Data Assimilation of GPS-RO Atmospheric Profile Data for Improved Rainfall Forecasts over West Africa

Dataassimilation av GPS-RO atmosfäriska profildata för förbättrade nederbördss-prognoser över Västafrika

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Abstract

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Forecasting rainfall is of great importance for the farmers in West Africa. However, due to lack of reliable weather observations, rainfall forecasts in West Africa are difficult and primarily based on satellite observations. This thesis will study a satellite dataset that could possibly work as a substitute for weather balloon soundings and thus improving the rainfall forecasts.

A satellite dataset with atmospheric temperature and humidity profiles, obtained from GPS-RO, was compared with radiosondes available from Abidjan, Bamako and Niamey, to study the potential of improving rainfall forecasts over West Africa. Two case studies with simulated weather forecasts with and without assimilated GPS-RO data was also compared. Data assimilation is used to produce an estimate of the atmospheric properties.

Temperature profiles obtained from GPS-RO data showed insignificant bias compared to the radiosondes. Probable humidity sensor failure resulted in problem analysing the dew point temperature. From simulations, it was shown that GPS-RO assimilation may have a large impact on the forecasts and could potentially be a substitute for radiosondes in West Africa.

Keywords: GPS-RO, West Africa, rainfall, satellite

Degree Project E in Meteorology, 1ME422, 30 credits
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ISSN 1650-6553, Examensarbete vid Institutionen för geovetenskaper, No. 357, 2016

The whole document is available at www.diva-portal.org
Populärvetenskaplig sammanfattning

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Regnprognoser är något som är viktigt för jordbrukare. I Västafrika saknas pålitliga väderobservationer och regnprognoser är istället baserade på satellit observationer. Denna uppsats riktar sig på att studera ett satellit dataset som har möjligheten att vara ett substitut för väderballongssoneringar och på så vis vara ett steg mot förbättrade regnprognoser.


Temperaturprofilerna erhållna från GPS-RO data visade ingen signifikant skillnad jämfört med radiosonderingarna. Troligt sensorfel i fuktighetsgivarna från radiosonderingarna ledde till problem med analysen av daggpunktstemperaturen. Simuleringar visade att assimilation med GPS-RO kan ha stor påverkan på prognoserna och har potential att bli ett substitut för radiosonderingar i Västafrika.

Nyckelord: GPS-RO, Västafrika, nederbörd, satellit

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ISSN 1650-6553, Examensarbete vid Institutionen för geovetenskaper, Nr 357, 2016

Hela publikationen finns tillgänglig på www.diva-portal.org
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1 Introduction

A large part of the population in Ghana are farmers which are very dependent on the weather for as small crop losses as possible. For farmers, the importance of knowing if there will be a heavy rainfall or no rainfall at all is of importance to better plan and keep a sustainable agriculture, thus the need for an accurate weather forecast, something that always can be improved. This study will analyse a substitute for weather balloon soundings as a tool to improve rainfall forecasts in West Africa. The analysis will compare a certain dataset of satellite data with weather balloon soundings, hereafter referred to as radiosondes, and also compare weather forecasts simulations with and without the dataset.

Good weather forecasts are reliable on good initial conditions. Weather stations which measure rainfall, wind and temperature for example together with radar are very good tools to get reliable forecasts. Radiosondes are the best tool to get a temperature profile of the atmosphere, a feature which also is of great use in forecasts. However, due to lack of operational weather stations and the absence of radar in West Africa, the importance of satellite data as input has a strong advantage. As a substitute to radiosondes, radio occultation technique is tried out for meteorological use, by using Global Position System satellites together with Low Earth Orbit satellites to perform a temperature profile of the atmosphere. The radio occultation technique is described more deeply in section 2.2. It is based on the signals sent by a Global Positioning System satellite to a Low Earth Orbit satellite while the later is set behind the earth making the signal go through the atmosphere of the earth. From the bending angle the signal is making when moving through the atmosphere, a temperature profile is received.

Two different GPS radio occultation datasets are used, the COSMIC2000 and COSMIC2013. The two GPS radio occultation datasets are compared to radiosondes from three stations in West Africa. The analysis is divided into two parts: the first major part analyse the errors in temperature and dew point temperature between the GPS radio occultation datasets and the radiosondes, the next part analyses the difference between a forecast without GPS radio occultation data and a forecast with GPS radio occultation data to see the impact.

This report will start with an insight of the weather and climate of West Africa, with fundamental descriptions on common weather systems and climatological features that affect the rainfall in the region. The section will be followed by a description on the datasets used in the analysis. Further, the method are described together with fundamental statistics used in the analysis. Last, the result is presented followed by a discussion on the most important feature.

2 Theory

2.1 West African weather and climate

2.1.1 Climate

The large-scale climate over West Africa can roughly be defined by two categories according to Köppen’s climate classification (Köppen and Geiger, 1936; Liljequist, 1970). First there is the northern Savannah climate with one rainy season during the summer. Then there is the coastal monsoon climate with two
rainy seasons which stretches from Sierra Leone to Cameroon. However, there is an exception to this model and that is the Dahomey Gap, an isolated patch of Savannah that covers southern coastal Ghana, Togo and Benin, thus separating the forest zone into two part one western (The Upper Guinean forest) and one eastern (the Lower Guinean forest). The reason for this drier part in the monsoonal belt can be explained in two ways (Leroux, 2001; GMET, 2015). Firstly, the coastline lies in the same direction as the monsoonal wind, thus the moisture in the incoming monsoonal air decreases as the air moves along the coast instead of straight on. Secondly, during the boreal summer, i.e. the monsoon season, there is a significant upwelling of cold water off the coast of Ghana and eastward to Togo. This upwelling cools the air and causes stable stratification and less moisture in the boundary layer resulting in less precipitation (Leroux, 2001). In figure 1 shows the mean annual rainfall between 2001 and 2013 and is based on satellite estimations.

![Figure 1 Mean annual rainfall between 2001 and 2013, in mm.](image)

2.1.2 Convection

The precipitation over West Africa is formed, as for most tropical areas, almost exclusively by convection (Sultan and Janicot, 2003a). There is, however, several mechanisms that can intensify or reduce the convection. Maybe one of the most prominent feature is that of the geography. West Africa is in many ways a lowland, rarely exceeding 500 meters in altitude (Leroux, 2001). However, highlands exist both in the east and the west where the altitude reaches well above 1000 meters. This lowland feature gives the air ability to move freely. The relatively flat topography can recieve sunlight all day resulting in perfect conditions for convection. The convection produced by the direct sunlight over the lowland together with its close proximity to the sea give rise to prominent sea breeze effects. 'Sea breeze' effect can also occur over land with soil-moisture gradient differences (Ookouchi et al., 1984; Yan and Anthes, 1987;
Taylor, Parker and Harris, 2007). The variation in soil-moisture over land can affect the convection and create a sea breeze like circulation almost as prominent and intense as the sea breeze itself. Studies have shown that the air temperature over wetter soil is significantly colder than the drier soil, creating conditions similar for sea breeze development.

A mechanism for organisation and the development of new convective cells is cold pools (Tompsonkines,engerer. Cold pools are areas of downdraft air underneath precipitating clouds that are cooled by evaporation and spread out horizontally. The warmer air is lifted when the cooler air moves forward with convective cell, developing new convective cells. The circulation in the boundary between the cold pool and the surrounding is the main mechanism for feeding new multicell thunderstorms. However, cold pools can, if moving faster than the convective cell, cut off the warm air supply resulting in the demise of the convective cell.

Deep convective systems in the tropics show two significant maxima, one in the afternoon-early evening and one during late night-early morning (Gray and Jacobson, 1977). The deep convective maximum in the afternoon-early evening is normally a result of intense solar radiation and surface heating during the day, while the night maximum is due to cooling of the cloud tops resulting in instability which allows deeper convection and more precipitation. During morning the cloud tops are heated which reduces the potential convection.

Studies have shown that another mechanism to induce convection is gravity waves (Uccellini, 1975; Stobie, Einaudi and Uccellini, 1983; Alexander, Holton and Durran, 1994). By wind shear the convective cells develop as they propagate along the wave.

As for mid-latitudes, convection related to jet streams occur also in the tropics (Williams and Knife-ton, 2001; Laing and Evans, 2015). Air moving into the jet is accelerating and decelerating when leaving the jet. The imbalance between the Coriolis force and pressure gradient induce the ageostrophic motion, this lead to divergence on the right side and convergence on the left side in the wind direction in the jet entrance and the opposite in the jet exit. Thus, convective precipitation can develop on the right-hand side in the jet entrance and on the left-hand side in the jet exit.

2.1.3 The Sea Breeze

The sea breeze is a local wind circulation system which is generated by the differences in heat capacity between sea and land. The differences in heat capacity are resulting in the land heating faster than the sea during the day. When the land is heated, a local low pressure at the surface develops while a corresponding local high is created over the sea. This causes the pressure gradient to increase, resulting in winds at lower level in the atmosphere blowing from the sea onto land. The opposite occurs during the evening until the system breaks down and starts over the next morning. Larger differences in temperature over land and sea cause stronger wind speed. Along the West African coast the sea breeze can reach up to 50 – 100 km in over land (Leroux, 2001). Compared to the mid-latitudes, the Coriolis effect have no (or negligibly small) impact on the sea breeze over West Africa (Laing and Evans, 2015).
2.1.4 The Monsoon

A monsoon is here defined as a wind flux originating in one hemisphere and moving into the other, which disturbs the circulation in the second geographical hemisphere (Leroux, 2001, Laing and Evans, 2015). The West African Monsoon (WAM) can be compared to a large-scale sea breeze with a seasonal cycle instead of a diurnal cycle, where the Saharan Heat Low is a major feature (Janicot, Lafore and Thorncroft, 2010). As for the sea breeze, the conditions over ocean and land are crucial for the character of the monsoon. The mean seasonal cycle corresponds to the movement of the Inter Tropical Convergence Zone (ITCZ). The cycle of the ITCZ over West Africa is characterised by several steps of active phases and pauses. The strongest of these steps are the "onset", usually occurring in the end of June, when the ITCZ "jumps" abruptly from 5°N to 10°N. This "jump" corresponds to a weakening in convection and occurs mainly between 10°W and 5°E (Sultan and Janicot, 2003b). The weakening in convective activity leads to a distinct minimum in rainfall during July close to 5°N. The ITCZ stays in the northern position (∼10°N) until late August and the period is the only rainy season of the Sahel. In August the ITCZ starts moving southward again and passes the coastal areas which leads to a second rainy season in the coastal region.

During the boreal winter, when the ITCZ is at its southerly limit, West Africa undergoes a distinct dry season which is dominated by the north-easterly trade winds coming from the Saharan desert, called harmattan (Leroux, 2001). The air that flows into the region by the harmattan is very dry and often brings sand and dust.

2.1.5 The Tropical Easterly Jet, African Easterly Jet and African Easterly Waves

The Tropical Easterly Jet (TEJ) is a dominant and intense feature at around 200 hPa (Chen and van Loon, 1987; Nicholson et al., 2006). It extends from Indochina to western Africa and has its maxima over the Indian Ocean around the latitudes of 5°N to 10°N with wind speeds up to 25 ms$^{-1}$. Some studies indicate that the intensity of the TEJ is one of the strongest differences between wet and dry years over West Africa. Despite this, TEJ is usually viewed as a passive system. Studies in the TEJ of the India has indicated that weaker intensity in the jet is correlated to drier years.

The seasonal movement of the ITCZ and the monsoon is closely linked with the African Easterly Jet (AEJ), which is mostly developed and controlled by the circulation between the dry harmattan and the moist air of the ITCZ. It is an important feature of the zonal wind and the vertical shear which organise the convection (thorncroft,sultan1b). The center of the AEJ is located at around 600 – 700 hPa between the dry harmattan air and the ITCZ, south of the Inter Tropical Front at the surface. Through baroclinic and barotropic perturbations, the AEJ is responsible for the formation of the African Easterly Waves (AEW) which are the major synoptic scale phenomena in West Africa (Thorncroft and Blackburn, 1999; Leroux, 2001; Janicot, Lafore and Thorncroft, 2010). They originate west of 20°E somewhere near the Darfur Mountains and the Ethiopian Highlands and move westward with a speed of ∼8 ms$^{-1}$ and a wavelength between 2000 and 4000 km, which gives a periodicity of 3 – 5 days (Diedhiou et al., 1999). The lifecycle of AEWs are often divided into three phases (Janicot, Lafore and Thorncroft, 2010). The initiation phase is triggered by convection over the highlands of Darfur and Ethiopia and the growth
of the AEW is accomplished through dynamic feedback (Janicot, Lafore and Thorncroft, 2010; Laing and Evans, 2015). Once in motion, the AEWs move westward and develop in response to baroclinic and barotropic instability along the AEJ. The waves continue growing while propagating westward and starts to affect the convection by wind shear. When approaching the West African coast, development of convection over the Guinea highlands is often significant (Janicot, Lafore and Thorncroft, 2010). The potential vorticity in the convection over the Guinea highlands interacting with the AEW creates a structure ideal for triggering tropical cyclones when the waves move out over the Atlantic. Studies have shown that there is a significant correlation between AEWs and tropical cyclone activity over the eastern Atlantic (Thorncroft and Hodges, 2000).

2.1.6 Squall Lines

An important convective system over West Africa is the Squall Line (SL). However, there is significant latitudinal differences in the contribution to the total rainfall. In the northern parts of the Sahel, SL contributes to over 90% of the total rainfall, while further south it counts for less than 50% of the total rainfall (Schrage and Fink, 2007). Factors that trigger the genesis of SLs are still uncertain and suggestions range from topographic factors, disturbance between two air masses to rise in anticyclonic core (Leroux, 2001).

The evolution of a SL can be divided into different phases (Leroux, 2001). A short description of the phases will be discussed if we assume that our initial conditions are an atmosphere with neutral stratification with a clear sky. A disturbance in the AEJ triggers an anticyclonic movement along the jet moving southward towards the colder moist monsoonal air. The disturbance cut off from the AEJ and is working as an isolated anticyclonic core. The anticyclonic core becomes an obstacle for the monsoonal air as the flow is in the opposite direction. As the anticyclonic core moves southward it forces the colder monsoonal air northward and upward. The monsoon starts moving around the anticyclonic core, thus the core sinks deeper into the colder moist air as the monsoonal flow moves upwards. This creates strong convective cloud formation which could give rise to heavy precipitation and thunderstorms that are often associated with the SLs. If the SL is strong enough, it will penetrate the monsoon towards the West African west coast until the Azores High neutralise its further evolution. The strength of a SL is affected by how deep into the monsoon the anticyclonic core can penetrate as well as the depth of the monsoon layer.

2.1.7 Madden-Julian Oscillation

The Madden-Julian Oscillation (MJO) is a dominant intraseasonal oscillation in the Tropics with a life cycle of 30 – 60 days. It is a coupled atmosphere-ocean circulation that is responsible for much of the weather variability in the region (Madden and Julian, 1971; Zhang, 2005). The MJO can be described as a large-scale center of convection and precipitation moving eastward with zones of weak convection and precipitation west and east of this center. Anomalies in rainfall over the Indian and Pacific Oceans are often the first signs of a MJO. As it propagates eastward with a speed of 5 ms⁻¹, it suppresses and enhances convection along its way. The speed of the MJO is one fundamental feature that distinguishes
it from other more fast-moving waves (e.g. Kelvin Waves). Over the cold waters of the eastern Pacific, the pattern often becomes indistinguishable, but reappears again over the tropical Atlantic and Africa (Zhang , 2005). Variability in the WAM, AEWs and in tropical cyclone activity, is often coupled to MJO variations. Thus monitoring the MJO is of importance for forecasting the monsoon and tropical cyclones (Ventrice, Thorncroft and Roundy, 2011).

2.1.8 Vertical Structure of the Troposphere

The tropical zone in the general circulations can resemble an inverted "V" of highs with dominating easterly flow, enclosed with an extratropical westerly flow. The axis of symmetry of the inverted "V" is the ITCZ, the zone of rising air and the engine in the circulation. Below the inverted "V" we have the Intertropical Low Pressure (ITLP), due to the "V" of highs the ITLP occupies only the lower layer of the troposphere. Over sea, the symmetry have very small pertubations, however, over land are heated differently causes a seasonal shift and changes in the structure at lower levels in the troposphere. The dynamic and relative position of the ITLP acts more deeper with larger annual changes over land compared to over sea, due to landmasses faster reaction on the Sun’s position and heating (Leroux, 2001).

From atmospheric soundings, it is possible to measure the vertical structure of the atmosphere and vertical distributions of temperature, wind direction and speed and air moisture (Leroux, 2001). Soundings from Abidjan of coastal Côte d’Ivoire give an approximate mean vertical structure for the coastal areas (University of Wyoming, 2015). The soundings show that the tropopause lies around 17000 meters above sea level (a.s.l.) at 100 hPa. At the surface, winds from south to southwest are the most frequent which do not change very much during the year. During the boreal summer, the AEJ and the TEJ are clearly visible in the soundings, where the AEJ is visible from 850 hPa up to approximate 400 hPa and TEJ is visible from 250 hPa up to 150 hPa. From 400 hPa to 300 hPa there are usually weaker southerly winds between the two jet streams. During the boreal winter however, the TEJ is at its minimum and is often not seen in the soundings at all, thus over 400 hPa, winds usually are between south and west. The stratification of the troposphere over West Africa is normally very unstable. This means that the temperature decreases with height as seen in the soundings. However, it is possible to distinguish a period of stable stratification during the summer months of July and August when the ITCZ is north of Abidjan (University of Wyoming, 2015). From the soundings it is also possible to see that the air is very humid during the rainy season, while the two dry seasons often show a much drier air. This is especially significant during the longer dry season in the boreal winter, when dry air from Sahara is pushing down southward.

Soundings made from Bamako, Mali and Niamey, Niger shows distinct differences in some features compared to soundings made in Abidjan (University of Wyoming, 2015). Most prominent difference is seen in air moisture. Bamako and Niamey lies in the dry Sahel belt, thus the only months which experience any kind of moisture are in July and August. While the wind direction is much the same as for Abidjan during the boreal summer months, the lack of any significant jet stream during the boreal winter give rise to more dominant westerly winds. The stable stratification that is shown in soundings from Abidjan in July and August is not seen in the Bamako and Niamey soundings as they are close to
the northern limit of the ITCZ.

2.2 Global Positioning System radio occultations

Satellite-to-satellite soundings using radio and microwave occultation techniques have great value in numerical weather prediction (NWP) (Syndergaard et al., 2004). The Global Positioning System (GPS) opened up for radio occultation techniques. The phase in a GPS signal is affected by atmospheric refraction. Global Positioning System radio occultations (GPS-RO) technique can provide radio refraction profiles distributed over the globe. This is important for NWP, since radio refraction is related to pressure, temperature and water vapour pressure, essential parameters for weather predictions (Syndergaard et al., 2004; Sokolovskiy, Kuo and Wang, 2004).

The basic idea of GPS-RO is to use satellite-to-satellite soundings from a GPS satellite and a Low Earth Orbit (LEO) satellite combined with basic optics like Snell’s Law (Syndergaard et al., 2004; Sokolovskiy, Kuo and Wang, 2004). Each of the 24 GPS satellites orbiting Earth transmits signals at two L-band frequencies (within the radio wave frequency), \( L_1 \) at \( f_1 = 1575.42 \text{ MHz} \) and \( L_2 \) at \( f_2 = 1227.60 \text{ MHz} \). The frequencies correspond to wavelengths of 19.0 cm and 24.4 cm respectively. When the signal emitted by the GPS satellite passes through the atmosphere, the phase and amplitude is changed due to refractivity (Kursinski et al., 2000). The occultation occurs when a GPS satellite rises or sets relative to the LEO satellite such that the signal is passing through the Earth’s atmosphere. Figure 2 shows a schematic view of the basic theory behind Radio Occultations, where a GPS satellite (1) transmits a signal to the LEO satellite (3) while it sets behind the earth (4) and a profile of the atmosphere is obtained at the occultation point (2). With 24 GPS satellites a single LEO satellite receiver will provide up to 500 vertical profiles each day. The signal received by the LEO satellite is derived into a bending angle profile and an impact parameter under the assumption of local spherical symmetry of the refraction index. By using Abel transform (for descriptions on the Abel transform, see Beerends (1987) and Weisstein (2015)) it is possible to invert the bending angle and obtain the refractivity index and by assuming static equilibrium, the refractivity can construct fundamental meteorological variables: pressure, temperature and water vapour pressure (Syndergaard et al., 2004; Sokolovskiy, Kuo and Wang, 2004). The result is very high-resolution vertical profiles of the troposphere and stratosphere, which can be obtained globally. However, the local refractivity approximation can result in significant errors in the bending angle from large refractivity gradients (e.g. fronts, strong convection etc.) (Syndergaard et al., 2004; Sokolovskiy, Kuo and Wang, 2004). Errors in the refractivity can be derived from horizontal water vapour structure in the lower troposphere. For the meteorological variables, most important errors are derived from the spherical assumptions, which start to fail in the troposphere (Kursinski et al., 2000).

At the moment, the Constellation Observing System for Meteorology, Ionosphere and Climate (COSMIC) program has six orbiting LEO satellites (COSMIC-1) which produces over 1000 atmospheric occultations each day (COSMIC, 2014). In early 2016, six more LEO satellites will be launched with another six in 2018, as part of the COSMIC-2 mission.
2.3 Data Assimilation

A Data Assimilation System combines all available meteorological information, observed and modelled, which is accumulated in the state model to produce an estimate of the atmospheric properties during a given time-window (Barker et al., 2004). Data Assimilation techniques are widely used in atmospheric sciences e.g. for NWP models and reanalysis models.

For the past two decades, a variational data assimilation technique has been developed to optimise forecasts (Barker et al., 2003, 2004). The variational data assimilation uses three input data sets (Skamarock et al., 2008). The inputs needed are an initial first guess, observations and the background errors. Assimilation of all data gives an analysis which uses the existing boundary condition to produce the output forecast. An advantage with variational data assimilation is the elimination of an initialisation step which is useful in regions where the spatial density of observations are low, e.g. the Tropics (Barker et al., 2003, 2004). The solution to the variational data assimilations found using all observations simultaneously. Another advantage is the possibility to assimilate data from non-synoptic system in its validity time. This is possible in three-dimensional data assimilation (3D-V AR) explicit by balance equations and in four-dimensional data assimilation (4D-V AR) implicit through the forecast model itself. The main difference between the two versions of variational data assimilation is the time-dependence of 4D-V AR which uses observations before and after the time window of the analysis. This means that 4D-V AR is a more data consuming technique compared to the 3D-V AR. However, the possibility to implicitly assimilate non-synoptic data and the ability to increase the restriction in the dynamic balance of the final analysis makes it possibly the preferred model in the Tropics (Tsuyuki, 1995; Barker et al., 2004; Huang et al., 2008).

2.4 Weather Research and Forecasting model

The Weather Research and Forecasting (WRF) model is developed to be a state-of-the-art, portable code for NWP (Skamarock et al., 2008). Developed by the National Center for Atmospheric Research (NCAR), the National Oceanic and Atmospheric Administration (NOAA), the National Centers for Environmental Prediction (NCEP), the Air Force Weather Agency (AFWA), the Naval Research Laboratory,
the University of Oklahoma, and the Federal Aviation Administration (FAA), to be available for both forecasting and research. The WRF model features a software framework that provides the infrastructure with a dynamics solver, initialisation programs and WRF variational data assimilation. Two dynamic solvers are available, the Advanced Research WRF (ARW) solver developed by NCAR and the Nonhydrostatic Mesoscale Model (NMM) solver developed by NCEP.

The ARW version (used in this project) of the WRF model uses the ARW dynamic solver and encompasses physics schemes, numeric and dynamic options and variational data assimilation package (WRF-Var) in producing simulations (Skamarock et al., 2008). The physics schemes describe physical features, such as cloud physics, planetary boundary layer, radiation etc.

3 Dataset

To estimate the accuracy of the GPS-RO data, radiosondes were used from three stations: Abidjan (5°19’N 4°02’W), Bamako (12°39’N 8°0’W) and Niamey (13°31’N 02°06’E). The radiosoundings obtained from the three stations were assumed to be representing the real atmospheric condition. Radiosondes are sent up two times per day at 00 UTC and 12 UTC. The time window was chosen to be 2014 and 2015 for the study. However, it is not uncommon with shorter or longer periods of time with missing data, e.g. there are no sounding data from Bamako between 7th of June 2014 and 18th of September 2014. Unfortunately, many soundings showed very large sampling intervals, which resulted in some pressure levels being poorly covered. Lack of data were especially prominent between the 650 hPa and 750 hPa level in the Abidjan soundings, where only 5-10% of the radiosondes had data. Only actual measured data were used and no interpolation were made. Weather balloon soundings were received from the University of Wyoming (University of Wyoming, 2015). It is important to remember, while using radiosondes, that sensor failure is not uncommon (Liu and Tang, 2014). Humidity sensor failure can happen when the sensor goes through deep clouds with high water content. Humidity sensor failure can be detected by very dry humidity (<2%) which often stays constant, with no response to real humidity changes. Non-physical soundings has, when obvious, been removed from the dataset, e.g. when relative humidity has been much larger than 100% or dew points unphysically low. From the year 2014, we got a total of 1668 soundings, with 684 soundings from Abidjan, 452 from Bamako and 532 from Niamey. The weather balloon soundings contained data for 11 meteorological parameters. However, in the analysis only 5 parameters were used: pressure, altitude, temperature, dew point temperature and relative humidity. Due to the problems with the radiosondes covered above, a further extension of the time window was given for Abidjan, where we also used data from January to September 2015, which gave an additional 474 sounding profiles, resulting in a total of 1158 sounding profiles from Abidjan.

For the GPS-RO data, two different datasets were used: COSMIC2000 and COSMIC2013 from the COSMIC-1 mission. COSMIC2013 contains occultation data for the first 120 days of 2014 (1 January to 30 April) with 828 profiles in the area of interest. The area of interest is defined as the area within longitudes 12°W and 10°E and between latitudes 1°N and 15°N, as seen in figure 3. COSMIC2000 contains occultation data for the remaining 245 days, from 1 May to 31 December. The dataset contains 1480 profiles in the area of interest. The two datasets differ in data processing software, where COSMIC2013
is reprocessed and COSMIC2000 is post processed data. The profiles are obtained by assimilating the atmospheric refractivity index or bending angle based on 1-dimensional variational analysis using European Center for Medium-Range Weather Forecasts (ECMWF) with low resolution analysis data and temperature, moisture and pressure from the refraction angle (CDAAC, 2015). The data is interpolated through the atmosphere with 100 m vertical resolution. From other studies, it is known that GPS-RO data has a dry bias in the boundary layer when super-refraction occurs (Kuo et al., 2005; Sun et al., 2010; Xie et al., 2006). This means that for the dew point temperature, lower values are expected from the GPS-RO compared to the weather balloon soundings. We used data from the 100 hPa level down to the surface. In some cases, the GPS-RO has failed and given non-physical atmospheric profiles. This has often been shown as temperature reaching more than 100°C in the troposphere or by the temperature rising or falling from one vertical sampling to the next by several ten °C. These occultations have been removed. Parameters obtained from the GPS-RO sounding is pressure, water vapour pressure, coordinates in latitude and longitude, and altitude.

Figure 3 Topographic map of the area of interest.

Figure 4 Percentage vertical observation density for each pressure level for Abidjan in 2014.  

Figure 5 Percentage vertical observation density for each pressure level for Abidjan in 2015.
In figure 4, the vertical density of observations for Abidjan is shown compared to the total number of profiles for each pressure level. Pressure levels are for each 25 hPa, and the gap around the 750 hPa level is here clearly visible. Note the differences in the vertical density of the observations between 2014 and 2015 for Abidjan, figure 4 and 5. Figure 6 shows the vertical coverage of the pressure levels for Bamako and figure 7 shows the vertical coverage of the pressure levels for Niamey. Due to the poor coverage of the vertical levels from Niamey, the comparison between GPS-RO and radiosonde data will mainly base on Abidjan and Bamako, while the comparison for Niamey can be found in Appendix A.

4 Method

The accuracy of the GPS-RO data compared to the radiosondes were analysed by studying the seasonal, radial and vertical error dependency. Also the errors (Root-mean square error (RMSE), standard deviation and bias) for each GPS-RO dataset, COSMIC2000 and COSMIC2013 were studied. For Abidjan, further studies on errors in maritime airmasses and continental airmasses were performed. The different cases are defined and further described in the following paragraphs. Each possible GPS-RO profile was compared to a corresponding radiosonde from the same day, hence, GPS-RO profiles from days with no radiosondes were not used and vice versa. We assumed that any meteorological changes are too slow to be developed in a single day due to synoptic time and length scales. Meteorological parameters of relevance: pressure, temperature, dew point temperature, relative humidity and water vapour pressure, were sorted into 25 hPa pressure levels, from 100 hPa down to the surface at 1025 hPa, to make a comparison with the GPS-RO data possible. This gives a total of 37 layers from the surface layer, 1000-1025 hPa, up to the top layer, 100-125 hPa. For profiles with more than one value within a 25 hPa pressure level, the mean value was calculated. Only values from layers which are represented in both GPS-RO profiles and the radiosondes were used for statistical calculations. This gave a total of 729 used GPS-RO profiles for Abidjan from 2014 and another 465 profiles from 2015, 413 profiles for Bamako and 240 profiles for Niamey. As the radiosondes often contained gaps in their profiles, a finer resolution of the pressure levels (10 hPa levels) would lead to levels with no balloon sounding data, hence, levels with no statistical use in the analysis. However, the vertical coverage for the Niamey soundings are particularly
bad, since 22 levels (59%) are without any values with a 25 hPa resolution, a broader resolution of 50 hPa would still give a bad vertical coverage with 7 empty levels (39%) of 18 in total. A broader resolution of the pressure level (50 hPa levels) would also result in an unwanted loss or smoothing of raw data from the radiosondes. Further, it would also mask the error between GPS-RO and radiosondes by naturally occurring temperature variations becoming dominant.

<table>
<thead>
<tr>
<th>Table 1 Seasons of Abidjan.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Long dry season</td>
</tr>
<tr>
<td>Pre-monsoon</td>
</tr>
<tr>
<td>Monsoon</td>
</tr>
<tr>
<td>Short dry season</td>
</tr>
<tr>
<td>Short monsoon</td>
</tr>
</tbody>
</table>

When estimating the seasonal error of the GPS-RO dataset, different definitions were used for different weather stations. The Abidjan weather station, located at the coast, was defined to have five seasons: a Pre-monsoon season occurring in March through April, the Monsoon from May to June, a weaker short dry season from July to September, a weak autumn monsoon when the ITCZ is moving south in October and November and a stronger long dry season occurring from December to February. The definitions of the seasons of Abidjan can be seen in table 1. We divided the error estimations into two different cases: 2014 and 2015. By comparing the two years it was possible to determine if the datasets from each year are independent. This makes it possible to study the particulars of the two COSMIC datasets and seasonal impact on the bias. Table 2 shows the set up for the seasons and the datasets, and for the long dry season and the pre-monsoon, we studied the influence of the dataset on the bias. For the monsoon and the short dry season, the seasonal influence on the bias are studied. For the short monsoon season we did not have any GPS-RO data from 2015. For Bamako and Niamey, both located in the Sahel, only two seasons were defined: one long dry season occurring from October until June and the Monsoon from July to September. The main interest was to see how well the GPS-RO dataset is performing for each season and if there is an error dependency on the moisture regime. The radial limit for each weather station was set to 1000 km, due to the synoptic scale assumption. Hence, no GPS-RO profile further than 1000 km from the weather stations were used for the error estimation.

| Table 2 Set up between datasets and seasons for Abidjan. |
|-----------------|---------|---------|
| Sessaons        | 2014    | 2015    |
| Long dry season | COSMIC2013 | COSMIC2000 |
| Pre-monsoon     | COSMIC2013 | COSMIC2000 |
| Monsoon         | COSMIC2000 | COSMIC2000 |
| Short dry season| COSMIC2000 | COSMIC2000 |
| Short monsoon   | COSMIC2000 | -- |

For the radial dependency error estimation, four segments from the weather station were used, with the inner segment being everything less than 50 km from the station. The second segment was defined as the segment between 50 and 200 km from the station. Third segment was defined as the segment between 200 km and 500 km from the station and the fourth and outer segment between 500 km and 1000 km. It
is expected that the error would increase for each segment, however, the magnitude of the error increase would determine the validity of the synoptic scale assumption. It is of interest to understand how the error will change with distance. This will also show how useful the radiosondes are compared to the GPS-RO profiles, i.e. on how spatially dependent the data are. If there is a large spatial dependency, then much care has to be taken as this would indicate high sensitivity at smaller than synoptic scale. The different segments are in part related to the site of different synoptic and mesoscale systems in West Africa.

By estimating the error for each pressure level, it is possible to estimate the accuracy of the GPS-RO profiles through the atmosphere and in our case the troposphere. From the result it could be possible to say if the RO is performing better in the upper troposphere than the lower which would be expected since the number of useful occultations decrease with depth into the atmosphere down to the surface. E.g., less than half of the RO reach below the 900 hPa level. The pressure levels, as defined earlier, give a total of 37 levels from the top level 100-125 hPa down to the surface level 1000-1025 hPa.

Since two different datasets from the COSMIC-1 were used, it is of interest how the two datasets are performing compared to the radiosondes. However, since the two datasets do not overlap it is not possible to directly compare the accuracy between the two. The result will, however, hint if one is performing better than the other by means of statistical comparison.

The error estimation for maritime and continental airmasses studied for Abidjan was to compare the performance of the GPS-RO data and to see if there was a difference in the airmass regimes. Since the GPS-RO has a documented dry bias it was expected to be a difference in the performance of capturing the moisture content. For the maritime airmass, all GPS-RO profiles south of the 5° latitude were used and so all profiles north of the 5° latitude were defined as being in the continental airmass, which is a rough approximation but in all essence dominated by continental profiles.

As a final part of the report, case studies will take place, where weather forecasts are simulated with and without usage of GPS-RO data, to study the actual impact of GPS-RO in a weather forecast. For each case study, simulations were made using a weather forecast with three different initial conditions: one without assimilation data based on Global Forecast System (GFS), one with GPS-RO assimilation and one with conventional assimilation of all available meteorological information by using several different datasets. The conventional data assimilation is based on surface synoptic observations, METAR, radiosondes, remote sensing data, observations from ships and bouys. The model used for the simulations is a WRF-ARW with 9 km resolution and 48 vertical levels. Time window of the simulation were set to 30 hours with start at 00UTC. The first case is from 11 September 2015, where a squall line producing thunderstorms in western Ghana was not predicted by any available weather forecast model. The case will simulate accumulated rainfall between 06UTC 11 September 2015 to 06UTC 12 September 2015 based on the 00UTC run. The GPS-RO assimilation was based on 5 profiles available in the area of interest for this case. The squall line started at around 14:00 over Benin and Togo and moved west over Ghana until it died at the border to Côte d’Ivoire around 20:00. The second case study is from the 13 September 2015, where rainfall following an approaching AEW arrived to Ghana 24h earlier than forecasted. For this case, three GPS-RO profiles were used in the simulation.
4.1 Statistics

For the error estimations of the temperature and the dew point temperature in the GPS-RO data, mean error, mean standard deviation, root-mean square error (RMSE) and bias, were used as statistic measures in the analysis and MATLAB was used as the program tool for the study. For the standard deviation calculations, MATLABs own command `std`, which is based on equation 1, was used.

\[
\sigma = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} |A_i|^2}
\]  
(1)

where \(A = T_{sat} - T_{sond}\) and \(N\) is the number of profiles.

\[
\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (X_{sat,i} - X_{sond,i})^2}
\]  
(2)

\(N\) is the total of values used for a given profile when the e.g. seasonal or radial RMSE is calculated. This gives a value for each profile, in the mean value is then calculated to get a single value to represent all profiles of the studied case.

\[
\text{RMSE}_{\text{m}} = \frac{1}{N} \sum_{j=1}^{N} \text{RMSE}_j
\]  
(3)

where \(M\) is the number of profiles.

To see whether there is general under- or overestimation in the dataset, called Bias, the cumulative difference in temperature and dew point temperature between the GPS-RO dataset and the radiosondes were calculated as seen in equation 4. Where \(X\) is either the temperature or dew point temperature and \(N\) the number of profiles.

\[
\text{Bias} = \frac{1}{M} \frac{1}{N} \sum_{j=1}^{M} \sum_{i=1}^{N} (X_{sat,i,j} - X_{sond,i,j})
\]  
(4)

\(N\) is the total number of values for each profile used in the calculation and \(M\) is the total number of profiles used.

However, for calculating the vertical bias the corresponding formula is shown in equation 5.

\[
\text{Bias} = \frac{1}{M} \sum_{j=1}^{M} (X_{sat,j} - X_{sond,j})
\]  
(5)

where \(M\) is the total number of used profiles.
To determine the differences between the two COSMIC datasets and detect seasonal dependency in the bias, two-sample Student’s t-test were used by assuming normal distribution of the error and independent samples. The error distributions were plotted against a normal distribution match line to verify correct assumption. The probability distributions can be seen in Appendix B and an example in figure 8 shows the temperature bias of Abidjan for the short dry season of 2015 plotted against a normal distribution match line. If the bias follows the normal distribution match line, the data can be treated as a normal distribution. Indeed, the data in figure 8 follows a normal distribution. The test is used to determine if the two sets of data, in our case data from 2014 and data from 2015, are significantly different from each other, which is the case if the null hypothesis can be rejected. By using the test on the data for 2014 and 2015 it is possible to determine if the differences in the bias is due to different COSMIC datasets or seasonal changes. We used MATLABs own command for two-sampled Student’s t-test, \texttt{ttest2}, which follows the equation 6.

\[
   t = \frac{\bar{x} - \bar{y}}{\sqrt{\frac{s_x^2}{n} + \frac{s_y^2}{m}}}
\]

where $\bar{x}$ and $\bar{y}$ are the samples’s means, $s_x$ and $s_y$ are the samples’s standard deviations and $n$ and $m$ are the respective sizes of the samples.

### 4.2 Energy spectra and predictability of atmospheric flows

The prediction of a flows movement has limitations due to chaotic behaviour of the flow. This limitation is related to a time and a length scale which is related to the energy spectra in figure 9, which is based on the relation $E(k) \sim k^{-5/3}$, for scales smaller than $\sim 500$ km or $E(k) \sim k^{-3}$ for larger scales, where $E$ is the energy and $k$ is the wave length, i.e. the range of the motion of the fluid. A small-scale system
with a wave length of a couple of hundred meters has a predictability range of a couple of hours, while a synoptic-scale system of over 2000 km has a predictability range of days until the error in the solution makes the outcome useless (Lorenz, 1969; Durran and Gingrich, 2014).

The climatic regime of West Africa is governed by convective weather which may couple with synoptic scale conditions. Any change in the initial condition of the model run will ultimately change the outcome in terms of spatial and temporal rainfall distribution. This means that the theory of predictability is of importance for this study since it will have large implications on the result. In figure 9 from the paper of Lorenz (1969) it is clear that errors on small scale may contaminate the prediction on synoptic scale already after 1-2 days. To avoid the result being completely governed by the effects of chaos and in order to make it reasonable to determine the differences of forecast to the effects of the different initializations we limited our studies to 30h forecast simulations.

Recently a study by Durran and Weyn, 2016, the predictability of thunderstorms in a homogeneous atmospheric environment was studied from a theoretical and experimental perspective (Durran and Weyn, 2016). It was argued that the critical scales for reducing error and increase forecast lead times, was to suppress errors in the 100-400 km range rather than the smallest resolvable scales. It was also interesting to note the speed of which error saturation propagates upscale in a more realistic model compared to the setting in Lorenz’s model. While a considerable contribution to the rainfall differences between the simulations from the effects of chaos is excepted, given that most rainfall occurs during day 1 between noon and sunset, we expect that the differences would still be mostly due to the type of initialization used, particularly from a larger scale pattern point of view, while individual small scale and short-lived convective storms should not be assumed to be a direct result of the initialization.
5 Result

5.1 GPS-RO and radiosonde comparison

Figure 10 and 12 show a scatter plot of the temperature data from radiosondes against GPS-RO data using all available data with GPS-RO data closer than 1000 km for Abidjan and Bamako respectively. Figure 11 and 13 show the same but for the dew point temperature. The figure shows the temperature from the radiosoundings plotted against the corresponding temperature from the GPS-RO profile. The red line in the figures are a fitting curve to the data.

![Figure 10](image1.png) **Figure 10** Scatter plot of temperature between Abidjan radiosondes and GPS-RO profiles.

![Figure 11](image2.png) **Figure 11** Scatter plot of dew point temperature between Abidjan radiosondes and GPS-RO profiles.

![Figure 12](image3.png) **Figure 12** Scatter plot of temperature between Bamako radiosondes and GPS-RO profiles.

![Figure 13](image4.png) **Figure 13** Scatter plot of dew point temperature between Bamako radiosondes and GPS-RO profiles.

Table 3 shows the seasonal error estimate for radiosondes from Abidjan and GPS-RO profiles closer than 1000 km to the Abidjan station. The first two columns are the standard deviation for temperature and dew point temperature, respectively. Column three and four are the root mean square error for temperature and dew point temperature. The last two columns show the bias between the weather balloon soundings and the GPS-RO profiles. The error in dew point temperature is larger than for temperature, as expected from literature. The negative bias for the dew point temperature can be seen during the monsoon
and the long dry season. The number of profiles are relatively evenly distributed among the seasons with 204 profiles during the short dry season and 100 profiles for the autumn monsoon. Here, the number of profiles relates to the number of GPS-RO profiles that have been compared with corresponding weather balloon soundings.

Results for Abidjan using data from 2015 are shown in Table 3. The profiles used for Abidjan are distributed as 92 profiles from the monsoon, 98 from the long dry season, 104 from the pre-monsoon and 171 profiles from the short dry season. No negative bias for the dew point temperature are detected.

<table>
<thead>
<tr>
<th>Season</th>
<th>$\sigma_T$</th>
<th>$\sigma_{T,d}$</th>
<th>RMSE$_T$</th>
<th>RMSE$_{T,d}$</th>
<th>Bias$_T$</th>
<th>Bias$_{T,d}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre-monsoon</td>
<td>1.6756</td>
<td>5.5087</td>
<td>2.0116</td>
<td>6.4671</td>
<td>-0.0177</td>
<td>0.6345</td>
</tr>
<tr>
<td>Monsoon</td>
<td>1.5711</td>
<td>4.7293</td>
<td>1.8253</td>
<td>5.7057</td>
<td>0.5507</td>
<td>-1.3698</td>
</tr>
<tr>
<td>Summer dry</td>
<td>1.9843</td>
<td>5.9477</td>
<td>2.2504</td>
<td>6.8927</td>
<td>0.2466</td>
<td>4.6047</td>
</tr>
<tr>
<td>Autumn monsoon</td>
<td>2.1366</td>
<td>6.9698</td>
<td>2.2403</td>
<td>9.4688</td>
<td>0.4188</td>
<td>5.8181</td>
</tr>
<tr>
<td>Winter dry</td>
<td>1.6160</td>
<td>7.2571</td>
<td>1.8728</td>
<td>8.2850</td>
<td>-0.1018</td>
<td>-0.3012</td>
</tr>
</tbody>
</table>

Table 3 Seasonal error estimate for Abidjan using data from 2014.

<table>
<thead>
<tr>
<th>Season</th>
<th>$\sigma_T$</th>
<th>$\sigma_{T,d}$</th>
<th>RMSE$_T$</th>
<th>RMSE$_{T,d}$</th>
<th>Bias$_T$</th>
<th>Bias$_{T,d}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre-monsoon</td>
<td>2.1980</td>
<td>8.8273</td>
<td>2.4183</td>
<td>10.8204</td>
<td>-0.5969</td>
<td>2.9824</td>
</tr>
<tr>
<td>Monsoon</td>
<td>2.0985</td>
<td>7.2095</td>
<td>2.7770</td>
<td>8.0386</td>
<td>0.1216</td>
<td>0.7786</td>
</tr>
<tr>
<td>Summer dry</td>
<td>1.9945</td>
<td>8.1985</td>
<td>2.1755</td>
<td>10.5868</td>
<td>-0.1293</td>
<td>8.0395</td>
</tr>
<tr>
<td>Winter dry</td>
<td>2.0400</td>
<td>11.3461</td>
<td>2.3106</td>
<td>12.7750</td>
<td>-0.5653</td>
<td>5.5858</td>
</tr>
</tbody>
</table>

Table 4 Seasonal error estimate for Abidjan using data from 2015.

In Table 5, the seasonal error estimations are shown for Bamako. The same radial limit, 1000 km, as for Abidjan is also used for Bamako. The same error patterns between temperature and dew point temperature seen in Abidjan are also seen for Bamako. In contrast to Abidjan, the profiles are very uneven with 392 used profiles for the dry season and only 13 profiles for the monsoon season. This makes it difficult to compare the estimated errors between the seasons with any significance.

The Student’s t-test showed that the null hypothesis could be rejected in all four studied seasons: pre-monsoon, monsoon, the short dry season and the long dry season. This means that it is not possible to say with any significance that the different COSMIC datasets or the season has any impact on the differences in the temperature and dew point temperature bias.

The radial dependency error estimate for Abidjan, as seen in Table 6, does not follow any clear pattern which would be expected if the synoptic scale assumption would be invalid. Even if there is an increase in the error for increasing radius, it is not significant. The pattern of the bias seems random. However, it is important to point out that there were only 6 useful profiles for the first radius section (<50 km) and 78 values for the second (50-200 km). For 200-500 km and 500-1000 km radius, number of used profiles were 368 and 760 profiles respectively reflecting the larger areal coverage.
For Bamako, there is no visible increase of the error for increasing radius as seen in Table 7. However, the distribution of number of used profiles are, as for Abidjan, uneven with 2 used profiles for radius less than 50 km and 25 for 50-200 km. 120 profiles were used for 200-500 km radius and 258 profiles for the 500-1000 km radius. Hence, any conclusions should be drawn with care.

| Table 6 Radial dependent error estimate for Abidjan. |
|--------|--------|--------|--------|--------|--------|
| <50 km | 1.9135 | 9.1467 | 2.1100 | 12.3749 | -0.0775 | 1.7919 |
| 50-200 km | 1.9151 | 7.1646 | 1.9382 | 8.1789 | -0.2002 | 5.0036 |
| 200-500 km | 1.9693 | 7.0213 | 1.8496 | 7.8541 | -0.1918 | 4.1929 |
| 500-1000 km | 2.1388 | 7.7590 | 2.3173 | 8.8281 | 0.0847 | 2.2351 |

| Table 7 Radial dependent error estimate for Bamako. |
|--------|--------|--------|--------|--------|--------|
| <50 km | 2.7521 | 9.5016 | 2.9167 | 11.5914 | 0.3720 | 3.4805 |
| 50-200 km | 2.0998 | 8.4757 | 2.1061 | 11.1917 | 0.1045 | 2.2762 |
| 200-500 km | 2.1564 | 7.8317 | 2.3147 | 11.0727 | 0.4340 | 3.0148 |
| 500-1000 km | 2.2310 | 8.2579 | 2.5740 | 11.4956 | 0.6031 | 4.8675 |

In Table 8 and Table 9, error estimations for COSMIC2013 and COSMIC2000 are shown for Abidjan and Bamako respectively. Maximum distance to the weather stations in Abidjan and Bamako is set to 1000 km, as for all cases. No obvious pattern is detected for either Abidjan nor Bamako.

| Table 8 Error estimation for respective dataset used for Abidjan using data from 2014. |
|--------|--------|--------|--------|--------|--------|
| COSMIC2013 | 1.6427 | 6.3832 | 2.0641 | 7.9747 | -0.0628 | 0.1080 |
| COSMIC2000 | 2.0659 | 6.3381 | 2.4277 | 8.1757 | 0.3621 | 2.9528 |

| Table 9 Error estimation for respective dataset used for Bamako. |
|--------|--------|--------|--------|--------|--------|
| COSMIC2013 | 2.2380 | 8.5315 | 2.5546 | 12.3242 | 0.6487 | 6.0195 |
| COSMIC2000 | 2.3566 | 7.3560 | 2.9671 | 9.5997 | 0.5073 | 2.5445 |

The bias in maritime and continental airmasses are very similar as seen in Table 10. Number of GPS-RO profiles used are 934 for continental and 278 for maritime locations.

| Table 10 Error estimation for maritime and continental profiles locations. |
|--------|--------|--------|--------|--------|--------|
| Maritime | 1.8354 | 7.1675 | 1.8837 | 9.5398 | -0.2232 | 4.6875 |
| Continental | 1.9154 | 7.0949 | 2.3624 | 9.4637 | 0.0844 | 2.5606 |

5.2 Vertical bias

Figure 14 – 19 show the vertical bias for temperature and dew point temperature for the three radiosonde stations. For the dew point temperature, the lower levels up to around 700 hPa shows a mainly negative or
close to zero bias while the upper levels show large positive bias. The temperature shows a clear negative bias at the surface, with positive or close to zero bias between 700–900 hPa levels. The mid levels differ slightly from each other; while Abidjan has a clear negative bias at 400–700 hPa, Bamako and Niamey shows no significant bias at these levels but a more prominent positive bias at the upper levels. The dew point temperature shows a clear positive bias at all levels through the troposphere for both Abidjan and Bamako. Note the wet bias in the boundary layer, as seen in e.g. Bamako and Abidjan 2014.

Figure 14 Temperature bias for each pressure level for Abidjan, 2014.

Figure 15 Temperature bias for each pressure level for Abidjan, 2015.

Figure 16 Dew point temperature bias for each pressure level for Abidjan, 2014.

Figure 17 Dew point temperature bias for each pressure level for Abidjan, 2015.

5.2.1 Seasonal differences of the vertical bias

The seasonal differences for the vertical bias for Abidjan are small, with a negative temperature bias at the surface level followed by a layer with positive bias up to 700 hPa. For the upper levels negative bias is dominating, however, values are normaly small (<2°C). The bias of the dew point temperature are, at the lower levels, dominated by negative values, i.e. the GPS-RO profile is too dry at these levels. From around 700 hPa up to the troposphere, the bias are positive with values exceeding 10°C, i.e. too humid. However, there are two exceptions during the long dry season and the pre-monsoon, when there is a layer around 400 – 500 hPa with a bias is close to zero.
Figure 18 Temperature bias for each pressure level for Bamako.

Figure 19 Dew point temperature bias for each pressure level for Bamako.

Figure 20 Vertical temperature bias during the long dry season for Abidjan.

Figure 21 Vertical dew point temperature bias during the long dry season for Abidjan.

Figure 22 Vertical temperature bias during the pre-monsoon for Abidjan.

Figure 23 Vertical dew point temperature bias during the pre-monsoon for Abidjan.
Figure 24 Vertical temperature bias during the monsoon for Abidjan.

Figure 25 Vertical dew point temperature bias during the monsoon for Abidjan.

Figure 26 Vertical temperature bias during the short dry season for Abidjan.

Figure 27 Vertical dew point temperature bias during the short dry season for Abidjan.

Figure 28 Vertical temperature bias during the short monsoon for Abidjan.

Figure 29 Vertical dew point temperature bias during the short monsoon for Abidjan.
5.3 Simulations

5.3.1 Case 1

Figures 30 – 32 show the simulated accumulated rainfall for the 24 hr period ending on 06UTC 12 September 2015. Figure 30 represents a simulation without any assimilation based on GFS, figure 31 is based on GPS-RO assimilated data, and figure 32 representing prediction based solely on conventional assimilation. All simulations are based on the 00Z run. Figure 33 shows the differences in rainfall between the simulation with GPS-RO and the simulation without any assimilated initial conditions. Figure 34 shows the differences in rainfall between the simulation with conventional assimilation initial conditions and the simulation without data assimilations. Note the higher amount of rainfall in western Ghana, which indicates that the GPS-RO dataset has a large impact on the forecast.

Figure 30 Accumulated rainfall between 06Z 2015-09-11 and 06Z 2015-09-12. Simulation without assimilation. Rainfall in mm.

Figure 31 Accumulated rainfall between 06Z 2015-09-11 and 06Z 2015-09-12. Simulation with GPS-RO data. Rainfall in mm.
Figure 32 Accumulated rainfall between 06Z 2015-09-11 and 06Z 2015-09-12. Simulation with conventional assimilation. Rainfall in mm.

Figure 33 Differences in rainfall between simulation without assimilation and with GPS-RO data [mm].

Figure 34 Differences in rainfall between simulation without assimilation and with conventional assimilation data [mm].
Figures 35 – 37, show the simulated mCAPE with the three different initial conditions at 12z 11 September 2015, just before the squall line developed. Convective Available Potential Energy (CAPE) is a measure on the convectivity in a region. mCAPE is defined as the CAPE at the most unstable level, in this case it is the surface level. The largest mCAPE is seen over Nigeria with over 3000 J/kg. This will later support the build up of an intense squall line over Benin and Togo which will move westward over Ghana. Figure 38 the lightning strikes linked to the squall line on the 11 September 2015. The map is based on lightning strikes registered by Vaisala’s global GLD360 dataset with a spatial accuracy of 2–4 km and around 70% of the lightning strikes is registered. Figure 39 shows the estimated accumulated rainfall, for the 24h period between 06Z on 11 September 2015 to 06Z 12 September 2015, based on satellite rainfall estimates (NOAA RFE 2.0).

![Map of mCAPE](image)

**Figure 35** mCAPE, without assimilation, valid for 12Z 2015-09-11. Units in J/kg.
Figure 36 mCAPE, with GPS-RO assimilation, valid for 12Z 2015-09-11. Units in J/kg.

Figure 37 mCAPE, with conventional assimilation, valid for 12Z 2015-09-11. Units in J/kg.
Figure 38  Lightning strikes between 06Z 2015-09-11 to 06Z 2015-09-12 with a total of 144811 lightning strikes during the 24h period. Representing the time of a lightning strike, allowing for propagating analysis. Units in hours.

Figure 39  Estimated accumulated rainfall between 06Z 2015-09-11 to 06Z 2015-09-12. Units in mm.
5.3.2 Case 2

Figure 40 – 42 show the simulated accumulated rainfall for the 24 h period ending on 06UTC 14 September 2015. Figure 40 represent a simulation with no assimilated initial condition, figure 41 represent a simulation with assimilated GPS-RO data as initial condition and figure 42 represent a simulation using conventional assimilation data. Figure 43 shows the differences in rainfall in mm between the simulation with assimilated GPS-RO data and the simulation without assimilation data. Figure 44 shows the differences between conventional assimilation data and the simulation with no assimilation. As seen in the figures, the GPS-RO have also for this case a large impact on the forecast and differ clearly from the simulation with no assimilated data.

![Figure 40](image)

**Figure 40** Accumulated rainfall between 06Z 2015-09-13 and 06Z 2015-09-14. Simulation without assimilation. Rainfall in mm.
Figure 41 Accumulated rainfall between 06Z 2015-09-13 and 06Z 2015-09-14. Simulation with GPS-RO assimilation. Rainfall in mm.

Figure 42 Accumulated rainfall between 06Z 2015-09-13 and 06Z 2015-09-14. Simulation with conventional assimilation. Rainfall in mm.
Figure 43 Differences in rainfall between simulation without assimilation and simulation with GPS-RO data, differences in mm.

Figure 44 Differences in rainfall between simulation without assimilation and simulation with conventional assimilation data, differences in mm.
Figure 45–47 show a cross section from north to south at 0.85°E longitude of the atmosphere, simulated with no assimilated data, with GPS-RO assimilation and with conventional assimilation respectively. The simulation is valid for 00Z 14 September 2015. The map shows the relative humidity, following the colorbar and the vertical wind velocity, where blue marks velocities larger than 10 cms$^{-1}$ downward and red marks velocities larger than 10 cms$^{-1}$ upward. Note the clear difference between the humid maritime air and the dry continental air at the surface. AEJ, at around 600 hPa, is marked with contour in the low left corner. The most interesting feature, of the cross section figures, is the AEJ that is clearly stronger for simulation with GPS-RO assimilated data compared to no assimilated data.

Figure 45 Cross section of the atmosphere, simulated with no assimilated data, showing relative humidity (colorbar) and wind direction (arrows) and vertical wind velocity (bottom colorbar). Coastline is marked at the top.
Figure 46 Cross section of the atmosphere, simulated with GPS-RO assimilated data, showing relative humidity (right colorbar) and wind direction (arrows) and vertical wind velocity (bottom colorbar). Coastline is marked at the top.

Figure 47 Cross section of the atmosphere, simulated with conventional assimilated data, showing relative humidity (colorbar) and wind direction (arrows) and vertical wind velocity (bottom colorbar). Coastline is marked at the top.
6 Discussion

6.1 The radiosondes

The poor and uneven distribution of the sounding samples through the troposphere as seen in figures 4, 6 and 7, have a large impact on the bias analysis, as the magnitude of the bias at certain pressure levels are more dominating than others, while the number of samples differ. This leads to difficulties in making a comparison of the bias in the upper levels of the troposphere to the bias of the lower troposphere. For this reason, the results from the 2014 dataset from Abidjan will be more affected by the bias at 400 hPa than the bias at 700 hPa. Hence, in several cases, the result will not be a true unweighted representation of the troposphere, but weighted towards certain pressure levels. This is most prominent for the Niamey soundings, where the result is based on 15 out of 37 pressure levels, out of which 10 have more than 20% coverage and only 3 levels are represented in 50% or more of the soundings. With more soundings, this effect would diminish away. However, the effect has a large impact when results with different amount of sounding samples are compared. This is, above all, important for the radial dependency comparison, where large differences in the number of soundings between each analysed circle segment are present, e.g. for Bamako only two soundings were used for GPS-RO profiles closer than 50 km which makes the comparison with the bias of the 500-1000 km segment difficult as there were 258 soundings used in that case. Hence, the significance of any conclusion on radial dependent error is limited. In the dataset of soundings from Abidjan in 2015, a more even vertical distribution of the soundings samples are observed, as seen in figure 5.

The actual reason for the uneven sample distribution through the troposphere has not yet been resolved. However, the most likely reason is poor sampling resolution and sensor failure. Poor sampling resolution would, in the soundings from Bamako, explain the larger amount of samplings from the upper troposphere compared to the lower troposphere. However, it does not explain why there is less than 10% coverage of the planetary boundary layer. For the 2014 soundings from Abidjan, poor sampling resolution can not explain the relative high sampling frequency around 900 hPa and then the large drop between 650 and 850 hPa. In general, the number of samplings per pressure level is very poor, only reaching about 50% cover around 300 and 400 hPa. Here, sensor failure is the most probable reason. Probable sensor failures in 2014 is supported by the sharp increase in sampling coverage, for all pressure levels except one having more than 50% coverage of the radiosondes, in the 2015 dataset. The 2015 dataset gives a better representation of the whole troposphere. We have not been able to obtain information about the sensors used for each sounding station, making it impossible to say for certain what causes the sampling problem.

Poor and uneven sampling distribution is not the only problem with the radiosondes. Periods with a complete lack of data have been a problem for the Bamako and Niamey sounding stations. Most prominent are the gaps for Bamako, which stretches from the 7th of June to the 18th of September 2014. Since the project is to study the potential for improving rainfall forecasts, this gap is particularly discomforting, since it covers more or less the whole rainy season for Bamako, resulting in only 13 soundings, which is not enough to base any conclusion on with any significance. The problem of gaps in
the dataset is only present for Bamako and Niamey. The radiosondes dataset from Abidjan is not affected by this, and the temporal distribution of the analysed dataset is only dependent on the availability on GPS-RO profiles.

6.2 GPS-RO and radiosonde comparison

6.2.1 Temperature

As mentioned in the previous subsection, an analysis of the radial dependent error, from table 6 and 7, should be taken with caution due to the large differences in number of used profiles for each segment. Thus, it is not possible to say if the error is changing by increasing distance from the analysed dataset. However, it is possible to say that even at distances of up to 1000 km from the radiosonde, the temperature bias and standard deviation is still comparably small. From the Student’s t-test, the null hypothesis could not be rejected, hence, it is not possible to say if the two COSMIC datasets or the seasons have any impact on the variations in the bias of temperature and dew point temperature studied for Abidjan. This means that the dataset and the differences in the bias are too small to draw any significant conclusion. The seasonal bias for Bamako (table 5) and Niamey (table 11, see Appendix A) are particularly difficult, since the number of used profiles differs largely between the seasons as mentioned in the previous subsection. The differences between maritime and continental areas are also not possible to say anything about with any significance except, as for the other cases, that the temperature shows a small bias and standard deviation. For the comparison between maritime and continental airmasses it is difficult to come to any significant conclusion, since, the differences between the standard deviation, RMSE and bias are small (table 10). However, this could point to that the GPS-RO data performs equally good for both maritime and continental regions, and that the profiles are representative of the condition at larger scale. This is in line with and support the validity of the synoptic scale assumption.

6.2.2 Dew point temperature

Much of what has been discussed in the above subsection about temperature is relevant and applicable to the dew point temperature. This concerns the uneven distribution of profiles per circular segment in the radial study, the Student’s t-test where the null hypothesis could not be rejected and the general small differences in the standard deviation, RMSE and bias within each case. However, one important observation is the wet bias of the dew point temperature, in the boundary layer, seen in several cases and also the general wet bias seen in the seasonal, radial and dataset dependent study as well as the maritime/continental study. This is contrary to most previous studies made on GPS-RO data and calls for particular attention. The reason for this obvious wet bias has not yet been answered with any significance. However, the main hypothesis is sensor failure of the humidity sensors on the radiosondes described by (Liu and Tang, 2014) where sensors were showing much lower dew point temperatures than compared to models or satellite data, particularly as the other studies have shown that the GPS-RO is bias free and the fact that other problems with the radiosondes have surfaced. The sensor would most likely fail around 700 hPa, which could explain the lack of data at this level. This is also supported by the figure of the
vertical bias on pages 20 – 21 which shows tendencies of having dry (or at least drier) bias at lower levels in the troposphere. The 700 hPa level is where deep convective clouds can be particularly heavy in water load during the wet season. Unfortunately, it was not possible to determine the manufactures models of the sensors used in West Africa, so it is unclear what the accuracy of the sensors actually are. Studies are needed to determine if the wet bias are accurate or if it is due to sensor failure, this has not been the aim of this project, why only different hypothesis can be made. Remember that the basic assumption was that radiosondes represented the real atmospheric condition. Overall, the seasonal vertical bias shows a dry bias in the boundary layer up to circa 3000 meters, and even if the seasonal differences are small, the dry bias seems to be larger during drier seasons compared to the pre-monsoon and monsoon. Above the boundary layer is the overall pattern a wet bias, this is possibly related to a potential sensor failure from 500 hPa. Note that the number of data at the levels around 600 and 700 hPa are very small compared to other levels. Thus, no conclusions should be made of the visible negative bias for some cases (e.g. figure 20).

6.3 Simulations

The most striking feature of the first case, shown in the figures 30 – 34, is the large impact the GPS-RO dataset has on the simulated rainfall. Even based on one dataset containing 5 GPS-RO profiles the result has a similar impact as a full-scale conventional data assimilation with many different datasets based on satellites and data from meteorological weather stations. From figure 39, the highest estimated accumulated rainfall for Ghana was 30 mm in the western parts. The rain stretches in a line from southern Ghana north up to Burkina Faso and Mali and into Togo, Benin and northern Nigeria. In this case, the simulation without assimilation completely missed the squall line event (seen in e.g. figure 38 and 39) and forecasted only insignificant amount of rainfall in the region which was hit by the event. The simulation with GPS-RO assimilation forecasted up to 50 mm rain in the southwest of Ghana, making a difference of 50 mm as seen in figure 33. As the estimated rainfall shows, the simulation with GPS-RO assimilation may not have given a more accurate forecast, but the differences are large, both in quantity and in regional distribution. This implies effects larger than what would be contributed from stochastic processes and chaos effects. It is interesting to note that the simulation predicted high amount of rain (>50 mm) in central Nigeria, which was not predicted by the simulations using GPS-RO and conventional assimilation initial data and the event did not happen, as the rainfall estimates during the 24h period shows (figure 39). The simulated mCAPE in figures 35 – 37 supports the potential for the simulated accumulated rainfall, since, the mCAPE for GPS-RO assimilation and the conventional assimilation are very similar, while both differ from the mCAPE simulated with no assimilation. A problem with all simulated predictions is the sensitivity to the initial condition, and after a certain time, the error in the solution will turn the outcome useless. However, in the case of this study, the length scale involved in the rainfall pattern is around 2000 km, and from the energy spectra, the time scale for length scales of 2000 km is >1 day, thus our 30 hour prediction in the study is within the range of predictability, particularly as most rain fell within 14 to 20 hours from the initialisation.

The great impact of the single GPS-RO dataset in the simulations is seen also in Case 2, where we
see a large difference in rainfall distribution between the simulation with assimilated GPS-RO data and the simulation with no assimilated data. As for Case 1, the GPS-RO dataset seems to have a very large impact on the outcome of the simulated forecast compared to when no assimilated data is used. From the cross section figures, it is shown that a stronger AEJ is present for both the cases of assimilated data simulations which affect the simulated forecast by producing rainfall further west compared to the simulation with no data assimilation. This is a positive signal, since the rainfall advected by the AEW came earlier than the current running forecast, without data assimilation. Since many rainfall events are related to the AEJ, it is important that this jet is represented and predicted correctly.

7 Conclusion

In general, the difference between the temperature given by GPS-RO data and the one given by radiosondes was small (<1°C). However, due to lack of data, it was not possible to determine any changes in the bias by increasing the distance between the GPS-RO profile and the radiosonde nor was it possible to determine any seasonal or dataset (COSMIC2000 or COSMIC2013) dependencies. Due to probable problems with the humidity sensor on the radiosondes, the dew point temperature bias shows some uncharacteristic features (e.g. large wet bias) not shown in other studies. This problem makes it difficult to draw any conclusions concerning the performance of the dew point temperature of the GPS-RO profile. Thus, more studies are needed with radiosondes comparison.

Due to time limitations in the project, only two cases were thoroughly studied. Despite this, a few interesting features have been seen: the impact of the GPS-RO dataset in the simulations were larger than expected and was comparable to the simulations with conventional assimilation; the AEJ is more intense with GPS-RO assimilation compared to simulation with no assimilation, as seen in case 2. It is not possible to draw any significant conclusion from only two case studies and more simulation comparisons is needed. However, considering the large impact the single COSMIC-1 dataset seems to have on the simulations, it will be interesting to see the effect when COSMIC-2 starts running in the end of year 2016 and supported by private initiatives during 2016 and 2017. GPS-RO has a real potential to take weather forecasts in the tropics to a new level and not only the Tropics but also over the oceans and the polar regions where data availability is scarce, particularly profile data.
Acknowledgements

As this study is part of an ongoing project in West Africa I first want to thank Ignitia and especially my supervisor Andreas Vallgren for all the help and support and also that I got the opportunity to work in Ghana during the study. Also thanks to my supervisor at Uppsala University, Anna Rutgersson.
Abbreviations

4D-var  Four-dimensional variational data assimilation
3D-var  Three-dimensional variational data assimilation
AEW    African Easterly Wave
AEJ    African Easterly Jet
AFWA   Air Force Weather Agency
ARW    Advanced Research WRF
CAPE   Convective Available Potential Energy
COSMIC Constellation Observing System for Meteorology, Ionosphere and Climate
ECMWF  European Center for Medium-Range Weather Forecasts
FAA    Federal Aviation Administration
GFS    Global Forecasting System
GPS-RO Global Position System Radio Occultation
ITCZ   Inter Tropical Convergence Zone
LEO    Low Earth Orbit (satellite)
MJO    Madden-Julian Oscillation
NCAR   National Center for Atmospheric Research
NCEP   National Centers for Environmental Prediction
NMM    Nonhydrostatic Mesoscale Model
NOAA   National Oceanic and Atmospheric Administration
NWP    Numerical Weather Prediction
RMSE   Root-Mean Square Error
SL     Squall Line
TEJ    Tropical Easterly Jet
WAM    West African Monsoon
WRF    Weather Research and Forecasting
References


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Appendix A

GPS-RO and radiosonde comparison

Figure 48 Scatter plot of temperature between Niamey radiosondes and GPS-RO.

Figure 49 Scatter plot of dew point temperature between Niamey radiosondes and GPS-RO.

Table 11 Seasonal error estimate for Niamey.

<table>
<thead>
<tr>
<th></th>
<th>$\sigma_T$</th>
<th>$\sigma_{T_d}$</th>
<th>RMSE$_T$</th>
<th>RMSE$_{T_d}$</th>
<th>Bias$_T$</th>
<th>Bias$_{T_d}$</th>
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</thead>
<tbody>
<tr>
<td>Dry</td>
<td>1.9306</td>
<td>6.8646</td>
<td>3.2438</td>
<td>13.3931</td>
<td>1.3683</td>
<td>4.6362</td>
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<td>Monsoon</td>
<td>2.1633</td>
<td>4.3426</td>
<td>3.8727</td>
<td>4.9061</td>
<td>0.5790</td>
<td>2.9429</td>
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</tbody>
</table>

Table 12 Radial dependent error estimate for Niamey.

<table>
<thead>
<tr>
<th></th>
<th>$\sigma_T$</th>
<th>$\sigma_{T_d}$</th>
<th>RMSE$_T$</th>
<th>RMSE$_{T_d}$</th>
<th>Bias$_T$</th>
<th>Bias$_{T_d}$</th>
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<tbody>
<tr>
<td>50-200 km</td>
<td>2.8774</td>
<td>6.6669</td>
<td>2.9958</td>
<td>7.4891</td>
<td>0.6930</td>
<td>2.4396</td>
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<td>200-500 km</td>
<td>1.6836</td>
<td>6.1528</td>
<td>2.6280</td>
<td>8.0687</td>
<td>1.3971</td>
<td>4.1321</td>
</tr>
<tr>
<td>500-1000 km</td>
<td>2.1018</td>
<td>5.8353</td>
<td>3.8137</td>
<td>9.4202</td>
<td>0.9811</td>
<td>4.0095</td>
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</table>

Table 13 Error estimation for respectively dataset used for Niamey.

<table>
<thead>
<tr>
<th></th>
<th>$\sigma_T$</th>
<th>$\sigma_{T_d}$</th>
<th>RMSE$_T$</th>
<th>RMSE$_{T_d}$</th>
<th>Bias$_T$</th>
<th>Bias$_{T_d}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>COSMIC2013</td>
<td>1.8818</td>
<td>7.5177</td>
<td>3.4489</td>
<td>13.7679</td>
<td>1.8687</td>
<td>4.6824</td>
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<tr>
<td>COSMIC2000</td>
<td>2.1505</td>
<td>6.2487</td>
<td>3.8302</td>
<td>9.1390</td>
<td>0.6399</td>
<td>3.6018</td>
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</table>
Table 11 shows the seasonal differences in the standard deviation, root-mean-square error and the bias for temperature and dew point for Niamey. For the dry season 92 profiles were used in the analysis and for the monsoon 154 profiles were used.

The table 12 shows the radial dependent error where there were 5 profiles for the 50 – 200 km segment, 60 for the 200 – 500 km segment and 181 for the 500 – 1000 km segment. Note that there were no GPS-RO profile available closer than 50 km.

For the different COSMIC datasets in table 13, 67 profiles were used for COSMIC2013 and 179 for COSMIC2000.
Appendix B

Probability distribution of the temperature bias

Figure 50 Probability distribution compared to a normal distribution for the long dry season 2014 of the temperature bias.

Figure 51 Probability distribution compared to a normal distribution for the long dry season 2015 of the temperature bias.

Figure 52 Probability distribution compared to a normal distribution for the pre-monsoon 2014 of the temperature bias.

Figure 53 Probability distribution compared to a normal distribution for the pre-monsoon 2015 of the temperature bias.
Figure 54 Probability distribution compared to a normal distribution for the monsoon 2014 of the temperature bias.

Figure 55 Probability distribution compared to a normal distribution for the monsoon 2015 of the temperature bias.

Figure 56 Probability distribution compared to a normal distribution for the short dry season 2014 of the temperature bias.

Figure 57 Probability distribution compared to a normal distribution for the short dry season 2015 of the temperature bias.
Probability distribution of the dew point temperature bias

Figure 58 Probability distribution compared to a normal distribution for the long dry season 2014 of the dew point temperature bias.

Figure 59 Probability distribution compared to a normal distribution for the long dry season 2015 of the dew point temperature bias.

Figure 60 Probability distribution compared to a normal distribution for the pre-monsoon 2014 of the dew point temperature bias.

Figure 61 Probability distribution compared to a normal distribution for the pre-monsoon 2015 of the dew point temperature bias.
Figure 62 Probability distribution compared to a normal distribution for the monsoon 2014 of the dew point temperature bias.

Figure 63 Probability distribution compared to a normal distribution for the monsoon 2015 of the dew point temperature bias.

Figure 64 Probability distribution compared to a normal distribution for the short dry season 2014 of the dew point temperature bias.

Figure 65 Probability distribution compared to a normal distribution for the short dry season 2015 of the dew point temperature bias.