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Development of cloud condensate background errors

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Development of cloud condensate background errors

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From the moment the first television pictures taken from space by the TIROS I satellite appeared on 1 April 1960, the public and meteorologists alike have been fascinated by the potential of cloud observations to help forecast the weather. For half a century these images have been employed extensively in the research and monitoring of weather phenomena such as hurricanes, as well as for predicting the weather, but meteorologists are still learning how to make full use of cloud affected observations in numerical weather forecasting.

The main cloud observations used by weather forecasting centres are indirect measurements; they are in the form of top of atmosphere outgoing infrared and microwave radiances which are affected by a whole column of the atmosphere and the surface. Much progress has been made at ECMWF to improve the use of microwave radiance observations in cloudy and precipitating areas in recent years (*Bauer et al.*, 2010; *Geer et al.*, 2010; *Geer & Bauer*, 2010) and currently there is a focus on extending the use of infrared observation into cloudy areas as well.

In this article we will concentrate on the development of cloud condensate background errors that are required for optimal use of cloud affected observations in data assimilation.

Use of cloud information in the analysis

The main difficulty in using radiance observations in a data assimilation system is that radiances are related to the model's state variables through a complex radiative transfer model. The radiative transfer model integrates the model fields in a column into a single number for comparison with the observed radiance – this process is called an observation operator. Conversely, when a radiance observation implies a change in the atmospheric state, a single number is distributed into updates to all those variables in the model column which affect the radiance.

How accurately each model variable is updated depends on the accuracy of the observation operator, the background state, and the estimated observation and background errors. In particular, if the background errors are not correctly estimated, then the signal can be attributed to the wrong variables. To give an example, specifying a humidity background error that is too large could cause radiance information on temperature and humidity to be excessively allocated to humidity. Accurate estimates of the background errors is thus essential to correctly attribute radiance observational information, in particular in cloudy and precipitating areas where the uncertainty is larger than in clear sky.

Currently the radiance observation operator RTTOV (Radiative Transfer for TOVS), developed by EUMETSAT's NWP Satellite Application Facility and used at ECMWF, takes prognostic temperature and humidity as input. It then diagnoses clouds and precipitation fluxes needed in the calculation of model equivalents of the observed radiances. With this approach, temperature and humidity are updated by the assimilation system, but the initial condition of cloud condensate is left unchanged. This approach has two significant limitations. First, errors in cloud condensate may be wrongly interpreted as errors in humidity and temperature, because the observation operator does not consider prognostic cloud condensate. Second, the forecast model may have to adjust the cloud condensate to the changes in temperature and humidity through a spin-up process.

A more accurate approach to the assimilation of cloud sensitive observations is to also include prognostic cloud condensate as input to the observation operator and update cloud condensate in the initial conditions along with humidity and temperature. This requires developments in three areas.

- Use of prognostic cloud condensate in cloud sensitive observation operators, in particular cloudy RTTOV.
- Inclusion of cloud condensate in the linear physics used by the data assimilation.
- Specification of background errors for cloud condensate.

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At ECMWF developments in all three areas are taking place in a concerted effort to make better use of cloud sensitive observations, in particular radiances. With this work we want to be able to answer two related questions:

- Does the inclusion of prognostic cloud condensate as input to the observation operator make a difference to the impact of the data on the forecast?
- Does updating the initial conditions of cloud condensate make a difference to the forecast of clouds and precipitation?

Here we report on the development of background errors for cloud condensate and show some initial, idealised assimilation results.

Choice of variables for the cloud analysis

The current forecast model at ECMWF has six variables that together describe the evolution of water in the atmosphere: water vapour, cloud water, cloud ice, cloud fraction, rain and snow. In the data assimilation on the other hand, only water vapour is updated. This difference is mainly due to the difficulty of accurately describing the dependency of cloud sensitive observations on cloud processes. This difficulty has made it preferable to ignore changes to the initial conditions of all cloud and precipitation variables in the assimilation process and only update humidity.

With the increasing use of cloud sensitive observations we decided to revisit whether only updating humidity is still the best approach. As a starting point we consider the previous version of the ECMWF cloud scheme, where water vapour, cloud condensate and cloud cover were the prognostic variables. Cloud condensate is a more fundamental variable than cloud cover, because cloud cover can be diagnosed quite accurately from the cloud condensate. There is also a fairly accurate way to split cloud condensate into cloud liquid and cloud ice as a function of temperature only, which was also used in the previous ECMWF cloud scheme.

Another very practical reason to prefer cloud condensate over cloud cover in the analysis is that the processes governing the evolution of cloud cover are more nonlinear than those governing cloud condensate. Choosing cloud condensate makes it much easier to develop the linear physics needed for the four-dimensional variational data assimilation (4D-Var). In 4D-Var an analysis is produced by finding a forecast that gives close to optimal fit to a weighted average of the observations available over a time period (currently 12 hours at ECMWF) and the background fields available at the start of the time period.

Adding cloud condensate to the analysis makes a distinct change to the treatment of water in parts of the 4D-Var that are linear (i.e. the inner loops). In the current linear model, all water is lost from the system once it condenses, because there is no cloud condensate variable in the linear system. When cloud condensate is included in the linear system, the new frontier now becomes precipitation, where water is again lost whenever there is precipitation due to there not being any linear precipitation variable. So the boundary of the unknown is extended from condensation to precipitation by adding cloud condensate in the analysis. Future developments will doubtless include precipitation in the analysis as well.

Cloud condensate background errors

The cloud condensate background error is determined from a large sample of forecast differences produced by an ensemble of analyses. The analysis ensemble, which has ten members using observations that have been differently perturbed for each member, produces ten independent forecasts; these can be subtracted from each other to produce nine independent samples of forecast differences valid at the start of the following assimilation cycle. It can be shown that these forecast error differences are proportional to the background errors, with forecast difference variances twice the value of the background error variances.

The background error has three factors, which when multiplied together give the total background error.

- ***'Balance operator'***. This describes the correlation of cloud condensate errors with errors in other analysis variables.
- ***Background error variance***. This is a statistically determined function which describes how the error variance of the unbalanced cloud condensate depends on the background state.
- ***Background error correlations***. These describe the vertical and horizontal correlations of the normalised unbalanced cloud condensate errors.

More details about these three factors are given in Box A.

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Factors determining the total background error

A

The following three factors, when multiplied together, give the total background error.

- ***'Balance operator'***. This describes the correlation of cloud condensate errors with errors in other analysis variables. For cloud condensate, the main correlation is with water vapour through the process of condensation. The balance relationship for cloud condensate that we use subtracts a statistically determined function of water vapour and relative humidity from the total cloud condensate to form 'unbalanced' cloud condensate with errors less correlated with those of other analysis variables.

- ***Background error variance***. This is a statistically determined function which describes how the error variance of the unbalanced cloud condensate depends on the background state. The unbalanced cloud condensate is divided by the background error standard deviation in this step to form a normalised unbalanced cloud condensate. Due to the large variability in cloud condensate and its errors, it is necessary to have a flow dependent model of the error variances which adjust to the weather of the day. The variance model we have developed for this depends on model level as well as the relative humidity and the cloud condensate content of the background. One particular difficulty is what to do in case there is no cloud condensate present in the background. For this case, the background error is put to a value which is relatively small, but large enough to allow cloud sensitive observations to add clouds in case they are seen by the observations.

- ***Background error correlations***. These describe the vertical and horizontal correlations of the normalised unbalanced cloud condensate errors. While also being statistically determined, the correlations remain constant in time. The correlations do however vary in space, with the horizontal and vertical correlations at each point on the globe reflecting the average conditions at that point.

All three factors determining the background error contribute to its geographic and/or flow-dependent variation. The balance operator explains a part of the cloud condensate error variance in terms of water vapour errors, with the strength of the balance varying with relative humidity and model level. It is in lower to mid tropospheric cloudy regions where the strongest balance occurs – here up to one third of the variance is explained by water vapour.

The background error correlations vary mainly with the average cloudiness of a region. In predominantly clear regions there is very little vertical correlation, whereas in predominantly cloudy regions the vertical correlations stretch over several model levels to reflect the correlation brought on by convection and other cloud processes. The background error variance shows the strongest flow dependency and so we will now consider it in more detail.

The statistical model of the error variance is applied to the background state at every analysis cycle to give an estimate of the background error of the day. This estimate can be compared with the ensemble spread obtained from ensemble forecasts valid at the same time. If the statistical model is accurate, the results should be similar. Such a comparison is shown in Figure 1, where the background state of the cloud condensate and the ensemble mean are also shown.

It can be seen that the estimated background error standard deviations agree fairly with the ensemble spread, but there are also several differences. First, the ensemble spread is zero where all ensemble members are cloud-free, whereas the estimated background error standard deviation defaults to a small value in cloud-free areas to allow observations to put clouds where the model background has none. Second, the largest values of the background error standard deviation are intentionally capped to allow for a smoother variation of the background error. This is because the exact location of the maximum error is fairly uncertain as can be seen by looking at how smooth the ensemble mean is compared with the background state. In this case the best policy is to be conservative and not commit to the error being very large at one particular location, which might be the wrong location.

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One may ask why the ensemble spread itself is not used instead of a statistical model. The answer is that the ensemble spread will be used when available, but that there are many configurations of the Integrated Forecasting System (IFS), for example re-analyses, where no ensembles of analyses are available and it is necessary to default to a statistical model. The fact that the statistical model agrees fairly well with the ensemble spread shows that this is a viable strategy.

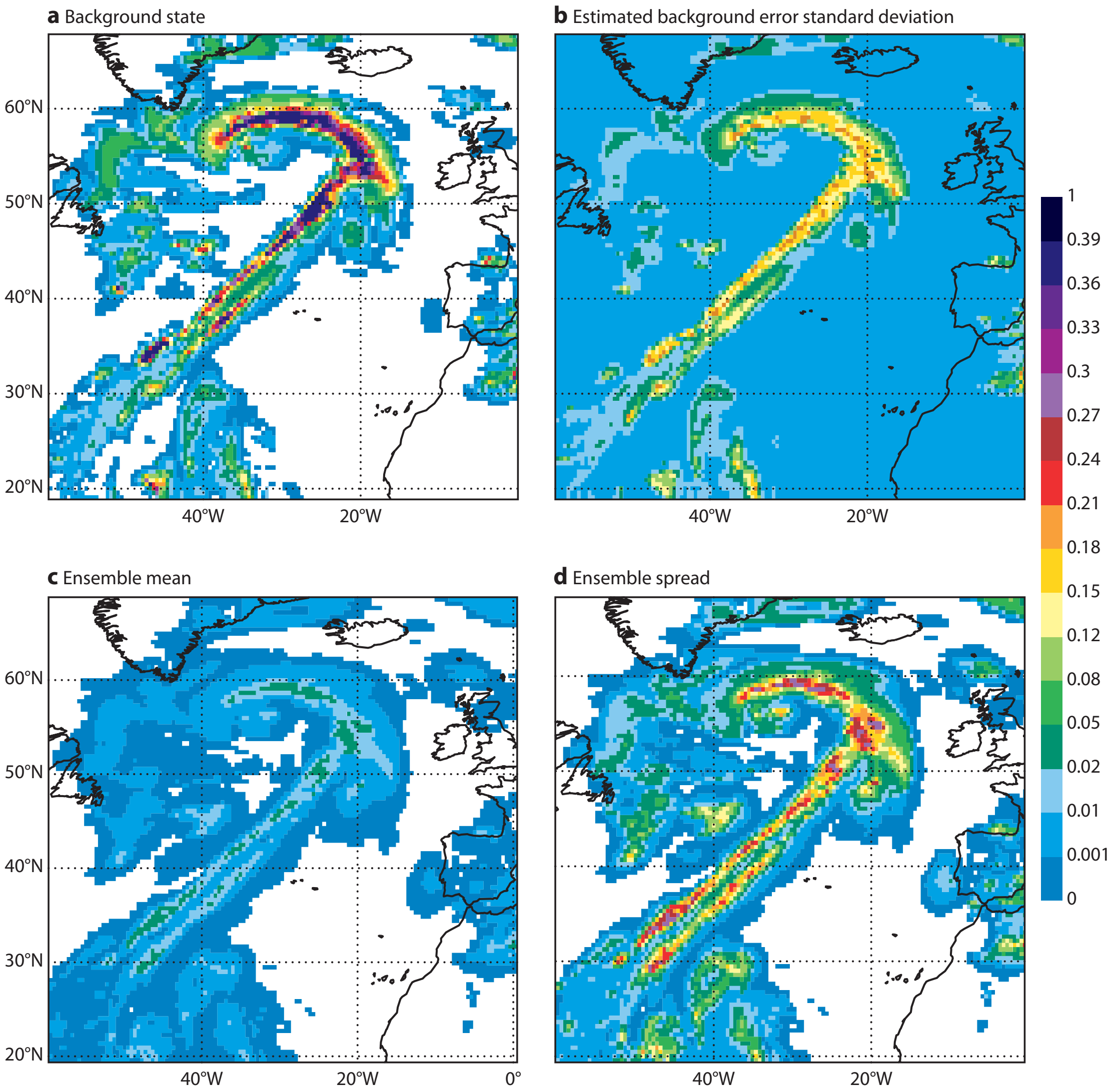

Figure 1 Cloud condensate background error standard deviation (at about 670 hPa) from a statistical model compared with the ensemble spread from ten ensemble forecast members valid at the same time: (a) background state, (b) statistically estimated background error standard deviation, (c) ensemble mean and (d) ensemble spread of the cloud condensate. Units are 1×10^{-3} kg/kg.

Single observation experiments

To investigate the behaviour of the cloud condensate background errors, data assimilation experiments were made with a single cloud liquid water observation in a single model layer. Although no such observations exist, they can be simulated and are useful in showing the response of the assimilation system. A few typical cases are shown in Figures 2, 3 and 4 where the observations are placed at the start of the 4D-Var assimilation window, which allows the effect of the background errors on the analysis increments to be studied in isolation from the effects of other components the 4D-Var. This is important because we want to know that all components of the cloud condensate assimilation work well on their own before we couple them together in the 4D-Var framework.

In Figure 2 the cloud liquid water observation is in a nearly saturated area with a frontal cloud. The cloud condensate increment (blue isolines) follows the background cloud (high relative humidity) and is nearly isotropic. The specific humidity increment (red isolines) coming from the balance relationship between cloud condensate and humidity in the background error shows that the balance relationship gives realistic changes to humidity which are confined to cloudy areas.

In Figure 3 the cloud liquid observation is located in a very dry area adjacent to the front. Now the cloud condensate and humidity increments are not isotropic, and they are no longer centred on the observation. This is because the cloud condensate variance increases rapidly in cloudy regions, resulting in an increment which extends the existing cloud towards the observation. The cloud condensate and humidity background error variances each mainly follow their respective background error values, which accounts for them not overlapping in the dry-moist transition zone. The vertical correlations of cloud condensate background error are narrower than those of humidity, especially in the boundary layer. This is shown in Figure 4 where a cloud liquid observation placed in the boundary layer gives a humidity increment which extends to the surface, whereas the cloud condensate increment remains localised around the observation in vertical.

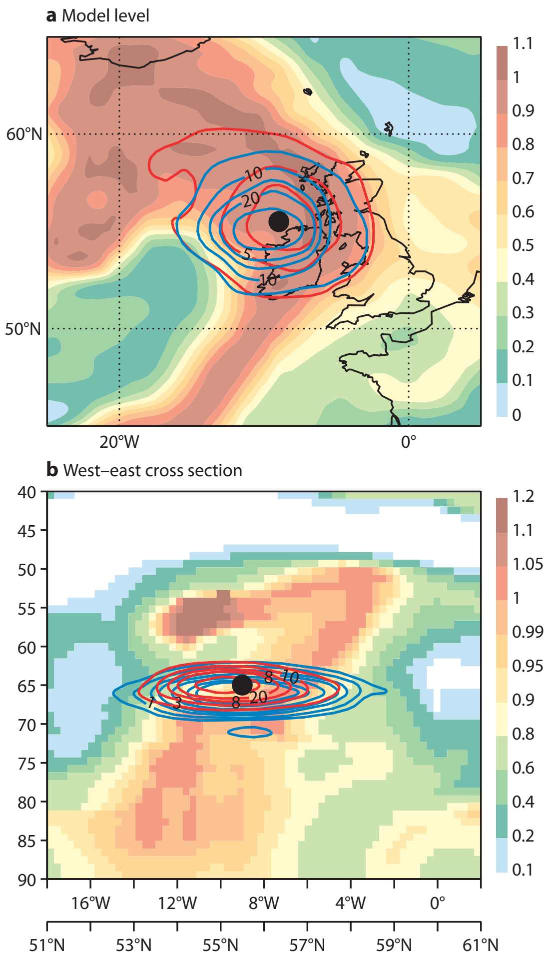

Figure 2 Single cloud liquid observation (black dot) in a nearly saturated area, at about 500 hPa, within a 3D-Var framework: cloud condensate analysis increments (blue isolines, units 1×10^{-6} kg/kg), specific humidity increments (red isolines, units 1×10^{-6} kg/kg) and background relative humidity (colour) for (a) model level and (b) west–east cross section at the observation location.

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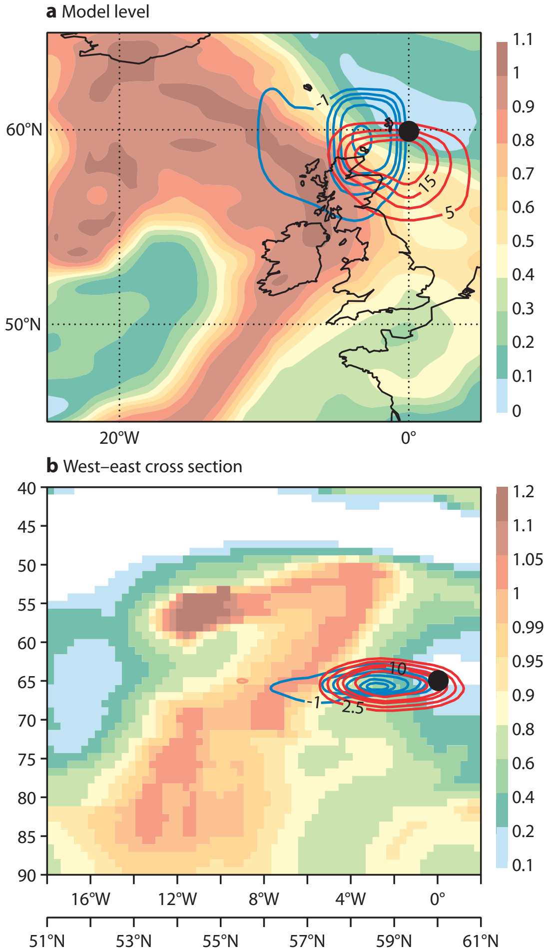

Figure 3 Single liquid observation (black dot) in very dry area with no background error condensate, at about 500 hPa, within a 3D-Var framework: cloud condensate analysis increments (blue isolines, units 1×10^{-6} kg/kg), specific humidity increments (red isolines, units 1×10^{-4} kg/kg), and background relative humidity (colour) for (a) model level and (b) west–east cross section at the observation location.

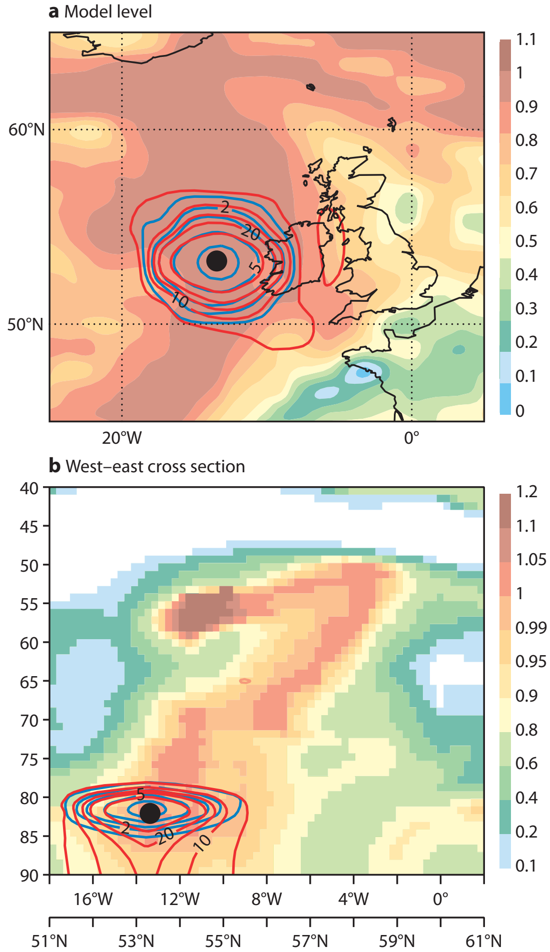

Figure 4 Single cloud liquid observation (black dot) in nearly saturated boundary layer, at about 960 hPa, within a 3D-Var framework: cloud condensate analysis increments (blue isolines, units 1×10^{-6} kg/kg), specific humidity increments (red isolines, units 1×10^{-4} kg/kg), and background relative humidity (colour) for (a) model level and (b) west–east cross section at the observation location.

Current and future work on cloud condensate assimilation

The initial tests reported here show that we have a model of cloud condensate background errors which give realistic increments of cloud condensate within the data assimilation, as well as implying specific humidity increments through a background error balance relationship predominantly coming from condensation effects. Current work focuses on coupling the background errors together with recently developed linearised physics which include cloud condensate. This is done by placing a single cloud observation later in the assimilation window to see how the linear model translates the signal from the observation time to the initial time. Furthermore, we are testing the behaviour of single microwave and infrared radiance observations with and without prognostic cloud condensate as input.

Once we have verified that all the individual components needed for cloud assimilation work together, we can address the two main scientific questions we mentioned at the outset, namely whether adding prognostic cloud condensate as input to the observation operators makes a difference to the impact of the data on the forecast and whether updating the initial conditions of cloud condensate makes a difference to the forecast of clouds and precipitation.

Further reading

Bauer, P., A.J. Geer, P. Lopez & **D. Salmond,** 2010: Direct 4D-Var assimilation of all-sky radiances. Part I: Implementation. *ECMWF Tech. Memo. No. 618*.

Geer, A.J., P. Bauer & **P. Lopez,** 2010: Direct 4D-Var assimilation of all-sky radiances. Part II: Assessment. *ECMWF Tech. Memo. No. 619*.

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