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Control Simulation Experiments with the Lorenz-96 Model

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Outline

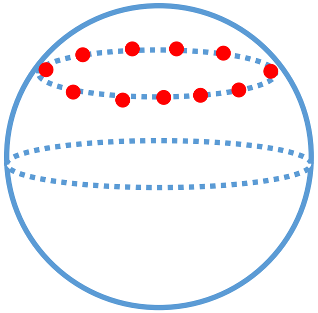
- Lorenz-96 model
- Extreme events
- Control Simulation Experiments
- Full control
- Partial control
- Partial observations
- Summary

Lorenz-96 Model

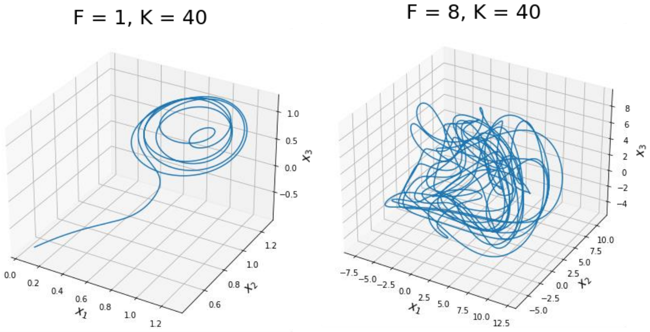
- A dynamical system defined by

$$\frac{dx_k}{dt} = (x_{k+1} - x_{k-2})x_{k-1} - x_k + F$$

where $k = 1, \cdots, K$, and $x_{k-K} = x_{k+K} = x_k, K > 3$[1].

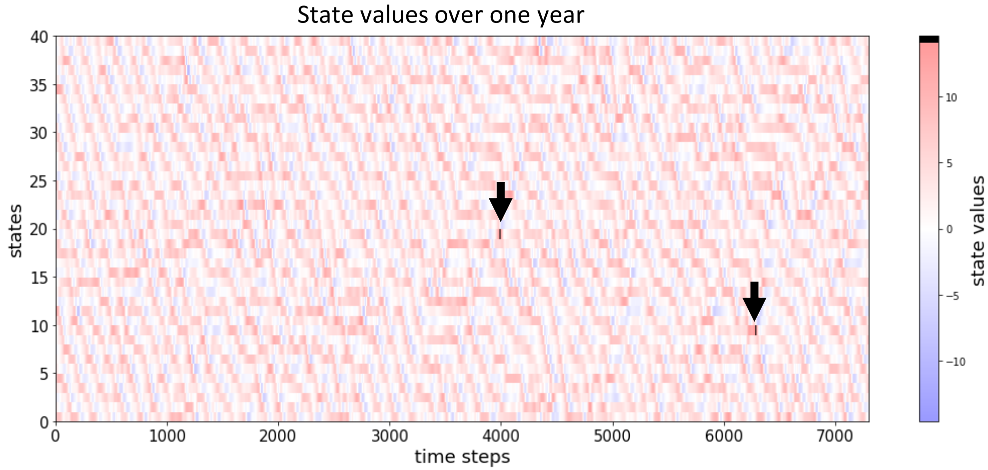


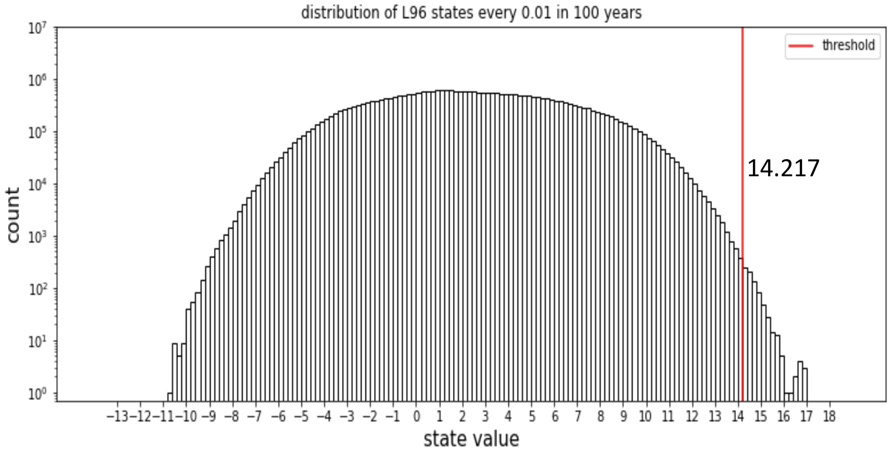
- x_k: values of some atmospheric quantity in K sectors of a latitude circle.
- F and the linear terms simulate the external forcing and internal dissipation.
- Quadratic terms simulate the advection.
- **1 time unit = 5 days** of atmospheric time.
- For the following experiments: $F = 8,\ K = 40$.



CSE - extreme events

- Aim: to avoid extreme values.
- Integrate L96 over 110 years, keep the record of every dt=0.01 for the last 100 years. Record the maximum value over each 6h period.

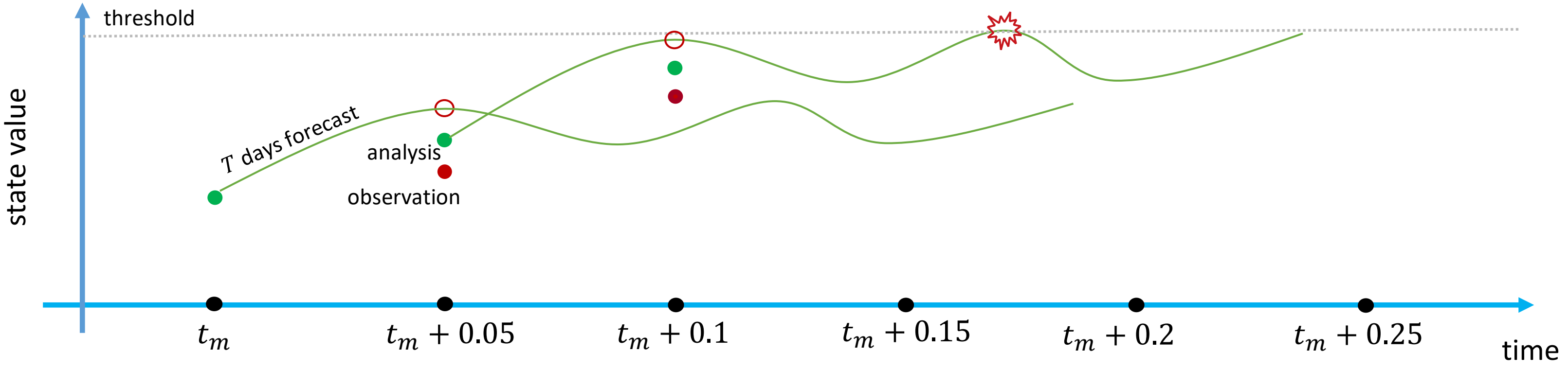


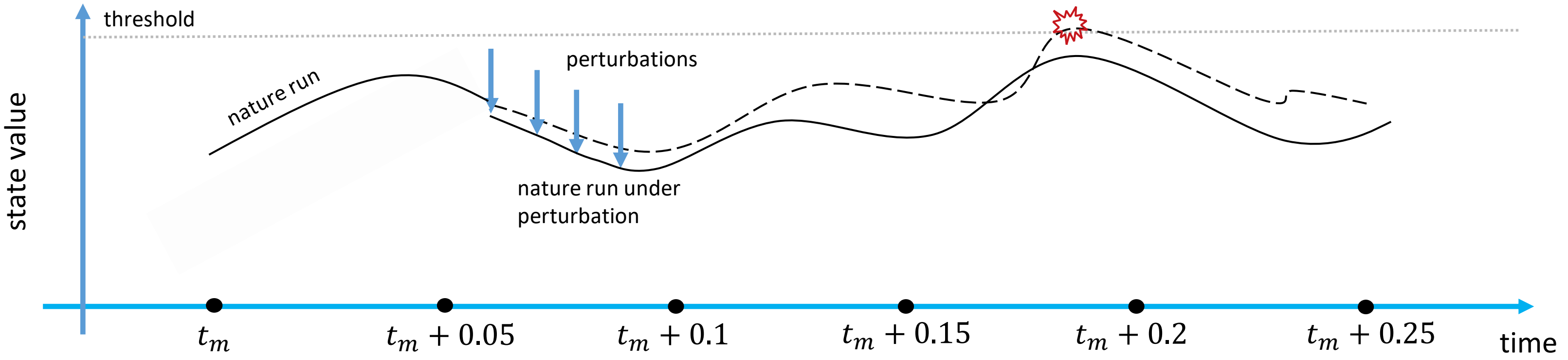


- The first 200 maximum values are extreme values (on average 2 times / year), the threshold for extreme events is 14.217.

CSE - procedure

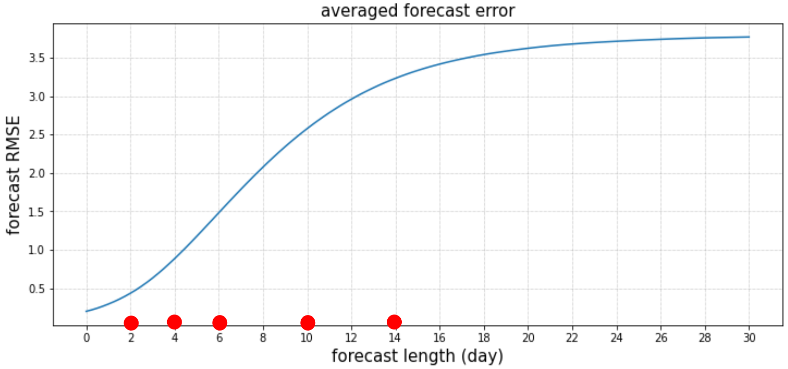
- The observations are noised (nature run + Normal(0, 1)).

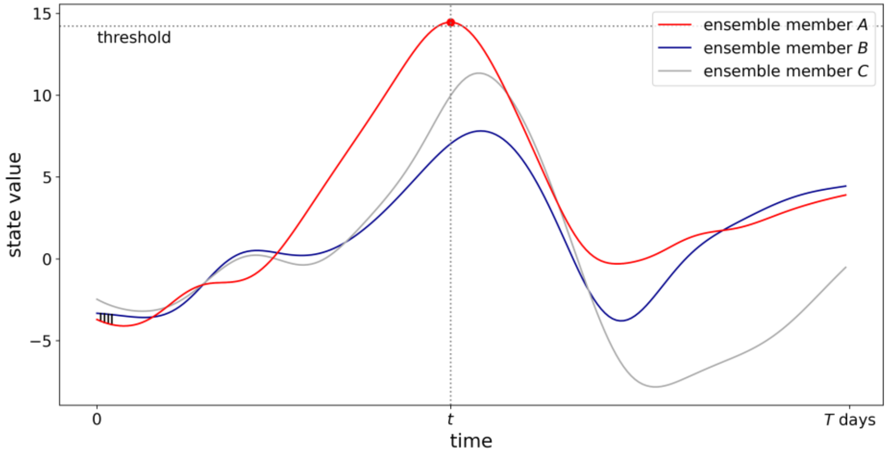




CSE - LETKF

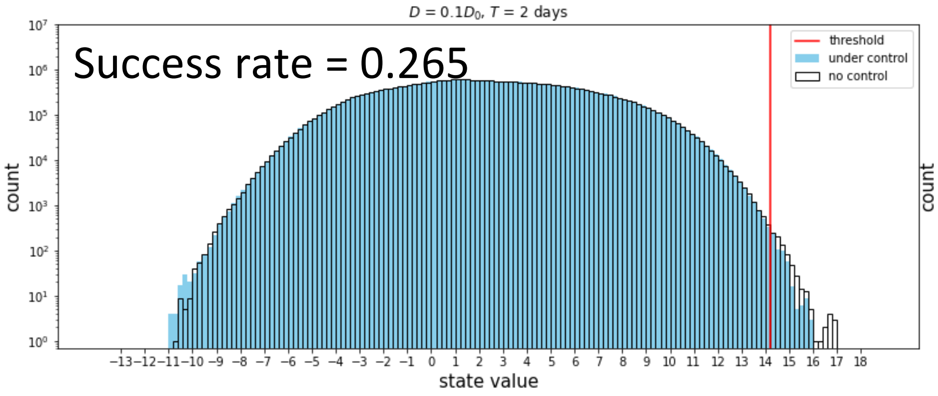
- We use LETKF with 10 ensemble members, $\rho = 1.06$, R-Localization (cut-off radius $2\sqrt{\frac{10}{3}} \times 5.45$) : analysis RMSE$\approx 0.19890 \ldots$
- Forecast length T.

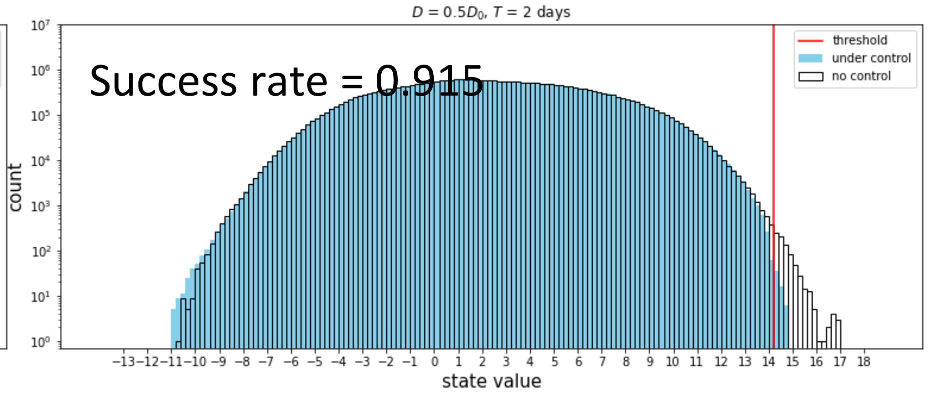


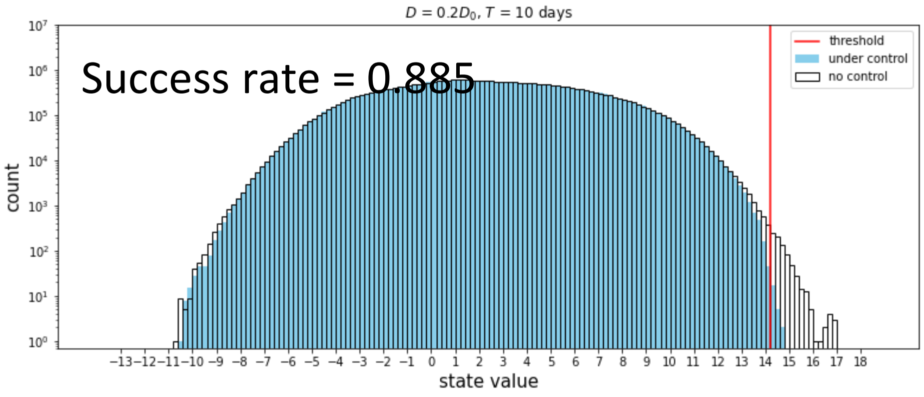


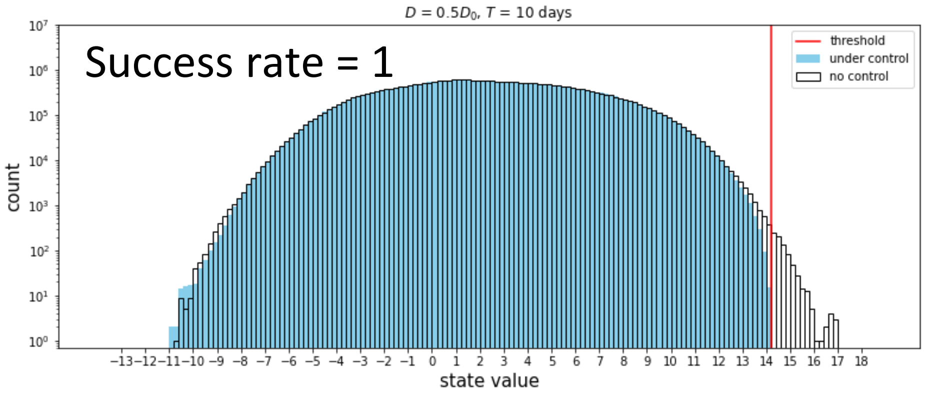
- Perturbation vector: the difference between two proper ensemble members at appropriate time points rescaled to a fixed norm.
- Norm of perturbation vectors : $D = \alpha D_0$ where D_0 is equal to the analysis RMSE.

Full control: results for 100 years





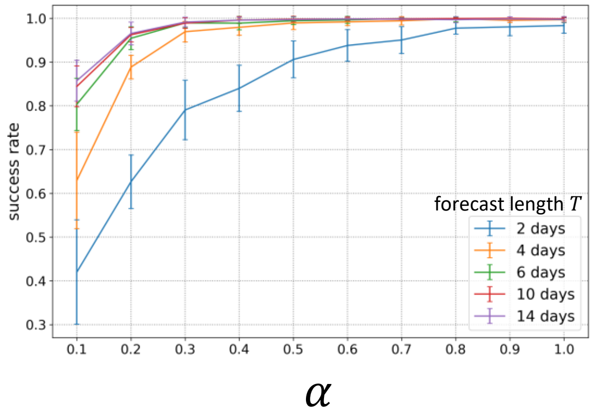




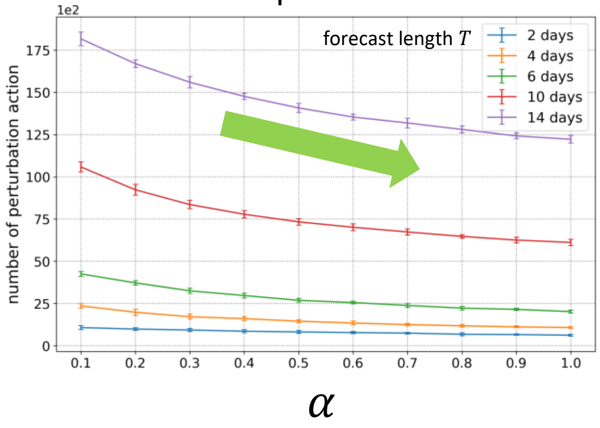
Success rate := 1- (#extreme events in 100 years) / 200

Full control – efficiency and perturbation energy

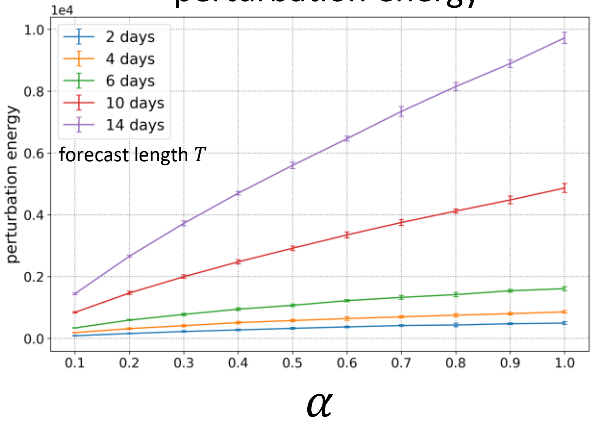
success rate



number of perturbation action



perturbation energy

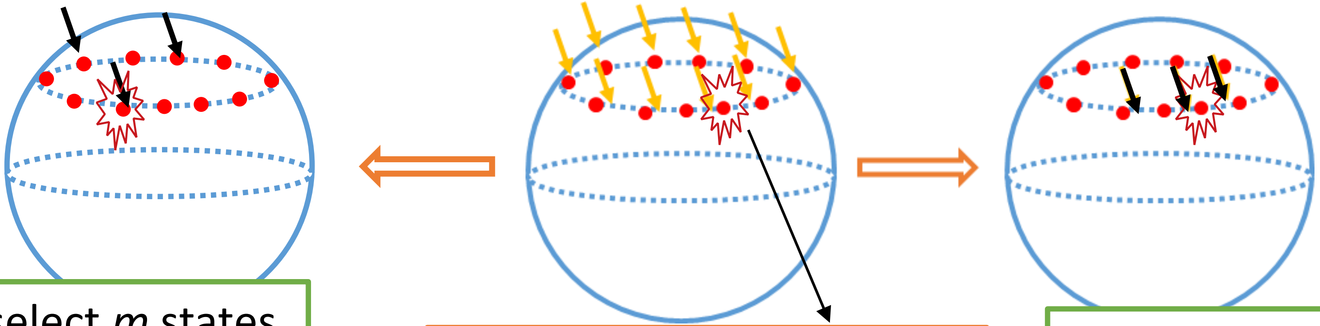


- norm of perturbation vectors $D = \alpha D_0$, D_0 = analysis RMSE

$$\text{perturbation energy} := 4\alpha D_0 \times \#(\text{perturbation actions})$$

- When the norm of perturbation vectors is small and the forecast length is short, the perturbation vectors are less efficient in terms of avoiding extreme events.
- In contrast, big norm and longer forecast require more energy of perturbations.

Partial control

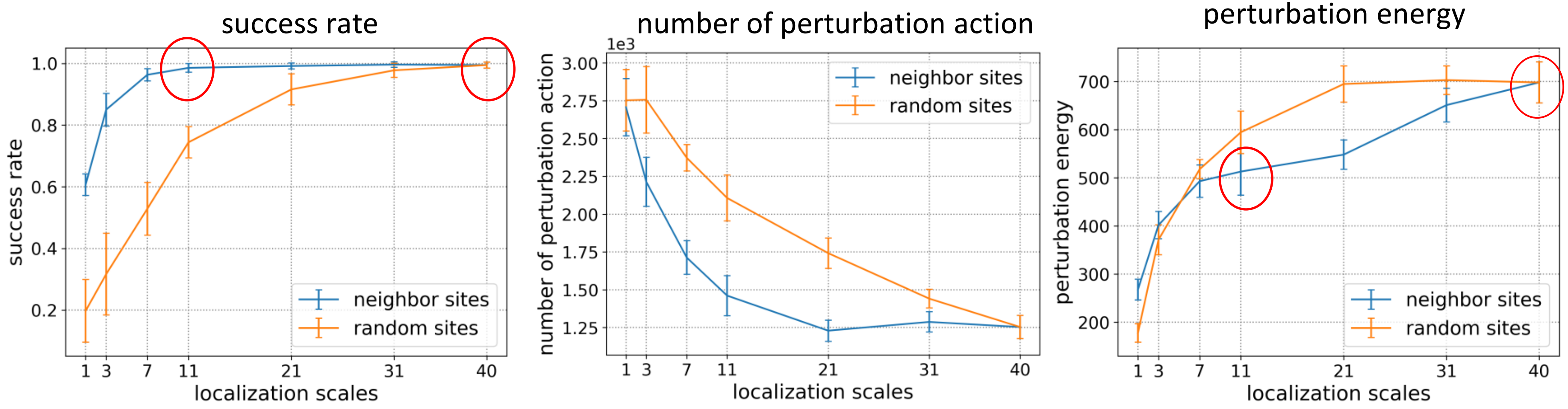


Randomly select *m* states.
Perturb these states when necessary.

State shows the most extreme value in forecast

Perturb the corresponding state (and its neighbors)

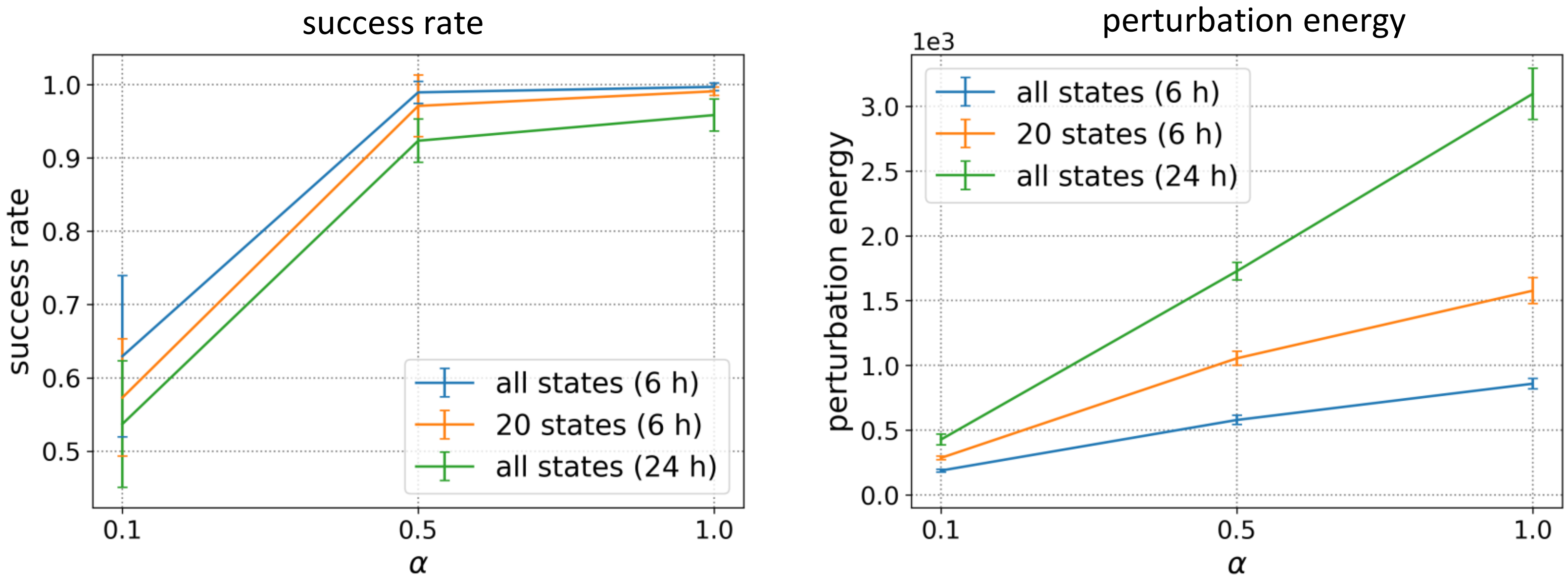
Partial control (forecast length $T = 4$ days, $\alpha = 0.7$)



- Perturb random positions generates more actions and cost more energy.
- Perturb random positions is less efficient.

Partial observations (forecast length $T = 4$ days, $\alpha = 0.7$)

- Observe 20 states in every 6 hours.
- Observe all states in every 24 hours.



- Partial observations are less efficient compared with observing all states in every 6 hours.

Summary

- The CSE results show effective control to avoid extreme values.
- Less effective control with

  1) perturbations with small norm

  2) short forecast length

  3) fewer observations, less accurate analysis
- Partial perturbation around the extreme value locations is found effective.

References

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[6] Brian R. Hunt, Eric J. Kostelich, Istvan Szunyogh, Efficient data assimilation for spatiotemporal chaos: A local ensemble transform Kalman filter, Physica D: Nonlinear Phenomena, Volume 230, Issues 1–2, 2007, 112-126, ISSN 0167-2789, 2007.

Thank you for your attention!