A Brief Assessment of the Impact of Nearly 40 Years of Assimilated Observations Over the Amazon Basin

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Abstract  Adding a Forecast Sensitivity-based Observation Impact component to Version 2 of the Modern Era Retrospective-analysis for Research and Applications, the present study provides an assessment of the impact of nearly 40 years of observations on short-range (24-hr) forecasts over the Amazon basin. Under self-verification, forecast errors are found to slightly increase from the early data-sparse days to the more recent years, when data dramatically increase. Throughout the reanalysis, satellite radiances dominate in volume, but only before 1999 they dominate the impacts. Beyond 1999, over 50% of forecast error reduction is associated with conventional observations (radiosondes). Atmospheric Motion Vectors are also found to be large contributors to error reduction, but their contribution reduces in dry periods. In opposition to Atmospheric Motion Vectors, satellite radiances tend to contribute more in the dry season. Results provide motivation for additional conventional observations and the use of all-sky treatment of radiances.

Plain Language Summary  Observations of atmospheric variables are of fundamental importance to allow for reliable weather predictions and to enable scientists to improve their modeling of the atmosphere. Conventional observing systems measure temperature, winds, humidity, and pressure directly. These amount to a small fraction of the global observing system, which is dominated by indirect satellite observations. Objective evaluation for how different components of the observing systems contribute to improving weather predictions have become essential to help scientists understand how best to build future observing systems. The present study provides an evaluation of nearly 40 years of observations used in the context of a procedure called reanalysis, which essentially blends observations and model predictions in a carefully designed manner. Our particular work examines the impact of observations over the Amazon basin. In this region, conventional observations are found to still contribute most to reducing forecast errors, especially in the later years of the reanalysis, while satellite-derived winds are found to contribute most in the wet season. The work suggests that improving the treatment of other satellite observations allowing their use over cloudy and precipitating regions might change their ranking in comparison to conventional observations.

1. Introduction

In a recent study, Diniz and Todling (2019) provide a comprehensive assessment of the impact of the observations on short-range (24-hr) forecasts from a multiyear reanalysis. Unlike typical examination of root-mean-square error of observation residuals that inherit the unit of the variables being examined and are thus not suitable for cross-comparison, the Forecast Sensitivity-based Observation Impact (FSOI) technique employed by Diniz and Todling (2019) standardizes units and thus allows for cross-comparison. FSOI was introduced by Langland and Baker (2004), and it has since become a standard tool for assessing the plethora of observations assimilated in global operational numerical weather prediction (NWP) systems. One disadvantage of relying on, say, time series of FSOI results from NWP applications is that these are affected not only by changes in the observing system but also by changes in the rest of the system, namely, updates to the underlying model and changes in the data assimilation technique being used in operations. Most FSOI studies in the literature have been carried out over short periods, with fixed versions of the corresponding NWP systems (e.g., Buehner et al., 2018; Cardinali, 2009; Gelaro & Zhu, 2009; Gelaro et al., 2010; Langland & Baker, 2004; Lorenc & Marriott, 2014; Ota et al., 2013). Jumps in NWP data sets due to system upgrades have long been recognized as undesirable, rendering such data sets unsuitable for climate and long-term
studies (e.g., National Research Council, 1991). Reanalysis provides a relatively better alternative since it is unaffected by system upgrades of any kind; its results are only affected by changes in the observing system. In many ways, reanalysis provides an ideal environment for conducting FSOI studies.

Diniz and Todling (2019) rely on the Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2; Gelaro et al., 2017), which is an ongoing exercise with nearly 40 years of assimilated products available for climate studies. Though not used in its ongoing integration, MERRA-2 has all necessary ingredients to perform FSOI, namely, an adjoint model Holdaway et al. (2014) of its nonlinear general circulation model and an adjoint Trémolet (2008) of its three-dimensional variational (3D-Var) analysis. FSOI requires the introduction of a forecast error measure (or metric), and it evaluates the sensitivity of this measure to changes in the observations. Implicit in this evaluation are sensitivities of forecasts to changes in the initial conditions, which are derived from the model adjoint. Since such adjoint models are only valid over relatively short periods, FSOI results are typically derived for the 24-hr forecasts. More specifically, the technique of Langland and Baker (2004) also requires the availability of 30-hr forecasts, valid at the same time as the 24-hr corresponding ones, to allow for a relatively accurate FSOI estimate (see Daescu & Todling, 2009; Errico, 2007).

The work of Diniz and Todling (2019) shows that, unlike other regions in the tropics, the Amazon basin forecast sensitivities change rather substantially from the first half of MERRA-2 to its latter half, with a consequent increase in forecast error. These changes are associated with changes in the observing system. The objective of the present study is to provide an assessment of the impact of observations in the 24-hr forecasts over the Amazon basin from 1980 to 2017 and to shed some light on the reasons for such increased error growth. Although the work here still relies on the global forecast error metric employed in Diniz and Todling (2019), conclusions are not expected to change in any significant way by the use of a regionally specific projection metrics. Indeed, work has been done showing that global error measures are just as effective in obtaining regional results as regionally projected measures are (see section 3.2 of Boulloot et al., 2016). This holds as long as the essence of the metric remains the same, specifically for the case here, as long as results are still sought out for total energy and not some other error measure based on, say, circulation or vorticity or something else. Directly related to these statements is the fact that any assessment that relies on the specification of a norm depends on that norm; thus, a change in the norm might, in some cases, change the results and corresponding conclusions. Examination of different norms is not part of the present work; readers interested in applications using alternative norms are referred to typical few-month-long evaluations such as those of Cardinali (2018), Kotsuki et al. (2019), Necker et al. (2018), Sommer and Weissmann (2016), and Todling (2013).

In 6-hourly cycling systems, such as those based on 3D-Var, FSOI can be thought of as a proxy for the error difference between two forecasts valid at the same time but issued 6 hr apart. These differences are referred to as nonlinear impacts, whereas FSOI is sometimes referred to as a linear impact. To reduce effects of correlation with initial conditions, nonlinear impacts are typically derived from the 6-hr differences between 24- and 30-hr forecast errors. An illustration of the time evolution of the monthly averaged 24-hr forecast errors and linear impacts throughout MERRA-2 is shown in Figure 1. The curves include results for January and July, from 1980 to 2017, and a one-cycle moving average is applied to the monthly means. The total impact is partitioned into four regions (panel b: Northern Hemisphere Extratropics [NHX], Southern Hemisphere Extratropics [SHX], Tropics, and Amazon basin; region encompassed within polygons in the panels of Figure 3); the first three curves appear in Figure 4c of Diniz and Todling (2019). Notice that the impact of observations in the NHX and SHX reduces quite substantially as MERRA-2 enters the so-called Earth Observing System (EOS), or modern, era (late 1999 onward). The impacts brought about by assimilating observations become much more alike between the two hemispheres in the modern era, as compared to the early pre-EOS period. In the tropics and the Amazon basin, the situation is opposite, with the impact of observations increasing (in absolute value) as the reanalysis enters the modern era (a zoom for these two regions appears in panel c). Results over the Amazon basin are only a small part of those over the whole tropics, but the same trend of increased impact is seen in both regions. In evaluating these results, it is essential to realize that, regardless of region, errors constructed from self-verification are bound to underestimate the true errors and also that self-verified forecast errors are small in the absence of observations because forecast and verification fields do not differ much. Consequently, under self-verification there are two reasons for observation impacts to be small (in absolute value): (i) little, and/or poor quality, observations being
Figure 1. Time series of (a) 24-hr forecast errors and (b and c) linear impacts in the Northern Hemisphere Extratropics (north of 20° N; thick continuous line), Southern Hemisphere Extratropics (south of 20° S; thin continuous line), Tropics (between 20° S and 20° N; dashed line), and Amazon basin (dotted line). Lines represent monthly mean values during January and July. The shading shows the differences in scores between the two extratropical hemispheres. Values are plotted in the form of annual running means, resulting in that values plotted for January (July) are averages over that month and the preceding January (July), and, as a consequence, we omit values for January 1980 for consistency with the whole time series. The units of energy are J/kg.
available, or (ii) many, and/or very high quality, observations being available. There is yet a third possibility related to system errors being so large that no matter what data are assimilated, little-to-no impact is obtained. This is considered a pathetic case of no relevance. In the extratropics, the decrease of impact in the modern era is associated with reason (ii): the increase and enhancement in quality of the observations introduced in the late 1990s and beyond amount to a consequence improvement in the background fields used in the analyses and corresponding forecasts. In the tropics, the low impact of observations in the early periods is associated with reason (i). Assuming that as time progresses, MERRA-2 assimilates more and better quality observations in the tropics, the increased forecast errors in this area combined with the steady rise in the observation impacts can be indication of either the observations not being used optimally in this region or that a certain level of balance between properly observing and predicting the tropics has not yet been achieved in the reanalysis. The precise reasons for the behavior of MERRA-2 observation impacts in the tropics are a topic of investigation beyond the present work. Comparison and possible corroboration of these results with those from other reanalyses, evaluated under the same metric, are left as future efforts.

What follows looks more closely at the evolution of impacts seen in Figure 1 over the Amazon and determines what changes in the observing system taking place between the pre-EOS and EOS era lead to the noticeable changes of impacts. Specifically, observations will be seen to impact forecasts during wet and dry seasons in different ways, with specific observing systems contributing to the impact in particular ways. Seasonality differences in the impact will be seen to link to corresponding forecast sensitivities. Finally, the observing systems that most contribute to reduce short-range forecast errors in the region will be identified. The ultimate hope of the present work is to provide an incentive for additional observations to be made available over the Amazon basin and to motivate improved treatment of certain observations already assimilated.

The manuscript is organized in the following way. Section 2 provides a summary of the methodology. Section 3 gives a summary of the MERRA-2 system. Section 4 presents FSOI results derived from MERRA-2. Closing remarks are presented in section 5.

2. Methodology

The FSOI technique used in this study uses a combination of the method proposed by Langland and Baker (2004) with the correction of Trémolet (2008) to accommodate multiple middle-loop strategies (i.e., successive linearization of the observation operators) in the underlying analysis. The approach relies on the definition of a forecast error measure

$$e \equiv (x^f - x^v)^T C (x^f - x^v),$$

(1)

which evaluates an $n$-dimensional forecast $x^f$ against a verification state $x^v$, using a positive definite matrix $C$ as providing weights that normalize units among different variables. Time subscripts are omitted here for simplicity.

Infinitesimal changes to $e$ are traced back to changes in the forecast initial condition $x_0$ and subsequently to changes in observations $y^o$, responsible for the corresponding changes in initial conditions. Specifically, the so-called observation impact $\delta e$ can be written as

$$\delta e = \sum_{j=1}^{J} < K^j L^j g, d_j > ,$$

(2)

where the summation (middle-loop) is performed over multiple linearizations of the nonlinear observation operator, with the $p \times n$ Jacobian $H$, embedded in the successive $n \times p$ analysis operator $K$, with $L_{j-1} = L_j K_j H_j$, and where $d_j$ stands for the $p$-dimensional $j$th observation-minus-guess residual vector, and

$$g \equiv \left( \frac{\partial x^f}{\partial x_0} \right)^T \frac{\partial e}{\partial x^f}$$

(3)

amounts to a forecast sensitivity vector whose approximation leads to all kinds of formulae Errico (2007); Daescu and Todling (2009). Diniz and Todling (2019), and the present work, employ the second-order
approximation for the forecast sensitivity component as introduced by Langland and Baker (2004), which can be written as
\[
g \equiv \frac{1}{2} \left( M_a^T C_a + M_b^T C_b \right). \tag{4}
\]
Here, the $n \times n$ matrix $M^T$ represents the adjoint of a tangent linear model of the nonlinear model associated with the forecasting model used to obtain $\mathbf{x}'$, $\mathbf{e} \equiv \mathbf{x}' - \mathbf{x}$ is the forecast error, and the subscripts $a$ and $b$ correspond to linearization, and error evaluation, of model predictions issued from analysis and corresponding background states, respectively. In the present work, forecasts are self-verified, with $\mathbf{x}'$ chosen to be MERRA-2 analyses.

The normalization operator $C$ in (1) is chosen to be a linearized version of the globally integrated total energy expression that includes a moist static energy term (Ehrendorfer et al., 1999). This scales all observation impacts to be in units of J/kg, thus allowing for direct comparison of, say, wind and temperature measurements. As mentioned in section 1, this global norm applies even when results are being examined over specific regions of the globe, as done later in this manuscript. It is worth remarking that the weights prescribed by this particular choice of $C$ tail off rapidly above 100 hPa and are nearly zero by about 10 hPa. This has consequences when assessing the impact of certain instruments measuring the middle to low stratosphere, such as certain satellite radiance channels (see Todling, 2013). The choice of the norm here is typically accepted as adequate to assess the impact of instruments measuring the troposphere.

3. Short Summary of MERRA-2

The GMAO MERRA-2 is a follow-up to MERRA (Rienecker et al., 2011) that primarily aims at providing an improved water cycle as compared not only to MERRA but also to other available reanalyses. In that, it relies on the dry mass conservation constraint approach of Takacs et al. (2016). MERRA-2 general circulation model relies on a C180 (roughly 50 km) finite-volume cubed-grid hydrodynamics (Lin, 2004) using 72 hybrid vertical coordinate levels. Additionally, MERRA-2 incorporates a radiatively active aerosol component through the Goddard Chemistry, Aerosol, Radiation, and Transport (Chin et al., 2002; Colarco et al., 2010) and employs a local displacement ensemble approach to update its corresponding aerosol fields concentration by assimilating aerosol optical depth through the Physical-space Statistical Analysis System of Randles et al. (2017).

With respect to MERRA, MERRA-2 includes a revised and retuned version of its general circulation model (see Cullather et al., 2014; Molod et al., 2015) and a revised version of its sea ice concentration and sea surface temperature boundary conditions. This latter relying on a merge of the daily 1/4° resolution Reynolds et al. (2007) product from 1982 to March 2006 with the Donlon et al. (2012) 1/20° resolution Operational Sea Surface Temperature and Sea Ice Analysis data set covering the modern period. Another feature of MERRA-2 is its implementation of a land precipitation correction procedure applied from low to middle latitudes that rely on the offline MERRA-Land of Reichle et al. (2017) and its assimilated precipitation product. The procedure is an attempt to reduce model biases in land precipitation and to ground MERRA-2 to realistic levels of precipitation, especially when affecting aerosol deposition. This precipitation correction procedure ensures, in particular, that anomalous precipitation events are reasonably well represented in MERRA-2.

The MERRA-2 atmospheric analysis uses the Grid-point Statistical Interpolation (GSI) software; see Kleist et al. (2009). The analysis operates on a regular latitude-longitude 361 × 576 grid with a horizontal resolution comparable to the atmospheric model, roughly 50 km, and the 72 model vertical levels. Key to this analysis system is its reliance on the Community Radiative Transfer Model (Release 2.1.3: Chen et al., 2008; Han et al., 2006); the use of the Tangent Linear Normal Mode Constraint of Kleist et al. (2009) for incremental balance adjustment; and the employment of the biconjugate gradient minimization procedure of El Akkraoui et al. (2013) in its 3D-Var form, using two middle-loop iterations to accommodate nonlinearities in the GSI observation operators, and 100 inner iterations in each outer loop.

The observing system used over nearly 40 years of MERRA-2 analysis is rich and varied and is described in detail in McCarty et al. (2016). It includes conventional observations from a variety of sources, many of which are not available in the Amazon region or are only sparsely available. The bulk of the observations in MERRA-2 is composed of satellite radiances, especially as the reanalysis enters the EOS era. The modern observing system is dominated by data from hyperspectral instruments such as the Atmospheric Infrared
4. Impact of Observations Over the Amazon Basin in MERRA-2
4.1. Observing System

An illustration of the reason (i) in section 1 for how small impacts can alternatively be due to near lack of observations is provided by examining the Amazon basin data coverage during the pre-EOS era shown in Figure 2. Comparing with Figure 1, we see that before the mid-1990s impacts are considerably low as compared to the impacts in the extratropics. In this early period of the reanalysis, there are not as many observations in the tropics as there are in the extratropics, especially those from conventional observing systems. As observation counts increase into the EOS era, their impact also increases. From the late 1990s to about the end of 2008, there is a considerable increase in coverage from MW instruments (largely AMSU-A) and Atmospheric Motion Vectors (AMVs). During this period, the former makes up about 55% of all data assimilated in the region, while the latter corresponds to about 30% of the data assimilated. From late 2008 and beyond hyperspectral infrared (IR) instruments such as Infrared Atmospheric Sounding Interferometer on Meteorological Operational A series and eventually on Meteorological Operational A come in the mix.

Figure 2. Time series of the monthly mean stacked observation count (top) and corresponding fractional count (bottom) for the 0000 UTC MERRA-2 analyses during January and July over the Amazon basin. The scale factor for observation count is 10^6, and the units for fractional counts are %. Numerical values in the legends are the mean nonscaled number of observations during the availability of each observing system. The vertical shaded and nonshaded areas separate the four streams of MERRA-2.
Figure 3. Eighteen-year averaged 24-hr vertically integrated energy in forecast sensitivities for January (top: a and b) and July (bottom: c and d) over pre-EOS (1982–1999; left: a and c) and EOS (2000–2017; right: b and d) era. The scale factor is $10^{-3}$, and the units of energy are J/kg. The Amazon basin is represented by polygons in black contour.

and dominate the observation count in the region (see percentage count in the bottom panel of Figure 2). All these contribute to an increase in observation impact as compared to the early, sparsely observed, era.

A relevant aspect of the observation count in Figure 2 that is especially noticeable during the period between the late 1990s and 2008 is the zigzagging of the counts of MW, IR, and AMV observations. Close examination reveals it to be a consequence of seasonality, particularly the increase in clouds during the wet (January) months versus the low cloud dry (July) months. The January months tend to have more AMV observations than the July months; it is the presence of clouds, and their movement, that allows for the estimation of AMV observation. Conversely, the GSI 3D-Var analysis of MERRA-2 handles only clear-sky radiances (see Gelaro et al., 2017) consequently resulting in less MW and IR observations in the wet (January) months than in the dry (July) months. Still, the largest variations in count between these instruments come from the presence of multiple water-vapor sensitive channels for IR instruments (especially hyperspectral)—the most water-vapor sensitive channels 1–3 and 15 of AMSU-A (MW) are not assimilated in MERRA-2.

4.2. Forecast Sensitivities

A key component associated with the impact of observations on the forecast is the forecast sensitivity derived through (4). A global evaluation of 24-hr vertically integrated energy in the forecast sensitivities of MERRA-2 in Diniz and Todling (2019) has shown the energy fields to be largest along the storm tracks of each hemisphere and to be more accentuated in the NHX in January with a flipped behavior to the SHX in July. Furthermore, Diniz and Todling (2019) also find considerable reduction in the 24-hr forecast energy of the sensitivity fields in the EOS era as compared to the pre-EOS era. This reduction is directly associated with the increase in data volume and the reduced observation impact in the two hemispheres as seen in Figures 1b and 1c.

A similar evaluation comparing 24-hr vertically integrated energy in forecast sensitivities for the pre-EOS and EOS era, but now focused over the Amazon basin, is shown here in Figure 3. These are 18-year, roughly 100-km-resolution, averaged forecast sensitivities for January and July for each half period of the reanalysis. In opposition to what happens in the extratropics, in the tropics, and in particular over the Amazon basin, the energy in the forecast sensitivities actually increases in magnitude between the two periods. This increase is directly associated with the increased impact of observations in the Tropics and Amazon basin over the same periods and illustrated in Figures 1b and 1c. Very noticeable is the contrast between January and July averaged sensitivities, especially during the EOS era.

Partitioning of the averaged energy associated with these sensitivities reveals the dominant parts of the sensitivities to project onto the available potential and latent heat components of the energy (not shown).
Figure 4. Time series of the monthly mean (a) total and (b) fractional impacts for all observations over the Amazon basin, grouped according to classes presented in Figure 2. The gray lines represent the sum of all bubble values for each month and the curve in (a) is referred to as the dotted line in Figures 1b and 1c, with a single modification related to the moving average that is not being applied here. The size of the bubbles is proportional to the monthly mean observation count for each partition of the observing system. The units of total impact are J/kg and for fractional impact are %.

This is in opposition to what is typically found with the global partitioning of the energy where the largest contribution is determined by the kinetic energy component associated with the winds along the storm tracks. This is not surprising given the relevance of thermodynamical effects in tropical regions.

4.3. FSOI Results

The impact of each observation on a given forecast can easily be derived from the individual terms of the dot product in the last equality of (2). Clearly, the impact from a single observation makes little sense and what is typically done to obtain meaningful results is to group the individual impacts into various categories and then apply regional and time averages to the grouped impacts. In what follows, we largely concentrate on observations (and their corresponding impacts) within the Amazon basin, with considerations of other regions presented only to help reinforce argumentation.

Figure 4 provides an overall summary of the (a) observation impact and (b) their fractional impact over the Amazon basin. As before, results include only January and July, from 1980 to 2017. Each bubble in panel a refers to monthly averaged observation impacts, and in panel b to fractional impacts for a whole given month. The size of the bubbles in each panel reflects the mean observation count over a particular month. The thin solid curve shown in panel a is the time series of total observation impact over the Amazon
basin and is similar to the dotted curves shown in Figures 1b and 1c, except that a moving average is not applied now. The solid gray curve in panel b shows the sum of fractional impact for each month. Except for cases when there are observing systems contributing to deteriorate the forecasts, this gray curve adds up to 100%. The observing system is split into different observation types. With a few exceptions, most of the types contribute to reduce forecast errors, most of the time (negative numbers in panel a), with some, occasionally contributing in the other direction (positive numbers in panel a; spikes in the gray curve of panel b). Note that in relatively confined regions, it is not uncommon, neither a concern to see observations sometimes contributing to deteriorate the forecast; globally, on the other hand, this would; readers interested in applications using FSOI techniques to identify and deny those malefic observations are referred to Hotta et al. (2017), Kotsuki et al. (2017), and Chen and Kalnay (2018).

In the pre-EOS era, the impact of each individual observing type is relatively small, but MW radiance observations (mainly Microwave Sounding Unit) tend to have a larger impact as compared to other observing types available during that period. As MERRA-2 enters the EOS era, considerably more observations become available (as we have seen in Figure 2), but now conventional observations seem to dominate the impact. This dominance of conventional observations is especially noticeable in Figure 4b when its fractional contribution moves around 55–60%. Observing systems such as AMVs and Aircrafts also provide consistently work to reduce forecast errors, at times contributing to slightly over 20%. Hyperspectral IR observations, once made available, account for as much as 30% of the error reduction. The fractional percentage contribution of GPSRO to error reduction falls a little under 10%. It should be pointed out that the low impact of surface observations, both globally and locally over the Amazon basin, must be taken with some caution. The weights of the total energy norm associated with $C$ in (1) and the modest representation of physical processes in the adjoint model required for the derivation of forecast sensitivities are two factors that can significantly downplay the importance of near-surface observations.

The bulk of what is classified here as conventional observations is dominated by radiosondes. A summary view of the count from radiosonde reports (based on temperature soundings) is shown in Figure 5. Panel a gives a broad view of the partitioning of the global network of radiosondes into NHX, SHX, Tropics, and over the Amazon basin. Consistent with other works, we find a substantial decrease of this type of observations in the NHX—mainly taking place during the periods between the mid-1990s to the early 2000s—and a mild decrease in the SHX, which suffers from considerable lack of radiosondes in comparison to the NHX. In the tropics, however, the situation is slightly more positive, with the network experiencing a steady rise in sounding reports from 2004 onward, reaching as much as a 40% rise late in the reanalysis period (e.g., Figure 18 of Dee et al., 2011, and Figure 7 of Gelaro et al., 2017). Over the Amazon basin this is even more favorable, with a rise in observations also starting in the late 1990s and getting to nearly as many as five times the number of averaged reports. Unfortunately, the total number of averaged reports in the region is so small to begin with that a five-time increase amounts to still a small count overall. But even just a few extra radiosonde reports seem to contribute remarkably, steadily, and consistently to a progressive reduction in forecast errors—see latter part of time series in Figure 4.

It is rather peculiar that in the midst of the data-rich EOS period, highly dominated by satellite observations, one finds a handful of conventional observations to dominate the fractional impact. It is possible that the somewhat concurrent introduction of hyperspectral instruments helps improve the use of other data types through an improvement in the underlying background fields. It is also conceivable that assimilation of all-sky MW and hyperspectral IR instruments might take over and get these instruments to become the dominant contributors to forecast error reduction in the Amazon basin. All-sky assimilation, however, is not part of MERRA-2. Work is being done in the GSI analysis to treat observations in cloudy and precipitating conditions, as it is already the case for how some instruments and channels used in other assimilation systems are treated (see Bauer et al., 2011; Geer et al., 2018).

### 4.4. Seasonal Effect on FSOI

The effectiveness of different components of the observing system and their relationship with corresponding impacts is, in some cases, driven by seasonal effects. This was noticed earlier when examining the zigzagging pattern in some of the types of observations shown in Figure 2 and when examining the behavior of MERRA-2 24-hr forecast energy in the fields of sensitivities over the Amazon basin in Figure 3.

A more specific illustration of the seasonality effect in the observing system is shown in Figure 6. Here, observation counts and corresponding total impacts for the 18 years of January and July months over the
Figure 5. Time series of the monthly mean number of radiosonde reports per analysis at 0000 UTC in the (a) Northern Hemisphere Extratropics (north of 20° N; thick continuous line), Southern Hemisphere Extratropics (south of 20° S; thin continuous line), Tropics (between 20° S and 20° N; dashed line), and Amazon basin (dotted line); (b) Tropics and Amazon basin; and (c) Amazon basin. Lines represent monthly mean values during January and July. Only reports including temperature are accounted for.

EOS era are shown in panels a and b, respectively, for the Amazon basin. These two periods are the same as considered in panels b and d of Figure 3 when examining the vertically integrated energy in forecast sensitivities in the EOS era. Not all observation types displayed in the bar plots of the present figure are available for the whole of the 18 years; the averaging procedure is calculated according to the availability of the observing types. We notice from the counts that the wet January months end up with more AMV observations than the corresponding dry July months. Conversely, wet periods show lower (clear-sky) MW and IR counts than dry periods. GPSRO also shows a small seasonal variability. The observation counts of other instruments remain mostly consistent irrespective of the season. Accordingly, panel b shows that the impact of AMV is larger in
Figure 6. Barplots of (a) observation counts and (b) total observation impacts for January (orange) and July (blue) over the Amazon basin during the EOS era (2000–2017). The whiskers in panel b represent the standard error of the mean with 95% confidence intervals calculated using the standard deviation from the averaged monthly variances for the January and July months of the EOS era. The scale factor for observation count is 10^6, and the units of total impact and their standard errors are J/kg.

As mentioned above, Figure 6 indicates that GPSRO (bending angle) is another observing system with sensitivity to seasonality. The wet periods have reduced counts and smaller impacts than dry periods. A closer look at GPSRO appears in Figure 7, where the averaged results for January (a) and July (b) are shown in the form of profiles for scaled observation-minus-background (OmB) residual mean (solid curves), standard deviations of the OmB (dashed curves), corresponding observation impact (bars), and associated standard deviations.
Figure 7. Vertical profile of mean (continuous line, bottom axis) and standard deviation (dashed line, bottom axis) of fractional observation-minus-background (OmB) residuals and total impact (bars, top axis) for GPSRO observations over the Amazon basin. Lines (bars) represent 13-year average, from 2005 to 2017, during (a) January and (b) July. The whiskers correspond to the standard error of the mean with 95% confidence intervals calculated using the standard deviation as in Figure 6b. The column on the right represents mean number of observations per analysis in each layer. The units of mean and standard deviation of fractional background residuals are % and of total impact, and their standard errors are 10^{-3} J/kg.

The scaled means and standard deviations of the OmB residuals are only mildly affected by seasonality, but a more considerable difference is noticed in the observation impacts themselves. In the dry season, the largest impacts from GPSRO occur in the layer between 10 and 25 km; in the wet season, the largest impacts are confined to a smaller layer between 13 and 20 km. The former is mainly in agreement with the findings of Cardinali and Healy (2014) on a study done over June 2011 (i.e., dry season). The more sensitive January forecasts (Figure 3b) affect the tropospheric contribution (up to 13 km) of GPSRO in the wet season, with a large part of the profile showing a deterioration of forecast error reduction (positive impacts), especially in the lower portion of the atmosphere. This reduced effectiveness of GPSRO in wet periods is attributed to the GSI bending angle forward observation operator sensitivities (reflected in the Jacobian operator) to moisture in the environment Cucurull et al. (2013). Cucurull et al. (2013) suggested that the incorporation of horizontal gradients of refractivity (mainly caused by water vapor) in the current GPSRO forward operator used in GSI is expected to improve the use of such observations, particularly in the lower troposphere.

5. Closing Remarks

This study is a follow-up to the work of Diniz and Todling (2019) and examines the impact of observations in short-range forecasts from the MERRA-2 reanalysis over the Amazon basin. The work employs the FSOI technique of Langland and Baker (2004), combined with the Trémolet (2008) correction to account for multiple linearizations of the observation operator, to assess the impact of nearly 40 years of assimilation of observations over this challenging region of the globe. In some respects, results in this region are found to be not much different from those obtained from the global picture. But its specificity serves as a reminder and motivation for the need to improve upon the usage of certain observation types with much potential over the Amazon in particular and in the tropics in general.

It is especially clear from this work that even with the advent of a dramatic increase in satellite observations over the past 20 years, 3D-Var reanalysis such as MERRA-2 reveals the importance and heavy reliance on conventional observations. Over the Amazon basin, in particular, the present work shows the dominance of only a minimal set of radiosondes in these same 20 years. The mild increase in the number of radiosonde reports over the basin after 2012 is seen to get the network to contribute to over 50% of the impact in reducing forecast errors as compared to the contribution from all other observations in the region. The relevance of radiosondes in the region has been emphasized in many works, some of which suggest approaches to
improve upon the network. Among these, there are innovative ideas to help enhance the availability of such observations on a routine basis, especially over remote regions such as the Amazon basin (e.g., gliders sondes of Lafon et al., 2014).

At the same time, it can be fairly argued that more advanced techniques to take advantage of radiance observations in cloudy and precipitating regions might mitigate the apparent need for an increase in radiosonde-like observations. The relatively low impact of radiance observations in the Amazon basin found in the present MERRA-2-based evaluation is likely different in a system that already treats some of the radiance observations as all sky. Indeed, global results show that radiance observations dominate the overall impact when some are treated as all sky (see Cardinalli & Prates, 2011). The potential improvement on the usage of satellite radiance through techniques allowing for all-sky conditions is also expected to affect the interplay between found in this work between the clear-sky radiance of MERRA-2 and AMVs observations. The presence of clouds and precipitation in the wet Amazon season should no longer be a reason to find the impact from radiance to be smaller than the impact from AMVs.

From its introduction in the early 2000s, GPSRO is found to contribute to about 10% to the overall reduction in forecast errors on a global scale. Over the Amazon basin, its contribution is slightly less than 10%, but it is seen to vary somewhat with season. The assimilation of bending angle in the MERRA-2 analysis seems quite sensitive to low and middle tropospheric water vapor, which in turn contributes to reduce the effectiveness of these observations in wet periods. There is potentially room for improvement in the GPSRO forward operator as implemented in the GSI analysis when it comes to handling sensitivity to water vapor.

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