



# ENSEMBLE-BASED ALGORITHMIC OPTIMISATION OF OPENIFS WEATHER MODEL

Lauri Tuppi, Madeleine Ekblom, Pirkka Ollinaho and Heikki Järvinen



# Introduction

- **Optimisation:** final adjustment of closure parameters of a numerical weather prediction model after fixing the model structure
- **Need** for optimisation: some parameters very difficult to quantify
- **Problem of optimisation:** labourious trial-and-error process → ensemble forecasting based algorithmic methods
  - Is it possible to optimise large parameter sets simultaneously?
  - How to efficiently search for optimised model versions?
  - How does the model forecast skill change after the optimisation?
  - Is it possible to use lower model resolution during optimisation?
  - Is expert judgment needed when using algorithmic optimisation methods?

# Tools

- OpenIFS T399; parameters of SPP scheme, 19 in total
- Optimisation algorithm: EPPES (Bayesian importance sampler)
- OpenEPS + ensemble initial states for 2017, for verification deterministic initial states of 2018
- Operational analyses for 2017 and 2018
- Metric for distance to analysis: moist total energy norm

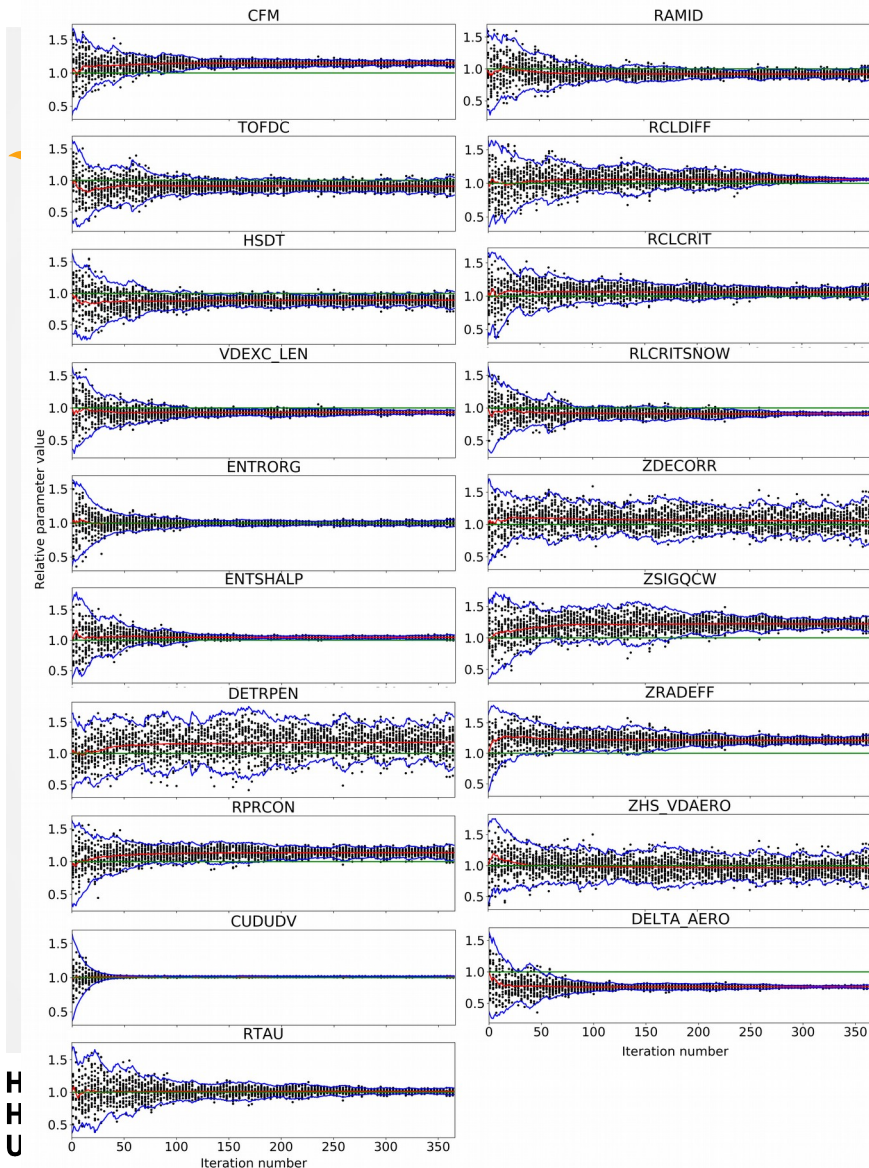
$$\langle \vec{x}', C_{TE} \vec{x}' \rangle = \frac{1}{2} \iint \left[ u'^2 + v'^2 + \frac{c_p}{T_r} T'^2 + c_q \frac{L^2}{c_p T_r} q'^2 \right] d\Sigma \frac{\partial p_r}{\partial \eta} d\eta + \frac{1}{2} \int \left[ R \frac{T_r}{p_r} \ln p_s'^2 \right] d\Sigma$$

- The purpose is to minimise the cost function



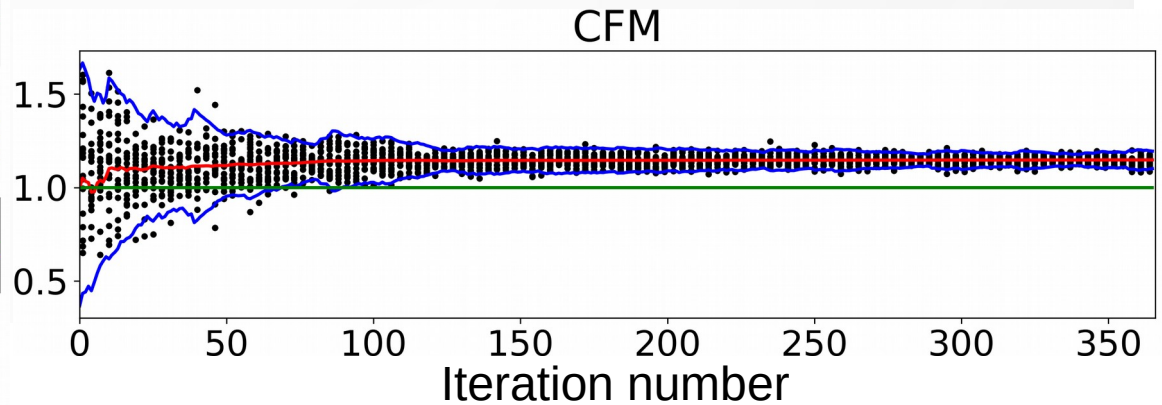
# Methods

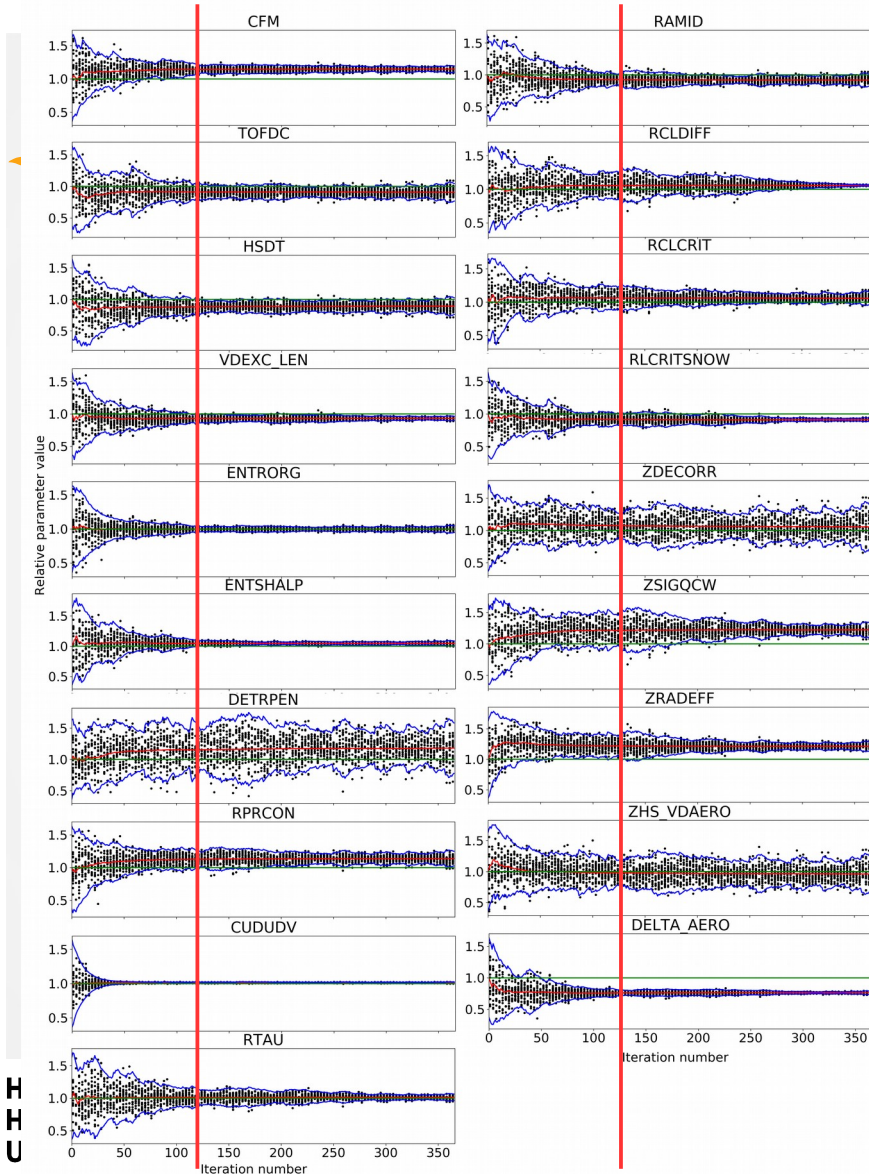
- Optimisation setup: ensemble size 20, forecast range 36h, ensembles every 3 days
- Workflow:
  - 1. use EPPEs to sample parameter values as 20 vectors of 19 elements
  - 2. assign one vector for each ensemble member
  - 3. run the ensemble forecast
  - 4. evaluate the cost function for each ensemble member
  - 5. use EPPEs to sample new 20 parameter vectors based on the cost function values
  - 6. go to 2
- Experiments: 1x 3-year, 4x 1-year
- Verification with global root mean squared error using forecasts of year 2018



# How does the convergence look like?

- Overview
- Year 2017 repeated 3 times → 365 iterations
- Mostly good convergence
- Mean values settle during the first year, uncertainty may decrease slower



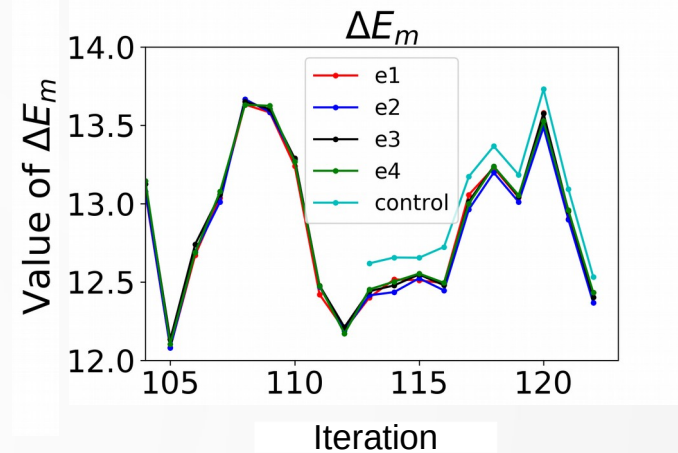
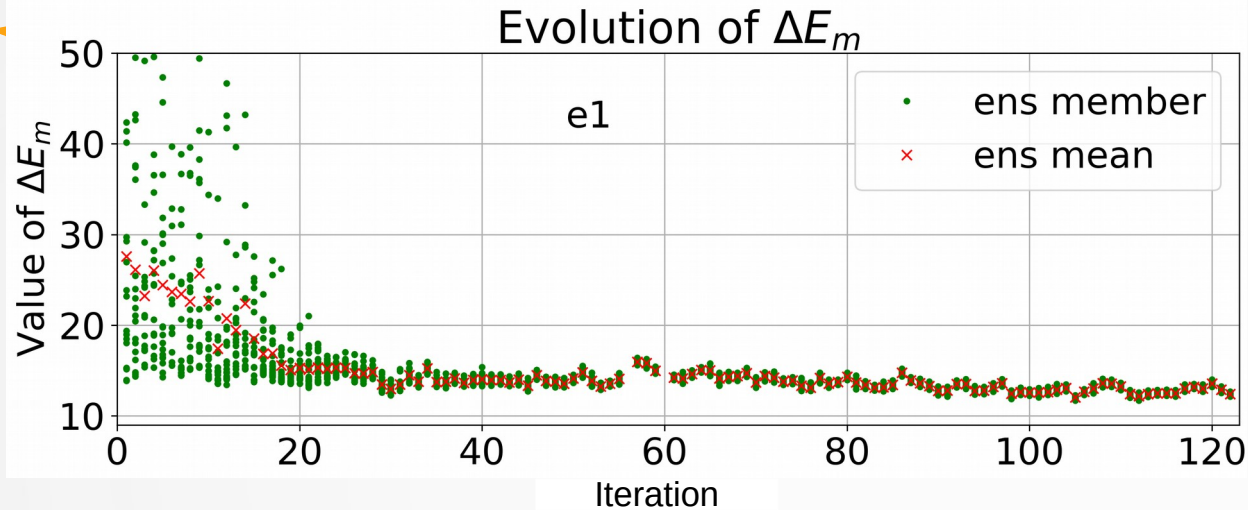


# How does the convergence look like?

- Overview
- Year 2017 repeated 3 times → 365 iterations
- Mostly good convergence
- Mean values settle during the first year, uncertainty may decrease slower
- Interested in the mean values → use 1 year (122 iterations) hereafter; lower cost, more efficiency



# Distance to reference

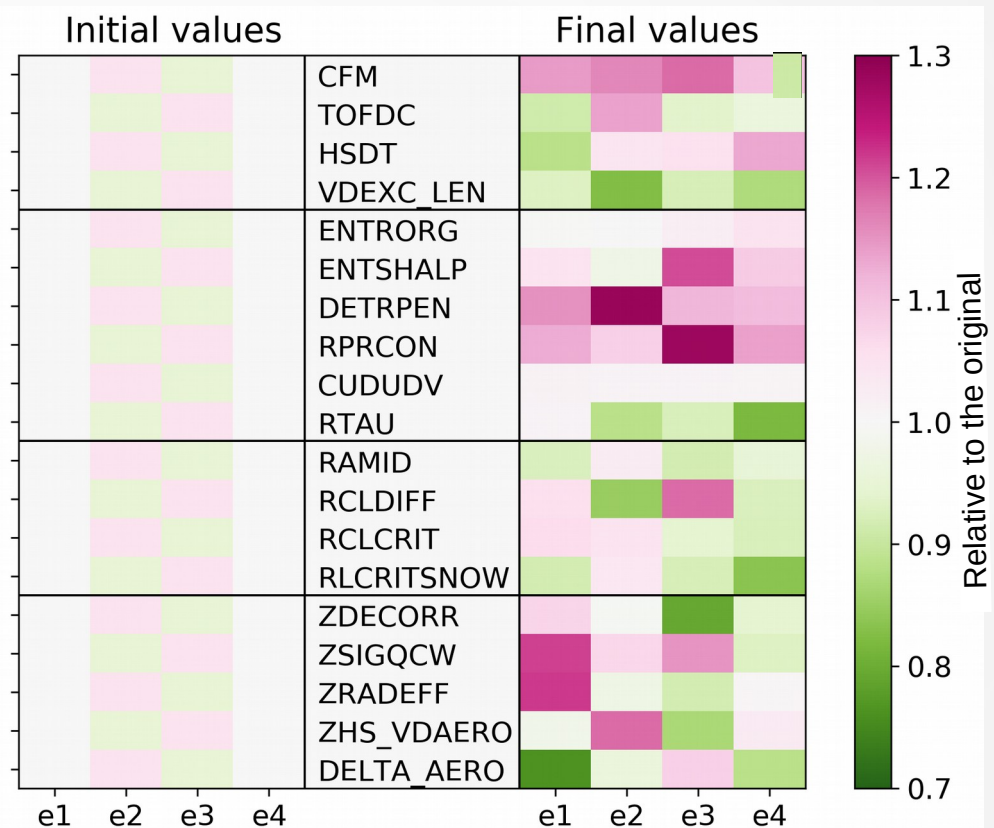


- Cost function: moist total energy norm
- Decreasing value  $\rightarrow$  optimisation progressing towards better model



# The optimisation results

- 4 experiments with different initial parameter values
- Different looking results but all are good models (cost function + verification)
- 10 additional short experiments: different outcomes as well
- Focus on e1

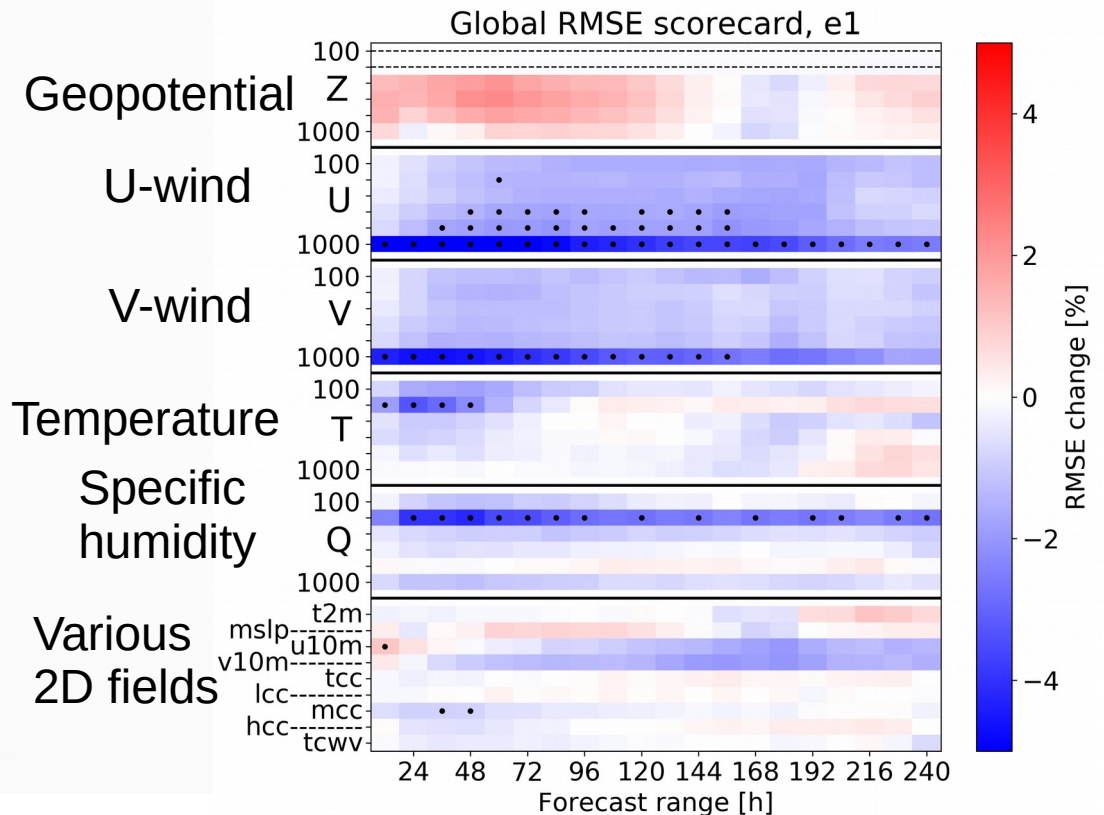
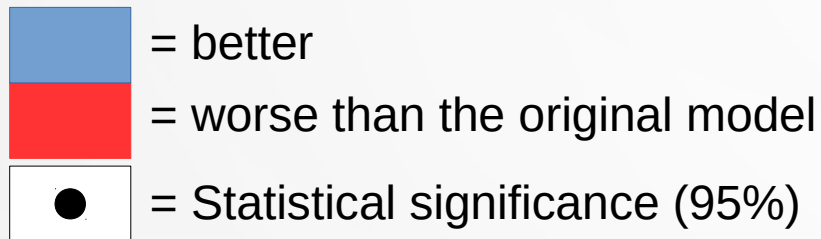






# Verification with global root mean squared error

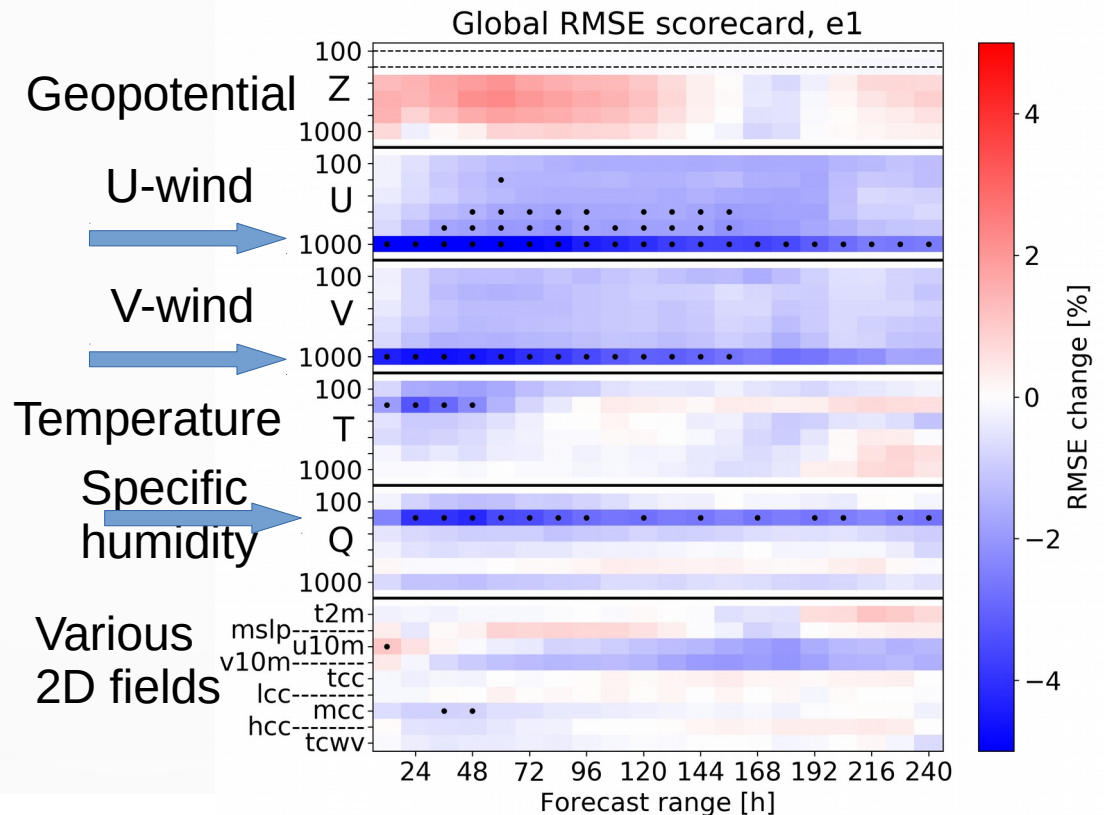
- Verification using independent set of forecasts: 53 deterministic forecasts in 2018
- With optimised and original model



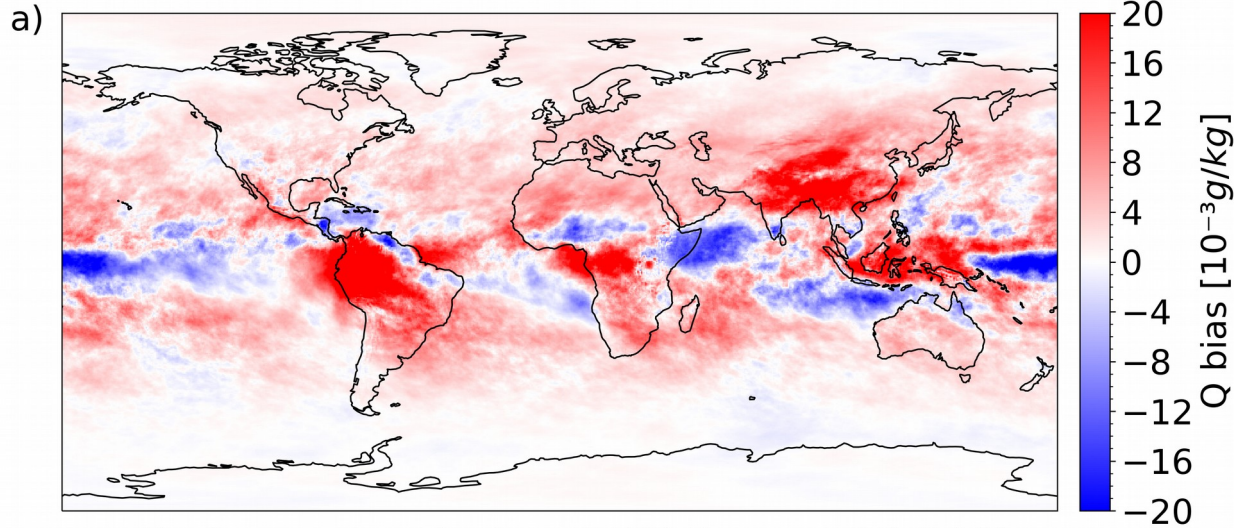


# Verification with global root mean squared error

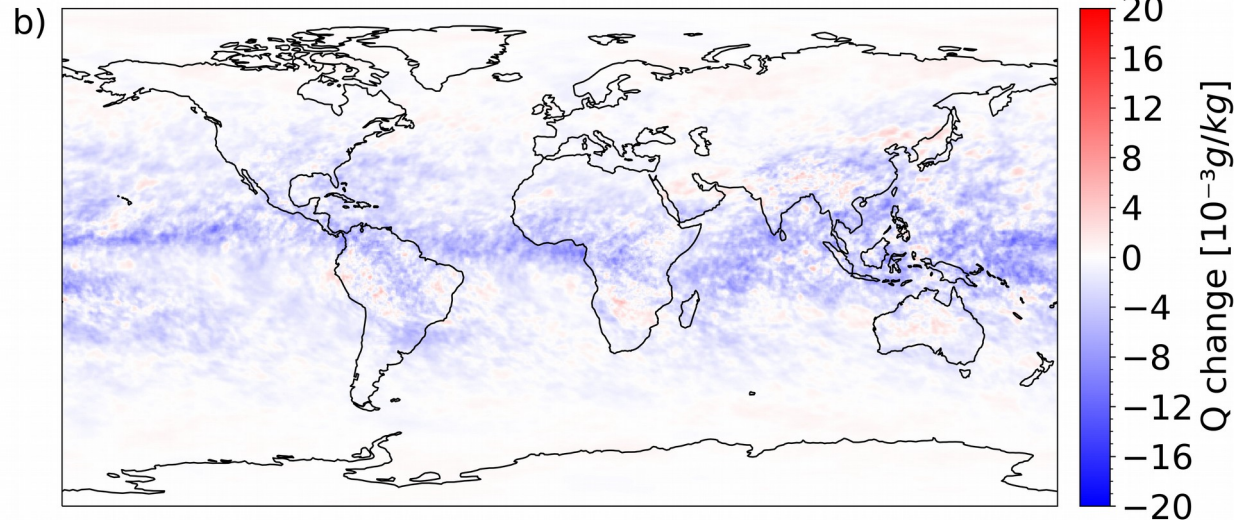
- Verification using independent set of forecasts: 53 deterministic forecasts in 2018
- With optimised and original model
- e2, e3 and e4 also better than the original model
- Next: focus on the most notable improvements in e1



## Q bias at p=250hPa, avg 12-240h



## Q change in e1 at p=250hPa, avg 12-240h

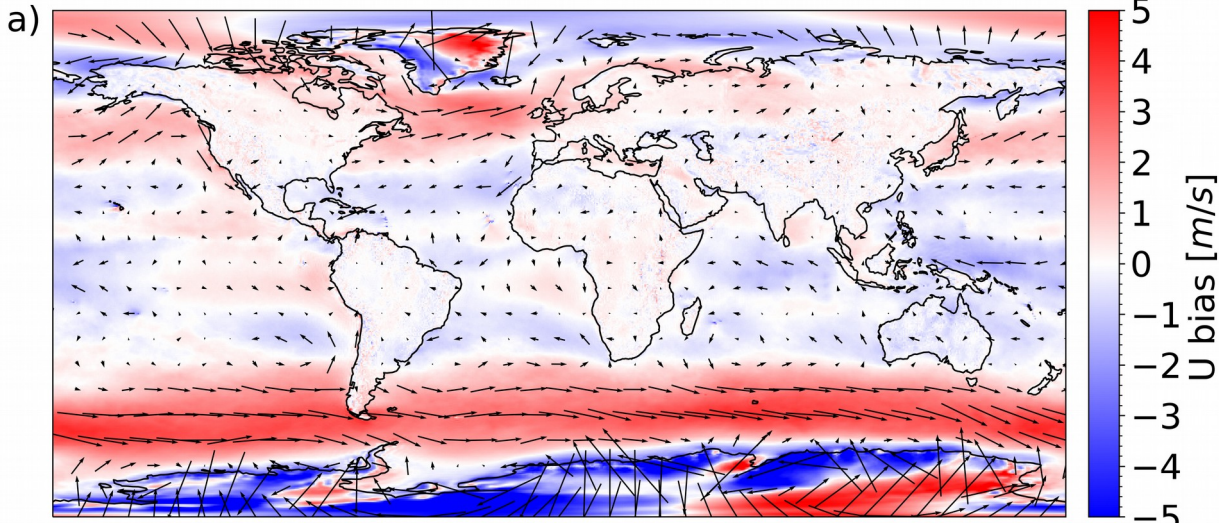


- Mostly too much moisture in the original model
- (reference: operational analyses)
- Some displacement errors as well

- e1 decreases the amount of moisture almost everywhere
- Cannot fix the displacement error → perhaps a structural model error

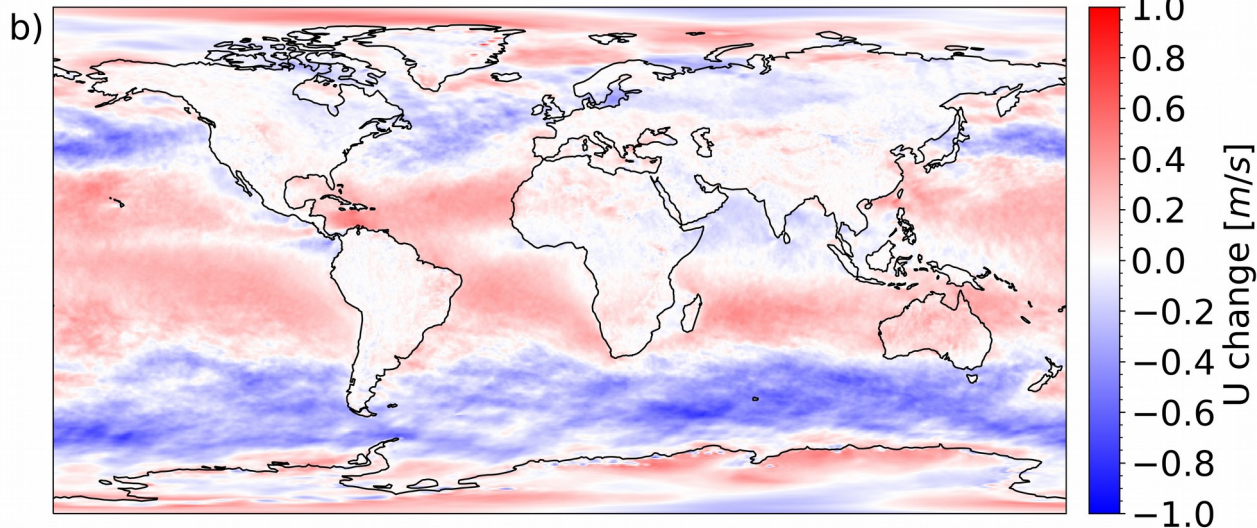


U bias at p=1000hPa, avg 12-240h  $\longrightarrow 5 \frac{m}{s}$



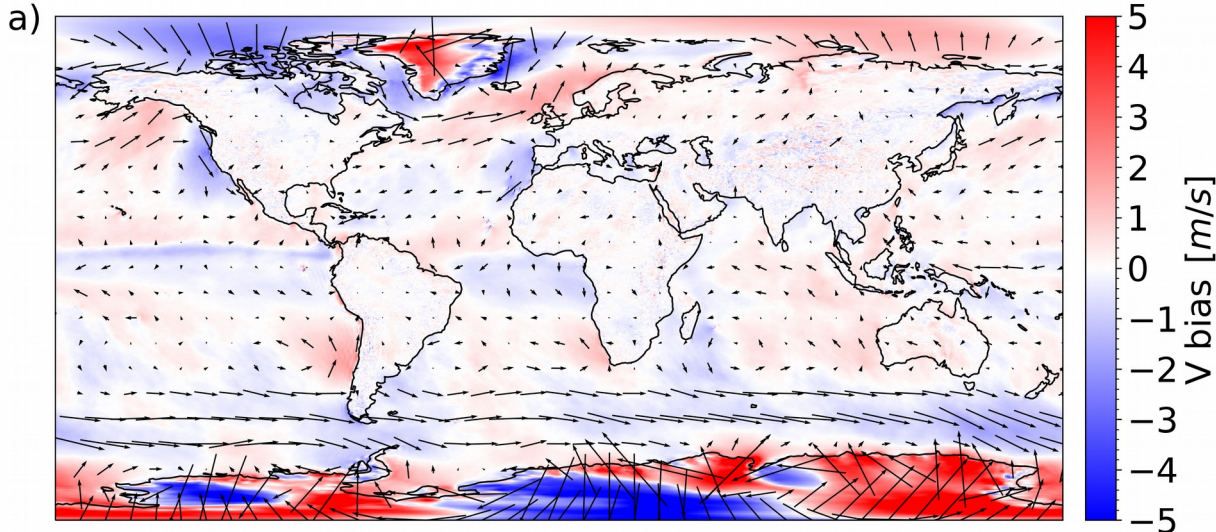
- Control model: U bias with colour and mean wind with arrows
- Too strong U wind in general

U change in e1 at p=1000hPa, avg 12-240h

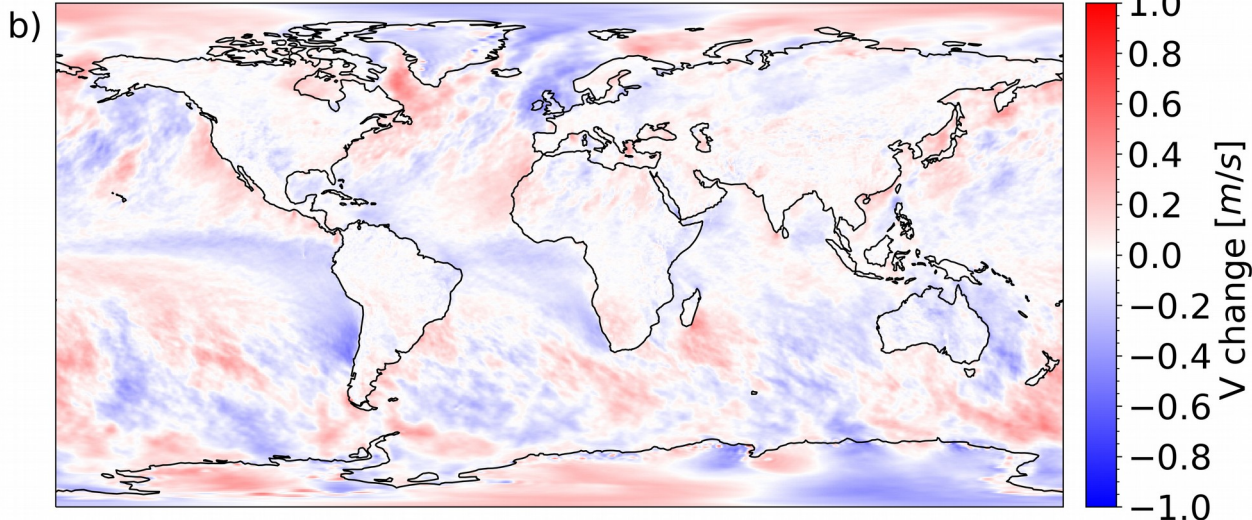


- e1 tends to slow down the wind
- Midlatitudes improve
- Some tropical areas degrade

V bias at p=1000hPa, avg 12-240h —  $5 \frac{m}{s}$



V change in e1 at p=1000hPa, avg 12-240h



- Mid and high latitudes: too strong V wind
- Tropics: too little convergence towards ITCZ

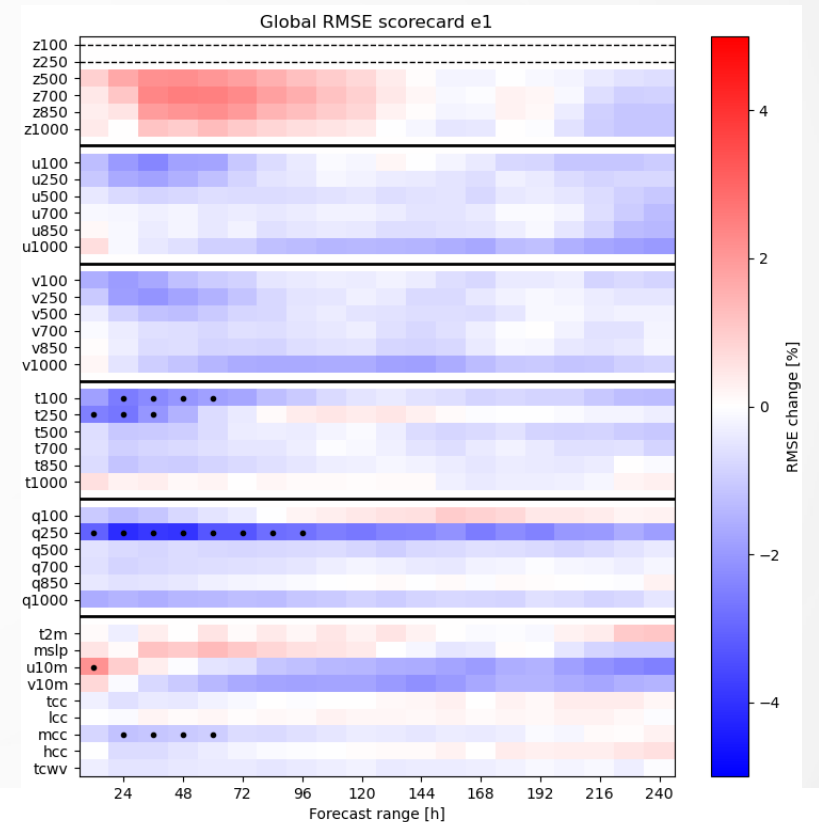
- Mid and high latitudes: improvement in many places
- Atlantic storm track shifts south, not correct
- Tropics: the lack of convergence towards ITCZ becomes more prominent → structural model error





## Applicability to higher resolutions

- Optimisation with T399 (~50 km), verification with T639 (~32 km)
- Milder improvement but generally outperforming the original model







# Conclusions

- Efficient algorithmic optimisation of OpenIFS is possible, 1 year experiment → ~10 simulation years
- Candidate model versions can be produced efficiently
- Expert judgment needed for making a choice from a number of optimal models
- Significant improvement of some systematic biases (with the cost of slight increase of some other biases)
- Optimisation using decreased model resolution possible

Contact: lauri.tuppi@helsinki.fi



## Extra slides

