

S. Barthélémy, F. Counillon, J. Brajard, L. Bertino

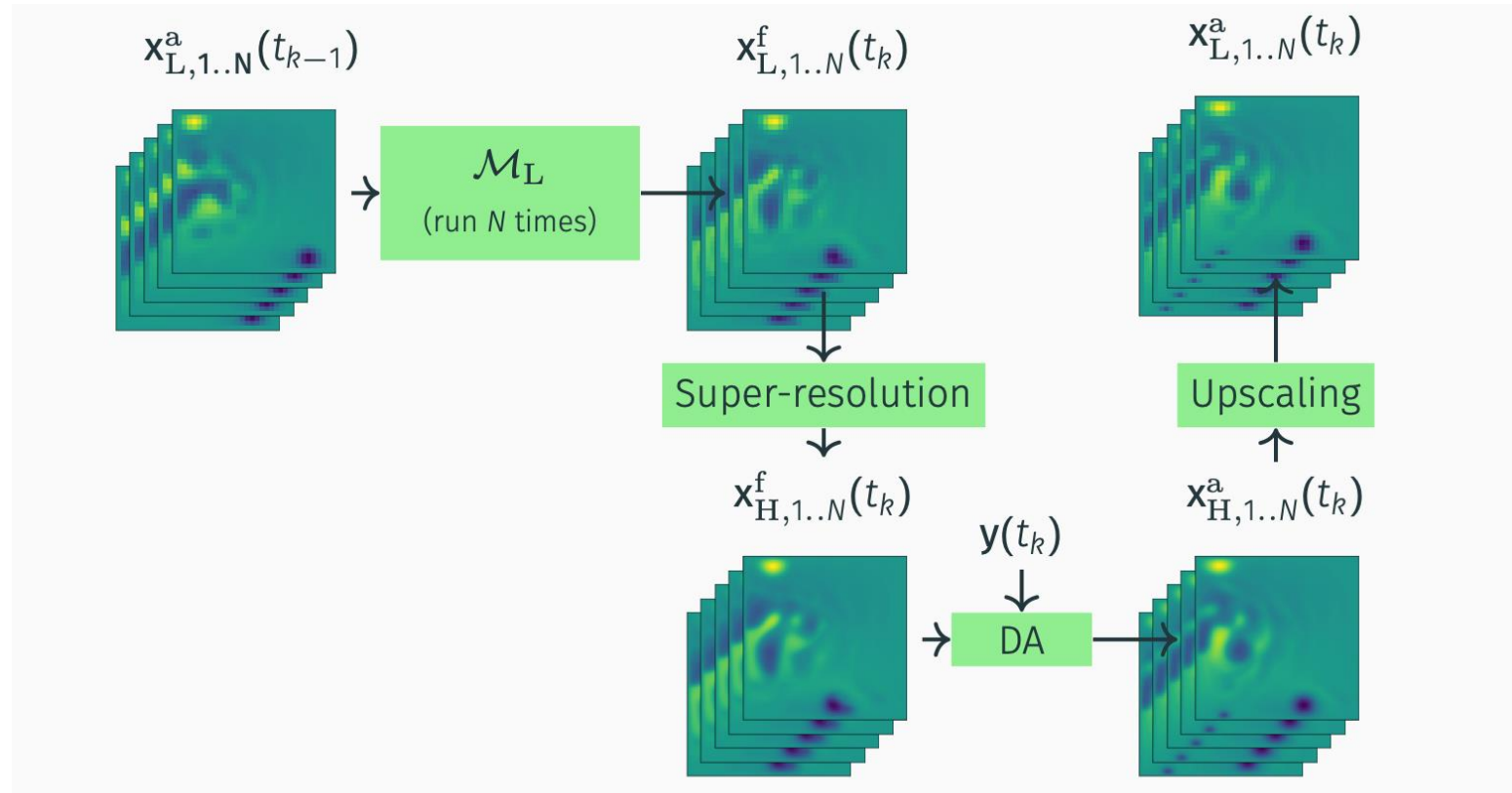
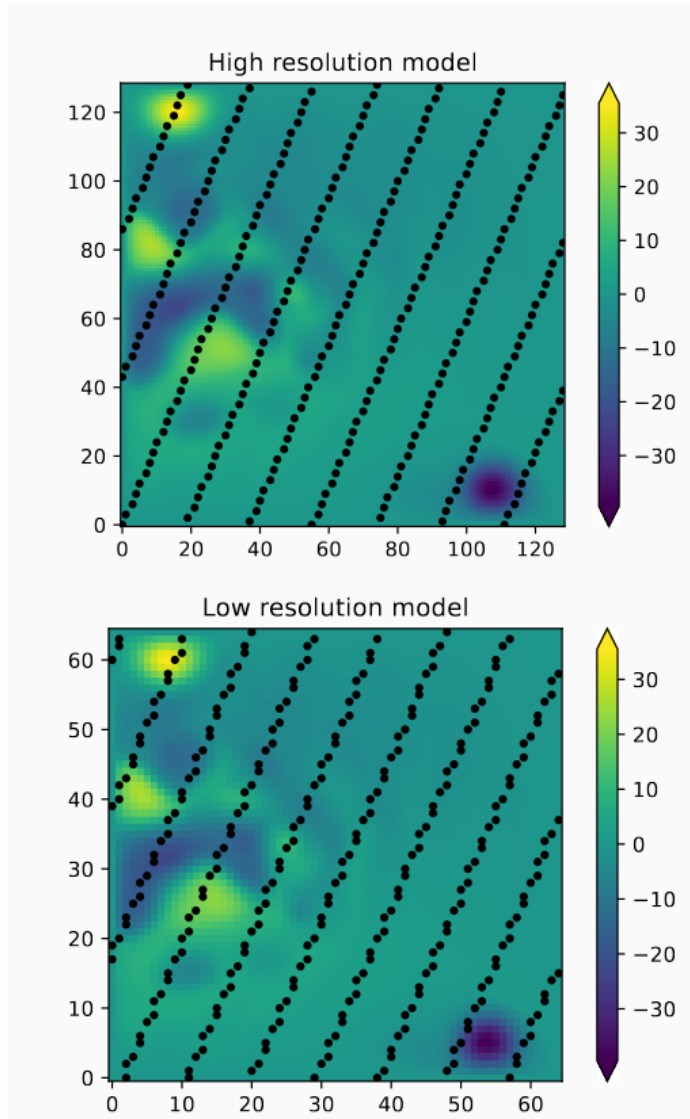
Introduction

- Many evidences that increasing model resolution reduces model error
- However, the cost of increasing the resolution is ramping up ($>^*8$) , often at the expenses of the complexity of data assimilation methods
- The observational data set in the ocean is very short and sparse making it challenging for ML to build emulator

Can we use ML to learn the resolution increase and improve our data assimilation system ?

Super-resolution data assimilation (SRDA)

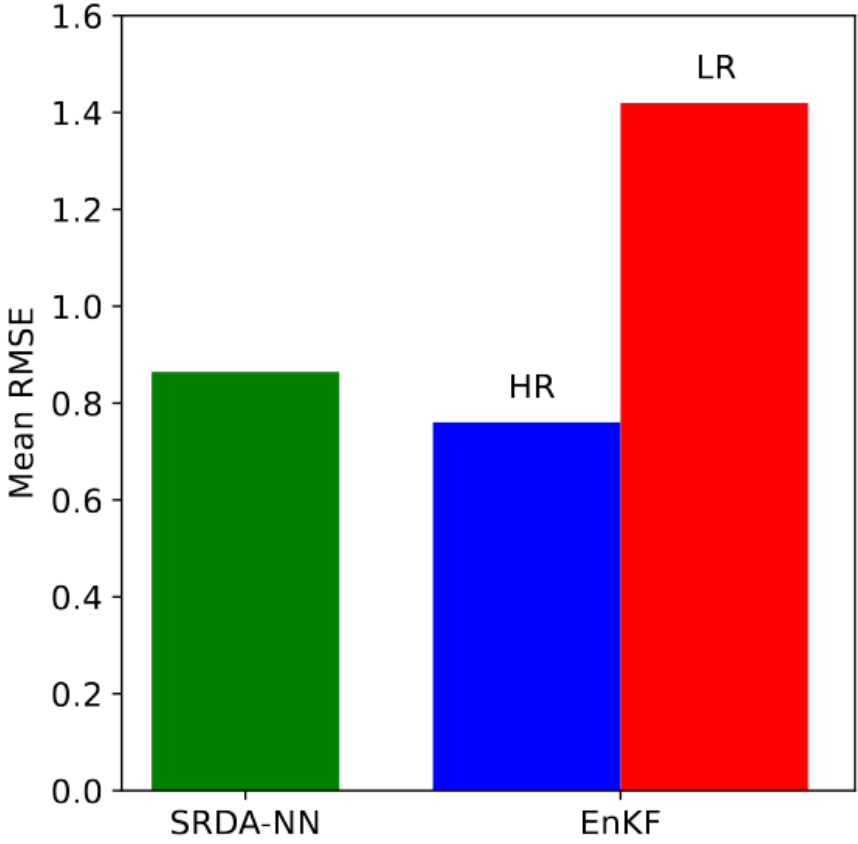
Robustly tested with a quasi-geostrophic model at 2 resolutions (HR,LR) in twin experiment



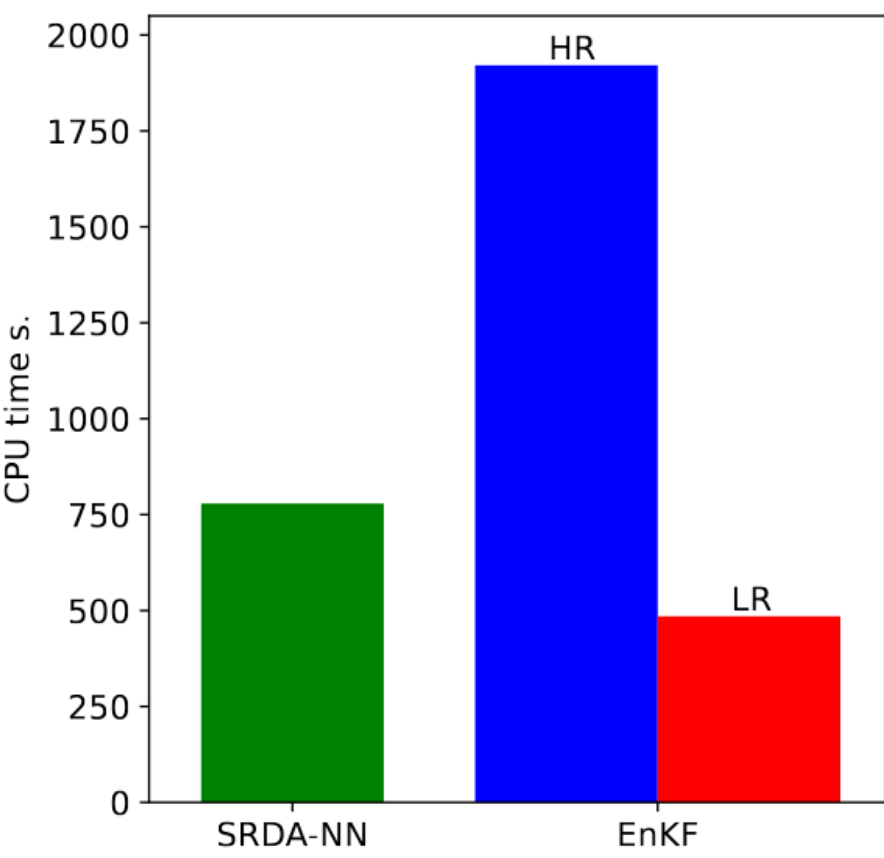
	EnKF-LR	EnKF-HR	SRDA
Observation error	High ✓	Low ✓	Low ✓
High-resolution processes	Poorly resolved ✓	Resolved ✓	Emulated ✓
Computational cost	Low ✓	High, $\mathcal{O}(n^3)$ ✓	Low ✓
Ensemble size	Large ✓	Small ✓	Large ✓
Error to the true \mathbf{P}^f	Large ✓	Small ✓	Medium ✓

How does SRDA compares to EnKF-LR & EnKF-HR

Error

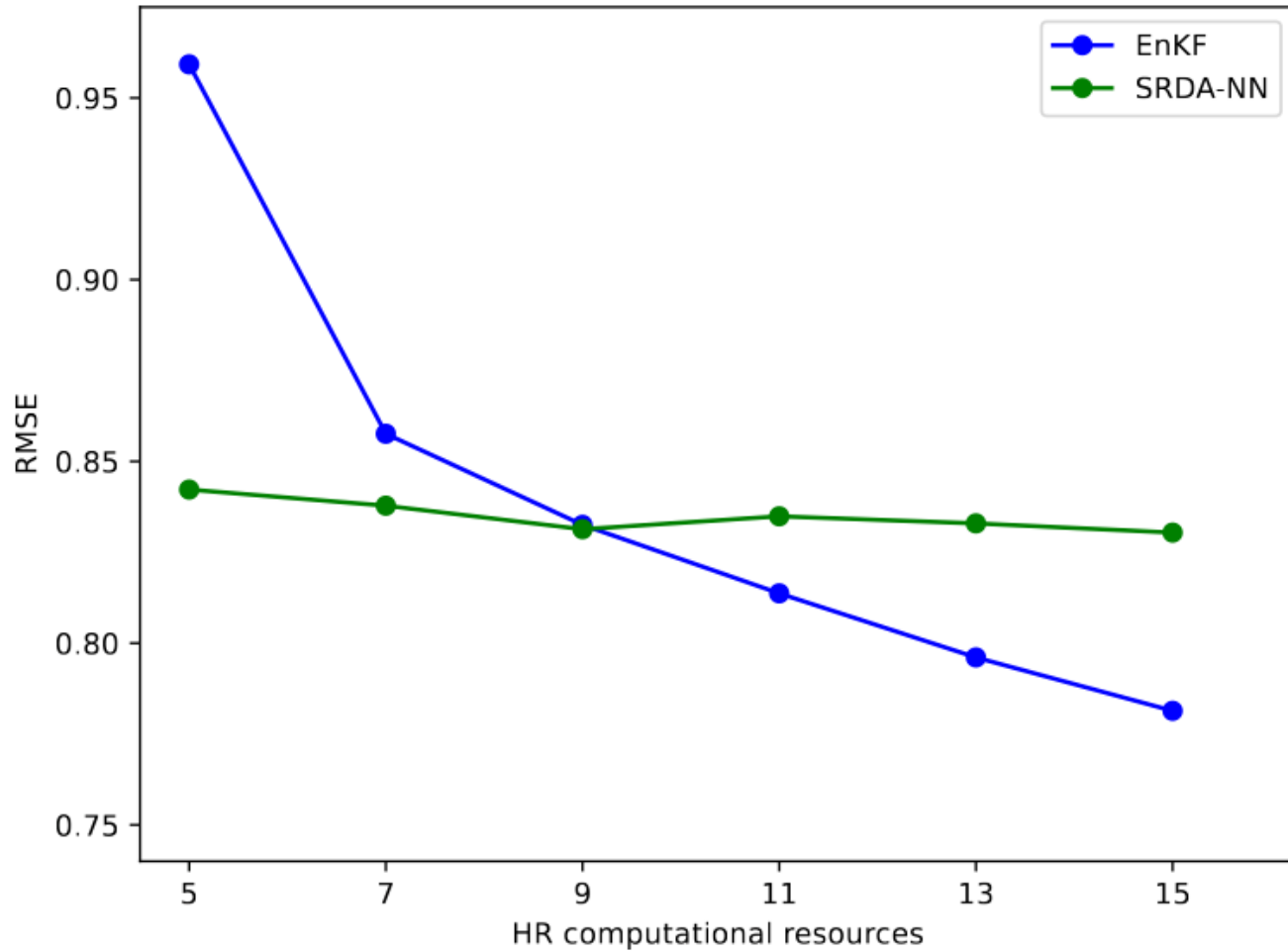


Cost



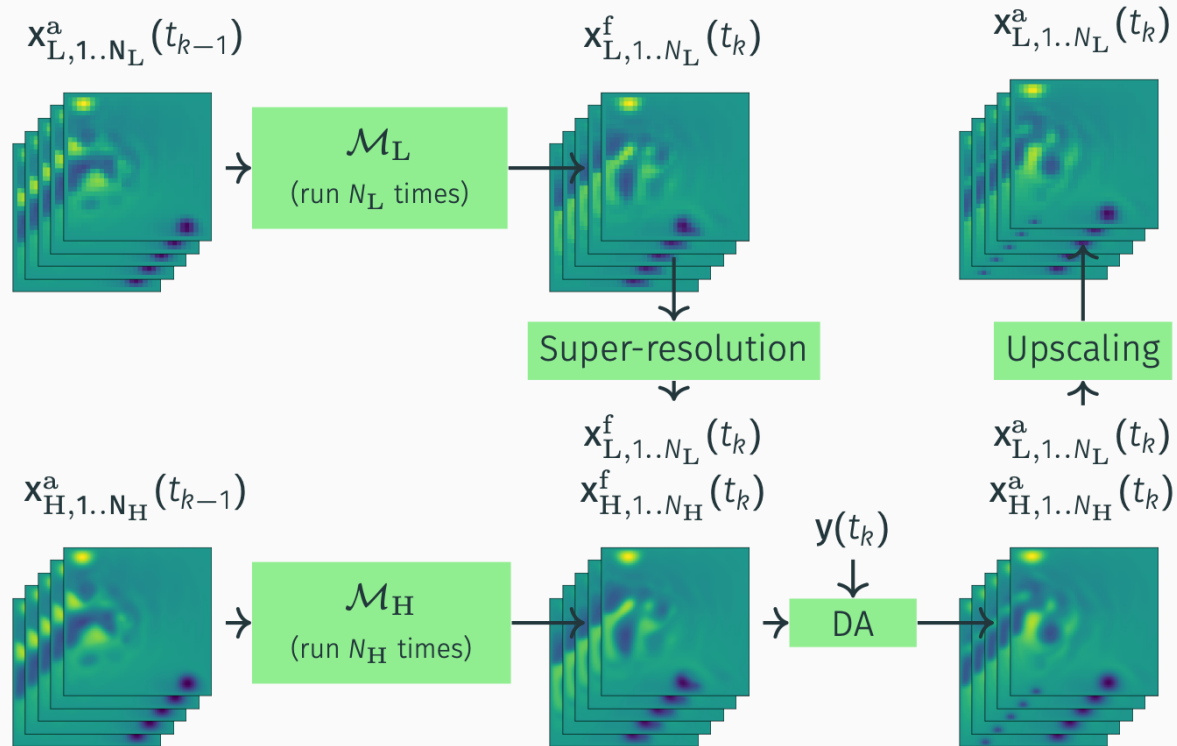
- Improved use of HR observations
- Corrects model bias

But performance quickly saturate



This may relate to irreducible error in the NN emulator

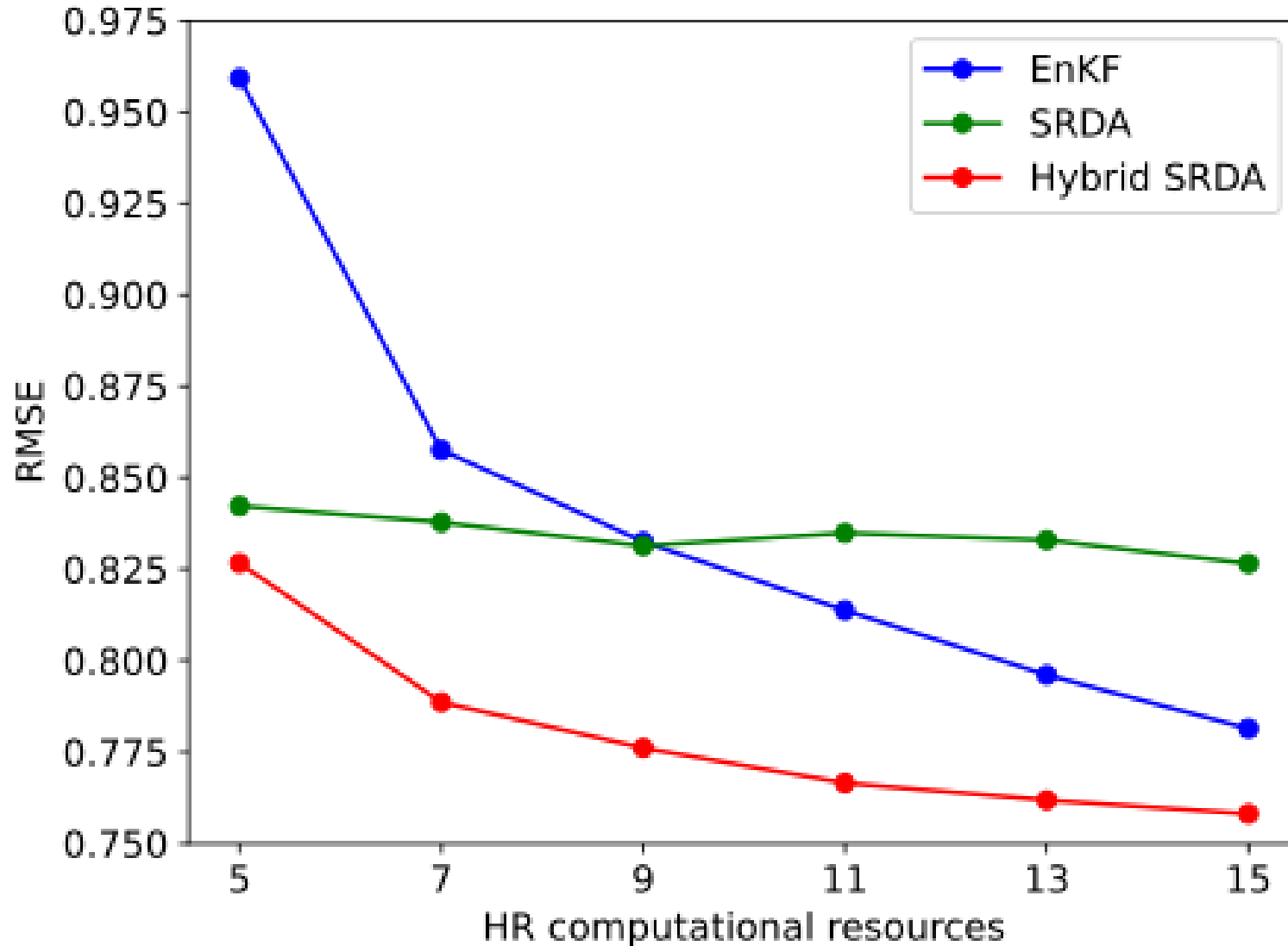
Hybrid Covariance SRDA



1. We run in parallel few HR member & a large LR ensemble
2. Assimilate hybrid covariance(HR+NN(LR))
3. Upscale back the LR members

	EnKF-LR	EnKF-HR	SRDA	Hybrid SRDA
Observation error	High ✓	Low ✓	Low ✓	Low ✓
HR processes	Poorly resolved ✓	Resolved ✓	Emulated ✓	Emulated (LR) ✓ / resolved (HR) ✓
Computational cost	Low ✓	High, $\mathcal{O}(n^3)$ ✓	Low ✓	Customizable(✓-✓)
Ensemble size	Big ✓	Small ✓	Big ✓	Big ✓
Error to the true P^f	Large ✓	Small ✓	Medium ✓	Customizable(✓-✓)

Hybrid covariance SRDA

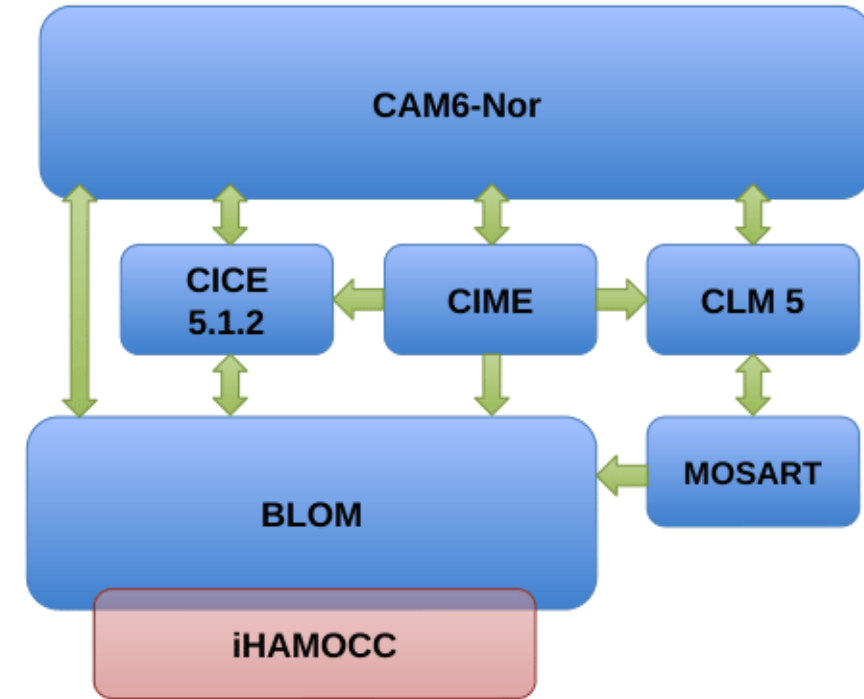


Using of a few HR can greatly enhance the performance

Application of (hybrid) SRDA with NorESM

- Training based on a 400 year long pre-industrial run
- Start NorESM-LM from NorESM-MM every month:
 - Training (80%) year 1056—1375
 - Validation (10%) year 1376—1415
 - Test (10%) 1416—1455

We learn the SST mismatch after 1 month integration from the 3D ocean state

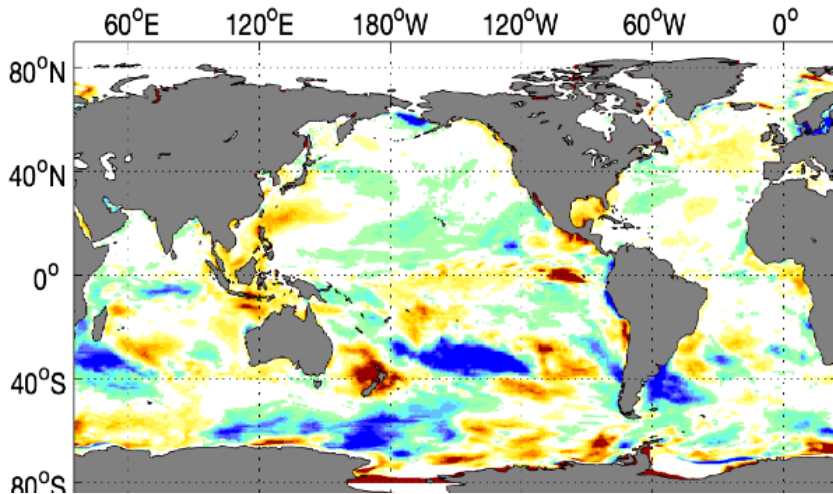


	Atmosphere / Land resolution	Ocean/sea ice resolution
NorESM2-LM	2°	tripolar 1°
NorESM2-MM	0.9 × 1.25°	tripolar 1°

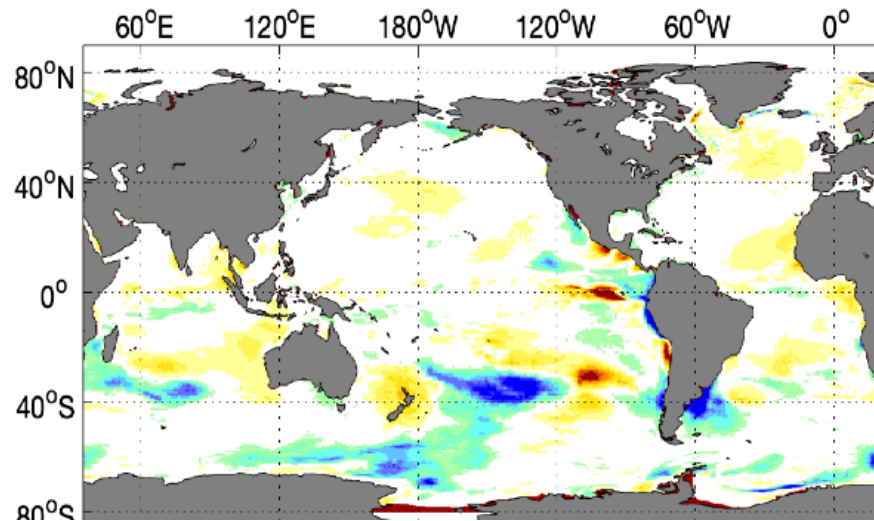
Predicted mismatch between HR and LR

An example during the test period

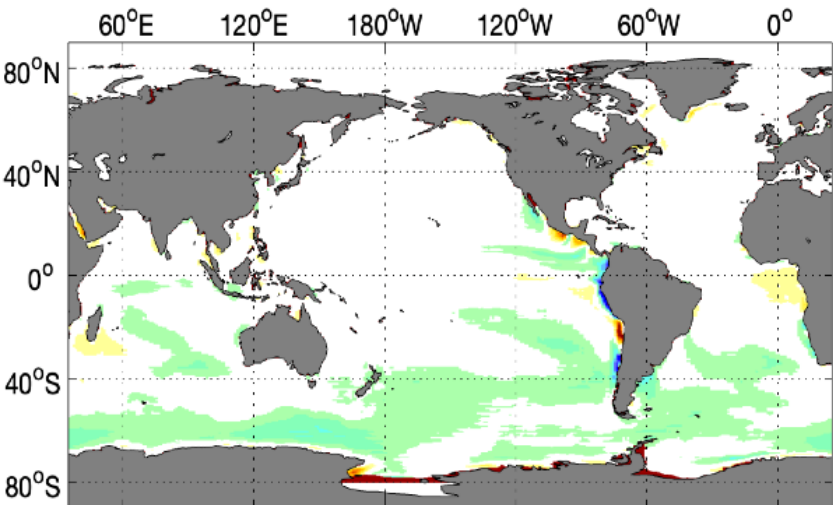
True increment January



NN increment January



Clim. increment January

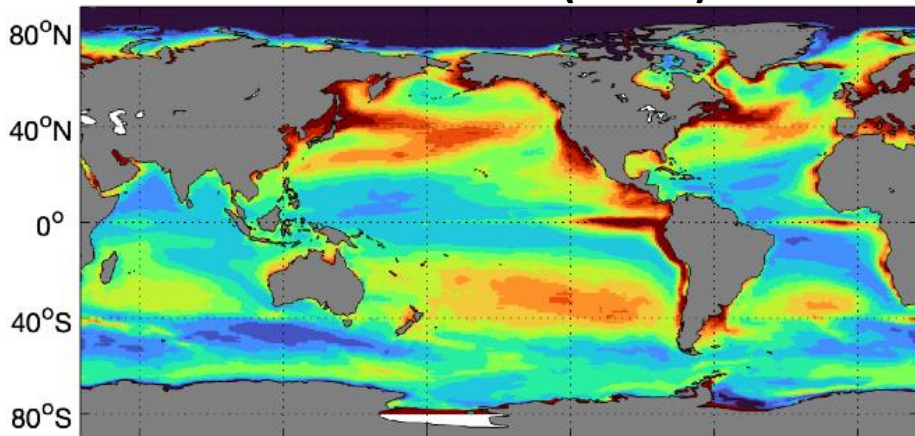


Capture regional misfits better than standard climatological corrections

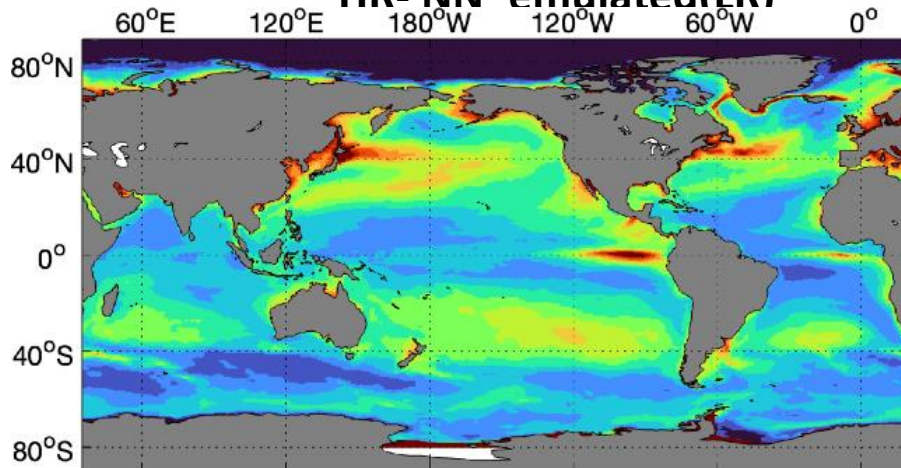
Predicted mismatch between HR and LR

Root mean square error (test period)

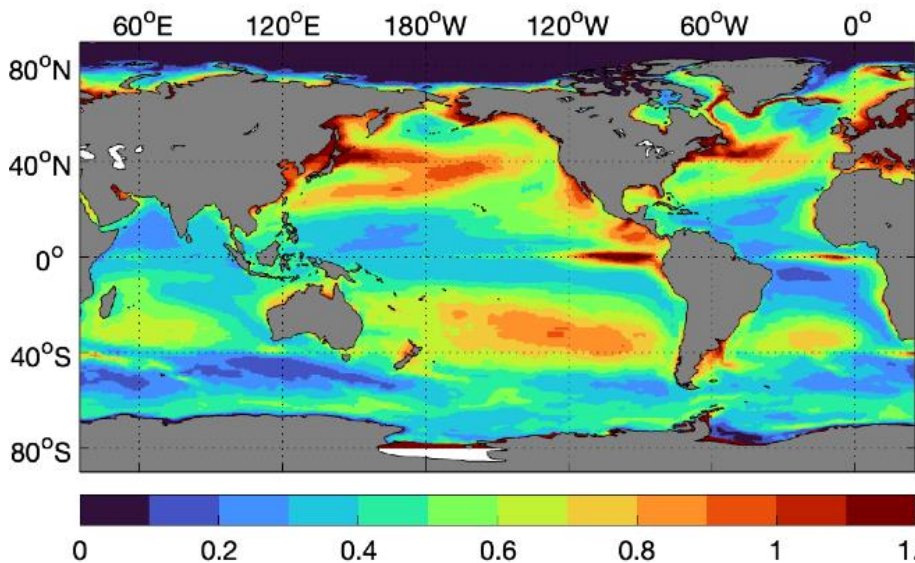
No correction (HR-LR)



HR- NN emulated(LR)



HR- seasonal_clim_corr(LR)



NN can strongly reduce error for SST over the test period

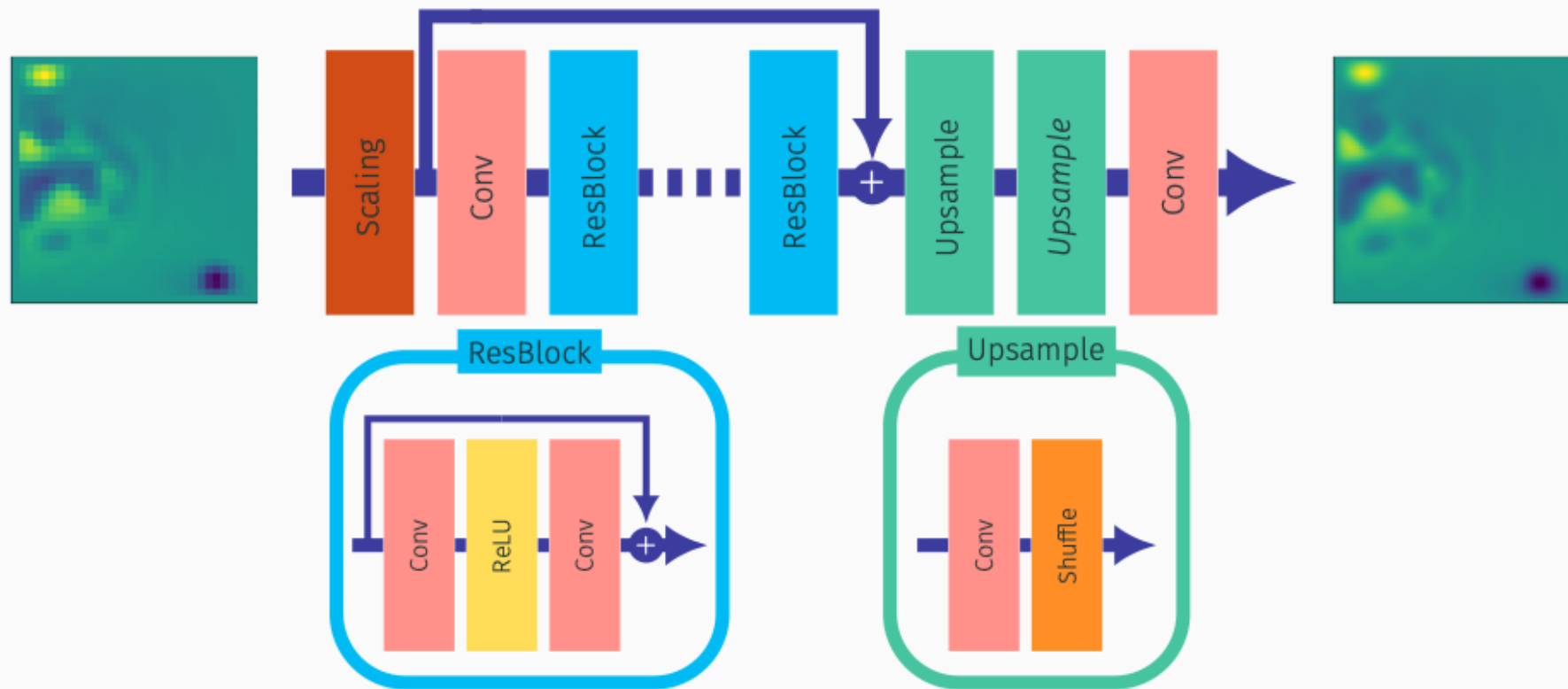
Conclusions

- We build an emulator for model resolution increase
 - Benefits:
 - We can train the emulator robustly on an extended multivariate data set
 - It is cheap if the HR simulation already exist
 - Less to learn since the model between LR and HR is the same
 - Can directly be used within the DA system
 - Limitation:
 - No guarantee that the HR model is best
- It can approaches the performance of the HR DA system at a fraction of the computational cost
- Hybridizing few dynamical members with a large ensemble of emulated LR member shows best performance
- We are testing the approach for ESM in idealise twin experiment

Future perspectives

- We will test the added value of the SRDA for seasonal predictions:
 - Is it best to train the NN on full 3D corrections or only on SST and use DA to formulate multivariate corrections ?
 - Would the emulator train under pre-industrial configuration also work for the recent period ?
 - How far can we push the resolution increase ?

Machine Learning training



Architecture of the enhanced deep super-resolution network (EDSR) [Lim et al., 2017]