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A Variational Approach for Estimating AMV Reassigned Heights

Stéphane Laroche

Data Assimilation and Satellite Meteorology section
Environment and Climate Change Canada, ECCC

Motivation

- Forsythe and Saunders (2008) proposed a situation dependent observation error estimation in which the tracking and the contribution of the height assignment errors are combined. This approach has been successfully implemented at the UK Met Office and ECMWF and will soon be operational at the Meteorological Service of Canada (see poster by Laroche et al. in this workshop).
- The height assignment error is used to increase the total observation error in present of vertical wind variation (shear). Thus the impact of the AMV in the analysis is reduced when the observation is located in strong vertical wind shear without modifying the vertical position of the AMV.



Motivation

- The impact of the systematic (bias) error of the assigned height as well as interpreting the AMV as a layer-averaged motion on NWP forecast have recently been examined using background best-fit pressure and lidar measurements (e.g. Salonen et al. 2016, Folger and Weissmann, 2016).
- Salonen and Bormann (2014, IWW12) showed that taking into account the systematic height errors clearly improves forecasts where as the impact of using a layer-averaging observation operator is mixed. These results suggest that the accuracy of the assigned height plays an important role in NWP forecast skill and reassign the height is beneficial.



Objectives of the present study

- Show how a variation of the AMV assigned height can be included in an incremental variational data assimilation scheme like 4D-EnVar.
- Discuss the difficulties and limitations of this approach.
- Examine a two-stage approach in which a reassigned height and observation error for each AMV are first calculated prior to assimilation.
- Assess the impact of the two-stage approach on short to medium range forecasts from two data assimilation experiments (two-month winter and summer periods).

Incremental variational data assimilation scheme

$$X = X_b + \Delta X \quad X : \text{analysis } (u, v, T, q, p_s)$$

$$J(\Delta X) = \underbrace{J_b(\Delta X)} + \underbrace{J_o(\Delta X)}$$

$$J(\Delta X) = 0.5\Delta X^T B^{-1} \Delta X + 0.5(H(\Delta X) - d)^T R^{-1} (H(\Delta X) - d)$$

ΔX : analysis increments ($X - X_b$)

d : innovations ($y - H(X_b)$)

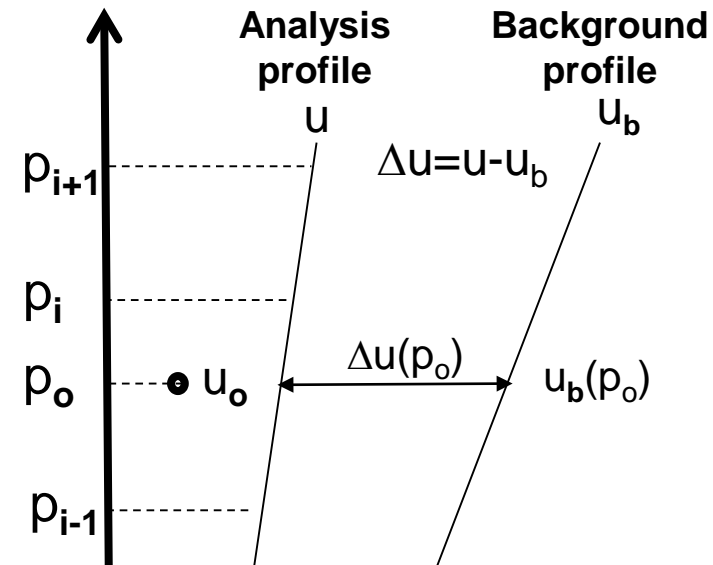
X_b : Background field

y : observations

H : observation operator

B : Background error covariances

R : Observation error covariances



Contribution of one AMV u component to J_o :

$$J_o(\Delta u) = \frac{0.5(\Delta u(p_o) - (u_o - u_b(p_o)))^2}{\sigma_o^2}$$

Δu : u increment profile

$\Delta u(p_o)$: u increment interpolated at p_o

$u_b(p_o)$: background u interpolated at p_o

u_o : AMV u component

σ_o^2 : observation error variance

Note that the position of the observations is assumed free of error.

J_o term with situation dependent observation error for one AMV wind component

$$J_o(\Delta u) = \frac{0.5(\Delta u(p_o) - (u_o - u_b(p_o)))^2}{\sigma_t^2 + \sigma_h^2}$$

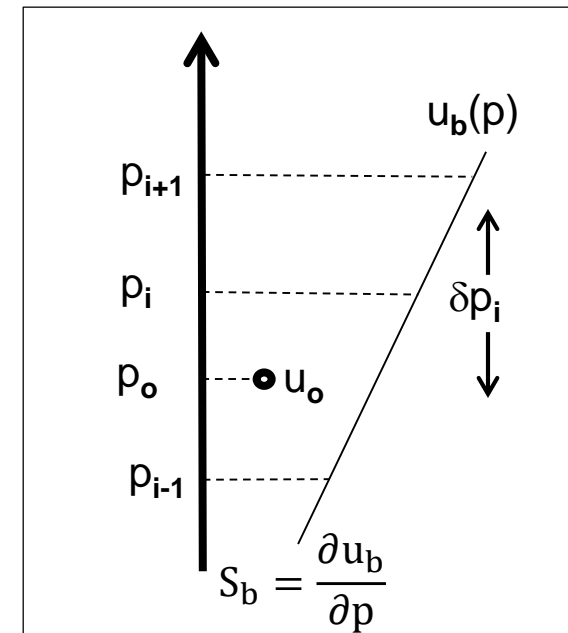
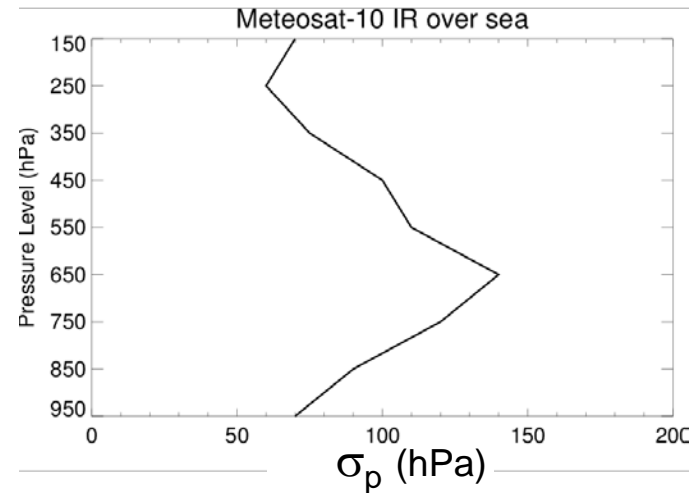
Formulation for σ_h proposed by Forsythe and Saunders (2008):

$$\sigma_t^2 = F(QI)$$

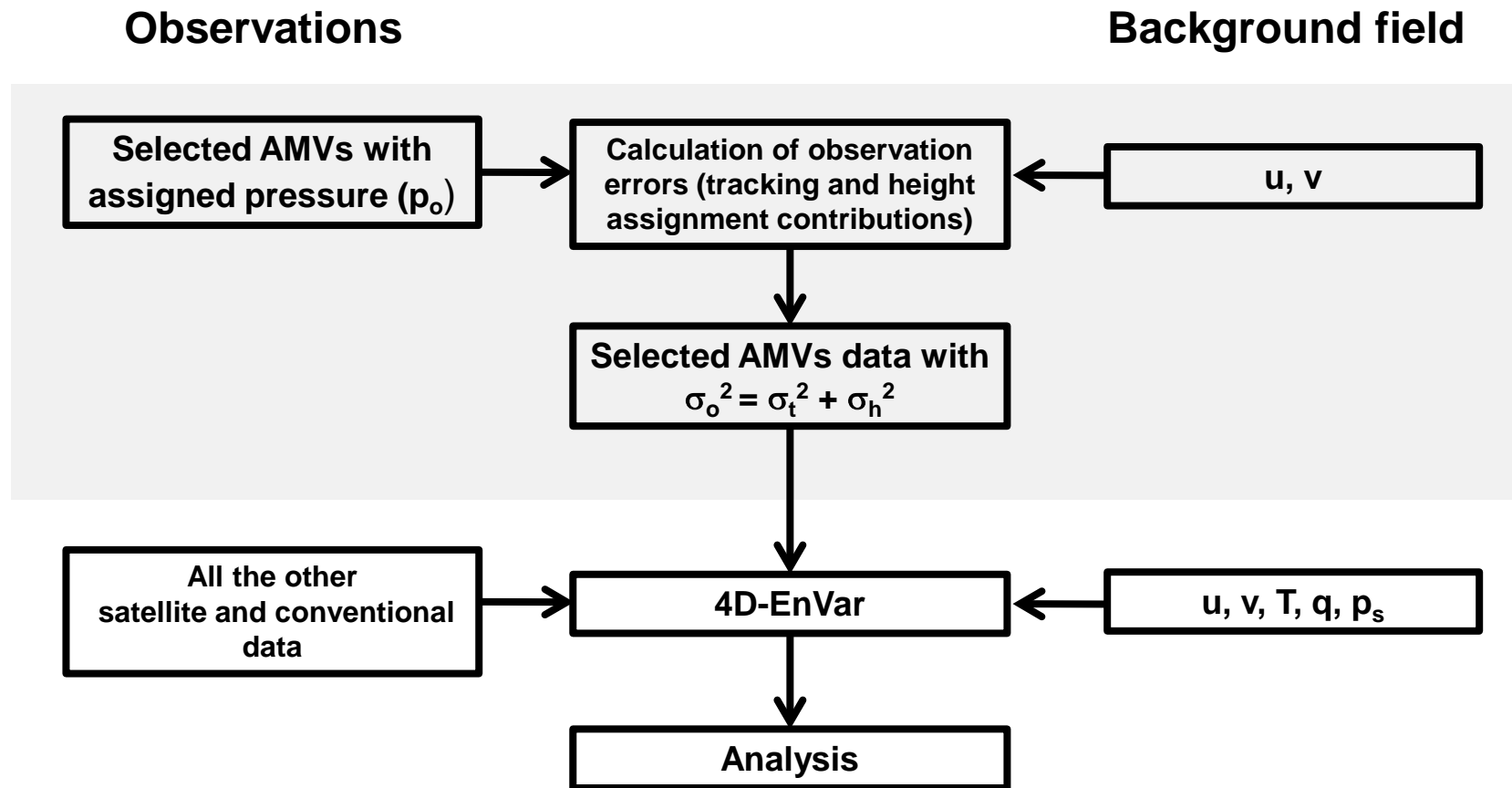
$$\sigma_h^2 = \frac{\sum_i W_i (u_o - u_b(p_i))^2 \delta p_i}{\sum_i W_i \delta p_i}$$

$$W_i = \exp\left(-\left[\frac{(p_i - p_o)^2}{2\sigma_p^2}\right]\right)$$

For $S_b = \text{cst}$: $\sigma_h^2 = S_b^2 \sigma_p^2$



Situation dependent observation error estimation for AMVs prior to the assimilation



J_o terms for one AMV wind component

J_o with adjustable AMV position ($p_o + \Delta p$) plus a penalty function:

$$J_o(\Delta u, \Delta p) = \frac{0.5(\Delta u(p_o + \Delta p) - (u_o - u_b(p_o + \Delta p)))^2}{\sigma_t^2} + \frac{0.5\Delta p^2}{\sigma_p^2}$$

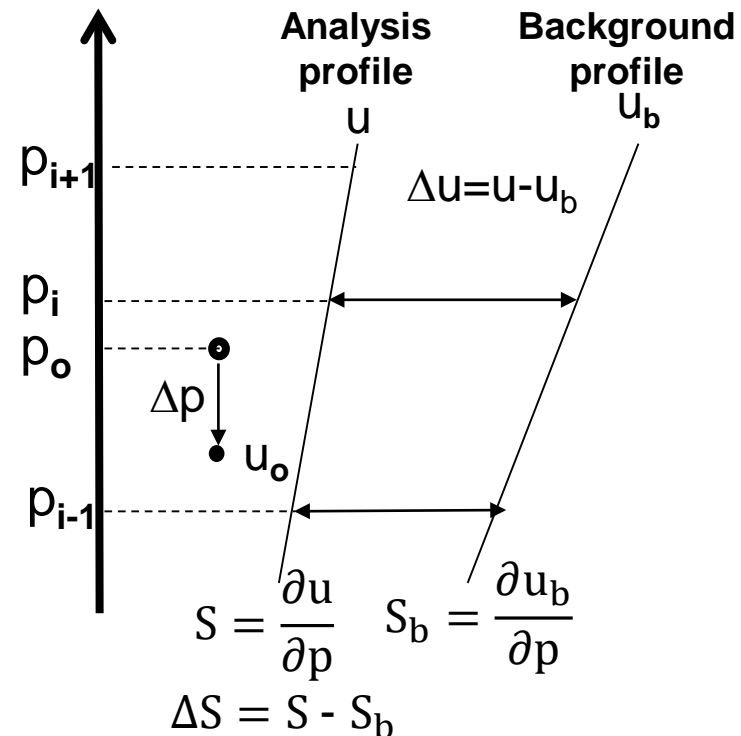
$$= \frac{0.5(\Delta u(p_o) - (u_o - u_b(p_o)) + \Delta p(S_b + \Delta S))^2}{\sigma_t^2} + \frac{0.5\Delta p^2}{\sigma_p^2}$$

Linear interpolation context

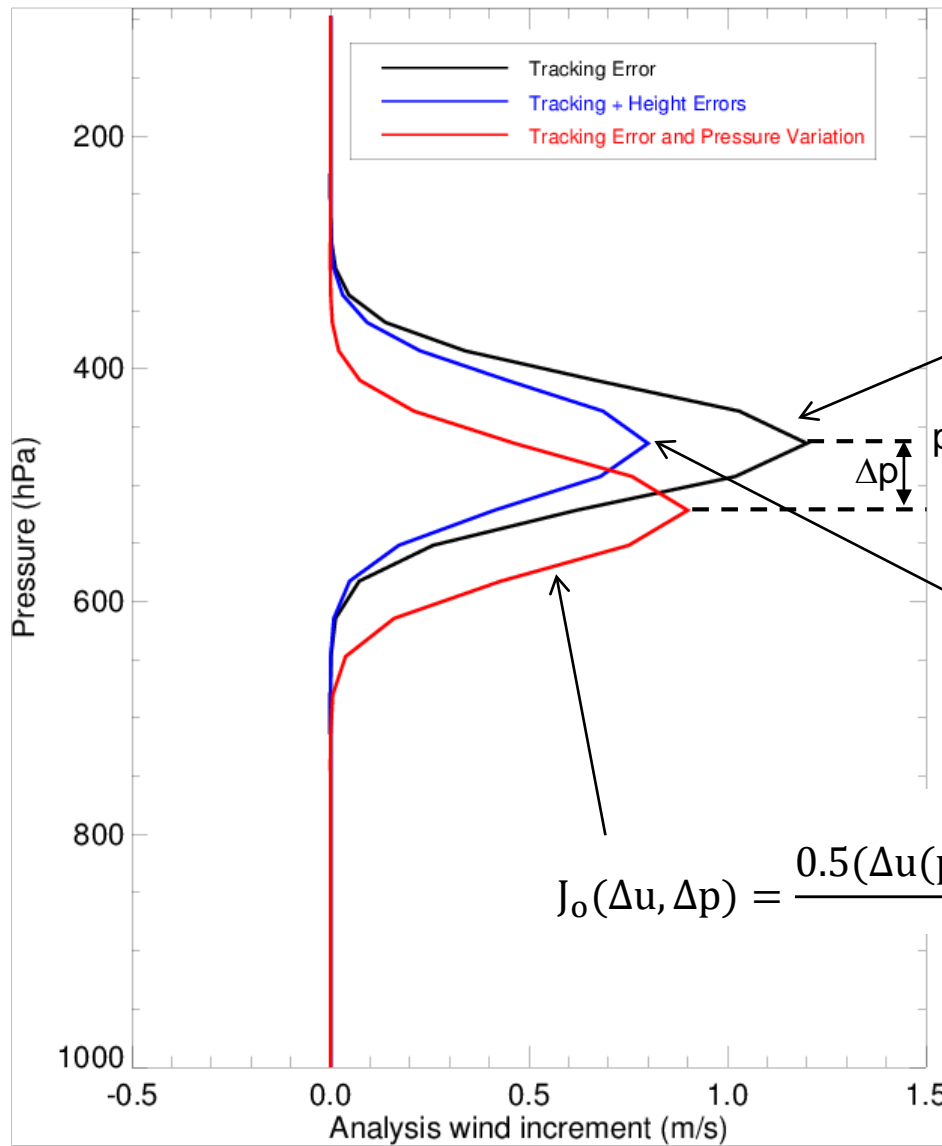
J_o with situation dependent observation error:

$$J_o(\Delta u) = \frac{0.5(\Delta u(p_o) - (u_o - u_b(p_o)))^2}{\sigma_t^2 + \sigma_h^2}$$

$\sigma_h^2 = S_b^2 \sigma_p^2$ when $S_b = \text{cst}$



Impact of the different observation errors and pressure variation Δp on the analysis increment



Idealized assimilation of one AMV component in presence of vertical wind shear

$$J_o(\Delta u) = \frac{0.5(\Delta u(p_o) - (u_o - u_b(p_o)))^2}{\sigma_t^2}$$

$$J_o(\Delta u) = \frac{0.5(\Delta u(p_o) - (u_o - u_b(p_o)))^2}{\sigma_t^2 + \sigma_h^2}$$

$$J_o(\Delta u, \Delta p) = \frac{0.5(\Delta u(p_o + \Delta p) - (u_o - u_b(p_o + \Delta p)))^2}{\sigma_t^2} + \frac{0.5\Delta p^2}{\sigma_p^2}$$

Limitations and Difficulties

- The reassigned height is only sensitive to the vertical wind variation (shear).
- As a result, the approach proposed here can be seen as an alternative way to mitigate the misrepresentation of AMVs in presence of vertical wind shear.
- The approach is valid only for small Δp in a 4D incremental variational data assimilation context.
- The vertical interpolation operator is performed between levels above and below the observation level and these levels remain the same during the minimization of $J(\Delta X)$. A more general vertical linear interpolation operator over multiple model levels should therefore be developed.
- A nonlinear term $\Delta p \Delta S$ appears in J_o , making $J(\Delta X)$ none quadratic.
- Given these difficulties and limitations, we first developed a two-stage approach in which the height variation of each AMV is estimated first using a 1D-Var scheme. AMVs are then assimilated with reassigned height in 4D-EnVar along with all the other types of observations.



First stage: 1D-Var scheme for estimating the reassigned height and its error

1D-Var formulation for one wind component:

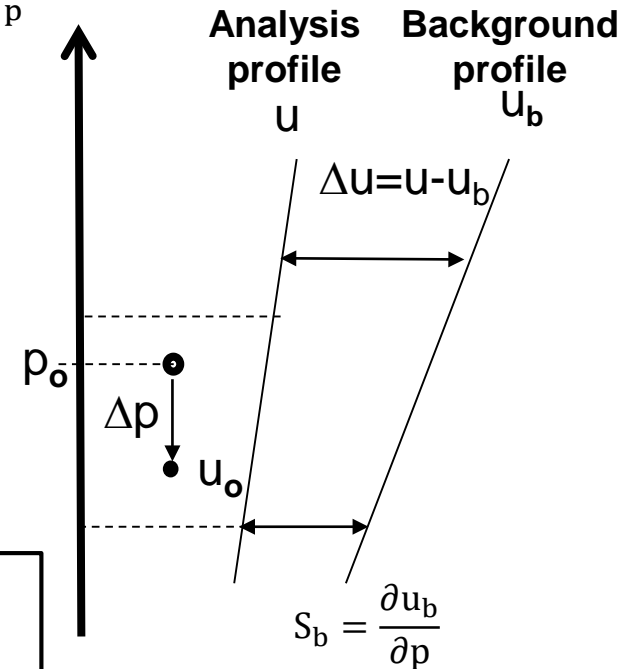
$$J(\Delta u, \Delta p) = \frac{0.5\Delta u^2}{\sigma_b} + \frac{0.5(\Delta u(p_o + \Delta p) - (u_o - u_b(p_o + \Delta p)))^2}{\sigma_t} + \frac{0.5\Delta p^2}{\sigma_p}$$

In a linear approximation and for one observation, it can be shown that the optimal Δp can also be found by minimizing the following cost function:

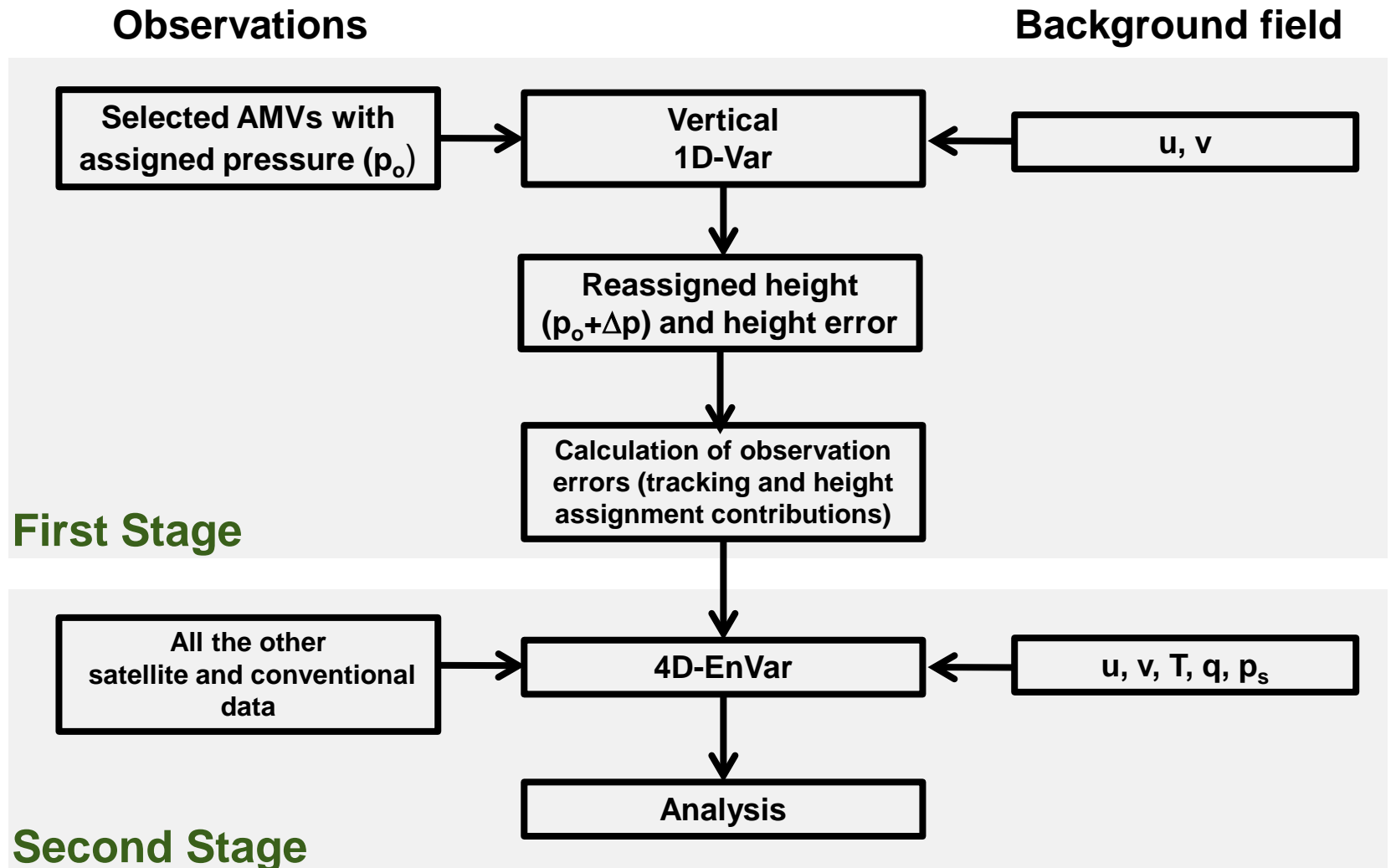
$$J(\Delta p) = \frac{0.5(u_o - u_b(p_o + \Delta p))^2}{\sigma_t^2 + \sigma_b^2} + \frac{0.5\Delta p^2}{\sigma_p^2}$$

$$\sigma_{pr}^2 = \sigma_p^2 \left(\frac{\sigma_t^2 + \sigma_b^2}{\sigma_t^2 + \sigma_b^2 + S_b^2 \sigma_p^2} \right)$$

Error variance estimation of the reassigned height



'1D-Var + 4D-EnVar' approach



Summer and Winter Experiments

- Experiments carried out with the operational Global Deterministic Prediction System (GDPS)
- Summer period : 15 June to 31 August 2016
- Winter period : 15 December to 28 February 2017

Experiment	Tracking error	Height error	Height
Control	σ_t^2	σ_p^2	p_o
First	σ_t^2	-	$p_o + \Delta p$
Second	σ_t^2	σ_{pr}^2	$p_o + \Delta p$

$$\sigma_t^2 = F(QI)$$

$$\sigma_{pr}^2 = \sigma_b^2 \left(\frac{\sigma_t^2 + \sigma_b^2}{\sigma_t^2 + \sigma_b^2 + S_b^2} \right)$$



Histograms of Δp from 1D-Var and model best-fit approaches for Meteosat-10

1D-Var approach

$$J(\Delta p) = \frac{0.5(u_o - u_b)^2}{\sigma_{ut}^2 + \sigma_{ub}^2} + \frac{0.5(v_o - v_b)^2}{\sigma_{vt}^2 + \sigma_{vb}^2} + \frac{0.5\Delta p^2}{\sigma_p^2}$$

In case of multiple minima, the minimum closest to the originally assigned pressure (p_o) is chosen.

Model best-fit pressure approach

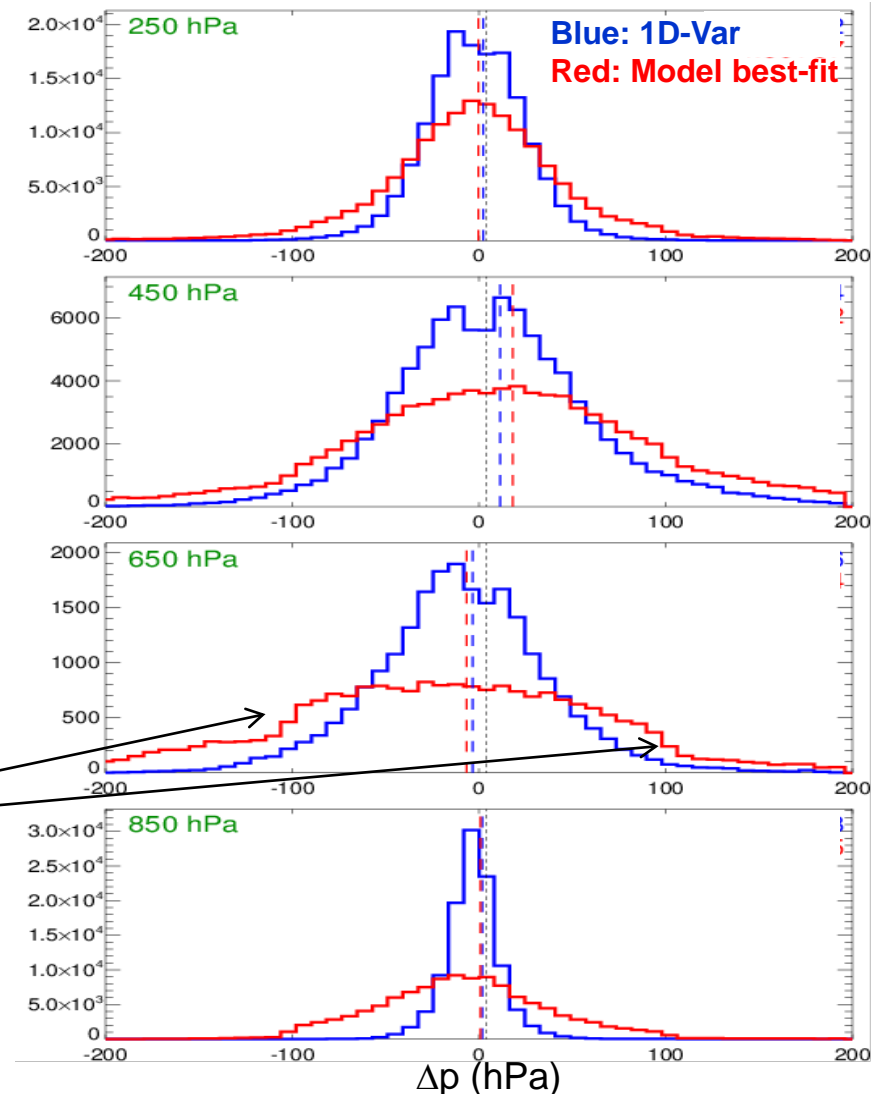
Salonen et al. (2015)

$$VD = [(u_o - u_b)^2 + (v_o - v_b)^2]^{1/2}$$

1. $VD_{\min} < 4 \text{ m/s}$
2. $VD_{\min} < (VD - 2 \text{ m/s})$ for $|p_o - p_{\min}| > 100 \text{ hPa}$

In case of multiple minima, the minimum closest to the originally assigned pressure (p_o) is chosen.

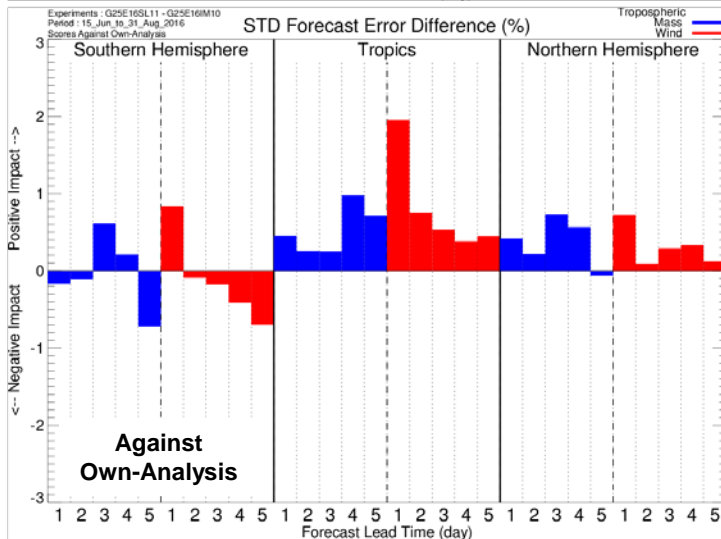
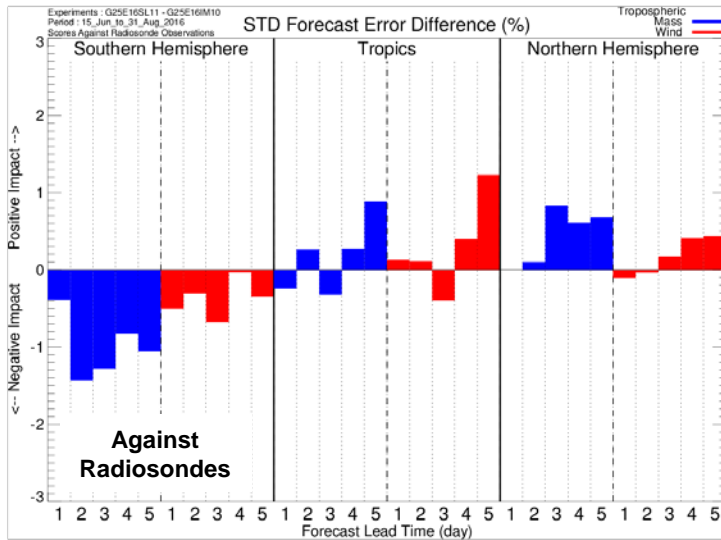
Winter period: 15 Dec – 28 Feb 2017



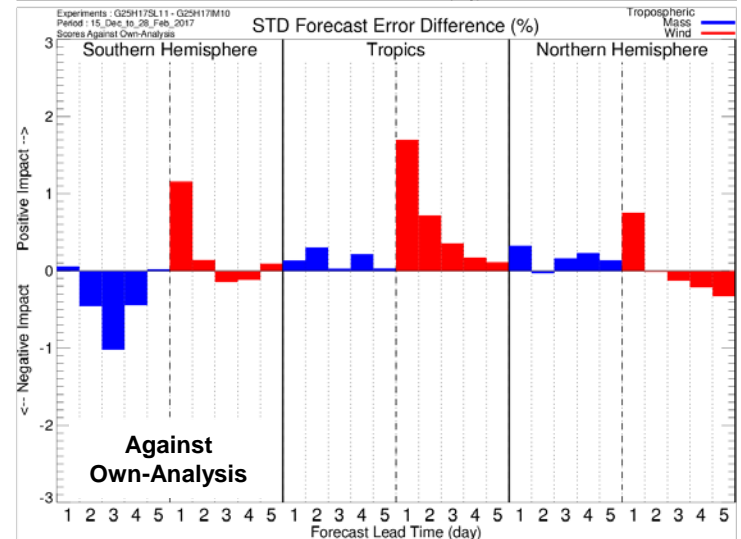
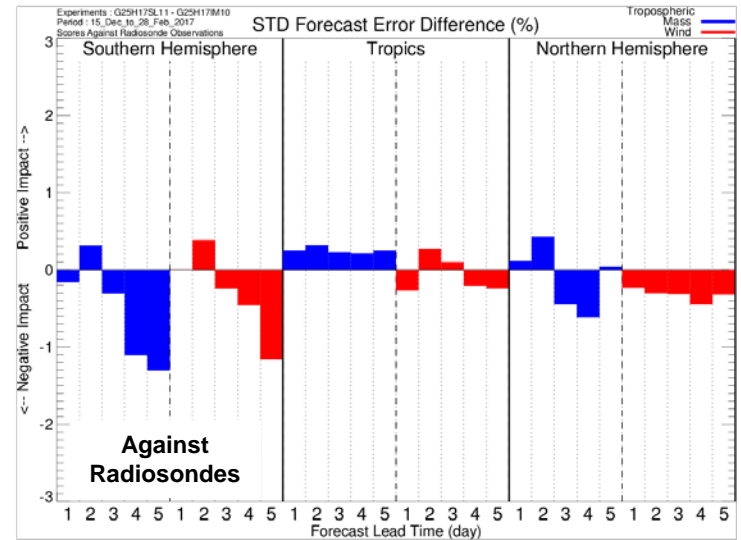
Verification scores for the first experiment

(tracking error and reassigned pressure level)

Summer period: 15 Jun – 31 Aug 2016



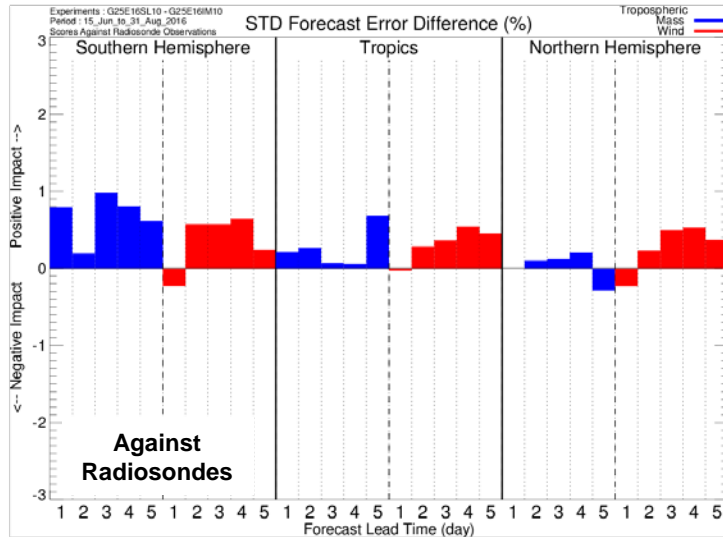
Winter period: 15 Dec – 28 Feb 2017



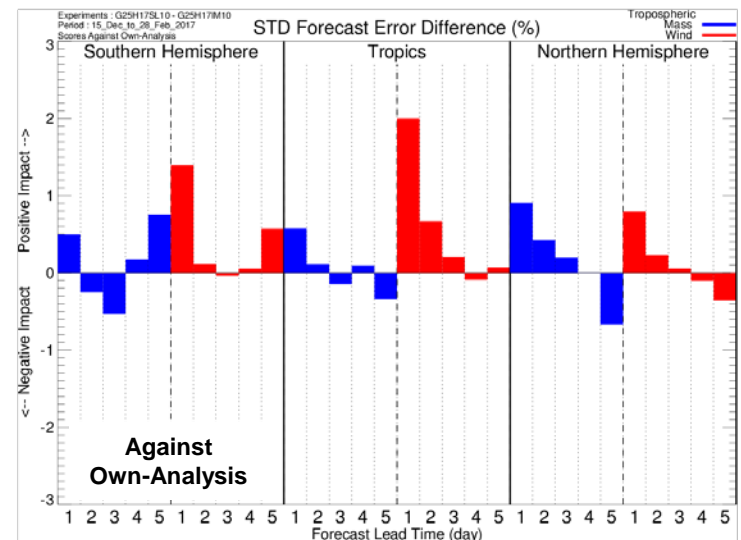
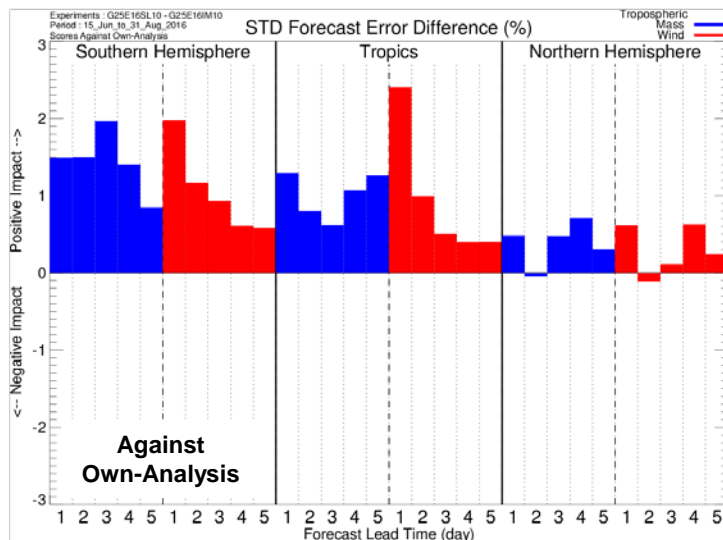
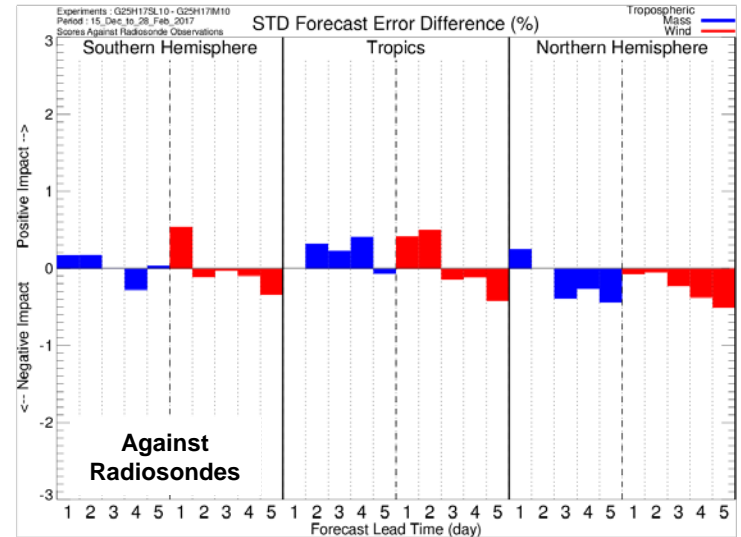
Verification scores for the second experiment

(tracking + updated height errors and reassigned pressure level)

Summer period: 15 Jun – 31 Aug 2016



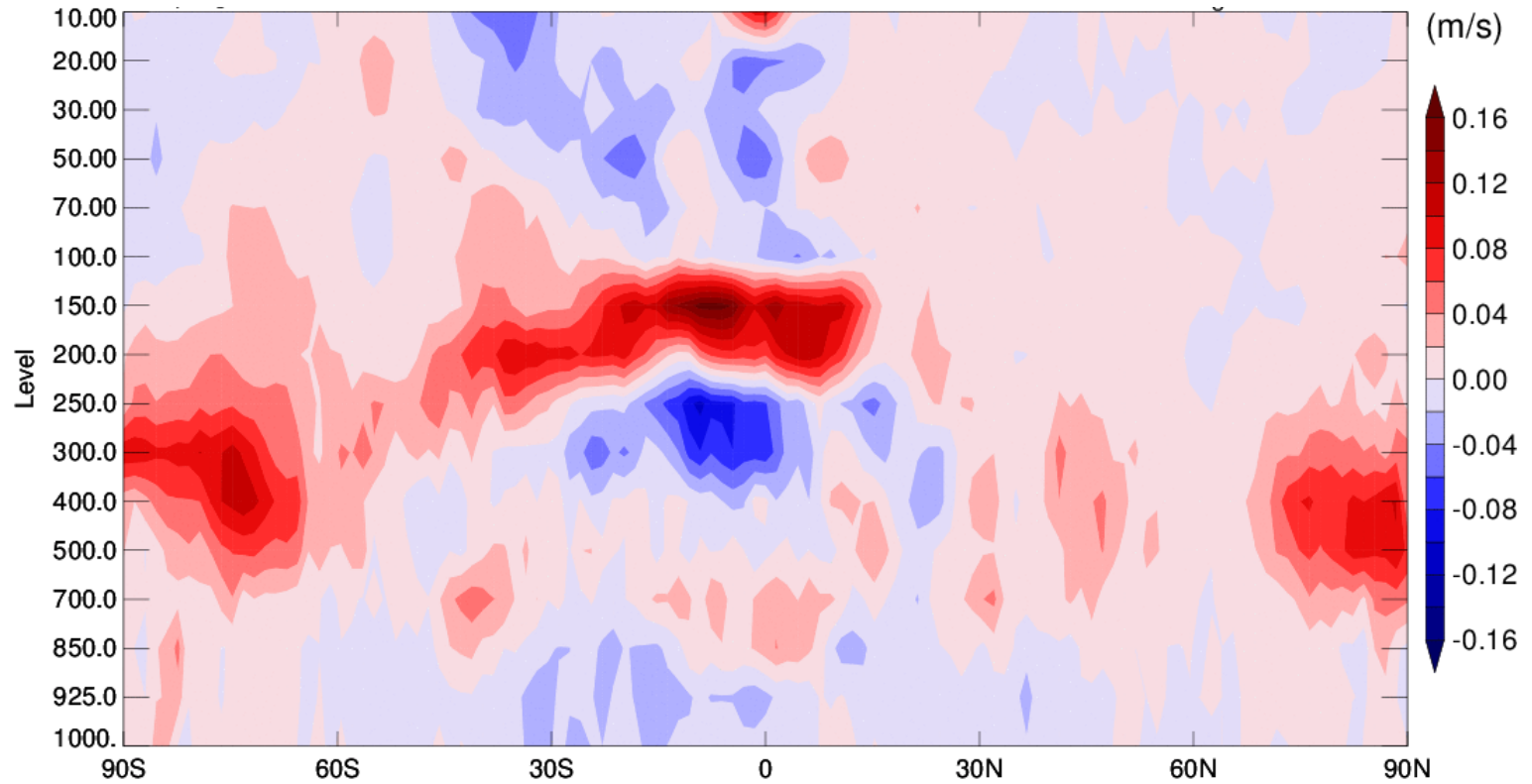
Winter period: 15 Dec – 28 Feb 2017



Zonal mean analysis wind speed difference

Winter period: 15 Dec – 28 Feb 2017

Second Experiment - Control



Concluding Remarks

- Although many difficulties remain to explicitly include a pressure variation for AMVs in a 4D incremental variational scheme, preliminary results with the '1D-Var + 4D-EnVar' approach explored in this study are encouraging (neutral or slightly positive against radiosondes).
- Better results are obtained when the tracking error is combined with the contribution of the reassigned height error, especially for the summer period.
- The proper estimation of the tracking and height error statistics remain an important issue.
- Reassigning the height of AMVs via a variational approach has been first proposed by Velden et al. (1998) and used as a post-processing step of AMV products. The main novelty of our work is to use explicitly the height error estimates in the variational data assimilation formulation.



References

- Folger and Weissmann, 2016: Lidar-based height correction for the assimilation of atmospheric motion vectors. *Journal of Applied Meteorology and Climatology*, 2211-2227.
- Forsythe and Saunders, 2008 : AMV errors: a new approach in NWP. Extended abstract, IWW09.
- Salonen and Bormann, 2014: Investigations of alternative interpretations of AMVs. Extended abstract, IWW12 .
- Salonen, Cotton, Bormann and Forsythe 2015: Characterizing AMV height-assignment error by comparing best-fit pressures statistics from the Met Office and ECMWF data assimilation systems. *J. Appl. Meteor. Climatol.*, 225–242.
- Velden, Olander, Wanzong, 1998 :The Impact of Multispectral *GOES-8* Wind Information on Atlantic Tropical Cyclone Track Forecasts in 1995. Part I: Dataset Methodology, Description, and Case Analysis. *Mon. Wea. Rev.*, 1202-1218.



Extra Slides

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Δp from 1D-Var and model best-fit pressure approaches

1D-Var approach

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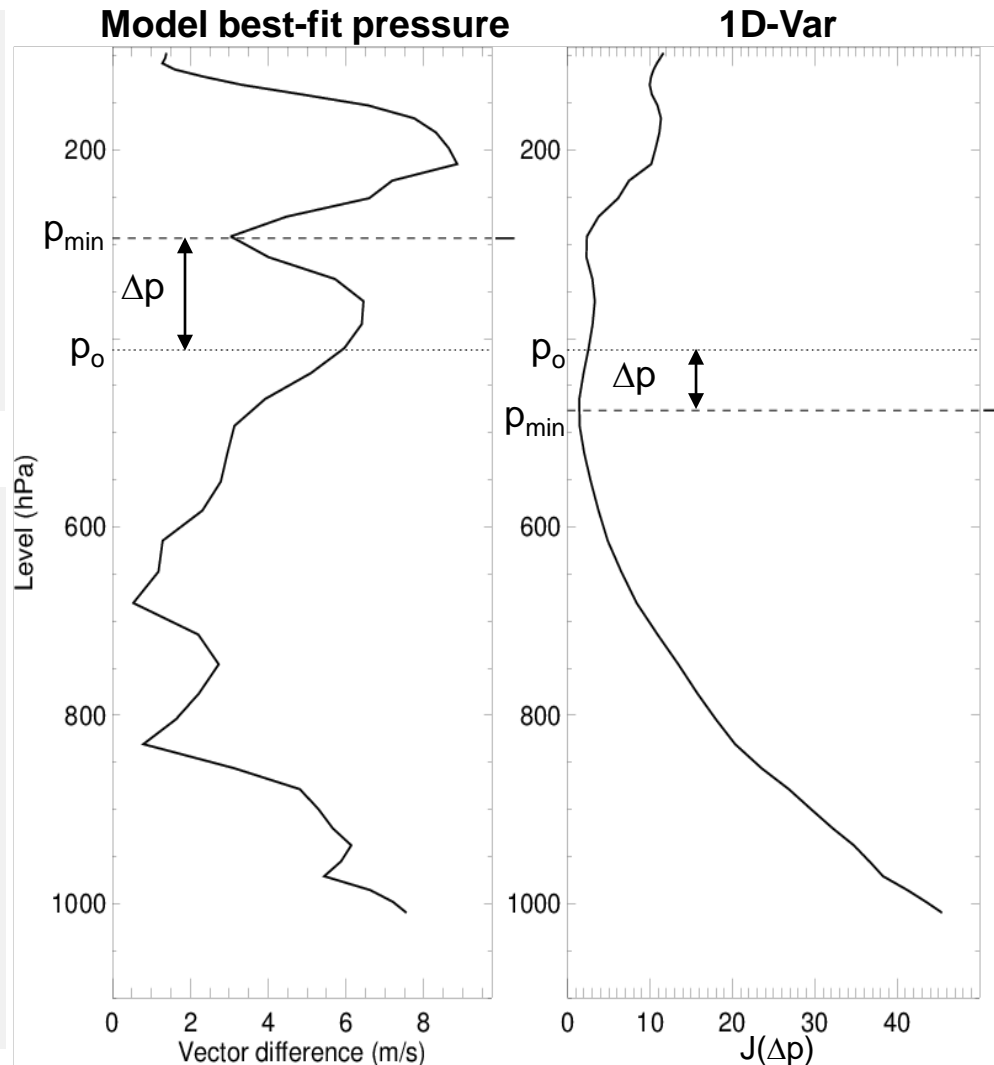
In case of multiple minima, the minimum closest to the originally assigned pressure (p_o) is chosen.

Model best-fit pressure approach Salonen et al. (2015)

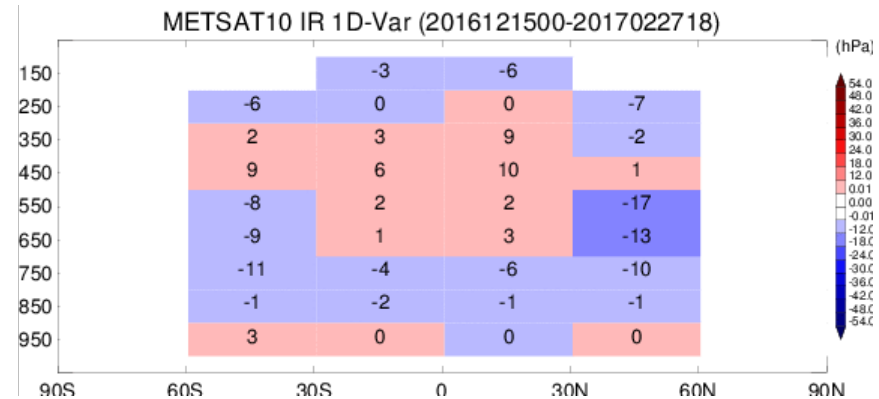
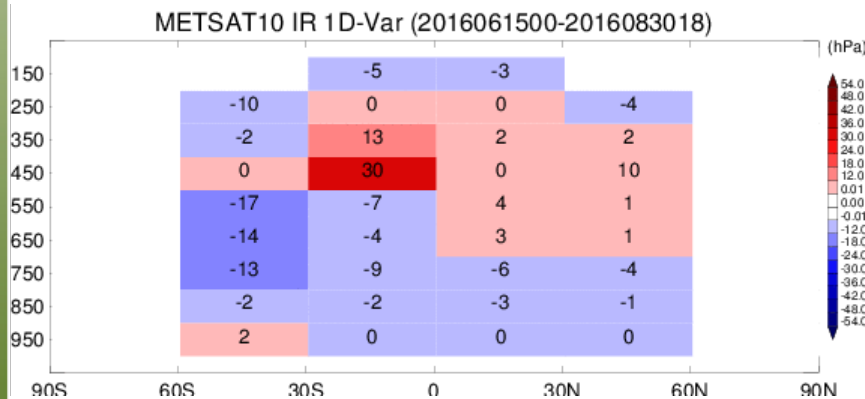
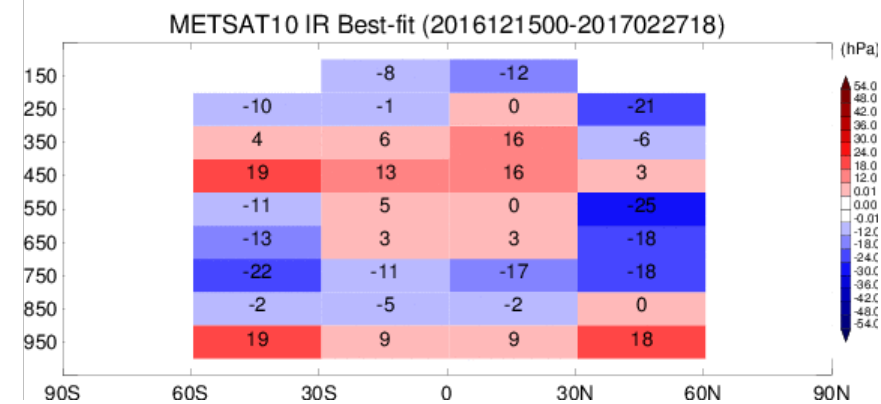
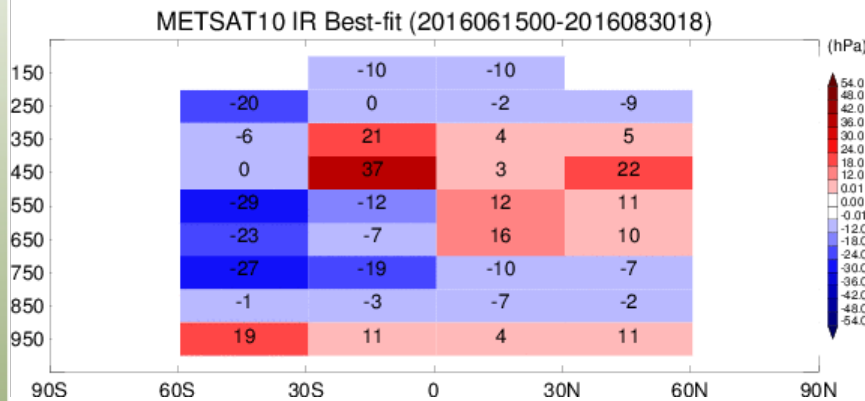
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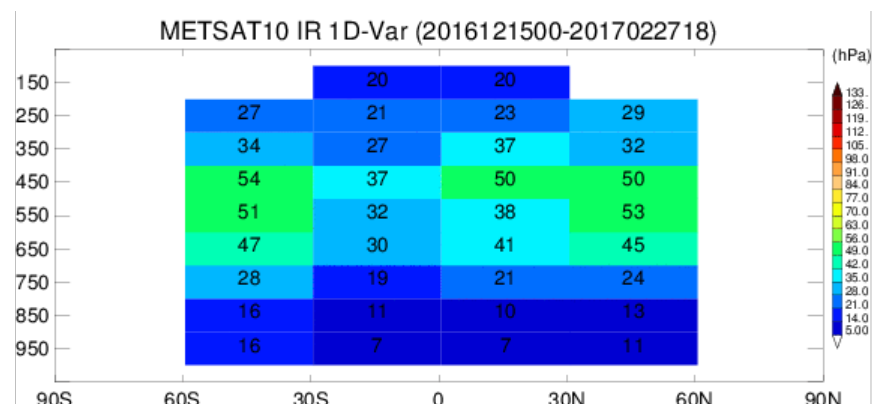
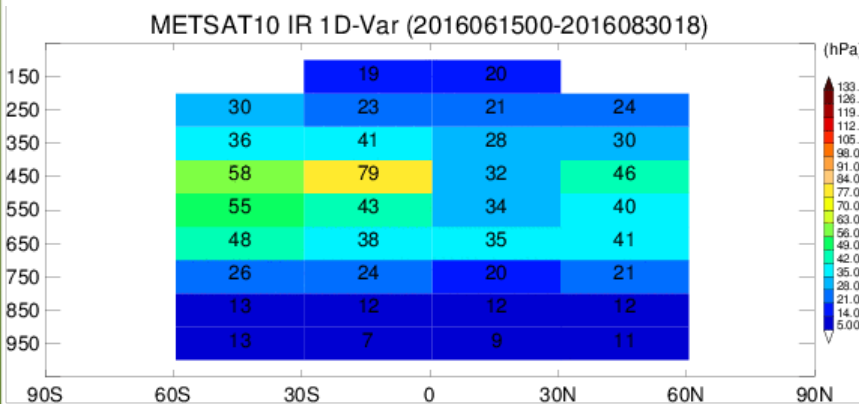
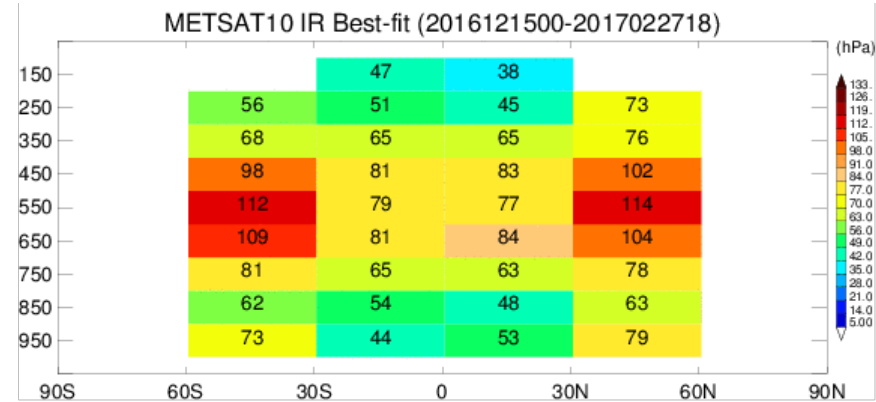
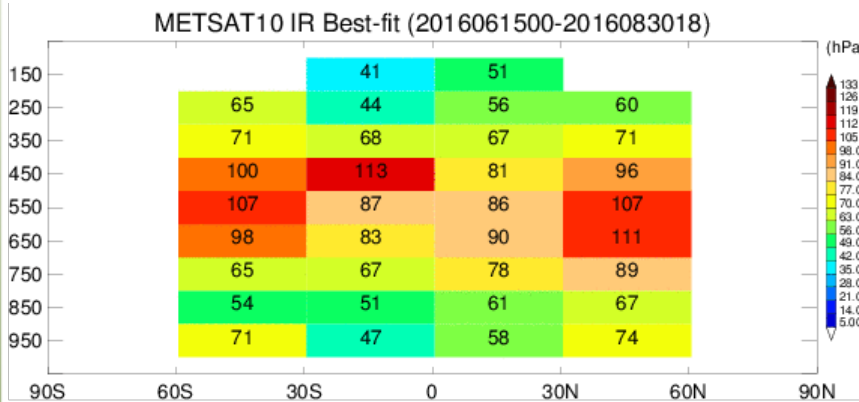
Δp biases from the model best-fit and 1D-Var (Meteosat-10)



Δp standard deviations from model best-fit and 1D-Var (Meteosat-10)

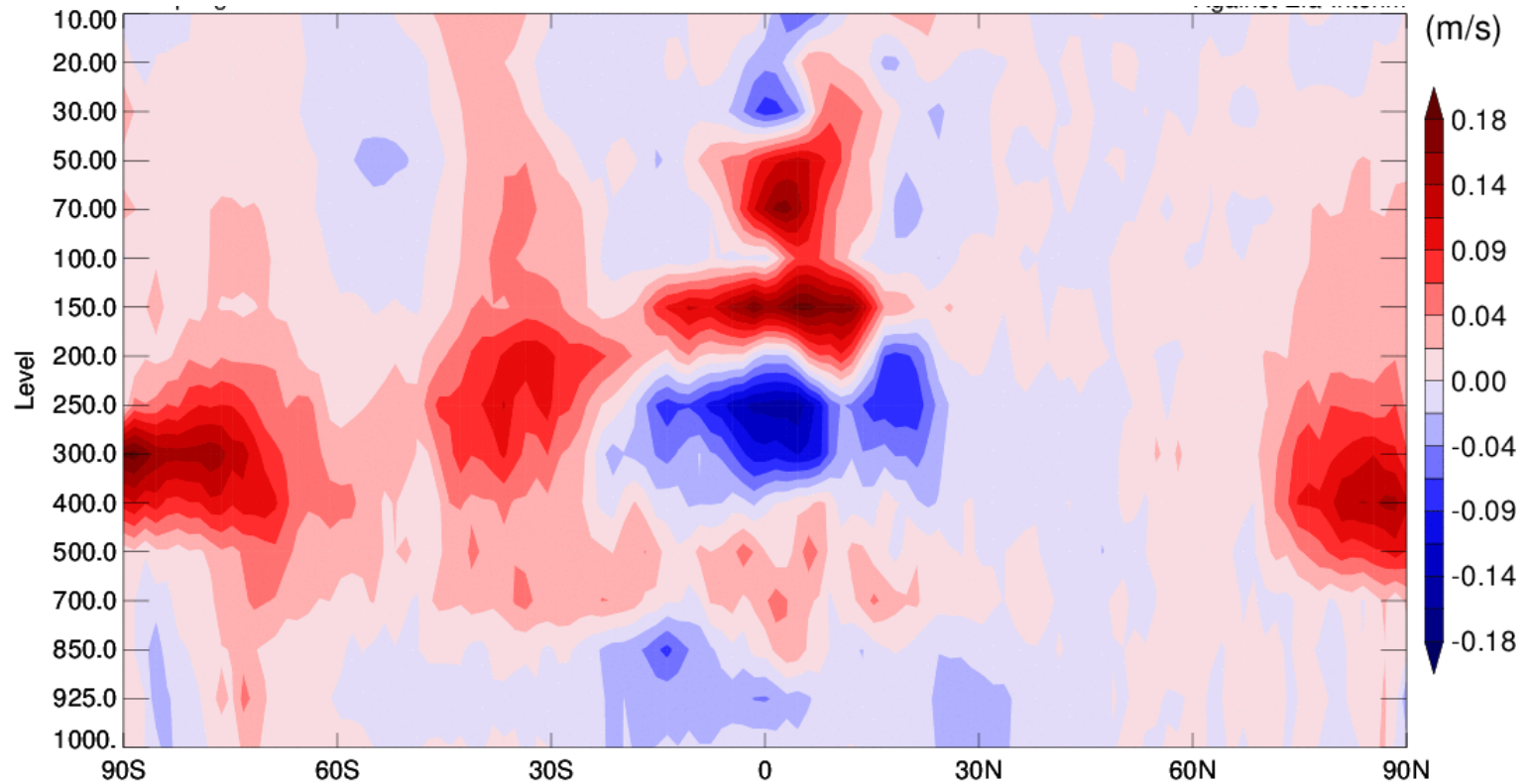
Summer period: 15 Jun – 31 Aug 2016

Winter period: 15 Dec – 28 Feb 2017



Zonal mean analysis wind speed difference

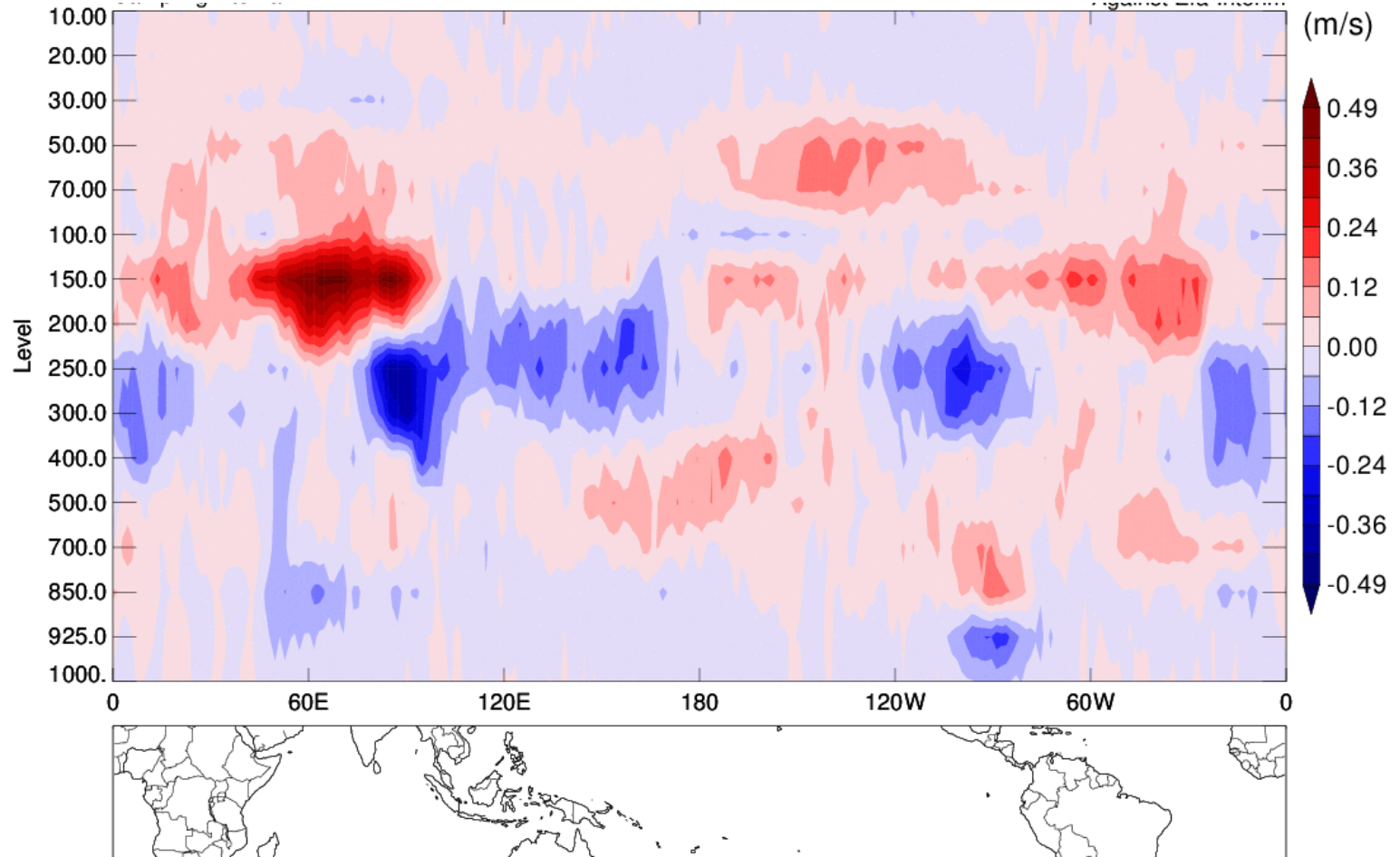
Summer period: 15 Jun – 31 Aug 2016



Second Experiment - Control

Mean analysis wind speed difference

Summer period: 15 Jun – 31 Aug 2016



Second Experiment - Control