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Generalised variational assimilation of cloud-affected brightness temperature using simulated hyper-spectral atmospheric infrared sounder data

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Abstract

Assimilated channel brightness temperature data from infrared sounders accounting for cloud effects have a positive effect on weather forecasting, especially in weather-sensitive areas. When cloud effects are included, the channel brightness temperature deviations follow a non-Gaussian distribution. However, classical variational data assimilation follows a Gaussian distribution. When processing the cloud-affected brightness temperature, useful data are lost through the cloud detection process, thus assimilating some channel brightness temperatures with weight function peaks above the cloud top. Furthermore, strict quality control of brightness temperature removes outliers. By adopting the generalised variational assimilation method, which assumes that errors follow a non-Gaussian distribution, this paper assimilates the cloud-affected brightness temperature using simulated data for the hyper-spectral atmospheric infrared sounder (AIRS). A channel set is formed by dynamically selecting AIRS channels. The experiments for retrieving temperature and humidity data demonstrate that the generalised variational assimilated cloud-affected brightness temperature method performs better than the classical method.

Keywords: AIRS; Cloud parameters; Generalised variational assimilation

1. Introduction

Numerical weather prediction (NWP) is an initial/boundary condition problem, but satellite data assimilation can provide accurate initial states for NWP models. One example of useful satellite data is the hyper-spectral Atmospheric InfraRed Sounder (AIRS) on Aqua satellite of the Earth Observing System (EOS). Because clouds affect infrared sounders, cloud detection must be performed prior to data assimilation. Cloud detection methods are primarily based on the field of view (FOV) and the specific channels. The former method requires finding an absolutely clear sky FOV. If one of the combinations of the selected channels contains a cloud in a specified FOV, the brightness temperature in all channels is selected from this FOV (English et al., 1999). Several methods currently exist for cloud detection, such as CO_2 slicing (Chahine, 1974; Menzel et al., 1983), the minimum residual method (Eyre and Menzel, 1989) and the minimum local emissivity variance (MLEV) algorithm (Huang et al., 2004). The latter method primarily looks for clear channels that are not affected by clouds. The standard method is the ECMWF scheme (McNally and Watts, 2003). Even after detecting clouds, the AIRS channel brightness temperature in cloudy conditions is not fully exploited. Cloud data have a positive impact on accurate

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forecasts in some meteorologically sensitive areas (McNally, 2002). On average, approximately 70% of the globe is covered by clouds (Wylie and Menzel, 1999). After including cloud parameters (i.e., effective cloud fraction and effective cloud-top pressure), the brightness temperature bias follows a strong non-Gaussian distribution.

There are 2378 channels covering the infrared spectrum (650–2700 cm^{-1}). AIRS is used to detect several high-resolution atmospheric variables, such as atmospheric temperature and humidity (Arai and Liang, 2009; Aumann et al., 2003). The assimilation of AIRS channel brightness temperatures has a positive effect on numerical forecasting models (Cameron et al., 2005; Marshall et al., 2006; McNally et al., 2006).

The classical variational assimilation method requires that the observational errors follow a Gaussian distribution to apply the least-squares method. The least-squares statistical method is very sensitive to outliers. Because of the mathematical theory surrounding the least-squares method, the end result is a compromise between the outliers and reality that can often be determined from the real solution. Therefore, parameter estimation is inaccurate. When the classical variational assimilation method is adopted, an appropriate algorithm to identify and remove outliers in the data before assimilating the dataset is required. However, much useful data are lost because the outliers are not always harmful. Because of the intensity of the observations and the inclusion of small-scale features, some correct observations may be eliminated during the quality control process. This problem occurs when the resolution of the analysed system (as determined by the background error covariance B-matrix and model resolution) is insufficient (Lsaksen, 2010). Some outliers may represent new information, such as weather phenomena.

A series of studies on infrared cloud-affected brightness temperature data assimilation have been conducted (Chevallier et al., 2004; Fourrie et al., 2006; Heilliette and Garand, 2007). Single channel brightness temperatures with weight function peaks under the cloud-top are eliminated in each FOV (McNally and Watts, 2003). These methods are far from ideal because only a small fraction of the data is used. Other scholars have proposed the assimilation of cloud-cleared radiances. Neighbouring FOVs are used to eliminate the cloud signal and reconstruct the clear-sky radiance (Eyre and Watts, 1987; Li et al., 2005). However, the assumption of homogeneous cloud characteristics implicit in the cloud-cleared method is unlikely to be satisfied in the majority of cases (Pavelin et al., 2008), and thus, the successful exploitation of cloud-cleared radiances in NWP is obscured. To make full use of cloud-affected radiances, a new assimilation method is required.

In this paper, we add the weighting function (Huber, 1981; Hampel et al., 2005; Bhar, 2007) of M-estimators (e.g., L2 estimator, Huber estimator, Fair estimator and Cauchy estimator) to classical variational assimilation (Liu and Qi, 2005), with the resulting method being called the generalised variational assimilation method. The generalised variational assimilation method considers the deviation (the difference between observational and simulated brightness temperature) of a non-Gaussian distribution. It is robust to outliers and includes quality control steps within the variational minimisation process. Therefore, the contribution rate of the observational data beyond the robust scale to the objective function is reduced.

2. M-Estimators and the generalised variational assimilation

2.1. M-estimators

The least-squares method uses the minimum sum of squared errors as the primary criterion. Therefore, it is sensitive to outliers. The M-estimators attempt to reduce the effect of outliers by replacing the squared residuals with a ρ-function that increases with a power less than 2 (Bhar, 2007). The objective function is minimised to attain the following solution:

$$\min \sum_i \rho(r_i) \tag{1}$$

The influence function φ and weighting function w are defined, respectively, as follows:

$$\varphi(r) = d\rho(r)/dr \tag{2}$$

$$w(r) = \varphi(r)/r \tag{3}$$

Then, the problem of minimising the objective function Eq. (1) is transformed into solving the following function:

$$\min \sum_i w\left(r_i^{(k-1)}\right) r_i^2 \tag{4}$$

Here, k indicates the iteration number. The weight $w(r_i^{(k-1)})$ should be recomputed after each step. The function w provides adaptive weighting. The observational influence will decrease when the deviation is very large and be entirely suppressed when the deviation is infinitely large.

The selected M-estimator should meet several constraints. The most important of which is that the individual ρ-function should be convex to ensure the eventual convergence to a unique solution. In this study, several M-estimators are applied in the generalised variational assimilation method. The M-estimators that are used in this paper are listed in Table 1.

It is worth noting that the L2 estimator, Huber estimator, Fair estimator and Cauchy estimator are elaborately selected. Considering the space limit, only these four estimators were chosen for this paper. The purpose of this paper is to provide a procedure to assimilate AIRS cloud-affected brightness temperature. The generalised variational method is used, which involves adding weighting functions of M-estimators to the classical variational method. To compare the assimilation retrieval effect between the generalised variational and classical variational method, first, the L2 estimator (elected to take the