ASSIMILATION OF REMOTE-SENSED CLOUDINESS OBSERVATIONS

Andrea Storto
Norwegian Meteorological Institute, PO BOX 43 Blindern 0313, Oslo, Norway (andrea.storto@met.no)

Abstract

A new approach for assimilating cloudiness observations is being developed at the Norwegian Meteorological Institute, consisting of retrieving humidity profiles from cloud fraction datasets. Classical Bayesian decision theory is applied to obtain super-observations of humidity by combining the a priori knowledge of the atmosphere from a previous forecast and the cloud cover observations. Hence, humidity retrievals can be directly used in variational assimilation system. This approach is applied to cloud fraction observations derived from the Cloud Profiling Radar (CPR) onboard CloudSat, that provides reflectivities at very high resolution both on the vertical and along the satellite track, and a work plan to extend this procedure to other cloud products is given.

INTRODUCTION

Cloudy radiances, and cloudiness observations in general, are usually not assimilated in Numerical Weather Prediction (NWP) models, though on-duty forecasters already take advantage of the information contained in such data, especially for correctly predicting severe weather events. The problems normally arise from inaccurate parametrizations for taking clouds into account in fast radiative transfer models (e.g. particles scattering, etc.). In the case of cloud fraction data, the on/off nature of cloud processes cannot easily be modelled within variational assimilation systems, where the tangent-linear approximation requires continuous derivatives of the observation operator with respect to the control variables. As a matter of course, NWP community is very concerned to find alternative approaches for exploiting the information contained in cloud observations, which can fruitfully improve humidity analysis.

This document summarizes an hybrid procedure to assimilate cloud observations, consisting of a Bayesian analysis to retrieve humidity profiles, which in turn are assimilated in a quasi-operational three-dimensional variational assimilation system. This technique is applied to observations from the CloudSat Cloud Profiling Radar (CPR), which offers a unique dataset of measurements for the study of cloud structures.

The basic idea stems from the belief that a theory for assimilating cloud fraction observations can be applied to several space-borne instruments. The 94 GHz cloud radar, aboard CloudSat, provides cross-sections of radar received echo powers, the CPR being an instrument that points only at nadir. Such powers are subsequently converted into cloud fraction profiles by means of a simple algorithm, that has been anyway successfully validated against other cloud products. The core of the strategy consists then of applying a Bayesian retrieval of humidity profiles by using a large-scale condensation scheme, and these retrievals are used as pseudo-profiles of humidity in 3D-Var, together with other conventional and satellite observations. The prior knowledge of the state of the atmosphere (background) is used twice for both the Bayesian retrievals and the variational assimilation, leading to humidity pseudo-observations errors theoretically correlated with the background errors; however, this hybrid procedure has been successfully implemented in many other Weather Services, since the correlation between retrievals and background represents only a very marginal problem. Figure 1 schematically illustrates the different steps of the assimilation procedure. The variational assimilation uses as control variables vorticity, divergence, temperature, logarithm of surface pressure and specific humidity. The background-error constraint is used to split the information contained in the CloudSat-derived pseudo-profiles of relative humidity into specific humidity and temperature.
USE OF CLOUDSAT DATA AND BAYESIAN RETRIEVALS

Cloud fractions are evaluated from the ratio between the net received radar power and the standard deviation of the noise power, calculated over some stratospheric levels that are assumed hydrometeor-free. A filter to eliminate surface clutter is also applied, based on a cross-check between neighbour pixels; a spatial averaging is then performed to make the cloud fraction profiles consistent with the NWP model horizontal resolution, which is of about 11 Km against the 2.5 Km of the CPR measurements (along the satellite track).

Bayesian theory provides the statistical framework for calculating the humidity retrievals, which are defined as the expected value of the distribution of the unknown true state of the atmosphere, given the binary cloud observations (i.e. the “cloud” or “no-cloud” occurrence) and the background information from a short-range forecast.

The observation operator is then defined as the probability of having a cloud given the true state of the atmosphere, according to the “statistical meaning” of cloud cover in NWP models, where clouds represent sub-grid processes and are not explicitly resolved. In other words, the relation between cloud cover and the state parameters (pressure, temperature and humidity) is used as probability of the cloud occurrence. Though radar measurements in general rely on a binary condition for the cloud occurrence, it can happen to have intermediate values for the cloud fraction (e.g. between 0 and 1) because of the spatial averaging. In such cases, the cloud fraction is decomposed in several independent binary observations.

Figure 1: Schematic illustration of the strategy adopted for assimilating cloudiness observations from CloudSat.

Figure 2: Comparison between cross-sections of CloudSat-derived cloud fraction (top panel), cloud fraction diagnosed through the S88 parameterization (middle panel) and cloud fraction computed through the Lopez 2002 prognostic scheme (bottom panel) for a CloudSat granule of January 2007.
A simple large-condensation scheme is implemented, adapted from Sundqvist et al. (1988) – hereafter S88 – and re-tuned by means of the Cloudnet dataset. This scheme is basically summarised by a $C=C(R, R_{\text{min}})$ relation, where $C$ is the cloud fraction, $R$ the relative humidity and $R_{\text{min}}$ the critical threshold below which clouds cannot form, which in turn depends on the model resolution, the season, the pressure and the orography. Such a diagnostic scheme has been intensively used in the past, and has showed good agreement with special measurements campaigns (in Figure 2 an illustrative case of inter-comparison between CloudSat-derived cloud fractions, the observation operator from S88 and an advanced prognostic microphysical scheme from Lopez, 2002, is presented).

**HUMIDITY RETRIEVALS**

By means of the Bayesian algorithm, profiles of humidity are generated for each CloudSat profile. These retrievals are suitable for ingestion in the NWP assimilation system. To avoid redundancy of the background information, non-cloudy CloudSat observations correspondent to a dry (i.e. non-cloudy) background state are rejected. This limits also the problems arising from the non-fully consistent cloud parametrizations as used by the Bayesian algorithm and within the NWP model microphysics. An example of the humidity corrections from the Bayesian algorithm is given in Figure 3.

![Figure 3](image)

*Figure 3: An example of humidity retrievals from the CloudSat received echo powers. Left panel shows the comparison between the CloudSat-derived (black) and the model-derived (red) cloud fractions; in the right panel the corrected profile of humidity after the use of CloudSat data (black) is plotted against the background profile (red).*

**ASSIMILATION TRIALS**

To determine the pseudo-observations errors, which are needed in the variational assimilation, a Monte Carlo approach is followed. Since the pseudo-observations can be explicitly calculated from the Bayesian algorithm, it is possible to set-up an ensemble of simulations to compute the pseudo-observations standard deviation as function of the CloudSat cloud fraction and the background profile. Error structure relies on the major uncertainty of the humidity retrievals for non-cloudy observations, which can be associated to a larger range of humidity values following the S88 large-condensation scheme. The error associated to the CloudSat observations is calculated from the cloud-mask algorithm presented above by means of covariances propagation and considering only the error in the noise power estimation as source. This leads to an under-estimation of the pseudo-observations errors, which is anyway retained to stress the impact of CloudSat data.

Pseudo-observations of humidity have been assimilated in the quasi-operational Norwegian HARMONIE-3DVar system. The basic configuration of the assimilation system counts the "NMC"-derived statistics for the background-error covariances, the assimilation of all the conventional
observations (radiosondes, synop stations, wind profiler, buoys and drifting buoys), airborne observations, atmospheric motion vectors from MSG platforms and assimilation of microwave radiances from NOAA and Metop satellites. Verification skill scores (Figure 4) show that humidity retrievals have a positive impact, especially on dynamical parameters (geopotential and wind) and clearly indicate that the use of such data is of benefit for the forecast model.

CONCLUSIONS AND PERSPECTIVES

A Bayesian approach for retrieving humidity pseudo-observations from cloud fraction data has been established, with the aim of being applied to different cloud products. The theory is based on exploiting the statistical diagnostic derivation of cloud cover for NWP models at cloud-non-resolving scale to define the probability associated to the “cloud” event. We have used this procedure in a hybrid scheme, where humidity retrievals are ingested in a three-dimensional variational assimilation scheme. Cloud fraction data are obtained by the CloudSat cross-sections of radar received echo powers by means of a cloud-mask algorithm. Assimilation results are very promising in terms of impact on verification skill scores, and demonstrate that the statistical multivariate assimilation (3D-Var) permits humidity pseudo-observations to improve wind and mass fields.

Further refinements of the technique here proposed will focus on the use of convection scheme to accompany the large-condensation scheme in order to improve the observation operator in the low atmosphere, and the inclusion of the Bayesian retrieval within the 3D-Var minimisation, thus updating the retrievals at each iteration. The extension of these achievements to other remote-sensed cloud products will firstly concentrate on using cloud products from nowcasting tools, both from geostationary (MSG/SEVIRI) and polar-orbiting platforms (AVHRR), which are more attractive for operational implementations. In this case, vertical correlations can not be neglected any more (rather than cloud cover profiles, cloud-type and cloud-height are being used) and the retrievals involve several vertical levels at once.

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