Proactive Quality Control to Improve NWP, Reanalysis, and Observations

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Abstract

Massive amounts of observations are being assimilated into modern-era climate retrospective reanalyses and Numerical Weather Prediction (NWP). This makes very difficult to estimate the impact of a new observing system with Observing System Experiments (OSEs) because there is already so much information provided by other observations. In addition, the large volume of data prevents monitoring the impact of each observation with OSEs and hence the quality of reanalysis and NWP are subject to degradation due to occasional low quality observations. We propose using Proactive Quality Control (PQC, Hotta, 2014, UMD) based on Ensemble Forecast Sensitivity to Observations (EFSO, Kalnay et al, 2012, Tellus) to improve NWP, reanalyses, and observations.

EFSO is used to efficiently examine the impact of all existing observing systems. We found in preliminary results that some observing systems (e.g., MODIS polar winds), even though their overall impact is beneficial, have a large detrimental impact under certain flow conditions, which EFSO can efficiently identify and thus help develop a better QC.

A PQC method is being developed to improve the quality of NWP. Preliminary results show that the quality of the analysis and the subsequent forecast can be significantly improved by rejecting detrimental observations based on EFSO. The same PQC method can be extended to improve the quality of reanalysis, for which it is possible to explore Assimilation in the Unstable Subspace (AUS, Trevisan et al., 2010, QJRMS) for reanalysis in the EnKF framework. Early results show that AUS can substantially improve the quality of analysis (~5% in 5-day forecasts).

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List of Abbreviations

AIRS	Advanced InfraRed Sounder
AUS	Assimilation in the Unstable Subspace
EFSO	Ensemble Forecast Sensitivity to Observations
FSO	Forecast Sensiticity to Observations
NWP	Numerical Weather Prediction
OSEs	Observing System Experiments
PAWR	Phase Array Weather Radar
PQC	Proactive Quality Control
QC	Quality Control

1. Introduction

One of the essential basis of the success of Numerical Weather Prediction (NWP) and Reanalysis is the massive amount of observations that is constantly growing in number and quality. Both maintaining existing observing systems and developing new ones require enormous resources. It is natural to evaluate the usefulness of the observed data. More specifically for NWP, it is desirable to learn the impact of each observing systems on day-to-day model forecasts. Direct comparison between control run (with all the observations) and data denial runs is a straightforward approach, known as Observing System Experiments (OSEs). However, with millions of observations assimilated every 6 hours (Fig. 1), this task is very challenging. In addition, more advanced new observing systems with higher spatial, temporal and spectral resolutions (e.g. phase array weather radar (PAWR) and new geostationary satellite series: GOES-R, Himawari) are being launched every once a while, which makes keeping track of the impact of the systems even harder. First, the computational expensive experiments limit the number of runs needed to separate the impact of observation subsets, so the discernibility is low. Second, the difference of having a subset of observations or not may not be significant enough even for 5-day forecasts, given that there are already a lot of additional observations assimilated. Hence accurate impact-estimation of small subsets of observations is virtually impossible.

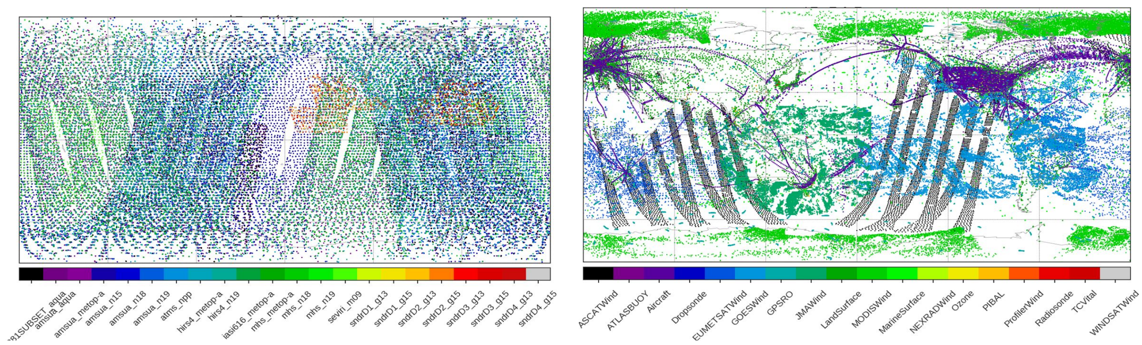

Fig. 1: The spatial distribution of assimilated radiance (left) and nonradiance (right) observations in NCEP operational data assimilation system on Feb/06/2012 18Z. Each dot represents an individual observation and the color indicates the providing observing systems.

To overcome the difficulties faced by OSEs, Forecast Sensitivity to Observations (FSO) was developed (Langland and Baker 2004). Taking advantage of the adjoint model, FSO attributes the changes of forecast back to each individual observation using a future analysis as verification. However, it has been found that the Moist and Dry Total Energy of the forecast error estimations obtained with FSO are inconsistent because of the problems of adjoint models in representing moist processes (Janisko and Cardinali 2016). By contrast, Ensemble Forecast Sensitivity to Observations (EFSO; Kalnay et al. 2012) that we propose to use does not require an adjoint model because it uses ensemble forecasts to estimate the impact of the observations on the forecasts, and the moist and dry estimations of the error are very consistent (Fig. 2).

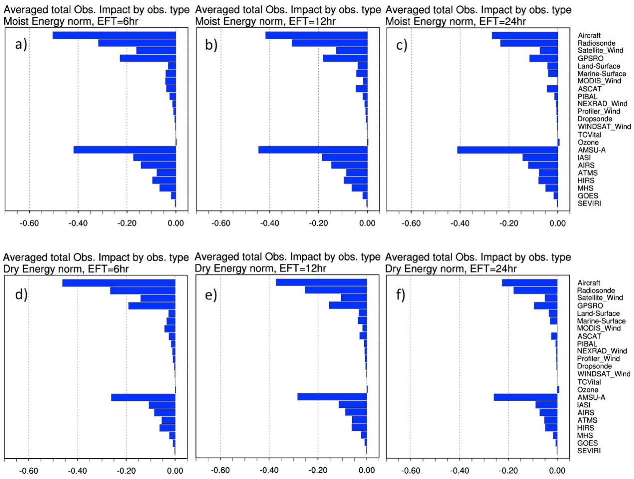

Fig. 2: Average Total Energy EFSO observation impact, by observation type and by different forecast lengths. Negative values indicate that the observations reduce the error. Top, using Moist Total Energy norm for the forecast error. Bottom, using Dry Total Energy norm. Left, center, and right panels correspond to 6hr, 12hr, and 24hr forecast errors respectively. Note that the results are consistent for both norms (moist or dry) and period (6-24hr). Courtesy of D. Hotta (2014).

One of the main objectives of this work is to improve NWP by EFSO, which makes quantification of observation impact on model forecast possible. There are two approaches to achieve this goal. The first is to improve the observations by identifying algorithm problems or modifying QC process using EFSO (Lien et al. 2017). The second approach is by Proactive Quality Control (PQC; Hotta 2014; Ota et al. 2013), which rejects detrimental observations identified by EFSO. We have already developed PQC approaches much more effective than those tested by Ota et al. (2013) and by Hotta (2014). In addition to improving

NWP, we have shown that EFSO can quantify the impact of each observation on different forecast times so that the powerful method "Assimilating in the Unstable Subspace" (AUS; Trevisan et al. 2010) in the EnKF framework becomes attainable. Although not affordable in operations, because it would require waiting 24 hours for the verifying analysis, it can be very valuable in Reanalysis mode and improve the quality of Reanalysis data.

2. Research Design and Methods

2.1 Improving Observations. *The goal is to identify potential instrumental or algorithm level problems and improve quality control for each observing system.*

One of the approaches to improve NWP using EFSO is through improving the quality of observations, which depends on the instrument, algorithm, and quality control procedure. EFSO quantifies the impact of each observation on any given short period of model forecasts. One valuable application of EFSO is that it could be used as an efficient online monitoring tool for observation quality. As an example, figure 3 shows the time evolution of total 6-hour impact of each observing systems throughout the 1-month experiment. It is clear that most of the observing systems are beneficial at all times as shown in figure 1, such as the top 3 beneficial systems: commercial aircrafts, GPSRO, and Radiosondes. However, there are several observing systems having occasional detrimental episodes, namely Profiler winds, PIBAL, Atlas buoy, Dropsondes, NEXRAD winds, and MODIS winds. This implies that even with overall beneficial impact, there could be some flow dependent condition that leads to detrimental impact in certain times and locations. Making use of EFSO, it is possible to quickly identify, if any, problems of an arbitrary subset of the observations in either the instrument, algorithm, or the quality control, even if it only takes place under special circumstances.

For example, MODIS polar winds, vital to NWP in higher latitudes, provide critical wind profiles over polar regions and an overall impact that is beneficial on model forecasts. However, we found with EFSO that the MODIS winds are frequently detrimental. Figure 4 shows the EFSO 6-hr forecast impact of all the non-radiance observations for a 6 hour period.

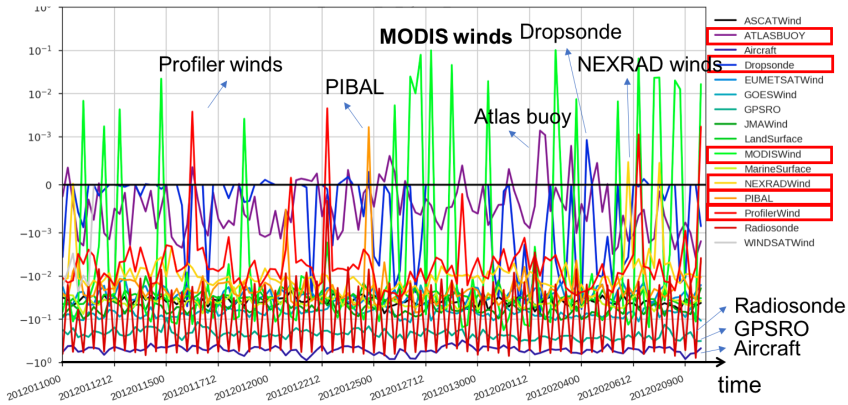

Fig. 3: The time evolution of 06-hr total impact of each observing systems for 1-month period. Positive values mean the impact of the system is detrimental (systems marked in red boxes.) and the negative means beneficial.

There are at least two regions of dense detrimental observations (red patches), most of which are MODIS winds, located north of Eurasia and south of Atlantic Ocean. Data denial experiments (Hotta 2014; Ota et al. 2013), confirmed that assimilating these detrimental MODIS winds degrades model forecast, showing that EFSO indeed captures the detrimental subset from massive amount of observations. And by analyzing EFSO impact of them, a specific set of conditions can be found which consistently produces detrimental observations. As shown in figure 5, we found such conditions for MODIS winds, in which the occurrence of detrimental observation depends highly on the innovation (observation-first guess) and on the observed wind direction. This shows that a simple QC method could be immediately implemented based on such dependence and have beneficial impact on NWP. More importantly, it gives clues to help identify the problem at the algorithm level and fundamentally improve the observation. We are collaborating with Wisconsin researchers Brett Hoover and David Santek, creators of the MODIS wind algorithm.

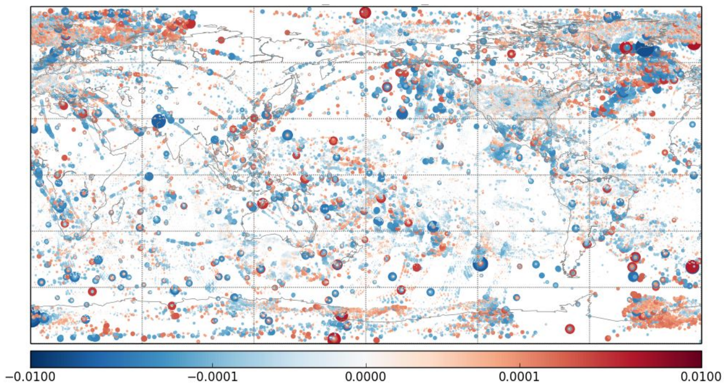

Fig. 4: Spatial distribution of EFSO estimated impact of each non-radiance observation on the 6h forecast at 18Z Feb/06/2012. Each dot represents one observation. Blue indicates a beneficial and red a Detrimental observation. The size is proportional to the magnitude of the impact. Note the red patches of detrimental observations associated with MODIS polar winds in the South Atlantic and Eurasia.

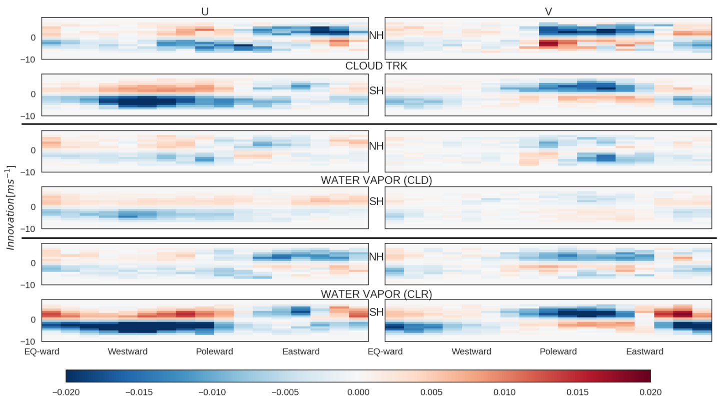

Fig. 5: EFSO impact of MODIS polar wind against innovation and observed wind direction. Blue is beneficial and red detrimental. Left: zonal wind, right: meridional wind. The top, middle and bottom two rows are for the 3 types of MODIS wind observations: cloud tracking, cloudy water vapor tracking and clear water vapor tracking winds. The top row is for the NH and the bottom for the SH. Note that the detrimental winds are strongly dependent on the sign of the innovation and on the direction of the wind.

Although this part of the study aims at examining all observing system in general, we will focus on the newly launched observing systems, including but not limit to the VIIRS unit and the next generation GOES and Himawari satellite series. The radiance data and the derived feature tracking winds are especially important, since they cover regions in open ocean and provide information of atmospheric moisture, temperature, and wind profiles. It is noteworthy that the derived winds from these new systems are using essentially the same algorithm as the MODIS winds with slight differences, which indicates the possible existence of such detrimental conditions. This would greatly improve the quality of the observations.

2.2 Proactive Quality Control (PQC): correcting the analysis: *The goal is to improve the analysis on the fly and subsequent forecast by fully flow dependent PQC based on EFSO.*

While EFSO makes possible to identify and fix flow dependent detrimental observations, the process might take quite some time and there is a way to avoid the detrimental observations from degrading the forecast: Proactive Quality Control. The basic algorithm (Fig. 6) is the following:

1. Compute EFSO using (green box in Fig. 6):
    a. 12-hr forecast from t = -06
    b. 06-hr forecast from t = 00
    c. analysis at t = 06
2. Determine a set of observations at t = 00 to be rejected based on EFSO
3. Repeat the analysis process without those observations.

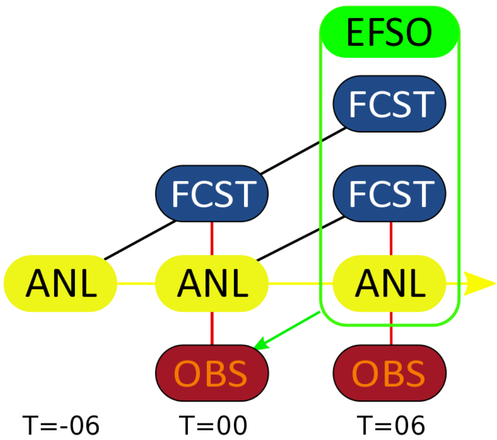

Fig. 6: Algorithm of Proactive Quality Control. Adapted from Hotta (2014).

The idea of PQC based on EFSO was first proposed and tested for short term forecasts (e.g. 24 hours; Ota et al. 2013; Hotta 2014). In this study, the performance examination was extended to 5-day forecast. In the initial results, the analyses and the subsequent 5-day forecasts were indeed improved by rejecting the 6-hr detrimental observations identified by EFSO (see figure 8 left, labeled Hotta). Given the success of these early results, we would like to explore whether it is possible to improve the current method and to prove that PQC is affordable and beneficial in operational implementation.

The rejecting strategy for PQC first tested by Ota et al. (2013) and Hotta (2014) was designed to use EFSO to identify any region of 30º latitude by 30º longitude that was strongly affected by detrimental observations. The EFSO impact of the observations in these regions were then examined to identify the probable culprit observations, and the ones with detrimental impact were rejected. The snapshots from several forecast lead-times (06, 24, 72, and 96 hours) of one typical case of the relative forecast improvement (%) by PQC is shown in figure 7. In the beginning, the improvements are located at the vicinity of the area of rejected observations (not shown). It is noticeable of the existence of a short-lived degradation at south pole, but it decays away very quickly. After 6 hours, it starts to grow in both magnitude and areal coverage with time and there is a clear sign of propagation of the improvement towards the downstream area, which is believed to be associated with dynamical instabilities. The peak of relative improvement is around 3-4 days and it begins to decay afterward, but he beneficial impact extends beyond 5 days (map view not shown, see figure 8.). It was very satisfying to note that applying this PQC reduced the average MTE error in the 5-day forecasts by about 0.5%.

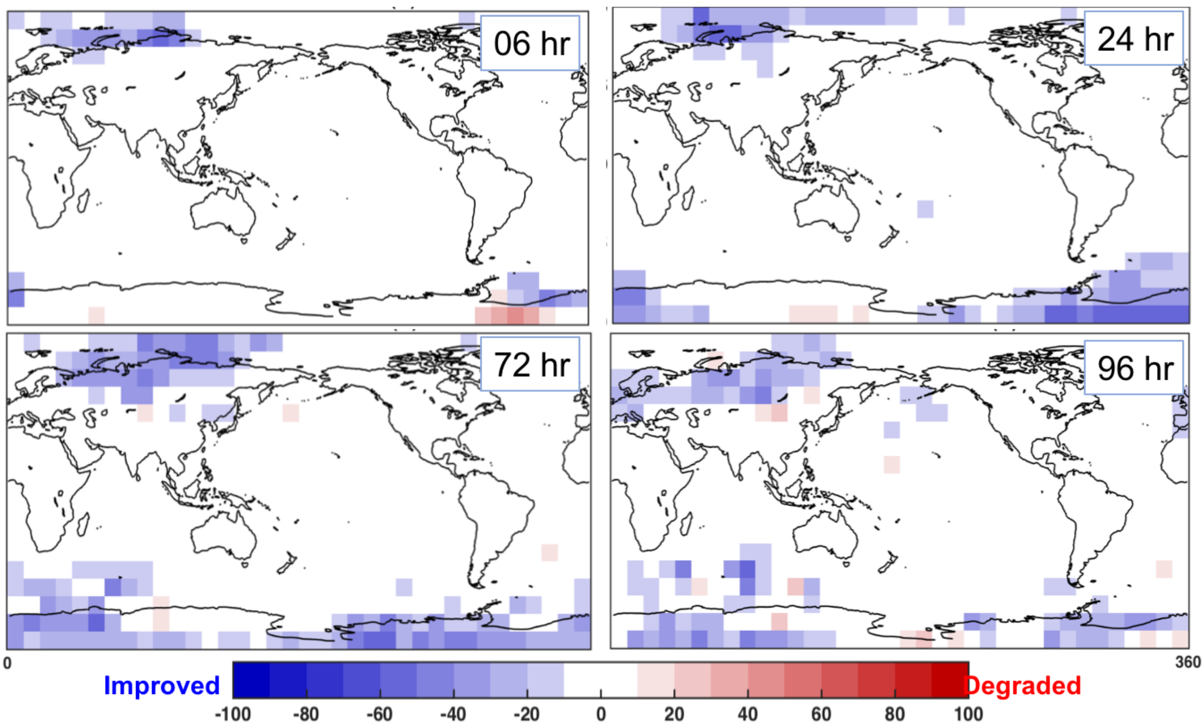

Fig. 7: Snapshots of the relative forecast improvement (%) from 06, 24, 72, and 96 hours. The forecasts are improved at the blue areas, whereas the red indicates forecast degradation.

One of the main purpose of this thesis is to improve the original very successful strategy for rejecting observations developed by Hotta (2014). Two new methods have been developed. The Threshold approach deletes all observations with a detrimental impact of 10^{-5} or more in MTE units. As shown in Fig. 8 (middle panel), this approach seems more successful, reducing the MTE 5-day forecast error by about 3%. The AUS method (Fig. 8, right), discussed in section 2.3, and shows further improvements now larger than 5%.

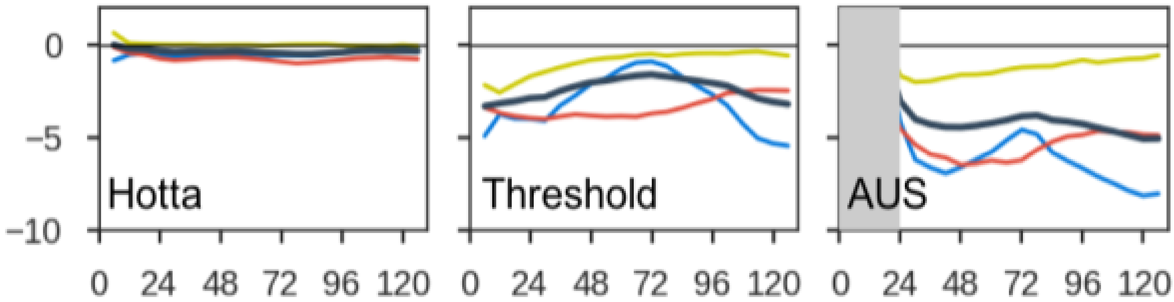

Fig. 8: Relative reduction of 5 day forecast errors in %, measured by the Moist Total Energy (MTE) of the forecast error. Left: MTE obtained with the original PQC approach of Ota et al. (2013) and Hotta (2014), which is successful and gives a reduction of O(0.5%). The Threshold approach deletes all observations with a detrimental impact of 10^{-5} in MTE units. The Analysis in the Unstable Space (AUS, Trevisan et al., 2010) deletes all detrimental observations whose negative impact increases from 6 to 12h, and from 12 to 24h. Since it would require a 24h verifying analysis, AUS can only be carried out in a Reanalysis, when future observations and analyses are available.

While offline experiments have shown that PQC improves the analyses and forecasts, online cycling experiments, in which the PQC corrected analysis will continue to be used in following data assimilation cycle, are necessary to demonstrate the long-term accumulated beneficial effect. Preliminary results are very encouraging, suggesting that the benefits of PQC accumulate as the data assimilation continues.

The practicality of operational implementation of PQC will be investigated. Current plan for performing PQC within the tight schedule of operational centers include making use of the early analysis and approximating the PQC correction. Most major operation centers implement a dual analysis system to deliver the forecast timely, in which the early analysis assimilates only observations before a cutoff deadline, whereas the final analysis assimilates full set of observations and is used in the following Data Assimilation (DA) cycle. Using the early analysis as verification would save 3 hours of wait time. In addition, we can approximate the Kalman gain K, the most expensive part in repeating the analysis without detrimental observations, by assuming that it is constant because only a small portion of observations are rejected. We have shown that the correction from approximated PQC is very similar to that from fully nonlinear PQC obtained by repeating the analysis without the rejected observations (Fig. 5).

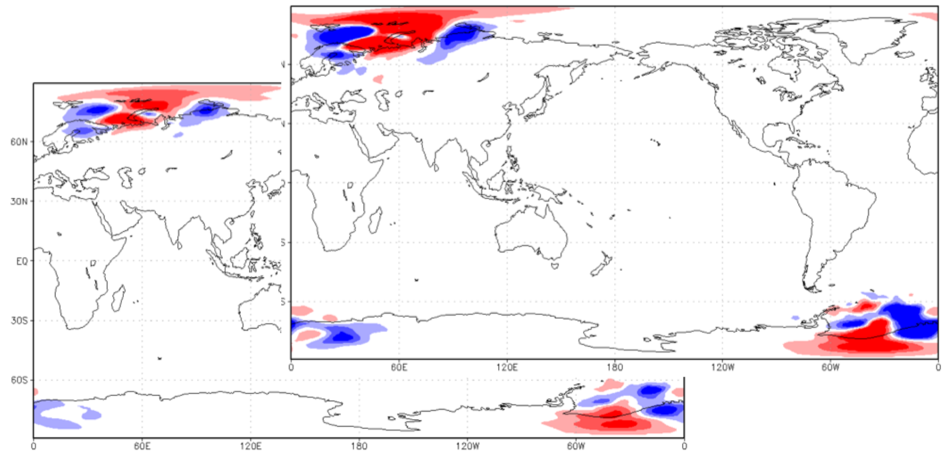

Fig. 9: Comparison of true PQC correction (left) with approximated PQC correction (right) assuming K is a constant in 500 hPa geopotential height of a case on Feb/06/2012 18Z. The two are highly correlated (not shown) and the patterns are very similar.

Furthermore, satellite channel selection is another difficult task for NWP centers that select a limited number of channels containing maximum information of the vertical profile of atmospheric moisture, temperature, and composition for assimilation efficiency. It is challenging to choose an optimal set of channels from hyper-spectral instruments like Advanced InfraRed Sounder (AIRS). This is especially true to the fact that this theoretical optimal choice should vary with geographical location and be atmospheric conditions. PQC being fully flow dependent is a perfect tool in finding the optimal set of channels that varies with the flow and location.

This part of the study will benefit operational NWP by increasing the accuracy of analysis and the subsequent forecast. The quality of daily weather prediction will be improved and hence reducing the damage of hazardous events.

2.3 Assimilation in Unstable Subspace (AUS): Reanalysis mode: *The goal here is to identify the unstable subspace of data assimilation by performing EFSO with respect to multiple forecast lead-times and improve the quality of reanalysis products.*

Reanalysis datasets, such as the widely used MERRA and the new, more advanced MERRA-2, which ingest as many observations as possible with a fixed version of model and data assimilation system, provide the most accurate multi-variate three-dimensional estimations state of the atmosphere for long periods (decades), which is essential for studies of climate change and variability.

The idea of AUS was first proposed in 4D-Var data assimilation framework by Trevisan et al. (2010). They reasoned that it was better to confine the analysis increments to the growing subspace, since the errors in the decaying mode subspace would decay in time anyway. This was shown to be true with 4D-Var in a simple nonlinear scenario with the Lorenz (1996) model, for which it was possible to explicitly calculate the leading growing Lyapunov vectors. The experiments showed that the analysis accuracy indeed improved. However, with a realistic model it is impossible to determine the growing subspace spanned by the leading Lyapinov vector. We realized that by performing EFSO with multiple forecast lead-times (e.g., 6h, 12h, 24h), such optimal growing subspace can be identified. Hence, EFSO provides an opportunity to adapt AUS to EnKF framework. In preliminary offline experiments, in which the improved analyses are not used to produce the following analyses, the ensemble version of AUS demonstrates extremely promising results (Fig. 4, right panel), with reduction of errors of O(5%).

However, before pushing towards implementation of AUS in, for example MERRA-2, several issues need to be addressed. Like in PQC, cycling experiments are necessary to prove the accumulated long-term beneficial impact from AUS. In addition, the unstable subspace is simply defined as those observations with beneficial impact, having the 24-hr impact larger that of the 6-hr forecast. It worths further explorations using different combinations of EFSO with several lead-times.

This part of the study should substantially improve the quality of the reanalysis, and therefore benefit other research related to climate variability and environmental change that rely heavily on the quality of reanalysis dataset.

3. Summary

The objective of this study is to improve the quality of observations, NWP, and reanalysis by using EFSO. In the first part, we have demonstrated the usefulness of EFSO in online monitoring of the impact of each observing systems or any arbitrary subsets and are developing techniques for identifying and finding fundamental problems causing detrimental observations. As an example, the production procedure of MODIS winds will be carefully examined in the collaboration with the developers. Second, PQC rejecting observations based on EFSO is shown to have large beneficial impact on the analyses and the subsequent forecasts. We have also demonstrated the feasibility of implementing PQC in operations by making use of GFS early analysis and a fairly accurate approximation of PQC correction to save time. Finally, PQC has been shown to be more powerful in reanalysis environment, in which has no tight schedule to meet. By constraining the assimilated observations to be in beneficial growthing mode, PQC-AUS can improve the analysis and forecasts much more than PQC-Threshold.

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