Super-resolution data assimilation (SRDA)

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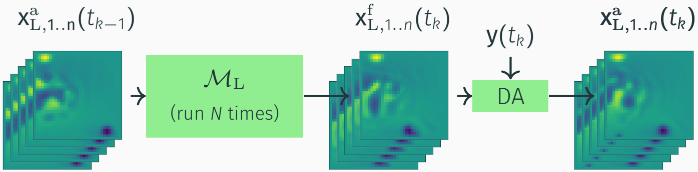
Objectives

The resolution of observations grows faster than model resolution.

1. Emulating a HR EnKF while running the forecast step with a LR model
2. Reduction of the computational cost of the EnKF
3. Taking advantage of HR observations with a LR model

EnKF - Low Resolution (EnKF-LR)



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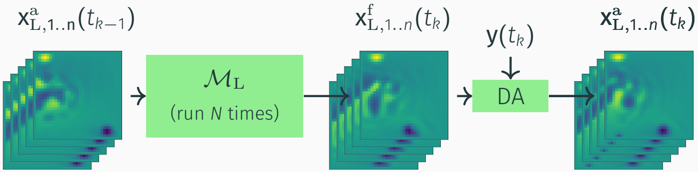

	EnKF-LR		
Observation error	High✔		
High-resolution processes	Poorly resolved✔		
Computational cost	Low✔		
Ensemble size	Big✔		

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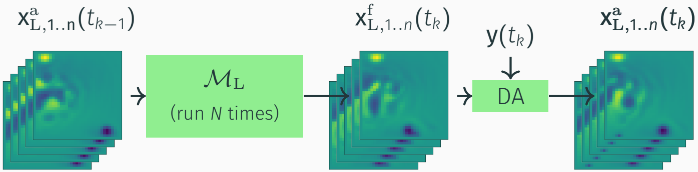
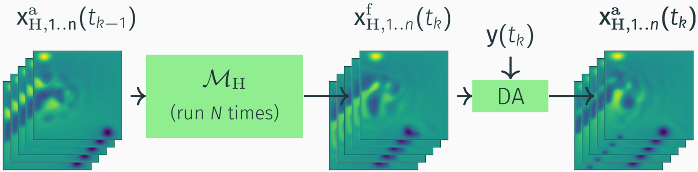
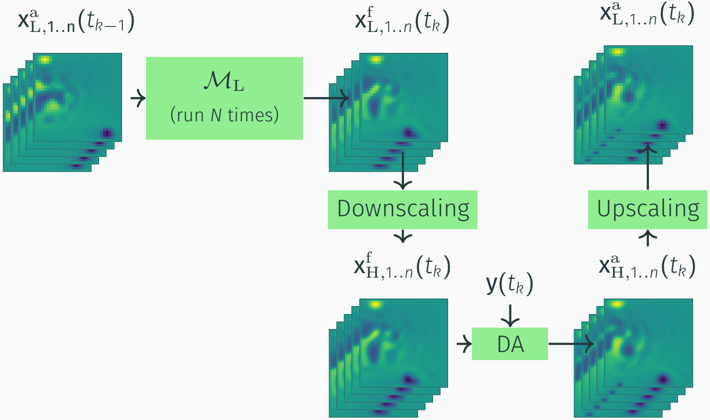


EnKF - High Resolution (EnKF-HR)



	EnKF-LR	EnKF-HR	
Observation error	High✔	Low✔	
High-resolution processes	Poorly resolved✔	Resolved✔	
Computational cost	Low✔	High, $\mathcal{O}\left(n^3\right)$✔	
Ensemble size	Big✔	Small✔	

EnKF - Super-resolution (SRDA)



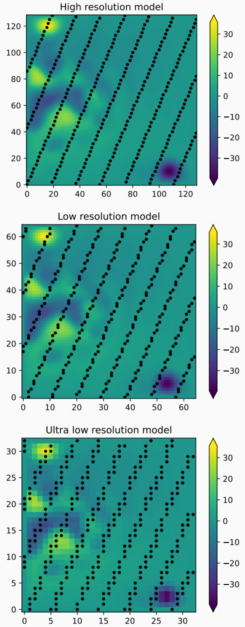
	EnKF-LR	EnKF-HR	SRDA
Observation error	High✔	Low✔	Low✔
High-resolution processes	Poorly resolved✔	Resolved✔	Emulated✔
Computational cost	Low✔	High, $\mathcal{O}(n^3)$✔	Low✔
Ensemble size	Big✔	Small✔	Big✔

Model used

- Model used: Quasi-geostrophic model[1]

Configuration	State size	Cost
HR	129×129	C
LR	65×65	$C/8$
ULR	33×33	$C/64$

- Observations:
  - True value perturbed by a gaussian noise of standard deviation 2
  - available every $\Delta t = 12$
  - positionned along simulated satellite tracks (black dots on the figures)



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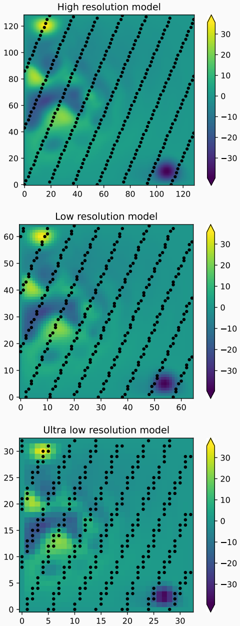
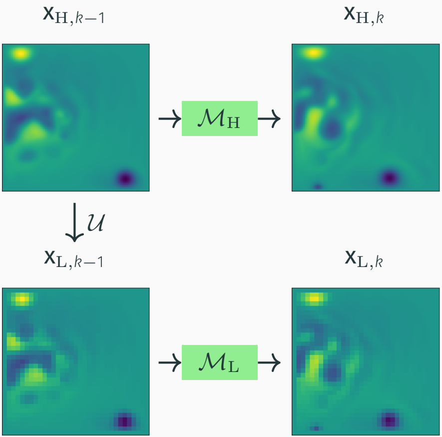
Downscaling operator?

- A simple cubic spline interpolation
- A neural network



Training set for the neural network

- Running one simulation of the HR model.
- Computing a dataset of matching pairs between a (U)LR and a HR state: $(\mathbf{x}_{\mathrm{L},k}, \mathbf{x}_{\mathrm{H},k})$



$\mathcal{U}$: Upscaling (subsampling operator)

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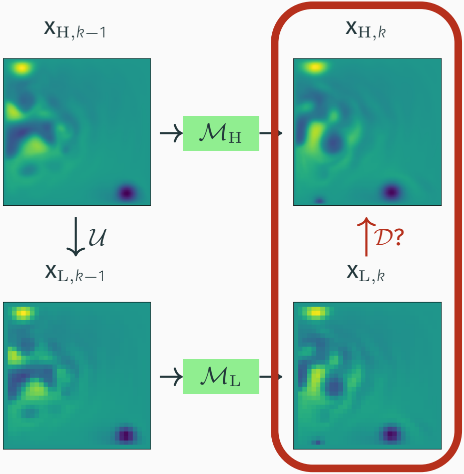
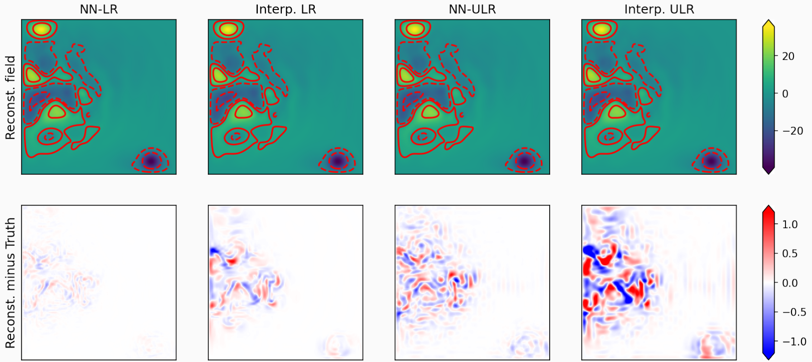


$\mathcal{U}$: Upscaling (subsampling operator)
$\mathcal{D}$: Downscaling (Neural network)

- Size of the dataset: 10,000
- 8000 for training / 2000 for validation
- Architecture of the enhanced deep super-resolution network (EDSR) [2]
- Training: minimization of the mean absolute error

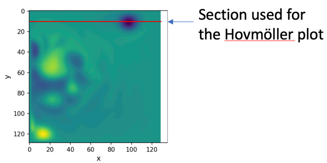
Downscaling performance

- Illustration with one typical sample

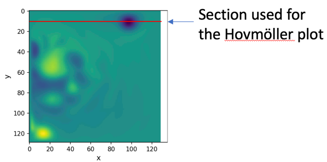


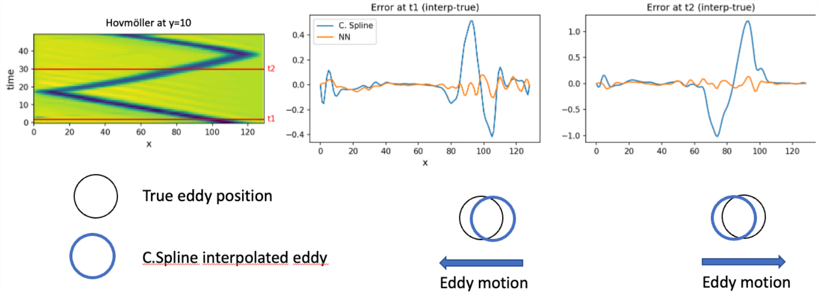
red lines: Contour of the true HR state

Model error correction



Model error correction



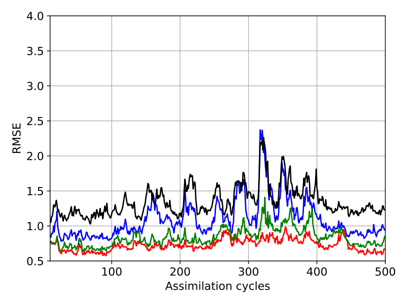


- Eddies move too slow with the LR model
- NN is smart enough to learn that

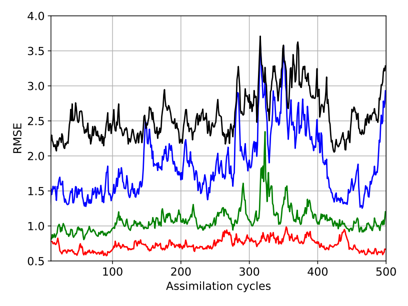
Super-resolution data assimilation performance

- Twin experiments with 500 assimilation cycles
- Sensitivity analysis to tune the optimal localisation and inflation
- Strong improvement irrespective of ensemble size
- Method able to predict uncertainties, same reliability as the EnKF

With the LR model



With the ULR model



DA in low-resolution

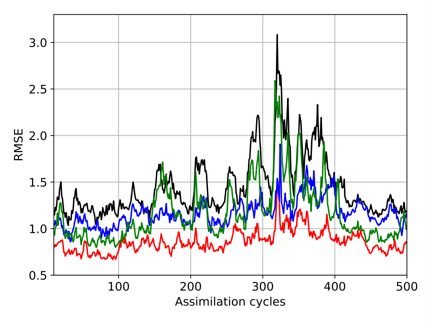
SRDA with cubic spline interpolation

SRDA with NN downscaling

DA in high-resolution

Super-resolution data assimilation performance

- Formulating the SRDA into a revised EnKF formulation we could disentangle the contribution from:
  1. the model error correction;
  2. the super-resolution observation operator.



- Model error correction improves performance during challenging events
- Super-resolution obs. operator reduces error over the whole period

EnKF-LR

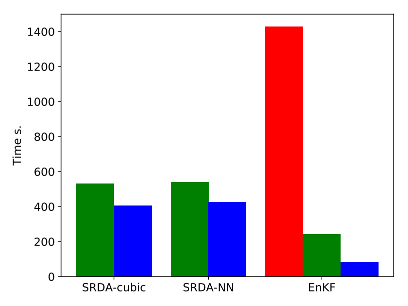
SRDA with only model error correction

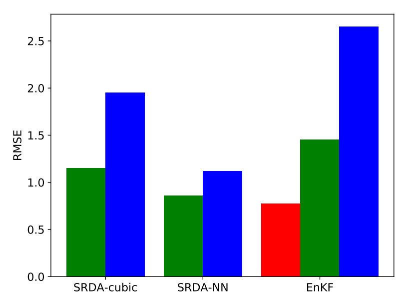
Standard SRDA

SRDA with only the super-res. observation operator

Computing performance - Total CPU time

- With 25 members sequentially
- Same inflation and localization coefficients





High resolution

Low resolution

Ultra low resolution

Conclusions/perspectives

Main results

- SRDA has an accuracy close to the EnKF with HR model at a cost close to an EnKF with the LR model,
- The NN can correct systematic differences of eddy propagation caused by the low resolution,
- The results are stable in time,
- The reliability of the ensemble system is well preserved.

Conclusions/perspectives

Main results

- **SRDA has an accuracy close to the EnKF with HR model at a cost close to an EnKF with the LR model**,
- The NN can correct systematic differences of eddy propagation caused by the low resolution,
- The results are stable in time,
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Perspectives

- Application to a more realistic (multivariate) model,
- Application only to local regions of the domain,
- Use NN-downscaling for the initialization of forecasts.

Paper available on arXiv!

http://arxiv.org/abs/2109.08017

Pavel Sakov and Peter R. Oke.
A deterministic formulation of the ensemble Kalman filter: An alternative to ensemble square root filters.
Tellus, Series A: Dynamic Meteorology and Oceanography, 60 A(2):361–371, 2008.
doi:10.1111/j.1600-0870.2007.00299.x.

Bee Lim, Sanghyun Son, Heewon Kim, Seungjun Nah, and Kyoung Mu Lee.
Enhanced deep residual networks for single image super-resolution.
In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) Workshops*, July 2017.

Sébastien Barthélémy, Julien Brajard, Laurent Bertino, and François Counillon.
Super-resolution data assimilation, 2021.
arXiv:2109.08017.

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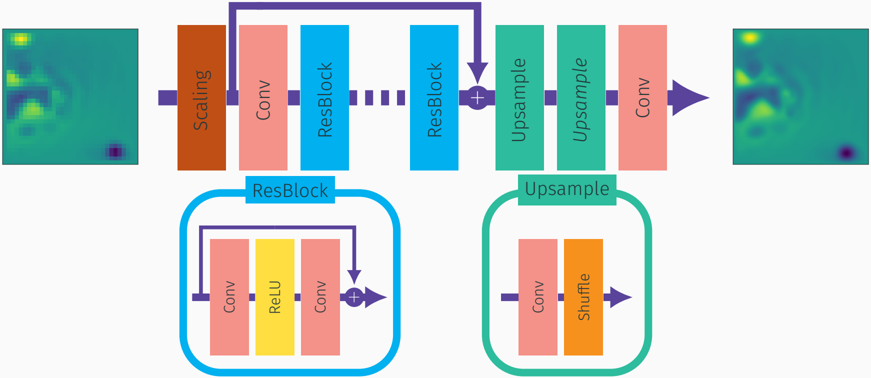
Setup of the neural network



Architecture of the enhanced deep super-resolution network (EDSR) [2]

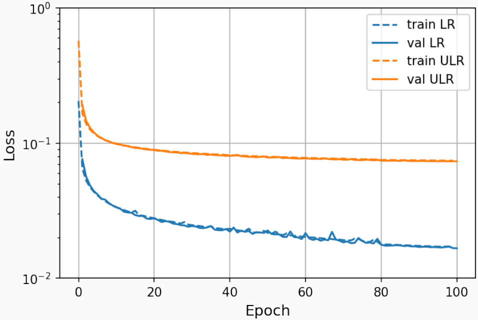
Training of the neural network

Minimize the mean absolute error (MAE):

$$L(\mathbf{w}) = \sum_{k=1}^{K} \sum_{i=1}^{S} \left| \mathcal{D}(\mathbf{x}_{\mathrm{L},k})_i - x_{\mathrm{H},k,i} \right| ,$$

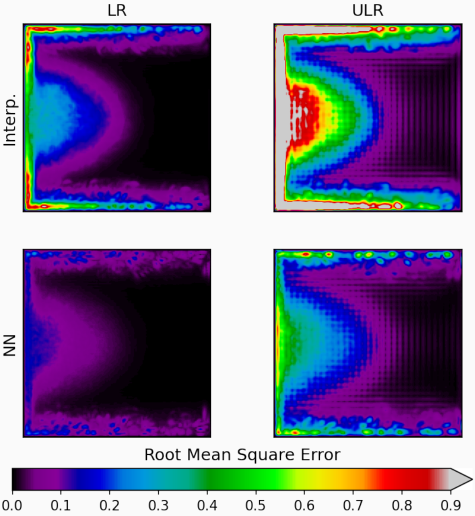
i:	the pixel index
S:	size of the state (129×129)
K:	size of the training set (K=8000)
$\mathbf{w}$:	weights of the neural network ($\sim 20,000$)

Training curve



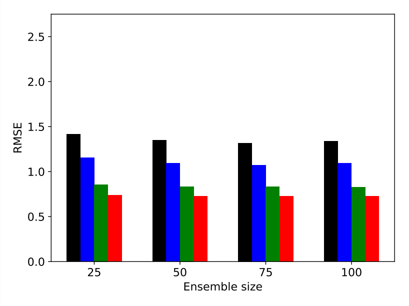
Downscaling performance (2)

- Score on the validation dataset

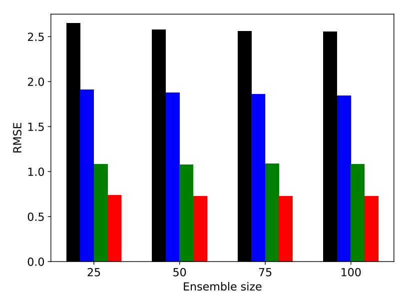


Super-resolution data assimilation performance

Low-resolution error



Ultra Low-resolution error



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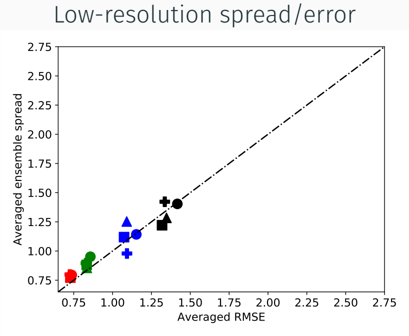
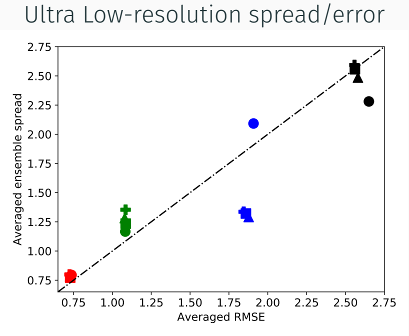
DA in high-resolution

Spread/error of the ensemble





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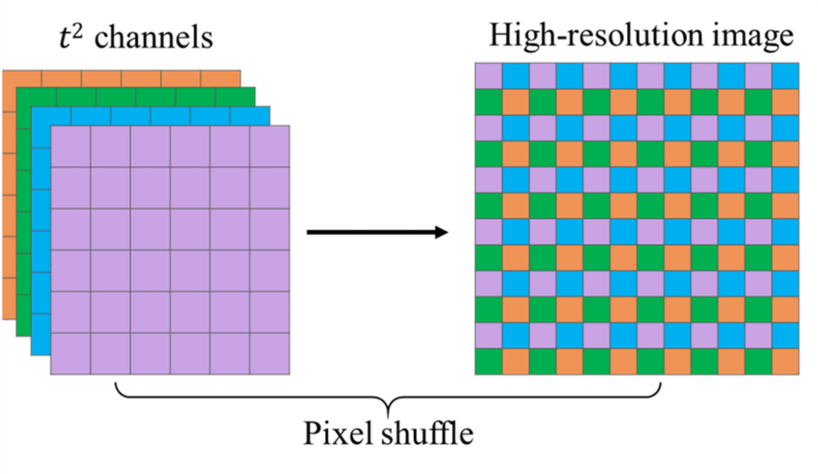
SRDA with NN downscaling

DA in high-resolution

The shuffle operator



Qin, Mengjiao, et al. **"Remote Sensing Single-Image Resolution Improvement Using A Deep Gradient-Aware Network with Image-Specific Enhancement."** *Remote Sensing* 12.5 (2020): 758.