed data separately to assess the best. Near nadir ATOVS data of Dakar region (Senegal) at 12:00 AM and 12:00 PM are used for the whole year 2013. Learning data are from radiosonde and in situ measurements. By comparing them with retrieved data, ECMWF reanalysis data help to validate the different methods. The multiple linear regression method provides good results for microwave data with an RMS of 4.65 mm, 2.27 °K and 2.37 % respectively for PWV, surface temperature and surface relative humidity retrieval. Mixed data presents the greatest RMS error, except for PWV retrieval (2.3 mm) whose regression equation, moreover, contains only microwave channels. The neural network significantly improve the results, providing RMS error of 0.56 mm for the PWV retrieval with the microwave neural network, 0.87 °K for the surface temperature restitution with the mixed data neural network and 8% for the surface relative humidity retrieval with the mixed data neural network too. Additionally with the neural network method we retrieved the temperature and relative humidity profiles at 33 pressure levels from the surface to 300 hPa. Mixed data provide better results with an RMS between 0.7 °K and 0.87 °K for the temperature profile and between 6% and 8% for the relative humidity profile.

KEYWORDS: AMSU-A, MHS, HIRS, PWV, Temperature, Humidity, Neural network, Regression.

1 INTRODUCTION

Radiosonde is the reference tool for atmospheric sounding; however the effectiveness of radiosonde is limited by their low and inhomogeneous spatial distribution on the globe, especially in African region, and also by their insufficient time availability (usually twice a day). Nowadays numerous atmospheric observation satellite platfoRMS orbiting around the earth embark, mostly, multiple sensors at different (microwave, visible, infrared) wavelengths. Despite the availability of these multi-frequency observations, little effort has been invested to design algorithms that exploit the best potential synergies for atmospheric variables retrieval. Several sensors can be sensitive to the same atmospheric variables, so using them in conjunction can improve the accuracy of the retrievals.

ATOVS (Advanced TIROS Operational Vertical Sounder) radiometers flying on the NOAA (National Oceanic and Atmospheric Administration), MetOp, AQUA and other polar orbiting satellites have several potential not exploited enough. ATOVS sounders AMSU-A, MHS (evolution of AMSU-B) and HIRS measure the outgoing radiances from the atmosphere and the Earth surface in the microwave band (AMSU-A and MHS) or the infrared band (HIRS).

Several retrieval techniques have been developed for temperature and/or humidity sounding with ATOVS and other sounders measurements [[1], [2], [3], [4], [5], [6], [7], etc.]. Over ocean, the ATOVS measurements are now routinely assimilated in NWP systems and they provide unique atmospheric profiling capabilities. Over land however, the ATOVS measurements are not fully exploited. At best, only the channels that are not contaminated by surface contributions are assimilated, thus limiting the profiling potential to the higher atmospheric layers.

Contrarily to the ocean emissivity, the land surface emissivity is high, often close to unity, leading to difficulties in discriminating between surface and atmosphere contributions. In the present study, we used AMSU-A, MHS and HIRS brightness temperature data to retrieve Precipitable Water Vapor (PWV), surface temperature and humidity with two (02) methods: A multiple linear regression method and a neural network approach. Initial guess data are radiosonde and in-situ measurements. ECMWF data are used for validation by comparing them with retrieved data.

Additionally with the neural network method, we retrieved the atmosphere's vertical temperature and humidity profiles from the surface to 300 hPa altitude. Information of temperature and moisture distribution in the vertical atmosphere is useful in Aviation meteorology, synoptic forecasting and numerical modeling.

In the first section we describe the study data. The retrieval approaches are presented in section 2. In the section 3 we will present the retrieval results and discussions. Section 5 concludes this study.

2 DATA

Several data sets are used for this study; it is mainly satellite ATOVS sounders AMSU-A, MHS and HIRS, radiosonde, climate observations tables and ECMWF reanalysis. The study area is that of Dakar, Senegal.

2.1 RADIOSONDE

Radiosonde observations provide independent and unique reference for many altitude meteorological variables such as PWV, temperature and humidity profiles, wind speed etc. However, they are unevenly distributed over the Earth with different measurement accuracy. They are particularly scarce in Africa. Launched at the Dakar point latitude 14.73° and longitude 17.5°, radiosonde system provides data at fixed times twice a day at 12:00 AM and 12:00 PM. Records of radiosonde measurements are archived at many meteorological centers. We used data available on the University of Wyoming (United States) website: http://weather.uwyo.edu/upperair/sounding.html.

2.2 ATOVS DATA

The main objective of our study is the use of ATOVS sounders retrieval potential. In keeping with the availability of radiosonde at 12:00 AM and 12:00 PM, we are interested in satellite data of Dakar at these times. By using a tracking satellites software, those passing over Dakar at any hours were listed, it is the NOAA 19 and Metop-A for the year 2013. A database of AMSU-A, MHS and HIRS sounders was formed for the Dakar region for the full year 2013 at 12:00 AM and 12:00 PM. ATOVS data are freely available on the website of the NOAA CLASS (Comprehensive Large Array-data Stewardship System): http: // www.class.noaa.gov/. The raw satellite data are pre-processed using the AAPP (ATOVS and AVHRR Pre-processing Package) software produced by the Met Office, in partnership with ECMWF, KNMI and Météo-France. Data's spatial resolution is 0.5° x 0.5° around the Dakar point 14.73 ° latitude and 17.5 ° longitude, the radiosonde balloon launching point. The brightness temperature data included in this grid are averaged.

2.2.1 AMSU

AMSU (Advanced Microwave Sounding Unit) radiometers measure microwave radiations emitted by the earth, the ocean and the atmosphere in different frequencies. This radiation is converted into brightness temperature. Microwave measurements at frequencies below 20 GHz have the advantage of having very large wavelengths compared to the size of water droplets in the atmosphere, and large enough to cross the atmosphere and reach the surface (Smith and Mugnai 1989).

They are two AMSU sensors, AMSU-A and AMSU-B (former to the MHS). With channels in the oxygen absorption band, AMSU-A is designed to retrieve the atmospheric temperature from about 3 hPa (~45 km) down to the Earth's surface. AMSU-B module makes measurements in the vicinity of the strong water vapor absorption line at 183 GHz and is used for atmospheric water vapor sounding. Therefore, the use of AMSU measurements in operational Numerical Weather Prediction (NWP) models can potentially provide accurate monitoring of both air temperature and moisture profiles with good temporal and spatial sampling. Compared to infrared sounding measurements, AMSU observations are less sensitive to high thin and non precipitating clouds.

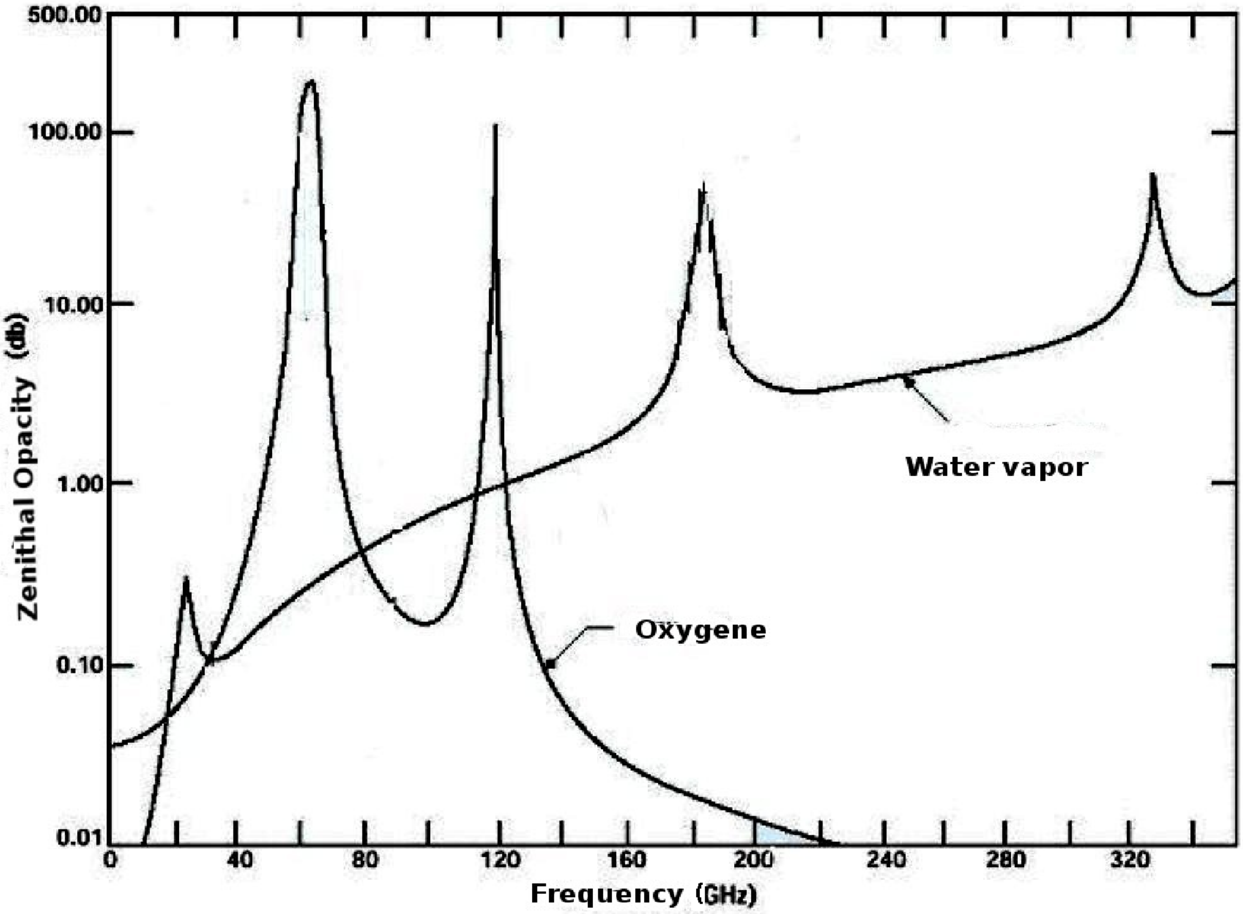

Fig. 1. Electromagnetic spectrum region used by microwave radiometers

AMSU-A is designed to measure radiances in 15 channels (Table 1) in discrete frequency. It is used to measure the vertical profile of atmospheric temperature and humidity and provides information on atmospheric water in all its foRMS (except for ice small particles transparent to microwave).

Table 1. Frequencies, absorbing constituent and atmospheric layer of maximum sensitivity corresponding to AMSU-A channels

Channel	Frequency (GHz)	Principal absorbing Constituant	Level of maximum sensitivity (hPa)
1	23.8	H_2O	Surface
2	31.4	H_2O	Surface
3	50.3	H_2O	Surface
4	52.8	H_2O	950
5	53.596 ± 0.115	O_2	750
6	54.4	O_2	400
7	54.94	O_2	250
8	55.5	O_2	150
9	57,290	O_2	85
10	57.29 ± 0.217	O_2	50
11	57.29 ± 0.322 ± 0.048	O_2	25
12	57.29 ± 0.322 ± 0.022	O_2	10
13	57.29 ± 0.322 ± 0.010	O_2	5
14	57.29 ± 0.322 ± 0.0045	O_2	2.5
15	89	H_2O	Surface

AMSU-B has 5 frequency channels created for humidity sounding and comprises (Table 2). Two (02) channels are centered at 89 GHz and 150 GHz, and the other three are centered on the water vapor absorption line at 183.31 GHz.

Table 2. Frequencies, absorbing constituent and atmospheric layer of maximum sensitivity corresponding to AMSU-B channels.

Channel	Frequency (GHz)	Principal absorbing Constituent	Level of maximum sensitivity (hPa)
1	89.9 ± 0.9	H_2O	Surface
2	150 ± 0.9	H_2O	Surface
3	183.31 ± 1.00	H_2O	500
4	183.31 ± 3.00	H_2O	700
5	183.31 ± 7.00	H_2O	950

Atmospheric maximum sensitivity level with respect to a molecule for each channels frequency channels, is determined using the sensors weighting functions (Figure 2). Figure 1 shows the opacity due to oxygen (O2) and water vapor (H2O) according to the microwave frequencies. At 23.8 GHz (Channel 1 of AMSU-A) we have a weak water vapor absorption ray. Around 89 GHz (Channel 15 of AMSU-A) and channel 1 of AMSU-B, we notice the existence of atmospheric windows (frequency band where the absorption by the atmosphere is minimal). These windows facilitate "access to the surface" and thus make possible its variables study.

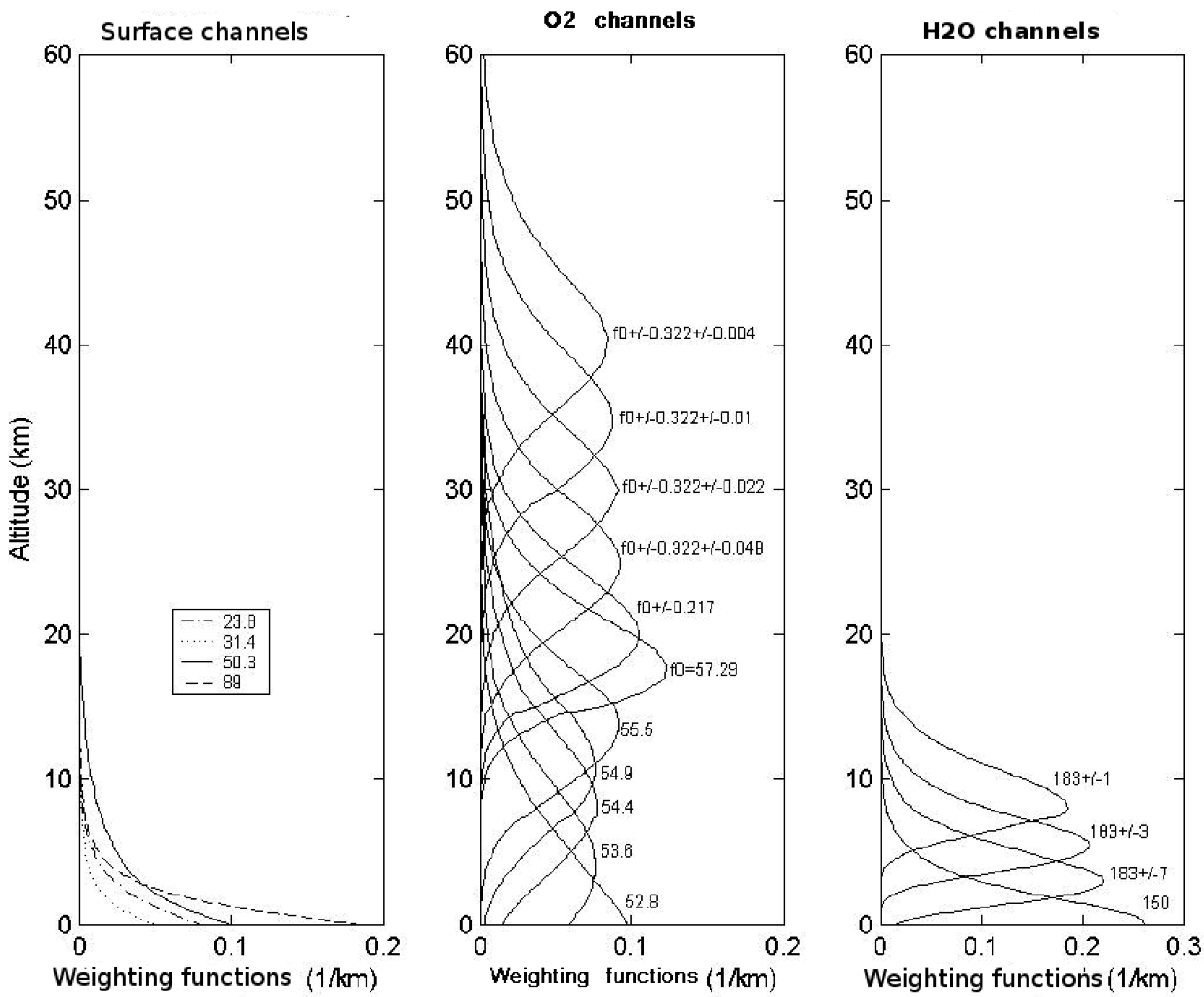

Fig. 2. AMSU frequencies Weighting functions (23 to 190 GHz) for a tropical atmosphere and a nadir measurement configuration (Karbou et al., 2006)

2.2.2 MHS

MHS (Microwave Humidity Sounder) is a 5 channels radiometer which is a development of AMSU-B. Channels 1, 3 and 4 are the same for the two sensors (Table 3).

Table 3. Frequencies, absorbing constituent and atmospheric layer of maximum sensitivity corresponding to MHS channels.

Channel	Frequency (GHz)	Principal absorbing Constituant	Level of maximum sensitivity (hPa)
1	89.9	H2O	Surface
2	157	H2O	950
3	183.31 ± 1.00	H2O	500
4	183.31 ± 3.00	H2O	700
5	190.3	H2O	900

2.2.3 HIRS

HIRS (High-resolution Infrared Radiation Sounder) is a 20 atmospheric sounding channels (Table 4) operating in the infrared. It provides multi-spectral data of a visible channel (0.69 microns), 07 shortwave channels (3.7 to 4.6 microns) and 12 long wave channels (6.7 to 15 microns) using one telescope and a rotating filter containing 20 individual spectral filters.

Table 4. Frequencies, absorbing constituent and atmospheric layer of maximum sensitivity corresponding to HIRS channels.

Channels	Frequency		Principal absorbing Constituant	Level of maximum sensitivity (hPa)
	(cm^{-1})	(µm)		
1	668	14,95	CO_2	30
2	680	14,71	CO_2	60
3	690	14,49	CO_2	100
4	703	14,22	CO_2	400
5	716	13,97	CO_2	600
6	733	13,64	CO_2 / H_2O	800
7	749	13,35	CO_2 / H_2O	900
8	900	11,11	Window	Surface
9	1,030	9,71	O_3	25
10	802	12,47	H_2O	900
11	1,365	7,33	H_2O	700
12	1,533	6,52	H_2O	500
13	2,188	4,57	N_2O	1000
14	2,210	4,52	N_2O	950
15	2,235	4,47	CO_2 / N_2O	700
16	2,245	4,45	CO_2 / N_2O	400
17	2,420	4,13	CO_2	5
18	2,515	4,00	CO_2	Surface
19	2,660	3,76	Window	Surface
20	14,500	0,69 (m)	Visible	Surface / Clouds

Since its first launch on NOAA TIROS-N in 1978, there have been four generations of HIRS but only minor changes were made to the original design. The basic sounding channels remain the same. The sensor measures the brightness temperatures in the infrared spectrum of which data can be used in conjunction with microwave data to calculate the temperature and humidity vertical profiles, oceans surface temperature, atmospheric ozone or cloud cover.

2.3 CLIMATE OBSERVATION TABLE

The daily climate observation table provides meteorological surface parameters every hour. They can provide almost instant overview of climate with various parameters such as temperature, humidity, dew point temperature, pressure, visibility, wind speed, wind direction, rainfall, etc.

2.4 ECMWF REANALYSIS

It is an operational model of the European Center for Medium range Weather Forecasting (ECMWF). It produces 04 global analyzes per day, 00, 06, 12 and 18H obtained from two cycles of assimilation 4D-var (method of fitting the model to observations). ERA-Interim reanalysis [8] realize the synthesis of all in situ and remote sensing data from 1979. The data we use are sized on the grid set around the radiosonde launch point in Dakar. They can be retrieved from the dedicated website: http://data-portal.ecmwf.int/data/d/interim_full_daily/.

3 METHODOLOGY

ATOVS sounders have meteorological parameters retrieval potential not fully exploited [5]. Over the ocean, temperature, humidity or PWV retrieval is now well advanced, and even assimilated into some global models (Météo-France, ECMWF, NOAA, etc.). Therefore it is very interesting to be able to implement effective retrieval methods over the continents.

Two (02) approaches are used in order to retrieve the temperature, humidity and PWV: Multiple linear regression, and neural networks. PWV, temperature and humidity profiles data used for learning are from radiosonde. Surface temperature and humidity are from climate observations tables. Each retrieval method uses three (03) types of data:

- Microwave data (AMSU-A and MHS): 19 channels are concerned, having held a malfunction at the channel 7 of AMSU-A.
- Infrared data (HIRS): Similarly, the HIRS channel 20 does not provide enough usable data, thus has 19 channels.
- Microwave and infrared data synergy: 19 microwave channels and 19 infrared channels, so a total of 38 channels.

This approach will allow us to measure the effectiveness of the data type in relation to the retrieved variable. Our objective is to retrieve the satellite data in all conditions, day or night, cloudy or clear sky, etc. Thus day time data (12:00 PM), night data (12:00 AM) and 2013 all seasons data are mixed.

So the final database that we have is:

- 617 microwave data;
- 546 Infrared data;
- 528 microwave and infrared mixed data.

The difference between the data numbers is due to the fact that for some samples, data from some sensors are unavailable (especially HIRS), according to the operational sensors independence. For each case, 1/3 of the data are assigned to the test database whereas 2/3 of the data are attributed to the learning database. ECMWF reanalysis data are used for validation.

4 Results And Discussions

4.1 Multiple Linear Regression Method

Multiple linear regression method allows identifying easily the predominant channels. A filter of inputs variables (channels) is set up with a significance test at 5 %. In the linear regression, each output of the algorithm is a linear combination of the inputs and an eventual bias. The parameters (different weights for each input and bias) of the regression are adjusted to minimize the difference between the retrieved variables and real variables (in the sense of least squares) through the learning base.

Statistical variables used to evaluate the model performance are: The model coefficient of determination R^2, the RMS (root mean squared) of the model, correlation coefficient (corr) and standard deviation (std) between real data of the test database and data predicted by the model. The RMS variable is the square of the residual variance of the model while R^2 measures the difference between the data and the fitted regression line.

The standard deviation (std) and the correlation between retrieved data and ECMWF data will evaluate the validation.

4.1.1 PWV Retrieval

The precipitable water vapor (PWV) is essential for weather studies because of its greenhouse effect and its influence on the prediction. Table 5 reports the model equations found for 03 types of data, which AMAi is channel i of AMSU-A, MHSi channel i of MHS and HIRSi channel i of HIRS.

Table 5. Multiple linear regression equations for precipitable water vapor restitution

Inputs	**Model equation**
AMSU-A and MHS	-202.20 + 0.68 * AMA1 – 0.57 * AMA2 + 0.41 * AMA3 – 1.31 * AMA4 + 1.68 * AMA6 + 0.43 * MHS1 – 0.20 * MHS2
HIRS	7.93 + 6.34 * HIRS2 – 7.14 * HIRS3 – 3.84 * HIRS4 + 7.49 * HIRS5 – 6.56 * HIRS7 + 2.51 * HIRS8 – 2.82 * HIRS9 + 1.22 * HIRS14 + 2.29 * HIRS15
AMSU-A, MHS and HIRS	-298.6 + 0.68 * AMA1 – 0.49 * AMA2 + 0.99 * AMA6 + 0.46 * MHS1 – 0.25 * MHS2

Performance parameters (statistics) of these equations (Table 6) can judge what kind of data retrieve the PWV with utmost accuracy. Retrievals model RMS errors clearly show that the infrared data are not informative enough for PWV retrieval (10.74 mm).

Microwave and infrared data used synergistically provide a better outcome with an RMS of 4.3 mm. Data are also well correlated (96 %) with the regression line the std between the rendered data and the actual data in the database test is 3.2 mm. The model using microwave data has results quite close to the model combining the microwave and infrared data. This explains why the model designed with mixed microwave and infrared data has no infrared channel.

Table 6. Regression equations for precipitable water vapor restitution performances.

Inputs	**R^2 (%)**	**RMS (mm)**	**corr (%)**	**std (mm)**	**ECMWF corr (%)**	**ECMWF std (mm)**
AMSU-A and MHS	93	4.65	93	3.8	87	4.4
HIRS	64	10.74	59	8.3	47	10.9
AMSU-A, MHS and HIRS	96	4.3	94	3.2	87	4.3

ECMWF Validation data confirm the results found above. The model using microwave and infrared data synergistically has the best results. PWV data retrieved with this model have a correlation of 87% and a standard deviation of 4.3 mm with reanalysis PWV data. Similarly, the validation of the microwave model presents a correlation of 87% and a standard deviation of 4.4 mm. PWV data retrieved from the infrared model are weakly correlated with the ECMWF data with a standard deviation of 10.9 mm.

4.1.2 Surface Temperature Restitution

The Ocean emissivity is about 0.5 which enables the sea surface temperature (SST) assimilation in NWP models. Continental surfaces emissivity close to 1 increases the difficulty of surface parameters restitution. Our study area, Dakar region is located on the coast so our remote sensing data are contaminated by continental emissivity. Table 7 details the regression algorithms implemented.

Table 7. Multiple linear regression equations for surface temperature retrieval

Inputs	**Model equation**
AMSU-A and MHS	-146.99 + 0.19 * AMA1 – 0.11 * AMA2 – 0.19 * AMA3 + 1.86 * AMA5 – 2.18 * AMA8 + 0.79 * AMA10 – 0.66 * AMA11
HIRS	17.95 – 0.6 * HIRS3 + 1.02 * HIRS4 + 0.94 * HIRS6 – 2.76 * HIRS7-0.39 * HIRS9 + 1.23 * HIRS10 + 0.5 * HIRS17
AMSU-A, MHS and HIRS	-276.86 + 1.4 * AMA5 – 1.09 * AMA6 + 0.09 * AMA9 – 1.02 * HIRS7 + 0.7 * HIRS10 – 1.23 * HIRS13 + 1.02 * HIRS15 + 1.38 * HIRS18 – 0.83 * HIRS19

The passive microwave emission can penetrate non-precipitating clouds, providing a better representation of the surface temperature in almost any condition with respect to cloud cover. Thus microwave data provide a better result with an RMS of 2.27 °K (Table 8).

The RMS of the infrared equation is quite close to that of the microwave (2.74 ° K) but the equation does not fit the regression line (R^2 = 0.49). This is confirmed by a correlation of 0.53 between the inverted data and real data of the test database. Microwave and infrared mixed data model is not accurate. Its RMS is 5.07 °K and the retrieved data has a correlation of 42 % with surface temperature data.

Table 8. Regression equations for surface temperature restitution performances.

Inputs	R^2 (%)	RMS (°K)	corr (%)	std (°K)	ECMWF corr (%)	ECMWF std (°K)
AMSU-A and MHS	82	2.27	86	2.24	82	2.47
HIRS	49	2.74	53	2.6	49	4.2
AMSU-A, MHS and HIRS	40	5.07	42	3.5	35	5.1

ECMWF data confirm the microwave model good performance with a correlation of 82 % and 2.47 °k standard deviation with retrieved data. Surface temperature retrieved from infrared model and mixed data model are poorly correlated with reanalysis data (respectively 49% and 35 %). these models are not accurate enough.

ATOVS sensors are not used enough to retrieve land surface temperature. Reference [2] retrieved the surface temperature over the state of Louisiana (United States). Using AMSU-A data, his model has an RMS of 4.8°C. In clear sky, [7] obtained an RMS of 2.2°K with a multiple regression model using AMSU-A and MHS data. They performed also a model using microwave AMSU-A and MHS in synergy with infrared IASI data, it provides an RMS of 1.8°K. While over ocean in clear sky, the RMS is 2.6° K for the microwave model, and 0.9°K for mixed data model. Land surface temperature retrieved are also performed with other sensors, [9] established a linear regression model between the microwave sensor AMSR-E (Advanced Microwave Scanning Radiometer-EOS) and MODIS (Moderate-Resolution Imaging Spectroradiometer) surface products. Data refer to the Guangdong Province of China and the RMS of the retrieval is about 3°K.

4.1.3 Surface Relative Humidity Restitution

Surface humidity retrieval over ocean from satellite data using a multiple linear regression method was the subject of much research. Reference [10] proposed an algorithm for the specific humidity retrieval by setting up an empirical relationship between the content of integrated water vapor and surface specific humidity between 10 and 20 m. This relationship was established using radiosonde data on four islands and verified using SMMR (Scanning Multichannel Microwave Radiometer) radiometer observations. The RMS between retrieved values and in situ observations is 0.8 g/kg.

To get a better specific humidity estimation using the SSM/I (Special Sensor Microwave/Imager) radiometer at instantaneous scale, [11] developed a method for the integrated water vapor retrieval over an altitude between 0 and 500m, whereas the majority of the water vapor in the boundary layer. To establish the algorithm, they used data from radiosonde carried out by different research boats in the Atlantic Ocean, the North Sea, the Indian Ocean and the North East Atlantic. To validate their results, they used the research boats data. Their results show a standard deviation of 1.2 g/kg compared with in situ measurements.

Reference [11] used SSM/I brightness temperatures measured at 19 GHz, 22 GHz and 37 GHz frequencies, as well as measurements of radiosonde to establish multiple linear regression model. The accuracy of this relation is 0.06 g/cm RMS.

Reference [12] have slightly improved the specific humidity estimation quality through the use of a more direct relationship between the brightness temperature and the humidity, which uses different frequencies from those operated by [11]. In their work, [12] used boats in situ observations instantaneously. The retrieval RMS is 1.1g/kg.

However, a comparison made by [11] between [12]'s model and in situ measurements, shows a low bias of 0.06 g/kg, but a significant RMS of 1.6 g/kg. This proves that model does not take account for all possible situations, and it is only suitable for a specific region.

Similarly, [13] showed that [11]'s model had a sizeable seasonal bias. To eliminate this bias they proposed, by the linear regression method, a new model that uses the same SSM/I channels frequency than [11], but in situ data are from buoys TAO, NDBC (National Data Buoy Center) and ODAS (European Offshore Data Acquisition System). This model was validated with COADS (Comprehensive Ocean Atmosphere Data Set) measurements which represent a collection of ocean surface observations from 1784 to 1997. Reference [13]'s algorithm has an RMS of 1.1 g/kg.

Reference [14] was the first to explore AMSU potential for specific humidity retrieval. They mainly focused on improving the specific humidity retrieved SSM/I. To this purpose, they developed a new instantaneously humidity retrieval method, based on AMSU data but also SSM/I data. In situ measurements used for the retrieval method adjustment are from a hygrometer operating at infrared wavelengths, and placed aboard research boats during several measurement campaigns. The difference found by [14] is 0.96 g/kg.

Using AMSU-A and AMSU-B data over the ocean, [6] developed an algorithm for specific humidity retrieval with an RMS of 1.01g/kg and 0.86 g/kg, compared to the validation data, which are hourly PIRATA and TAO observations.

Table 9. Multiple linear regression equations for surface relative humidity retrieval

Inputs	Model equation
AMSU-A and MHS	552.93 – 4.6 * AMA5 + 6.74 * AMA6 – 4.47 * AMA8 - 2.39 * AMA10 + 1.93 * AMA11 + 0.54 * MHS1
HIRS	94.68 + 1.81 * HIRS3 – 2.68 * HIRS4 + 1.44 * HIRS6 – 1.7 * HIRS9 – 1.87 * HIRS13 + 2.66 * HIRS14 + 0.94 * HIRS17 – 0.59 * HIRS19
AMSU-A, MHS and HIRS	339.96 – 4.34 * AMA5 + 6.4 * AMA6 – 4.08 * AMA8 + 0.61 * MHS1 + 0.3 * MHS2 – 3.37 * HIRS8 + 3.79 * HIRS10 – 0.45 * HIRS19

Table 9 reports algorithms found from the three used data sets. The maximum emissivity over continents strongly influences the surface parameters retrieval from satellite data. Microwave model have accurate retrieval RMS of 2.37% but the model fitted 75% the regression line (Table 10). The correlation between retrieved surface relative humidity from this model and real data is about 70%. Infrared model's RMS increase to 6.7% for R^2=0.44 and a correlation of 52%. Mixed data model provide a 15.5 % with R^2=0.23 and 25 % of correlation. Microwave model provide best results.

Table 10. Regression equations for surface relative humidity restitution performances.

Inputs	R^2 (%)	RMS (%)	corr (%)	std (%)	ECMWF corr (%)	ECMWF std (%)
AMSU-A and MHS	75	2.37	70	6.4	63	9
HIRS	44	6.7	52	10.2	43	15.2
AMSU-A, MHS and HIRS	23	15.5	25	14.8	31	18.3

Validation performances are in respect with models performances. So the biggest standard deviation is for the mixed data model (18.3%), then the infrared model (15.2%) and finally the microwave model (9%).Correlations are distributed inversely with 63% for the microwave model, 43 % for the infrared model and 31 % for the mixed data model.

4.2 NEURAL NETWORK APPROACH

Multiple linear regression, as the name suggests is a linear method, which can be inadequate to simulate non-linear relationships between inputs and outputs. It is common to use this method as a first test for neuronal method used thereafter [7]. Neural methods are particularly efficient algorithms for remote sensing. Retrievals done following are with neural networks. Neural networks that we use are Multi Layer Perceptrons [15]. If enough samples are provided, all continuous relations, as complex as they are, between inputs and outputs can be represented by a multi-layer perceptron.

This study is divided into two parts; firstly, we will retrieve the previous study parameters: PWV, surface temperature and relative humidity. Then a method to retrieve 33 temperature and relative humidity profiles from surface to 300 hPa is performed. Data of 33 pressure levels are from radiosonde.

Retrievals will be made with three (03) data sets: Microwave, infrared and mixed. Neural networks are a form of non-linear regression. Thus for each data type temperature, relative humidity and/or PWV will retrieve simultaneously. This allows us to design a network by data type (Table 11). 2/3 of the database are used for learning, the third to test the network and ECMWF data will be compared with data returned for validation (only for PWV, surface temperature and humidity retrieval).

The neural network using microwave data for PWV, surface temperature and specific humidity retrievals have 19 inputs (15 AMSU-A channels and 5 MHS channels), 2 hidden layers of 20 neurons each. The number of outputs is 3 (Table 10).

Similarly for the neural network using infrared data, the number of inputs is 19 (channels 1 to 19 HIRS), the provisions of hidden layers are the same. Network using data synergy will therefore have 38 inputs (2 x 19).

Table 11. Retrieval neural networks Architectures.

Retrieval type	Data	Inputs	Hidden layers	Neurons per hidden layer	Outputs
03 parameters	Microwave	19	2	20-20	3
03 parameters	Infrared	19	2	20-20	3
03 parameters	Microwave and infrared	38	2	30-20	3
Temperature and relative humidity profiles	Microwave	52	2	40-35	66
Temperature and relative humidity profiles	Infrared	52	3	40-40	66
Temperature and relative humidity profiles	Microwave and infrared	71	3	50-40	66

For the vertical profile of temperature and relative humidity at 33 pressure levels retrieval, we set these pressure levels as inputs. Thus the network using microwave data have 52 (19 + 33) inputs, even for the network using infrared data. Network using data synergy has 71 inputs (19 x 2 + 33). The number of outputs is the same for the various networks and equal to 66 (33 temperature profiles and 33 humidity profiles).

Three (03) variables are used for statistical evaluation of PWV, surface temperature and specific humidity retrievals. The RMS (between retrieved data and test data), correlation (corr) and standard deviation (std) between the ECMWF data and retrieved data. Only RMS will evaluate the temperature and humidity profiles neural networks performances.

4.2.1 PWV RESTITUTION

Reference [16] was the first to use AMSU-B data to retrieve the PWV with a neural network. Above the Arctic region they got a 1 mm RMS. Using MHS data combined with AMSU-A, we got a 0.56 mm RMS (Table 12). Infrared data show the largest RMS, in keeping infrared radiation absorption by water particles. However, neural networks improve the restitution relative to the multiple linear regressions with an RMS difference of 7.34 mm for infrared data and 2.05 mm for the data used in synergy.

Table 12. Performances of PWV retrieval neural networks.

Inputs	RMS (mm)	ECMWF corr (%)	ECMWF std (mm)
AMSU-A and MHS	0.56	92	2.7
HIRS	3.4	73	5.6
AMSU-A, MHS and HIRS	2.25	81	3.4

Reanalysis data are well correlated (92%) with the retrieves PWV by the microwave network whose standard deviation is 2.7 mm data. The standard deviation is 5.6 mm (73 % of correlation) with the infrared network retrieved data and 4.4 mm (81 % of correlation) with the mixed network retrieved data. Improvements are respectively 5.6 mm and 0.9 mm from the multiple linear regression models.

Retrieval RMS with the microwave sensor AMSR-E data using a neural network is about 3 mm above Europe [17], and the infrared data to 6.8 mm above the Europe and Africa [18].

4.2.2 SURFACE TEMPERATURE RETRIEVAL

Reference [3] developed a new neural network and variant assimilation method, and the theoretical RMS of land surface temperature retrieval over globe is 1.3K in clear-sky conditions and 1.6K in cloudy scenes. Reference [19] performed a neural network with 2.9 °K RMS for the surface temperature restitution using the SSM/I and ISCCP data. Reference [5] retrieved land surface temperature using neural network model with a RMS of 2.1 °K taking into account emissivity data with AMSU-A and AMSU-B, ECMWF and ISCCP data.

The RMS of the neural network (Table 13) designed with microwave data is 1.18 °K thus a decrease in RMS of 1.09 °K relative to the multiple linear regression model. Synergy data network give the best result with an RMS of 0.87 °K, 4.2 °K less than the regression model RMS. The neural network using infrared data provides an RMS of 2.75 °K.

Table 13. Performances of surface temperature retrieval neural networks

Inputs	RMS (°K)	ECMWF corr (%)	ECMWF std (°K)
AMSU-A and MHS	1.18	88	2.3
HIRS	2.75	79	1.7
AMSU-A, MHS and HIRS	0.87	92	1.2

Surface temperature retrieved data using the microwave neural network is well correlated with the ECMWF surface temperature data. The standard deviation is 2.3 °K. For the network using infrared data, performances are slightly lower. But the data used synergistically improve validation results with a correlation of 92% and a standard deviation of 1.2 °K.

4.2.3 SURFACE RELATIVE HUMIDITY RESTITUTION

Using a neural network model, [5] retrieved specific humidity on a land surface with a RMS of 9% with AMSU-A and AMSU-B, ISCCP and ECMWF data taking into account the emissivity. This same RMS is found with the neural network designed by learning microwave data (Table 14). The RMS of the microwave network is slightly lower (8%) than the while the infrared neural network has an RMS of 13%.

Table 14. Performances of surface relative humidity retrieval neural networks

Inputs	RMS (%)	ECMWF corr (%)	ECMWF std (%)
AMSU-A and MHS	9	84	9
HIRS	13	64	15
AMSU-A, MHS and HIRS	8	88	7

ECMWF data show good correlation (80 %) and lower standard deviation (7%) with surface relative humidity retrieved from the neural network using microwave and infrared data synergistically. The network using microwave data has similar results. For the infrared neural network the correlation is weak (64%) and 15% of standard deviation.

4.2.4 TEMPERATURE AND HUMDITY PROFILES RETRIEVAL

4.2.4.1 TEMPERATURE PROFILE RETRIEVAL

Temperature profiles, from the surface to 300 hPa, retrieved with three (03) datasets are presented in Figure 3. The network with the mixed data has an RMS of 0.87 °K at the surface, which decreases with the height reaching a minimum of 0.7 °K. The microwave network has an RMS of 1.18 °K on the surface; it reaches a minimum of 0.86 ° K at 552 hPa and remains constant up to 300 hPa.

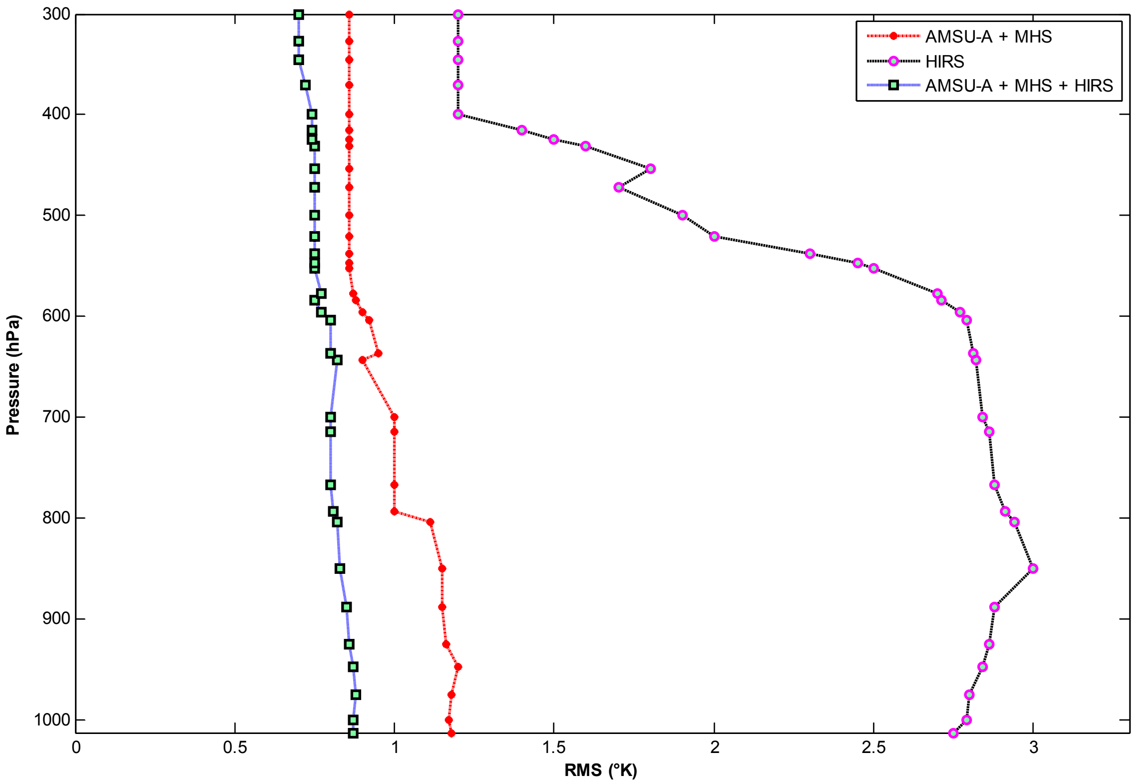

Fig. 3. ***RMS error profiles for temperature profile retrieval***

The network performed with infrared data has the largest RMS of all datasets. The surface RMS is 2.75 °K, peaking 3° K at 850 hPa, it begins to decrease with altitude. A minimum of 1.2 °K is reached at level 400 hPa and remains constant up to 300 hPa.

Reference [2] carried out temperature profile retrieval with a neural network using AMSU-A data over Louisiana State (United States). The RMS on the surface is 3.2 °C, decreasing to 2.4 °C at 1000 hPa, 1.6 °C at 800 hPa, 1.2 °C to 600 hPa. The RMS level remains constant until 300 hPa.

Microwaves (AMSU and HSB) and infrared data (AIRS) used in synergy [20] provide an RMS less than 1 °K from the surface to 300 hPa at partial cloud cover situation.

Reference [5] combined AMSU A and AMSU-B data taking into account the surface emissivity improve the restitution with an RMS of 2.1°K at the surface. The RMS decreases to 1.2°K at 930 hPa and 0.9°K at 850hPa. Between 800 and 300hPa it remains constant at 0.8°K. Using AMSU-A, AMSU-B and HIRS January 2002 data over India, [21] developed a neural network retrieving the vertical temperature profiles. The RMS obtained throughout the profile is superior or equal to 4°K. This result is probably due to their very limited data base.

Reference [22] also uses a neural network approach for temperature profile retrieval from AMSU-A measurements of 2006 and 2007 over the Indian region. The RMS is about 3 °C at the surface, 0.9 °C to 2.2 °C between 700 and 300 hPa.

Reference [7] is the first to use AMSU-A and MHS data to retrieve the temperature profile on continental surface. In cloudless situation, they get an RMS of 2.3 °k at 938.53 hPa, which decreases to 1.3 °K at 600 hPa and remains constant between 600 and 300 hPa. Using these data in synergy with the IASI infrared data, they improve retrievals.

4.2.4.2 Relative Humidity Profile Retrieval

The vertical relative humidity profile retrieved from the 03 datasets neural networks present enough similarity to the temperature profile (Figure 4). The data used in synergy help to minimize the RMS which is between 8% and 6% from the surface to 300 hPa altitude. The network using microwave data presents a 9% RMS at the surface reaching a minimum of 7% at the 430 hPa; it remains constant up to 300 hPa altitude.

The infrared network provides the biggest restitution errors. With an RMS of 13% at the surface, it grows, and reaches its maximum peak of 20.7% at the altitude 700 hPa. It started to decrease and reached its minimum of 10.4% at 450 hPa level. This RMS remains constant up to the altitude 300 hPa.

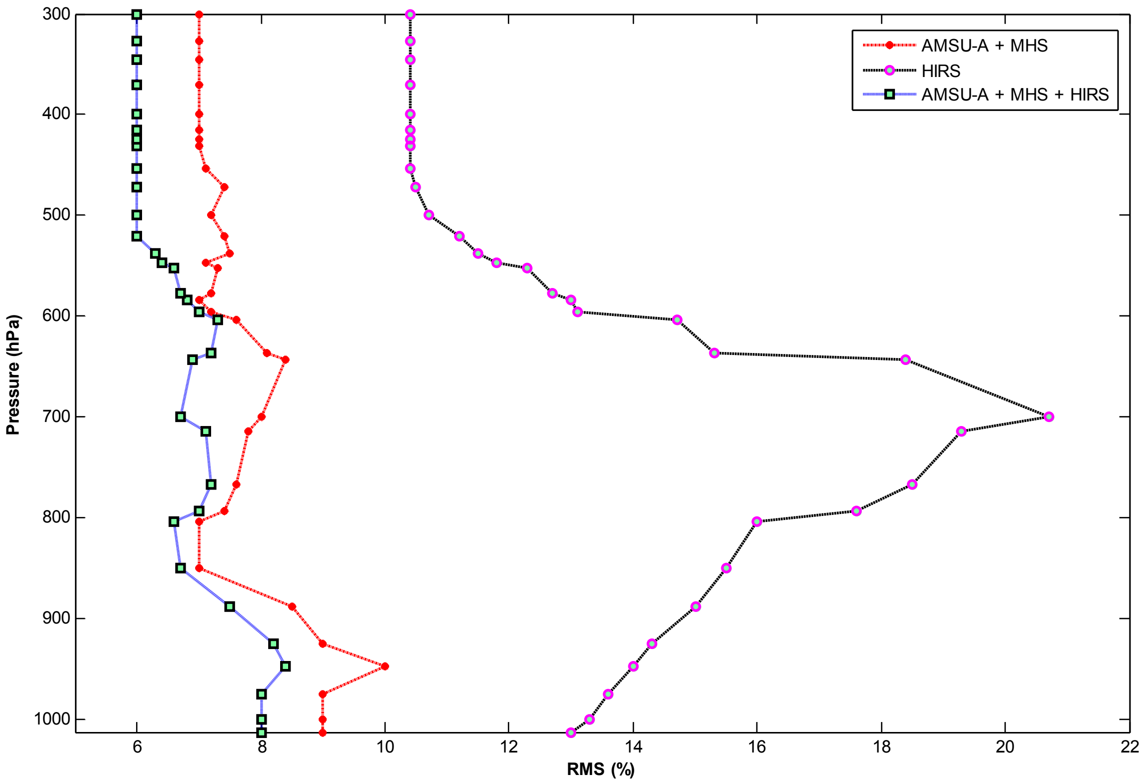

Fig. 4. RMS error profiles for relative humidity profile retrieval

Reference [5] conducted humidity profile retrieval simultaneously with temperature profile retrieval described in the previous section. The network they have designed has an RMS of 9% at the surface which decreases to 7.5% at 910 hPa. The RMS returns to 9% at 800 hPa altitude before reaching its maximum of 10% at 700 hPa. Finally, it decreases to 7.5% at the 300 hPa altitude. Similarly, [7] retrieved the humidity profile with a RMS from 7% to 9% between 300 and 938.53 hPa.

5 CONCLUSION

In this study, we use two methods to retrieve PWV, surface temperature and surface relative humidity from ATOVS microwave sounders (AMSU-A, MHS) data, infrared (HIRS) data, and mixed data (AMSUA, MHS and HIRS); Multi-linear regression and neural network methods.

With the multiple linear regression method, results show that microwave data are more suitable for the retrievals, with an RMS of 4.65 mm, 2.27 °K and 2.37 % respectively for PWV, surface temperature and surface relative humidity. While mixed microwave and infrared data are not appropriate.

Neural Network (NN) techniques have proved very successful in developing computationally efficient algorithms for remote sensing applications. They are found capable of connecting the nonlinear relation between ATOVS channel measurements and atmospheric variables, providing RMS error of 0.56 mm for the PWV retrieval with the microwave neural network. The mixed data neural network provides the smallest RMS for surface temperature (0.87°K) and surface relative humidity (8%) retrievals. ECMWF data show good correlation and relatively small standard deviation with mixed neural network retrieved data.

Additionally, with the neural network approach, we retrieved temperature and relative humidity profiles from surface to 300 hPa altitude at 33 pressure levels. A neural network uses maximum a priori information to limit the number of free parameters in the neural model so as to constrain the retrieval to a ‘‘better-posed’’ problem. Therefore mixed microwave and infrared data provide the best results with a RMS between 0.7 °K and 0.87 °K for the temperature profile, respecting the World Meteorological Organization (WMO) specifications; 1 °K RMS error for the instantaneous temperature retrieval with 1-km vertical resolution. Mixed neural network relative humidity retrieval RMS is 8% at the surface, which decreases with altitude to its minimum 6%.

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