



Physics-Informed Sampling-Based Model Predictive Control for Event-Scale Precipitation Regulation

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Abstract. Extreme rainfall events pose serious risks to human life, infrastructure, and economic systems. To mitigate such events, this paper proposes an effective event-scale precipitation control framework that deploys distributed offshore drag-inducing actuators to perturb the local wind and humidity fields and thereby influence precipitation formation. Existing rainfall-intervention methods are generally limited either to long-term, open-loop interventions at the climate scale or to simplified models that are difficult to extend to realistic weather systems. In contrast, the proposed framework directly integrates high-fidelity numerical weather prediction (NWP) models to preserve realistic atmospheric conditions while enabling closed-loop regulation of individual rainfall events through model predictive control (MPC). Sampling-based optimization makes this integration feasible by avoiding the need for gradient information and supporting efficient parallel computation for real-time implementation. Crucially, a physics-informed spatial prior is introduced to support the sampling process by guiding candidate layouts toward physically plausible regions with high control potential, thereby improving search efficiency. This is key to enhancing the robustness and practical viability of sampling-based optimization for such a complex rainfall control problem. Ensemble-based numerical experiments demonstrate that the proposed framework achieves effective and robust event-scale rainfall regulation under realistic weather conditions.

1 Introduction

Extreme rainfall events trigger major natural hazards, including floods, landslides, and urban inundation, and pose serious threats to human safety and socio-economic systems (Petley, 2012; Bauer et al., 2015). Accordingly, in addition to improving the accuracy of weather prediction, active intervention in rainfall processes has long been an important objective in both meteorological and engineering research.

Weather systems are high-dimensional, strongly nonlinear, and sensitive to initial conditions, with extreme rainfall arising from multiscale interactions among atmospheric circulation, moisture transport, terrain, convection, and cloud microphysics (Slingo and Palmer, 2011). These complexities, together with limitations in observations, computational resources, and NWP accuracy, have kept most conventional rainfall-intervention studies at the meteorological or climatological scale, relying largely on empirical and open-loop evaluations (National Research Council, 2003; Geerts and Rauber, 2022). Cloud seeding is



the most established precipitation-enhancement technique and introduces artificial ice nuclei, such as silver iodide, to modify cloud microphysical processes (Flossmann et al., 2019; Hiraga et al., 2026). Its effectiveness and the broader aerosol–cloud–precipitation interactions have been investigated through operational programs and field campaigns, such as the long-term activities in the United Arab Emirates and CAIPEEX (Al Hosari et al., 2021; Prabhakaran et al., 2023). Climate-engineering approaches, including stratospheric aerosol injection, marine cloud brightening, and cirrus cloud thinning, further seek to influence hydrological processes by altering cloud radiative properties (Crutzen, 2006; Latham et al., 2012; Diamond et al., 2022). Climate-model studies indicate that these perturbations can produce measurable yet spatially heterogeneous changes in precipitation and the hydrological cycle (Kristjánsson et al., 2015). Nevertheless, aerosol–cloud–precipitation interactions remain strongly regime-dependent and uncertain, making it difficult to establish a reliable deterministic relationship between intervention and precipitation response and thereby limiting stable control of individual rainfall events (Fan et al., 2016).

Given the strong condition dependence and uncertainty of existing weather-intervention approaches (Feingold et al., 2024), this paper employs distributed offshore drag-inducing structures as actuators to enable more controllable intervention for individual rainfall events. Unlike conventional open-loop interventions that rely heavily on environmental conditions, the proposed approach actively extracts local momentum through additional aerodynamic drag, thereby perturbing the near-surface wind and humidity fields and influencing downstream moisture transport and precipitation formation (Higuchi et al., 2026). This actuation concept is supported by wind-farm studies showing that momentum extraction can modify regional wind, humidity, and precipitation (Haywood et al., 2020; Fischereit et al., 2022). More importantly, the spatial distribution of actuators can be continuously adjusted, providing tunable and repeatable control inputs and thereby enabling stable closed-loop regulation. Under this actuation mechanism, rainfall regulation can be naturally formulated as an optimal control problem in which the spatial layout and temporal evolution of the actuators are optimized to minimize accumulated precipitation over a target region.

However, direct control using the real weather system is impractical because alternative control actions cannot be evaluated in advance and large-scale intervention experiments cannot be repeatedly conducted owing to practical constraints. In recent years, advances in high-resolution NWP have substantially improved short-term weather prediction, providing the predictive capability needed for event-scale intervention and control (Bauer et al., 2015). Therefore, a high-fidelity NWP model is used as a physically consistent and reproducible surrogate for control optimization and evaluation, providing detailed representations of atmospheric dynamics and comprehensive physical parameterizations of precipitation processes. However, high-fidelity NWP models involve extremely large state spaces and complex nonlinear dynamics and are computationally expensive, while explicit gradient information is generally unavailable. Consequently, the resulting control problem takes the form of a high-dimensional black-box optimization problem that is difficult to solve efficiently using conventional optimization methods.

To alleviate this issue, existing studies commonly employ simplified low-dimensional models as substitutes for high-fidelity NWP models (Huang and Fu, 2025), in which the interactions among water vapor, clouds, and precipitation are represented by reduced dynamical systems. Although these approaches are computationally tractable, they depend on strong simplifying assumptions and are primarily suited to idealized settings, limiting their ability to capture the multiscale complexity of realistic atmospheric systems (Soldatenko, 2017; Nagai et al., 2025). In addition, existing methods generally do not incorporate uncertainty in a systematic manner, which restricts their ability to address the inherent stochasticity and sensitivity of atmospheric



dynamics in practical applications (Tripathi et al., 2025). Overall, the combined reliance on simplified models and insufficient treatment of uncertainty makes these approaches difficult to extend to rainfall control involving high-fidelity NWP models.

To address the above challenges, this paper proposes a sampling-based model predictive control (SBMPC) framework for event-scale precipitation regulation. The proposed framework directly integrates high-fidelity NWP models under realistic weather conditions and realizes closed-loop control through an MPC scheme implemented in a receding-horizon control (RHC) manner. This is enabled by sampling-based optimization, which avoids the need for gradient information while supporting efficient parallel computation for real-time implementation. Nevertheless, purely sampling-based methods often exhibit low search efficiency in high-dimensional spatial layout optimization. To address this issue, we introduce a humidity-informed centroidal Voronoi tessellation (CVT)-based spatial prior that imposes a structured form on the actuator layout and directs the search toward physically plausible regions with high control potential, thereby improving search efficiency. This design is essential for enhancing the robustness and practical viability of sampling-based methods in such a complex rainfall control problem. Finally, numerical experiments using the NWP model, including stochastic perturbations and ensemble evaluations, are conducted to assess the effectiveness and robustness of the proposed framework in reducing accumulated precipitation over the target region.

The rest of this paper is organized as follows. Sect. 2 formulates the control problem by introducing the system dynamics and optimization objective. Sect. 3 presents the proposed SBMPC framework, including the RHC structure, sampling-based optimization, and humidity-informed layout search strategy. Sect. 4 describes the numerical experiments used to evaluate the effectiveness and robustness of the proposed method. Finally, Sect. 5 provides the conclusions.

2 Control Problem Statement

In this study, we address the reduction of accumulated precipitation over a prescribed target region during a rainfall event. To this end, offshore drag-inducing structures, such as giant sails, are employed as control actuators that exert aerodynamic drag on the local airflow, thereby affecting the wind and humidity fields, perturbing moisture transport, and ultimately influencing precipitation formation (Fischereit et al., 2022). Because the influence of an individual sail on large-scale atmospheric dynamics is limited (Haywood et al., 2020; Higuchi et al., 2026), multiple sails are arranged into line-shaped arrays, each of which serves as a single actuator unit. These actuators are distributed across offshore regions to form a spatially distributed control system.

By continuously adjusting the spatial configuration of the distributed actuators, the induced drag field can be actively modulated, thereby enabling control over moisture transport and precipitation formation. Therefore, rainfall regulation can be naturally formulated as an optimal control problem in which the spatial layout and temporal evolution of the actuators are designed to minimize accumulated precipitation over a target region. To formulate this problem, we first represent the high-fidelity NWP model with distributed actuators as a stochastic dynamical system and then define the corresponding stochastic optimal control objective.

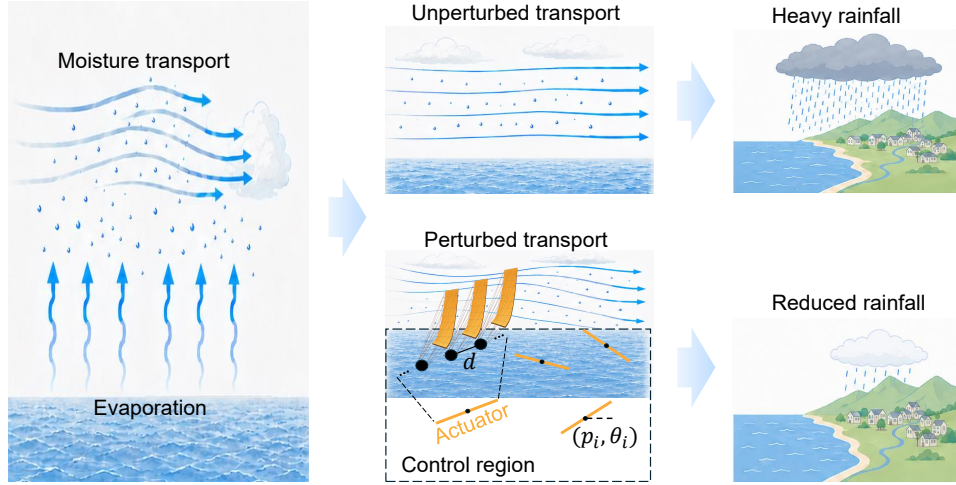


Figure 1. Illustration of precipitation control via distributed offshore drag-inducing actuators (e.g., sail arrays), where multiple actuators perturb the local wind and humidity fields to influence moisture transport and regulate precipitation through active spatial layout adjustment. Here, (p_i, θ_i) denote the position and orientation of the i -th actuator, and d denotes the inter-element spacing.

90 2.1 System Modeling

The real weather system cannot be directly used for control framework design and evaluation for two main reasons. First, the future atmospheric responses to alternative control actions cannot be directly evaluated before those actions are implemented. Second, large-scale intervention experiments are costly and constrained by practical and safety considerations, making it infeasible to repeatedly evaluate numerous control actions in the real environment. Therefore, a high-fidelity NWP model is employed as a surrogate for the real weather system, providing a physically consistent and reproducible environment that pre-

95 serves the essential characteristics of real atmospheric processes for control optimization and evaluation (Bauer et al., 2015). Consider a high-fidelity NWP model with distributed actuators described by stochastic nonlinear dynamics. The control input u is defined as the spatial layout of the offshore actuators, and the output $y \in \mathcal{Y}$ represents the spatial precipitation-rate field over the target region $\Omega \subset \mathbb{R}^2$. For numerical implementation, Ω is discretized into a finite set of grid points, and the corresponding discrete output space is defined as $\mathcal{Y} := \mathbb{R}_{\geq 0}^{|\Omega|}$. In the NWP model, the underlying atmospheric state $x \in \mathbb{R}^{n_x}$ includes atmospheric variables and physical fields, such as wind, humidity, temperature, and pressure. Consequently, the NWP model at time step t is represented by the following stochastic discrete-time system:

$$\begin{aligned} x_{t+1} &= f(x_t, u_t, \xi_t), \quad \xi_t \sim \mathcal{D}, \\ y_t &= h(x_t), \end{aligned} \tag{1}$$

where $f(\cdot)$ denotes the weather dynamics, and $h(\cdot)$ represents the output mapping from the atmospheric state to the precipitation field. The variable $\xi_t \in \mathbb{R}^{n_\xi}$ represents inherent uncertainties in atmospheric evolution, including unresolved-scale variability and stochastic perturbations. These uncertainties are assumed to be independent and identically distributed (i.i.d.)



according to an empirical distribution $\mathcal{D}$. This formulation shows that the control input affects precipitation by modifying atmospheric variables, such as the wind and humidity fields, which in turn alter moisture transport and precipitation formation.

In the above system, the spatial layout u of the multiple actuators can be continuously adjusted, offering the potential for stable control. To represent u explicitly, we parameterize it by a set of positions P and orientations Θ . As shown in Fig. 1, we assume that m_a actuators are deployed in the offshore control region $\Omega_c \subset \mathbb{R}^2$. Each actuator consists of n_e elements arranged in a linear configuration, where n_e is assumed to be odd. Let $p_i \in \Omega_c$ and $\theta_i \in [-\pi, \pi)$ denote the center location and orientation of the i -th actuator, respectively. The resulting distributed actuator layout is expressed as

$$(P, \Theta) = \{(p_i, \theta_i)\}_{i=1}^{m_a}. \quad (2)$$

For numerical implementation, the actuator layout is equivalently represented by the coordinates of all $m_a \times n_e$ resistance sails. Given the orientation θ_i , the longitude and latitude coordinates $p_{i,x}$ and $p_{i,y}$ of the i -th actuator center, respectively, are written as $p_i = (p_{i,x}, p_{i,y})$. The inter-sail distance d is converted to the corresponding geographic scale according to the underlying grid resolution. The approximate coordinates of the n -th sail are then computed as

$$p_{i,n} = p_i + nd \begin{bmatrix} \cos \theta_i \\ \sin \theta_i \end{bmatrix}, \quad (3)$$

where $n \in \{-(n_e - 1)/2, \dots, 0, \dots, (n_e - 1)/2\}$.

2.2 Control Objective

In this study, the control objective is to reduce accumulated precipitation over a prescribed target region by designing an optimal sequence of offshore actuator layouts within the NWP system over a finite time horizon. To quantify the performance of a control sequence $U := \{u_t\}_{t=0}^{T-1} \in \mathcal{U}^T$ over a finite prediction horizon T , we introduce the accumulated-precipitation cost function $C : \mathcal{U}^T \times \mathbb{R}^{n_\xi \times T} \rightarrow \mathbb{R}_{\geq 0}$, defined as

$$C(U, \Xi) = \sum_{t=1}^T l(y_t) \Delta t, \quad (4)$$

where each time step corresponds to a fixed duration Δt ; $\Xi = \{\xi_t\}_{t=0}^{T-1} \in \mathbb{R}^{n_\xi \times T}$ is the uncertainty sequence; $\{y_t\}_{t=1}^T$ is the sequence of precipitation-rate fields recursively generated by the system dynamics (1) under the inputs U and uncertainties Ξ ; and $l : \mathcal{Y} \rightarrow \mathbb{R}_{\geq 0}$ denotes the spatially averaged precipitation rate over the target region Ω , given by

$$l(y_t) = \frac{1}{|\Omega|} \sum_{q \in \Omega} y_t(q), \quad (5)$$

where $y_t(q)$ denotes the precipitation-rate at location q .

Under the above definitions, the precipitation regulation problem is formulated as a finite-horizon stochastic optimization problem. Specifically, for a given control sequence U , different realizations of the uncertainty sequence Ξ can produce different atmospheric trajectories and, consequently, different values of the trajectory cost $C(U, \Xi)$ defined in (4). Therefore, $C(U, \Xi)$



135 is treated as a random variable, and the control objective is to determine an optimal sequence U^* that minimizes its expected value with respect to the uncertainty distribution $\mathcal{D}$. The resulting optimization problem is formulated as

$$U^* = \arg \min_{U \in \mathcal{U}^T} \mathbb{E}_{\Xi \sim \mathcal{D}^T} [C(U, \Xi)]. \quad (6)$$

140 However, because the high-dimensional, strongly nonlinear NWP dynamics are represented implicitly through numerical simulations, explicit gradients of the expected objective with respect to the control variables are generally unavailable, making conventional gradient-based optimization impractical.

3 Physics-Informed SBMPC Framework Design

To solve the optimization problem formulated above, we develop an SBMPC framework for designing an approximate optimal sequence of actuator layouts that minimizes precipitation over the target region. The proposed framework combines the feedback capability of predictive control with the flexibility of data-driven zeroth-order optimization. To guarantee real-
145 time responsiveness, the MPC controller uses receding-horizon feedback to adapt to evolving atmospheric conditions while decomposing the long-term regulation task into tractable finite-horizon layout optimization problem. Within the framework, sampling-based optimization is used to evaluate candidate layout sequences without requiring explicit gradient information, allowing the controller to be directly coupled with a high-fidelity NWP model under realistic atmospheric conditions. To improve sampling efficiency in the high-dimensional layout space, a humidity-informed CVT-based spatial prior is introduced to
150 direct the search toward physically relevant and high-potential regions. This design is essential for improving the robustness and practical viability of sampling-based methods in such a complex rainfall control problem. In the following subsections, we first establish the fundamental RHC architecture, followed by a detailed formulation of the sampling-based optimization strategy for layout sequence design. A humidity-informed layout exploration strategy is then introduced to improve search efficiency. Finally, we present the execution of the proposed SBMPC-based control framework.

155 3.1 Receding Horizon Control

MPC plays a central role in the proposed framework by converting NWP predictions into adaptive closed-loop control decisions. At each sampling instant, it predicts atmospheric evolution over a finite horizon, optimizes the actuator layout sequence, applies only the first control action, and repeats the procedure using the latest state information (Rawlings and Mayne, 2009). This receding-horizon feedback enables the controller to respond to evolving weather conditions and disturbances rather than
160 relying on a fixed open-loop intervention. The detailed procedure is described as follows.

For the stochastic weather system in (1), at each sampling instant t , given the current state measurement x_t , subject to the system dynamics and constraints, the sequence that minimizes the expected cumulative cost over a fixed prediction horizon T is selected as the optimal sequence U_t^* , defined as

$$\begin{aligned} U_t^* &:= \{u_{0|t}^*, u_{1|t}^*, \dots, u_{T-1|t}^*\} \\ &= \{(P_{0|t}^*, \Theta_{0|t}^*), (P_{1|t}^*, \Theta_{1|t}^*), \dots, (P_{T-1|t}^*, \Theta_{T-1|t}^*)\}. \end{aligned} \quad (7)$$



165 Once the optimal sequence has been determined, the key feature of RHC lies in how this sequence is implemented: although a control sequence of length T is computed, only its first element $u_{0|t}^*$ is applied as the actual control input u_t to the system.

At the subsequent time step, the atmospheric state is updated using the latest measurements, after which forward prediction, sequence optimization, and first-step execution are repeated. This receding-horizon process introduces closed-loop feedback, enabling the controller to respond to disturbances as the weather system evolves.

170 3.2 Sampling-Based Optimization

Because the NWP model in (1) is a computationally expensive black-box simulator for which explicit gradients are unavailable, conventional gradient-based optimization cannot be directly applied. Sampling-based optimization is therefore used to approximate the ideal sequence U^* by an empirical sequence $\hat{U}^*$ using only forward NWP simulations, while allowing candidate evaluations to be performed in parallel. Specifically, given $K \in \mathbb{N}$ candidate sequences, each candidate is evaluated through forward prediction, and the sequence with the minimum predicted cost is selected as the approximate optimal sequence $\hat{U}^*$, defined as:

$$\hat{U}^* = U^{k^*}, \quad k^* = \underset{k \in \{1, \dots, K\}}{\operatorname{argmin}} J(U^k), \quad (8)$$

where the k -th candidate control sequence U^k is defined as

$$U^k = (P^k, \Theta^k), \quad (9)$$

180 where P^k denotes the k -th candidate location sequence and Θ^k is its corresponding orientation sequence. Each P^k is generated from the warm-start sequence $\bar{P}$ through structured spatial adjustments of the actuator locations over the prediction horizon. The sampling procedure is performed only in the location space, while the orientation sequence is determined separately. The construction of Θ^k , $\bar{P}$, and the structured location-sampling strategy are described in the following sections.

For each candidate sequence U^k , the term $J(U^k)$ in (8) denotes an empirical approximation of the expected cost. Specifically, $M \in \mathbb{N}$ independent Monte Carlo roll-outs are performed using the NWP model (1), where each roll-out samples one realization of the system uncertainty and predicts the corresponding precipitation evolution. The resulting trajectory costs are then averaged to approximate the expectation, as follows:

$$J(U^k) = \frac{1}{M} \sum_{m=1}^M C(U^k, \Xi^m), \quad (10)$$

where $\Xi^m \stackrel{\text{i.i.d.}}{\sim} \mathcal{D}^T$.

190 3.3 Physics-Informed Sampling Strategy

In the proposed SBMPC framework, exhaustive search over the full solution space is computationally prohibitive because of the high dimensionality of the actuator layout variables, making uninformed sampling inefficient. To improve search efficiency, we introduce a physics-informed layout sampling strategy that incorporates information from both the wind and humidity fields.



Specifically, actuator orientations are aligned with the local wind directions to enhance their influence on moisture transport, while a humidity-informed CVT-based spatial prior guides actuator placement toward moisture-rich regions with greater potential to affect moisture supply and accumulated precipitation over the target region. Based on this prior, candidate trajectories are generated by applying structured spatial perturbations to the CVT-based warm-start trajectory, with the dominant transport direction serving as a physical reference for exploring a reduced and relevant subspace of the solution space. The detailed procedure is described as follows.

3.3.1 Orientation Assignment

Our exploratory experiments indicate that aligning the actuators with the local wind direction allows the induced aerodynamic drag to more effectively alter moisture transport and precipitation formation. Accordingly, in the control region Ω_c , the orientation of the i -th actuator centered at p_i is determined from the local wind direction represented by the effective wind field v_{eff} , which is constructed as a vertically weighted average of wind vectors across multiple height levels to account for the overall near-surface flow structure and maximize the actuator influence. The field is defined as:

$$v_{\text{eff}}(p_i) = \sum_{z \in Z_{\text{wind}}} w_z(p_i) v_z(p_i),$$

$$w_z(p_i) = \frac{\|v_z(p_i)\|}{\sum_{z' \in Z_{\text{wind}}} \|v_{z'}(p_i)\| + \epsilon_w},$$
(11)

where $v_z : \Omega_c \rightarrow \mathbb{R}^2$ denotes the horizontal wind vector at altitude z , i.e., $v_z(p_i) = [v_{x,z}(p_i), v_{y,z}(p_i)]^\top$, $Z_{\text{wind}} := \{z_g\}_{g=1}^{n_z}$ is the set of discrete altitudes, $\|\cdot\|$ denotes the Euclidean norm, and $\epsilon_w > 0$ is a small constant introduced to avoid division by zero.

At time t , the orientation of the i -th actuator is determined by the effective wind vector evaluated at its center location $p_{i,t}$:

$$\theta_{i,t} = \angle v_{\text{eff},t}(p_{i,t}),$$
(12)

where $\angle(\cdot)$ denotes the direction angle measured from the positive x -axis, and $v_{\text{eff},t}(p_{i,t})$ is obtained by spatially interpolating the effective wind field at the actuator center $p_{i,t}$. Over the prediction horizon, the orientation of each actuator at each prediction step is determined from the corresponding predicted effective wind field according to (12), allowing the orientation sequence to adapt to the evolving atmospheric flow.

3.3.2 Location Generation

Regions with higher humidity contain more available water vapor and therefore provide greater opportunities for actuator-induced wind perturbations to influence moisture transport associated with precipitation over the target region (Banacos and Schultz, 2005). Placing actuators in such regions is thus expected to increase their control potential. To balance moisture-oriented concentration with spatial coverage, the warm-start actuator locations $\bar{P}$ are determined using a humidity-informed CVT, where the humidity field defines the density function. Rather than placing actuators directly at local humidity maxima, the



CVT partitions the control domain into distance-based Voronoi cells and iteratively moves each actuator toward the humidity-weighted centroid of its corresponding cell. This avoids excessive clustering while producing a physically informed warm start that guides the subsequent search toward regions with greater control potential.

225 Let the region $V_i(P)$ denote the Voronoi cell associated with the i -th actuator center p_i , defined as

$$V_i(P) = \{q \in \Omega_c \mid \|q - p_i\| \leq \|q - p_j\|, \forall j \neq i\}, \quad (13)$$

where $P = \{p_i\}_{i=1}^{m_a}$ denotes the set of actuator locations. To evaluate the quality of a given actuator layout, we use the humidity-weighted squared distance between each location in the control domain and the actuator assigned to its Voronoi cell as the locational cost. This metric reflects both the proximity of the actuators to high-humidity regions and their spatial coverage of
230 the control domain. Accordingly, at time t , the locational cost is defined as:

$$\mathcal{H}_t(P_t) = \sum_{i=1}^{m_a} \sum_{q \in V_i(P_t)} \|q - p_{i,t}\|^2 \rho_t(q), \quad (14)$$

where the humidity-based density function is defined as:

$$\rho_t(q) = (1 - \alpha) + \alpha \frac{\chi_{\text{eff},t}(q)}{\max_{q \in \Omega_c} \chi_{\text{eff},t}(q)}, \quad \alpha \in (0, 1], \quad (15)$$

where $\chi_{\text{eff},t}(q)$ denotes the effective humidity at location q , constructed using the same vertical weighting scheme as the
235 effective wind field in (11), with the wind-speed variable replaced by humidity. At each time step, minimizing the locational cost $\mathcal{H}(P)$ yields a centroidal Voronoi tessellation, which is efficiently computed using an iterative Lloyd-type algorithm and serves as the warm-start trajectory $\bar{P}$ for subsequent candidate generation (Du et al., 2006).

After obtaining the warm-start trajectory from the humidity-informed CVT, the sail arrays are preferentially placed in high-potential regions. Sampling around this trajectory then enables focused exploration of promising layouts, reducing unnecessary
240 search over the full solution space and thereby improving search efficiency. At time t , let $\bar{P}_t$ denote the warm-start location trajectory generated using the humidity-informed CVT. The dominant transport direction e_t is determined from the effective wind vectors $v_{\text{eff},t}$ evaluated at the corresponding CVT centers, defined as:

$$e_t = \frac{\sum_{i=1}^{m_a} v_{\text{eff},t}(\bar{p}_{i,t})}{\|\sum_{i=1}^{m_a} v_{\text{eff},t}(\bar{p}_{i,t})\| + \epsilon_e}, \quad (16)$$

where $\epsilon_e > 0$ is a small constant introduced to avoid division by zero.

245 Based on e_t and the prescribed sampling distance d_s , K candidate location trajectories are generated by applying structured spatial perturbations to the CVT-based warm-start trajectory $\bar{P}_t$. Specifically, e_t serves as the reference direction for constructing physically relevant perturbations, while d_s specifies the displacement magnitude used to generate candidate locations along each selected direction, thereby enabling the candidates to explore diverse spatial variations around the warm-start trajectory. This strategy concentrates the search around the humidity-informed CVT solution while maintaining sufficient diversity for
250 the SBMPC optimization.



Algorithm 1 Execution of the SBMPC algorithm

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1: RHC Outer Loop
2: for each sampling instant  $t = 0, 1, \dots$  do
3:   Measure current system state and calculate  $v_{\text{eff},t}(q)$ ,  $\chi_{\text{eff},t}(q)$  from the NWP system.
4:   Construct humidity-based density function  $\rho_t(q)$  (15).
5:   Generate warm-start location trajectory  $\bar{P}_t$  based on the humidity-informed CVT optimization (14).
6:   Sampling-Based Optimizer
7:   Input:  $\bar{P}_t$ ,  $v_{\text{eff},t}(q)$ .
8:   Sample  $K$  candidate location sequences  $P_t^k$  around the warm-start location trajectory  $\bar{P}_t$ .
9:   Determine the corresponding orientation sequence  $\Theta_t^k$  for each candidate sequence according to  $v_{\text{eff},t}(q)$  via (12).
10:  Obtain  $K$  candidate layout sequences:  $U_t^k = (P_t^k, \Theta_t^k)$ .
11:  Evaluate predicted cumulative cost  $J(U_t^k)$  using the NWP model (1) according to (10).
12:  Select the new optimal sequence  $\hat{U}_t^*$  via strategy (8).
13:  Extract and apply  $u_t = (\hat{U}_t^*)_0$  as the next control input.
14:  Output: return  $u_t$  to the RHC Outer Loop.
15: end for

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3.4 Control Framework Implementation

The proposed framework is implemented through a systematic receding-horizon loop. At each decision epoch t , the controller functionally maps the effective wind field $v_{\text{eff},t}(q)$, the effective humidity field $\chi_{\text{eff},t}(q)$, and the warm-start location trajectory $\bar{P}_t$ to an updated control sequence $\hat{U}_t^*$. Internally, this selection process is carried out in three sequential phases.

255 First, the algorithm samples K candidate sequences, which are subsequently evaluated using the NWP model (1) to compute the prediction cost estimates in (10). Finally, the surrogate optimal control sequence $\hat{U}_t^*$ is selected based on the resulting prediction costs.

At the start of each optimization cycle, the controller constructs the humidity-based density function $\rho_t(q)$ and obtains the warm-start location trajectory $\bar{P}_t$ through the humidity-informed CVT optimization, thereby providing a structured spatial
260 prior for the current RHC iteration. Based on the dominant transport direction e_t and the prescribed sampling distance d_s , K candidate location trajectories are then generated around the CVT-based warm-start trajectory $\bar{P}_t$. For each candidate location sequence, the corresponding orientation sequence is determined from the effective wind field $v_{\text{eff},t}(q)$ according to (12). The predicted performance of the candidate sequences is evaluated using the high-fidelity NWP model (1) under the formulation in (10). Based on the resulting model-based estimates, the surrogate optimal control solution $\hat{U}_t^*$ is selected according to (8).
265 To close the feedback loop, the first control action extracted from $\hat{U}_t^*$ is applied to the system as u_t . The complete execution procedure is summarized in Algorithm 1.

**Table 1.** Parameter settings for the humidity-informed experiments.

Parameter	m_a	n_e	K	M	d (km)	d_s (km)	α
Value	6	7	5	1	4.8	15	0.9

4 Numerical Experiments

To evaluate the effectiveness and robustness of the proposed framework, we adopt an ensemble-based numerical experiment design that explicitly accounts for the inherent uncertainty in atmospheric systems.

270 4.1 Experimental Setup

The proposed framework is evaluated using the extreme rainfall event that affected Kyushu, Japan, from August 10 to August 13, 2021. The target region covers the most severely affected inland area (129.5°E–131.0°E, 32.5°N–33.5°N), whereas the actuators are deployed over adjacent offshore regions. Numerical simulations are conducted on the Fugaku supercomputer using Scalable Computing for Advanced Library and Environment-Regional Model (SCALE-RM) version 5.5.4 (Nishizawa et al., 2015). SCALE-RM provides a regional dynamical core together with configurable representations of cloud microphysics, boundary-layer processes, and radiation, making it suitable for high-resolution simulation of heavy rainfall events. The sails are implemented in SCALE-RM as additional aerodynamic drag forcings acting against the local wind, and their influence is restricted to a 300 m layer above the sea surface. Actuator relocation and reorientation are assumed to occur instantaneously at each control update, without explicitly modeling the transition process or imposing movement-speed constraints. Specifically, each simulation uses 24 message passing interface (MPI) processes, with up to four processes allocated per compute node.

To represent realistic forecast uncertainty, an additive random perturbation is applied at each control step to the water vapor mixing ratio throughout the horizontal computational domain within the 0–300 m layer. The moisture perturbation is uniformly sampled within $\pm 0.001 \text{ kg} \cdot \text{kg}^{-1}$, corresponding to approximately 6% of the reference moisture value of $0.018 \text{ kg} \cdot \text{kg}^{-1}$ used in the SCALE-RM configuration. The main parameters for the humidity-informed experiments are summarized in Table 1. At each control step, the wind and humidity fields are extracted at heights of 10, 30, 70, 100, 130, 170, 200, 230, 270, and 300 m. The fields are then vertically aggregated to construct the effective wind and humidity fields. Five candidate layouts are considered at each prediction step: the warm-start CVT layout and four sampled layouts generated according to the direction set $\{e_t, -e_t, e_t^\perp, -e_t^\perp\}$, corresponding to the downstream, upstream, and two cross-directional layouts, respectively. Each control interval lasts 12 hours, with a three-step prediction horizon covering 36 hours. The prediction and control procedure is repeated over six RHC loops, resulting in a total simulation period of 72 hours. The complete computation required for each 12-hour control interval, including both prediction and execution simulations, takes approximately 7 hours. Thus, the computational time remains shorter than the corresponding physical control interval, supporting the feasibility of real-time closed-loop precipitation regulation.



Under the same experimental configuration, multiple stochastic realizations are generated to form the humidity-informed control ensemble, hereafter referred to as the humidity-informed ensemble. Corresponding uncontrolled and random-placement control ensembles are constructed under identical experimental conditions over the same 72-hour simulation period for comparison, where the random-placement control refers to a strategy using randomly generated actuator layouts within the control region and is hereafter referred to as the random-placement ensemble. In all three ensembles, water vapor perturbations are applied every 12 hours using the same sampling procedure and perturbation distribution described above. For the random-placement ensemble, actuator centers and orientation angles are uniformly sampled within the control region and from $[-\pi, \pi)$, respectively, using fixed random seeds to ensure reproducibility. This comparison enables the overall control effect and the additional benefit of the physics-informed strategy to be evaluated separately. Control performance is assessed using ensemble statistics of the 72-hour accumulated area-averaged precipitation over the target region.

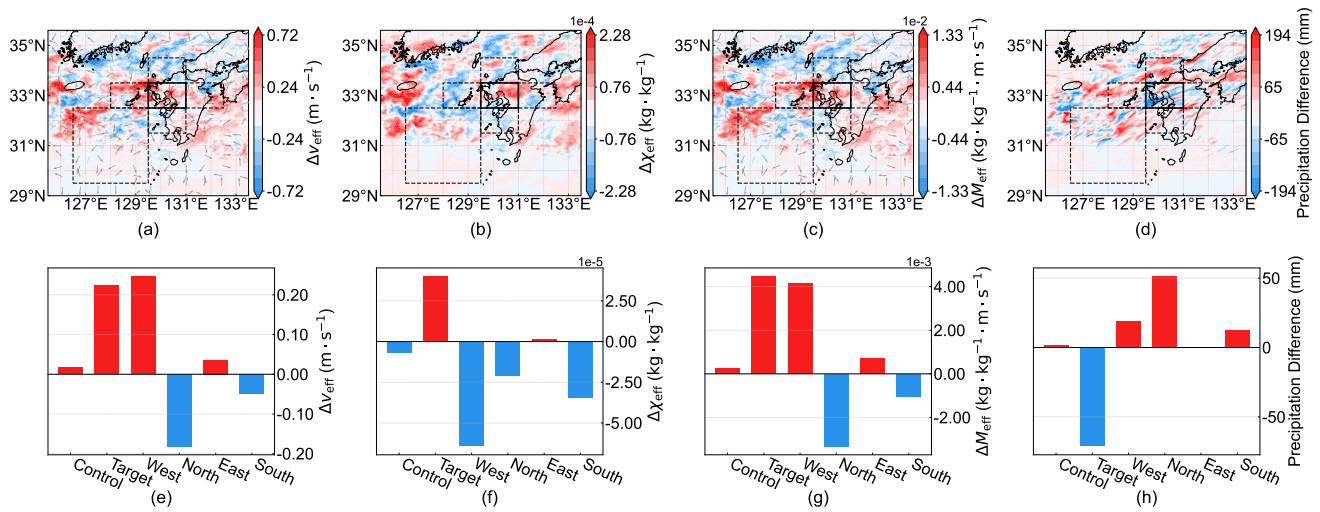


Figure 2. Physical diagnostic analysis of the humidity-informed control effect relative to the uncontrolled case over the simulation period. Panels (a)–(c) show the spatial distributions of the 72-hour mean control-minus-uncontrolled differences in effective wind (v_{eff}), effective humidity (χ_{eff}), and effective moisture transport (M_{eff}), while panel (d) shows the difference in 72-hour accumulated precipitation. The arrows in panels (a) and (c) indicate the effective wind and moisture-transport directions, respectively. Panels (e)–(h) show the corresponding regional means for the control region, target region, and the West, North, East, and South adjacent regions.

4.2 Experimental Results

We first investigate the physical responses associated with humidity-informed control by comparing the selected uncontrolled and humidity-informed control cases. Specifically, we analyze the 72-hour mean differences in effective wind (v_{eff}), effective humidity (χ_{eff}), effective moisture transport ($M_{eff} = v_{eff} \chi_{eff}$), and the difference in 72-hour accumulated precipitation across the control, target, and four target-adjacent regions, as shown in Fig. 2. The M_{eff} follows the conventional representation of horizontal moisture flux as the product of atmospheric humidity and horizontal wind, while providing a simplified two-

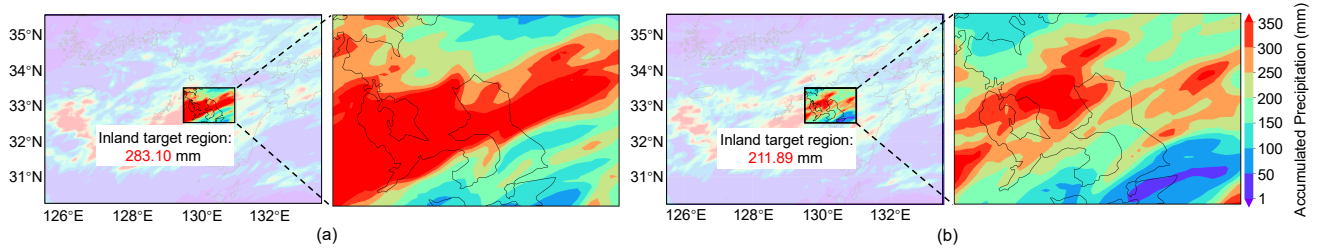


Figure 3. Comparison of 72-hour accumulated precipitation over the inland target region experiencing the heaviest rainfall during the extreme rainfall event from two single experimental cases. (a) Uncontrolled case and (b) humidity-informed control case.

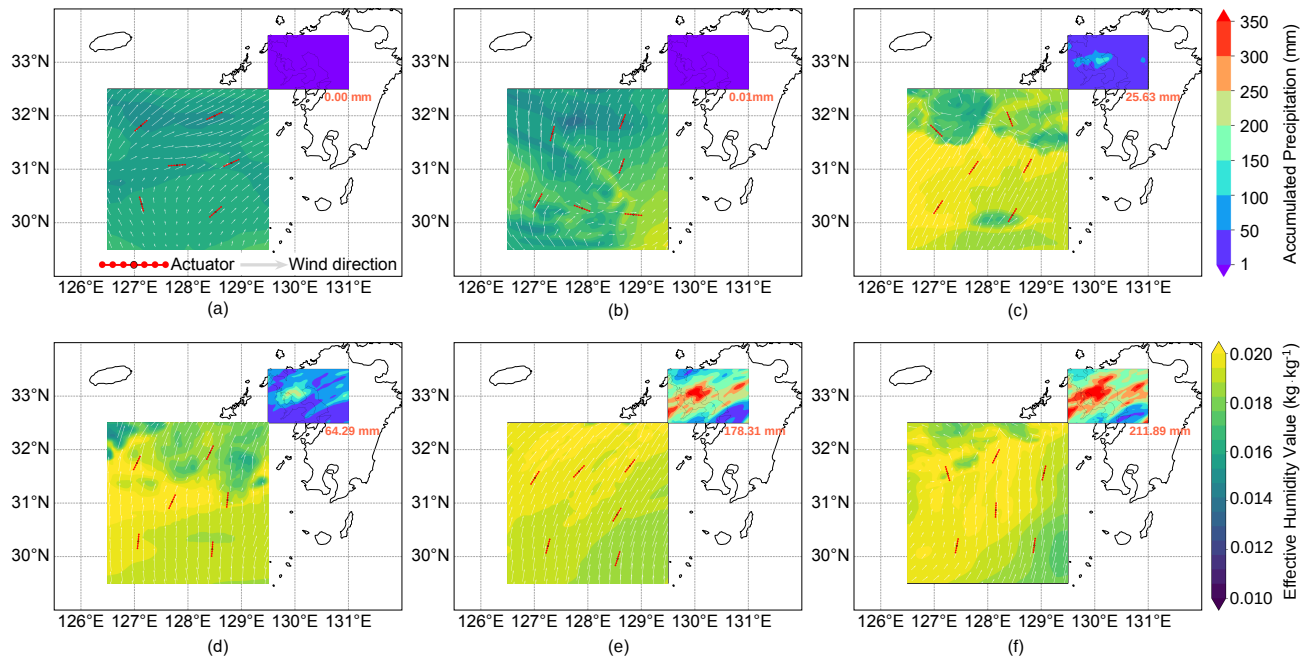


Figure 4. Effective humidity fields, effective wind directions and actuator layouts at the beginning of each control step, together with the corresponding precipitation distributions at the end of each step over the inland target region experiencing the heaviest rainfall during the extreme rainfall event, for a single case under humidity-informed control. Panels (a)–(f) show the results over six control intervals from 00:00 on August 10, 2021 to 00:00 on August 13, 2021.

310 dimensional diagnostic based on the effective fields used in this study (Liu and Stewart, 2003). The regional analysis reveals spatially heterogeneous responses across the four variables. Effective wind speed increases over the target and western regions but decreases mainly to the north and south. Effective humidity increases over the target region while generally declining in the surrounding regions, and effective moisture transport exhibits a similar spatial pattern, with increases over the target and western regions and decreases mainly to the north and south. In contrast, accumulated precipitation decreases substantially



315 over the target region but increases in several adjacent regions. The reduction in target-region precipitation cannot be directly explained by local changes in the effective wind and humidity fields and therefore cannot be attributed solely to local drying or weakened moisture transport. Instead, the results suggest a plausible mechanism in which the distributed actuators may stimulate mesoscale perturbation growth in the atmosphere (Ono and Inatsu, 2025), thereby altering the atmospheric dynamics and reorganizing the wind, humidity, and moisture transport fields, which may ultimately contribute to the redistribution of
320 precipitation across the broader region. Notably, the present analysis focuses on the physical responses associated with precipitation reduction over the target region, while the implications of this redistribution for surrounding regions remain a topic for future research.

Fig. 3 more clearly illustrates the changes in precipitation distribution over the target region between the two selected cases described above. It is observed that the 72-hour accumulated precipitation decreases from 283.10 mm in the uncontrolled
325 case to 211.89 mm under humidity-informed control, corresponding to a reduction of 25.15%. To further examine the control process, Fig. 4 shows the actuator layouts, humidity fields, wind directions, and resulting precipitation distributions over the six control steps. The actuator orientations remain aligned with the effective wind directions, while their positions are preferentially distributed in regions with higher humidity. The layouts are progressively updated in response to the evolving effective humidity field, enabling the controller to adapt its intervention throughout the control period. These results are consistent with the
330 humidity-informed density design and demonstrate that the proposed controller effectively utilizes the spatial structure of the humidity field.

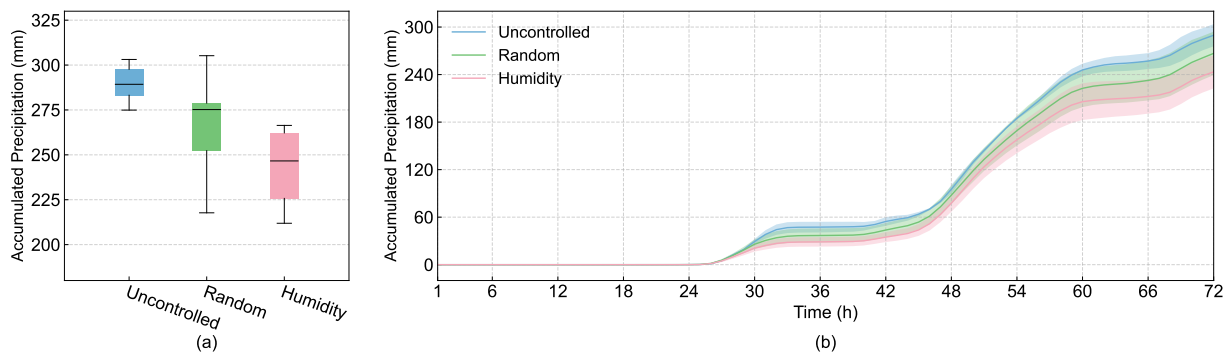


Figure 5. Comparison of accumulated precipitation over the inland target region among the uncontrolled, random-placement, and humidity-informed cases under ensemble simulations. “Random” and “Humidity” denote the random-placement and humidity-informed cases, respectively. (a) Distributions of the 72-hour accumulated precipitation and (b) temporal evolution of the ensemble means, with the shaded bands representing the mean $\pm$ sample standard deviation.

To further evaluate the effectiveness and robustness of the proposed framework, multiple independent experiments are performed under stochastic perturbations. Table 2 summarizes the ensemble results for the uncontrolled, random-placement control, and humidity-informed control cases. Across the ensemble simulations, the humidity-informed approach consistently
335 reduces 72-hour accumulated area-averaged precipitation relative to the uncontrolled cases and generally produces lower

**Table 2.** 72-hour accumulated area-averaged precipitation over the inland target region for multiple experimental cases.

Case No.	1	2	3	4	5	6	7	8	9	10
Uncontrolled (mm)	283.10	280.91	303.13	294.54	293.05	298.73	283.45	285.53	274.92	299.31
Random-placement (mm)	246.38	229.18	292.34	279.42	277.10	274.37	305.22	217.71	276.05	270.08
Humidity-informed (mm)	211.89	220.30	254.46	264.82	215.54	242.64	242.07	266.39	250.58	265.57

precipitation than the random-placement strategy. Relative to the uncontrolled ensemble mean of 289.67 mm, the random-placement ensemble reduces the accumulated precipitation to 266.79 mm, corresponding to a decrease of 22.88 mm (7.90%). The humidity-informed ensemble achieves a lower mean of 243.43 mm, representing a reduction of 46.24 mm (15.96%) from the uncontrolled ensemble and an additional decrease of 23.36 mm compared with random-placement ensemble. As illustrated in Fig. 5(a), the median accumulated precipitation is reduced from 289.29 mm in the uncontrolled ensemble to 275.21 mm in the random-placement ensemble and further to 246.61 mm in the humidity-informed ensemble. The corresponding sample standard deviations are 27.47 mm and 20.97 mm for the random-placement and humidity-informed ensembles, respectively, showing that the proposed strategy yields more consistent outcomes. Fig. 5(b) further confirms that accumulated precipitation remains lower under humidity-informed ensemble throughout the simulation period. Overall, these results demonstrate that the proposed method achieves greater precipitation reduction and improved robustness compared with the random-placement strategy, suggesting that the physics-informed sampling strategy enhances search efficiency by guiding the optimization toward more effective rainfall-reducing layouts.

5 Conclusions

In this paper, we propose a physics-informed SBMPC framework for event-scale precipitation regulation that is designed to control individual rainfall events effectively. Offshore drag-inducing structures are used as control actuators, and their spatial layouts are adjusted to actively modulate the resulting drag field, thereby influencing moisture transport and precipitation formation. Compared with methods based on long-term open-loop interventions or simplified models that cannot adequately represent realistic atmospheric dynamics, the proposed framework can be directly integrated with high-fidelity NWP models to ensure realistic atmospheric conditions. Closed-loop control is achieved within the MPC structure through forward prediction and receding-horizon execution. The proposed method relies on sampling-based optimization, which avoids the need for gradient information and enables efficient parallel computation for real-time implementation. To improve the efficiency of layout optimization in the high-dimensional solution space, a humidity-informed CVT-based spatial prior is introduced to impose structure on the actuator layout and guide the search toward physically plausible regions with high control potential.

Ensemble-based evaluations demonstrated the effectiveness and robustness of the proposed framework for mitigating event-scale rainfall under realistic, high-dimensional, and highly uncertain atmospheric conditions. Compared with the random-placement strategy, the humidity-informed method improves search efficiency by directing candidate layouts toward physi-



365 cally relevant regions, resulting in stronger precipitation reduction and more consistent control outcomes. For the regulation of individual rainfall events governed by strongly nonlinear physical processes, the proposed framework supports a viable transition from empirical or low-dimensional approaches toward feedback-based weather intervention. Although the framework was evaluated using a representative extreme rainfall event, its general formulation allows it to be extended to other weather systems. The current objective focuses on precipitation reduction over the target region and does not explicitly account for potential increases in surrounding areas. Future work will incorporate spatial risk measures and constraints to manage precipitation redistribution across the broader region.

370 *Code and data availability.* The code and data supporting the findings of this study are available from the corresponding author upon reasonable request.

Author contributions. YB, MO, and BQ conceived the research. BQ, QR, and YH conducted the experiments and analyzed the data. BQ and YB wrote the manuscript. MO, HH, and KY supervised the research and reviewed and revised the manuscript.

Competing interests. The authors declare that they have no conflict of interest.

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References

- Al Hosari, T., Al Mandous, A., Wehbe, Y., Shalaby, A., Al Shamsi, N., Al Naqbi, H., Al Yazeedi, O., Al Mazroui, A., and Farrah, S.: The UAE cloud seeding program: A statistical and physical evaluation, *Atmosphere*, 12, 1013, <https://doi.org/10.3390/atmos12081013>, 2021.
- Banacos, P. C. and Schultz, D. M.: The Use of Moisture Flux Convergence in Forecasting Convective Initiation: Historical and Operational Perspectives, *Weather and Forecasting*, 20, 351–366, <https://doi.org/10.1175/WAF858.1>, 2005.
- Bauer, P., Thorpe, A., and Brunet, G.: The Quiet Revolution of Numerical Weather Prediction, *Nature*, 525, 47–55, <https://doi.org/10.1038/nature14956>, 2015.
- Crutzen, P. J.: Albedo enhancement by stratospheric sulfur injections: A contribution to resolve a policy dilemma?, *Climatic Change*, 77, 211–220, <https://doi.org/10.1007/s10584-006-9101-y>, 2006.
- Diamond, M. S., Gettelman, A., Lebsock, M. D., McComiskey, A., Russell, L. M., Wood, R., and Feingold, G.: To assess marine cloud brightening’s technical feasibility, we need to know what to study—and when to stop, *Proceedings of the National Academy of Sciences*, 119, e2118379 119, <https://doi.org/10.1073/pnas.2118379119>, 2022.
- Du, Q., Emelianenko, M., and Ju, L.: Convergence of the Lloyd Algorithm for Computing Centroidal Voronoi Tessellations, *SIAM Journal on Numerical Analysis*, 44, 102–119, <https://doi.org/10.1137/040617364>, 2006.
- Fan, J., Wang, Y., Rosenfeld, D., and Liu, X.: Review of Aerosol–Cloud Interactions: Mechanisms, Significance, and Challenges, *Journal of the Atmospheric Sciences*, 73, 4221–4252, <https://doi.org/10.1175/JAS-D-16-0037.1>, 2016.
- Feingold, G., Ghate, V. P., Russell, L. M., Blossey, P. N., Cantrell, W., Christensen, M., Diamond, M. S., et al.: Physical science research needed to evaluate the viability and risks of marine cloud brightening, *Science Advances*, 10, eadi8594, <https://doi.org/10.1126/sciadv.adi8594>, 2024.
- Fischereit, J., Brown, R., Larsén, X. G., Badger, J., and Hawkes, G.: Review of mesoscale wind-farm parametrizations and their applications, *Boundary-Layer Meteorology*, 182, 175–224, <https://doi.org/10.1007/s10546-021-00652-y>, 2022.
- Flossmann, A. I., Manton, M., Abshaev, A., Brientjes, R., Murakami, M., Prabhakaran, T., and Yao, Z.: Review of Advances in Precipitation Enhancement Research, *Bulletin of the American Meteorological Society*, 100, 1465–1480, <https://doi.org/10.1175/BAMS-D-18-0160.1>, 2019.
- Geerts, B. and Rauber, R. M.: Glaciogenic Seeding of Cold-Season Orographic Clouds to Enhance Precipitation: Status and Prospects, *Bulletin of the American Meteorological Society*, 103, E2302–E2314, <https://doi.org/10.1175/BAMS-D-21-0279.1>, 2022.
- Haywood, J. S., Sescu, A., and Adkins, K. A.: Large Eddy Simulation Study of the Humidity Variation in the Shadow of a Large Wind Farm, *Wind Energy*, 23, 423–431, <https://doi.org/10.1002/we.2434>, 2020.
- Higuchi, Y., Nagai, R., Bai, Y., Okazaki, A., Wakamiya, N., and Ogura, M.: Development and evaluation of a black-box optimization framework for weather-intervention design, *Journal of Computational Science*, 97, 102 850, <https://doi.org/10.1016/j.jocs.2026.102850>, 2026.
- Hiraga, Y., Mbugua, J. M., Kotsuki, S., Suzuki, Y., Chen, S.-H., Hamada, A., Yasunaga, K., and Funatomi, T.: Numerical experiments of cloud seeding for mitigating localization of heavy rainfall: a case study of Mesoscale Convective System in Japan, *Natural Hazards and Earth System Sciences*, 26, 1287–1303, <https://doi.org/10.5194/nhess-26-1287-2026>, 2026.
- Huang, J. and Fu, X.: Asymptotic properties and optimal control of rainfall models involving forest-lake effects, *Mathematical Modelling of Natural Phenomena*, 20, 8, <https://doi.org/10.1051/mmnp/2025005>, 2025.



- Kristjánsson, J. E., Muri, H., and Schmidt, H.: The hydrological cycle response to cirrus cloud thinning, *Geophysical Research Letters*, 42, 10 807–10 815, <https://doi.org/10.1002/2015GL066795>, 2015.
- Latham, J., Bower, K., Choularton, T., Coe, H., Connolly, P., Cooper, G., Craft, T., Foster, J., Gadian, A., Galbraith, L., et al.: Marine cloud
415 brightening, *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 370, 4217–4262, <https://doi.org/10.1098/rsta.2012.0086>, 2012.
- Liu, J. and Stewart, R. E.: Water Vapor Fluxes over the Saskatchewan River Basin, *Journal of Hydrometeorology*, 4, 944–959, [https://doi.org/10.1175/1525-7541\(2003\)004<0944:WVFOTS>2.0.CO;2](https://doi.org/10.1175/1525-7541(2003)004<0944:WVFOTS>2.0.CO;2), 2003.
- Nagai, R., Bai, Y., Ogura, M., Kotsuki, S., and Wakamiya, N.: Evaluation of the effectiveness of an intervention strategy in a con-
420 trol simulation experiment through comparison with model predictive control, *Nonlinear Processes in Geophysics*, 32, 281–292, <https://doi.org/10.5194/npg-32-281-2025>, 2025.
- National Research Council: Critical Issues in Weather Modification Research, The National Academies Press, Washington, DC, <https://doi.org/10.17226/10829>, 2003.
- Nishizawa, S., Yashiro, H., Sato, Y., Miyamoto, Y., and Tomita, H.: Influence of Grid Aspect Ratio on Planetary Boundary Layer Turbulence
425 in Large-Eddy Simulations, *Geoscientific Model Development*, 8, 3393–3419, <https://doi.org/10.5194/gmd-8-3393-2015>, 2015.
- Ono, K. and Inatsu, M.: Nonlinear Perturbation Growth at Mesoscale Related to Upscaling Processes from a Mesoscale Convective System, *Journal of the Meteorological Society of Japan. Ser. II*, 103, 127–146, 2025.
- Petley, D.: Global Patterns of Loss of Life from Landslides, *Geology*, 40, 927–930, <https://doi.org/10.1130/G33217.1>, 2012.
- Prabhakaran, T., Murugavel, P., Konwar, M., Malap, N., Gayatri, K., Dixit, S., Samanta, S., Chowdhuri, S., Bera, S., Varghese, M.,
430 et al.: CAIPEEX: Indian cloud seeding scientific experiment, *Bulletin of the American Meteorological Society*, 104, E2095–E2120, <https://doi.org/10.1175/BAMS-D-21-0291.1>, 2023.
- Rawlings, J. B. and Mayne, D. Q.: *Model Predictive Control: Theory and Design*, Nob Hill Publishing, Madison, WI, ISBN 978-0-9759377-0-9, 2009.
- Slingo, J. and Palmer, T. N.: Uncertainty in Weather and Climate Prediction, *Philosophical Transactions of the Royal Society A: Mathemat-
435 ical, Physical and Engineering Sciences*, 369, 4751–4767, <https://doi.org/10.1098/rsta.2011.0161>, 2011.
- Soldatenko, S. A.: Weather and Climate Manipulation as an Optimal Control for Adaptive Dynamical Systems, *Complexity*, 2017, 1–12, <https://doi.org/10.1155/2017/4615072>, 2017.
- Tripathi, A., Mandal, S., Tiwari, P. K., Misra, A. K., and Martcheva, M.: A Comprehensive Investigation into Deterministic and Stochastic Models Concerning the Effects of Seeding on Rainfall and Atmospheric Pollution, *Journal of Biological Systems*, 33, 699–728,
440 <https://doi.org/10.1142/S0218339025500196>, 2025.