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Earth and Environmental Data Science

Literature review

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Literature Review

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APPLICATION PAPER

Deep prior in variational assimilation to estimate an ocean circulation without explicit regularization

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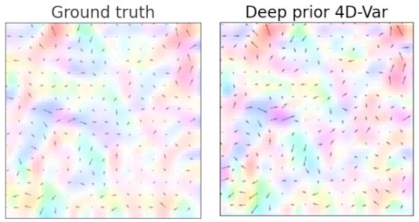
Keywords: Deep prior; ocean circulation; regularization; twin experiment; variational data assimilation

Ocean Modelling
Special Issue Python

Variational data assimilation with deep prior (CIRC23)



Pahari *et al.* (2023)

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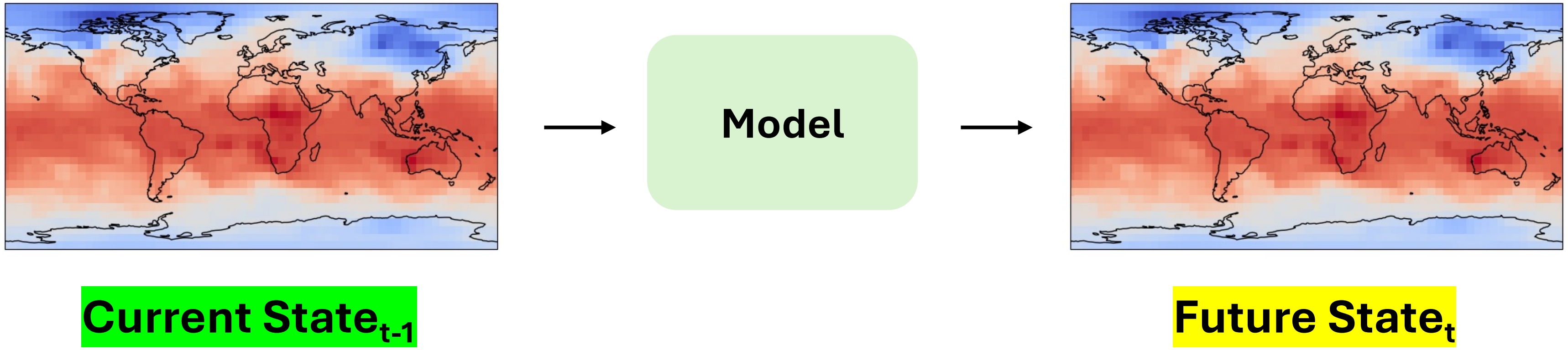
What is Data Assimilation?



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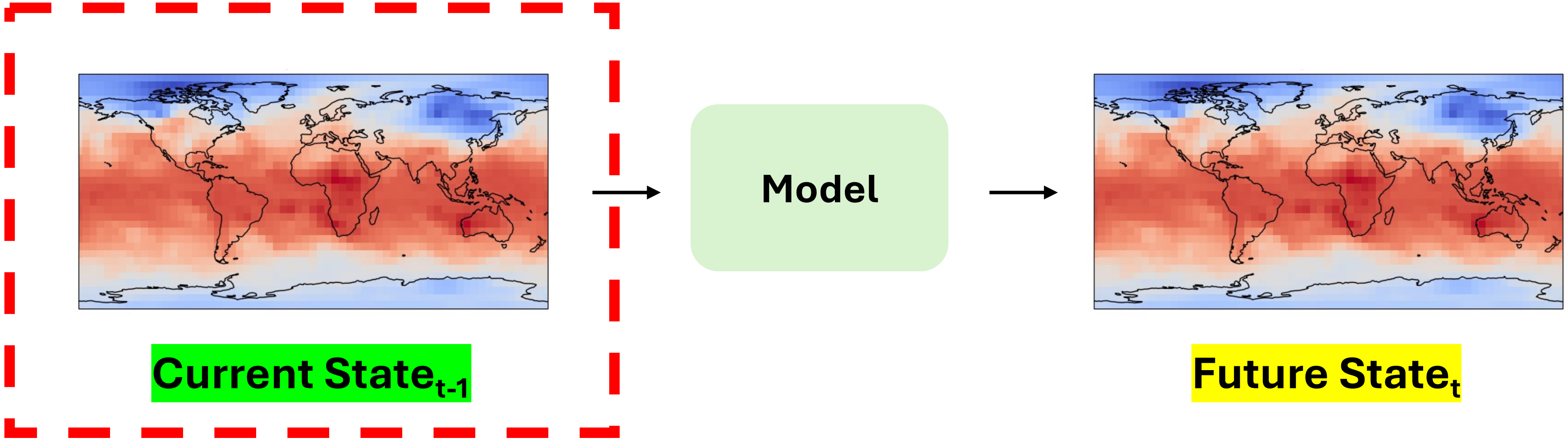

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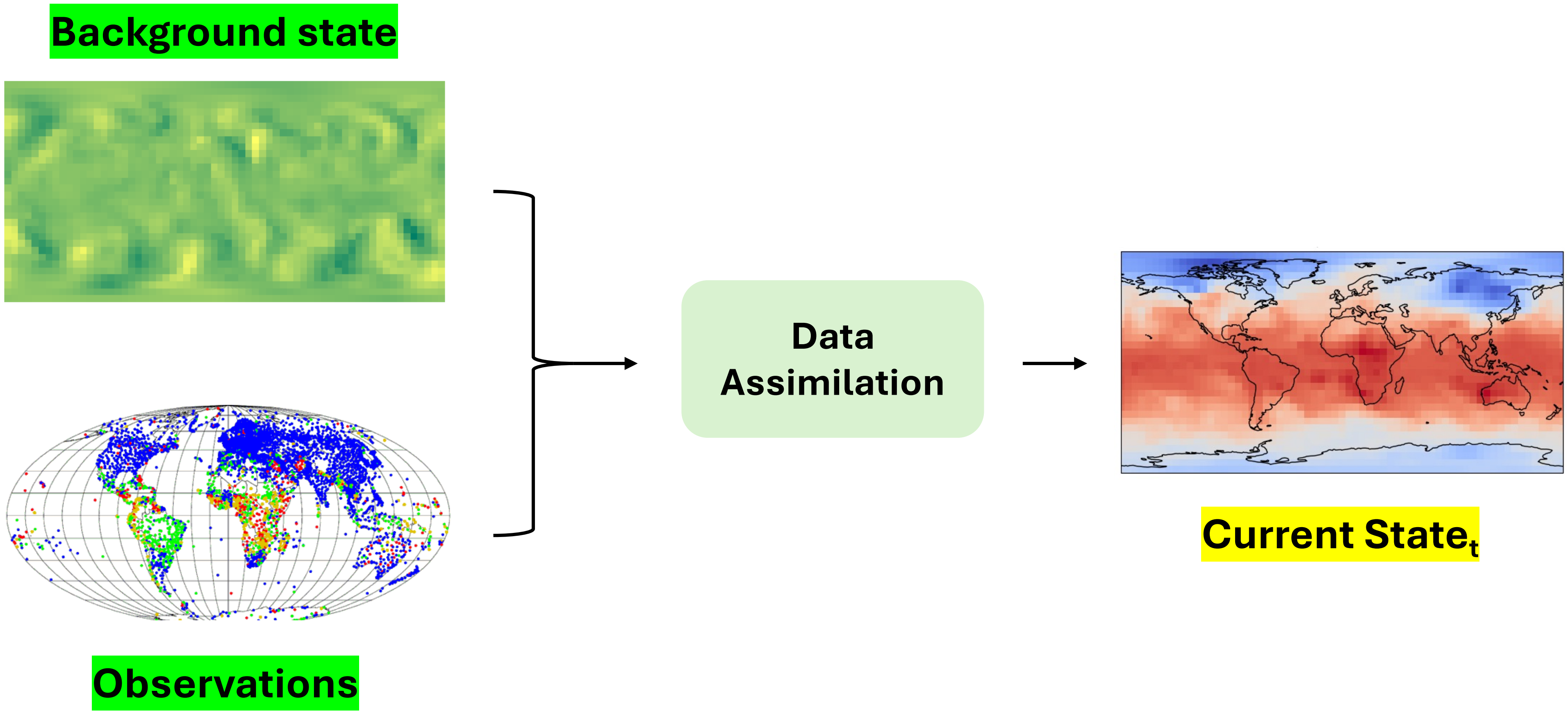

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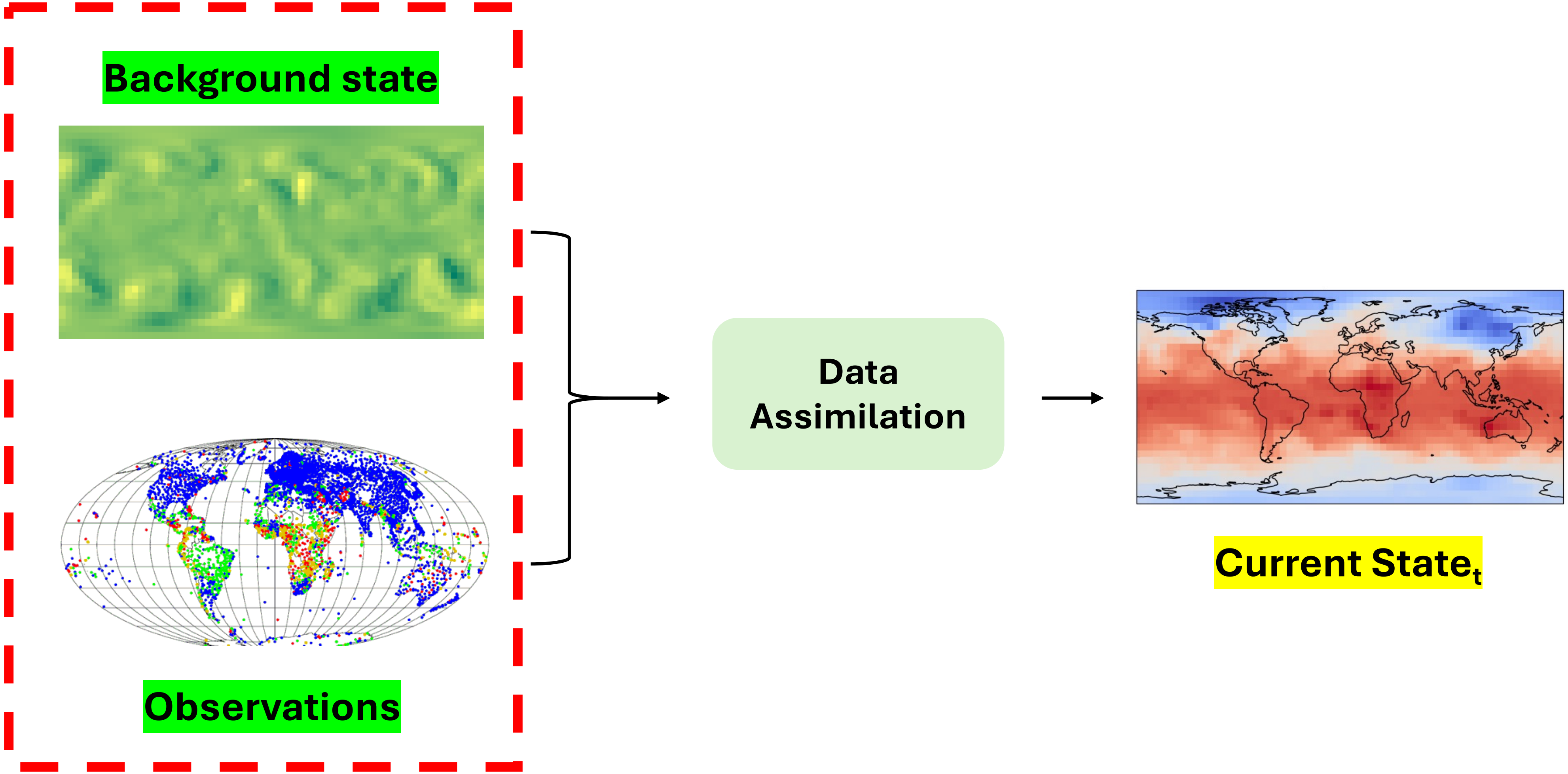

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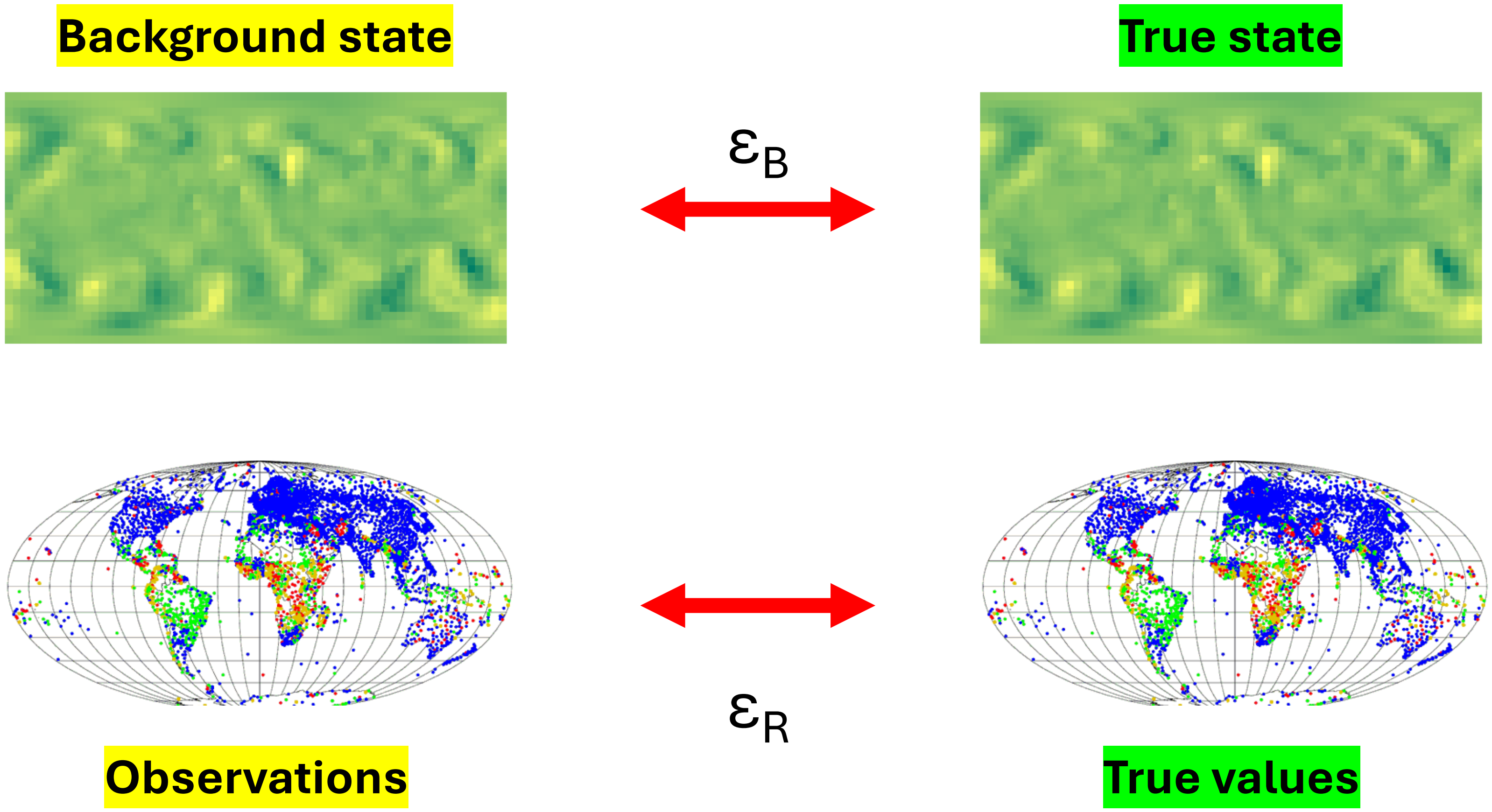


$$\text{Background}: \quad \mathbf{X}_0 = \mathbf{X}_B + \varepsilon_B$$

$$\text{Observation}: \quad \mathbf{Y}_t = \mathbb{H}_t(\mathbf{X}_t) + \varepsilon_{R_t}$$

Traditional approach

Accurate Estimation

≈ Minimising Error

≈ Minimising Cost Function

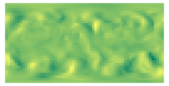
Traditional approach

Accurate Estimation

≈ Minimising Error

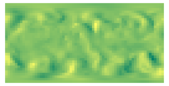
≈ Minimising Cost Function

Background state



ε_B

True state



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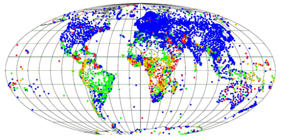
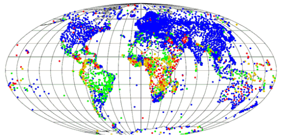
$$\underset{\mathbf{X}_0}{\arg\min} \quad \mathcal{J}_{4\mathrm{DVar}}(\mathbf{X}_0) = \frac{1}{2}\|\mathbf{X}_0 - \mathbf{X}_b\|_{\mathbf{B}}^2 + \frac{1}{2}\sum_{t=0}^{T}\|\mathbf{Y}_t - \mathbb{H}_t(\mathbf{X}_t)\|_{\mathbf{R}_t}^2,$$

$$\text{s.t.} \quad \mathbf{X}_{t+1} = \mathbb{M}_t(\mathbf{X}_t).$$



Observations

ε_R



True values

Traditional approach

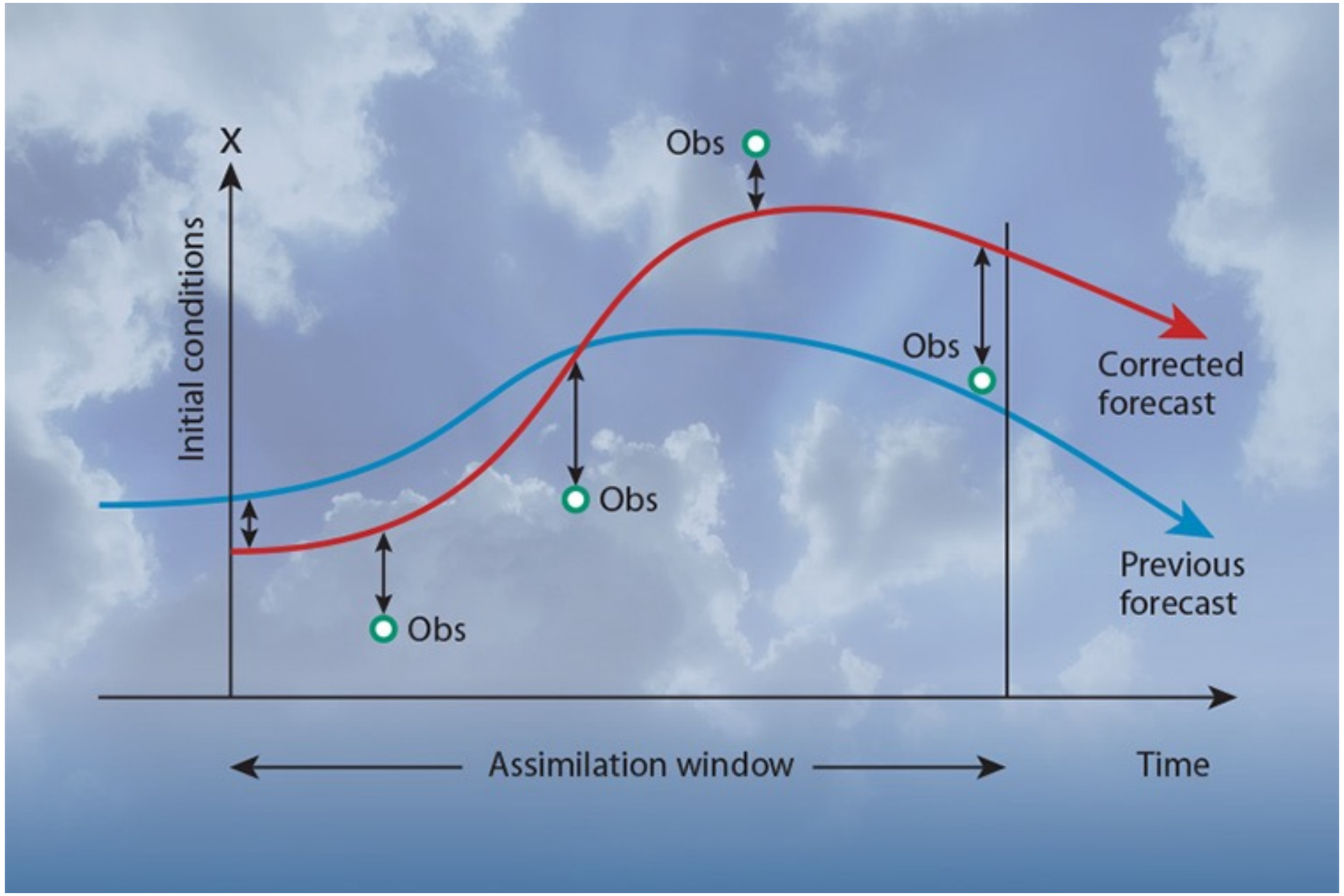


Image source: *ECMWF, (https://www.ecmwf.int/en/about/media-centre/news/2017/20-years-4d-var-better-forecasts-through-better-use-observations)*

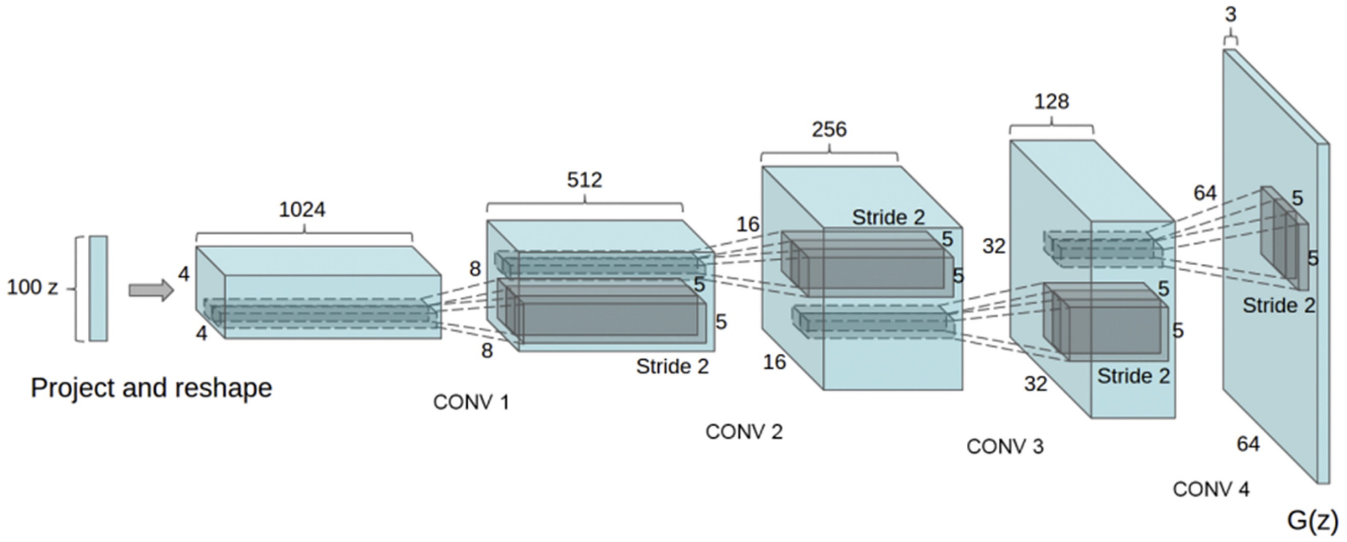
‘Deep prior’ approach

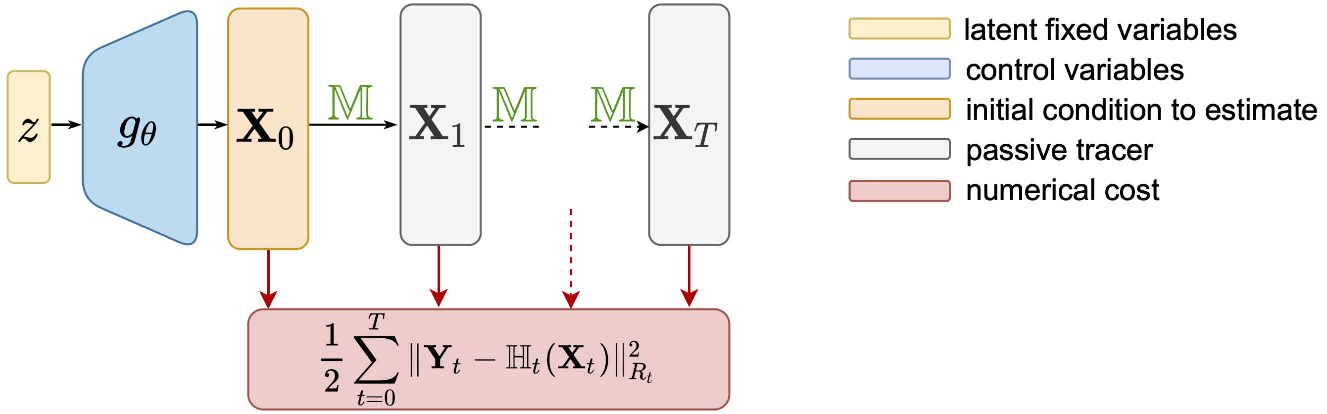
- **No Explicit Background State**
- **Implicit Regularization**

$$\mathcal{J}(\theta) = \frac{1}{2}\sum_{t=0}^{T} \|\mathbf{Y}_t - \mathbb{H}_t(\mathbb{M}_{0\rightarrow t}(g_\theta(z)))\|_{R_t}^2$$

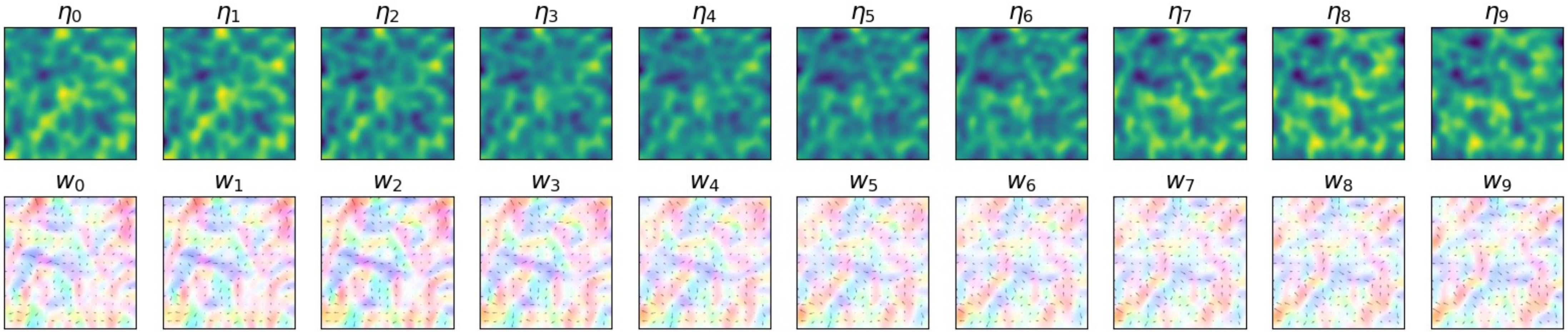
Neural Network

‘Deep prior’ approach





Data

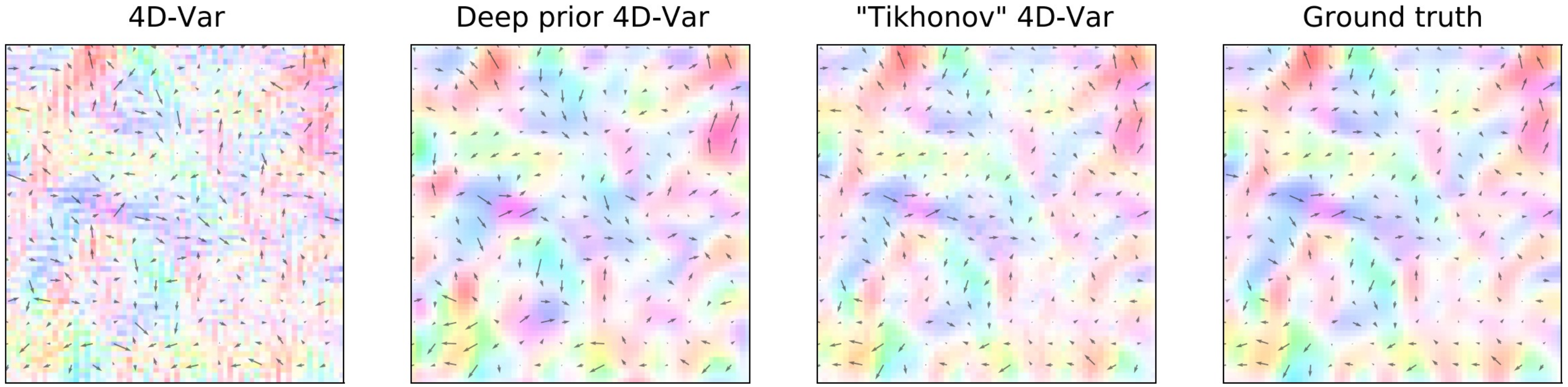


Simulated data from shallow water model

Result

Table 1. Metrics quantifying the quality of the estimated motion field $\mathbf{w}_0$ over the assimilated database.

	Assimilation score		Smoothness statistics		
Metric[a]	Endpoint error $(\times 10^2)$	Angular error	$\|\nabla \mathbf{w}_0\|_2$	$\|\nabla . \mathbf{w}_0\|_2$	$\|\Delta \mathbf{w}_0\|_2$
4D-Var	04.2 ± 0.4	028.4 ± 9.8	06.1 ± 0.6	05.3 ± 0.5	09.9 ± 1.0
Deep prior 4D-Var	04.6 ± 2.0	026.7 ± 5.0	01.9 ± 0.1	01.6 ± 0.9	01.0 ± 0.3
"Tikhonov" 4D-Var	01.6 ± 0.6	09.9 ± 9.8	02.0 ± 0.1	01.8 ± 0.1	01.9 ± 0.1
Ground truth	00	00	01.7 ± 0.9	01.6 ± 0.1	00.7 ± 0.3



Result

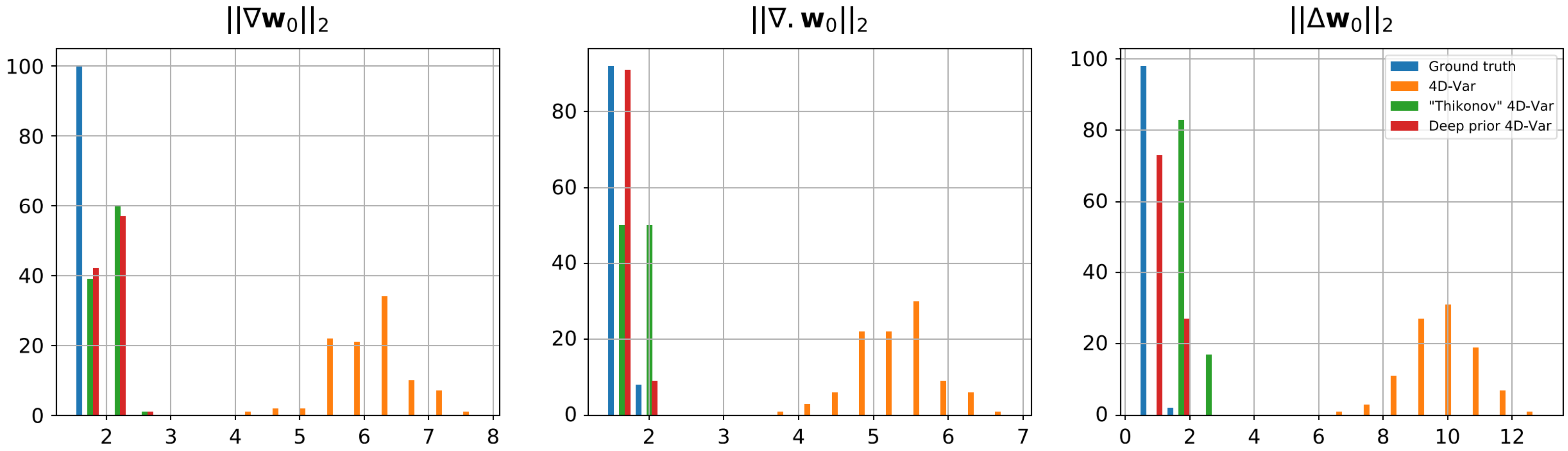


Figure 5. *Histograms of smoothness statistics from the estimated motion field* $\mathbf{w}_0$ *with various algorithms.*

Code

- Dataset
- Modelling
- Experiments
- Figures

Conclusion

- Neural network approach for substituting data assimilation.
- This approach can be an alternative when prior knowledge is not available since it shows comparable accuracy.
- However, still expert-driven handcrafted regularization provides better performances.