On the effective resolution of deterministic AI weather models

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Mathematical argument

1) Target of training

$$\theta^* = \arg\min_{\theta} \sum_{\tau=1}^{\tau_{\mathrm{train}}} \mathbb{E}_{p(x_t)} \left[||\mu_{t+\tau|t} - \hat{x}^{\theta}_{t+\tau}(x_t)||^2 \right]$$

2) An ideal and perfectly trained AI model predicts the expectation of the transition distribution function

$$\hat{x}^{\theta^*}_{t+\tau}(x_t) = \mathbb{E}[x_{t+\tau}|x_t] =: \mu_{t+\tau|t}, \text{ for } \tau \in \{1, \ldots, \tau_{\mathrm{train}}\}$$

3) The transition distribution function can be approximated by a NWP ensemble

$$p(x_{t+\tau}|x_t) = \int \mathrm{d}\tilde{x}_{t+\tau}\, p(x_{t+\tau}|\tilde{x}_{t+\tau}) \int \mathrm{d}\tilde{x}_t\, p(\tilde{x}_{t+\tau}|\tilde{x}_t)\, p(\tilde{x}_t|x_t)$$

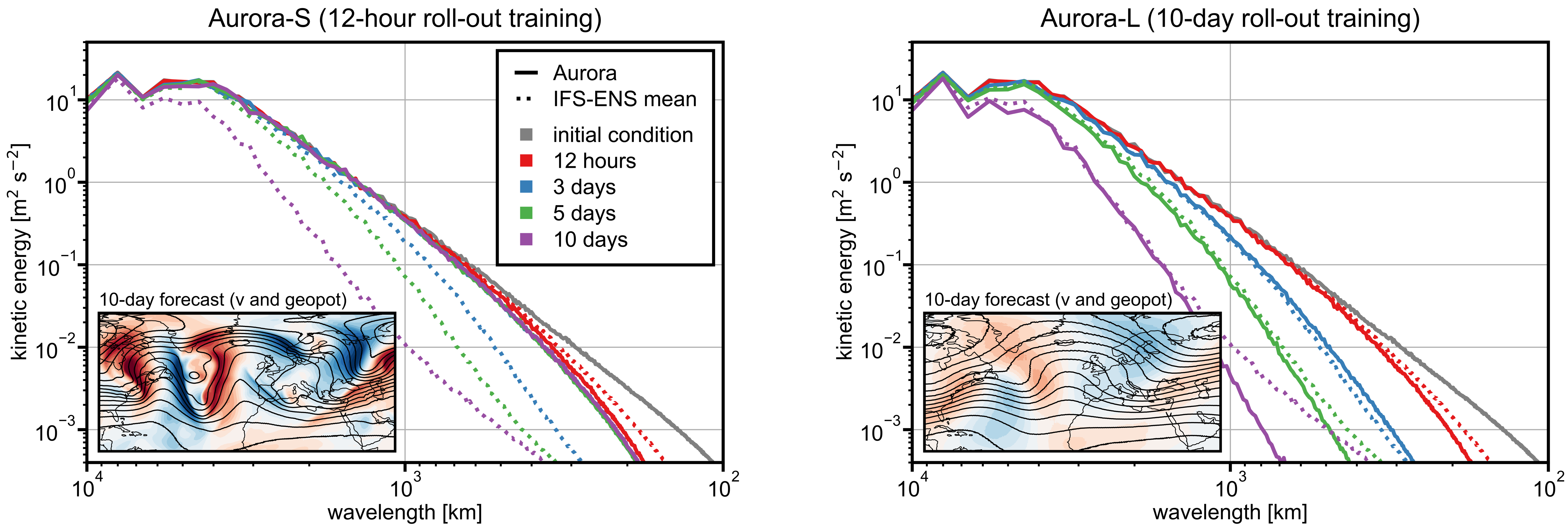
4) Unpredictable modes cancel in the expectation → smoothing

Notation:

$\tilde{x}$: true state vector
$\hat{x}$: forecast state vector
x : estimated state vector (analysis)
θ : learnable parameters

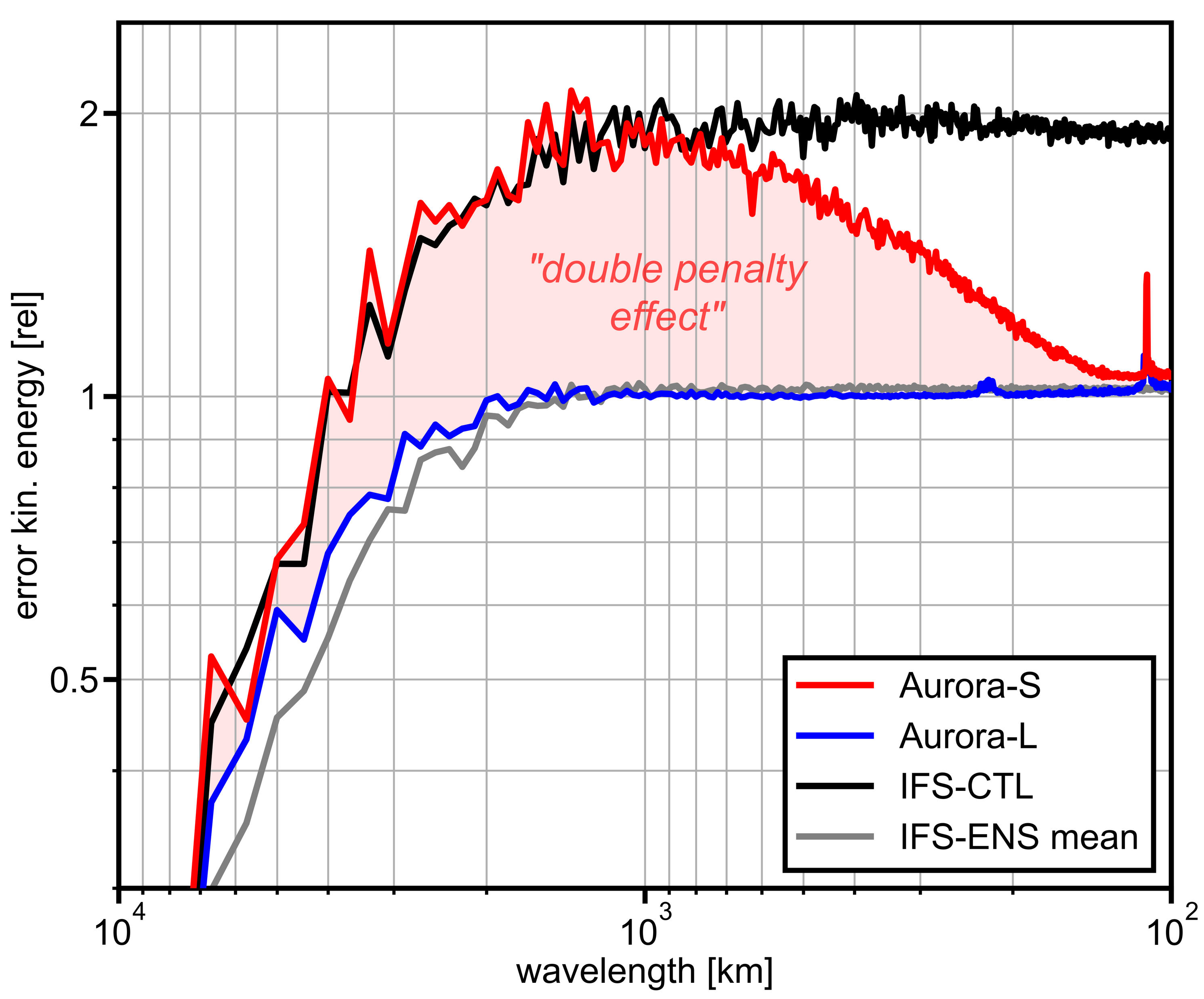
The effect of different roll-out training intervals

300hPa global kinetic energy spectrum



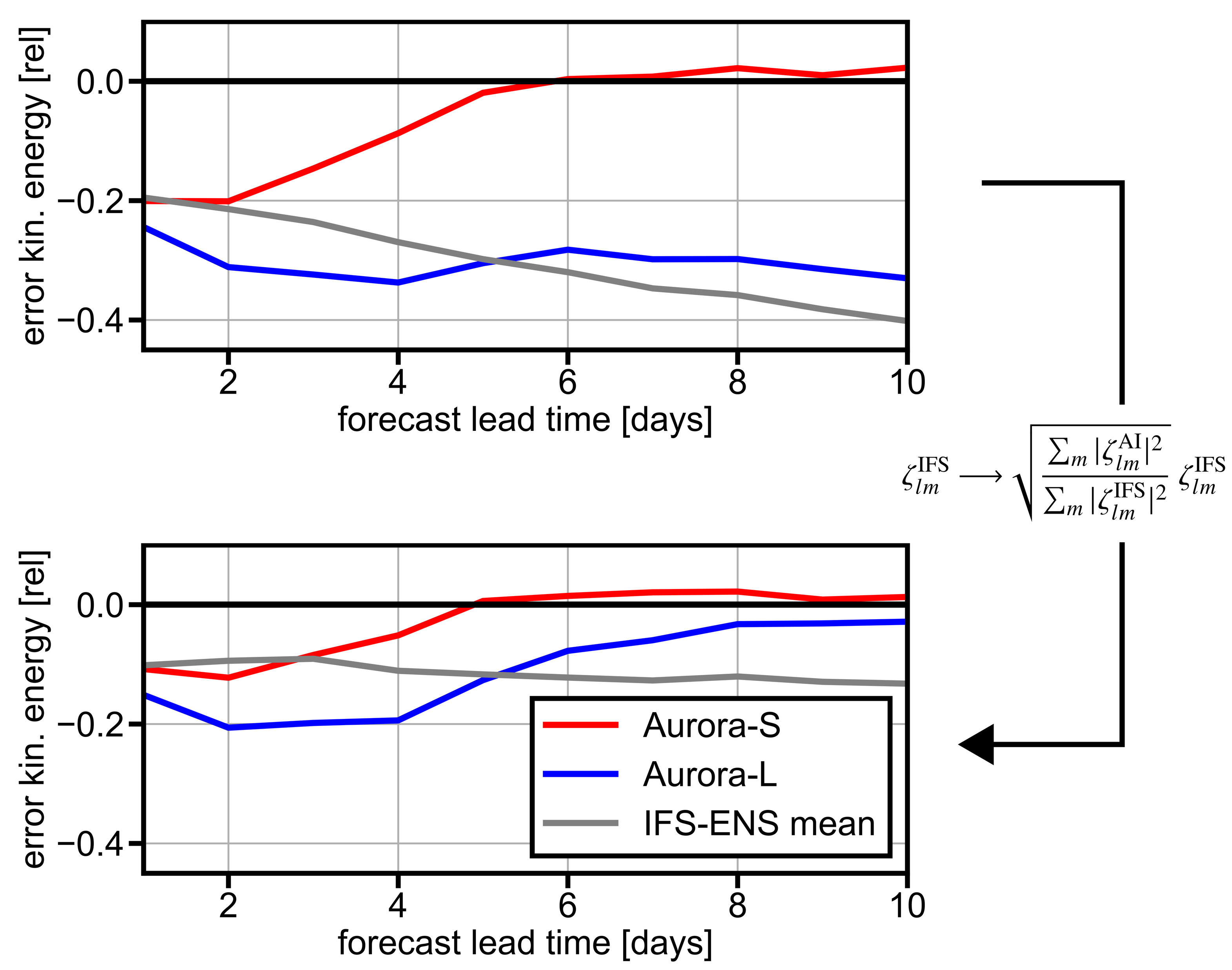
Error kinetic energy spectra

10-day forecasts, 300 hPa



Fairer comparison to IFS-CTL

Make IFS-CTL as smooth as the AI model



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