ASSIMILATION OF LOW-LEVEL

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INTRODUCTION

•In Variational data assimilation (Var) an analysis is found by minimising a cost function, *J*. This analysis can then be used as the initial conditions for a weather forecast.

$J(\underline{\mathbf{x}}) = \frac{1}{2} (\underline{\mathbf{x}} - \underline{\mathbf{x}}_{\mathrm{B}})^{\mathrm{T}} \mathbf{B}^{-1} (\underline{\mathbf{x}} - \underline{\mathbf{x}}_{\mathrm{B}}) + \frac{1}{2} (\underline{\mathbf{y}} - \mathbf{h}(\underline{\mathbf{x}}))^{\mathrm{T}} \mathbf{R}^{-1} (\underline{\mathbf{y}} - \mathbf{h}(\underline{\mathbf{x}}))$ (1)

 \underline{x}_B is the **background**, \underline{y} is the **observation** vector and \mathbf{h} is the **observation operator**.

•The minimum of *J* gives the most probable state of the atmosphere (the analysis, \underline{x}_A), assuming that the background errors, **B**, and the observed errors, **R**, are **Gaussian** and **non-biased**.

Observations of clouds can have a large impact on the quality of a forecast, due to the sensitivity of such areas [5].

On average around 70% of the globe is covered by cloud [4].

THE PROBLEM

Clouds can complicate data assimilation in a number of ways:

•Cloud variables' errors are difficult to model as Gaussian. •Cloud variables are a non-linear function of other state variables.

•Cloud processes and structures can occur on a sub-grid scale.

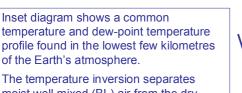
•Background errors associated with cloudy conditions can be **flow dependent** and so cannot be represented in a static matrix. Difficulty in defining the errors of the model cloud field means that in 1D-Var [1] the errors are assumed to be very large and so cloud parameters in the background vector are effectively ignored.

The problem of assimilating cloudy observations means that a great deal of data is discarded and observations must firstly be pre-processed [6,7,8].

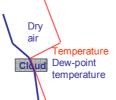
Low-level stratocumulus cloud can be a particular problem. Its top is often associated with a sharp temperature inversion [9].

 It is difficult to describe the background errors for this kind of structure in a way which will allow you to move the analysis inversion away from the height of that prescribed by the background [2] whilst retaining its structure.

•Stratocumulus cloud has a large impact on surface temperatures and therefore are important for forecasting minimum and maximum temperatures and fog [9].



The temperature inversion separates moist well mixed (BL) air from the dry stable air above. Acting as a strict upper bound for cloud.



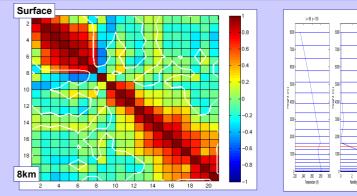


Figure 1. Background Error correlation matrix for temperature on 20 model levels in the lowest 8 km of the atmosphere.

B has been calculated as the spread in a set of MOGREPS [11] ensembles when a strong temperature inversion is present (see right-hand figure).
Decoupling between well mixed BL air and the more stable and drier air above can clearly be seen (the top of the BL is approximately level 8, 1300m).

CONCLUSIONS

In order to successfully assimilate low-level clouds:

•Accurate analysis of the height of the temperature inversion is needed as this acts to cap low-level cloud. Due to the variability of this height it is desirable for the analysis's inversion height to be able to vary from that of the background without loosing information of its structure. This has been successfully achieved by adding in a variable to the background state which allows the levels around the inversion to move, representing the error in the height of the background inversion.

•The **B-matrix must be accurate** and **include cross correlations** between model variables such as temperature and humidity so that the analysis's diagnosed cloud is consistent with both temperature and humidity fields. The B-matrix should evolve to suit the current state of the atmosphere. This can be achieved by implementing a **change of variables**.

ζ	=	Uχ		

(3)

•U is a $(b \ge q)$ transform which takes you from new control variable space, $\chi \in q \ge 1$, to model space, $x \in b \ge 1$. The cost function is now minimised w.r.t. the new control variables.

•New control variables can be chosen with errors that are Gaussian and linearly related to one another.

•The U-transform can be state dependent introducing **flow-dependence** into the implied errors for the Background. $\mathbf{B}_{\mathbf{x}} = \mathbf{U} \mathbf{B}_{\mathbf{y}} \mathbf{U}^{\mathrm{T}}$ (4)

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Properties of the B-matrix:

•The B-matrix spreads out information given by observations in space. **Smoothing out fields** giving a more realistic analysis.

•Including multivariate error correlations enables the analysis to be physically consistent between fields. It is particularly important that temperature and humidity fields are consistent when clouds are present.

•The B-matrix **allows observations to see each other** and reinforce the information to reduce the analysis error.

 It can be difficult to implement correlations between variables as many variables have non-linear relationships with one another which breaks down the assumption of Gaussian error distributions.

•It is therefore necessary to choose carefully the variables used to minimise the cost function.