

Can General Circulation Toy Models run with lossy-compressed states?

An investigation into **safely lossy-compressing model states**

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Brief Overview

Why compression, why compress model ~~outputs~~ **states**?

How do we compress and which **toy** models do we use?

What happens if we compress model **restart states**?

Lossy compression of model states is **safe** when ...

Why compress?

General Circulation Model data is growing rapidly
(CMIP6 $\times 10^3$ for km-resolution [11], larger ensembles, more experiments)

Data compression is vital

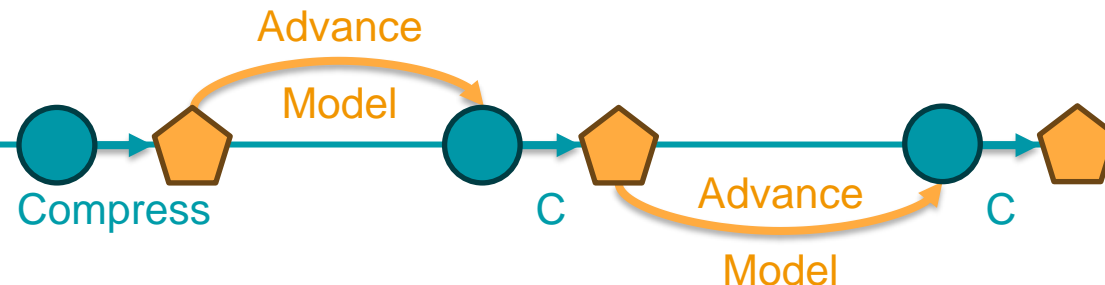
Promise of **lossy** compression using info loss
(higher compression ratio than lossless compression by discarding noise,
e.g. $\times 1.5-4$ (fpzip, lossless) vs $\times 100$ (ZFP, lossy) [5])

Why not compress model outputs?

Most research focuses on compressing **outputs**
(e.g. compressing output variables with different precisions [4, 10])

What level of compression is **safe**?
(differs per-variable & for visualization vs computing derivatives)

We instead compress model (restart) **states**

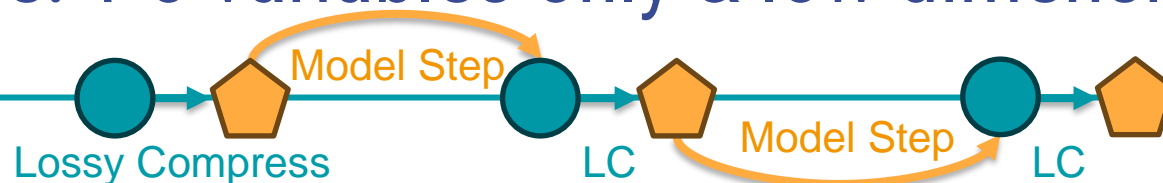


Why compress toy model states?

Restart files are a form of lossless compression
(rerunning the model reproduces all outputs)

Lossy-compress model states every n^{th} timestep
(extreme case: no cross-timestep compression; extends
ESiWACE3 hackathon with UH+NeSC [12] and builds on [3])

Examine the impact on dynamics in **toy models**
(extreme case: 1-3 variables only & low dimensionality and size)



Research Question

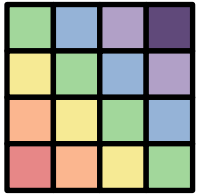
Can lossy compression be
safely applied to model states?
How are model dynamics impacted?

Compression Codecs



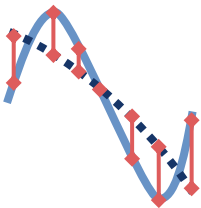
Stochastic Round: Per-element

Idealised codec with noise and round, compression is separate



ZFP: Transform-based [2, 8]

4^d blocks are normalised, bitplane-truncated, and compressed



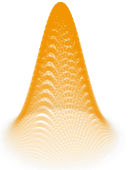
SZ3: Prediction-based [6, 7, 14]

Lorenzo predictor errors are quantized, encoded, and compressed

Toy Models

F64 Model run Bit Information [4]

99% BI: [60.0b | 26.8b] / 64b



Shallow Water Model (1D | 2D)

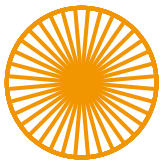
Homogeneous and incompressible shallow-depth fluid (h, u, v)



Lorenz'63 [1]

99% BI: 60.9b / 64b

Chaotic, simplified 3-scalar model of atmospheric convection



Lorenz'96 [13]

99% BI: 63.1b / 64b

Chaotic, K -sized 1-variable model with NWP-like error growth
Variants: original, with smaller scale, Wilks'05 [9] parameterisation

Hypotheses

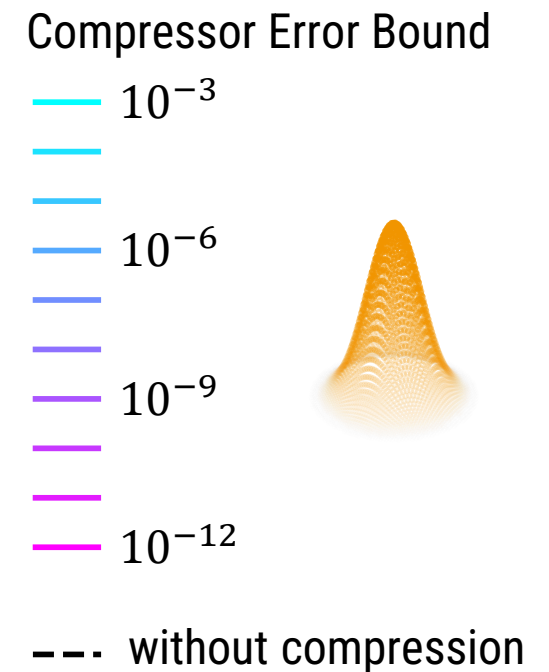
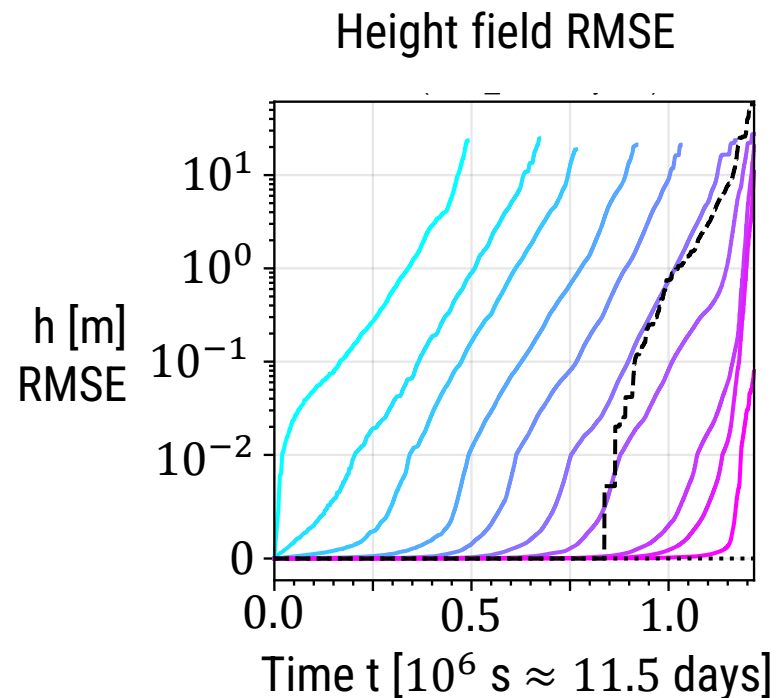
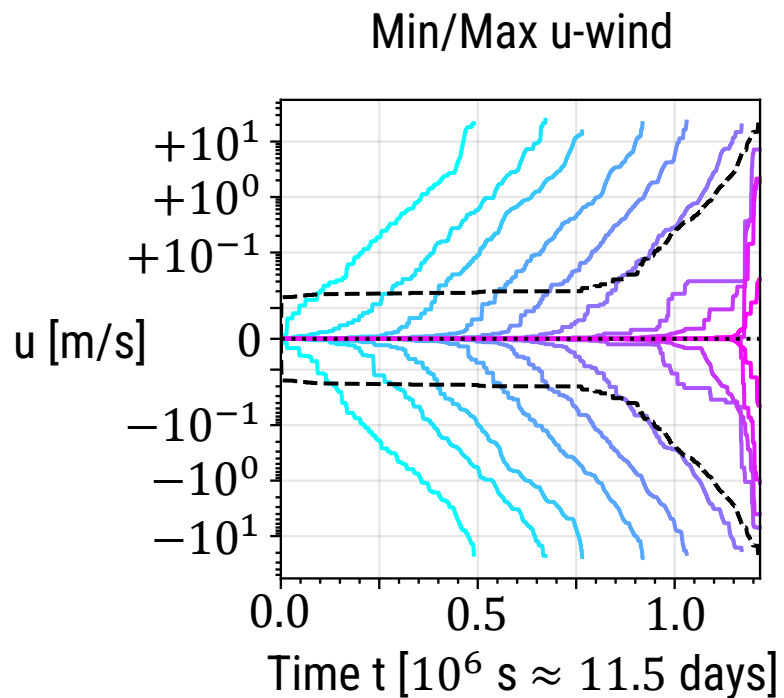
(H1) Lossy compression increases numerical instability

(H2) Higher-resolution & -dimension states compress more


(H3) Lossy-compression errors relate to perturbations

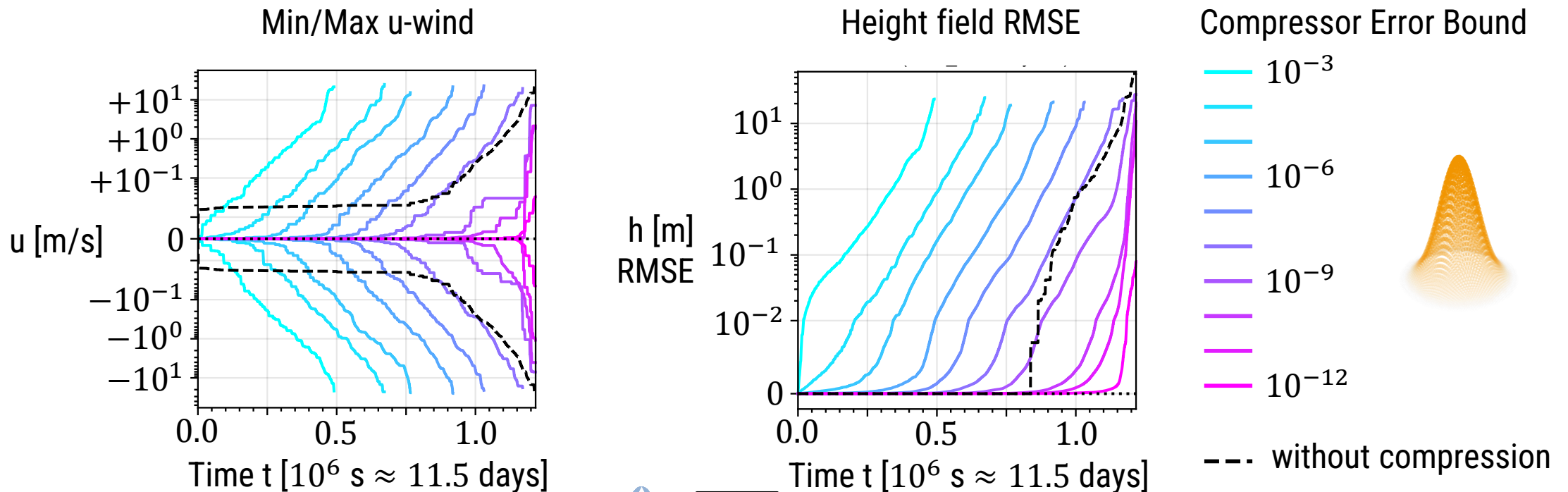
(H4) Stochastic ensembles may be lossy-compressed safely

(H1): Decrease in Numerical Stability



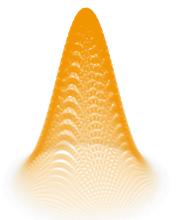
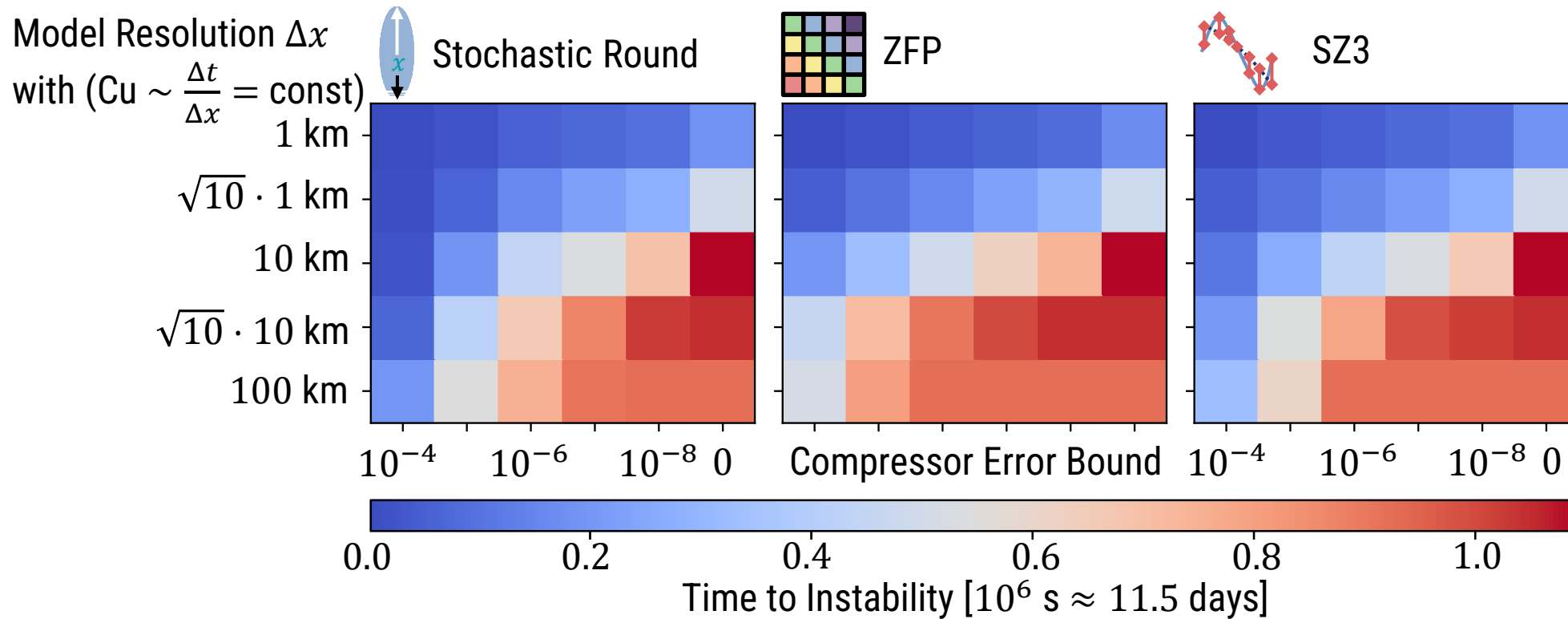
(H1): Decrease in Numerical Stability

Lossier compression makes the 1D  unstable earlier, compensating with lower loss is only possible while the original model is stable

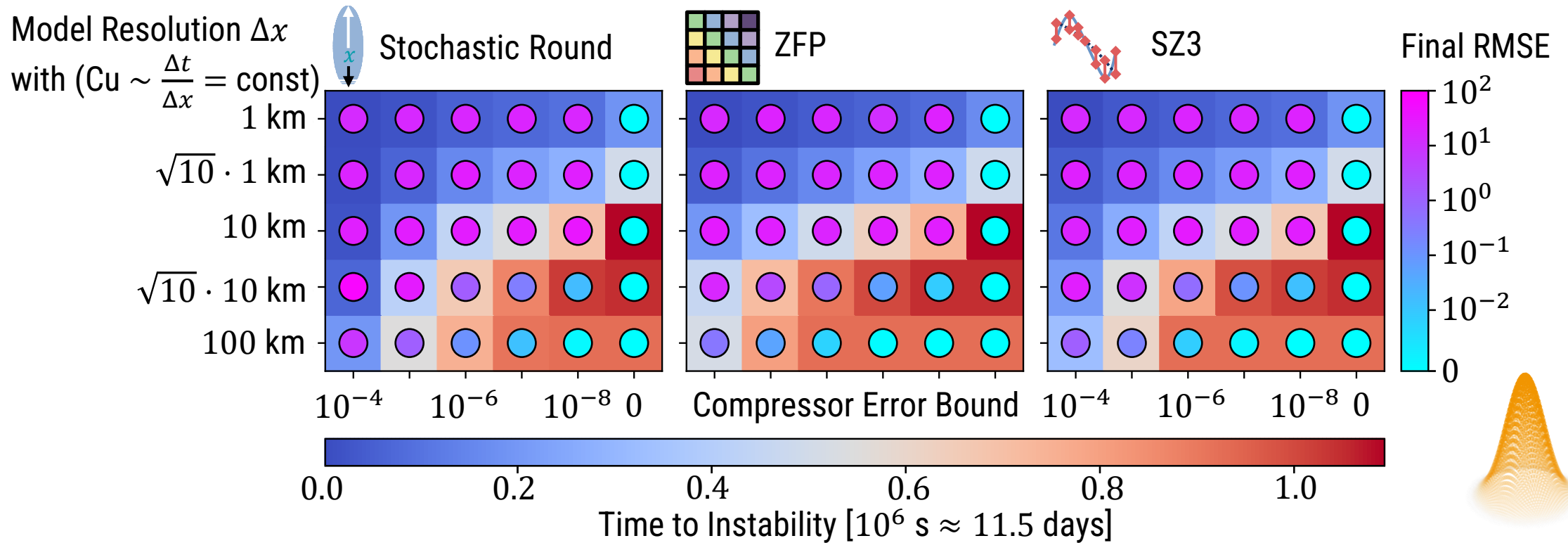


Equivalent results for , , and  and 1D and 2D ,
 Higher-order time extrapolation helps but does not lessen the loss impact

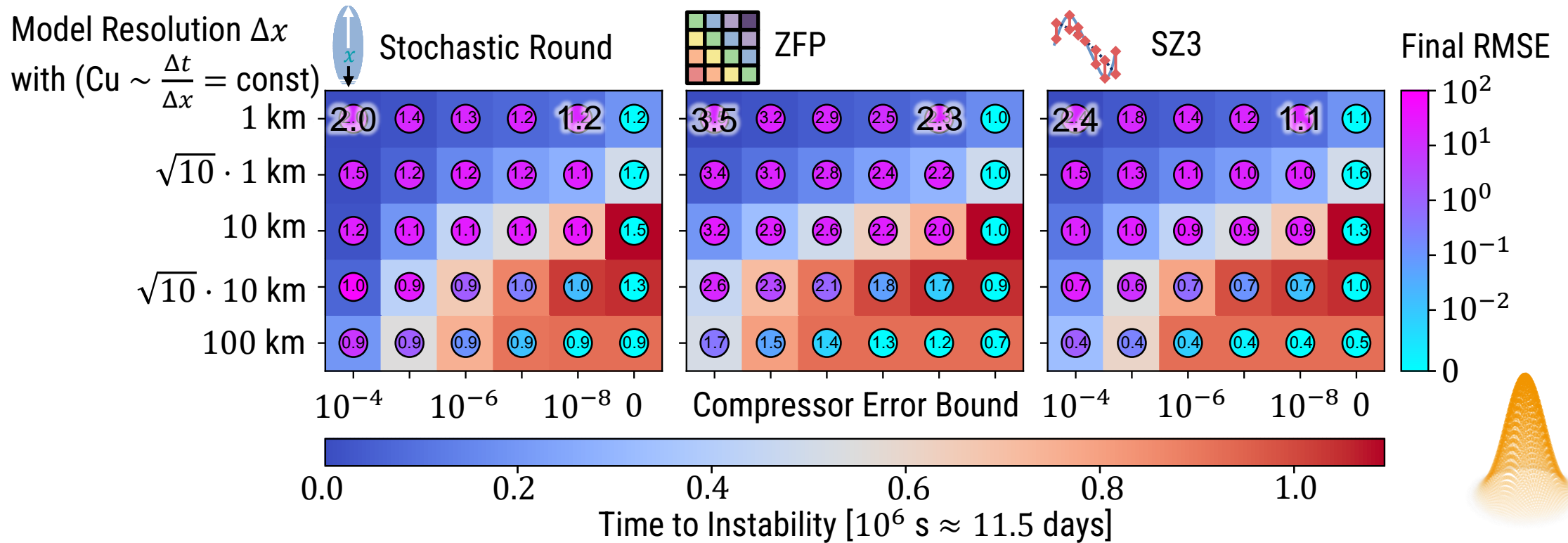
(H2): Low compression ratios



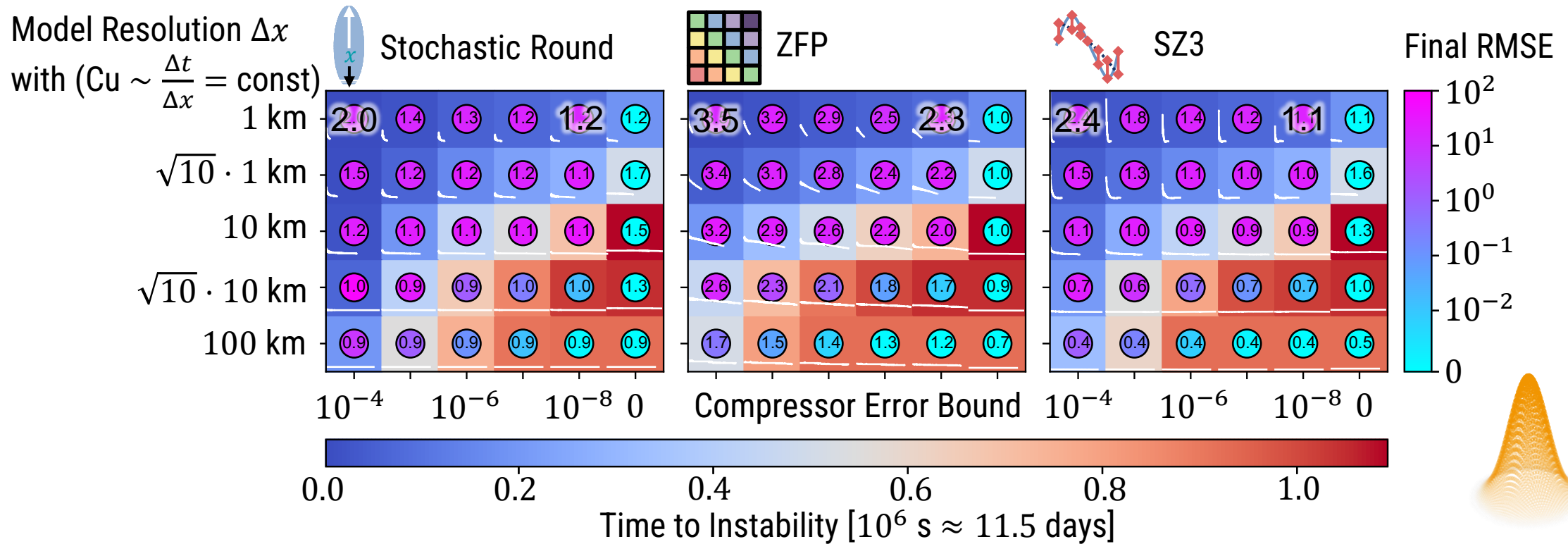
(H2): Low compression ratios



(H2): Low compression ratios

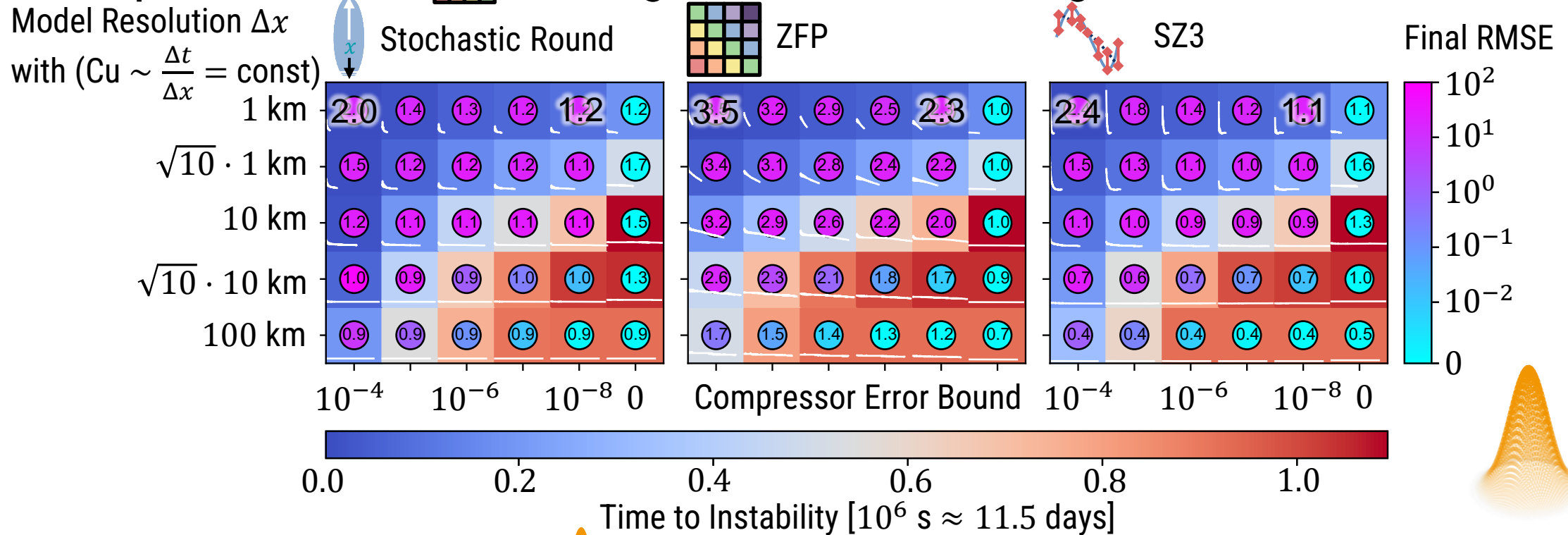



(H2): Low compression ratios



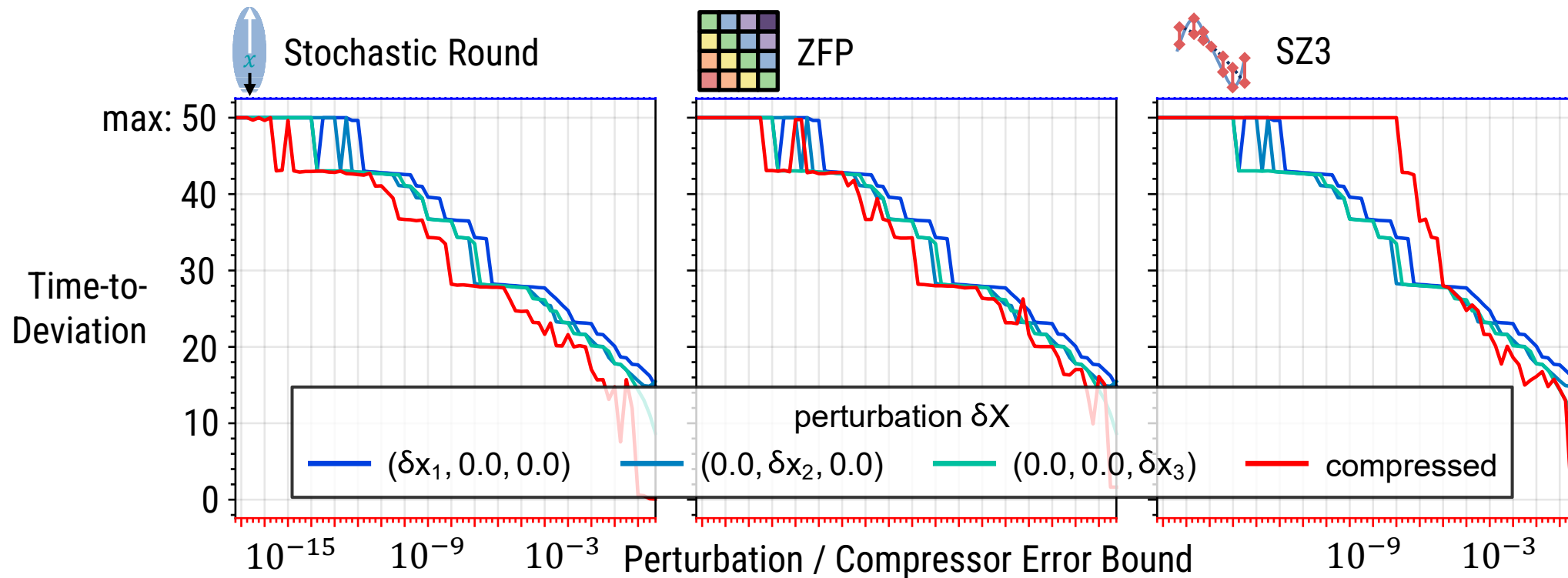
(H2): Low compression ratios

Higher loss and high resolution make the 1D  unstable earlier, best compression with  and high resolution and high loss and stable model




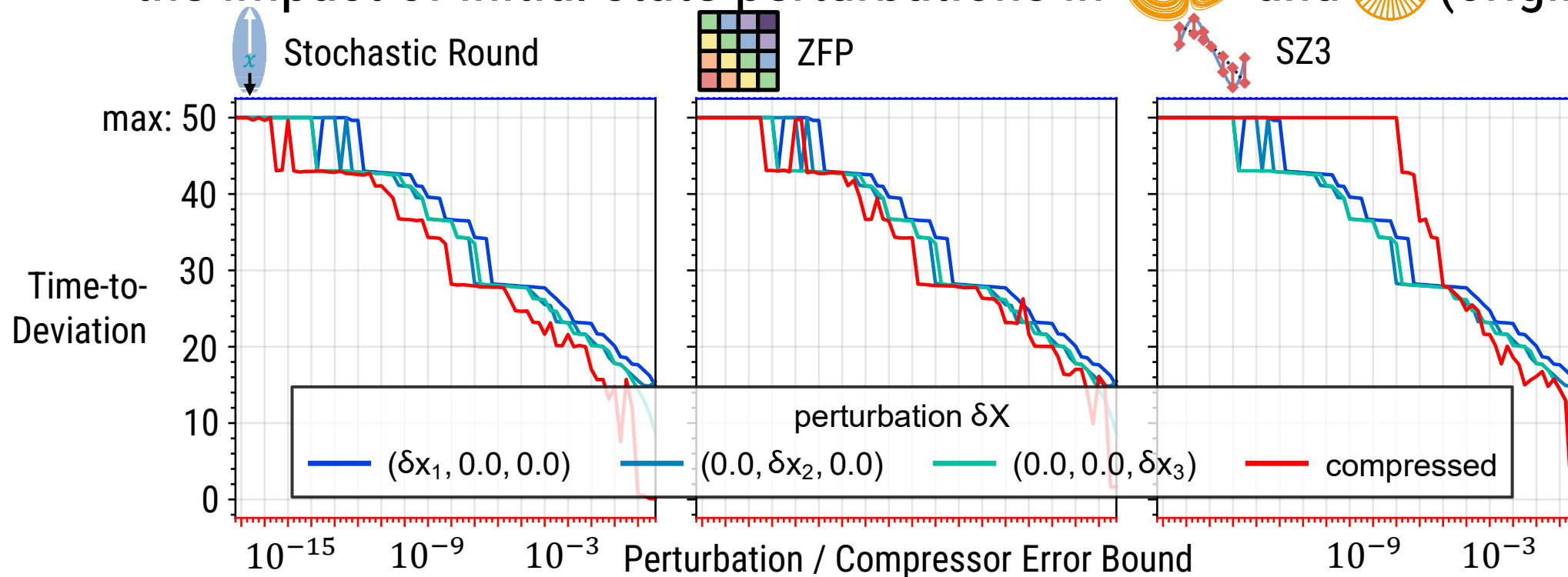
Compressing 2D  roughly doubles the compression ratio
 Compressing state variables (h, u, [v]) together only has marginal benefits

(H3): Analogy to initial perturbations



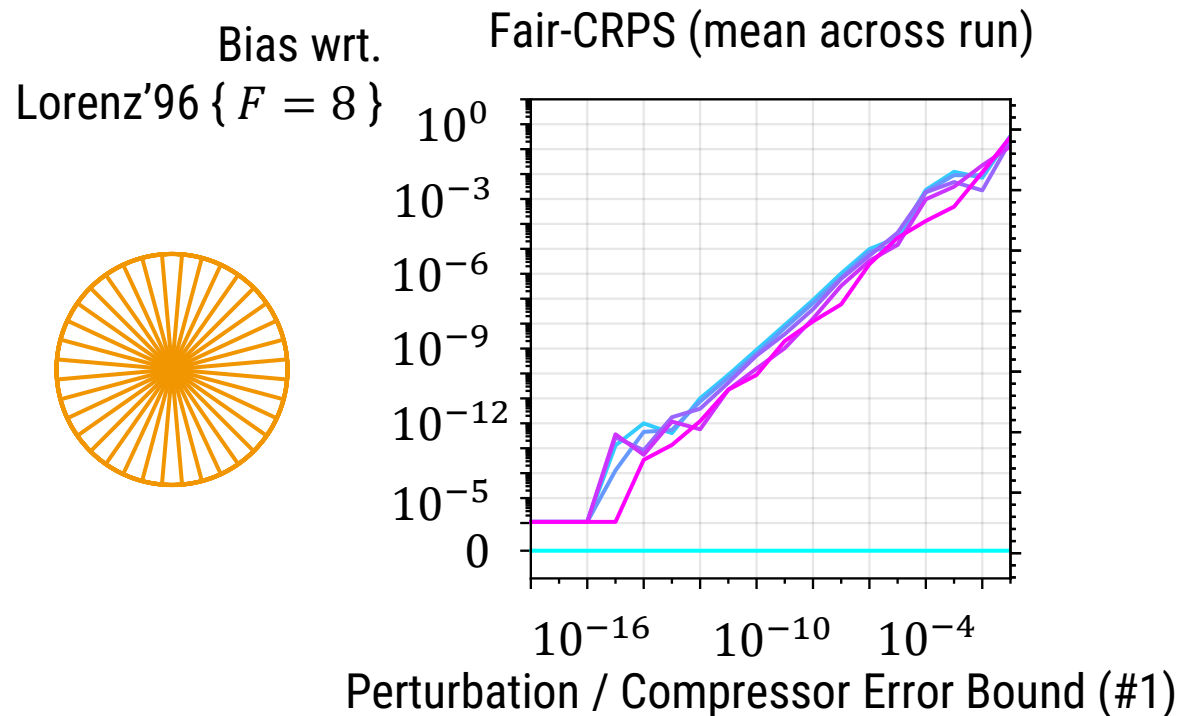
(H3): Analogy to initial perturbations

The impact of lossy compression on time-to-deviation linearly relates to the impact of initial state perturbations in  and  (original)



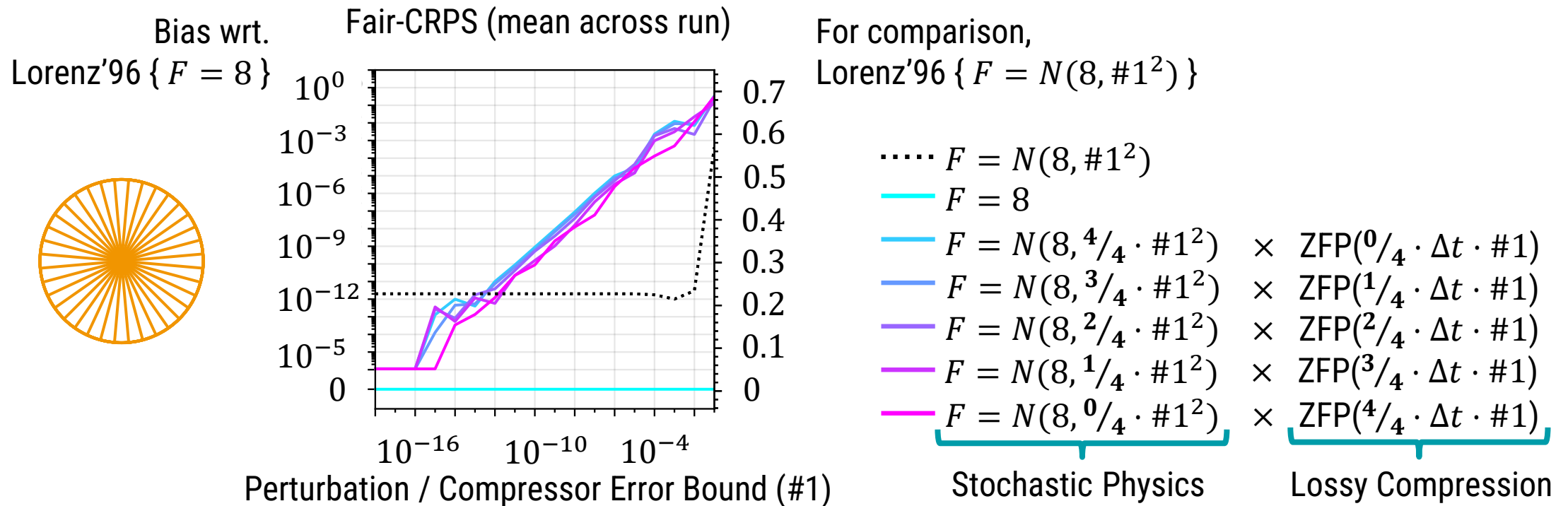
Difference is larger for smaller Δt and smaller for more chaotic origins
 Also, high-loss compression increases sensitivity to initial perturbations

(H3+H4): Replacing model perturbations with compression



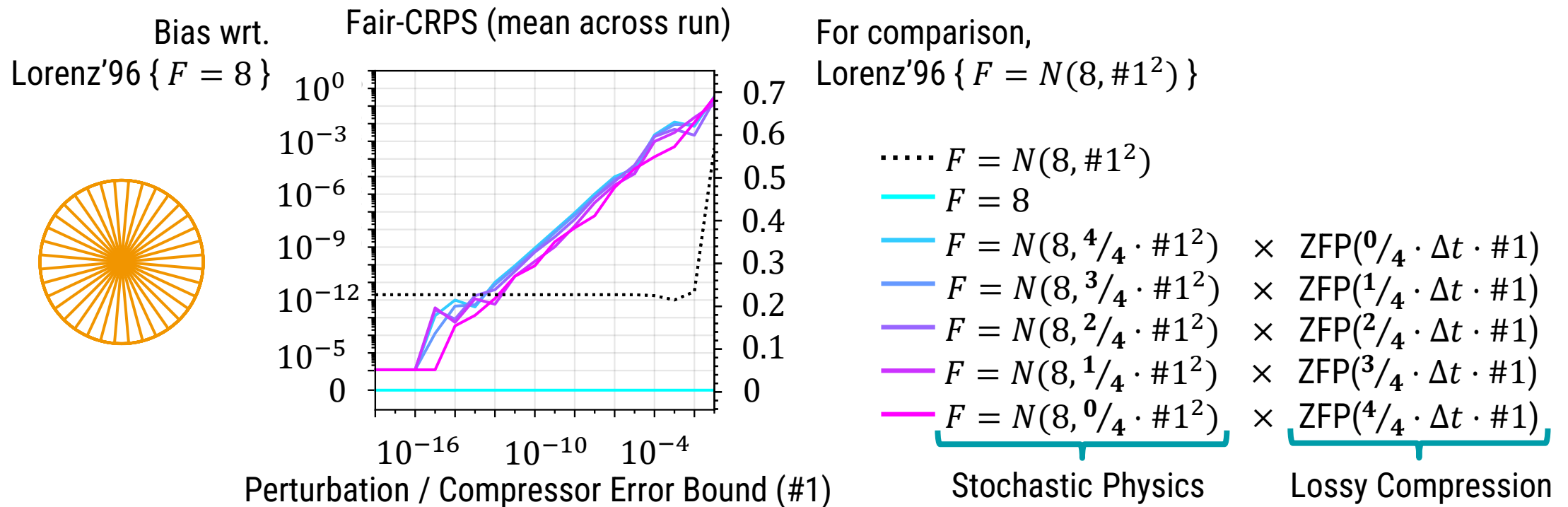
$F = 8$	
$F = N(8, 4/4 \cdot \#1^2)$	$\times \text{ZFP}(0/4 \cdot \Delta t \cdot \#1)$
$F = N(8, 3/4 \cdot \#1^2)$	$\times \text{ZFP}(1/4 \cdot \Delta t \cdot \#1)$
$F = N(8, 2/4 \cdot \#1^2)$	$\times \text{ZFP}(2/4 \cdot \Delta t \cdot \#1)$
$F = N(8, 1/4 \cdot \#1^2)$	$\times \text{ZFP}(3/4 \cdot \Delta t \cdot \#1)$
$F = N(8, 0/4 \cdot \#1^2)$	$\times \text{ZFP}(4/4 \cdot \Delta t \cdot \#1)$
<u>Stochastic Physics</u>	<u>Lossy Compression</u>

(H3+H4): Replacing model perturbations with compression



(H3+H4): Replacing model perturbations with compression

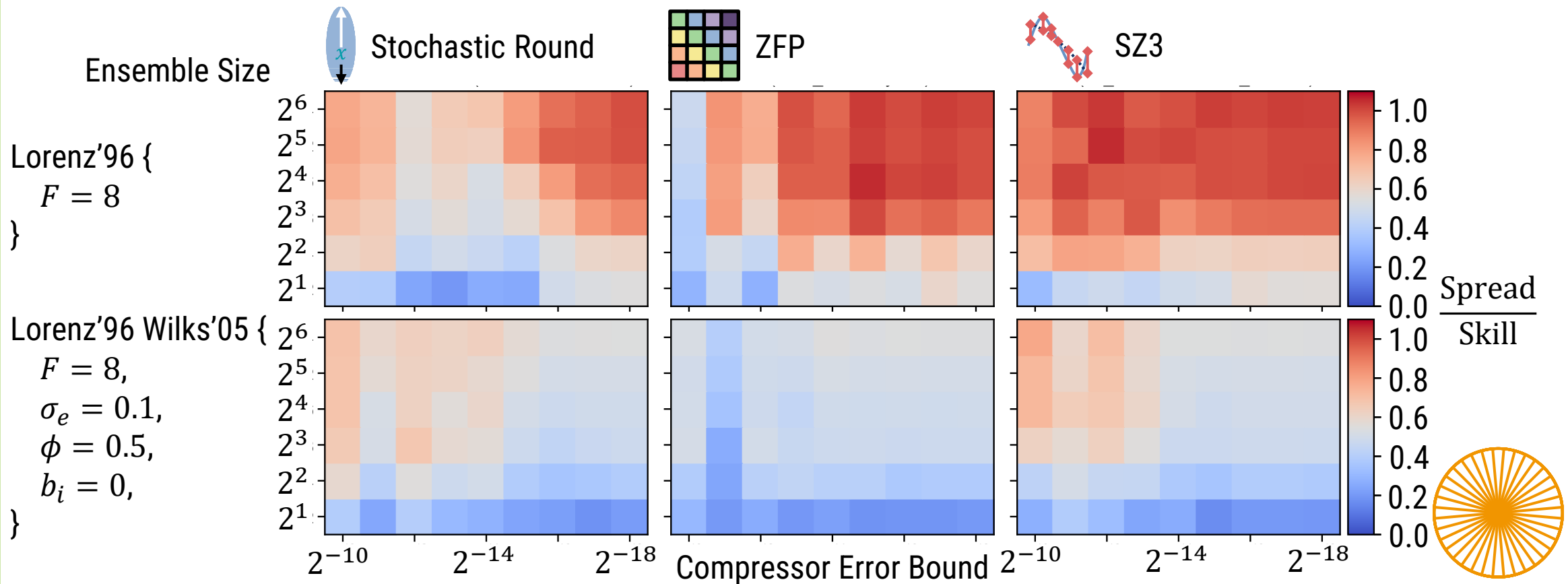
Substituting stochastic physics in a  ensemble with lossy compression has equivalent fair-CRPS / RMSE / Skill-Spread performance with 



Equivalent results for  (slightly worse) and  (slightly better).

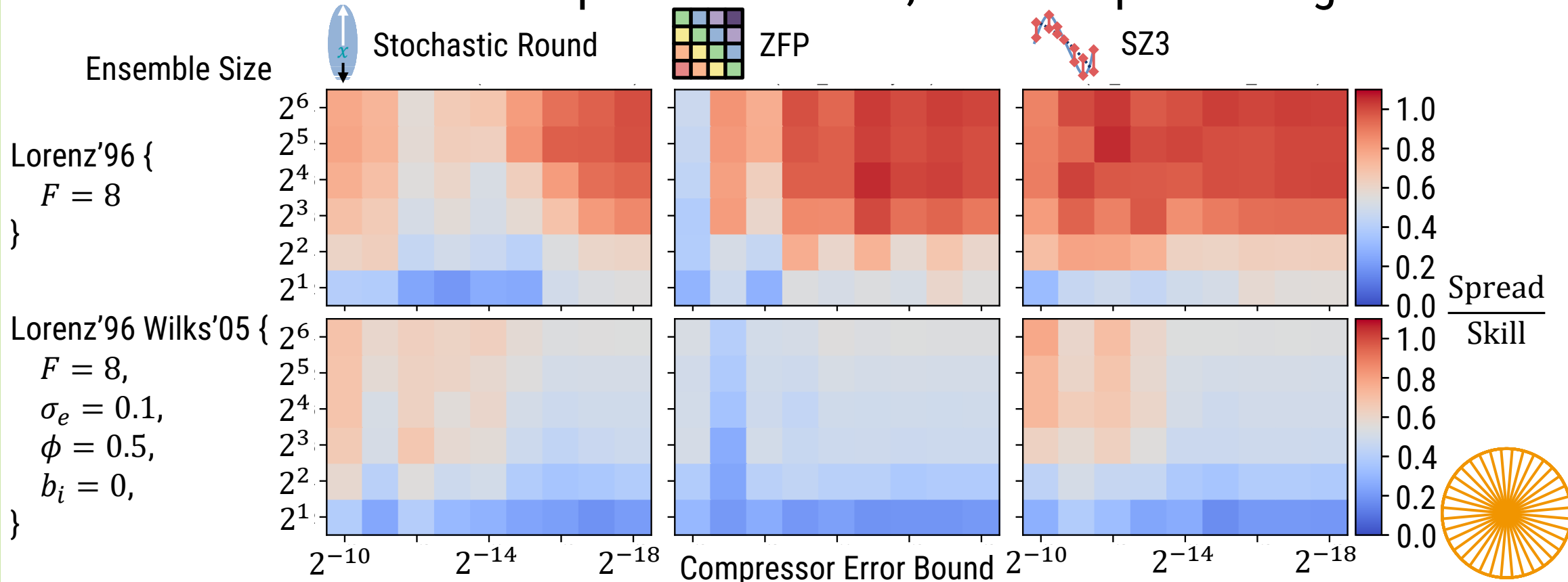
Adding lossy compression to stochastic physics increases stochasticity.

(H4) Little help from larger ensembles



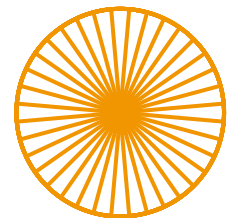
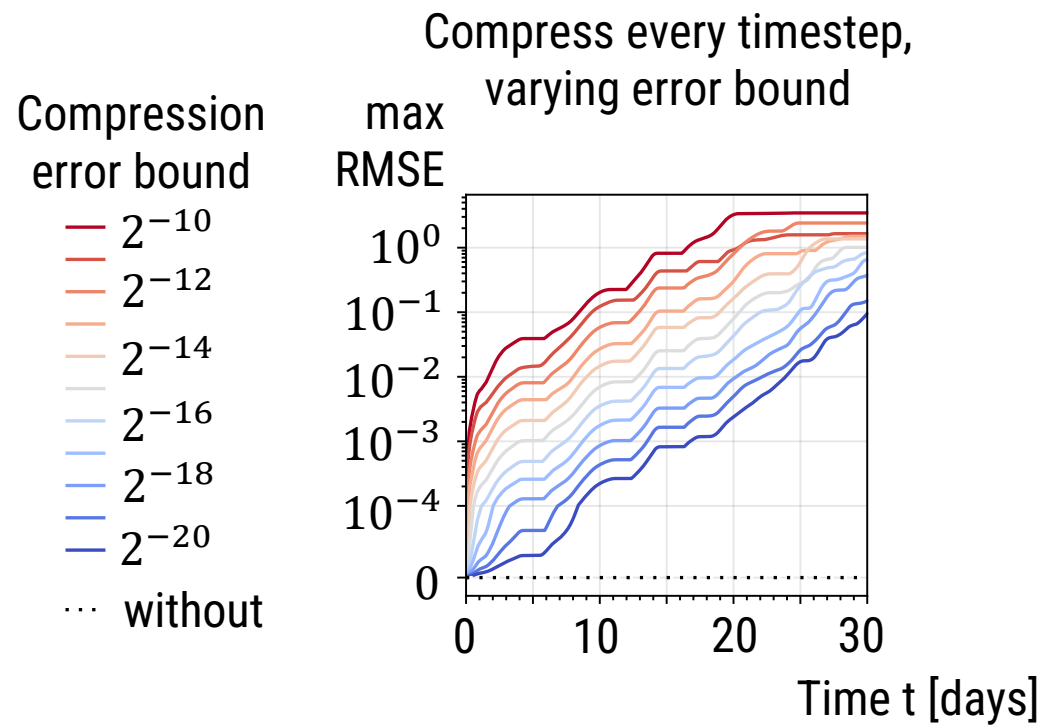
(H4) Little help from larger ensembles

Larger ensembles can minimally compensate spread/skill from higher loss
 Deterministic ensemble prefers low loss, Wilks'05 prefers higher loss

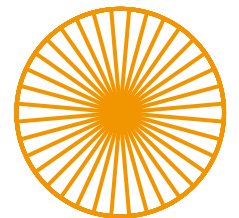
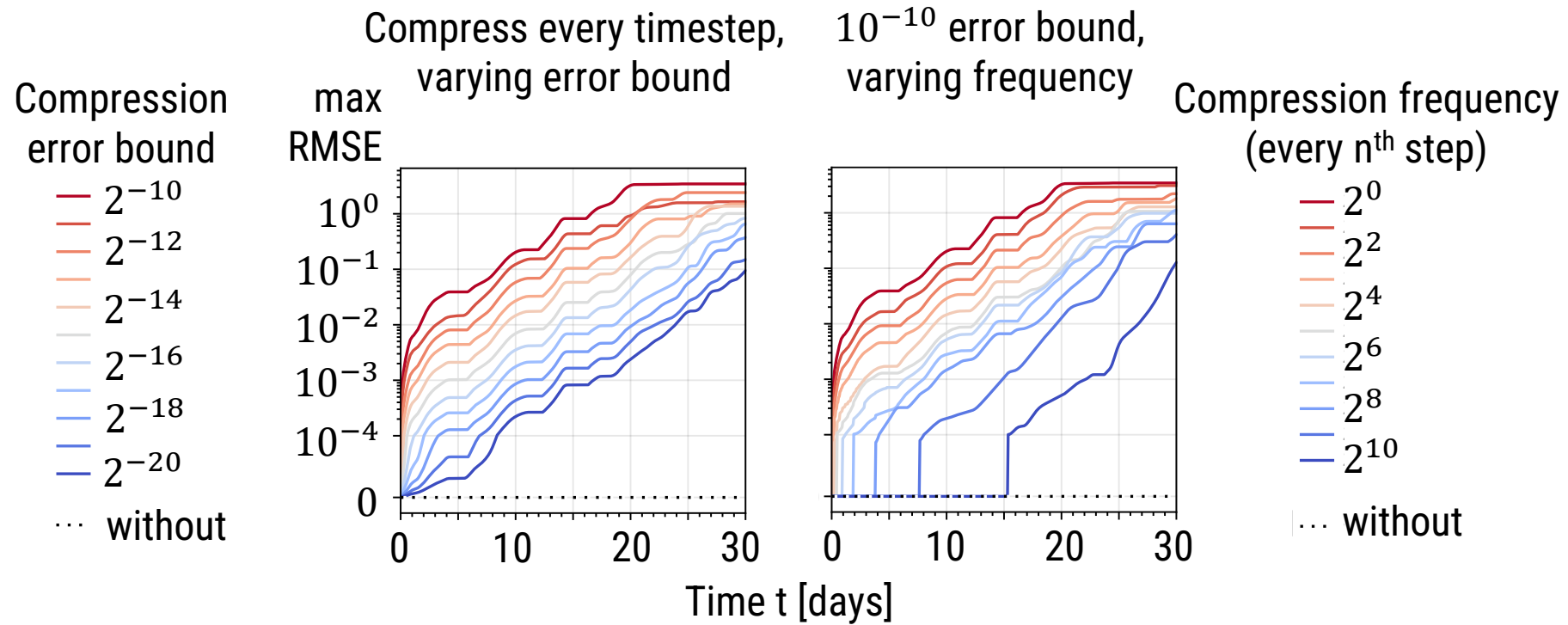


Larger ensembles cannot compensate fair-CRPS & RMSE from higher loss




Caution on compression frequencies

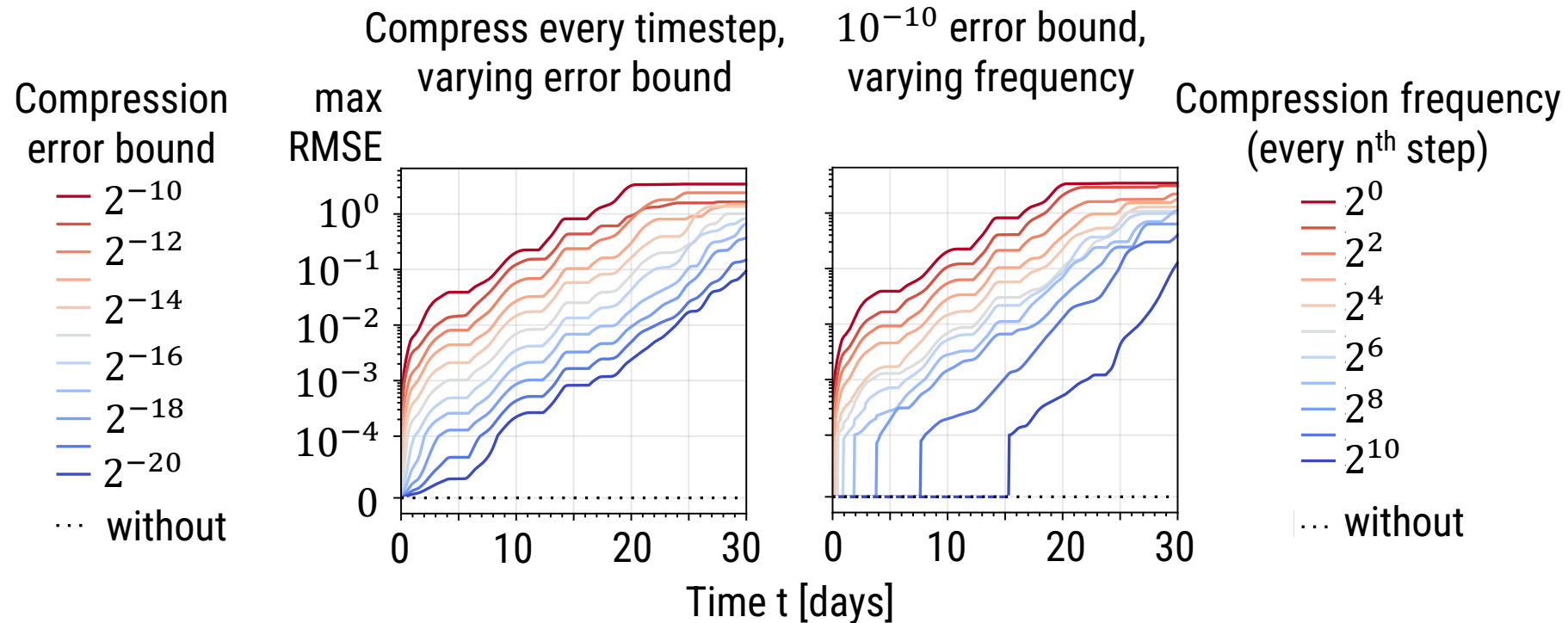


Caution on compression frequencies

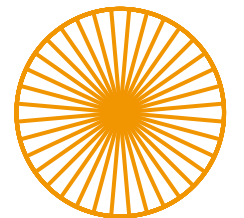


Caution on compression frequencies




Compression Level & Frequency have very similar impacts on RMSE / ensemble spread / spread-skill / fair-CRPS growth in  and  with 

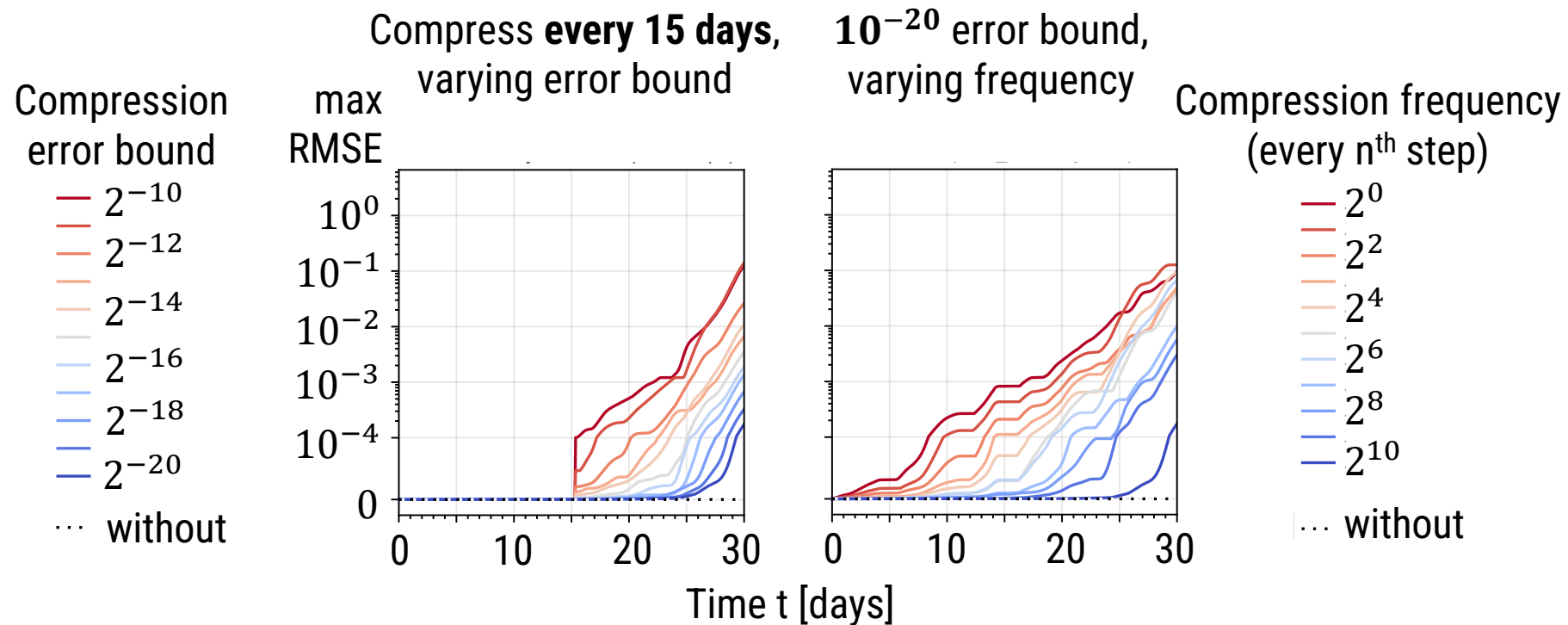


With , the error bound is slightly more important than frequency

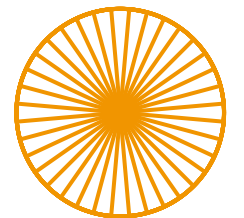


Caution on compression frequencies

Compression Level & Frequency have very similar impacts on RMSE / ensemble spread / spread-skill / fair-CRPS growth in  and  with 



With , the error bound is slightly more important than frequency



Conclusions

(H1) Low loss is needed to retain numerical stability

(H2) Per-variable, per-timestep compression is insufficient

(H3) Lossy-compression relates to (initial) model perturbations

(H4) Larger ensembles / infrequent restarts cannot hide loss

Lossy compression of model (restart) states can
be safe **iff** the compression error replaces
stochastic initial state / model perturbations



Thank you!

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