We gratefully thank the editor for his very careful review. We have revised the paper accordingly. In addition to the editor's comments, we made some minor changes in the abstract. The responses to the editor's comments are given below. The changes in the manuscript are also attached in the end (only for pages with changes).

Response to Editor, Zoltan Toth

Thank you for your response and revisions. I may be missing something, but looking at Fig 3 and the associated discussion, I do not see a reference whether you show moist or dry energy results in these figures? Please add this information into the figure legend and text (if missing from there, too). Other than that, your manuscript is ready for publication.

Thank you very much for pointing out this mistake we made. Except for the second column of Fig. 2, all other EFSO statistics figures show results using the moist total energy norm. We added this information into the captions of Figs. 3 (P.12) and 4 (P. 14) and the texts (P.11, L.11; P.13, L.15).

Accelerating assimilation development for new observing systems using EFSO

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Abstract. To successfully assimilate data from a new observing system, it is necessary to develop appropriate data selection strategies, assimilating only the generally useful data. This development work is usually done by trial-and-error using Observing System Experiments (OSEs), which are very time- and resource-consuming. This study proposes a new, efficient methodology to accelerate the development using the Ensemble Forecast Sensitivity to Observations (EFSO). First, non-cycled assimilation of the new observation data is conducted to compute EFSO diagnostics for each observation within a large sample. Second, the average EFSO conditionally sampled in terms of various factors is computed. Third, potential data selection criteria are designed based on the non-cycled EFSO statistics, and tested in cycled OSEs to verify the actual assimilation impact. The usefulness of this method is demonstrated with the assimilation of satellite precipitation data. It is shown that the EFSO based method can efficiently suggest data selection criteria that significantly improve the assimilation results.

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1 Introduction

Improvements in Numerical Weather Prediction (NWP) depend fundamentally on the efficient assimilation of available observations. Technological advances in remote sensing have introduced a growing number of new observing systems. However, in most cases, assimilation of a new observing system is a difficult task: naively assimilating every observation usually degrades the forecasts. It is necessary to implement an appropriate data selection process, such as selection based on channels, locations, data quality flags, and background conditions, to assimilate mostly useful data that improve model forecasts. Sometimes this data selection process is called, or overlapped with the process of quality control (QC). However, the "intrinsic" quality of the observational data is usually not the only reason for their "usefulness" in data assimilation (DA). Therefore, in this article, we use a more general term "data selection criteria" to refer to all data selection processes prior to the assimilation of a dataset.

A common approach to test the impact of assimilating a new set of observations is to perform Observing System Experiments (OSEs), which compare two otherwise identical experiments, one which includes the assimilation of the new case of no precipitation in all members, there are more observations when there are many precipitating members (red lines in Fig. 2e,f).

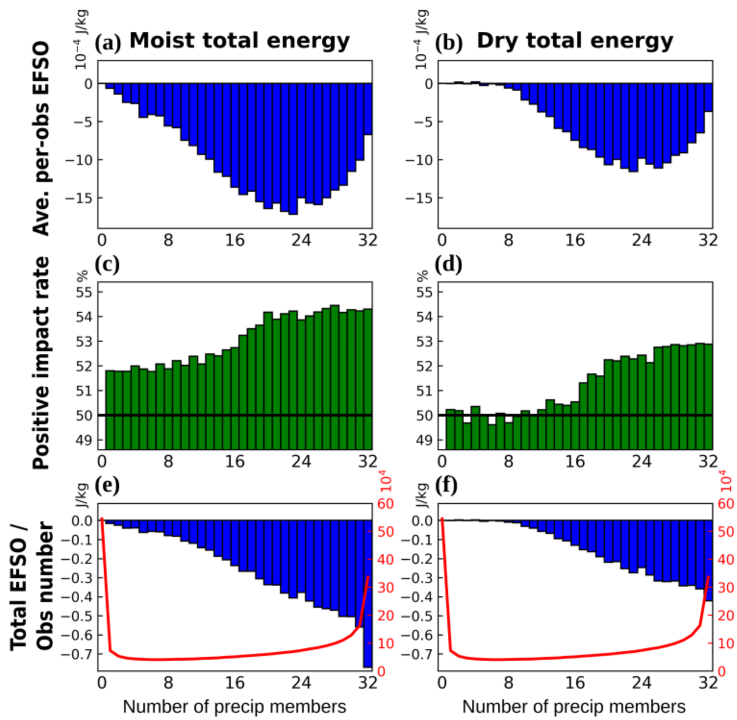

Figure 2: EFSO statistics for TMPA observations grouped by the number of precipitating members in the background and measured by (first column) the moist total energy norm, and (second column) the dry total energy norm in 6-hour forecasts during the year 2008. (a)–(b): average per-obs EFSO (10^{-4} J kg^{-1}). (c)–(d): percentage of observations with positive impacts. (e)–(f): total EFSO per cycle (J kg^{-1}). Also shown in red curves in (e)–(f) are the total numbers of observations (i.e., EFSO samples) in all 293 offline cycles (10^4; secondary y-axis).

In addition, the EFSO statistics using the moist total energy norm are also computed separately under the condition of nonzero precipitation in the observation (hereafter R>0; first column in Fig. 3) and zero precipitation in the observation (hereafter R=0; second column in Fig. 3). For R>0 observations, the average per-obs EFSO (Fig. 3a) is all beneficial (reduction of the error), but it is most beneficial when about half of the ensemble forecasts are precipitating and half are not, indicating that the observations of precipitation are most useful when there is high uncertainty in the forecasts. The percentage of the R>0 observations that are beneficial (Fig. 3c) is astonishingly high, reaching almost 70% under the condition that the number of precipitating members is between 5 and 13. Similarly it shows lower percentages with fewer or more precipitating members, but still much above 50%. We note that in a realistic data assimilation system such very high beneficial rates should only be found when taking subsets of observations as in this example. Besides, the relatively inaccurate rawinsonde-only CONTROL, which allows the precipitation observations to contribute a larger amount of information, would be another reason for this high beneficial rate. With a modern operational system, such extremely high rates would be more difficult to be seen. The situation is quite different for R=0 observations: If the number of precipitating ensemble members is 20 or less, assimilating the R=0 observations has a detrimental effect, and it only becomes beneficial when most of the ensemble members are (wrongly) precipitating (Fig. 3b). The percentage of beneficial R=0 observations is less than 50% unless essentially all the ensemble members are precipitating (Fig. 3d).

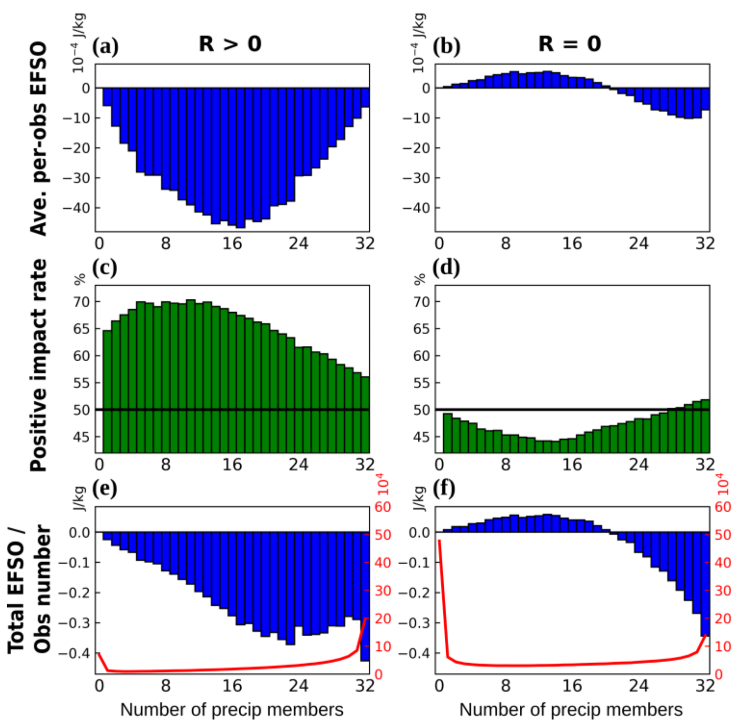

Figure 3: Same as Fig. 2, but for EFSO measured by the moist total energy norm and computed separately for (first column) non-zero precipitation observations (R>0) and (second column) zero precipitation observations (R=0).

To validate if these EFSO statistics computed based on the 32-member ensemble are robust, we compute the same EFSO statistics using only the first 8, 16, and 24 members. We note that this check only varies the number of ensemble members for the EFSO computation but not that in the (offline) DA; namely, the precipitation observations are still assimilated using 32 members, but the EFSO is computed [Eq. (5)] using ensemble forecasts of fewer members to the evaluation time ($\mathbf{X}_{t|0}^{f}$). Figures like Fig. 3 but computed from fewer members are shown in Supplement. Comparing Fig. 3 and Figs. S1–3 in Supplement, we conclude that the average per-obs EFSO statistics over the large samples hardly change even with a very small ensemble size, 8 members, but the rates of beneficial observations become generally closer to 50% with fewer members. We think that the insensitivity of per-obs EFSO to the ensemble sizes is due to the average over large samples from multiple cycles, that overcomes the errors in individual observations. In contrast, the beneficial rates are more sensitive to the ensemble size because small errors in near-neutral impact observations can easily change their signs. However, for the purpose of this work, since the important information we like to know from these EFSO statistics is just the qualitative usefulness among different groups of observations, an ensemble size of 32 or even fewer is shown to be enough for the EFSO computation given the sufficient sample size.

Next, Fig. 4a,b shows the EFSO statistics (using the moist total energy norm) with respect to the geographic locations. Overall, the areas benefitted the most by the precipitation assimilation are the storm-track regions, located within 30–50°N and °S over the three major oceans. Most of the ocean regions show positive impacts and greater-than-50% positive impact rates. The marine stratocumulus regions are an exception showing detrimental impacts over the ocean. The land regions show marginal or negative impacts. These two different measures show generally similar patterns, but the detrimental regions over the land are more clearly highlighted with the positive impact rate. Here we show an interesting comparison of these EFSO maps to the correlation map between the 6-hour accumulated precipitation in the 3 to 9-hour T62 GFS model forecasts and the TMPA observations at the corresponding times (Fig. 4c), which was obtained in Lien et al. (2016a). Note that Fig. 4c is similar to Fig. 10 in Lien et al. (2016a) but for all seasons combined. This correlation score represents a simple measure of the statistical "consistency" between the model and the observation climatology, whereas details on this correlation calculation are described in Lien et al. (2016a). It was hypothesized in Lien et al. (2016a) that the precipitation observations distributed over the regions with higher correlations could be more useful for data assimilation, but that the data over very low correlation regions would be difficult to be used mainly because of large model errors. Here a great similarity is found between the average EFSO map (Fig. 4a) and the correlation map (Fig. 4c), indicating that the hypothesis in Lien et al. (2016a) was reasonable, and that the effectiveness of the precipitation assimilation is in fact strongly dependent on the geographic locations, which can be explained by the systematic inconsistency between model and observed precipitation (Lien et al., 2016a). We note again that the intrinsic quality of each observation is not the only reason for its good or bad EFSO or assimilation impact.

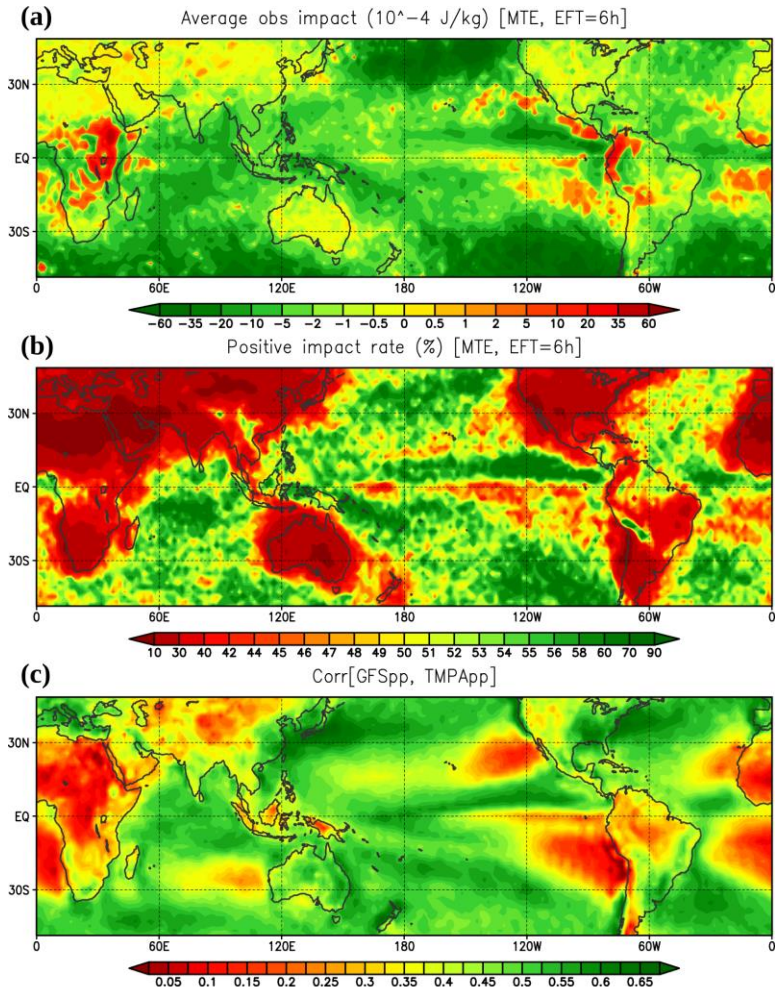

Figure 4: The maps of (a) the average per-obs EFSO (10^{-4} J kg^{-1}) and (b) the rate (%) of observations having positive impacts from the same precipitation EFSO sample (measured by the moist total energy norm) used in Fig. 2. (c) The maps of correlation between the 6-hour accumulated precipitation in the 3 to 9-hour T62 GFS model forecasts and the TMPA observations at the corresponding times during the year 2001–2010 period. This correlation map is similar to Fig. 10 in Lien et al. (2016a) but for all seasons combined. Details on this correlation calculation are described in Lien et al. (2016a).

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