Leading the dynamical system toward the prescribed regime by model predictive control coupled with data assimilation

Fumitoshi Kawasaki[1] and Shunji Kotsuki[2]

[1] Graduate School, Chiba U. [2] IAAR, Chiba U.

(fkawasaki@chiba-u.jp)

Link to our related paper

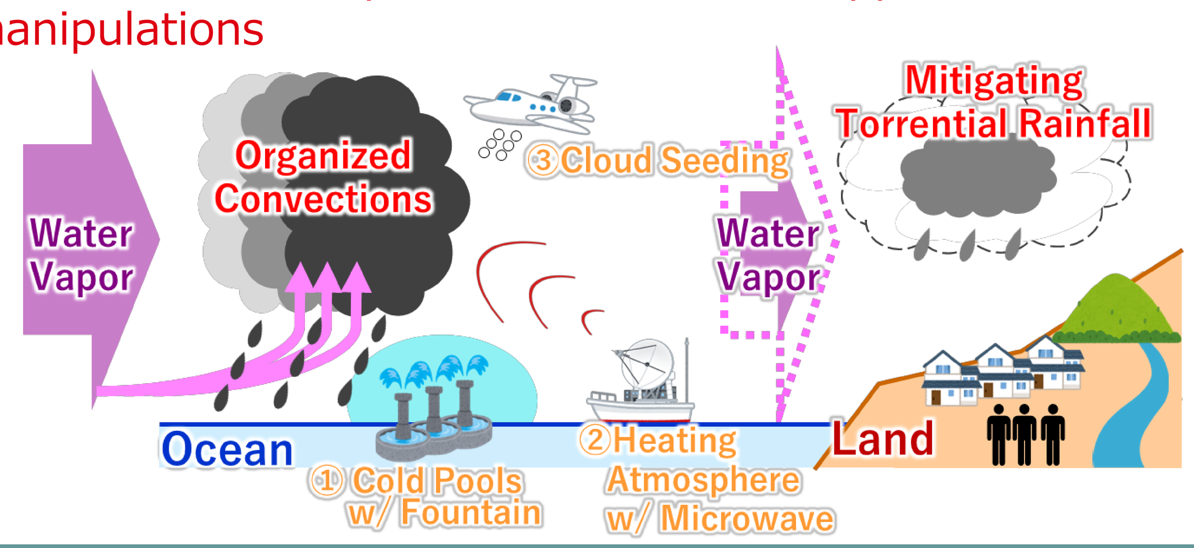
Overview

- To develop an efficient control approach for leading the atmosphere toward the desirable directions with feasible manipulations by ensemble Kalman filter and model predictive control
- Our experiments showed that the proposed method successfully mitigated extreme events with the Lorenz-96 model

Introduction

Background

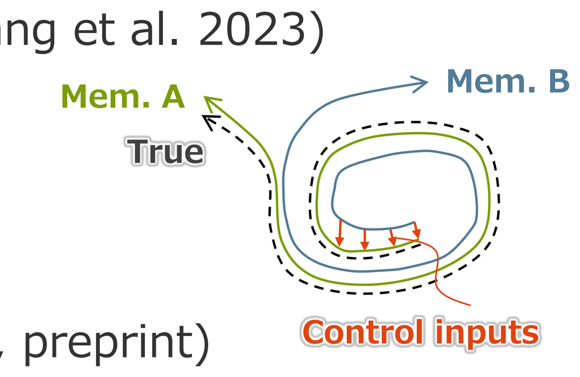
- Aiming to mitigate torrential rainfall on land by generating artificial rainfall over ocean using various engineering interventions
- However, possible magnitudes of control inputs are limited
- We need to develop an efficient control approach with feasible manipulations



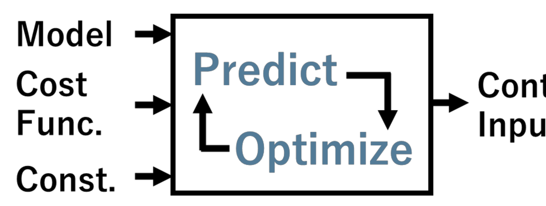
Previous studies

At present, there are two main streams in weather control approaches

1. **CSE studies**: (**Miyoshi and Sun, 2022**; Sun et al. 2023; Ouyang et al. 2023)
   - Proposing a Control Simulation Experiment, which is an experimental framework extended from OSSE
   - Successfully controlled the L63 & L96 w/ small control inputs
   - The method cannot consider constraints explicitly



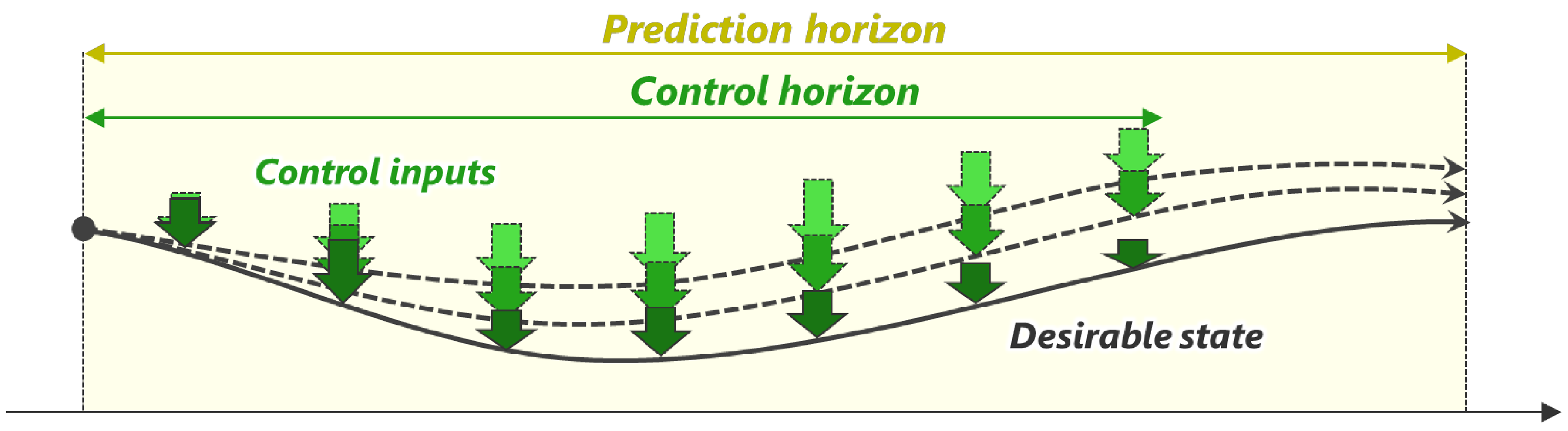
2. **Opt.-based studies**: (**Kawasaki and Kotsuki, 2024**; Sawada, preprint)
   - Introducing model predictive control (MPC) for the weather control method
   - Successfully controlled the L63 by considering constraints explicitly
   - The method requires huge computational costs
     → Difficult to apply to high-dimensional numerical weather prediction models



Method

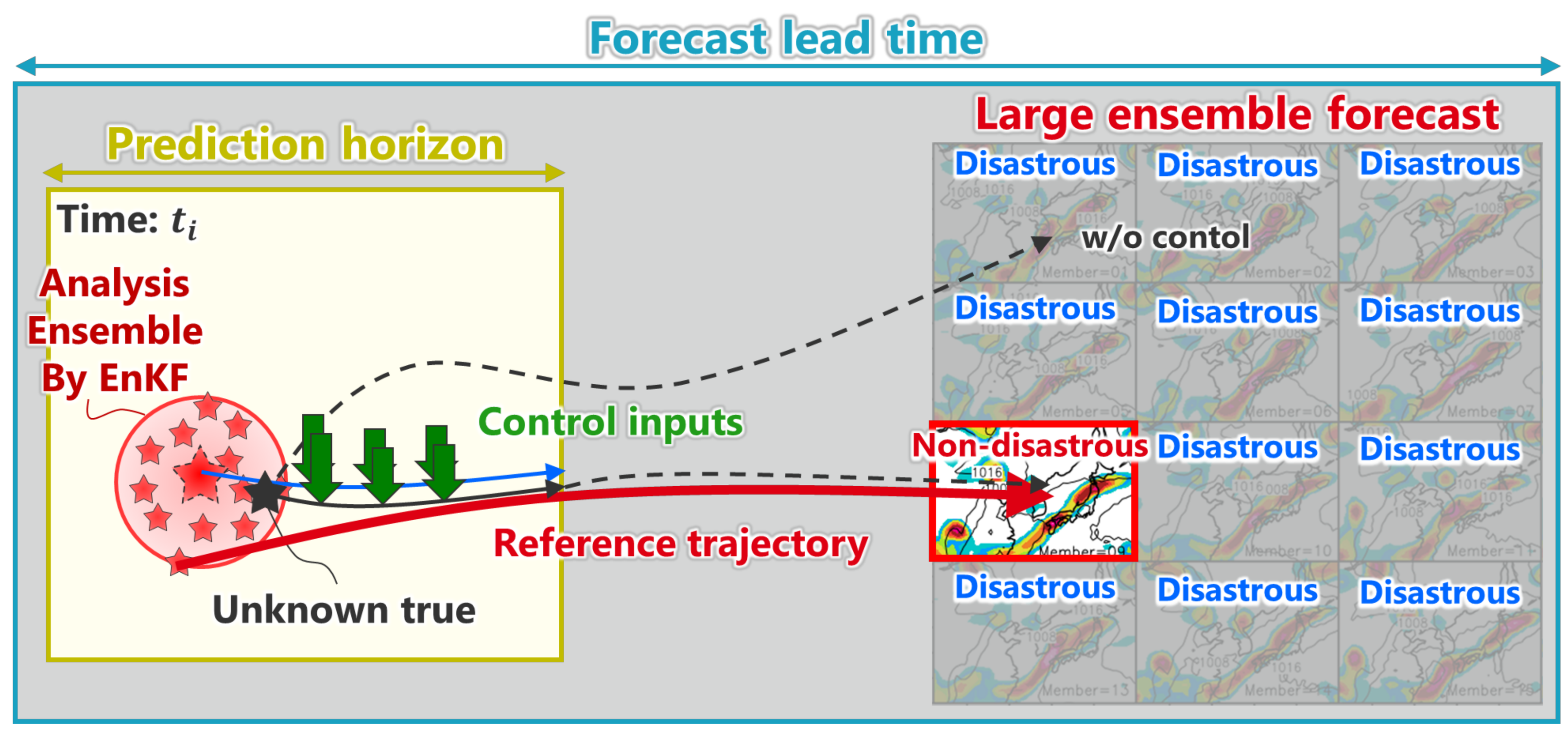
What's MPC?

- MPC is an advanced control method for identifying optimal control inputs based on model-based prediction and optimization theory
- MPC is a variational problem (i.e., MPC is similar to 4DVAR)
- MPC can perform control that explicitly considers control objectives and constraints based on a cost function
- Solving the Euler-Lagrange (EL) equation iteratively



The proposed method

- Introducing large ensemble forecast and forecast lead time
- Pursuing reference trajectories, not finding better trajectories
- Reducing cost function directly, not solving EL equation



Experiments and Results

Basic experimental setting

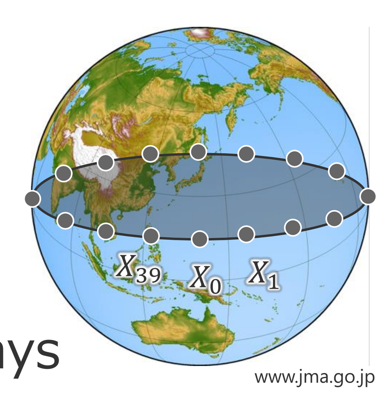
- Model: Lorenz-96 model (40 variables, $F = 8.0$)

$$\frac{dX_i}{dt} = (X_{i+1} - X_{i-2})X_{i-1} - X_i + F + u_i$$

- DA method: PO method
- Ensemble size: 200 mem.
- Prediction horizon T_p and Control horizon T_c: 2 days
- Forecast lead time T_f: 7 days

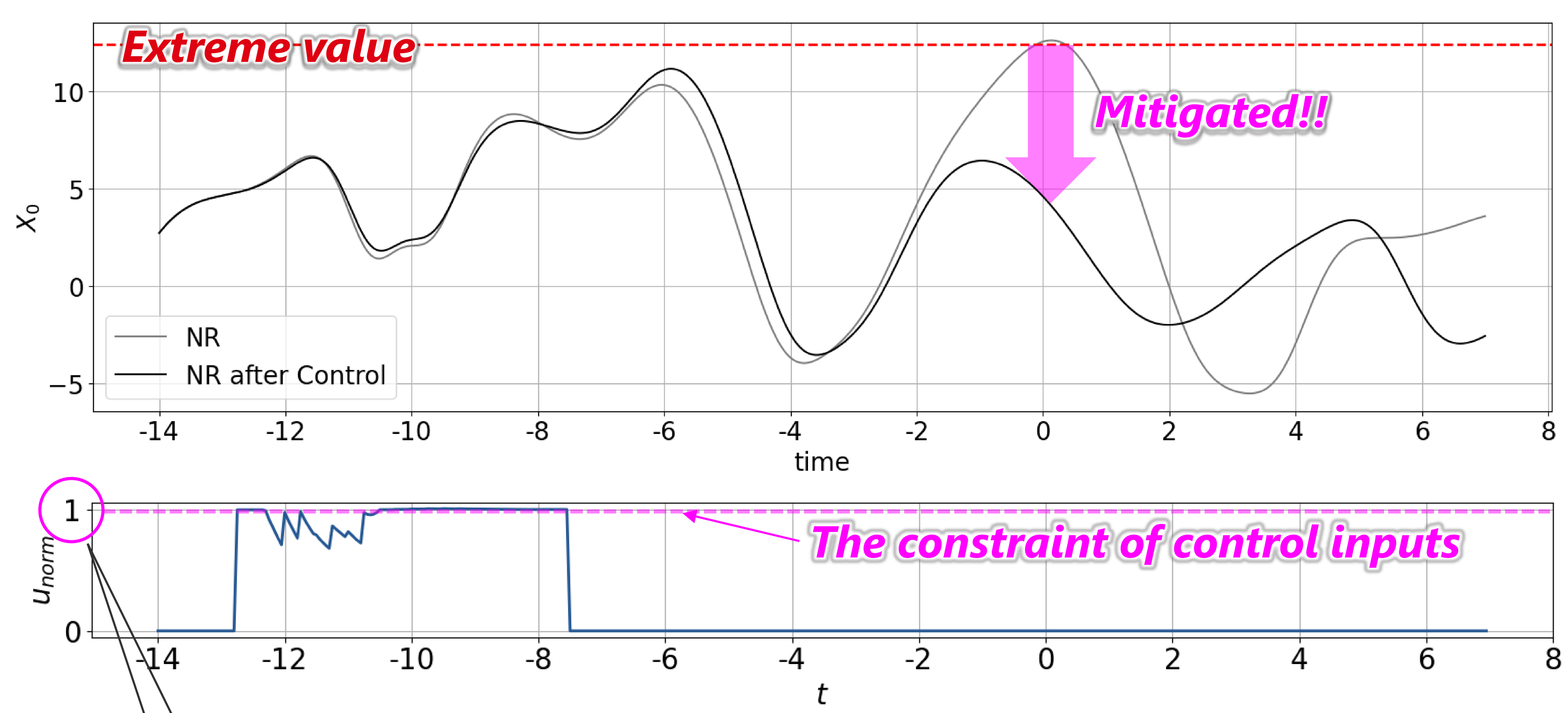
Constraint $|\mathbf{u}| \le 1$

- Cost function: $J = \sum_{i=0}^{T_c} \left(\mathbf{u}_i^T \mathbf{W}_\mathbf{u} \mathbf{u}_i + \alpha \cdot P(\mathbf{u}_i)\right) + \sum_{i=0}^{T_p} (\mathbf{x}_i^r - \mathbf{x}_i)^T \mathbf{W}_\mathbf{x} (\mathbf{x}_i^r - \mathbf{x}_i)$



Experiment 1

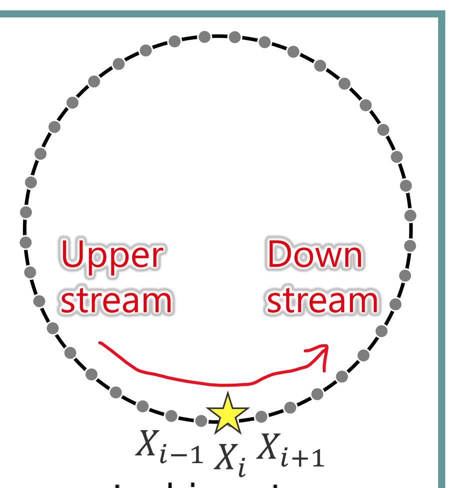
- Mitigating extreme events in X_0 by adding control inputs to X_{39}, X_0 and X_1
- Successfully mitigated extreme events while satisfying the constraints
- However, not all cases are successful → Parameter tuning is needed

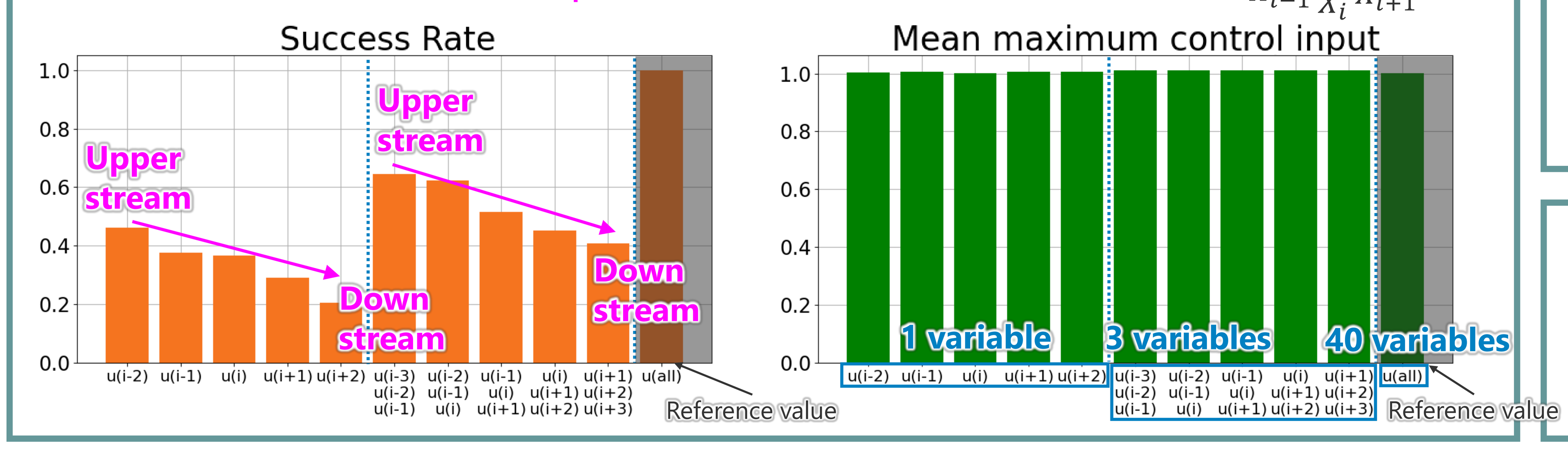


- When $|\mathbf{u}| = 1$, the control input added to the state during dt=0.01 is 0.01
- $|\mathbf{u}| = 1$ is almost equivalent to average rate of change in the state

Experiment 2

- The sensitivity experiment for control inputs (The number of samples: 93)
- Adding control inputs at the upstream side tends to improve the success rate
- Increasing the number of control input variables tends to improve the success rate





Future works

- Other sensitivity experiments will be continued to tune the parameters
- Further development of approaches to reduce computational time (e.g., using quantum annealing; Kotsuki, Kawasaki, and Ohashi, 2024)