Inter-comparison of AIRS temperature and relative humidity profiles with AMMA and DACCIWA radiosonde observations over West Africa

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Abstract

The vertical profiles of temperature and water vapour from the Atmospheric InfraRed Sounder (AIRS) have been validated across various regions of the globe as an effort to provide a substitute for radiosonde observations. But there is a paucity of inter-comparisons over West Africa where local convective processes dominate and RAOBs are limited. This study validates AIRS temperature and relative humidity profiles for selected radiosonde stations in West Africa. Radiosonde data was obtained from the AMMA and DACCIWA campaigns which spanned 2006 - 2008 and June-July 2016 respectively and offered a period of prolonged radiosonde observations in West Africa. AIRS performance was evaluated with the bias and root mean square difference (RMSD) at seven RAOB stations which were grouped into coastal and inland. Evaluation was performed on diurnal and seasonal timescales, cloud screening conditions and derived thunderstorm instability indices. At all timescales, the temperature RMSD was higher than the AIRS accuracy mission goal of ± 1 K. Relative humidity RMSD was satisfactory for the entire troposphere with deviations < 20% and < 50% respectively. AIRS retrieval of water vapour under cloudy and cloud-free conditions had no significant difference whereas cloud-free temperature was found to be more accurate. The seasonal evolution of some thunderstorm convective indices were also found to be comparable for AIRS and RAOB. The ability of AIRS to capture the evolution of these indices imply its applicability for determining the thunderstorm probability over West Africa under the Global Challenges Research Fund African Science for Weather Information and Forecasting Techniques project.

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Key Points:

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11	•	Diurnal and seasonal temperature RMSD of AIRS was >1 $^{\circ}\mathrm{K}$ whereas the RH
12		profiles were more accurate.
13	•	The seasonal AIRS and RAOB derived thunderstorm instability indices were com-
14		parable at the stations.
15	•	Capability of monitoring storm evolution with AIRS profiles under the GCRF African
16		SWIFT project.

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17 Abstract

The vertical profiles of temperature and water vapour from the Atmospheric InfraRed 18 Sounder (AIRS) have been validated across various regions of the globe as an effort to pro-19 vide a substitute for radiosonde observations. But there is a paucity of inter-comparisons 20 over West Africa where local convective processes dominate and RAOBs are limited. This 21 study validates AIRS temperature and relative humidity profiles for selected radiosonde 22 stations in West Africa. Radiosonde data was obtained from the AMMA and DACCIWA 23 campaigns which spanned 2006 - 2008 and June-July 2016 respectively and offered a pe-24 riod of prolonged radiosonde observations in West Africa. AIRS performance was evaluated 25 with the bias and root mean square difference (RMSD) at seven RAOB stations which 26 were grouped into coastal and inland. Evaluation was performed on diurnal and seasonal 27 timescales, cloud screening conditions and derived thunderstorm instability indices. At all 28 timescales, the temperature RMSD was higher than the AIRS accuracy mission goal of ± 1 29 $^{\circ}$ K. Relative humidity RMSD was satisfactory for the entire troposphere with deviations <30 20% and < 50% respectively. AIRS retrieval of water vapour under cloudy and cloud-free 31 conditions had no significant difference whereas cloud-free temperature was found to be 32 more accurate. The seasonal evolution of some thunderstorm convective indices were also 33 found to be comparable for AIRS and RAOB. The ability of AIRS to capture the evolu-34 tion of these indices imply its applicability for determining the thunderstorm probability 35 over West Africa under the Global Challenges Research Fund African Science for Weather 36 Information and Forecasting Techniques project. 37

38 1 Introduction

Quantification of atmospheric temperature and water vapour are critical for assessing and 39 improvement of numerical weather and climate prediction models (Diao et al. (2013); Di-40 vakarla et al. (2006) and references therein). The initialization process for these models 41 demand the use of denser and homogeneous satellite radiance which must be corrected for 42 cloud contamination. This radiance correction allows for the effective and efficient retrieval 43 of atmospheric profiles such as water vapour, temperature, ozone and other trace gases. 44 Retrieval skill is dependent on sensor accuracy, the atmospheric transmittance functions, 45 cloud clearing and inversion algorithms (Divakarla et al., 2006). The availability and accu-46 racy of observational calibration/validation data, especially observations from radiosondes 47 is critical to the development of robust atmospheric profile retrieval algorithms and prod-48 ucts. Water vapour is a particularly important because its presence in the form of clouds 49 can induce either a positive or negative temperature feedback in the climate system based 50 on height of occurrence (e.g., (Mears et al., 2015)). Therefore understanding and modeling 51 the spatiotemporal variability of atmospheric moisture is essential to weather and climate 52 prediction. 53

Radiosonde observations (RAOB) offer an adequate platform for the monitoring of the 54 vertical profile of water vapour, temperature, wind, and geopotential height. When as-55 similated into weather forecast models, RAOBs can enhance the prediction of convective 56 storm evolution in terms of initiation, propagation and decay (Madhulatha et al., 2013; 57 Chen et al., 2014). However the spatial distribution of radiosondes are limited with few 58 launches in the equatorial tropical region that is characterized by strong convective activi-59 ties (He et al., 2015; Taylor et al., 2017; Parker, 2017). The radiosonde has the advantage 60 of being highly accurate with high vertical resolution (Flores et al., 2013), but the fre-61 quency of sonde launches in time and space is low due to the large operational cost (Flores 62 et al., 2013; Bayat & Maleki, 2018). The African Monsoon Multidisciplinary Analysis 63 (AMMA) (Redelsperger et al., 2006) and Dynamics-aerosol-chemistry-cloud interactions in 64 West Africa (DACCIWA) (Knippertz et al., 2017) campaigns in 2006 and 2016 respectively 65 mark years in which RAOBs are available for West Africa. 66

⁶⁷ With advances in remote sensing, sounders aboard satellites offer alternate sources for the

acquisition of RAOB-like vertical profiles. The majority of these validation studies have

focused on inter-comparing the retrievals from satellite-based platforms with correspond-69 ing collocated radiosonde measurements. A well-known sensor is the Atmospheric Infrared 70 Sounder (AIRS) aboard NASA's Earth Observing System (EOS) Aqua satellite (Aumann 71 et al., 2003). AIRS was constructed to provide atmospheric temperature profiles to a root 72 mean square difference (RMSD) of 1 °K for every 1 km tropospheric layer and 1 °K for every 73 4 km stratospheric layer up to an altitude of 40 km (Olsen et al., 2017). The correspond-74 ing humidity RMSD of the sensor is of order 20% in 2 km layers in the lower troposphere 75 and approximately 50% in the upper troposphere (Susskind et al., 2003; Susskind, 2006). 76 These error estimates are considered to be applicable for scenes of up to 80% effective cloud 77 cover (Susskind, 2007). According to McMillin et al. (2007) (and see references therein). 78 the AIRS instrument has provided a set of unique datasets by which to validate climate and 79 weather models and analyse the global distribution of water vapour and ice supersaturation. 80 AIRS temperature and water vapour datasets have also been evaluated to improve param-81 eterisation of sub-grid scale models (Quaas, 2012) and to understand regional climatology, 82 including land-atmosphere coupling (Ferguson & Wood, 2010, 2011). 83

Currently, there is a rigorous ongoing AIRS validation efforts using various ground truths 84 across the world, Iran (Bayat & Maleki, 2018), India (Prasad & Singh, 2009; Singh et al., 85 2017), Antarctica (Boylan et al., 2015) and continental United States (Ferguson & Wood, 86 2010; McMillin et al., 2007). The studies also provide information on performance improve-87 ments of recent AIRS version releases over earlier releases (Milstein & Blackwell, 2016). 88 Most of these studies observed a good agreement between AIRS and RAOB profiles with 89 an overall accuracy within mission-specified accuracy bounds (Xuebao et al., 2005; Milstein 90 & Blackwell, 2016; Prasad & Singh, 2009). Bayat and Maleki (2018) validated AIRS de-91 rived precipitable water vapour profiles with a ground-based sun photometer measurements 92 and obtained an acceptable agreement with a 93% coefficient of determination. Seasonal 93 analysis over Iran showed higher dry biases of the precipitable water vapour during spring 94 with lower values in the winter. Over India, Singh et al. (2017) found that AIRS and the 95 Indian National Satellite (INSAT-3D) agree comparatively well with RAOB observations at 96 the lower and upper troposphere but quickly degrades in the middle troposphere probably 97 due to improper bias correction coefficients used for brightness temperature. Their findings 98 observed the influence of surface emissivity on the AIRS profile retrievals which resulted 99 in larger errors over land and in dry atmosphere. Divakarla et al. (2006) also observed a 100 decreased performance of AIRS temperature and water vapour profiles relative to the Ad-101 vanced TIROS Operational Vertical Sounder (ATOVS) (Reale et al., 2008) retrievals and the 102 National Center for Environmental Prediction Global Forecasting System (NCEP_GFS) and 103 European Center for Medium Range Forecast (ECMWF) forecast profiles over land mea-104 surements which exhibited a seasonal and annual variability that correlates with changes 105 in CO_2 concentrations. However, the overall agreement was satisfactory for both land and 106 sea surface categories. Furthermore, AIRS was merged with the Microwave Limb Sounder 107 (MLS) temperature and water vapour records to successfully study the inter-annual vari-108 ability of these parameters over tropical Pacific (Liang et al., 2011). Their findings revealed 109 the spatial and seasonal distribution of temperature and humidity to be located over the 110 deep convection zone of the tropical western Pacific whereas subsidence dominates at the 111 tropical central Pacific. Based on these datasets, the authors (Liang et al., 2011) were 112 able to observe and link the inter-annual variability of major tele-connections such as the 113 El Nino Southern Oscillation (ENSO), Quasi-Biennial Oscillation (QBO). To date, there 114 have been no dedicated analysis of AIRS retrieval performance over West Africa. For ex-115 ample, Ferguson and Wood (2011) could only utilise four radiosonde observations stations 116 from the AMMA project into the validation section (AIRS versus radiosonde) of their land-117 atmosphere coupling study. 118

Our study inter-compares AIRS vertical profiles of temperature and relative humidity with AMMA and DACCIWA radiosonde observations at some selected West African stations for which there are sufficient data matchups. For context, AIRS retrieval skill is compared against that of NCEP_R2 at the same sites. Notably, NCEP-R2 does not assimilate AIRS, as do more modern atmospheric reanalyses, but does assimilate RAOBs. Results from this

study will give a first hand confidence in the use of the AIRS datasets for the profiling 124 of temperature and relative humidity that exist in a pre-convective environment for thun-125 derstorm initiation. It is also in accordance with the Global Challenges Research Fund 126 (GCRF) African Science for Weather Information and Forecasting Techniques (SWIFT) 127 project which seeks to develop a sustainable research capability in tropical weather fore-128 casting. The remaining part of the paper is structured into three sections which includes 129 the methodology in Section 2, results and discussions in Section 3 and finally the conclusion 130 in Section 4. 131

132 **2** Methodology

¹³³ 2.1 Radiosonde Observations over West Africa

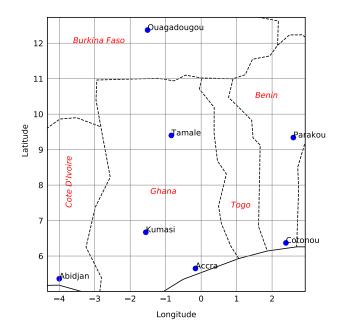


Figure 1. Spatial locations of radiosonde soundings in blue filled circles. Kumasi and Accra are DACCIWA sites while the remaining are AMMA sounding sites. Country of which station sounding was launched is in red italised.

RAOB of temperature and relative humidity profiles were obtained from AMMA (http:// 134 database.amma-international.org/) and DACCIWA (http://baobab.sedoo.fr/DACCIWA/ 135 for the period of January 1 2006 to December 31 2008 and June 1 to July 31st 2016, with 136 locations of RAOB locations are distributed between longitudes 4° W to 2° E and latitudes 137 5° N to 13° N (see Figure 1). The stations Ougadougou (Burkina Faso), Abidjan (Ivory 138 Coast), Parakou, Cotonou (Benin) and Tamale (Ghana) fall within the AMMA project 139 sites whiles Kumasi and Accra (Ghana) fall under the DACCIWA jurisdiction. Under the 140 SWIFT project, Ghana is a country of prime focus and convective activities from neigh-141 bouring countries affect the country's weather and hence, this formed the basis for station 142 selections. The Vaisala sondes RS92 were deployed at Abidjan, Tamale, Kumasi, Accra 143 and Parakou, whiles Cotonou and Ougadougou utilised the MODEM SR2K2 radiosondes. 144 Aside from the measured parameters, the radiosonde also provides other parameters such as 145

dew-point temperature, wind speed, wind direction, upward balloon velocity and altitude at standard pressure levels. A limiting element of the Vaisala RS92 instruments is its negative humidity bias obtained during daytime sounding (see Singh et al. (2017) and references therein) resulting from the absorption of gases by the capacitor in sites which otherwise should have been made available for the absorption of water vapour molecules (McMillin et al., 2007). Nonetheless data originating from these instruments have been bias corrected and quality-controlled with appropriate algorithms by the source bodies before release for research activities.

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2.2 AIRS temperature and humidity profiles

The AIRS sensor has been operational aboard the AQUA satellite since September 155 2002 with a nadir polar orbiting mode. It is a cross-track scanning sounder, hyper-spectral 156 resolved, sun-synchronous and a twice daily global scan with an equator overpass at 1:30 am 157 and 1:30 pm for descending and ascending orbits respectively. The sounder provides compre-158 hensive information on the vertical thermodynamic structure of the atmosphere by viewing 159 in 2378 channels along with four visible and near-infrared channels (Olsen et al., 2017; Singh 160 et al., 2017). It as well retrieves infrared and microwave surface emissivity as a function of 161 frequency, total ozone and cloud parameters (Divakarla et al., 2006). The AIRS IR-Only 162 level 3 standard retrieval (AIRS3STD) version 6 algorithm 0.31.0 profiles of temperature 163 and relative humidity has been used for the present study. These products were obtained 164 at a $1^{\circ} \times 1^{\circ}$ grid at twice daily temporal resolution. The air temperature were extracted 165 from 11 standard pressure levels (925 hPa - 100 hPa) whiles relative humidity was retrieved 166 at 9 water pressure levels of 925 hPa to 200 hPa. The dataset has been quality controlled 167 with appropriate and improved cloud screening algorithms and uncertainty measures as de-168 scribed in Susskind et al. (2003); Susskind (2006, 2007); Susskind et al. (2011). AIRS3STD 169 is derived from Level-2 data products in which the quality control of every parameter field 170 has been flagged as best (0) or good (1) (Olsen, 2016). This ensures that all grids have 171 the highest quality level datasets for each field and pressure level. Since the analysis of 172 the study depended on the correlation between two parameters at different pressure levels, 173 the combined parameter field (TqJoint grids) for both ascending and descending passes as 174 recommended by Olsen (2016) was used. The TqJoint field applies a single, unified quality 175 control criterion for all parameter fields and has flags of either 0 or 1. The AIRS dataset 176 can be accessed at http://disc.sci.gsfc.nasa.gov/AIRS/data_access.shtml. 177

178 2.3 NCEP_R2 datasets

The NCEP-DOE Reanalysis 2 (herein NCEP_R2) is an improved version of the NCEP 179 Reanalysis 1 project with an updated parameterisation scheme for physical processes such 180 as new shortwave radiation and changes in boundary layer and minor tuning of convective 181 parameterisation (Kanamitsu et al., 2002). The model uses analysis/forecast system to 182 produce data assimilation from past datasets (1979) to present. The Reanalysis data has 183 been subset into four main categories of Pressure, Gaussian Grid, Spectral Coefficient and 184 Surface Data. Temperature and humidity profiles which are of interest to this study was 185 taken at a 4-times daily and $2.5^{\circ} \times 2.5^{\circ}$ spatial resolutions. Observational data which are 186 obtained from NCEP_R2 global upper air Global Telecommunication System (GTS) by the 187 National Center for Atmospheric Research (NCAR) are combined with other datasets such as 188 satellite, marine and surface winds to obtain a desired output parameter (Wang et al., 2016). 189 These datasets can be obtained at the NOAA website https://www.esrl.noaa.gov/psd/. 190

2.4 Data Collocation and Statistical Analysis

192 2.4.1 Data Sampling

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¹⁹³ To inter-compare the temperature and relative humidity profile datasets from RAOB, ¹⁹⁴ AIRS and NCEP_R2, the datasets were first collocated in both space and time. A temporal

sampling window of ± 3 hours within a spatial radius of 100 km as used by other AIRS 195 validation studies (Divakarla et al., 2006; Milstein & Blackwell, 2016) was applied to extract 196 the RAOB and NCEP_R2 daily profiles. Table 1 shows the number of retrieved samples 197 from the RAOB to AIRS that satisfied the collocation criteria. The NCEP_R2 profiles which 198 passed this criterion were obtained from synoptic times 00 hours (to match with descending 199 pass) and 12 hours (to match with the ascending pass). A total collocated days of profiles 200 for RAOB and NCEP_R2 each for the AMMA and DACCIWA field campaign sites were 201 totaled at 278 (Abidjan), 176 (Cotonou), 43 (Ougadougou), 104 (Parakou), 27 (Tamale), 8 202 (Kumasi) and 30 (Accra) (see Table 1). It must be noted that, no temporal interpolation 203 was performed on the AIRS or NCEP_R2 data. Since the accurate retrieval of temperature 204 and water vapour profiles by satellites strongly dependent on the land surface emissivity 205 and skin temperature (Ferguson & Wood, 2010; Singh et al., 2017), these stations have 206 been grouped into "coast" (Abidjan, Accra and Cotonou) and "inland" (Kumasi, Tamale, 207 Ougadougou and Parakou) for analyses. All stations are situated below 925 hPa, therefore 208 profile analyses was initialised at this level to 100 hPa for temperature and 200 hPa for 209 relative humidity. 210

Station	Ascending overpass	Descending overpass	Dry Season (December-February)	Wet Season (March-November)
Abidjan	30	248	91	187
Accra	18	12	-	30
Cotonou	58	118	56	120
Kumasi	5	3	-	8
Parakou	18	86	7	97
Tamale	14	13	3	24
Ougadougou	12	31	5	38

Table 1. Number of samples retrieved from AIRS-RAOB collocations

211 2.4.2 Temperature and humidity profile statistics

Equation 1 and 2 with units of °K was used to evaluate the temperature profiles at each pressure level of AIRS and NCEP_R2:

$$Bias = \frac{1}{N} \sum_{i=1}^{N} (T_{DATA} - T_{RAOB}) \tag{1}$$

$$RMSD = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (T_{DATA} - T_{RAOB})^2}$$
(2)

The bias and RMSD for calculating water vapour errors were normalised to account for the vertical and temporal variability of water vapour in the atmosphere (Equations 3 and 4) as implemented in Singh et al. (2017). Units of the normalised bias and RMSD for relative humidity is given in percentage (%).

$$Bias_{norm} = \frac{\frac{1}{N}\sum_{i=1}^{N} (RH_{DATA} - RH_{RAOB})}{\frac{1}{N}\sum_{i=1}^{N} RH_{RAOB}} \times 100$$
(3)

$$RMSD_{norm} = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N} (RH_{DATA} - RH_{RAOB})^2}}{\frac{1}{N}\sum_{i=1}^{N} RH_{RAOB}} \times 100$$
(4)

where N is the number of collocated temperature or relative humidity profiles for each pressure level, T_{DATA} is the AIRS or NCEP_R2 temperature profile, T_{RAOB} correspond to the radiosonde temperature observations, RH_{DATA} is the AIRS or NCEP_R2 relative humidity profile, RH_{RAOB} imply the radiosonde relative humidity retrievals, RMSD and $RMSD_{norm}$ represent the root mean square difference and normalised root mean square difference derived for the pressure levels respectively.

2.4.3 Thunderstorm convective indices

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The AIRS and NCEP_R2 temperature and relative humidity profiles were used to derive three stability indices that affect the evolution of severe and non-severe (Peppler, 1988) thunderstorm occurrences. The derived indices were then used to compare with derived indices of the radiosonde at these observation stations on the seasonal timescale. The indices include the George's K-Index, Total Totals Index and the Humidity Index.

George's K-Index (George, 1960), given by Equation 5 gives a measure of the thickness of
 low-level and mid-level tropospheric moisture content (Peppler, 1988). Higher values usually
 >20 °C is indicative of higher probabilities for the occurrence of showers and thunderstorms.

$$K = (T_{850} - T_{500}) + Td_{850} - (T_{700} - Td_{700})$$
(5)

The Total Totals (TT) Index (Miller, 1975) (Equation 6) is a severe thunderstorm indicator which shows the static stability between the 850hPa and 500 hPa levels (Peppler, 1988). It is the sum of vertical totals $(T_{850} - T_{500})$ and cross totals $(Td_{850} - T_{500})$ of temperature and dewpoint temperature. The likelihood of showers and thunderstorms increase as TT index becomes ≥ 30 °C.

$$TT = T_{850} + Td_{850} - 2T_{500} \tag{6}$$

The Humidity (H) Index given in Equation 7 assesses the extent of saturation at given pressure levels [(Jacovides & Yonetani, 1990; Marinaki et al., 2006) and references therein]. A significant threshold for thunderstorm occurrence should usually be less or equal to 30 °C.

$$HI = (T - Td)_{850} + (T - Td)_{700} + (T - Td)_{500}$$
(7)

In all cases, where T and Td are the temperature and dewpoint temperatures in degree Celsius at the reference pressure levels.

2.4.4 Cloud/Cloud-Free Analysis

To further check the strength of the AIRS temperature and relative humidity profiles 245 over the stations, the data was also extracted into days of cloudy conditions and cloud-free 246 conditions. A day is said to be cloud-free if the cloud-fraction is ≤ 0.4 . The dataset of which 247 cloud and cloud-free days were extracted for the corresponding radiosonde observations was 248 from the AIRS3STD cloud fraction which is available from http://disc.sci.gsfc.nasa 249 .gov/AIRS/data_products.shtml. Prior to this, lower thresholds less than the stipulated 250 was used but it was observed that, either the collocated criteria was not satisfied, or all 251 radiosonde launch were on days of cloud fraction > 0.4. 252

3 Results and Discussion

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3.1 Diurnal analysis of AIRS temperature and relative humidity

Figure 2 shows the diurnal bias and RMSD for the vertical profile of temperature and 255 relative humidity according to zonal classification. A total of 474 and 182 collocations were 256 found for coast and inland regions respectively. The temperature profile for all passes and 257 locations observed a predominant cold and low biases from the lower to upper troposphere. 258 The biases (Figure 2a) were also found to be increasing with altitude with a sharp inversion 259 observed at the coast (ascending and descending) and inland (ascending). An inversion at 260 the inland for the descending pass is however observed at the 300 hPa pressure level. At 261 the inland stations, the bias between AIRS and RAOB temperature profiles was found to 262 be reduced during daytime passes than the night with an overall pressure level difference 263 about 0.33 °K. In addition this daytime performance inland is also lower than the coastal 264 daytime biases. There were no significant differences between the ascending and descending 265 passes at the coast as was observed inland. Although the biases show AIRS temperature to 266 be constantly underestimated with the RAOB, the retrievals are better at the coast (mean 267 difference) than inland regions. The temperature RMSD profile is shown in Figure 2b with 268 the broken vertical line denoting the AIRS mission temperature accuracy goal of ± 1 °K. It 269 can be observed that all over-passes were unable to meet this 1 °K goal with the descending 270 pass of the inland region obtaining between a 4 - 5 $^{\circ}$ K temperature RMSD. The low bias 271 obtained at the inland ascending pass (Figure 2a) is reflected in the corresponding low 272 RMSD temperature profile (Figure 2b). However the ascending pass for inland also reveals 273 a higher RMSD at the near surface (925 hPa) level denoting the inability of AIRS to retrieve 274 the temperature at this level. On the other hand, at the coast, the 1 °K RMSD is achieved 275 only at the 200 hPa and 300 hPa levels in the ascending pass. The diurnal coastal RMSD 276 ranged between 1 - 4 °K with better retrievals during the ascending than descending pass. 277 Above 200 hPa, there is a degradation in the RMSD for all locations and passes. In general, 278 the daytime analyses show that AIRS temperature profiles for the inland stations have a 279 lower RMSD than the coastal stations, whereas the opposite holds at night. This can be 280 attributed to the diurnal effect of sea and night breezes which is stronger at the coast than 281 inland and invariable affect the temperature retrievals by AIRS. 282

The statistical analyses for the diurnal retrievals of relative humidity is shown in Figure 2c 283 (bias) and d (RMSD). The RH bias is observed to be warm and positive at the coast 284 and inland for all passes except the inland nighttime retrievals. Biases are also observed 285 to be lower for the coastal region with a near overlap at the surface (925 hPa) to mid-286 troposphere (500 hPa), above which there exists a relatively small deviation in both day 287 and night passes. AIRS over-estimates the RH for the inland stations during the day and 288 underestimates at night due to the poor retrieval of night-time temperatures as found in 289 Figure 2 a and b. The inland profile for the day increases steadily from 10% - 25% at the 290 lower to upper troposphere (925 hPa to 200 hPa) as compared to the decreasing trend (<-291 10%) observed for the nighttime pass. The RH accuracy goal for AIRS is about $\pm 15\%$ - 20% 292 (Susskind, 2006; Divakarla et al., 2006) for the lower to mid-troposphere and better than 293 50% (Olsen et al., 2017) for the upper troposphere. Unlike the temperature, the relative 294 humidity RMSD (see Figure 2d) was found to be within the AIRS accuracy goal with a 295 slight exceedance (about 3%) at the 200 hPa level for the inland and coastal ascending 296 pass. Although the accuracy goal for the lower to middle troposphere was not satisfied 297 for both locations in the ascending pass, nonetheless the RMSD is quite acceptable. The 298 RMSD for the descending pass was observed to lower than 15% with the upper troposphere 299 ranging between 16 - 20%. Deviations between the coastal and inland regions were highest 300 below 400 hPa and 500 hPa for the descending and ascending passes respectively. The 301 general underestimation of temperature and over-estimation of relative humidity show the 302 effects of temperature retrievals on the RH by AIRS. Pfahl and Niedermann (2011) state 303 that a strong anti-correlation exists between temperature and relative humidity, arising 304 primarily from convective precipitation that decrease local temperatures due to vertical 305 mixing and insolation reduction from clouds. The existence of an indirect relationship 306

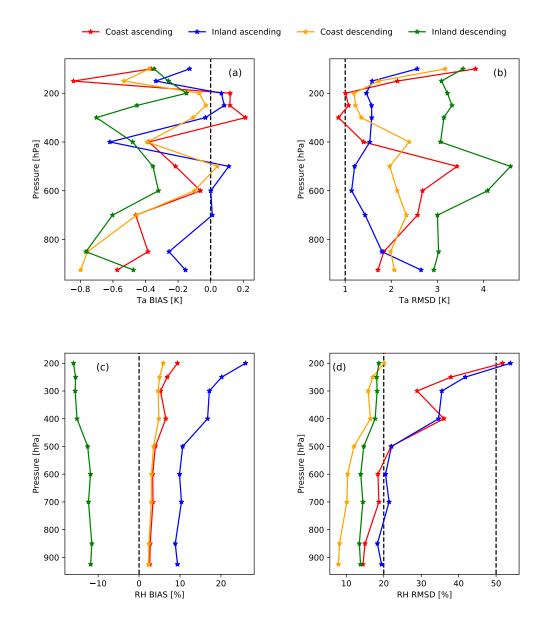


Figure 2. Diurnal retrieval statistics of AIRS for temperature (a and b) and relative humidity (c and d) for coastal and inland stations. Broken vertical lines in RMSD represent AIRS accuracy goal for temperature (b) and relative humidity (d). The first and second vertical lines at 20% and 50% in the RH RMSD shows the accuracy goal for lower and upper troposphere respectively. Recommended bias at broken vertical line 0 °K.

between temperature and relative humidity mean that the relatively lower temperatures
 (dry bias profile) retrieved by the sensor is translated into a warm bias in the corresponding
 RH profiles.

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3.2 Seasonal analysis of AIRS temperature and relative humidity profiles

Figure 3 shows the seasonal vertical temperature and relative humidity profiles for the coast and inland regions. The seasonal analysis consists of a dry and wet with stations such as Abidjan, Accra, Cotonou and Kumasi experience a bi-modal pattern of rainfall with the major rains occurring between March to July and a minor wet season between September to early November (Amekudzi et al., 2015; Baidu et al., 2017; Parker, 2017). The dry season at these stations also occurs from late November to February. Tamale, Parakou and Ougadougou have a uni-modal rainfall pattern occurring between April to October and a dry season from November to March (Amekudzi et al., 2015; Parker, 2017). The locations which have bi-modal rain pattern observes annually a temporal break in the month of August which is termed as the "little dry spell" (Parker, 2017).

From Figure 3a, the temperature bias was found within a -2.5 to 0 °K with a consistent cold

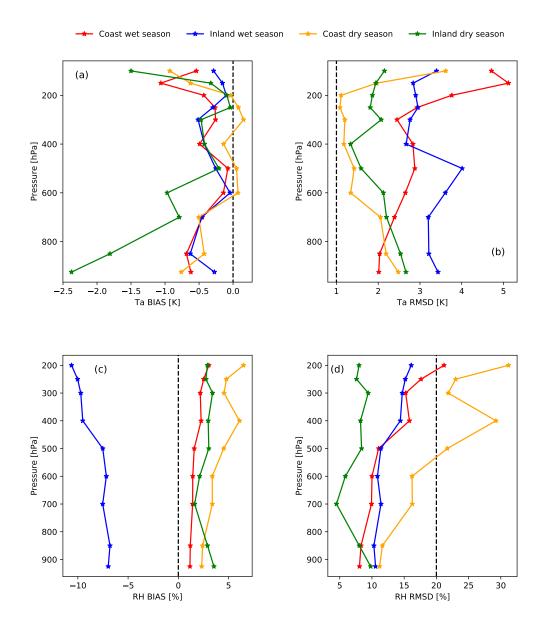


Figure 3. Seasonal statistics of AIRS for temperature (**a** and **b**) and relative humidity (**c** and **d**) for coastal and inland stations. Broken vertical lines in RMSD represent AIRS accuracy goal for temperature (**b**) and relative humidity (**d**). The first and second vertical lines at 20% and 50% in the RH RMSD shows the accuracy goal for lower and upper troposphere respectively. Recommended bias at broken vertical line 0 °K.

bias at all vertical levels. Inland dry season temperatures obtained the highest deviation 322 occurring at the surface to middle troposphere (925 hPa to 500 hPa). The dry season 323 coastal bias was larger above 200 hPa. Between 600 hPa to about 200 hPa, both RAOB 324 temperatures and AIRS retrievals were observed to be similar and accurate for AIRS as 325 the bias was found to be close to zero. Furthermore, AIRS temperature bias and RMSD 326 (see Figure 3a and b) for the dry season are observed to be more accurate than the wet 327 season possibly due to the effect of increasing cloud cover in the wet season that lowers 328 the accuracy of temperature retrievals. According to Ferguson and Wood (2011) increasing 329 cloud cover attenuates the infrared waves for accurate retrievals of temperature by the AIRS 330 sensor. The deviation found at the 925 hPa to 500 hPa for the inland dry season bias is 331 due to higher retrievals from the radiosonde for the season. The coast also obtained smaller 332 biases as compared to the inland stations. The bias at the coast was found to sharply 333 deviate at the 150 hPa level (≈ -1.2 °K) whereas the inland region was quite consistent. 334 The RMSD of the seasonal temperature (Figure 3b), similar to the diurnal temperature 335 RMSD (Figure 2b), failed to meet the AIRS accuracy goal with a spread of 1.5 - 5 °K. The 336 retrieval pass with skill is close to the targeted accuracy was observed in the coastal dry 337 seasonal sample. This can be observed at the 600 hPa to 200 hPa pressure levels where 338 the was a close agreement with the lowest bias between the AIRS and RAOB datasets. 339 In addition, the lower tropospheric (925 hPa to 700 hPa) temperature for the coastal dry 340 season was found to be higher between 2 - 3 °K. For both coastal wet and dry seasons, 341 higher RMSD existed at the upper atmospheric levels with the coastal wet season obtaining 342 a larger deviation. The inland seasons also observed to be accurate than the wet season. 343 In general, the dry season RMSD temperature profiles was found to be lower than the wet 344 season profiles with the coast out-performing the inland stations at all temporal scales. 345

The bias and RMSD for the relative humidity is shown in Figure 3 c and d. A warm 346 bias (Figure 3c) exists at the coast for both seasons and inland for the dry season only, 347 suggesting an over-estimation of water vapour profiles by the AIRS sensor. On the other 348 hand, the inland wet season is observed to be negatively (cold) biased which can be linked 349 to the occurrence of convection during this season (Prasad & Singh, 2009) and the relatively 350 longer distance traversed by the satellite to retrieve relative humidity inland (McMillin et al., 351 2007). This cold bias (about 6%) further declined at the upper troposphere. The positive 352 bias was observed between 0 - 5%, which is low and acceptable for a difference between AIRS 353 and RAOB water vapour profiles. At the coast, the wet season although positively biased 354 has the best accuracy (about 1 - 1.5%) as compared to the dry season and inland regions. 355 The RMSD profile (Figure 3d) reveals a satisfactory performance of the AIRS dataset. 356 Tropospheric water vapour profiles at all pressure levels were mostly within 20% and 50%357 at the coast and inland. Inland dry season AIRS retrievals were observed to be superior with 358 total vertical RMSD less than 10%. The RMSD performance for the inland dry season imply 359 the presence of clear sky conditions which is a major characteristic of the inland stations 360 during this season. Although the bias observed for inland wet season (see Figure 3c), the 361 RMSD is comparable to the coast wet season profile and both were found to be within 362 an acceptable range. The warm bias obtained for the coastal wet season was also found 363 translate into higher RMSD in Figure 3d. In conclusion, the diurnal and seasonal inter-364 comparisons enhance understanding on the usefulness of AIRS temperature and relative 365 humidity profiles for thunderstorm prediction based on the derivation of instability indices. 366

367 368

3.3 Cloud dependence of AIRS temperature and relative humidity retrieval accuracy

To assess the impact of clouds on the retrieval of temperature and relative humidity by AIRS, the data was separated into days of cloudy retrieval and days of cloud-free retrievals over all overpasses. Only stations Accra, Abidjan, Cotonou and Ougadougou satisfied the cloud and cloud-free (cloud fraction less than 0.4) criteria. The remaining stations, Parakou, Kumasi and Tamale either had no cloud-free days or the collocation window was beyond that stipulated for in this study (\pm 3 hours and a 100 km radius).

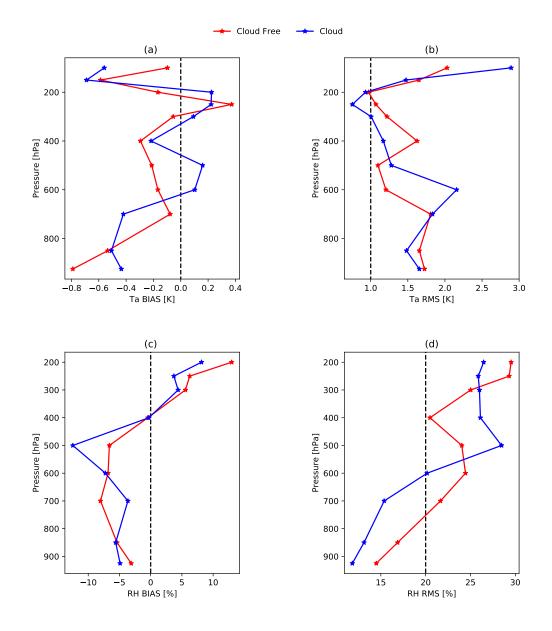


Figure 4. Cloud conditional analyses for all AIRS matchups (ascending and descending overpass) at all stations (see Table 1) for temperature and relative humidity.

The total bias and RMSD profile for the temperature and RH at these stations is shown in 375 Figure 4. The temperature bias (Figure 4a) shows lower bias on cloud days as compared to 376 cloud free days. The bias for both profiles was found to be mostly cold with a warm bias 377 found at the 250 hPa level on cloud free days. On cloudy days, a warm bias was observed 378 at the middle (600 and 500 hPa) and upper (300 to 200 hPa) troposphere. Temperature 379 retrievals at the near surface (Figure 4a) by AIRS was found to be drier on cloud-free days 380 than cloudy days. The RMSD profile shows that the overall performance of AIRS on cloud 381 free days is closer to the mission goal than on cloudy days. There is a higher deviation 382 in both cases at the upper troposphere (150 to 100 hPa) with the largest RMSD found 383 during cloudy days. Upper tropospheric temperature errors on the cloudy days could reach 384 a maximum of 3 °K with a 2 - 2.5 °K on cloud-free occasions. Interestingly, although AIRS 385 cloud-free profile could not meet the accuracy goal at any level, cloudy profile observed a 386

between 0.5 - 1.0 °K RMSD at the 300 hPa to 200 hPa. This corresponded to the upper
tropospheric levels with warm temperature bias (Figure 4a). The alternating RMSD profile
also suggests that the accuracy of cloud-free retrievals is better at 700 hPa to 500 hPa and
100 hPa levels whereas cloud retrieval accuracy is better at all other levels.

Figure 4c and d shows the AIRS bias and RMSD for relative humidity on cloud and cloud 391 free days. In general, cold to warm biases are observed to exist on both cloud and cloud 392 free days. Bias in cloud free days is minimal as compared to cloudy conditions. The lower 393 to mid-tropospheric dry bias under cloudy conditions was also observed by Ferguson and 394 Wood (2010) who found a maximum -29% bias in increasing cloud coverage and -15 to -40% 395 by Wong et al. (2015). The cold bias present for both cloud and cloud-free days occurred at 396 the surface to about 500 hPa (Figure 4c). Beyond this level, a warmer bias is observed to 397 reflect an over-estimation of the AIRS profiles especially at the 150 hPa and 100 hPa levels. 398 The effect of clouds on retrievals at the 850 hPa and 500 hPa were found to be negligible 399 as there was an overlap for both scenarios. Overall bias range was within a $\pm 10\%$. On the 400 other hand, RMSD profile (Figure 4d) shows accurate retrievals under cloudy conditions 401 than non-cloudy condition. AIRS accuracy mission goal is satisfied under all occasions for 402 the lower and upper troposphere. Upper tropospheric relative humidity RMSD was observed 403 to be less than 30% for the cloud and cloud-free days with the cloud-free days slightly out-404 performing the cloudy days. For the lower to middle troposphere, the RMSD for cloudy 405 conditions was observed to be lower than cloud-free days. At the 850 hPa, a higher RMSD 406 exceeding the goal limit of < 20%. 407

408

3.4 AIRS and NCEP_R2 retrieval skill comparisons

Figure 5 shows the performance of AIRS and NCEP_R2 with RAOB temperature and 409 relative humidity profiles for the coastal and inland regions. To find the overall performance 410 of both AIRS and NCEP_R2, all overpasses of AIRS were merged and compared with 411 the corresponding profiles of NCEP_R2. Cold biases are observed to dominate the coastal 412 AIRS temperature retrievals whereas the inland AIRS temperature profile decreases from 413 warm (below 600 hPa) to cold (above 600 hPa) (see Figure 5a). NCEP_R2 for the coast 414 alternates between cold bias at the surface to mid-troposphere, beyond which a warm bias 415 exists. The inland NCEP_R2 temperature bias profile is also pre-dominantly cold except 416 at the 925 hPa and 250 - 200 hPa pressure levels. Comparing the location biases of AIRS 417 and NCEP_R2 temperature, inland AIRS over-estimates NCEP_R2 profiles at the surface 418 to middle troposphere and under-estimates at the upper troposphere. Alternatively, the 419 coastal performance observes NCEP_R2 to over-estimate the AIRS temperature bias profile 420 at the upper troposphere. The temperature RMSD profile is shown in Figure 5b for AIRS 421 and NCEP_R2. Both AIRS and NCEP_R2 were unable to reach the AIRS accuracy goal 422 except at the 600 hPa and 250 hPa for NCEP_R2 inland statistics. The performance for 423 both datasets was observed to be better for the inland region than the coast. The inland 424 AIRS and NCEP_R2 showed temperature profiles with decreasing RMSD from 3 °K to 425 about 1 °K from the surface to 600 hPa and a significant increasing RMSD from 250 hPa 426 to 150 hPa. The RMSD at the coast was relatively higher with greater deviation within the 427 NCEP_R2 datasets. The highest difference between the coast and inland regions for AIRS 428 and NCEP_R2 occurred from the 850 hPa to 250 hPa levels. Regardless of station, there 429 was a tendency for higher RMSD at the upper troposphere with the maxima occurring in 430 the the NCEP_R2 coastal temperature and the least in the AIRS inland temperature. 431

The bias and RMSD profile for AIRS/NCEP_R2 relative humidity is observed in Figure 5c 432 and d. Bias (Figure 5c) was found to be in range of -6% to 10% for both datasets. AIRS and 433 NCEP_R2 coastal water vapour is observed to be constantly under-estimated as compared 434 to an over-estimation for the inland. The coastal under-estimation is however observed to 435 be smaller (\approx -2% to -3%) than the inland RH over-estimations (\approx 4% to 6%). Bias was 436 also observed to be increasingly higher (inland) and lower (coast) at the upper levels. In 437 addition, the bias reveals lower values of AIRS at the coast than inland with the reverse 438 being observed in the NCEP_R2 relative humidity profile. The RMSD (Figure 5d) reveal 439

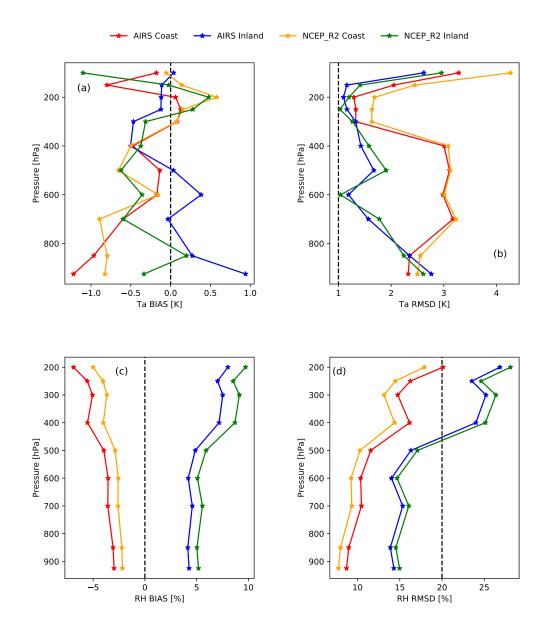


Figure 5. Diurnal uncertainty statistics of AIRS and NCEP_R2 for temperature (\mathbf{a} and \mathbf{b}) and relative humidity (\mathbf{c} and \mathbf{d}) profiles for coastal and inland stations. Coastal and inland statistics are a merge between the daytime and nighttime datasets. Broken vertical lines in RMSD represent AIRS accuracy goal for temperature (\mathbf{b}) and relative humidity (\mathbf{d}). The first and second vertical lines at 20% and 50% in the RH RMSD shows the accuracy goal for lower and upper troposphere respectively. Recommended bias at broken vertical line 0 °K.

the datasets to achieve both lower and upper tropospheric water vapour accuracy goal. 440 As lower biases were obtained over the coast, this is reflected in the higher satisfactory 441 performance in the RMSD (< 20%) for the upper and lower troposphere. Furthermore, the 442 NCEP_R2 is found to give relatively accurate estimates of the tropospheric water vapour 443 content than AIRS along the coast, probably due to the better representation of coastal 444 RAOB information into NCEP_R2 model run. Although the upper tropospheric RMSD 445 was acceptable for both datasets inland, the profile was observed to be sharper from the 500 446 hPa level as compared to the coast. AIRS is also observed to outperform NCEP_R2 inland 447

than at the coast. In general, the performance of AIRS and NCEP_R2 for RH is acceptable
and satisfactory. The satisfactory performance of NCEP_R2 is expected as global RAOB
information is incorporated in the estimation of temperature and relative humidity profiles
Divakarla et al. (2006). Table 2 is a summary of the AIRS performance at the various
atmospheric pressure levels for temperature and relative humidity.

Table 2. Summary of RMSD AIRS-RAOB accuracy for temperature and relative humidity. Values in bold represent atmospheric levels at which RMSD for temperature was atleast closer to the AIRS accuracy goal (1 ± 0.5 °K).

Pressure level (hPa)	Temperature RMSD (%)		RH RMSD (%)	
	Coast	Inland	Coast	Inland
925	2.32	2.76	8.68	7.73
850	2.35	2.34	8.96	7.97
700	3.17	1.56	10.45	9.30
600	2.98	1.18	10.36	9.22
500	3.10	1.67	11.55	10.28
400	3.00	1.42	16.16	14.38
300	1.32	1.32	14.75	13.13
250	1.33	1.67	16.25	14.46
200	1.29	1.09	20.10	17.89
150	2.05	1.16		
100	3.28	2.62		

453

3.5 Variation of thunderstorm convective indices at the stations

According to Ferguson and Wood (2011), the AIRS sensor has the potential to be used 454 for local convective rainfall prediction based on thunderstorm convective indices. They de-455 rived the convective triggering potential and humidity index (from 50 hPa to 150 hPa above 456 ground level) from AIRS temperature and relative humidity profiles and found these indices 457 useful at geographical locations where the predictive power was high. Therefore, our study 458 also evaluated the AIRS and NCEP_R2 derived convective instability indices: K-index, TT 459 index and HI for West Africa against RAOB derived indices. We have evaluated the seasonal 460 biases in AIRS and NCEP derived convective indices here, which in the future, will need 461 to be translated into terms of actual thunderstorm probability and strength for the region. 462 Figure 6 shows the three year (2006-2008) seasonal climatology of the indices for both AIRS 463 and NCEP_R2. The climatology of the indices for both datasets was observed to be similar 464 with NCEP_R2 overestimating slightly at all seasons. The dry season climatology reveals 465 a high probability of convective activities and rain over the southern part of West Africa 466 especially along the coast as compared to inland areas. The Sahelian region which is further 467 northward of West Africa observes low likelihood of rains. Low K-Index are found over the 468 Sudano-Savanna belt with a decreasingly lower negative probability. Furthermore the HI for 469 the dry period elaborates on the effects of sea breeze on the along the coastal areas which 470 results in relatively high humidity and a corresponding low humidity index. Inland low HI 471 is a consequence of the deciduous and semi-deciduous forest which characterises this zone. 472 On the other hand, the dry harmattan winds which engulf the region with the most affected 473 being the Sudano-Savanna zone observes higher than usual humidity index; exceeding two 474 to three times the recommended threshold of $\leq 30^{\circ}$ C. This observation is captured in both 475 AIRS and NCEP_R2. 476

The migration of the ITB, evident in the increased convective activities in over West Africa can also be monitored with these thunderstorm convective indices in the wet season. As

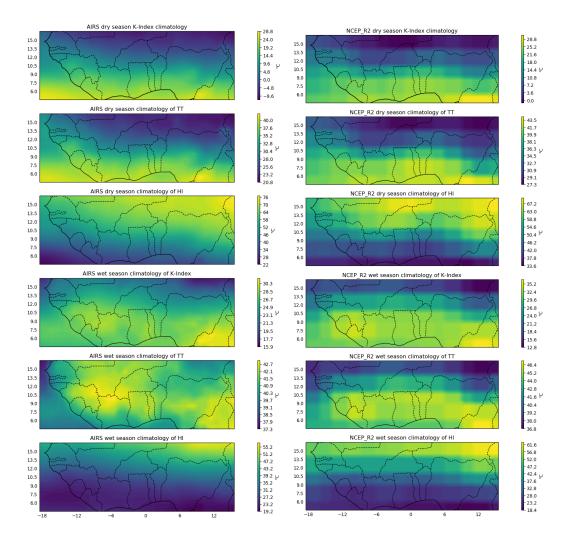


Figure 6. 3 year (2006 - 2008) dry and wet season index climatology from AIRS and NCEP_R2 for the entire West Africa. Dry season include months December, January and February whereas the wet season includes all other months.

can be observed, AIRS shows an under-estimation of K-Index and Total Totals (TT) index 479 probably due to the retrieved relative humidity being lower than the estimates of NCEP_R2 480 (Figure 6). The HI on the other hand has good correlation for both datasets except at the 481 north-western portion of West Africa which is closer to the Saharan desert. The TT index 482 for NCEP_R2 shows the wet season to have a higher probability of thunderstorm occurrence 483 around latitudes 6° N to 10° N while AIRS shows an isolated maximum concentration of 484 these activities converging over Northern Ivory Coast, North-eastern Guinea, Southern Mali 485 and Burkina Faso (Figure 6). In general, AIRS and NCEP_R2 are able to show the seasonal 486 likelihood of thunderstorm activities over West Africa. 487

Figure 7 presents the AIRS and NCEP_R2 differences (AIRS-NCEP_R2) for the thunderstorm indices based on the seasonal climatology. Generally, NCEP_R2 is found to overestimate the occurrence of precipitation in the dry season based on the indices. However, this over-estimation is also found to be lower and reduced in during the wet season. Deviations were highest for the HI in both dry and wet season as compared to the other indices. The dry season K-Index reveals an over-estimation of NCEP_R2 over the entire West African sub-region with AIRS over-estimating off the coast of Liberia and Senegal. This is likely

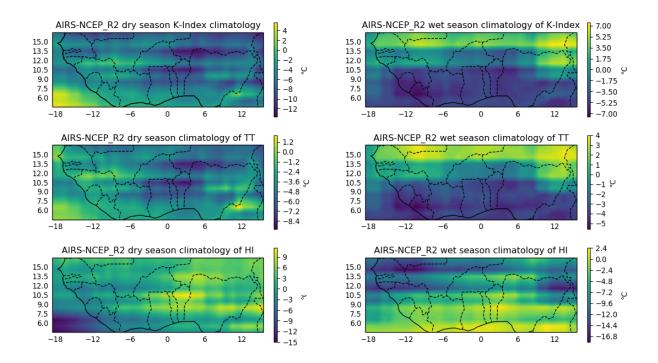


Figure 7. Difference in the index seasonal index climatology between AIRS and NCEP_R2 (AIRS-NCEP_R2). Dry season include months December, January and February whereas the wet season includes all other months.

due to the accuracy of AIRS in retrieving relative humidity profiles over the sea than coast 495 and inland (Divakarla et al., 2006), resulting in a direct effect on the calculation of K-Index 496 from AIRS datasets. The corresponding wet season climatology shows a high thunderstorm 497 probability from NCEP_R2 analysis situated over inland Liberia (< -7 °C). Few areas are 498 found to have no difference in thunderstorm prediction over West Africa in the wet sea-499 son from the K-Index (0 $^{\circ}$ C). A higher thunderstorm probability in AIRS is observed in 500 the inland regions the vicinity of the Sahelian with over-estimated values reaching about 501 7 °C. In the dry season (Figure 7), the AIRS TT index over-estimates the rainfall activi-502 ties by locating a hotspot (> $1.2 \,^{\circ}$ C difference) at the Nigeria-Cameroonian border. This 503 was also captured by the K-Index however at a difference of ≈ 3 °C. It can be observed 504 that the seasonal differences in AIRS and NCEP_R2 for the derivation of the TT index is 505 relatively lower than the other indices. The wet season TT index likewise the K-index is 506 also observed to have a higher rainfall likelihood (from AIRS) at the Sahelian region and 507 no difference at the sudano-savanna region. In addition, the observation for the K and TT 508 wet season indices show that the AIRS over-estimations have a latitudinal increase from 509 the coast to further inland regions of West Africa (Figure 7). The intensity of over- and 510 under-estimation of AIRS in the dry season HI is observed to be in complete opposite to 511 the K-index dry season climatology. On the other hand, inland areas where AIRS obtained 512 larger under-estimations in K-index corresponded to higher over-estimations in the HI for 513 the dry season. Nonetheless, the western regions of West Africa was obtained relatively no 514 difference in thunderstorm prediction for AIRS and NCEP_R2 in the dry season. For the 515 wet season, HI differences although lower than the dry season, has AIRS over-predicting 516 rainfall in most areas of the West African sub-region (Figure 7). 517

The seasonal comparison of the indices derived from AIRS and NCEP_R2 collocations with radiosonde calculated indices is given in Tables 3 and 4. A general observation was a better correlation between AIRS and RAOB calculated indices at the stations. The slight overestimation found in NCEP_R2 from Figure 5 is also observed in the extracted indices at

Station	K-Index RAOB	AIRS		'T index RAOB AI	RS NCEP	HI RAOB	AIRS	NCEP
Abidjan	23.86	25.13	25.80	38.43 40	.64 40.65	29.73	29.55	28.80
Cotonou	23.18	25.47	20.58	37.30 40	.47 38.78	29.58	22.33	40.34
Ougadougou	-1.85	-9.37	9.44	21.81 13	.50 27.78	77.31	95.89	63.57
Parakou	21.05	23.50	28.82	37.52 38	.02 43.80	42.53	42.75	38.00
Tamale	-2.26	-0.66	21.88	27.97 30	.53 46.05	76.75	72.46	45.61

Table 3. Comparison of AIRS and NCEP_R2 derived stability indices in the dry season (December-February). Units of all indices in degree Celsius (°C)

the stations was also found to be higher than RAOB calculated indices. In the dry season, 522 the coastal stations Abidjan and Cotonou had lower bias as compared to the RAOB, in 523 the K-Index, TT index and the HI for both AIRS and NCEP_R2. The HI however has 524 a larger difference for NCEP_R2 with the RAOB over Cotonou to suggest the low chance 525 of thunderstorm formation at the coastal station. Over Ougadougou, the difference in K-526 Index between AIRS and RAOB was found to be low $(-7.59 \,^{\circ}\text{C})$ as compared to RAOB and 527 NCEP_R2 (11.29 $^{\circ}$ C). The TT index and HI revealed on the other hand obtained a higher 528 bias between AIRS and RAOB (Table 3). The capability of AIRS in measuring the very 529 low dry season humidity conditions over Ougadougou is observed to translate into the low 530 TT and corresponding HI. The AIRS derived indices suggest virtually no probability for 531 thunderstorm occurrence which is to be expected over the station during this period. Over 532 Parakou there was a good agreement between RAOB and AIRS derived indices although 533 NCEP_R2 was also not highly biased. The K-Index at Tamale agreed only in the AIRS 534 (-0.66° C) and RAOB (-2.26° C) datasets with the NCEP_R2 over-estimating in both K-535 index and TT and underestimating in the HI (Table 3). But in general, the low probability 536 of thunderstorm occurrence at these stations were well observed by the indices for the dry 537 season. 538

The RAOB indices for the wet season at the stations is shown in Table 4. The derived 539 indices for RAOB, AIRS and NCEP_R2 were in agreement with low biases. The humidity 540 index also observed values which were below 30° C and supports the the increased chances 541 of thunderstorm events as moisture is advected by the south-western winds towards these 542 stations. Close agreement was found at the Accra station between ROAB and NCEP_R2 for 543 George's K and TT indices. In most instances, AIRS and NCEP_R2 had a relatively per-544 fect agreement for thunderstorm prediction. Furthermore, AIRS and NCEP_R2 marginally 545 over-estimate the indices (K and TT indices) compared to RAOB and under-estimates the 546 HI. But there exists a good correspondence between AIRS and RAOB HI over Accra and 547 Kumasi. 548

549 4 Conclusions

Determination of a pre-convective environment for thunderstorm formation requires a long time-series of sounding data. Radiosonde observation offer the most accurate vertical profiles of temperature and relative humidity. However these observations are scarce in West Africa and hence the need to rely on suitable satellite products for convection assessment.

Station	K-Index RAOB	AIRS	NCEP	TT index RAOB	AIRS	NCEP	HI RAOB	AIRS	NCEP
Abidjan	27.77	28.20	30.01	40.18	41.26	41.45	21.57	21.56	17.95
Accra	28.50	30.99	28.61	39.95	40.83	39.73	19.44	15.18	14.29
Cotonou	23.35	32.21	31.26	35.51	42.04	42.05	21.78	14.24	15.90
Kumasi	28.19	31.32	32.74	40.51	42.37	42.80	18.82	15.55	12.51
Ougadougou	22.72	31.80	33.57	37.45	45.27	46.36	28.90	22.78	23.74
Parakou	29.15	33.52	33.79	41.82	43.39	44.37	21.44	14.24	15.64
Tamale	29.78	32.48	32.36	42.76	45.40	46.99	23.97	23.21	17.24

Table 4. Comparison of AIRS and NCEP_R2 derived stability indices in the wet season (March-November). Units of all indices in degree Celsius (°C)

The Atmospheric InfraRed Sounder on-board the AQUA satellite provides atmospheric 554 sounding information twice daily, which may be used as a reliable substitute for RAOB 555 observation globally. The study assessed the performance of the AIRS IR-Only level 3 556 standard retrieval version 6 and for context, NCEP_R2 vertical temperature and relative 557 humidity profiles for some select AMMA and DACCIWA radiosonde observation stations in 558 West Africa within spatio-temporal collocation radius of 100 km and ± 3 hours for AIRS and 559 NCEP_R2. The performance of AIRS vertical profiles for diurnal, seasonal, cloud and cloud-560 free analyses as well as with collocated NCEP_R2 profiles were assessed. Finally seasonal 561 variation of three thunderstorm convective indices (K-Index, TT index and HI) for each 562 station was computed and compared for RAOB, AIRS and NCEP_R2. 563

The diurnal temperature profile reveals lower biases however with corresponding higher 564 RMSD above the AIRS mission goal of ± 1 °K. AIRS temperature RMSD show higher 565 values at the coast as compared to inland regions, possibly due to complications in surface 566 emissivity, skin temperature and the diurnal sea and land breeze effect which is strongest 567 along the coast. The reverse of the temperature RMSD however is observed to occur at night. 568 The relative humidity on the other hand, was found to be more accurate for the descending pass than ascending for all zones with the coastal stations dominating in all passes. On 570 the seasonal timescale, the temperature bias for the dry season is pre-dominantly cold. The 571 corresponding RMSD were also higher and deviated towards the inland wet season profile. 572 The coastal dry season was the least deviated, albeit, all zonal deviations were higher (≈ 1.0 -573 5 °K). Inland wet season RH profile was the most biased (cold) whereas the RMSD showed 574 satisfactory performance at all level tropospheric levels for all zones and seasons. Cloudy 575 conditions were found to have no significant effect on the RH retrievals by AIRS as the bias 576 and RMSD between cloudy and non-cloudy days were found to have marginal differences and 577 both achieving the AIRS accuracy goal of < 20% and 50% for lower and upper troposphere 578 respectively. The temperature retrievals however are better on cloud-free than cloudy days. 579 Comparison of the temperature and RH retrievals of AIRS with NCEP_R2 reveal AIRS to be 580 a better substitute for RAOB vertical profiles at the coast and inland. Finally, the seasonal 581 derived thunderstorm indices for AIRS and NCEP_R2 showed that both datasets can be 582 utilised for the occurrence and non-occurrence of thunderstorms in the wet and dry seasons 583 though NCEP_R2 generally over-estimates the thunderstorm probability. Comparing the 584 derived indices of AIRS and NCEP_R2 with RAOB indices at the seven stations also show 585 a higher agreement for all seasons. 586

In general, the performance of AIRS at these West African stations has been satisfactory for the temperature (although with slight over-estimations) and the RH. Based on the performance of AIRS for the derivation of thunderstorm convective instability indices, it is
 proposed to be used further for the determining the probability of convection initiation over
 West Africa under the GCRF African SWIFT project by focusing on the statistical analysis

⁵⁹² of thunderstorm convective indices over the region.

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