Ensemble forecasting at ECMWF

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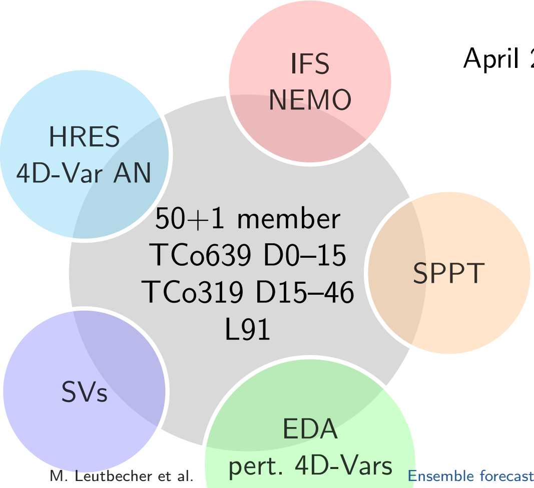
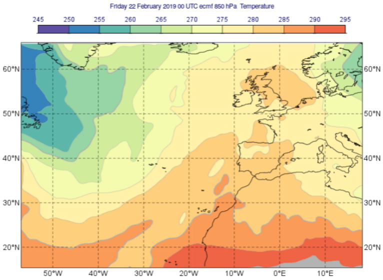


Initial conditions

T850hPa

HRES Analysis 00 UTC



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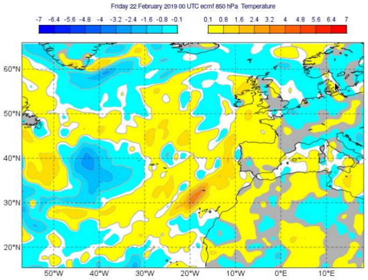
EDA-Pert 1



SV-Pert 1

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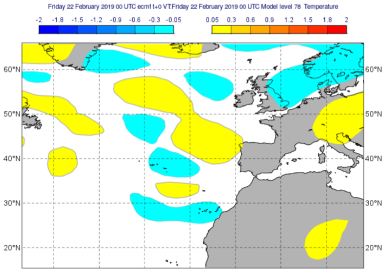

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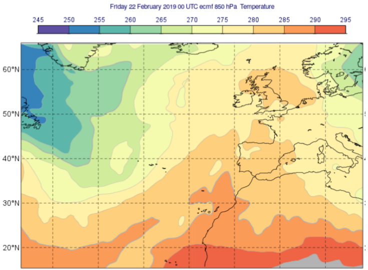
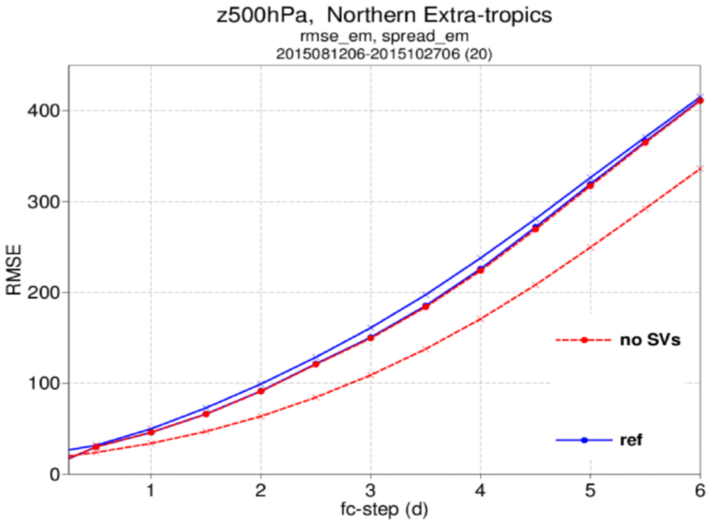
Initial conditions for ENS member 1



Singular vectors and reliability



—•— ens. mean RMSE
—x— ens. stdev

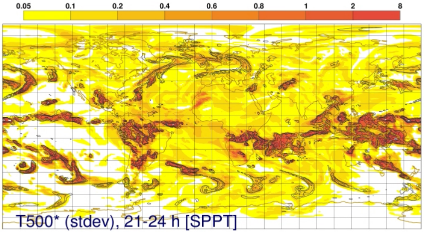
EDA and SPPT generate spread also in the directions of the leading SVs. Just not enough though.

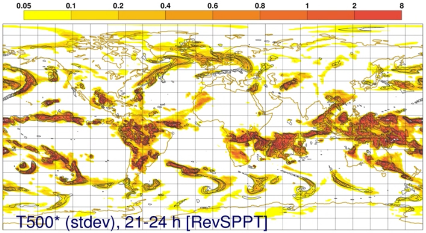
When to stop using SVs? See Leutbecher, M. and Lang, S. T. (2014) QJ

Future directions for ICs

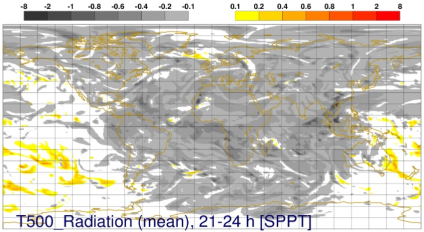
- Centre of ensemble at initial time
  - single deterministic AN
  - EDA (Lang, Bonavita and Leutbecher, 2015, QJ)
  - multiple deterministic analyses (Hólm et al. 2018, FUSION)
- Exchangeable initial conditions for atmosphere (Lang et al 2019, ECMWF Newsletter No. 158)
  - abandon $\pm$ symmetry
  - 50 EDA members
  - joint distribution of members does not depend on their order
  - efficient testing configuration with small ensemble size based on fair scores (Leutbecher, 2018)

Stochastically Perturbed Parametrization Tendencies





temperature tendency perturbations due to SPPT only (K/3h, shading)
precipitation (ens. mean, .5/1/2/4/8/... mm, black contours)
2015011000, t=+21–24 h



- **More realistic diurnal cycle of tendency perturbations in SPPT** by not perturbing the clear-sky radiative tendency;
- Perturbations in stratosphere and weaker tapering of perturbations in boundary layer
- Same SPPT in ENS and EDA, and cycling of random fields in EDA
- 20% reduced SPPT amplitude
- **SKEB deactivation** (2.5% saving)

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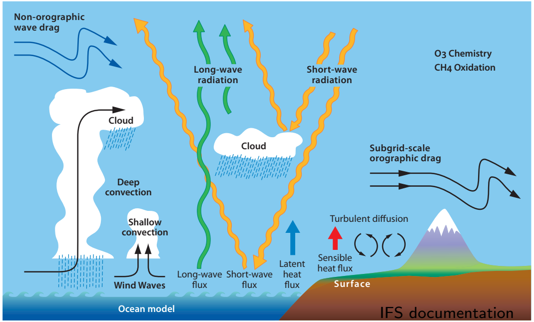
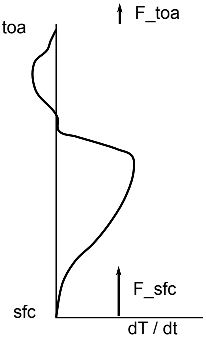
Future directions for representation of MU

- represent uncertainty close to the assumed sources of the errors
- physical consistency of perturbation
- e.g. preserve local energy or moisture budget through flux perturbations at surface and at the top-of-the-atmosphere consistent with the tendency perturbation
- beyond an amplitude error, e.g. uncertainty in shape of heating profile





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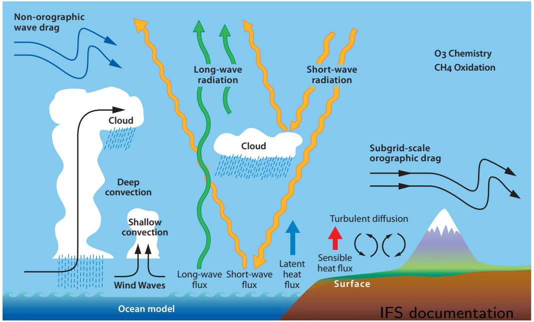

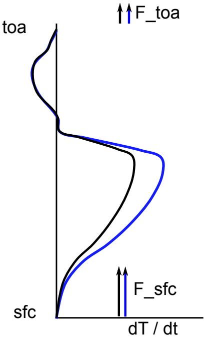

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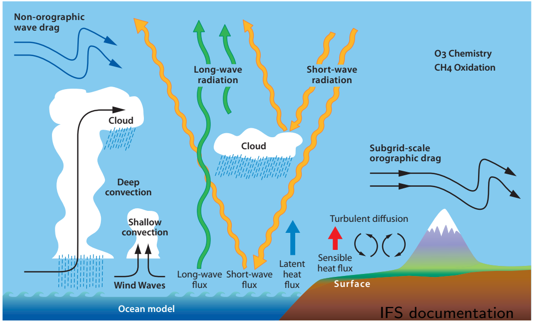

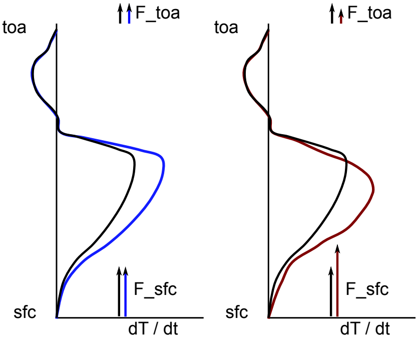

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Ongoing research on model uncertainties

- Stochastically Perturbed Parametrization Tendencies (SPP)
- Quantitative comparison of the tendency perturbations from SPP and SPPT
- Dynamical Core uncertainties

see Ollinaho et al. (2017) and Leutbecher et al. (2017).

Predictive verification for design of multi-model ensembles

- Consider: m_A members from model A, m_B members from model B, ...
- How does the skill of the multi-model ensemble depend on $m_A, m_B, \ldots$?
- If computational cost was constrained globally for all NWP centers, how many members would we like to have from model A, B, C, ...?
- Can this be answered without having to run ensembles with largest $m_A, m_B, \ldots$ one would like to consider.

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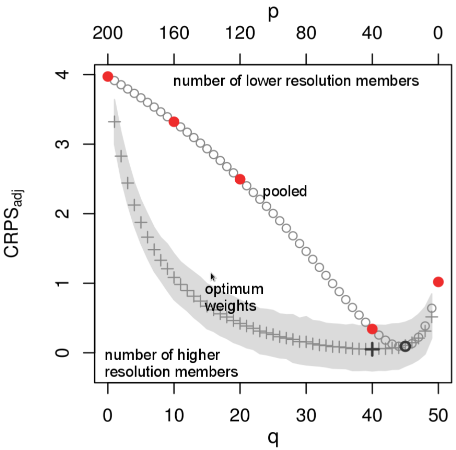
- Answer for CRPS using kernel representation and assuming a kind of exchangeability

$$\sum_{i=1}^{k} \frac{\lambda_i}{m_i} \sum_{g=1}^{m_i} | z_{ig} - y | - \frac{1}{2} \sum_{i,j} \frac{\lambda_i \lambda_j}{m_i m_j} \sum_{g=1}^{m_i} \sum_{h=1}^{m_j} | z_{ig} - z_{jh} |$$

$\sum$ denote sums over different models i, j with respective weights λ_j and number of members m_j and $\sum$ denote sums over members of a specific model.

Predictive verification for dual-resolution ensembles

- p members with lower resolution (say TCo399) and q members at higher resolution (say TCo639).
- cost ratio for example is 4; $(p, q) = (200, 0), (160, 10), (120, 20), (40, 40), (0, 50)$ have same computational cost
- compute 5 terms that enter in kernel representation of CRPS for two distinct models from small ensembles $(p_E, q_E) = (8, 8)$
- derive formula that gives expected CRPS for any (p, q)
- expression for optimum weights as function of stats



Ben Bouallègue et al. (2019)
Tellus in review

Summary

- Flow-dependent initial perturbations from EDA and SVs: Both components essential to achieve reasonable reliability
- Revision of SPPT brings different flow-dependent representation of model uncertainties through removing spurious diurnal cycle in perturbations
- The desire for physical consistency of perturbations motivates development of alternative schemes that represent uncertainty close to its sources
- Work on CRPS score adjustments permits to study large range of multi-model combinations without having to run/verify each configuration separately; optimum weights can be determined directly (without need for numerical optimisation).