Natural Disaster-Resilient Spaceport Network Planning

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Geohazards, including landslides, flooding, and erosion, have consistently posed challenges to US infrastructure. As commercial and governmental space transportation become more widespread, the effect of natural disasters on space launch infrastructure also grows more pronounced. For example, hurricanes have significantly disrupted operations at Cape Canaveral Space Force Station and Kennedy Space Center, notably the Space Launch System tests in 2022. To sustain the growth of the space industry and accommodate future launch demands, new spaceports may need to be constructed: This paper develops a spaceport network design model, in order to rigorously identify new spaceport locations that satisfy launch demand while remaining resilient to natural disaster impacts. We begin with a deterministic facility location planning model, then advance to a chance-constrained (CC) version to address the stochastic nature of natural disasters. We base our probability distributions for natural disaster occurrences on annual frequency data, which supports the formulation of our Chance-Constrained Spaceport Facility Location Planning (CC-SPFLP) model. This model also incorporates *impact factors*— frequency and duration of different natural disaster types, as well as the spatial correlations between adjacent location candidates to optimize spaceport placement. Our experimental results demonstrate that the CC-SPFLP model ensures a probability of satisfying all demands at a level greater than or equal to $1-\epsilon$, where ϵ represents a predefined confidence level.

I. Introduction

A. Background and motivation

Resilient launch infrastructure is crucial as we continue to explore space with goals of advancing scientific knowledge, ensuring national security, and developing the national economy. Data from the United Nations Office for Outer Space Affairs indicates that the US alone launched over two thousand satellites in 2023, with Cape Canaveral, Kennedy Space Center, and Vandenberg Space Force Base being responsible for launching the vast majority of these missions [1]. However, the vulnerability of these facilities to natural disasters poses significant challenges to mission success. By strategically placing new spaceports in locations less prone to natural hazards such as hurricanes, earthquakes, and thunderstorms, we can minimize the risks associated with launch operations and ensure that scientific and exploratory endeavors in space are not interrupted [2]. Having a resilient network of spaceports in the future aligns with the focus on Space Access, Mobility, and Logistics (SAML), as outlined in the US Space Force Commercial Space Strategy [3].

The strategic placement of spaceports is also critical for bolstering national security. The US, China, and the Russian Federation each operate more than 100 military satellites [4]. However, the susceptibility of spaceports to natural hazards poses a threat to the deployment of these defense assets. The resilience of space infrastructure and, by extension, national security interests, rely heavily on a network of resilient spaceports.

The development of resilient spaceports is also partly influenced by economic incentives. The space industry has seen a remarkable pattern of growth in the past few decades, exceeding $350 billion in total value in 2023. Commercial ventures including satellite construction, private launches, and ground equipment sales accounted for over two-thirds

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of this value [5]. The vulnerability of spaceports to natural disasters poses risks to investment, job creation, and technological advancement in the space domain. To draw analogy to other industries, the failure of major infrastructure can result in significant setbacks. For instance, a minor disturbance to a port affecting roughly 20 shipping containers can incur a loss of over $200,000 per day [6]. An event damaging railroad infrastructure may lead to losses of close to $2B a day [7]. Spaceports, while not yet as integral to the economy, are becoming increasingly significant and merit careful consideration to avoid catastrophic shutdowns.

B. Research problem

With the growing demand for commercial satellite services, advancements in reusable vehicle technology, and the anticipation of increased human spaceflight, the Federal Aviation Administration (FAA) forecasts a gradual rise in rocket demand. Projections indicate a low-to-high range of 61-94 launches in fiscal year 2023, expanding to a range of 123-288 launches by FY2027 [8]. This trend has sparked interest from government entities, private corporations, and industry stakeholders in addressing the challenges of spaceport location planning.

By deploying resilient space infrastructure in regions less prone to natural hazards, we can mitigate risks, attract private capital, and foster the development of new technologies and industries. This paper aims to design a discrete facility location planning model to identify locations suitable for spaceports, representing a step forward in ensuring the sustainability and success of space endeavors.

C. Prior works

We begin by examining previous research on the impacts of natural disasters. [9] sorts disasters into several categories, including geophysical (earthquakes, volcanoes, tsunamis), meteorological (hurricanes, thunderstorms, tornadoes, lightning), and hydrological (flood, inundation). Each listed disaster represents a specific threat posed to infrastructure as a direct result of its intensity, frequency, or formation speed. The authors suggest both structural solutions, such as design modifications, and non-structural solutions, such as relocation, to mitigate the impacts of these events. Other studies, including [10] and [11], identify key negative impacts of natural disasters on infrastructure, including increased stress levels caused by an uptick in demand, reduced response times, lower serviceability, and diminished performance. Both papers stress the need to design resilient infrastructure to prevent these adverse situations. [12] investigates the economic impacts of natural disasters on infrastructure, focusing on losses caused by damages to infrastructural development, foreign direct investment, and human capital. A critical gap in the literature exists regarding spaceports, which remain relatively rare compared to other infrastructure [13].

Our previous work in [14] focuses on establishing a set of spaceport locations which minimize costs (e.g., launch costs, flight rerouting expenses, etc.) However, achieving this objective is contingent upon addressing numerous constraints, including meeting the demands of space launches, avoiding densely populated areas along launch trajectories, and enforcing minimum distance requirements for selected spaceports to mitigate the risks posed by natural disasters. To effectively navigate these challenges, the paper utilizes a *deterministic* facility location planning model, without nuanced consideration of natural disaster risk. Thus, while the spaceport locations suggested by the model in [14] is cost-optimized, it does not account for resilience against natural disaster impact.

To build a resilient spaceport network, we employ the chance-constrained (CC) programming approach. [15] provides a comprehensive review of the fundamentals and recent advancements in CC programming. This method categorizes problems into two main types based on the source of uncertainty: Right-hand side (RHS) and left-hand side (LHS). The distinction between these types lies in the location of uncertainty within the chance constraints. For our CC-SPFLP model, the uncertainty originates from the capacities of spaceports, classifying it as an LHS problem. LHS problems can be effectively addressed using the Sample Average Approximation (SAA) method [16], which approximates the original chance constraint with a finite discrete distribution. This reformulation allows the CC programming model to be tractably solved as a Mixed-Integer Linear Program (MILP).

II. Contributions of Work

The contributions of the work described in this paper are as follows:

1) We develop an algorithm for spaceport location planning that integrates joint-distributional considerations to account for the impact of multiple different types of natural disasters.
2) We implement a criticality analysis to differentiate between the impact of various types of disasters. This allows

us to estimate the annual occurrences of eight different types of natural disasters at a county-level, and determine the launches affected per year.

III. Methodology

Drawing upon previous research on deterministic spaceport location planning, this section delves into the CC programming approach. We detail the random variables incorporated into the algorithm, the structure of the CC-SPFLP optimization problem, and introduce the concept of impact factors to gauge the severity of natural disaster impact on launch infrastructure.

To decide optimal locations for a spaceport network, we employ the facility location planning problem, which is a discrete optimization problem that involves determining the placement of facilities which optimizes an objective function while meeting specified constraints. Typical examples include placing factories, warehouses, healthcare centers, or other service centers in a way that minimizes costs, maximizes efficiency, or satisfies demand [17]. For the natural disaster-resilient spaceport network planning problem, we initially develop a deterministic spaceport location planning model (SPFLP) [14] that requires chosen locations to be situated more than a pre-set distance apart from each other. This constraint establishes a physical separation between spaceports, acting as a buffer to insulate against natural disasters. However, this is a deterministic approach (i.e., we do not account for uncertainties associated with natural disasters), and is not very nuanced (i.e., it is difficult to rigorously select a pre-set distance). Thus, we augment the SPFLP by incorporating chance constraints that integrates probabilistic data regarding natural disasters, thereby allowing for the determination of optimal spaceport locations which factor in the variability and uncertainty of natural disaster occurrences.

A. Natural disaster selection

A total of eight natural disasters were chosen for their potential to significantly damage or restrict spaceport operations. The relative severity of each event as well as its probability to occur were taken into account during the construction of the model. A breakdown of each disaster is as follows:

1) *Hurricanes:* A common occurrence near coastal regions such as Florida, hurricanes pose a significant threat to spaceports due to high winds, storm surges, and heavy rainfall which can cause extensive structural damage to both spaceports and spacecraft [18].
2) *Coastal flooding:* Though rare in many areas, coastal flooding events may overwhelm critical infrastructure and equipment, leading prolonged closures of spaceport facilities. They are especially dangerous in low-lying coastal regions [19].
3) *Lightning:* Lightning storms and other similar events will immediately lead to a full shutdown of all launches at NASA sites; even the presence of a thundercloud has the potential to cause launch delays due to the risk of lightning strikes [20].
4) *Earthquakes:* These events can cause severe structural damage to launch pads, control centers, and other critical infrastructure. Seismic activity may also disrupt ground-based navigation systems and communication networks, resulting in delayed or aborted launches. Though the impact of earthquakes on spaceports has not been directly studied, several works have examined their impacts on other infrastructure such as railways [21].
5) *Tornadoes:* Though localized, tornadoes can cause extensive damage to buildings, vehicles, and other infrastructure at spaceports. The high winds and flying debris associated with tornadoes can also result in significant operational delays [22].
6) *Ice storms:* Ice storms can coat surfaces with a thick layer of ice, leading to hazardous conditions for personnel, damage to infrastructure, and delays in launch schedules. The weight of the ice can also lead to communication disruptions or even structural collapses [23].
7) *Wind:* High wind speeds, even outside of hurricanes and tornadoes, can impact launch schedules and safety. Strong winds can cause physical damage to launch vehicles and infrastructure, and make ground operations hazardous [20].
8) *Hail:* Hailstorms can cause significant damage to vehicles, buildings, personnel, and sensitive equipment. Hail can puncture surfaces, shatter windows, and lead to costly repairs and operational delays [24].

B. Deterministic SPFLP

We begin with a summary of the SPFLP model from our previous work in [14]. The goal of the SPFLP model is to determine the set of locations to serve as a network of spaceports such that the cost of selecting that launch location (e.g., transportation, operations, per-rocket launch costs, aircraft rerouting costs, etc.) is minimized. Spaceport candidates are evaluated at the county level, where the set of all continental US counties serves as possible locations to build a spaceport. The counties selected must satisfy the following problem constraints:

- Given a space launch mission, we categorize it by its payload's intended semi-major axis and orbital inclination once it is in orbit. Based on historical launch data, we find the number of launch missions per category and estimate demand for each mission type. The selected group of spaceport counties must satisfy the demand of all mission types.
- Trajectories of rockets launched from a selected spaceport cannot traverse over areas with high population and territories of neighbouring countries (e.g., Canada and Mexico).
- Each pair of selected spaceports must be adequately separated to ensure continued launch capabilities in the event of a natural disaster. Note that this constraint is a deterministic, non-tailored physical separation buffer in the deterministic SPFLP. In the augmented version herein (CC-SPFLP), we will refine this constraint.

For the deterministic SPFLP, there are three groups of decision variables $\{x_i\}$, $\{y_{i,j}\}$, and $\{z\}$, encompassing respectively the following decisions: (1) whether a specific county is selected as a spaceport candidate; (2) what types of missions will be launched from a spaceport candidate county (and how many of each type); and (3) auxiliary decision variables for the physical separation buffer constraint. The objective function is the sum of the following costs: The operation cost and transportation cost are approximated by the median house value and average travel time of each county. The launch cost measures the amount of thrust needed to launch a rocket into a specific orbit. Additionally, given a predetermined launch angle and its surrounding hazardous area, we can keep track of the number of impacted commercial flights. Multiplying the number of impacted flight by the unit re-routing cost per flight from [25], we are able to estimate the flight re-routing cost for all launch mission types.

To parameterize launch demand within our model, we first project and estimate the US space launch demand by the year 2030. This estimation is grounded in historical launch data as sourced from the FAA [26]. Utilizing this estimated demand, we then calculate the required number of spaceports, denoted by K. This calculation hinges on the anticipated capacity of a single spaceport and the estimated demand of space launch determined by 2030. Furthermore, the SPFLP generates couplings between decisions of which county is selected as a spaceport candidate, and the assigned mission types and quantity per spaceport candidate. This provides an assignment plan for each mission type. For additional details on the deterministic SPFLP model, we refer readers to [14].

C. CC-SPFLP

For the deterministic SPFLP, we apply distance constraints to ensure that the spaceport network is robust with respect to a generic disaster of a specified size. However, there are different types of natural disasters that can severely impact the functionality of a spaceport, such as earthquakes, tornadoes, ice storms, and so on. Furthermore, the range and frequency of each natural disaster also vary widely. Therefore, the minimum-distance constraint is insufficient to deal with all types of natural disasters.

Given historical data of natural disasters' annual frequencies (such as those obtained from, e.g., [27]), we formulate the Chance-Constrained SPFLP model (CC-SPFLP). In CC-SPFLP, we denote ξ as a random variable of a natural disaster's annual occurrence and ϵ as the confidence level. The idea behind the CC-SPFLP is that we generate samples of the random variable ξ based on the annualized frequency data, and for at least $(1-\epsilon)\times 100$ percent of all samples the demand of all types of missions are satisfied. For instance, we consider ξ to represent the annual occurrence of hurricanes, generate samples of ξ with the size of 10000 and set $\epsilon = 0.01$. The CC-SPFLP then ensures that at least $(1-\epsilon)\times 100 = 99\%$ (or 9900 of out 10000) of the cases, the spaceport locations remain unaffected by hurricanes. To present this idea in an optimization model, we add a constraint stating that the probability of all demands being satisfied has to be larger than or equal to $1-\epsilon$. This can be represented as

$$\Pr\left(\sum_{i=1}^{N}(P-\xi_i)x_i \geq K\right) \geq 1-\epsilon, \tag{1}$$

where P is set as the capacity of a spaceport and $P-\xi_i$ represents the number of launches a spaceport can accommodate when a natural disaster occurs. With the chance constraint defined above, we formulate the CC-SPFLP as follow:

$$\min_{x,y,z} \quad \sum_{i=1}^{N} \left(C_{T_i} + C_{O_i}\right) x_i + \sum_{i=1}^{N} \sum_{j=1}^{T} \left(C_{L_{i,j}} + C_{R_{i,j}}\right) y_{i,j}, \tag{2a}$$

$$\text{s.t.} \quad \Pr\left(\sum_{i=1}^{N} \left(P - \xi_i\right) x_i \geq K\right) \geq 1 - \epsilon, \tag{2b}$$

$$\sum_{i=1}^{N} y_{i,j} \geq k_j, \quad \forall j = 1, 2, \ldots, T, \tag{2c}$$

$$\sum_{j=1}^{T} y_{i,j} \leq P, \quad \forall i = 1, 2, \ldots, N, \tag{2d}$$

$$\frac{1}{m} \sum_{j=1}^{T} y_{i,j} \leq x_i, \quad \forall i = 1, 2, \ldots, N, \tag{2e}$$

$$x_i \leq \sum_{j=1}^{T} y_{i,j}, \quad \forall i = 1, 2, \ldots, N, \tag{2f}$$

$$x_i \in \{0, 1\}, y_{i,j} \in \mathbb{N}_{\geq 0}, \quad \forall i = 1, 2, \ldots, N, j = 1, 2, \ldots, T. \tag{2g}$$

In addition to defined variables above, we use the same notation as the previous deterministic SPFLP model in [14].

Given that the chance-constrained term is non-convex, we propose an MILP reformulation to guarantee that in at least 95% of scenarios (where ϵ= 0.05), the demand for all types of missions will be met, even under the impact of a natural disaster. To achieve this, we represent the probability distribution as an expectation:

$$\Pr\left(\sum_{i=1}^{N} \left(P - \xi_i\right) x_i \geq K\right) = \mathbb{E}_{\xi}\left[\mathbf{1}_{\left(\sum_{i=1}^{N}(P-\xi_i)x_i \geq k\right)}\right] = \frac{1}{N_s} \sum_{s=1}^{N_s} \mathbf{1}_{\left(\sum_{i=1}^{N}\left(P-\xi_i^{(s)}\right)x_i \geq k\right)}. \tag{3}$$

In the above formulation, N_s represents the sample size and $\mathbf{1}_{\left(\sum_{i=1}^{N}(P-\xi_i)x_i \geq k\right)}$ is an indicator function with the value of one if the demand constraint is satisfied. Moreover, based on the definition of expectation, we can model the chance constraint as

$$\frac{1}{N_s} \sum_{s=1}^{N_s} \mathbf{1}_{\left(\sum_{i=1}^{N}(P-\xi_i^{(s)})x_i \geq k\right)} \geq 1 - \epsilon. \tag{4}$$

The indicator function within the formulation is still non-convex and thus making the optimization model not tractable. Therefore, we introduce a binary variable z to model the indicator function and apply the big-M technique to integrate the chance constraint into the optimization model. We denote z_s as a binary variable for sample s, with $z_s = 1$ when the demand constraint cannot be satisfied. Therefore, the constraint that under at least $N_s(1 - \epsilon)$ scenarios the demand constraint holds is equivalent to the statement that the total number of scenarios where the demand constraint does not hold is less than or equal to ϵN_s. By introducing the big-M term, we are able to reformulate the CC-SPFLP as follow:

$$\min_{x,y,z} \quad \sum_{i=1}^{N} \left(C_{T_i} + C_{O_i}\right) x_i + \sum_{i=1}^{N}\sum_{j=1}^{T} \left(C_{L_{i,j}} + C_{R_{i,j}}\right) y_{i,j}, \tag{5a}$$

$$\text{s.t.} \quad \sum_{i=1}^{N} \left(P - \xi_{s,i}\right) x_i \geq K - M z_s, \quad \forall s = 1, 2, \ldots, N_s, \tag{5b}$$

$$\frac{1}{N_s} \sum_{s=1}^{N_s} z_s \leq \epsilon, \tag{5c}$$

$$\sum_{i=1}^{N} y_{i,j} \geq k_j - M z_s, \quad \forall j = 1, 2, \ldots, T, \forall s = 1, 2, \ldots, N_s, \tag{5d}$$

$$\sum_{j=1}^{T} y_{i,j} \leq \left(P - \xi_{s,i}\right) + M z_s, \quad \forall i = 1, 2, \ldots, N, \forall s = 1, 2, \ldots, N_s, \tag{5e}$$

$$x_i \leq \sum_{j=1}^{T} y_{i,j}, \quad \forall i = 1, 2, \ldots, N, \tag{5f}$$

$$x_i \in \{0, 1\}, y_{i,j} \in \mathbb{N}_{\geq 0}, z_s \in \{0, 1\}, \quad \forall i = 1, 2, \ldots, N, j = 1, 2, \ldots, T, s = 1, 2, \ldots, N_s. \tag{5g}$$

The M term is a very large positive number. When $z_s = 1$, $K - M z_s$ is a very large negative number and thus constraint (5b) will always hold. Moreover, it is obvious that the demand constraint is satisfied when $z_s = 0$. Therefore, by controlling the number of z_s where it is equal to 1 (constraint (5c)), we can make the chance constraint hold and thus deriving the tractable MILP form of the CC-SPFLP model.

D. Correlated samples of natural disasters

One key element of the CC-SPFLP is the sampling of each type of natural disaster. In this paper, we derive the distribution of occurrences from the annual frequency data of eight types of natural disasters, enabling us to obtain samples from these distributions. However, in our initial approach, the samples of occurrences at each candidate location are assumed to be independent. This assumption does not hold in practical scenarios, as adjacent location candidates often experience simultaneous impacts during natural disasters. Therefore, to account for the correlations among occurrences at adjacent locations, we assume that the random variables representing natural disaster occurrences follow a Gaussian distribution. With this assumption, we are able to construct a covariance matrix and obtain correlated samples (which is represented as a random vector of size N).

$$\begin{bmatrix} \xi_1 \\ \xi_2 \\ \vdots \\ \xi_N \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_N \end{bmatrix}, \Sigma \right). \tag{6}$$

For the two-dimensional case the covariance matrix of random variables ξ_1, ξ_2 can be represented as

$$\Sigma = \begin{bmatrix} \sigma_1^2 & \rho_{1,2}\sigma_1\sigma_2 \\ \rho_{2,1}\sigma_2\sigma_1 & \sigma_2^2 \end{bmatrix}, \tag{7}$$

where σ and ρ are the standard deviation and the correlation between ξ_1 and ξ_2, respectively. If we have occurrence data at each county, we will be able to derive the variance of data at each county σ_{ξ_i} and the correlation at any two counties ρ_{ξ_i,ξ_j}, and thus sampling correlated N dimension random vectors via

$$Y = \begin{bmatrix} \xi_1 \\ \xi_2 \\ \vdots \\ \xi_N \end{bmatrix} = \mu + \sqrt{\Sigma} \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_N \end{bmatrix}, u_i \sim \mathcal{N}(0, 1). \tag{8}$$

In practice, deriving correlations between random variables can be challenging due to issues like missing data points at some locations or having only mean values of the variables available. In such cases, non-parametric methods can be utilized to construct the covariance matrix. In this paper, given our access only to frequency data of each type of natural disaster at each candidate location, we employ the squared exponential covariance function to generate the covariance matrix. The function is defined as follows:

$$k(x, x') = \tau \exp\left(-\frac{|d - d'|}{l^2}\right), \tag{9}$$

where $|d - d'|$ represents the spatial distance between two location candidates. The larger the spatial distance between the candidates, the smaller the covariance between these locations. Moreover, l is a parameter to determine how quickly the correlation between locations decay with distance, while τ scales the output value of the covariance function. By tuning both l and τ, we can generate a covariance matrix with reasonable values and thus obtaining correlated sample using (8).

E. Impact factor consideration

To incorporate uncertainties into the CC-SPFLP, it is imperative to quantify the occurrences of natural disasters within a county and their respective impacts. Each type of disaster exhibits varying levels of impact; for instance, in Mobile, Alabama, lightning strikes occur approximately 156.4 times annually [28], with an average system recovery duration (ready for the next launch operation) of 3 hours [20]. Conversely, hurricanes occur at a rate of only 0.3 events per year, but they necessitate potentially much longer recovery periods. These distinct impact characteristics are quantified through the incorporation of impact factors in the CC-SPFLP.

In order to ascertain the impact factors, we introduce the Criticality Analysis (CA) methodology [29]. CA evaluates the potential failure of components, subsystems, or systems in the event of adverse occurrences such as natural disasters. This methodology takes into account criteria such as event frequency, system impact, and event duration to accurately quantify the impact factors. The relationship between these parameters is given in (10), where C represents the criticality of the event occurring (in this case, a natural disaster), f represents the frequency of the event, and d represents the duration of the event, with the recovery time estimated based on analyzed historical data.

$$C = f \cdot d. \tag{10}$$

We utilized the annualized frequency data [28] from the Federal Emergency Management Agency (FEMA) in the CC-SPFLP model. This annualized frequency is defined as the number of historical occurrences (i.e., recorded events or event-days) of a specific hazard type within a known period of record per geographic area. For events such as earthquakes and coastal flooding, the annualized frequency value signifies the likelihood of a hazard occurring within a given year. It is important to note that not all hazard occurrences are deemed relevant for the calculation of annualized frequency. Subject matter experts have established criteria to determine which hazard occurrences are included, typically focusing on events capable of causing significant damage (e.g., hail with a diameter greater than 0.75 inches).

To assess the criticality across various natural disasters, Table 1 presents the average duration d (in days) required for businesses to restore physical operations—we make the assumption that this is equal to the recovery time required to resume launches. With the derived impact factor for each type of natural disaster, the chance constraint is reformulated as follows:

$$\Pr\left(\sum_{i=1}^{N} (P - C\xi_i)x_i \geq K\right) \geq 1 - \epsilon, \tag{11}$$

where $(P - C\xi_i)$ is the capacity of a spaceport after being impacted by the natural disaster, with C calculated via (10).

IV. Experiment and Discussion

A. Experiment setup

For the flight trajectory data and cost information used in our CC-SPFLP model, we adopt the same settings as those detailed for the SPFLP model. For further details, we refer readers to the paper on the deterministic SPFLP model [14]. In our experiments, we consider the eight types of natural disasters previously mentioned, constructing samples for each

Hazard type	Mean time for a county to regain physical functionality (days)
Hurricane [30]	14
Coastal Flooding [31]	4
Lightning [20]	0.125
Earthquake [32]	561
Tornado [33]	6.45
Ice Storm [34]	0.88
Strong Wind [35]	0.125
Hail [36]	0.5

Table 1 Estimated mean time for infrastructures to regain physical functionality after each type of natural disasters. Source cited per row.

type based on annual frequency data [28]. To generate correlated samples of occurrences, we utilize the non-parametric squared exponential covariance function, described in Section III.D. This method is chosen due to our limited data, which only includes the mean values of occurrences. The log-scale parameter is set as $l = \ln 2$ and the scale factor τ is set as $0.1V_j$, $j = 1, 2, \ldots, T$, where V_j is the variance of occurrences of type j across all locations. We use this value to approximate the variance of occurrences at each location candidate.

B. Experiment results

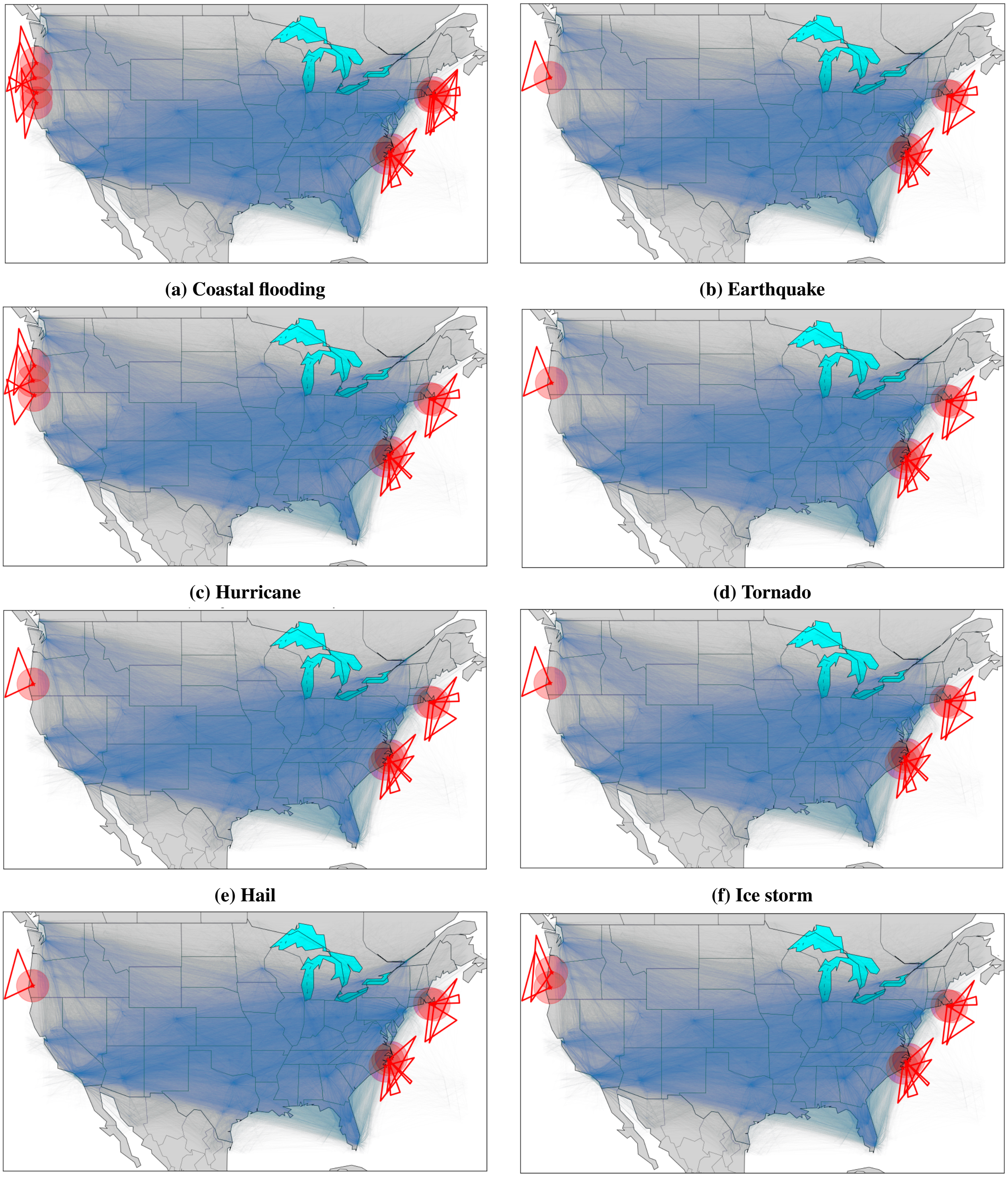
1. Individual impact of natural disaster

The optimal solutions of the CC-SPFLP, impacted by each individual type of natural disaster, are illustrated in Figures 1a-1h. Additionally, visualizations of the frequency data for all types of natural disasters are presented in Figures 3a- 3h. From these figures, we note that the spaceport network layouts under the impact of earthquakes, tornadoes, hail, ice storms, and strong winds are identical. This uniformity is due to the combined influence of frequency and criticality in determining a spaceport's vulnerability to natural disasters. For disasters like earthquakes and tornadoes, which have high criticality but low frequency, their significant potential impacts do not preclude spaceport construction at those locations due to the low likelihood of occurrence. From the CC-SPFLP perspective, the chance constraints are not violated. Conversely, for natural disasters such as lightning, strong winds, ice storms, and hail, which occur frequently but have low criticality, the high occurrence rate is ameliorated by the mild impact of each individual event. We also note that even if the optimal solutions of locations are the same for the aforementioned natural disasters, the optimal solutions in terms of mission assignments differ from each other.

Lightning, hurricanes, and coastal flooding significantly impact spaceport operations. Although lightning has a relatively low criticality, its high frequency makes it a significant natural disaster. As illustrated in Figure 3h, lightning occurrences are more frequent along the East and Gulf coasts compared to the West Coast, leading to a preference for selecting spaceports on the West Coast. A similar geographical pattern is observed with hurricanes, which are prevalent along the Gulf and West Coasts. In response, the CC-SPFLP model strategically selects four West Coast locations and assigns the majority of missions there. Coastal flooding presents the greatest challenge due to its relatively high criticality and significant occurrence across the West, East, and Gulf Coasts. To manage this risk within the constraints of demand, the CC-SPFLP model mitigates the uncertainty of coastal flooding by favoring the construction of more spaceports on the West Coast.

2. Joint impacts of natural disasters

In practice, multiple occurrences of various types of natural disasters throughout a year necessitate the design of a spaceport network that is resilient against *all* considered types of natural disasters. In developing our model, we initially assign a set of decision variables to each type of natural disaster, and then incorporate a consensus constraint to ensure resilience under the combined impact of all natural disasters. As depicted in Figure 2, the analysis reveals that ten



(a) **Coastal flooding**

(b) **Earthquake**

(c) **Hurricane**

(d) **Tornado**

(e) **Hail**

(f) **Ice storm**

(g) **Strong wind**

(h) **Lightning**

Fig. 1 CC-SPFLP results for different types of natural disasters.

spaceports have been selected, with five located on the West Coast. Compared to solutions optimized under separate uncertainties, the joint CC-SPFLP model tends to favor more spaceport selections on the West Coast to meet the chance constraint for launch demand. Additionally, the pattern of results from the joint CC-SPFLP model exhibits similarities

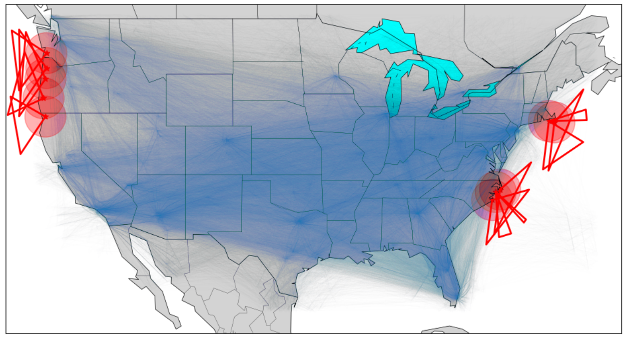
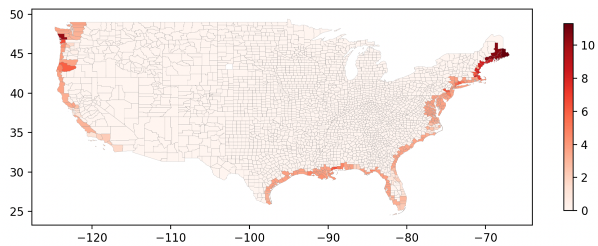
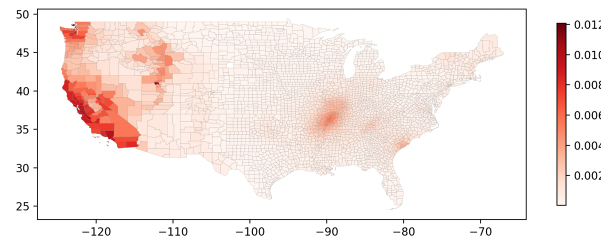


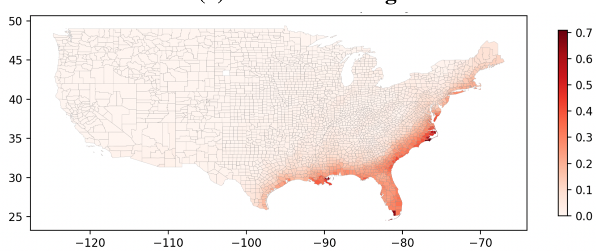
Fig. 2 CC-SPFLP results under the joint distribution of all natural disasters.



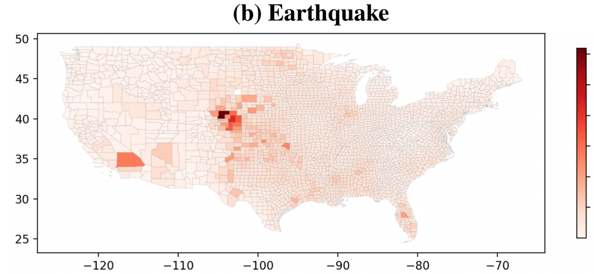
(a) Coastal flooding



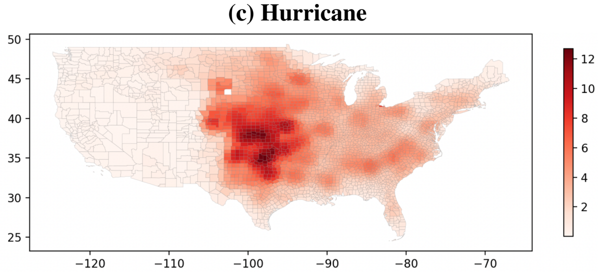
(b) Earthquake



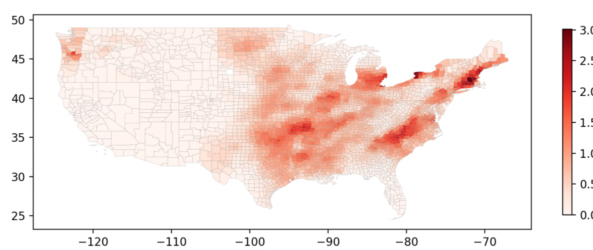
(c) Hurricane



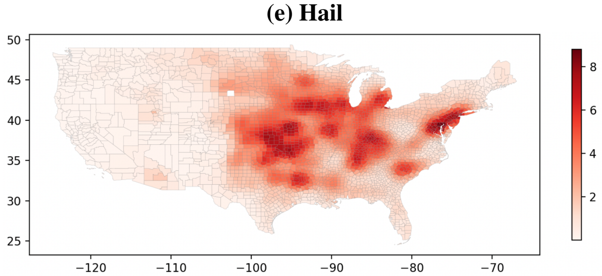
(d) Tornado



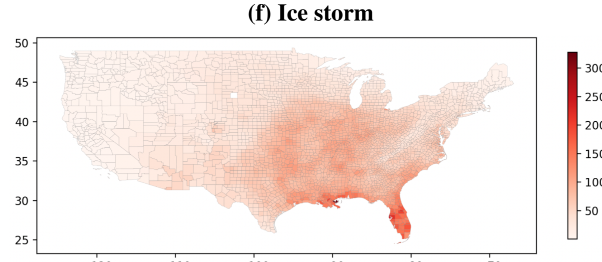
(e) Hail



(f) Ice storm



(g) Strong wind



(h) Lightning

Fig. 3 Annualized frequencies of the eight different types of natural disasters.

to those obtained from individual disaster considerations.

V. Conclusion

Motivated by the goal of designing future spaceport networks that are resilient to natural disaster risks, in this work we introduce a facility location planning model for spaceports with chance constraints that account for risks such as coastal flooding, hurricanes, and ice storms. The proposed chance-constrained spaceport facility location planning model (CC-SPFLP) determines an optimal set of discrete locations for spaceports, considering the uncertainty of all natural disasters and a predetermined confidence level of launch demand satisfaction. We note that this study has several limitations: The non-parametric method (cf. Section III.D) used to approximate the true covariance matrix is not entirely accurate and is highly sensitive to parameter selection. Furthermore, this paper generates only a relatively small number of samples ($N_s = 100$) for each type of natural disaster, which may be insufficient for capturing rare but significant events (e.g., earthquakes). As a future direction, we propose integrating the importance sampling technique into the CC-SPFLP model. This approach could potentially reduce sample variance and expedite the sampling process, enhancing the model's robustness and efficiency.

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References

[1] UNOOSA, "Search OSOidx," *Online Index of Objects Launched into Outer Space*, 2023. [Online; accessed 2024-05-17].

[2] Rosenzweig, C., Horton, R. M., Bader, D. A., Brown, M. E., DeYoung, R., Dominguez, O., Fellows, M., Friedl, L., Graham, W., Hall, C., Higuchi, S., Iraci, L., Jedlovec, G., Kaye, J., Loewenstein, M., Mace, T., Milesi, C., Patzert, W., Stackhouse, P. W., Jr., and Toufectis, K., "Enhancing climate resilience at NASA centers: A collaboration between science and stewardship," *Bulletin of the American Meteorological Society*, Vol. 95, No. 9, 2014, pp. 1351–1363. [Online; accessed 2024-03-26].

[3] US Space Force, "US Space Force Commercial Space Strategy," Tech. rep., US Space Force, 2024.

[4] UCS, "UCS satellite database," *Union of Concerned Scientists*, 2023. [Online; accessed 2024-05-17].

[5] Crane, K. W., Linck, E., Lal, B., and Wei, R. Y., "Measuring the Space Economy: Estimating the Value of Economic Activities in and for Space," Tech. rep., Institute for Defense Analyses, 2020. URL `http://www.jstor.org/stable/resrep25331.1`.

[6] Loh, H. S. and Thai, V. V., "Cost consequences of a port-related supply chain disruption," *The Asian Journal of Shipping and Logistics*, Vol. 31, No. 3, 2015, p. 319–340. https://doi.org/10.1016/j.ajsl.2015.09.001.

[7] Keen, D., "The Economic Impact of a Railroad Shutdown," , 2022. URL https://www.aar.org/wp-content/uploads/2022/09/AAR-Rail-Shutdown-Report-September-2022.pdf.

[8] Federal Aviation Administration, "FAA Aerospace Forecast, Fiscal Years 2023-2043," , 2023.

[9] Mijalković, S. and Cvetković, V., "Vulnerability of critical infrastructure by natural disasters," *national critical infrastructure protection–regional perspective, University of Belgrade- Faculty of Security Studies, Institute for Corporative Security Studies in Ljubljana, Belgrade*, 2013, pp. 91–102.

[10] Choi, J., Deshmukh, A., and Hastak, M., "Increase in stress on infrastructure facilities due to natural disasters," *International Journal of Urban Sciences*, Vol. 20, No. sup1, 2016, pp. 77–89. [Online; accessed 2024-06-21].

[11] Rouhanizadeh, B., Kermanshachi, S., and Dhamangaonkar, V. S., "Reconstruction of Critical and Interdependent Infrastructure Due to Catastrophic Natural Disasters: Lessons Learned," *Construction Research Congress 2020*, 2020, pp. 895–904. https://doi.org/10.1061/9780784482858.096, URL https://ascelibrary.org/doi/abs/10.1061/9780784482858.096.

[12] Khan, M. T. I., Anwar, S., Sarkodie, S. A., Yaseen, M. R., and Nadeem, A. M., "Do natural disasters affect economic growth? The role of human capital, foreign direct investment, and infrastructure dynamics," *Heliyon*, Vol. 9, No. 1, 2023, p. e12911. [Online; accessed 2024-06-21].

[13] Roberts, T., “Spaceports of the World,” , 03 2019. https://doi.org/10.13140/RG.2.2.10985.75362.

[14] Wu, H., Sun, K. R., Miller, J. A., Jia-Richards, O., and Li, M. Z., “Spaceport Facility Location Planning within the US National Airspace System,” , 2024.

[15] Küçükyavuz, S. and Jiang, R., “Chance-constrained optimization under limited distributional information: A review of reformulations based on sampling and distributional robustness,” *EURO Journal on Computational Optimization*, Vol. 10, 2022, p. 100030.

[16] Barrera, J., Homem-de Mello, T., Moreno, E., Pagnoncelli, B. K., and Canessa, G., “Chance-constrained problems and rare events: an importance sampling approach,” *Mathematical Programming*, Vol. 157, 2016, pp. 153–189.

[17] Daskin, M. S., *Network and Discrete Location Models, Algorithms, and Applications 2nd Edition*, John Wiley & Sons, Inc., Hoboken, New Jersey, USA, 2014.

[18] Alcorn, J., Rosenzweig, C., Horton, R., and Higuchi, I., Jr, “US space transportation and climate change: Potential impacts of climate change on access to space,” *Earth & Space 2008: Engineering, Science, Construction, and Operations in Challenging Environments*, ASCE Library, 2008, pp. 1–8.

[19] Martello, M. V. and Whittle, A. J., “Estimating coastal flood damage costs to transit infrastructure under future sea level rise,” *Communications Earth & Environment*, Vol. 4, No. 1, 2023, pp. 1–10.

[20] NASA, “Space Shuttle Weather Launch Commit Criteria and KSC End of Mission Weather Landing Criteria,” https://www3.nasa.gov/centers/kennedy/pdf/167476main_Weather-07R.pdf, 2024. [Online; accessed 2024-06-09].

[21] Lakusic, S., Haladin, I., and Vranesic, K., “Railway infrastructure in earthquake affected areas,” *Journal of the Croatian Association of Civil Engineers*, Vol. 72, No. 10, 2020, pp. 905–921. [Online; accessed 2024-06-17].

[22] Huang, Z., Fan, X., Cai, L., and Shi, S. Q., “Tornado hazard for structural engineering,” *Natural Hazards*, 2016. [Online; accessed 2024-06-17].

[23] Degelia, S. K., Christian, J. I., Basara, J. B., Mitchell, T. J., Gardner, D. F., Jackson, S. E., Ragland, J. C., and Mahan, H. R., “An overview of ice storms and their impact in the United States,” *International Journal of Climatology*, Vol. 36, No. 8, 2015, pp. 2811–2822. [Online; accessed 2024-06-17].

[24] Kim, M. H., Lee, J., and Lee, S.-J., “Hail: Mechanisms, monitoring, forecasting, damages, financial compensation systems, and prevention,” *Atmosphere*, Vol. 14, No. 11, 2023, p. 1642. [Online; accessed 2024-06-17].

[25] O’Neill, G. and Hansman, J., “A Commercial Space Operator Cost Model for Analyzing Airspace Launch Equity,” Tech. rep., MIT International Center for Air Transportation, 2018.

[26] Federal Aviation Administration, “Commercial Space Data,” https://www.faa.gov/data_research/commercial_space_data, Accessed: 08-Dec-2023.

[27] Federal Emergency Management Agency, “Natural Hazards,” https://hazards.fema.gov/nri/natural-hazards, Accessed: 10-Dec-2023.

[28] Zuzak, C., Goodenough, E., Stanton, C., Mowrer, M., A.Sheehan, Roberts, B., McGuire, P., and Rozelle, J., “National Risk Index Technical Documentation,” Tech. rep., Federal Emergency Management Agency, Washington, DC, 2023.

[29] Mill, G., “Criticality Analysis Methodology,” Tech. Rep. FAA-RD-76-77, U.S. Department of Transportation Federal Aviation Administration Systems Research & Development Service, 1975.

[30] Beutel, A. and Humphries, K., “NASA’s Johnson Space Center Closes Through Labor Day for Tropical Storm Harvey,” , aug 30 2017. [Online; accessed 2024-06-21].

[31] Sweet, W., Hamlington, B., Kopp, R., Weaver, C., Barnard, P., Bekaert, D., Brooks, W., Craghan, M., Dusek, G., Frederikse, T., Garner, G., Genz, A., Krasting, J., Larour, E., Marcy, D., Marra, J., Obeysekera, J., Osler, M., Pendleton, M., Roman, D., Schmied, L., Veatch, W., White, K., and Zuzak, C., “Global and Regional Sea Level Rise Scenarios for the United States: Updated Mean Projections and Extreme Water Level Probabilities Along U.S. Coastlines.” Tech. rep., National Oceanic and Atmospheric Administration, 2022.

[32] Cremen, G., Seville, E., and Baker, J. W., “Modeling post-earthquake business recovery time: An analytical framework,” *International Journal of Disaster Risk Reduction*, Vol. 42, 2020, p. 101328. https://doi.org/https://doi.org/10.1016/j.ijdrr.2019.101328, URL https://www.sciencedirect.com/science/article/pii/S2212420919312294.

[33] Han, X. and Koliou, M., "Investigation of effects of hazard geometry and mitigation strategies on community resilience under tornado hazards using an Agent-based modeling approach," *Resilient Cities and Structures*, Vol. 3, No. 2, 2024, p. 9. https://doi.org/https://doi.org/10.1016/j.rcns.2024.03.003, URL https://www.sciencedirect.com/science/article/pii/S2772741624000061, from Performance-Based Engineering to Cityscape Resilience.

[34] Rauber, R. M., Olthoff, L. S., Ramamurthy, M. K., Miller, D., and Kunkel, K. E., "A Synoptic Weather Pattern and Sounding-Based Climatology of Freezing Precipitation in the United States East of the Rocky Mountains," *American Meteorological Society*, Vol. 40, No. 10, 2001, p. 1724–1747. https://doi.org/https://doi.org/10.1175/1520-0450(2001)040<1724:ASWPAS>2.0.CO;2, URL https://journals.ametsoc.org/view/journals/apme/40/10/1520-0450_2001_040_1724_aswpas_2.0.co_2.xml.

[35] NASA, "Space Shuttle Weather Launch Commit Criteria and KSC End of Mission Weather Landing Criteria," Tech. rep., NASA, 2007.

[36] "Hail damage forces delay in shuttle launch," , 2 2007.