Current Issues and Challenges in Ensemble Forecasting

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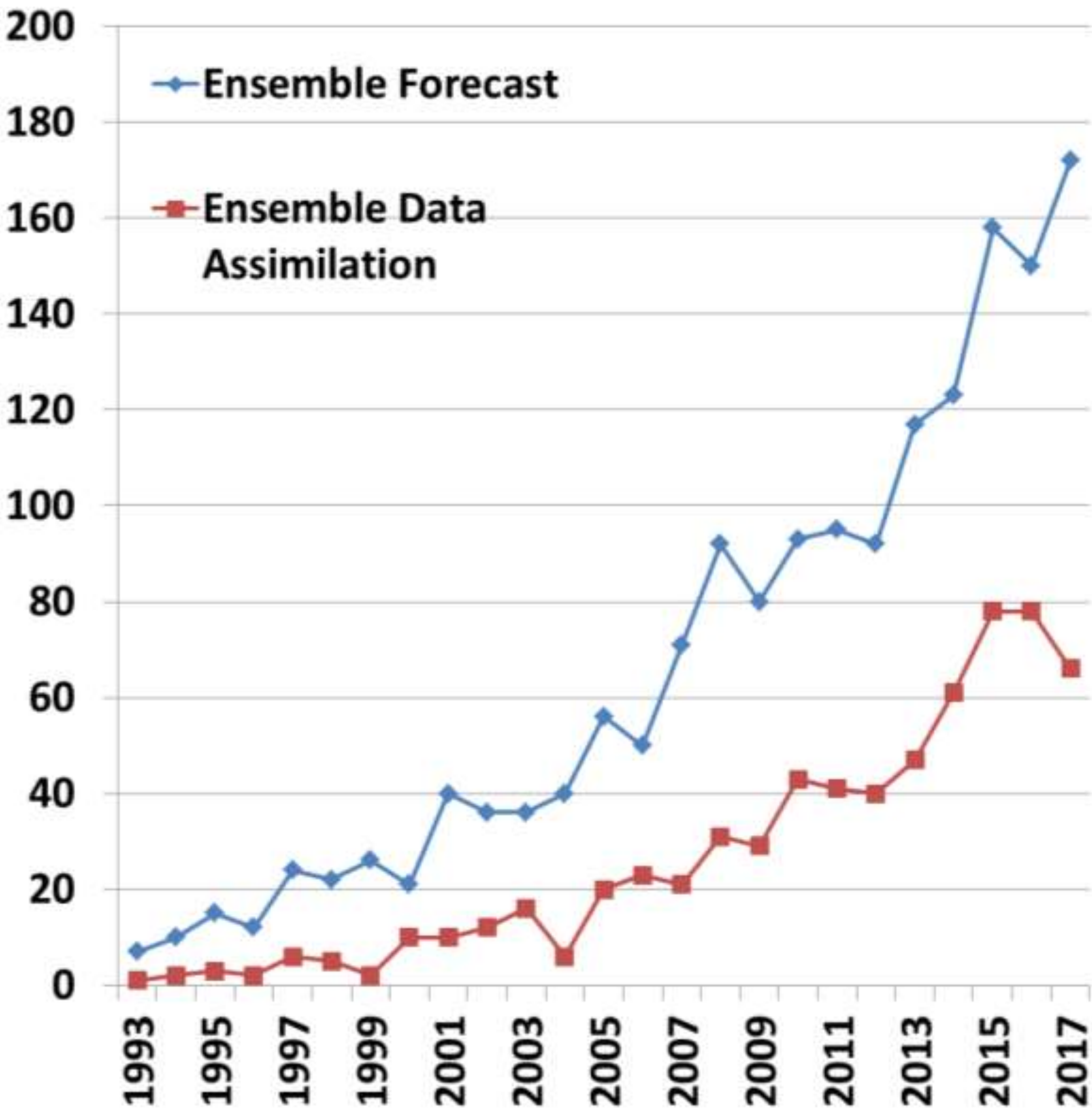
Focus on Model Uncertainty Representation

*Number of Article/Year with These Words in the Abstract**



Research in ensemble forecasting and ensemble data assimilation continues to be active.

***AMS journals only**

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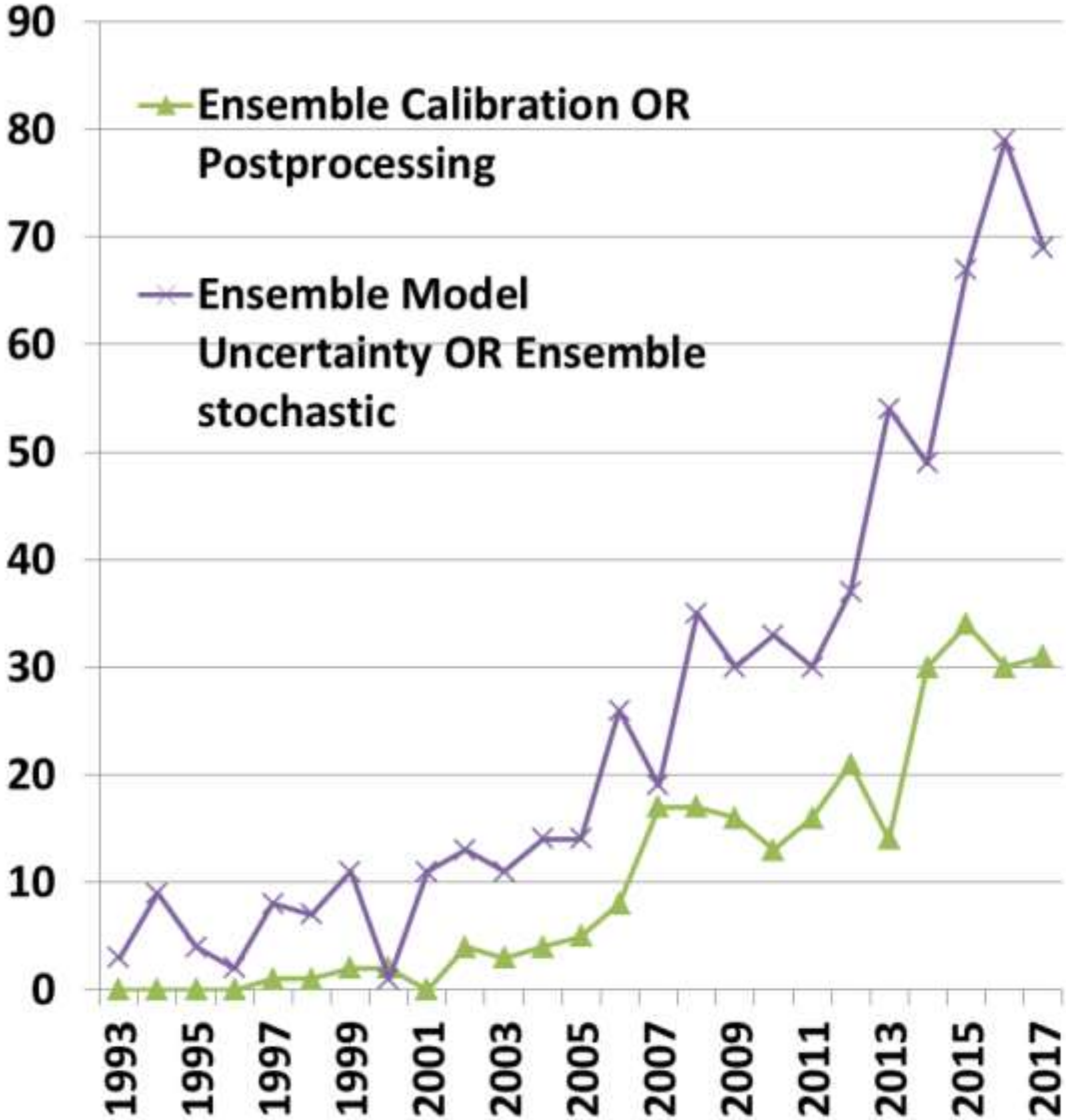


Research in model uncertainty continues to grow rapidly.

Interest in calibration and post-processing also substantially larger than in the early 2000s.

***AMS journals only**

Model Uncertainty: New Developments

- **DWD: Stochastic model for model error tendency (based on analysis increments)**
- **ECCC: Testing stochastic deep convection in regional ESPS**
- **ECMWF: Abandoning +/- pairs, Stochastic Parameter Perturbations (SPP), dynamical core departure point uncertainty, stochastic convective backscatter**
- **Met Office: Stochastic perturbed tendencies, analysis increment additive inflation, stochastic boundary layer perturbations, process evaluation group to investigate lack of spread in convective-scale ensembles**
- **MeteoFrance: Global- SPPT and SPP; regional- SPPT improvements, testing SPP**
- **NCEP: From STTP to SKEB + SPPT + SHUM**
- **NRL: Analysis correction-based additive inflation**
- **ROSHYDROMET: Additive model-error perturbations scaled by physical tendencies (similarities to coarse-graining, analysis increments)**

Met Office

Additive inflation

Improves ensemble dispersion effectively

Keep archive of analysis increments from oper runs $\delta\mathbf{x}_a^k \quad k=1 \ldots N_a$

Average analysis increment $\overline{\delta\mathbf{x}_a} = \frac{1}{N_a}\sum_{k=1}^{N_a}\delta\mathbf{x}_a^k$

Contains information on the model bias

Randomly select N_e increments from the archive $i_j \quad , j=1 \ldots N_e$

For each 6h window, add these increments to the ensemble, removing the sample average

$$\delta\mathbf{x}_e^j = \alpha\left(\delta\mathbf{x}_a^{i_j} - \frac{1}{N_e}\sum_{m=1}^{N_e}\delta\mathbf{x}_a^{i_m}\right) + \overline{\delta\mathbf{x}_a}$$

After Piccolo and Cullen MWR 2016
Similar methods being tested at DWD and NRL

NRL: Analysis Correction based Additive Inflation (ACAI)

One month of 10-day, 20-member ensemble forecasts for summer 2016

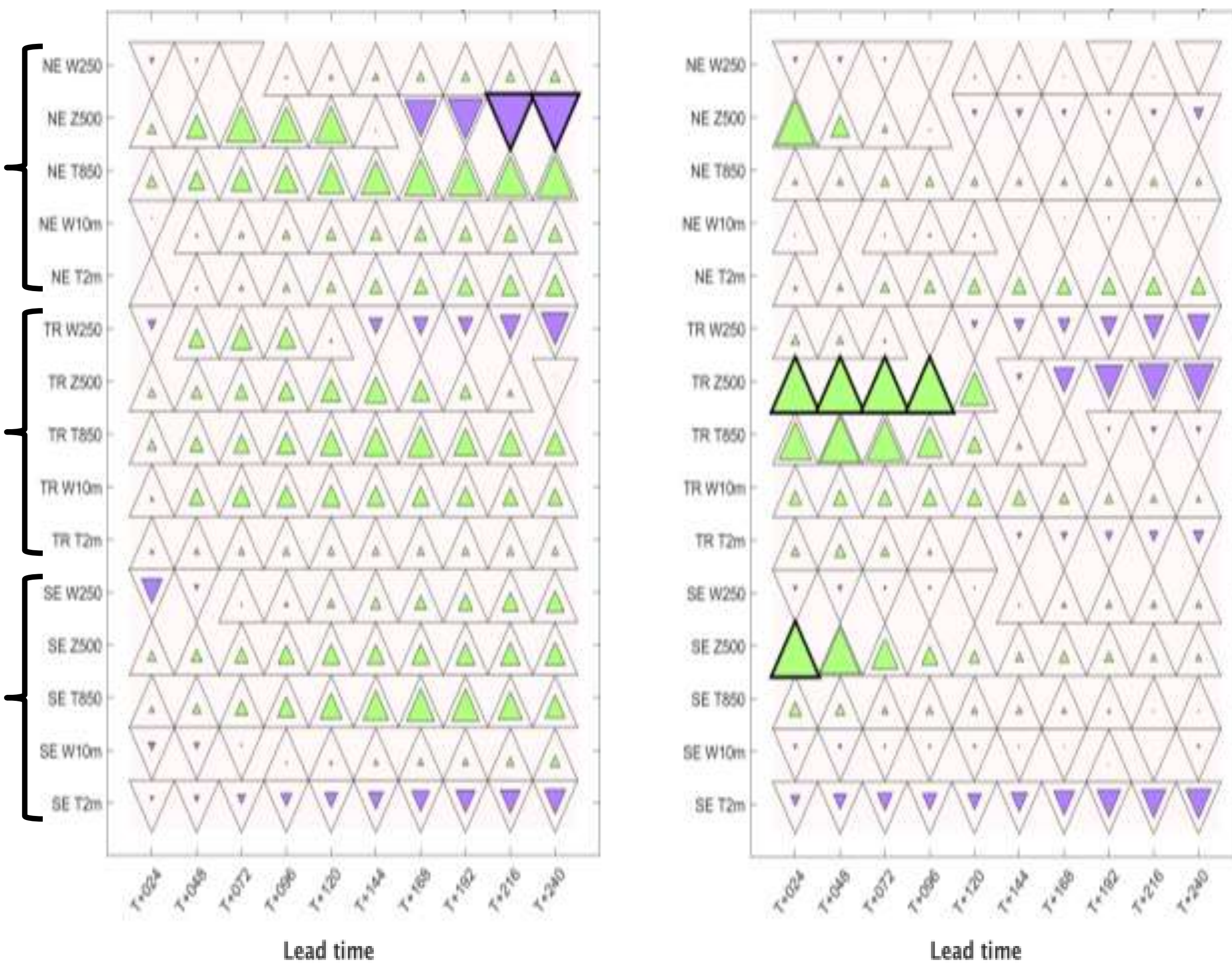
Change in bias : baseline vs ACAI

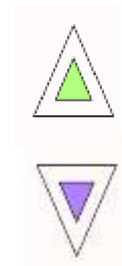
Change in RMSE : baseline vs ACAI

Northern Extra-tropics

Tropics

Southern Extra-tropics





Positive impact

Negative impact

Outside triangle represents:

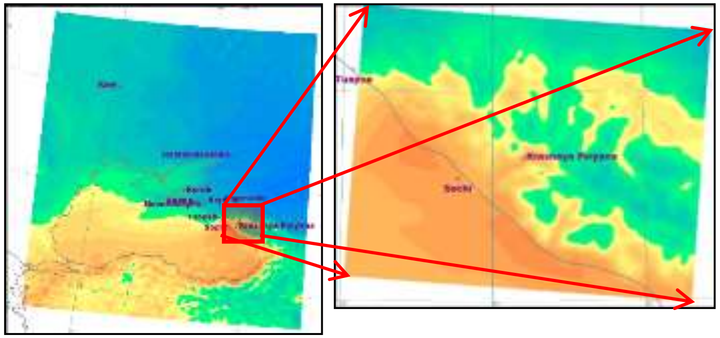
- 100% change in bias
- 10% change in RMSE

Runaway bias issue for 500Z

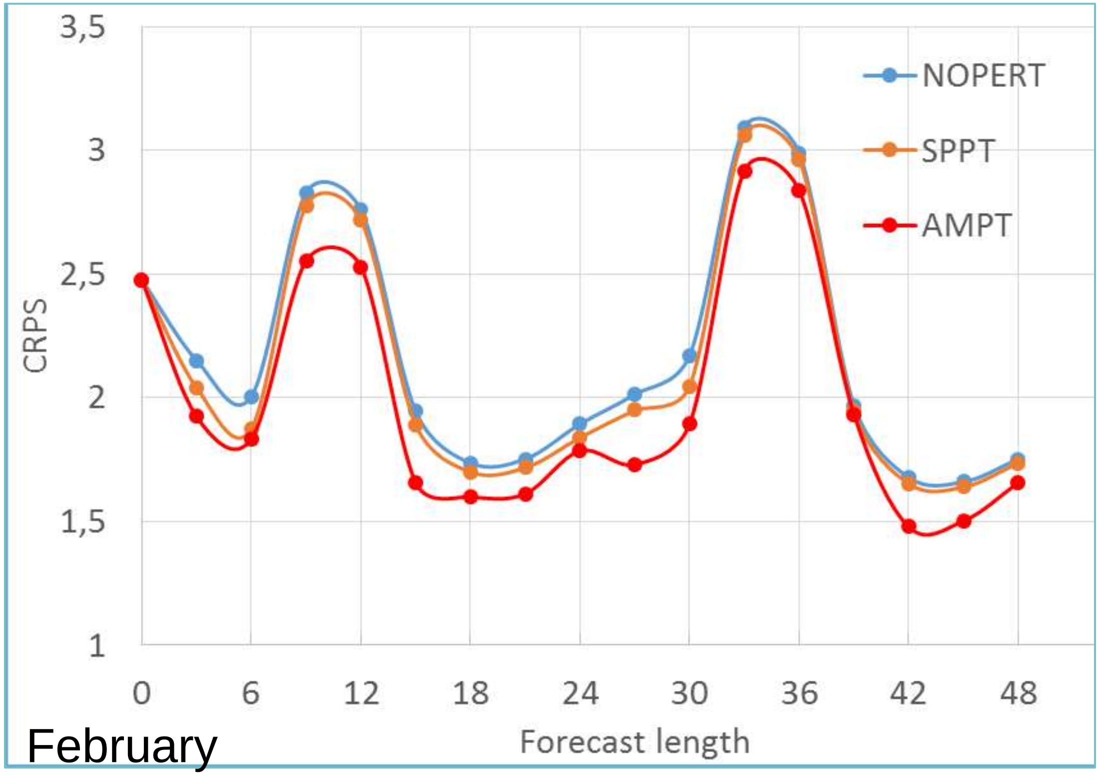
Additive Model-error perturbations scaled by Physical Tendencies (using high-res vs. lower res model divergence as proxy for error).

COSMO-Ru2-EPS

Δx~2.2 km, L51, M10, fc+48h, IC&BCs from a clone of COSMO-LEPS for Sochi region

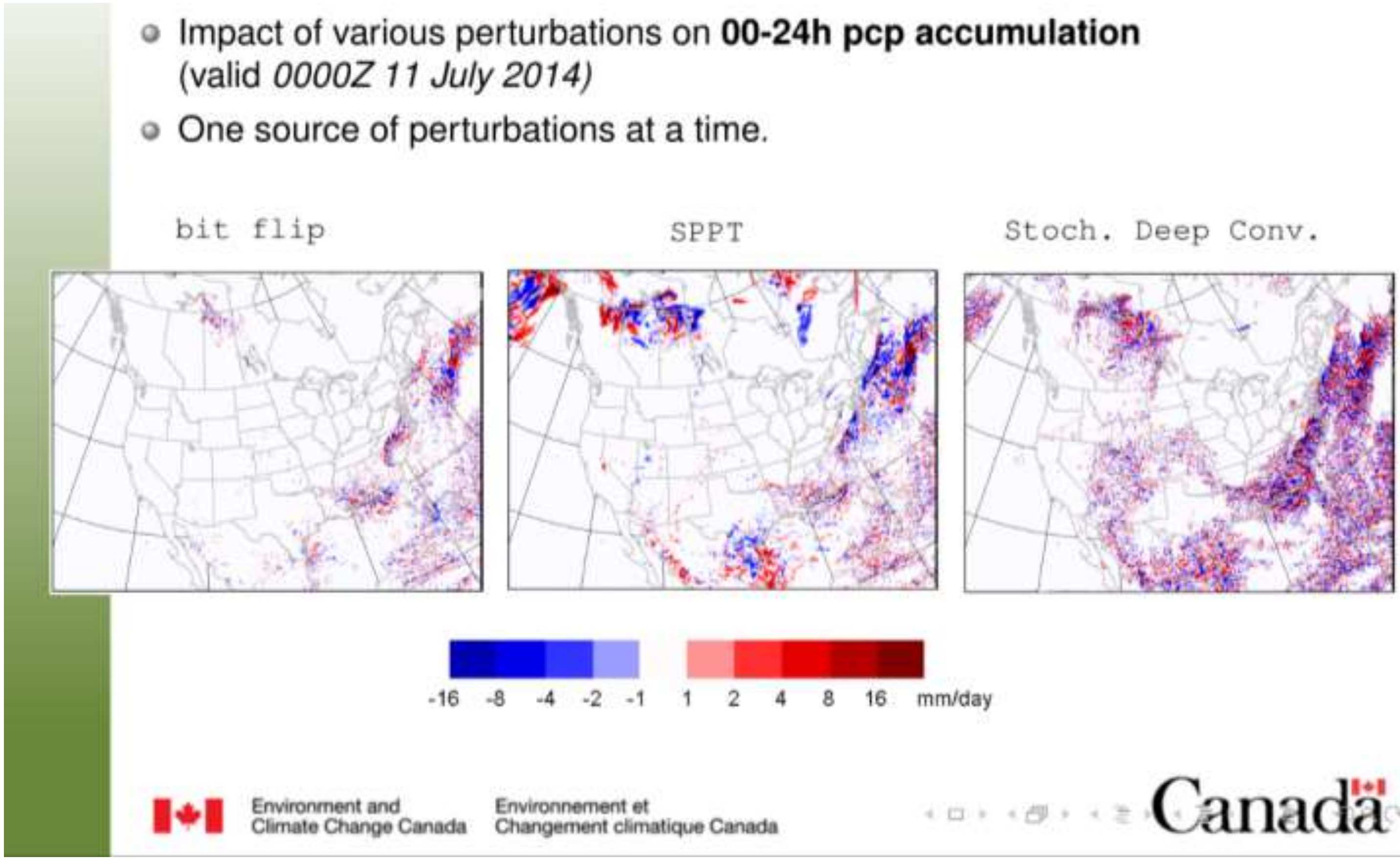


CRPS (the lower the better).



In an 11-day trial, additive perturbations (AMPT without humidity and cloud field perturbations, no tapering in the PBL) appeared to yield better results than SPPT.

Stochastic Deep Convection Testing at ECCC



- Expectations from the stochastic deep convection scheme:
  - Help increase spread in situations with weak large-scale forcing – especially at scales below 1000 km in the early stages of the forecast.
  - Accelerate the upscale propagation of the inter-member differences.
- Next steps:
  - Scheme adds fine-scale variability (grainy precip patterns) – fine tuning required and input averaging needed?
  - Optimization- currently the scheme considerably increases the computational cost.

Model uncertainty challenges

- Objective comparison of different schemes for representing model uncertainties across models when initial perturbations (and — if applicable — limited-area model lateral boundary perturbations) differ as well.
- Representation of observation uncertainties in ensemble verification and development of consistent observation error models suitable for verification and assimilation
- Development of stochastic representations of model uncertainties that respect local conservation (energy, mass, momentum)

Stochastic sub-seasonal to seasonal prediction project: $S^2$2S – A proposal

- Joint WWRP/WCRP S2S/PDEF/WGNE project targeted as the quantifying the benefits of stochastic parameterization on the S2S timescale
- One-time research dataset to complement S2S operational database
- Forecasts with and without Stochastically Perturbed Parameterization Scheme SPPT (operational complement) - this schemes is widely used and relatively easy to implement
- Quantify impact of SPPT on mean bias, probabilistic skill and process-based verification

Center-Contributed Slides on Model Uncertainty Research

The stochastic model for the model error tendency

- In COSMO-D2-EPS the model error tendency is $\eta = \frac{\Delta forecast - \Delta analysis}{\Delta t}$
- Aim is to correct tendency of variable X (e.g. T, u, v, …) in forecast as

$$\frac{dX}{dt} = \left[\frac{dX}{dt}\right]_{det} + \eta$$

- First approach to model η:

$$\frac{d\eta}{dt} = -\gamma(\tau)\eta + \gamma(\tau)\nabla \cdot (\lambda^2(\tau)\nabla\eta) + \sigma(\tau)\xi$$

  - γ damping, λ diffusion, σ noise strength, ξ Gaussian random field
  - τ is tendency of predictor variable → all parameters are **flow-dependent** and accommodate for the current weather condition
- For ICON-EPS the best approximation of the model error tendency is currently investigated due to incremental analysis update

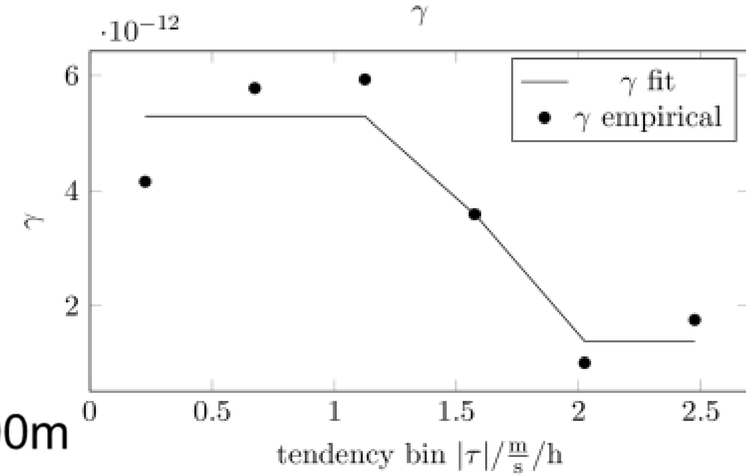
First results

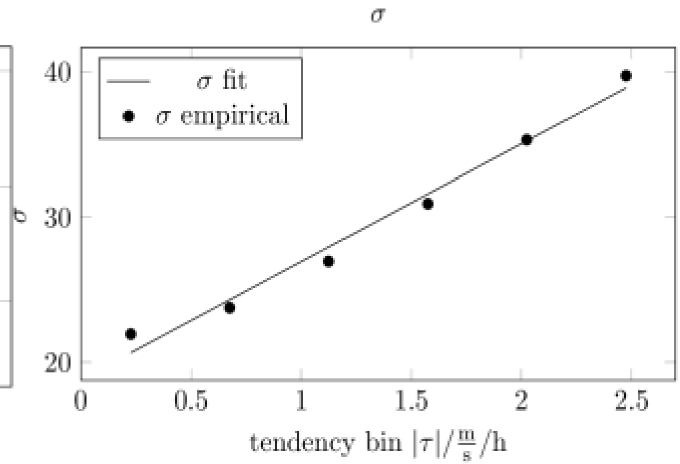
COSMO-D2-EPS

Estimation of

the parameters

for zonal wind@300m



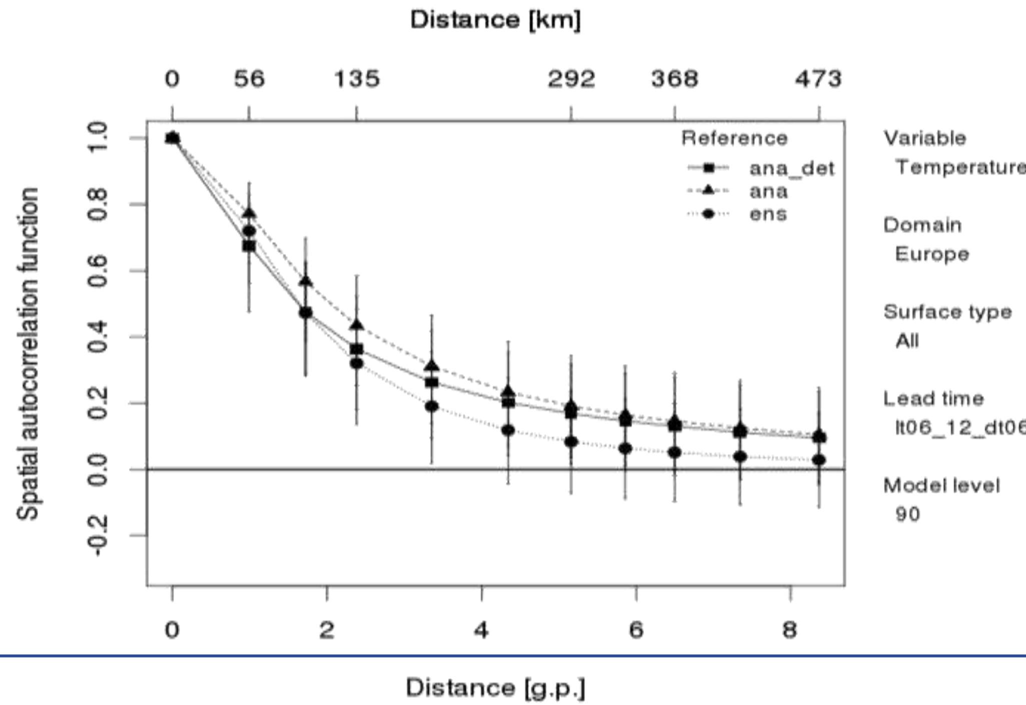


ICON-EPS: spatial auto-

correlation for different

reference fields

(determines the parameter λ)



Coming implementation: Canadian EPS – GEPS 5.0.0

To be implemented on September 18 2018!

- Members:
  - 20+1 members:
  - GEM Yin-Yang grid with 0.35° grid spacing (~39 km resolution)
  - Vertical levels 45 (forecast), 81 (analyses) top at 0.1 hPa.
  - 16-day integration (32 days on Thursdays at 00Z).
  - Twice a day (00 and 12 UTC).
- Simulation of initial condition uncertainties:
  - Perturbed ensemble Kalman filter data assimilation.
- Simulation of model uncertainties:
  - A multi-model approach, each member having its own physics parameterizations set.
  - Stochastic perturbations added to tendencies in the parameterized physical processes.
  - Stochastic kinetic energy back-scattering scheme

Summary of the GEPS5.0 results

- Trial fields quality are improved especially in the Troposphere and upper Stratosphere, as well as surface temperature and mean sea level pressure.
- The forecasts performance of the new system GEPS 5.0.0 is generally higher in the first 7-10 days in Northern Hemisphere for all upper air fields.
- The forecast surface fields (MSLP, 1.5-m temperature and dew-point depression and precipitation) are also improved significantly during the first week except the 10-m wind speed which is degraded.
- The forecast spread is usually greater during days 8 to 15 for most of fields. The wind spread is now smaller during the first 5 days in lower troposphere.

Summary of coupling with NEMO

- Large improvement in week 2 in the Tropics for Temperature, winds and MSL pressure as well as precipitation. Smaller improvements are noticed in Northern Hemisphere. Almost no impact on precipitation.
- There is generally less spread in the forecasts with the coupling. This is in line with a reduction of the forecast error so the balance between spread and error is unchanged.
- We expect improvement for the monthly time scale. More to come in Hai's presentation on wednesday…

Coupling with the ocean

- European NEMO ocean model (Madec et al. 1998)
- 0.25 degree horizontal resolution
- 80 levels in the vertical
- CICE sea ice model (Hunke and Lipscomb 2010)
- Full 2-way coupling via GOSSIP coupler
- Initialized with SAM2 ocean analyses

Environment and Climate Change Canada
Environnement et Changement climatique Canada
Canada

Recent Work at RPN-A on the Regional EPS Stochastic Physics

L. Šeparović[1], M. Charron[1], N. Gagnon[2], R. McTaggart-Cowan[1], A. Erfani[2], P. Vaillancourt[1], J. Yang[1], A. Zadra[1]

[1]Recherche en Prévision Numérique Atmosphérique (RPN-A)
[2]Canadian Meteorological Centre (CMC)
Environment and Climate Change Canada

9th NAEFS workshop
September 11-13, 2018, Monterey, CA, USA

Stochastic deep convection scheme at RPN/CMC

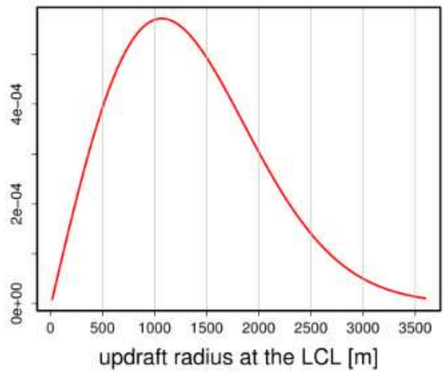
- **Approach is based on the Plant-Craig (PC) stochastic deep convection scheme** (Plant and Craig, 2008).

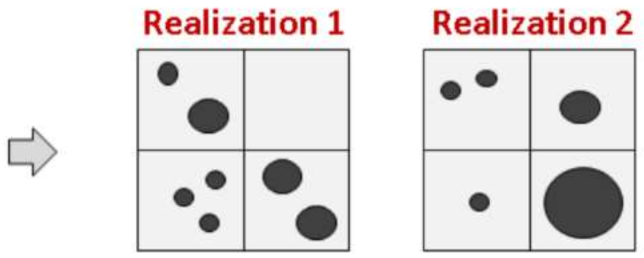
- **Plume model adopted from Bechtold scheme (Bechtold, 2001) :**
  - A bulk mass-flux parametrization very similar to Kain-Fritsch (KF used in the original PC scheme)
  - CAPE-type closure – based on the assumption that 90% of CAPE is removed within a specified adjustment period ~ 60 min
  - The plume model used with this scheme, however, differ to some extent from KF (e.g., triggering mechanism, conservation of enthalpy and mixing ratio).

- **Rationale for the use of Bechtold scheme :**
  - Modular structure and consistent deep and shallow convection representation – possible extension to shallow convection.

Stochastic deep convection scheme at RPN/CMC

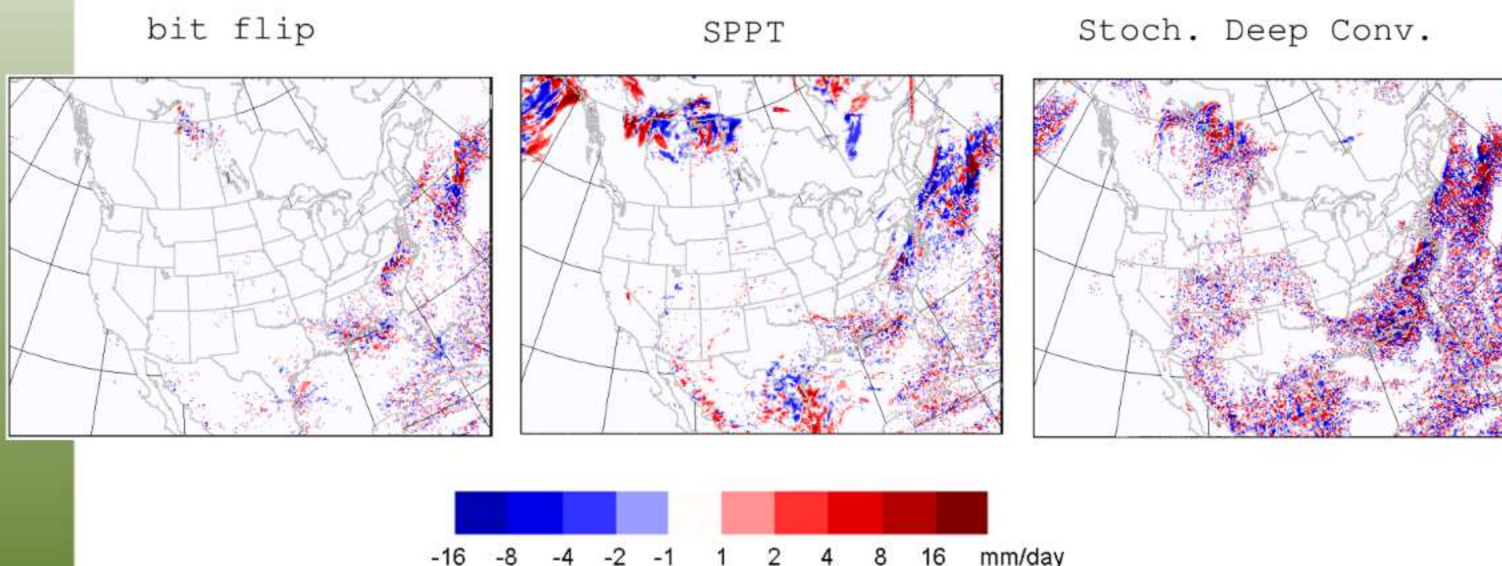
- **Deterministic version of the Bechtold scheme :** A single plume represents the mean properties of the entire subgrid-scale population of clouds.
- **Stochastic version :** in a given grid cell a cluster of convective activity with different intensities and sizes occurs.
  - Multiple plumes are randomly drawn from the radius distribution
  - Population size scaled by the closure assumptions.





Preliminary results

- Impact of various perturbations on **00-24h pcp accumulation** (valid *0000Z 11 July 2014)*
- One source of perturbations at a time.



Summary of the deep convection scheme

- **Expectations from the stochastic deep convection scheme :**

  - Help increase spread in situations with **weak large-scale forcing** – especially at scales **below 1000 km** in the **early** stages of the forecast.

  - Accelerate the **upscale propagation** of the inter-member differences.

  - It is not expected to have a large impact in situations with strong large-scale forcing.

- **Next steps**

  - Scheme adds fine-scale variability (grainy precipitation patterns) – fine tuning required and input averaging needed ?

  - Optimization – currently the scheme considerably increases the computational cost.

  - Systematic evaluation of the scheme within the REPS.

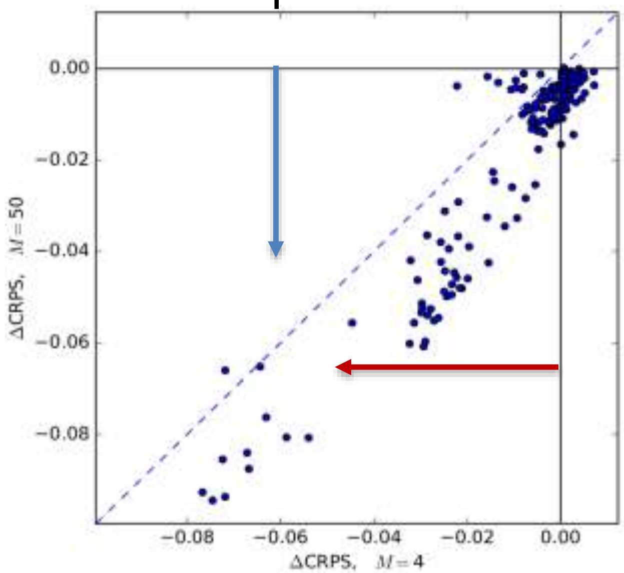
Does ensemble size matter?

- Improving the understanding for sufficient ensemble size, see recent QJ paper: https://doi.org/10.1002/qj.3387

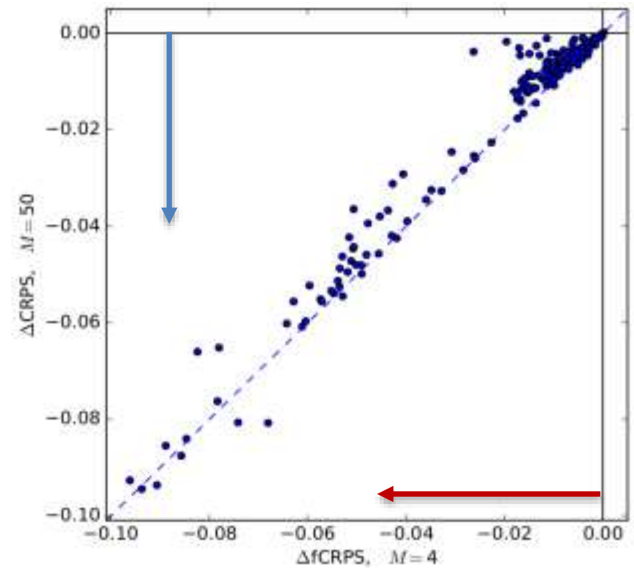
- More efficient NWP development with moderate ensemble sizes, say 4–8 members, using fair scores (right panel) and exchangeable members.

x-axis: Score differences due to activation of a model uncertainty representation in 4-member ensemble

y-axis: Actual score diff. in 50-member ensemble



Regular CRPS



Fair CRPS

Progress on representing model uncertainties in ensembles

- Work continues at ECMWF along the directions described in QJ paper https://doi.org/10.1002/qj.3094
- SPP
  - Random field evolution: computational efficiency increased considerably
  - Extension to four additional perturbations in cloud microphysics
- Dynamical core:
  - Code development for departure point perturbations in semi-Lagrangian advection scheme ongoing
- Stochastic convective backscatter
  - Results from Shutts (2015) reproduced with a more recent version of IFS

Representation of model uncertainties revised in 2018

Revision in medium-range and extended range ensemble forecasts and EDA implemented in June 2018 (cycle 45r1):

- SKEB has been switched off due to marginal impact of current configuration
- SPPT revised (cf. last year's WGNE slides)
  - Perturbations to (total phys. ten.)−(clear-sky rad. ten.) instead of (total phys. tendency)
  - Boundary layer tapering closer to surface
  - No tapering in stratosphere
  - 20% reduction of stdev of random fields
- Consistent model uncertainty representation in ensemble of data assimilation and ensemble forecasts

Planned changes for 2019 (cycle 46r1)

- 50 member EDA

- Exchangeable initial conditions (+/- symmetry of initial perturbations will be abandoned)

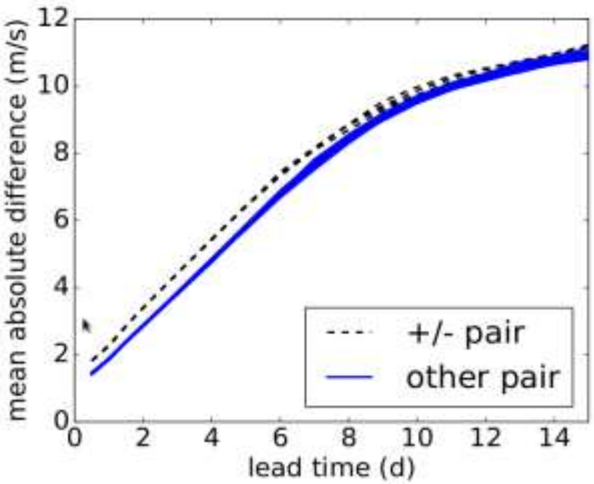


Figure 3. Mean absolute difference of different pairs of ensemble forecasts versus lead time for 200 hPa zonal wind in the northern extratropics.

See https://doi.org/10.1002/qj.3387

- Radiation time step in medium-range ensemble consistent with unperturbed high-resolution forecast

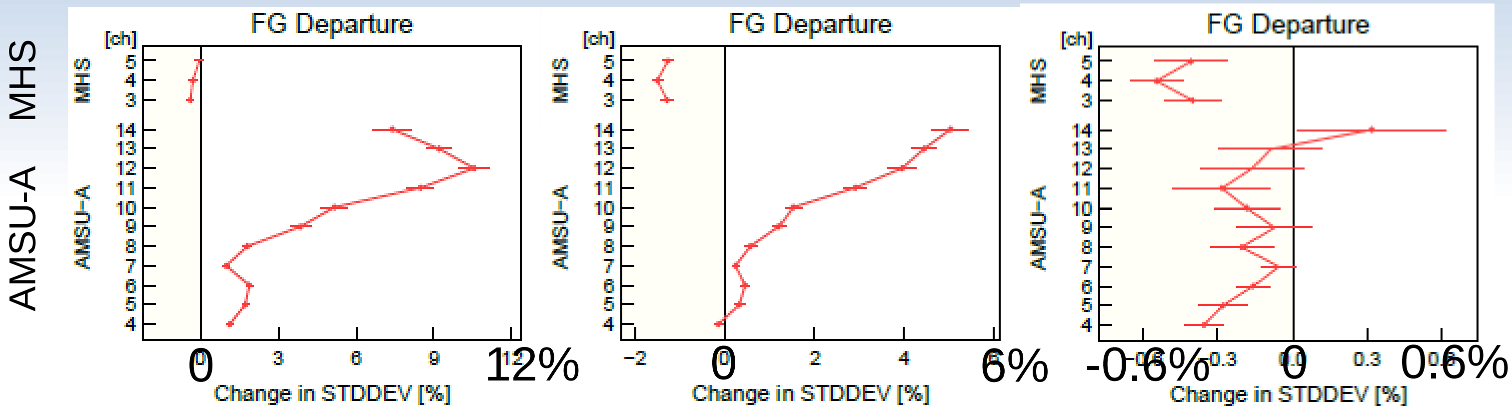
Model uncertainty challenges

- Objective comparison of different schemes for representing model uncertainties across models when initial perturbations (and — if applicable — limited-area model lateral boundary perturbations) differ as well.
- Representation of observation uncertainties in ensemble verification and development of consistent observation error models suitable for verification and assimilation
- Development of stochastic representations of model uncertainties that respect local conservation (energy, mass, momentum)

Optimal Localization for LETKF

- There are growing number of observations such as hyper-spectral sounders available for data assimilation.
- Some challenges specific to the EnKF
  - The EnKF has the limitation on utilizing the information from large number of observations due to the limited ensemble size.
    →Which determines the optimal localization scale, S/N ratio of ensemble-based B or number of observations in localized domain?
    →Optimal localization scale is likely determined by the S/N ratio of ensemble-based B (at least with current observation coverage).
  - Observation space localization is problematic for non-local observations such as satellite radiance.
    →Motivations to use model space vertical localization.
    →It can be implemented by increasing the computational cost by the factor of O(10), but the impact seems to be moderate.

Sensitivities on horizontal localization



Adaptively shorten the scale based on number of obs.

Uniformly shorten the scale

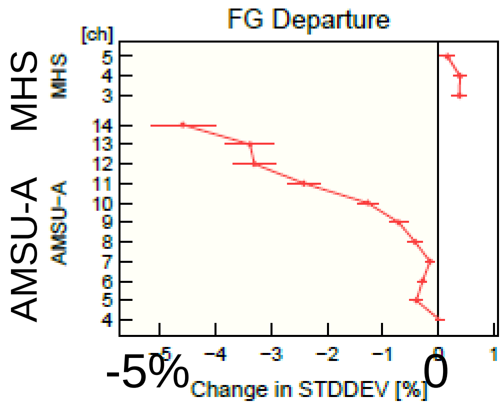
Shorten the scale only for humidity sensitive obs.

Relative changes [%] in standard deviation of O-B for AMSU-A and MHS of the pure LETKF experiment compared to that uses default localization settings.

- Localization scale adjustment based on observation numbers is not better than simple uniform localization change.
- O-B of stratospheric channels is degraded by shortening the horizontal localization scale which suggests the wider localization is preferable in the stratosphere.
- O-B has been decreased if the horizontal localization scale is shortened only for humidity sensitive observations (based on the fact that self- or cross- correlation with Q has shorter horizontal scale than other variables)
  → This suggests that the S/N ratio of ensemble-based background error covariance likely determines the optimal localization scale.

Model space vertical localization

- Gain form of ETKF with modulated ensemble enables the model space vertical localization in the LETKF (Bishop et al. 2017).
- It is effective in assimilating non-local observations such as satellite radiance observations.
- The first-guess fit to observations has been improved especially on stratosphere.



Relative changes [%] in standard deviation of O-B for AMSU-A and MHS of the pure LETKF experiment compared to that uses default localization settings.

- The computational cost of the LETKF ensemble update has been increased by the factor of O(10).
  → It is not feasible for the operational system at this point.

ETKF Replacement Project - 2018

- Aim: To replace the ETKF with a more sophisticated (and more sustainable) ensemble update. To go operational in 2019.
- ETKF – transform the ensemble perturbations using information from the latest observations
  - Sophisticated adaptive inflation scheme
  - Simple localisation
- En-4DEnVar – perform data assimilation for each member using VAR code
  - Sophisticated localisation
  - Simple inflation (based on relaxation to prior, given less need for inflation)
- **Changes to Stochastic Physics include:**
  - **Retirement of Random Parameter Scheme**
  - **Introduce Stochastic Perturbed Tendencies (SPT) (already includes SKEB)**
  - **Introduce analysis increment additive inflation (AI) – see next slide**

Additive inflation

Improves ensemble dispersion effectively

Keep archive of analysis increments from oper runs $\delta\mathbf{x}_a^k \quad k=1\ldots N_a$

Average analysis increment $\overline{\delta\mathbf{x}_a} = \frac{1}{N_a}\sum_{k=1}^{N_a}\delta\mathbf{x}_a^k$

Contains information on the model bias

Randomly select N_e increments from the archive $i_j \quad , j=1\ldots N_e$

For each 6h window, add these increments to the ensemble, removing the sample average

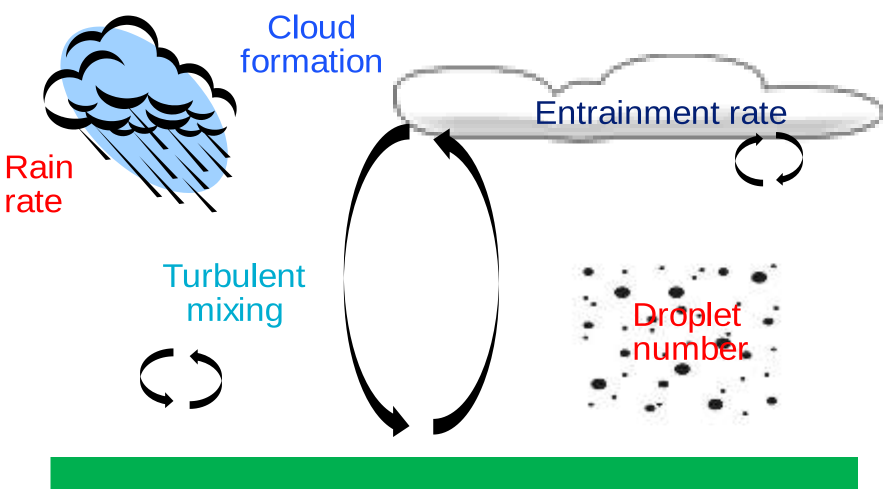
$$\delta\mathbf{x}_e^j = \alpha\left(\delta\mathbf{x}_a^{i_j} - \frac{1}{N_e}\sum_{m=1}^{N_e}\delta\mathbf{x}_a^{i_m}\right) + \overline{\delta\mathbf{x}_a}$$

Met Office

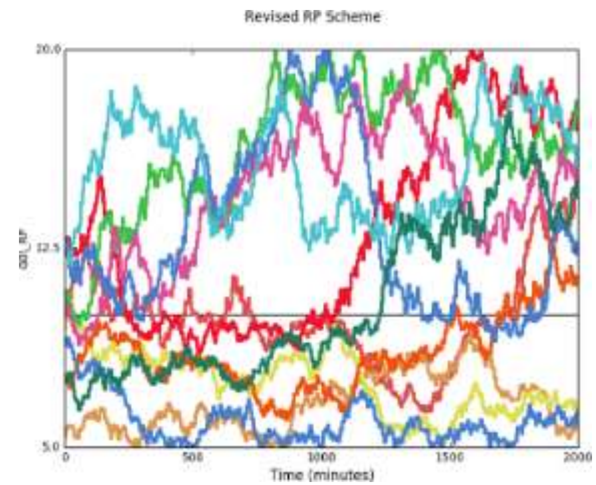
Model uncertainty is represented in MOGREPS-UK using the Random Parameter (RP) Scheme

Parameters are chosen to target uncertainty at the small scales

Physical processes represented in the RP scheme



Example random parameter



- Parameters are initialised randomly within a range of plausible values
- They are then stochastically perturbed in time throughout the forecast
- Perturbations are spatially homogeneous

Stochastic Boundary Layer Perturbations

Stochastic perturbations are applied in the boundary layer in convectively unstable atmospheres

Motivation: to improve the growth of convection from the small (sub-grid) scales to the larger (resolved) scales in both the UKV and MOGREPS-UK

The magnitude of the perturbations depends on the subgrid flow

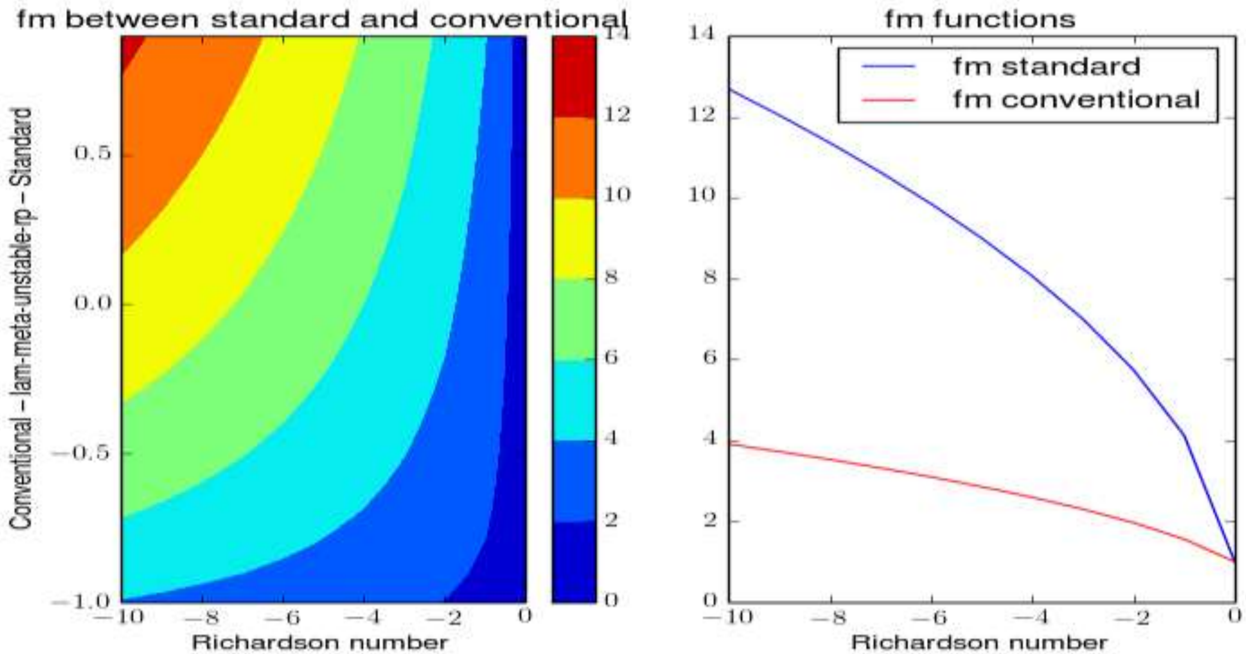
- *i.e. the larger the surface heat flux, the larger the 'backscatter' of temperature variability to the resolved scales*

Extension to ensembles: Developed for the UKV but extended to MOGREPS-UK – adds variability by using a different seed for each ensemble member

Future changes to the stochastic physics

1) New random parameters from the land-surface scheme

2) New random parameter for controlling unstability tail functions as well as Smagorinsky coefficient



In this example, a new simple parameter (lam_meta_unstable_rp) is introduced to capture the variability between the standard and the conventional momentum functions.

Investigating the lack of spread in convective-scale ensembles

- Operational meteorologists have identified lack of spread in MOGREPS-UK as a top model development priority
- A **P**rocess **E**valuation **G**roup (PEG) has been formed to investigate further
- Aim: to bring together scientists and operational meteorologists to evaluate the ensemble and develop new strategies to improve the value of MOGREPS-UK to forecasters
- Initial plans focus on sensitivity tests to understand the relative contribution to the spread from the initial conditions, LBCs and stochastic physics; sensitivity to the driving model (mogreps-g vs ecmwf) and comparisons with multi-model ensembles using data from TIGGE-LAM

Arpege-EPS : on-going work

- testing of alternatives approaches for the model perturbations : SPPT and SPP ;
  - SPPT : preliminary results are encouraging. However, tuning the water tank is necessary in order to preserve the water balance.
  - SPP : preliminary results show less spread than SPPT. A sensibility study on parameter values is ongoing.

- testing of an implementation of sea surface temperature perturbations.

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METEO FRANCE

Arome-France EPS: model perturbations

Currently :

SPPT scheme (Bouttier et al 2012, similar to Palmer et al 2009 ECMWF scheme) :

- random scaling of physics tendencies for atmospheric U V T Q Ps
- static correlations in space & time
- **improvements** to humidity treatment & noise generator have been developed by Hungarian Met Service colleagues (not implemented yet)
- amplitude is limited to avoid numerical blow-ups in thunderstorm situations
- SPPT causes undesirable **dry bias**

Surface is perturbed by static noise :

- SST, soil/vegetation parameters
- (soil moisture & temperature have initial perturbations only)
- simple, but effective for low-level T & HU spread
- fails to correct windspeed biases

Plans :

- test **SPP stochastic parameters** scheme
- **need to better understand water balance and tuning issues, before complexifying the perturbation algorithm.**

METEO FRANCE

FV3-GEFS evaluation run

- Period: - Summer: 06/01/2017 – 08/06/2017
  - Winter: 12/01/2017 – 01/31/2018
- Verification: model own analysis

FV3-GEFS (21 members)	OPS-GEFS (21 members)
FV3	GSM
GFDL MP	ZHAO-CARR MP
C384L64 (~25km) (d1-16)	TL574L64 (~33km) (d1-8)+TL382 (~50km) (d9-16)
NSST (2tier SST replacing Tf)	RTGSST
Stochastic physics (SPPT + SHUM + SKEB)	Stochastic physics STTP
FV3-GFS EnKF 06h fcst	GSM-GFS EnKF 06 fcst

Summary

- Four months evaluation (2 months for summer, 2 months for winter) of FV3-GEFS was finished.
- FV3-GEFS shows improved skills in terms of most standard verification metrics
- One of the significant improvements is error-spread relationship
- Substantial improvement can also be found in FV3-GEFS precipitation forecast, especially from reliability diagrams.

Plan for GEFS v13

Atmospheric model – GFS v16

Initial perturbations – EnKF analysis from early cycle

- Coupling DA???

Full coupling with Ocean, Land, Sea-ice, Wave and Aerosol

Model uncertainties

- Process based stochastic parameterization

Ensemble resolution and size

- Undecided

To cover monthly forecast

- Out to 58 days

Reanalysis(?)/Reforecast to support model upgrade

Target implementation time

- 2022?

NRL: Analysis Correction based Additive Inflation (ACAI)

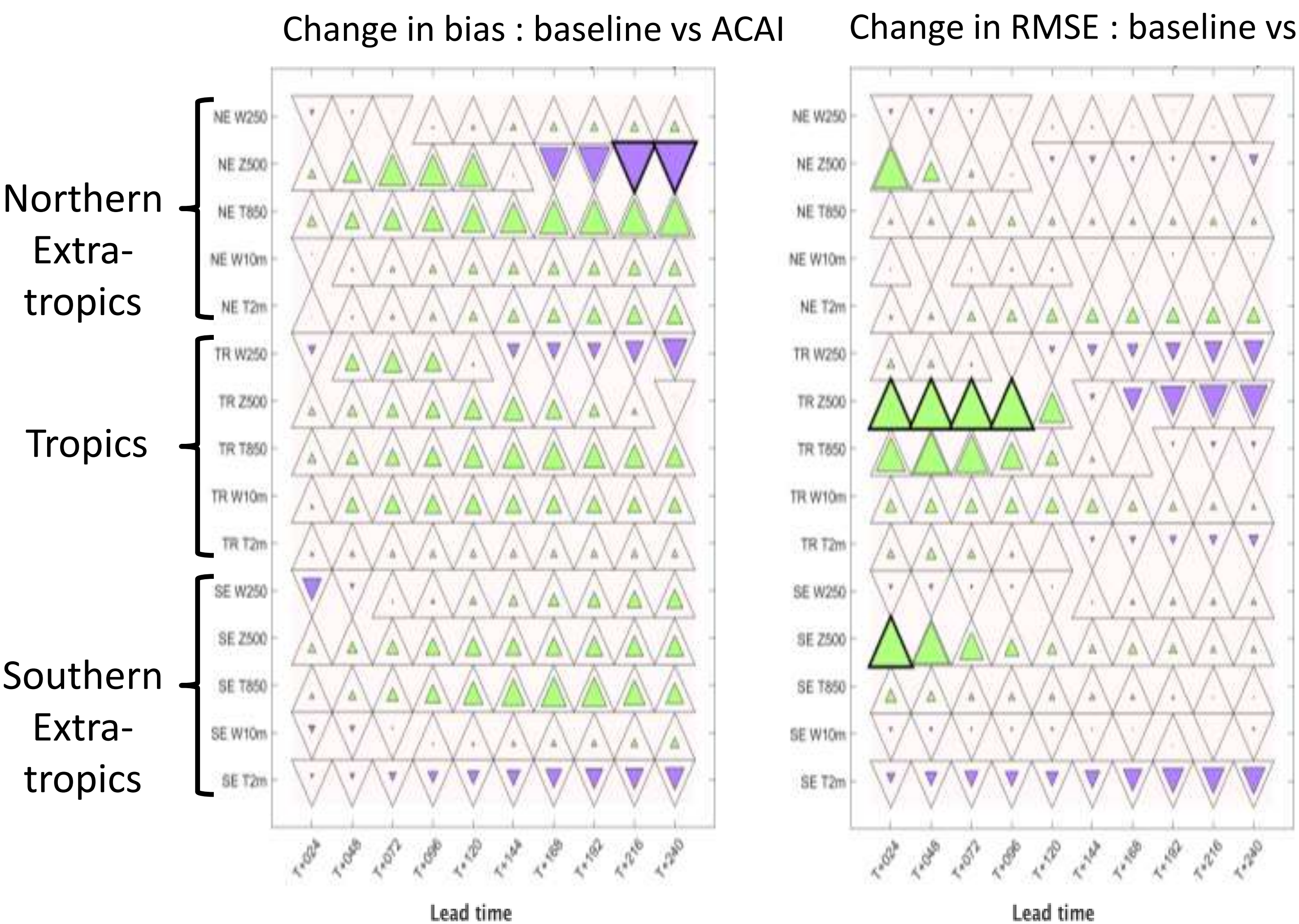
- Aim to decrease model bias and increase spread in ensemble forecasts
  - Compute $\delta x_m^F = \overline{\delta x_s^a} + \alpha\left[\delta x_m^a - \overline{\delta x_e^a}\right]$

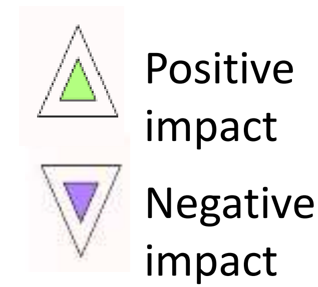
    $\overline{\delta x_s^a}$: seasonal average analysis correction; address bias

    $\alpha\left[\delta x_m^a - \overline{\delta x_e^a}\right]$: stochastic component; address model error (spread)
- Incrementally add $\frac{\delta x_m^F}{T}$ at each time step, T = # of time steps per 6-hr forecast
- Add a new δx_m^F over each 6-hr period of the forecast

NRL: Impact of ACAI on ensemble forecast

One month of 10-day, 20-member ensemble forecasts for summer 2016



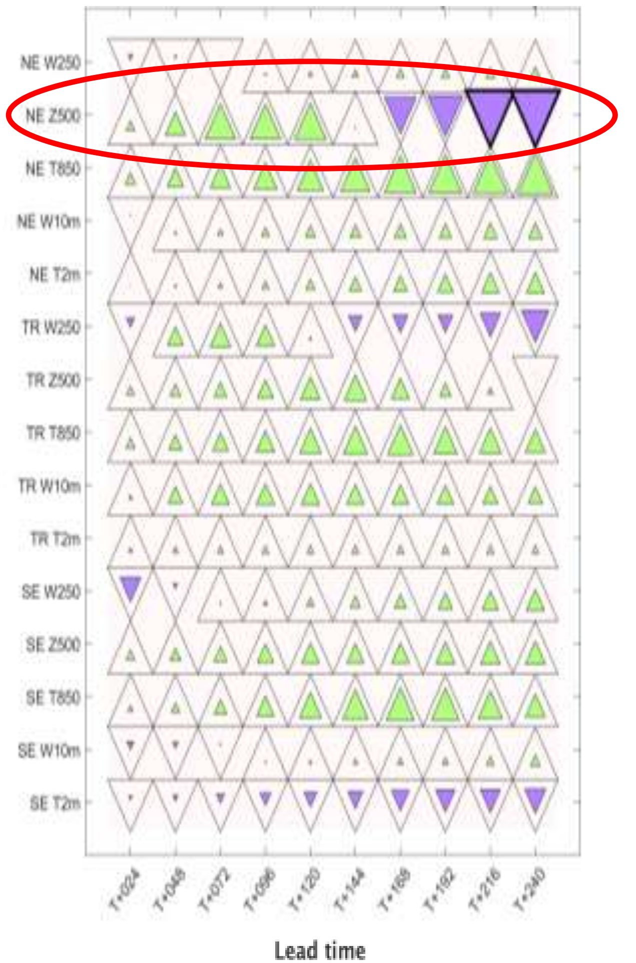


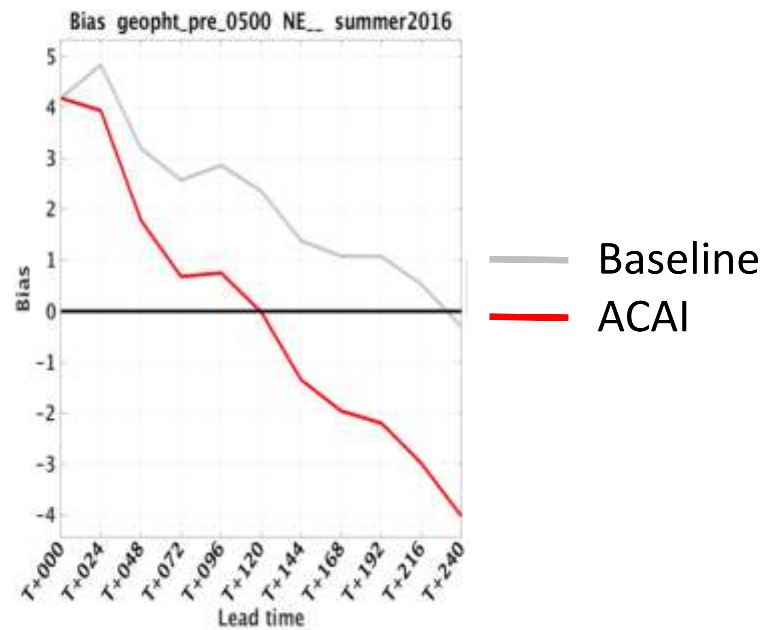
Outside triangle represents:

- 100% change in bias
- 10% change in RMSE

NRL: Impact of ACAI on ensemble forecast

Change in bias : baseline vs ACAI



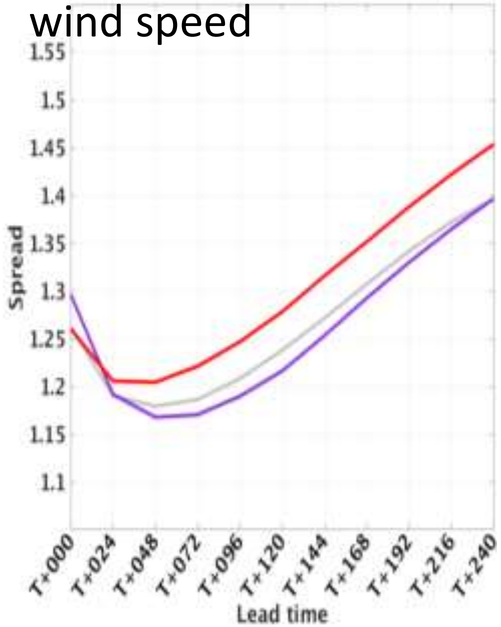


- For some variables, ACAI pushes through zero creating a runaway bias effect
- Generally happens about midway through the forecast (day-5)

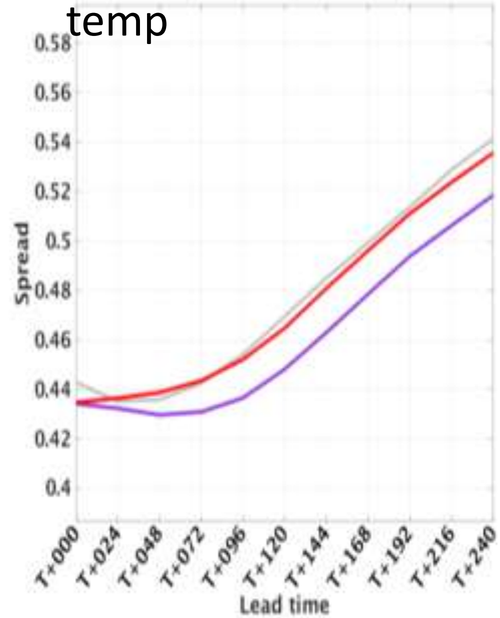
NRL: Impact of ACAI on ensemble forecast

- The second goal of ACAI is to generate additional spread in the ensemble
- Have seen that SKEB+ACAI does not always generate more spread that either method alone
- Aim to implement RTPP to further increase ensemble spread

Spread : Tropical 10m wind speed



Spread : Tropical 2m air temp



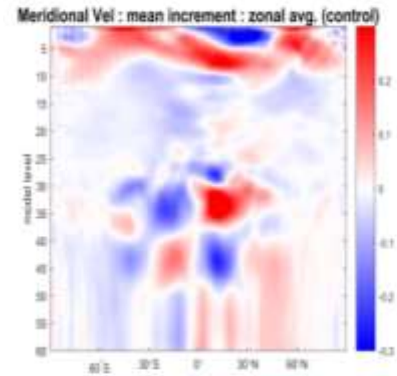
Baseline (SKEB)
ACAI only
SKEB+ACAI

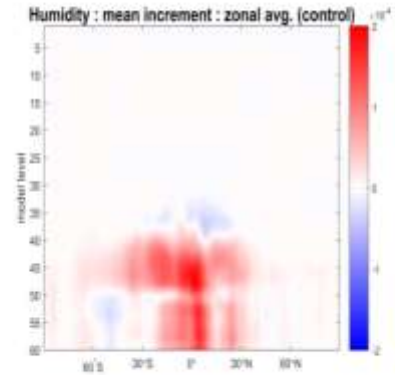
NRL: Impact on deterministic system

- Have also begun exploring use of the bias only component of ACAI in the deterministic system
- See a decrease in the magnitude of the analysis increments (right) and a positive impact on the bias and RMSE (bottom)

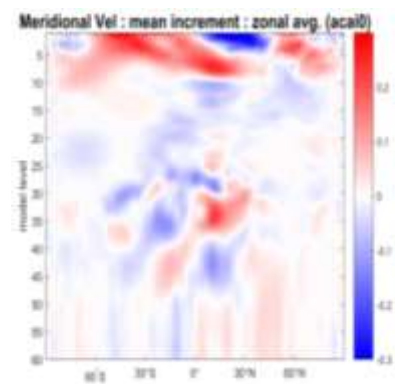
Change in mean analysis increment

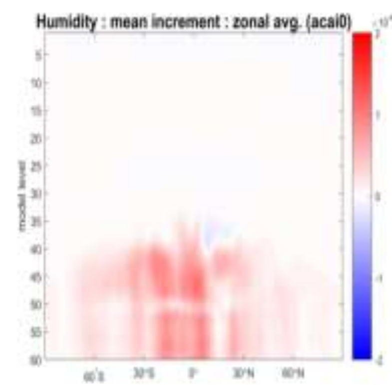
CONTROL



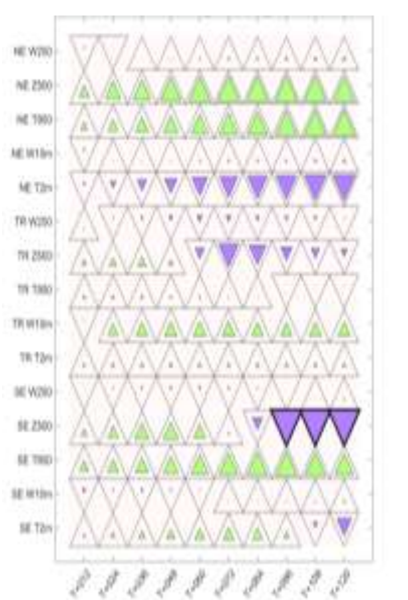


ACAI

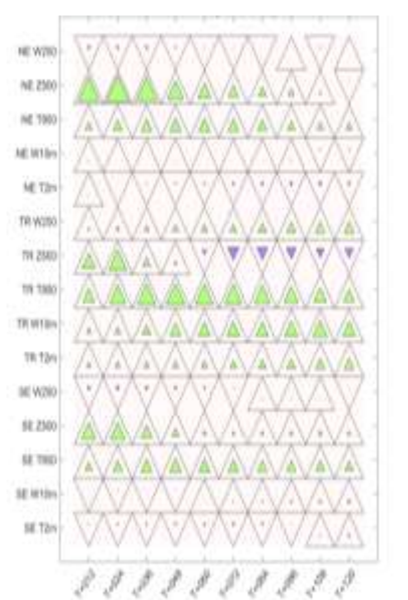




Change in bias : control vs ACAI



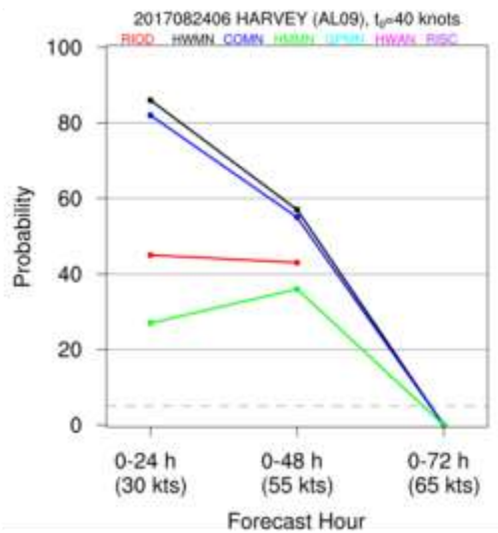
Change in RMSE : control vs ACAI

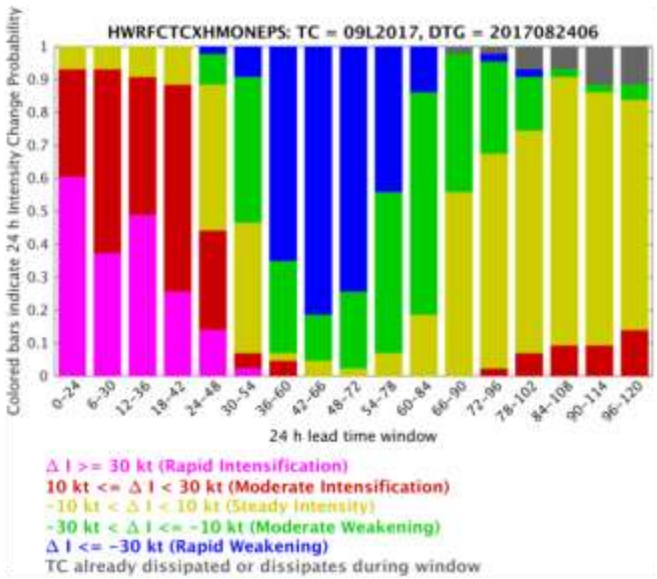


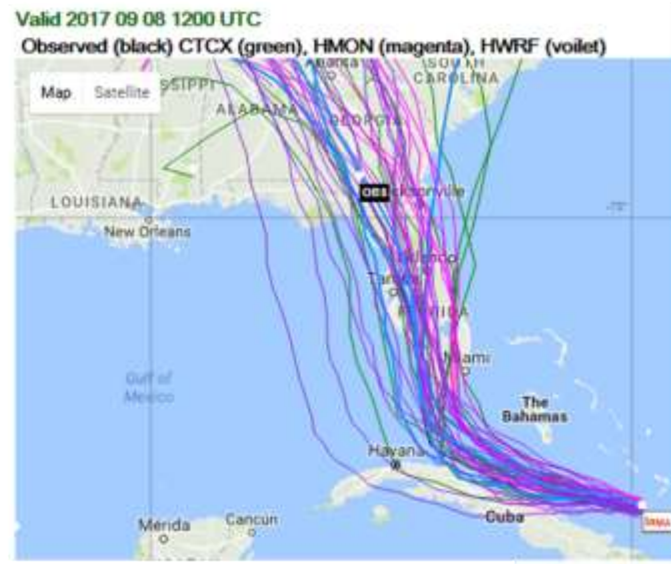
NRL COAMPS-TC
Future Plans

Objectives for FY18+:

- Keep running the real-time demo system for the Atlantic and Eastern Pacific
- Continued contribution to HFIP multi-model ensemble
- Continued product development (e.g. R34 products, clustering), interfacing with JTWC and NHC







Stochastic representation of model-related uncertainty: three steps in research

1. Evaluation of model error

2. Building a stochastic model for model-error

3. Implementation in an atmospheric model and testing in an ensemble prediction system

RHMC

Stochastic representation of model-related uncertainty: three steps in research

1. Evaluation of model error

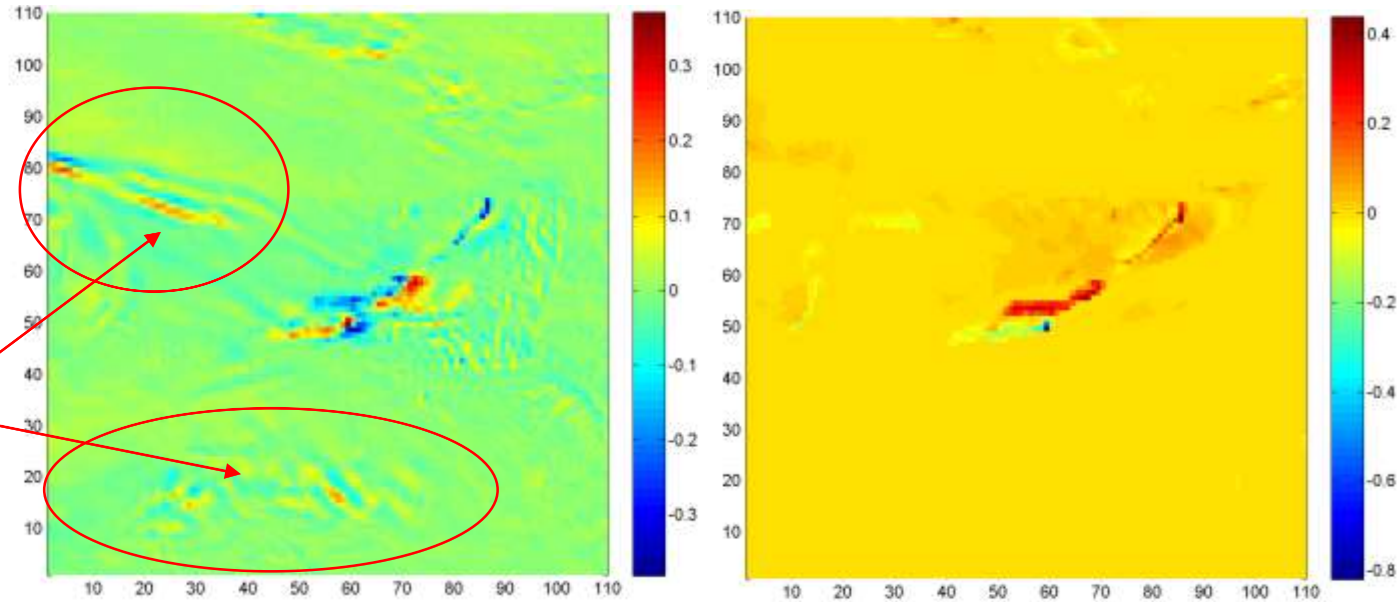
The following approach was adopted.

- Take a model in question (*COSMO 2.2 km L51, timestep=20s, parameterized shallow convection*).
- Select a significantly more sophisticated model considered as truth (*COSMO 0.55 km L51, timestep=5s, no parameterized convection, more advanced other physical parameterizations)*
- Start both models from the same point in phase space.
- Compare the two short-time tendencies; their difference gives the model error ε.

The widely used method to represent uncertainties due to model integrations is SPPT, in which the tendencies from the physical parameterisation scheme are randomly perturbed.

Let’s compare model errors (left) and physical tendencies (right)

No coincidence with the right plot!



Wind at 3km above ground. dt=60s

- Physical tendencies are informative but not always ⇒ the need for both multiplicative (SPPT) and additive model-error-model components.

- A similar conclusion has been drawn on model errors due to *numerics* – with the caveat that the *total* tendency should be used instead of the *physical* tendency here.

2. Building a stochastic model for model-error

- A new method is suggested to define the additive model-error-model component. It's named AMPT: Additive Model-error perturbations scaled by Physical Tendencies

✓ AMPT relies on the Stochastic Pattern Generator (SPG)* as the spatio-temporal stochastic source.

✓ Each model variable (including humidity and cloud fields) is perturbed every time step with an independent SPG-generated 4D random field.

✓ **The magnitude of the perturbation is specified to be the area averaged (in the horizontal) absolute value of the physical tendency.**

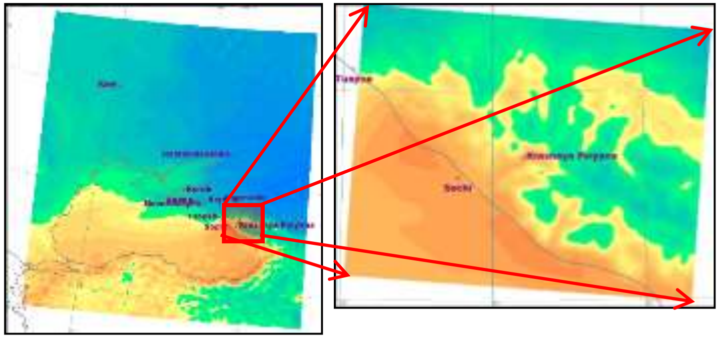
- The final model-error-model is a linear combination of AMPT and SPPT.

* *M.Tsyrulnikov and D. Gayfulin. A limited-area spatio-temporal stochastic pattern generator for simulation of uncertainties in ensemble applications. Meteorologische Zeitschrift (2017): 549-566*.

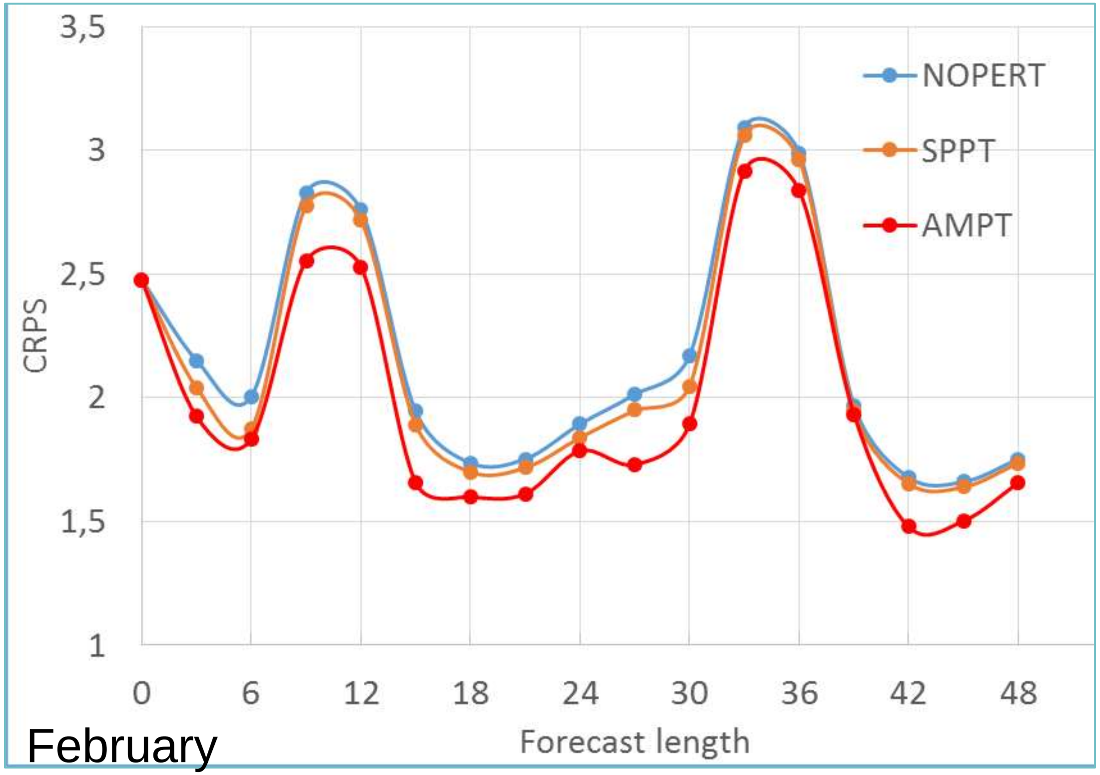
3. Testing in an ensemble prediction system

COSMO-Ru2-EPS

$\Delta x \sim 2.2$ km, L51, M10, fc+48h, IC&BCs from a clone of COSMO-LEPS for Sochi region



CRPS (the lower the better).



In an 11-day trial, additive perturbations (AMPT without humidity and cloud field perturbations, no tapering in the PBL) appeared to yield better results than SPPT.

Progress on representing model uncertainties in ensembles

- Work continues at ECMWF along the directions described in QJ paper https://doi.org/10.1002/qj.3094
- SPP
  - Random field evolution: computational efficiency increased considerably
  - Extension to four additional perturbations in cloud microphysics
- Dynamical core:
  - Code development for departure point perturbations in semi-Lagrangian advection scheme ongoing
- Stochastic convective backscatter
  - Results from Shutts (2015) reproduced with a more recent version of IFS