Super-resolution data assimilation (SRDA)

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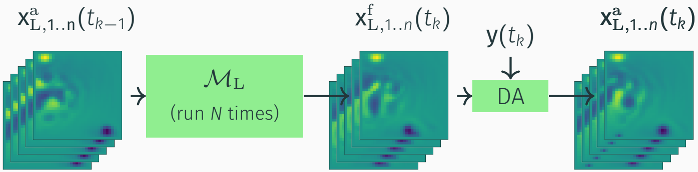
Overview

Overview

EnKF - Low Resolution (EnKF-LR)



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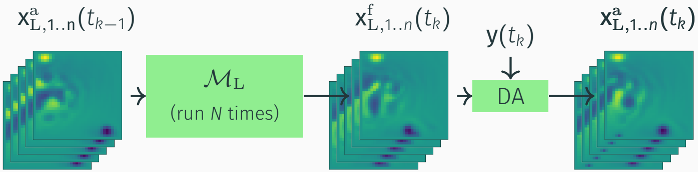
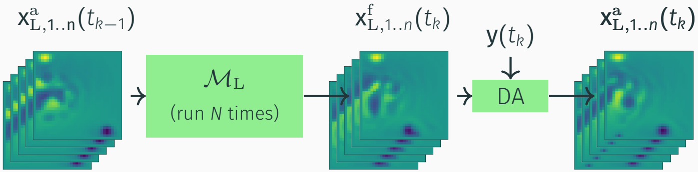


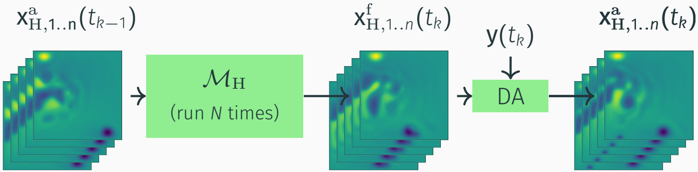
	EnKF-LR		
Observation error	High✔		
High-resolution processes	Poorly resolved✔		
Computational cost	Low✔		
Ensemble size	Big✔		

Motivation and method

EnKF - Low Resolution (EnKF-LR)



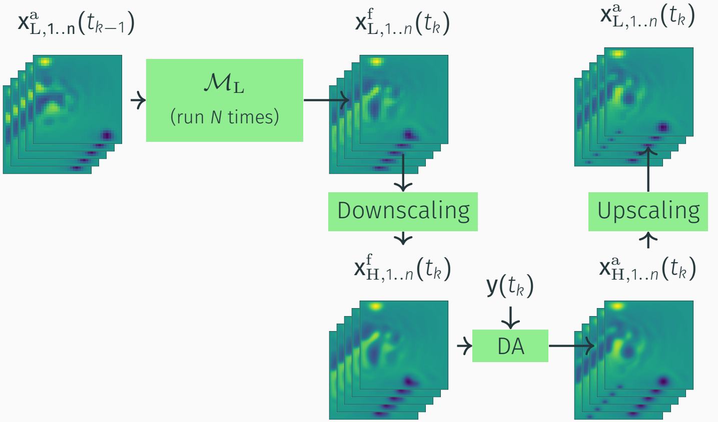
EnKF - High Resolution (EnKF-HR)



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

Motivation and method

EnKF - Super-resolution (SRDA)



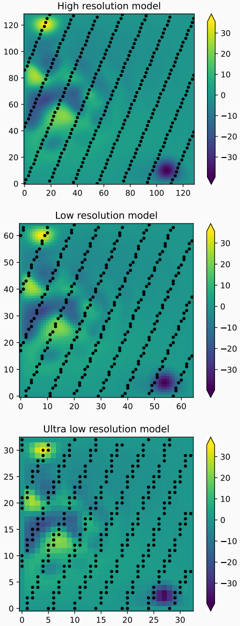
	EnKF-LR	EnKF-HR	SRDA
Observation error	High✔	Low✔	Low✔
High-resolution processes	Poorly resolved✔	Resolved✔	Emulated✔
Computational cost	Low✔	High✔	Low✔
Ensemble size	Big✔	Small✔	Big✔

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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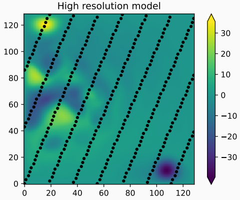
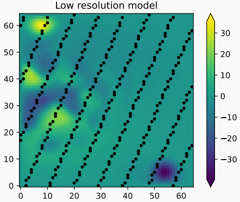
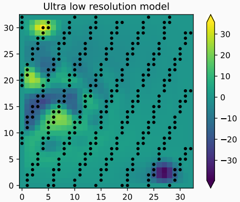
Downscaling operator?

- A simple cubic spline interpolation
- A neural network



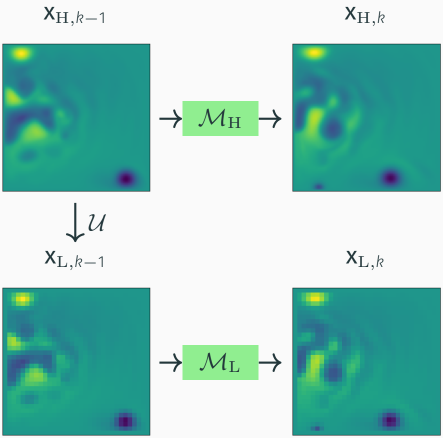




Overview

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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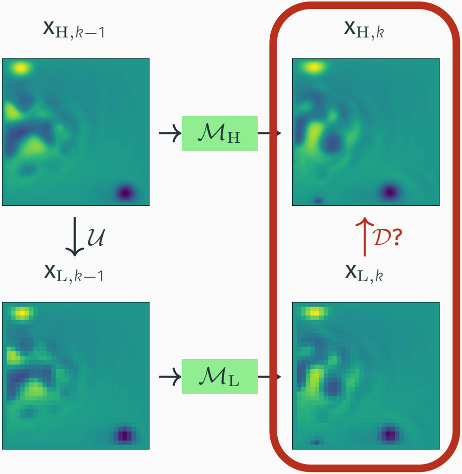
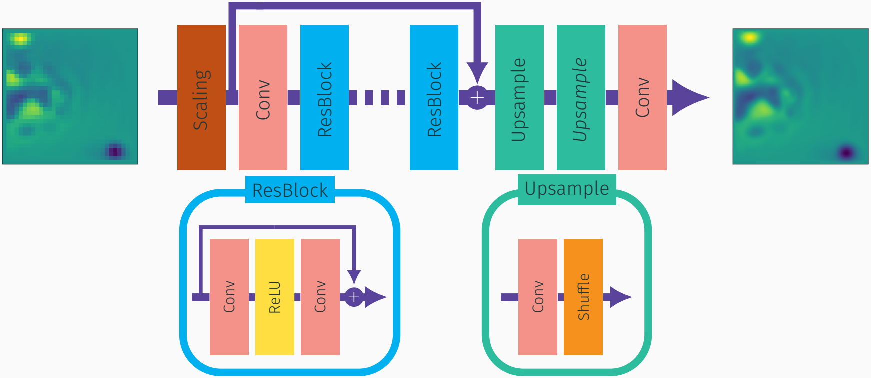


$\mathcal{U}$: Upscaling (subsampling operator)
$\mathcal{D}$: Downscaling (Neural network)

- Size of the dataset: 10,000
- 8000 for training / 2000 for validation

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 of the neural network

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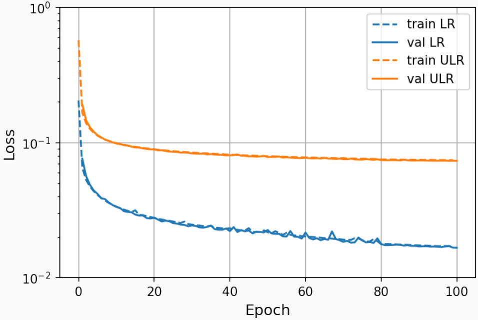
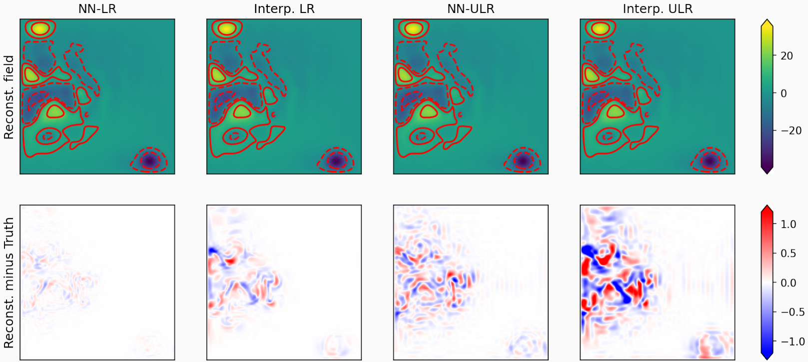
Training curve



Overview

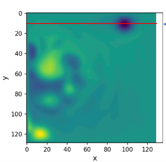
Downscaling performance (1)

- Illustration with one sample



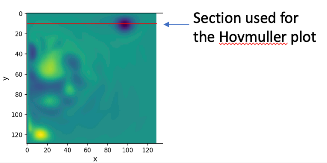
red lines: Contour of the true HR state

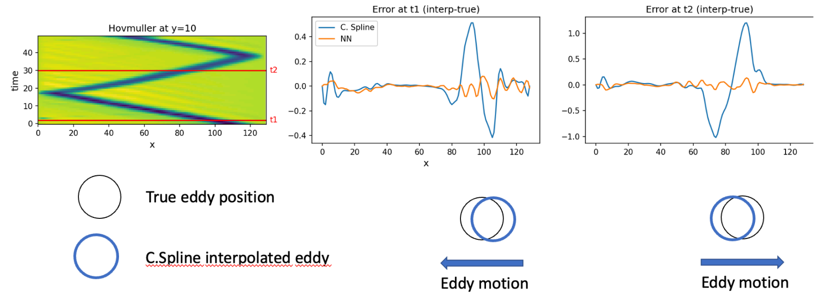
Model error correction



Section used for the Hovmuller plot

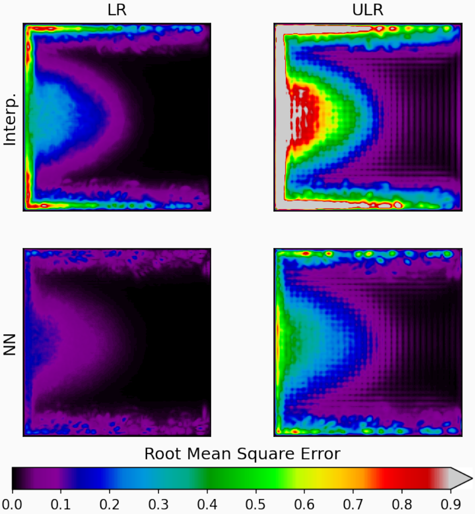
Model error correction





Downscaling performance (2)

- Score on the validation dataset

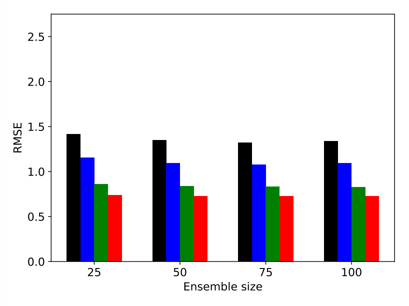


Overview

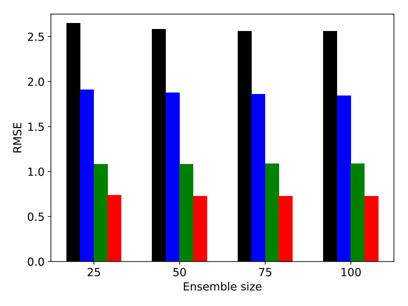
Super-resolution data assimilation performance

- Twin experiments with 500 assimilation cycles
- Sensitivity analysis to find the optimal localisation and inflation

Low-resolution error



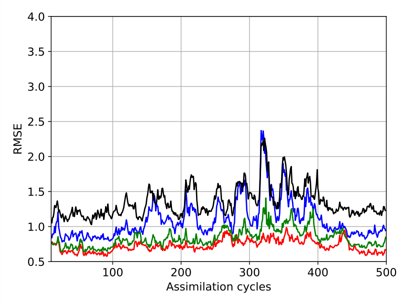
Ultra Low-resolution error



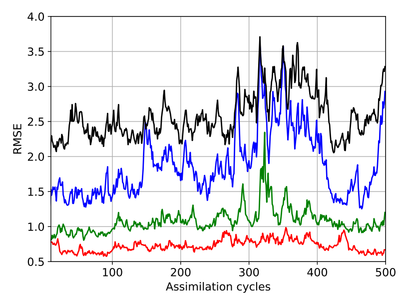
DA in low-resolution
SRDA with cubic spline interpolation
SRDA with NN downscaling
DA in high-resolution

Super-resolution data assimilation performance

Low-resolution error (in time)



Ultra Low-resolution error (in time)



DA in low-resolution

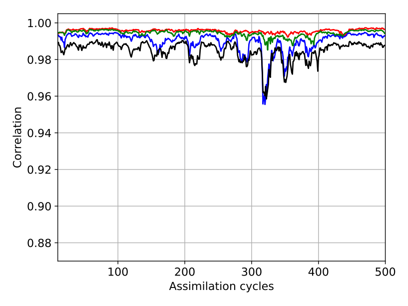
SRDA with cubic spline interpolation

SRDA with NN downscaling

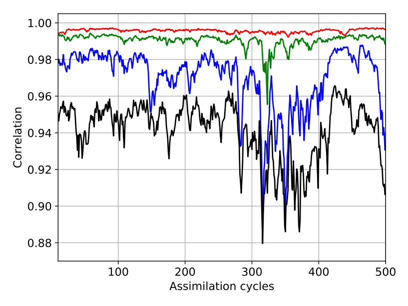
DA in high-resolution

Super-resolution data assimilation performance

Low-resolution correlation



Ultra Low-resolution correlation



DA in low-resolution

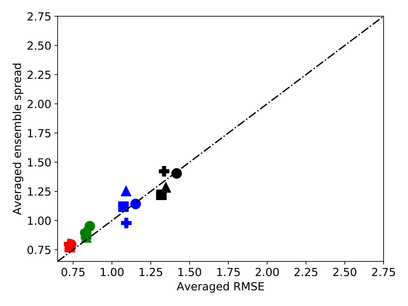
SRDA with cubic spline interpolation

SRDA with NN downscaling

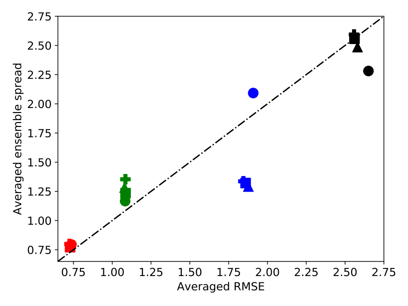
DA in high-resolution

Spread/error of the ensemble

Low-resolution spread/error



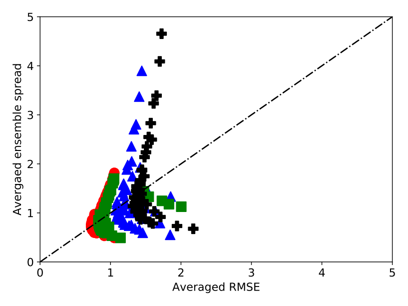
Ultra Low-resolution spread/error



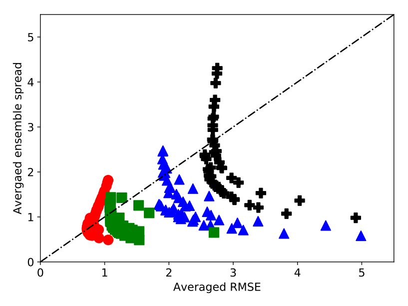
- DA in low-resolution
- SRDA with cubic spline interpolation
- SRDA with NN downscaling
- DA in high-resolution

Spread/error of the ensemble

Low-resolution spread/error



Ultra Low-resolution spread/error



DA in low-resolution
SRDA with cubic spline interpolation
SRDA with NN downscaling
DA in high-resolution

Time performance

- Running 25 members sequentially
- Same inflation and localization coefficients

Time s.	SRDA-cubic		SRDA-NN		EnKF		
	LR	ULR	LR	ULR	HR	LR	ULR
Integration	**192**	**84**	**188**	**82**	**1144**	**168**	**62**
Downscaling	13	11	34	38	–	–	–
Assimilation	**313**	**298**	**304**	**294**	**284**	**76**	**22**
Upscaling	14	12	13	12	–	–	–
Total	**532**	**405**	**539**	**426**	**1428**	**244**	**84**

Time s.	LR	ULR
Training	494	531

Overview

1. Motivation and method
2. Model used
3. Training and set-up of the neural network
4. Numerical results
5. Conclusion and perspectives

Conclusions/perspectives

Main results

- **SRDA performs a DA close to the High-resolution model, accuracy for the cost of a low-resolution model**,
- The NN can correct systematic differences of eddy propagation caused by low resolution,
- The results are stable in time,
- The spread is well represented.

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- The NN can correct systematic differences of eddy propagation caused by low resolution,
- The results are stable in time,
- The spread is well represented.

Perspectives

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

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.

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Acknowledgement:

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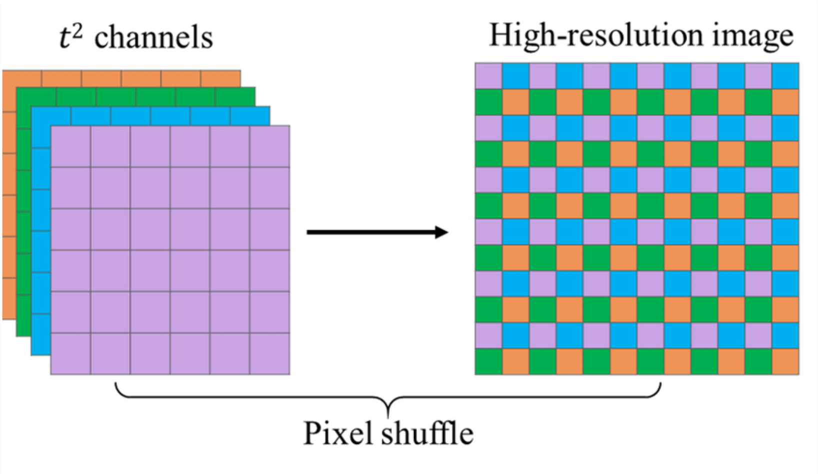
The shuffle operator



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.