

Article

Vertiport Selection and Staging Node Deployment for UAVs in Forest Wildfire Rescue Areas

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Abstract

In mountainous wildfire response, unmanned aerial vehicle (UAV) emergency services depend on rapidly deployable and spatially reliable vertiports. However, existing site-selection methods insufficiently support continuous UAV operations in topographically complex terrain. This study develops a geographic information system (GIS)-based framework integrating Multi-Criteria Decision-Making (MCDM) and k-medoids clustering to shift UAV vertiport planning from individual site suitability ranking to networked deployment. The framework organizes feasible vertiport candidates into sector-based support staging nodes for coordinated multi-node wildfire response. Applied to the Xichang wildfire, the selected vertiport candidates reduced the mean first-arrival time by up to 71.4% compared with existing fire stations. Under differentiated reload-time assumptions, the staging node support mode further reduced the mean sortie cycle time by up to 56.85% and increased the mean delivery capacity from 17 to 42 fire-extinguishing bombs per UAV per hour. These results indicate that combining vertiport suitability evaluation with staging node-based logistical coordination improves the spatial organization and operational efficiency of UAV-enabled wildfire suppression. The framework offers decision support for networked UAV vertiport and staging node deployment in mountainous wildfire response.

Keywords: wildfires; multi-criteria decision making; site selection; unmanned aerial vehicles; geographic information systems



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1. Introduction

In recent years, the increasing frequency of wildfires in mountainous regions has placed growing demands on the timeliness, flexibility, and forward-deployment capacity of emergency response systems [1]. Wildfires typically occur suddenly, spread rapidly, and are highly susceptible to the combined effects of terrain and weather conditions [1]. During the 2020 Xichang forest wildfire rescue operation in China, cross-regional coordination of helicopters and unmanned aerial vehicles (UAVs) significantly enhanced wildfire reconnaissance and information acquisition capabilities [2–6]. In several recent major wildfires in California, rugged terrain and complex meteorological conditions hindered both ground forces and aviation resources operating from fixed airfields, limiting their ability to rapidly

reach core wildfire zones and intervene effectively [7–10]. Similar operational challenges have also been observed in major disaster response operations [11–13].

UAVs, characterized by flexible deployment, relatively low takeoff and landing requirements, and high maneuverability, have gradually emerged as a crucial technological tool for building distributed and resilient emergency response systems [14–18]. They have demonstrated significant potential in rescue operations, emergency communication coverage, disaster assessment, wildfire monitoring, and search-and-rescue missions [19–27]. With the continuous development of low-altitude aviation and related support mechanisms, the coordination among vertiport selection, UAV route planning, endurance management, and emergency support has become increasingly important for improving mission continuity and response efficiency [14,28–30].

GIS-based multi-criteria decision analysis (GIS-MCDA) has been widely used in spatial site selection to identify feasible areas, exclude unsuitable locations, define evaluation indicators, assign criterion weights, and rank candidate sites [31–36]. Methods such as analytic hierarchy process (AHP), technique for order preference by similarity to ideal solution (TOPSIS), and entropy weight method (EWM) are commonly applied in this process [37–39].

The National Aeronautics and Space Administration (NASA) vertiport considerations study indicates that takeoff-and-landing infrastructure planning should account for siting, design, safety, environmental conditions, utilities, contingency support, and operational integration [40]. Following this operational perspective, this study combines single-site selection with network-based deployment to support rational UAV resource allocation and enhance the sustained operational capability of UAVs in emergency response.

Nevertheless, existing vertiport planning concepts cannot be directly transferred to mountainous wildfire response. Most vertiport guidelines are developed for planned vertical take-off and landing (VTOL) operations in structured urban or aviation environments [41,42]. Urban vertiport planning usually emphasizes passenger demand, charging processes, ground–air transport integration, and commercial operation scenarios. In contrast, UAV vertiports in wildfire emergency scenarios are often temporary or semi-prepared support nodes rather than fully equipped commercial vertiports. Their feasibility is mainly constrained by terrain safety, fire standoff distance, road accessibility, hydrological conditions, land cover, and local terrain barriers [43,44]. In addition, mountainous wildfire response requires coordination among multiple sectors and support nodes. Therefore, the network-oriented logic of vertiport planning should be adapted to terrain-constrained emergency UAV deployment.

Current research on UAV applications in firefighting mainly focuses on remote sensing, wildfire detection, fire-front monitoring, and flight navigation [45,46]. Less attention has been paid to the pre-planning of vertiports that support continuous UAV operations before and during wildfire response [47,48]. Existing studies have provided useful foundations for GIS-based site suitability assessment, local UAV landing detection [34,35,49,50], and vertiport planning [41,42]. However, an integrated framework linking terrain-constrained vertiport screening, accessibility-network construction, staging node deployment, and multi-UAV validation for mountainous wildfire response remains insufficient. In complex mountainous environments, UAV operational effectiveness depends not only on platform performance or local landing feasibility, but also on whether suitable vertiports can be spatially connected, logistically supported, and organized into a robust deployment network.

To address the above limitations, this study proposes a GIS-based framework that extends UAV vertiport planning from individual site suitability evaluation to networked staging node deployment for sustained mountainous wildfire response. The main contributions of this study are summarized as follows:

- (1) A systematic evaluation framework for UAV vertiport site selection is established using GIS spatial analysis and Multi-Criteria Decision-Making (MCDM), encompassing multi-dimensional constraints—terrain, land-cover, hydrology, safety buffers, and wildfire-response proximity—and a CRiteria Importance Through Intercriteria Correlation (CRITIC)-TOPSIS suitability ranking as the primary method; rank-percentile transformation and entropy weighting are employed as comparative normalization and weighting schemes for robustness assessment, thereby providing an objective spatial foundation for safe UAV deployment and mitigating the fragmentation and subjectivity of site selection in complex mountainous environments.
- (2) A sector-based staging node deployment method is proposed to organize high-ranking vertiport candidates into spatially coherent operating areas and to select actual vertiport candidates as staging nodes using k-medoids and three-dimensional assignment cost, thereby establishing a support network that minimizes inter-site transit costs and ensures continuous operational capacity;
- (3) Fire-suppression sortie simulations are conducted to compare fire-station, ordinary vertiport, and staging node operation modes in terms of first-arrival time, cycle time, and bomb-delivery rate, demonstrating that the proposed framework significantly reduces initial response times and enhances sustained fire-suppression efficiency compared to traditional approaches.

The remainder of this paper is organized as follows. Section 2 details the study area, data sources, GIS-based vertiport screening, MCDM suitability evaluation, and the sector-based staging node allocation method. Section 3 presents the evaluation results, including the suitability ranking, staging node selection, and operational validation of fire-suppression sorties. Finally, Section 4 discusses the implications of the proposed framework, its scalability, and future research directions.

2. Materials and Methods

2.1. Emergency UAV Platforms

This study focuses on vertiport planning for large UAVs used in wildfire suppression. Unlike small portable drones, these platforms are usually used for fire-agent delivery, emergency material transport, and communication support. Wildfire suppression is often not a single-flight task. It may involve repeated delivery, return for resupply, and follow-up operations. Therefore, large firefighting UAVs require not only higher payload and endurance capacity, but also safer and larger sites with ground-support conditions.

To define the research object and its application scope, we reviewed publicly available technical documents, product specifications, news reports, and demonstration records. Over 40 global firefighting and emergency-support UAV platforms were analyzed, and their dimensional information is summarized in Appendix A.1, Table A1. Based on this review, the AutoFlight CarryAll (V2000CGF; AutoFlight, Shanghai, China) was finally selected as the reference platform for vertiport dimensional analysis in this study. Among the reviewed firefighting UAVs, it has the largest overall dimensions and a strong suppression-oriented payload capability, as it can carry 400 kg fire-extinguishing canisters [51,52].

2.2. Flow Chart of Analysis

As shown in Figure 1, this study proposes a hierarchical workflow for UAV vertiport deployment in complex mountainous wildfire scenarios. First, multi-source geospatial data, including digital elevation model (DEM), road networks, water bodies, and wildfire locations, are collected and processed to derive terrain and accessibility indicators. Candidate vertiport points are generated on a regular grid, and a preliminary GIS-based feasibility screening is applied to remove unsuitable locations.

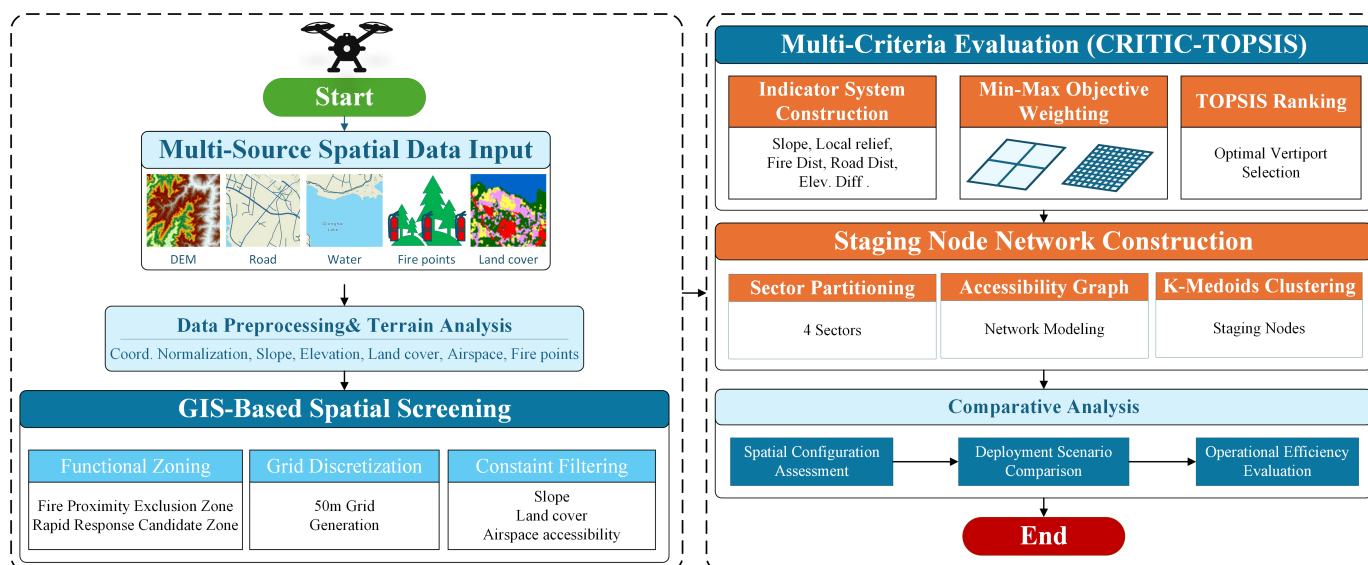


Figure 1. Research workflow of the proposed UAV vertiport planning framework.

Next, a multi-criteria decision-making (MCDM) evaluation is performed on all feasible vertiport candidates to obtain suitability scores and rankings. The top 100 and top 200 vertiport candidates are then selected for further analysis. Following vertiport evaluation, a four-sector deployment strategy is applied. Within each sector, staging nodes are identified by minimizing the three-dimensional path cost.

Finally, an operational validation is conducted using the V2000CGF fire-suppression UAV. Three scenarios are simulated: vertiport-origin closed loop, vertiport-to-staging node transition, and staging nodes steady closed loop. Performance metrics such as flight time, sortie cycle, and bomb-delivery rate are calculated to evaluate the effectiveness of the hierarchical vertiport network.

2.3. Input Data

The study area is located in Xichang City, Liangshan Yi Autonomous Prefecture, Sichuan Province, China. A typical mountainous wildfire-affected area and its surrounding region were selected for analysis, covering approximately 500 km² [3,5]. This area lies within the transitional terrain zone along the eastern edge of the Qinghai–Xizang Plateau, extending toward the mountainous region of western Sichuan. The terrain is characterized by significant topographic variability and pronounced spatial heterogeneity. The surface vegetation is primarily composed of *Pinus yunnanensis* and shrubs, exhibiting features of a plateau–slope composite landscape, as illustrated in Figure 2.

The Xichang region faces persistent wildfire risk due to monsoon climate conditions and complex mountainous terrain. Fires in this area often start suddenly, spread rapidly, and are difficult to suppress. Steep slopes and sparse roads limit the access of ground emergency forces to the fire front. This delay may reduce the effectiveness of early response.

2.4. Data Sources and Preprocessing

This study integrated multi-source geospatial data, preprocessed all datasets in ArcGIS Pro 3.6 (Esri, Redlands, CA, USA), and unified them under the World Geodetic System 1984 Universal Transverse Mercator Zone 47 North (WGS 1984 UTM Zone 47N) coordinate system.

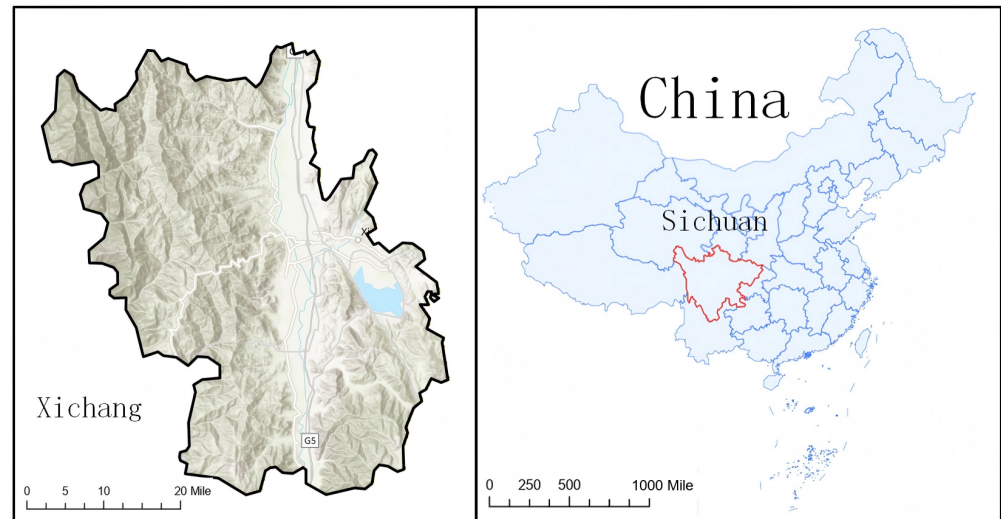


Figure 2. Location of the study area.

(a) Terrain and Auxiliary Geographic Data

Digital elevation model (DEM) data provide the basic input for terrain feature extraction. In this study, the DEM was used to derive elevation, slope, and elevation variation. These variables were used to quantify the safety and operational difficulty of UAV vertiports.

To describe the operating environment, the terrain variables were integrated with other geographic layers in the study area. These layers include 50 m contour lines, road networks, railways, land use, buildings, airports, and water bodies, as shown in Figure 3. The road network covers major highways, secondary roads, and accessible rural roads. The spatial proximity between UAV vertiports and the road network was then analyzed.

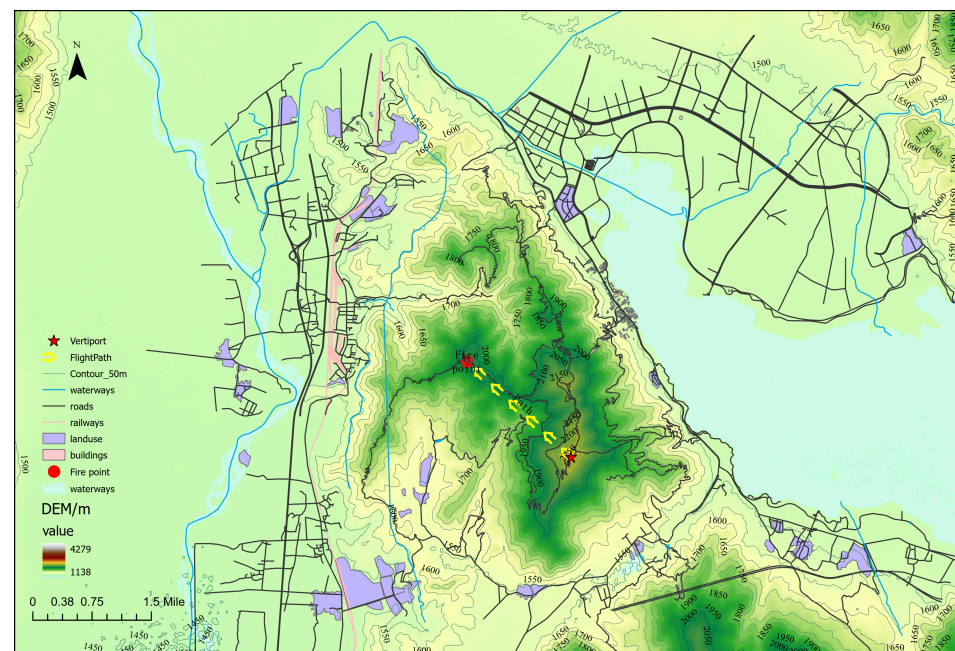


Figure 3. Multi-source geographic information and terrain features in the study area.

(b) Land-cover feasibility screening

Land-cover information was obtained from the European Space Agency (ESA) World-Cover 10 m 2021 v200 product. The dataset was used to identify surface types within the candidate UAV vertiport units and to remove land-cover classes that are physically

unsuitable for temporary UAV deployment. According to the land-cover classes appearing in the study area, four classes were retained as potentially feasible surface types: grassland, cropland, built-up areas, and bare/sparse vegetation. Although built-up areas may contain buildings and obstacles, they were not directly removed at this stage because the 10 m land-cover pixels in mountainous settlements may also include accessible hard-surface open spaces. The land-cover distribution of the study area is shown in Figure 4.

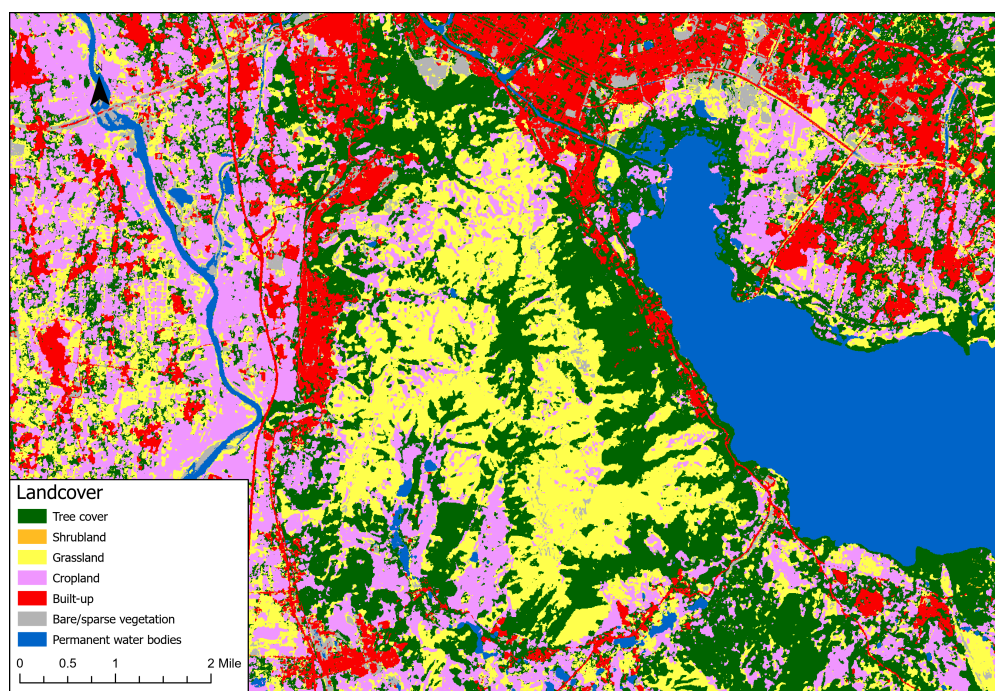


Figure 4. Land cover distribution in the study area.

(c) Data Preprocessing and Derivative Analysis

Multi-source data were integrated and processed in ArcGIS Pro 3.6. Derived layers were then generated to describe terrain conditions, infrastructure, environmental constraints, and airspace-related factors. These layers formed the spatial database used in the subsequent analysis. Table 1 lists the data sources used in this study.

Table 1. Summary of input layers used in the analysis.

Input Layer	Data Source	Resolution/Scale
DEM	ALOS PALSAR	12.5 m
Road network	OpenStreetMap	Vector
Water bodies and rivers	Geospatial Data Cloud	Vector/raster
Land cover	ESA WorldCover 10 m 2021 v200	10 m
Buildings	OpenStreetMap	Vector
Railways	OpenStreetMap	Vector
Airports and fire stations	1:25,000 topographic map	Vector
Airspace requirements	Relevant policy documents	-
Wildfire active fire points	NASA LANCE FIRMS VIIRS S-NPP	375 m

2.5. Key Factors for Emergency UAV Vertiport Planning

This study refers to more than 450 vertiport planning considerations collected by the NASA Advanced Air Mobility (AAM) Ecosystem Working Groups based on expert input. These considerations cover site selection, design, regulation, safety, environmental impact, social acceptance, and operational integration [40]. Among them, factors related to physical

obstacles, surrounding land use, airspace, environmental conditions, mission demand, contingency, utilities, communication, and safety are relevant for UAV vertiport planning in forest wildfire response.

In addition, Huang et al. developed a systematic decision indicator system for helicopter vertiports in wildfire emergency response. The system includes four dimensions: geographical location, site conditions, meteorological factors, and obstacle limitations [44]. Although helicopters and UAVs differ in operation, this method provides useful guidance for vertiport planning in mountainous wildfire scenarios. It complements the AAM framework by considering high-frequency takeoff and landing, dynamic environments, and safety constraints.

Based on these considerations, this study reorganizes the relevant influencing factors into eight dimensions for vertiport planning under wildfire emergency scenarios, as summarized in Table 2.

Table 2. Core factors affecting UAV vertiport planning in mountainous wildfire response.

Dimension	Description
Terrain and surface	Conditions ensuring safe UAV takeoff, landing, and ground handling.
Ground accessibility	Feasibility and speed of ground access for crew deployment and logistical resupply.
Airspace and obstacle	Airspace constraints and collision risks from terrain and infrastructural obstacles.
Environmental disturbance	Hazards from smoke, thermal updrafts, turbulence, and unpredictable microclimates.
Mission capability	Capacity of a vertiport to support core wildfire response tasks.
Network resilience	Network capacity to sustain operations despite localized site failures.
Operational resource	Availability of essential resources for sustained UAV operations.
Communication	Assurance of communication infrastructure for interagency interoperability, reliable command, and coordination.

To quantitatively evaluate these eight dimensions, this study defines five measurable indicators to assess the suitability of candidate vertiport locations. The remaining factors were not ignored, but were treated as qualitative operational considerations because they are difficult to quantify using available regional-scale spatial data. They should be further examined during detailed site design, field survey, and emergency deployment planning.

2.6. GIS-Based Site Selection Process

Functional Zoning and Service Radius

Based on the wildfire scenario and mountainous terrain of Xichang City, this study defined a distance-based functional zoning scheme for UAV vertiport planning, as shown in Figure 5.

Official active fire data were obtained from the Fire Information for Resource Management System (FIRMS) of the National Aeronautics and Space Administration (NASA). Fire points outside Xichang City were removed by spatial clipping.

Active fire points were detected at three acquisition times: 18:13, 19:53, and 19:54 (UTC+8). The fire points detected at 18:13 were mainly located within 2 km of the ignition center in Jingjiu Township. At 19:53, the detected fire points had expanded to about 5 km

from the ignition center. Based on the active fire distribution, functional zones were defined around the ignition point.

The area within 0–2 km from the ignition point was defined as the Fire Proximity Exclusion Zone. This zone is close to the active fire front and may be affected by high temperature, unstable airflow, smoke, and falling debris. Therefore, this area was not considered for vertiport deployment. The 2–5 km range was defined as the Rapid Response Candidate Zone. This range corresponds to the main area of early wildfire activity observed from the satellite active fire data. To reduce low-intensity fires and potential false detections, only fire points with a fire radiative power (FRP) greater than 10 MW were retained. Finally, the data were filtered to focus on the early stage 18:13 of the 2020 “3·30” Xichang wildfire.

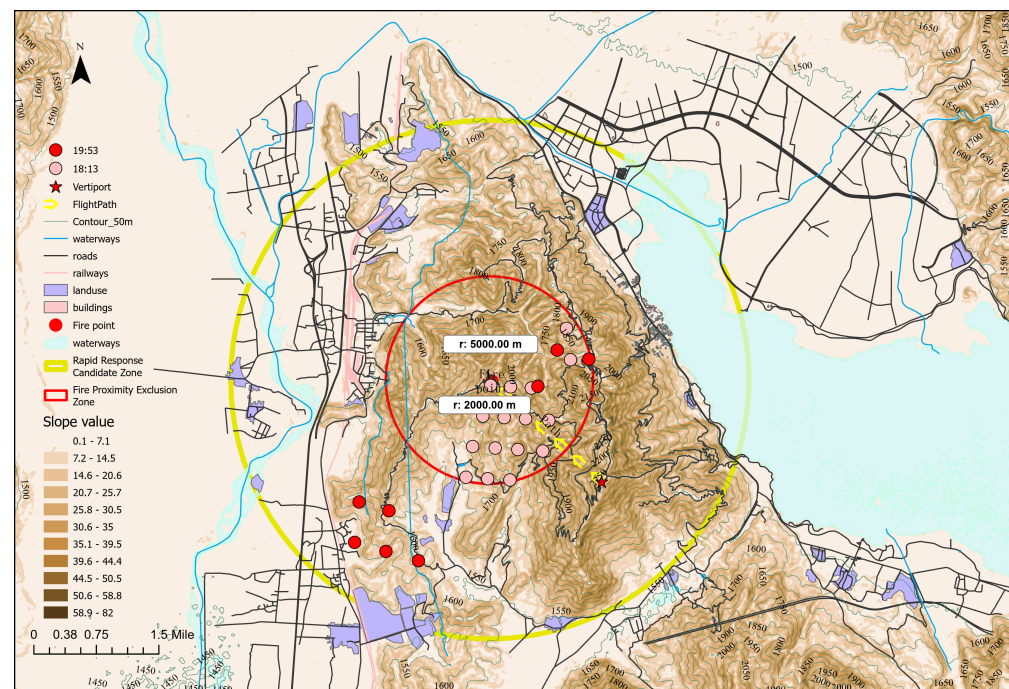


Figure 5. Functional zoning scheme for UAV vertiport planning.

2.7. Candidate Landing Point Discretization Method

During wildfire emergency operations, UAV takeoff and landing procedures are susceptible to the combined effects of complex terrain, unstable near-surface air currents, and local obstacles. These factors significantly reduce the available space for safe takeoff, landing, and ground support operations. Currently, there remains a lack of specialized design specifications for UAV vertiports in mountainous wildfire emergency scenarios.

To reasonably determine the spatial scale of candidate vertiport, this paper systematically reviews existing standards, guidelines, and research related to UAV landing zones, electric vertical take-off and landing (eVTOL) vertiports, helicopter landing pads, and AAM takeoff and landing facility planning. Although these materials address different types of aircraft and application scenarios, they share a common principle: the spatial requirements for vertical takeoff and landing facilities should not be determined solely by the minimum footprint; instead, they must comprehensively consider factors such as the touchdown and lift-off area (TLOF), final approach and takeoff area (FATO), safety zones, approach and departure protection, downwash effects, space for personnel and equipment operations, and operational buffers. Relevant standard references and dimension calculation processes are provided in Appendix A.

To determine the appropriate dimensions for this functional unit, this study uses the V2000CGF firefighting eVTOL drone as a case study. This drone has the largest dimensions among available models and relatively complete public specifications.

Based on the representative external dimension of approximately 15.0 m, the minimum operational envelope calculated according to Federal Aviation Administration (FAA) Engineering Brief (EB) 105A is approximately 37.5 m. For conservative verification, the domestic technical requirements for civil vertical vertiports were also considered, under which the corresponding overall vertiport dimension is approximately 45.0 m. Therefore, a 50 m × 50 m grid cell was adopted as the GIS-level spatial discretization unit for candidate UAV vertiports. This grid size exceeds both reference dimensions and provides additional space for local terrain leveling, temporary equipment deployment, material loading and unloading, personnel movement, drainage organization, and safety buffering in mountainous wildfire emergency scenarios.

2.8. Constraint Screening

Preliminary screening of the grid cells was conducted in ArcGIS Pro 3.6. The screening process considered three main constraints: terrain conditions, surface environment, and safety buffers.

Terrain slope (α) is an important factor reflecting local surface flatness. Relevant standards mandate slope assessment in vertiport design [53–55]. Acceptable slope limits vary across different UAV models and landing configurations. Previous studies on robot landing gear (RLG) and related landing configurations have shown that conventional designs are generally suitable only for ground slopes of approximately 6°–15°, while specialized designs may extend the allowable slope to around 26° [56,57]. However, such expanded limits are typically associated with site-specific engineering adaptations rather than regional-scale preliminary screening. Based on the target UAV platforms, this study defined a maximum slope threshold of 20°. Terrain slope (α) was thus utilized as a macro-scale spatial screening metric. This parameter effectively filters out steep areas with high deployment risks. The process exclusively retains candidate cells with suitably gentle terrain for safe ground operations.

Surface environment screening was then performed. Permanent water bodies were removed because they cannot support UAV takeoff, landing, loading, temporary parking, or ground support operations. Land-use types that were unsuitable for these activities were also excluded.

Finally, safety buffer screening was conducted. Grid cells located within railway safety buffer zones were removed. This step reduced potential risks to existing ground transport facilities, personnel safety, and emergency operations. The final screening results are shown in Figure 6.

2.9. MCDM Evaluation Method

2.9.1. Evaluation Index System

This study considers terrain safety, spatial accessibility, and mission response characteristics when constructing the evaluation index system. Five key evaluation indicators were selected to construct a comprehensive evaluation index system for UAV vertiports. All indicators were treated as cost-type indicators. A smaller value means better suitability. The evaluation index system is shown in Table 3.

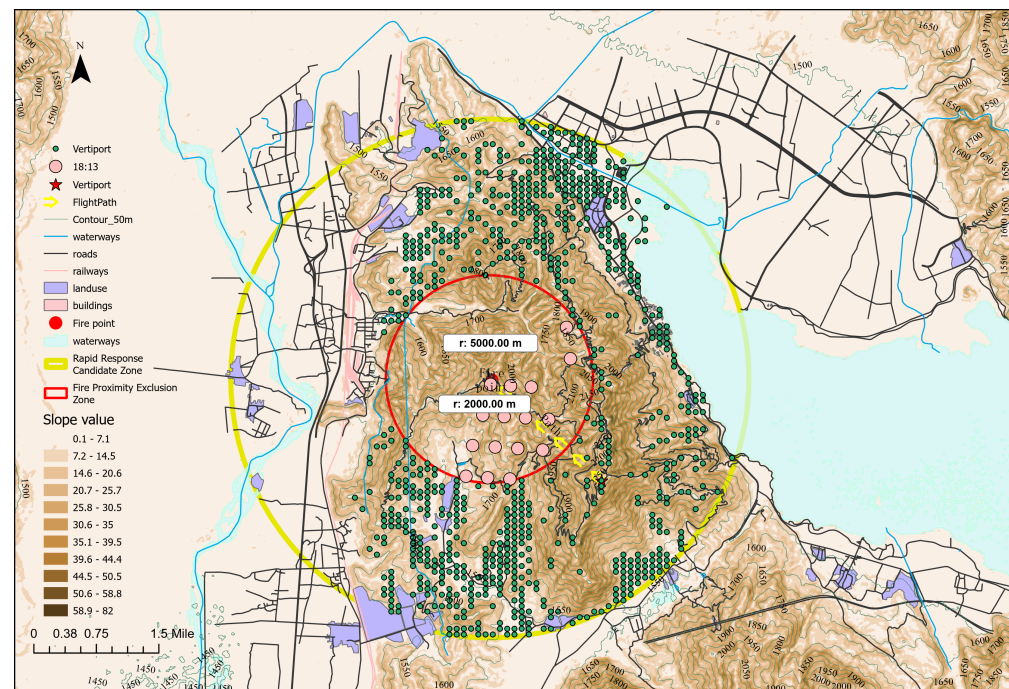


Figure 6. Candidate vertiport points after constraint-based screening.

Table 3. Evaluation index system for UAV vertiport candidates.

ID	Indicator	Description	Main Effect
A1	Slope	Terrain slope of the candidate vertiport grid cell	Takeoff and landing safety
A2	Local relief	Elevation range within the 50 m × 50 m grid cell	Local terrain flatness
A3	Fire distance	Horizontal distance to wildfire points	Response distance
A4	Road distance	Distance to nearest road	Ground accessibility
A5	Elevation difference	Elevation difference to wildfire area	Flight energy demand

2.9.2. CRITIC Weighting and Primary Ranking

The raw values were first transformed into normalized suitability values as follows:

$$z_{ij} = \frac{x_j^{\max} - x_{ij}}{x_j^{\max} - x_j^{\min}}, \quad (1)$$

where z_{ij} is the normalized suitability value of candidate i under indicator j , x_{ij} is the raw value, and $x_j^{\max}$ and $x_j^{\min}$ are the maximum and minimum values of indicator j , respectively. A larger z_{ij} indicates a higher suitability level.

The CRITIC method was used to determine the objective weights of the indicators. This method considers both the variation of each indicator and its conflict with other indicators. The information amount of indicator j was calculated as follows:

$$I_j = \sigma_j \sum_{\ell=1}^m (1 - \rho_{j\ell}), \quad (2)$$

where I_j is the information amount of indicator j , σ_j is the standard deviation of indicator j , $\rho_{j\ell}$ is the correlation coefficient between indicators j and ℓ , and m is the number of indicators. The CRITIC weight of indicator j was then calculated as follows:

$$w_j = \frac{I_j}{\sum_{\ell=1}^m I_{\ell}}. \quad (3)$$

After min–max cost normalization, all normalized suitability values were treated as benefit-type indicators in TOPSIS. The weighted normalized matrix was first constructed using the CRITIC weights. The positive ideal solution and the negative ideal solution were then identified. For each candidate grid cell, the Euclidean distances to these two ideal solutions were calculated. The closeness coefficient of candidate i was calculated as follows:

$$S_i = \frac{D_i^-}{D_i^+ + D_i^-}, \quad (4)$$

where S_i is the closeness coefficient of candidate i , D_i^+ is the distance to the positive ideal solution, and D_i^- is the distance to the negative ideal solution. A larger S_i indicates a higher suitability level.

2.9.3. Sensitivity Comparison

To assess the robustness of the primary ranking obtained from the Min-Max CRITIC-TOPSIS method, two alternative ranking schemes were introduced for comparison. The first comparative scheme utilized the empirical rank–percentile transformation. The second scheme employed the ordinary entropy weight method based on min–max normalized raw indicators.

In the first comparative scheme, to eliminate scale effects among the five indicators with different units, a rank–percentile transformation was applied. For each indicator, the candidate vertiport grid cells ($n = 847$) were ranked in ascending order according to their raw values. Because all indicators were treated as cost-type, a lower raw value indicates higher suitability. The standardized suitability score was calculated as follows:

$$s_{ij} = 1 - \frac{r_{ij} - 1}{n - 1}, \quad (5)$$

where s_{ij} is the suitability value of candidate i under indicator j , r_{ij} is the ascending rank of candidate i , and n is the number of candidates. A higher s_{ij} indicates higher suitability.

This transformation does not require fixed best or worst thresholds; rather, it reflects the relative position of each candidate within the study-area candidate set. These rank–percentile scores were then combined with CRITIC weights and TOPSIS to form the first comparison set.

For the entropy-weight scheme, all indicators were treated as cost-type indicators. After standardizing the raw data, the proportion of candidate i under indicator j was then calculated as follows:

$$p_{ij} = \frac{z_{ij}}{\sum_{i=1}^n z_{ij}}. \quad (6)$$

The entropy value of indicator j was calculated as follows:

$$e_j = -\frac{1}{\ln n} \sum_{i=1}^n p_{ij} \ln p_{ij}. \quad (7)$$

To avoid numerical instability caused by zero values, a small constant (10^{-10}) is added to p_{ij} before calculating the logarithm.

The entropy weight of indicator j was then obtained as follows:

$$w_j^E = \frac{1 - e_j}{\sum_{\ell=1}^m (1 - e_{\ell})}. \quad (8)$$

where w_j^E denotes the entropy weight of indicator j . The candidate vertiport grid cells were ranked using the entropy weights and the normalized suitability values.

2.10. Construction of Staging Node Vertipoint Networks Under Sector Constraints

In mountainous terrain, large elevation differences, ridges, valleys, and limited ground access can weaken the operational connectivity between adjacent vertipoints. Some vertipoints may be close in planar distance, but their connection for resource allocation and field operations may still be limited by terrain conditions. High-suitability vertipoints may also be spatially dispersed. However, firefighting resources, energy supply, and ground support capacity are usually limited during emergency response. A uniform allocation of resources to all dispersed vertipoints would increase the pressure on resource scheduling. It may also reduce the continuity and overall efficiency of UAV firefighting operations.

Therefore, staging nodes were introduced after the suitability ranking. These staging nodes were used to support the continuous operation of the vertipoint network under regional constraints. The role of a staging node is to concentrate limited firefighting resources, energy supply, and mission support capacity within each deployment sector. Each staging node can then provide nearby vertipoints with rapid and efficient replenishment and operational support. This structure helps maintain the spatial coverage of the vertipoint network. It also improves resource-use efficiency and network stability in mountainous wildfire UAV response.

2.10.1. Four-Sector Spatial Partition

Four sectors were adopted as a planning-level partition to balance spatial differentiation and operational manageability. This setting divides high-suitability candidates into local support areas without causing excessive fragmentation of logistics coordination. The number of sectors can be adjusted according to wildfire scale, terrain barriers, available support resources, and command requirements in other scenarios.

To obtain spatially coherent and size-balanced sectors, the planar coordinates of high-suitability vertipoint candidates were first normalized and then divided using a balanced k-means-based spatial grouping method. A contiguity check was then applied to reduce local sector mixing. If the initial grouping produced mixed local neighborhoods, a recursive median split was used as a fallback partition.

Finally, a local-neighborhood repair procedure was conducted. For each candidate, the labels of its eight nearest neighbors were examined. If at least five neighbors belonged to another sector, the candidate was reassigned to that dominant sector, provided that the sector-size deviation did not exceed two candidates.

2.10.2. Sector Based Selection of Vertipoint Staging Nodes

This paper employs the k-medoids clustering method for staging node selection. Unlike k-means, k-medoids directly uses actual vertipoints as centers, avoiding the generation of physically unfeasible virtual nodes.

The staging node selection was simplified as a three-dimensional distance-based support assignment. This cost considered both the planar distance and the elevation difference between candidate vertipoints and candidate staging nodes. For candidate vertipoint i and staging node candidate h , the assignment cost was defined as follows:

$$C_{ih} = \sqrt{d_{ih}^2 + \Delta h_{ih}^2}, \quad (9)$$

where C_{ih} is the assignment cost from candidate vertipoint i to staging node h , d_{ih} is the planar distance between candidate vertipoint i and staging node h , and Δh_{ih} is the absolute elevation difference between candidate vertipoint i and staging node h .

The number of staging nodes in each sector was determined by the local density of candidate vertipoints and the service capacity. Let T_{window} denote the critical response window for initial wildfire attack. Let N_{pads} denote the maximum number of UAVs that a

staging node can simultaneously accommodate for service. Let $t_{service}$ denote the ground servicing time. The effective cluster capacity threshold (β) represents the maximum number of candidate vertiports a staging node can safely manage. Including the staging node itself, β is calculated as follows:

$$\beta = 1 + \left\lfloor \frac{T_{window} \cdot N_{pads}}{t_{service}} \right\rfloor. \quad (10)$$

Operational characteristics and ground service requirements vary significantly across different UAV models. In this study, T_{window} was set to 60 min, and $t_{service}$ was set to 2.5 min for the V2000CGF platform. The parameter N_{pads} was set to 1 based on the spatial constraints of the candidate vertiports. Consequently, the effective cluster capacity threshold (β) evaluates to 25.

Based on this capacity threshold, the number of staging nodes required in sector s was calculated as follows:

$$K_s = \min\left(4, \max\left(1, \left\lceil \frac{n_s}{\beta} \right\rceil\right)\right), \quad (11)$$

where n_s is the number of candidate vertiports in sector s , and K_s is the number of staging nodes selected in that sector.

For each sector s , the staging node set was selected from $\mathcal{S}_s$ by minimizing the total assignment cost from all candidate vertiports to their nearest staging node:

$$H_s^* = \arg \min_{\substack{H_s \subseteq \mathcal{S}_s \\ |H_s|=K_s}} \sum_{i \in \mathcal{S}_s} \min_{h \in H_s} C_{ih}, \quad (12)$$

where H_s^* is the selected staging node set in sector s , $\mathcal{S}_s$ is the candidate vertiport set in sector s , H_s is a candidate staging node set satisfying $H_s \subseteq \mathcal{S}_s$ and $|H_s| = K_s$, K_s is the number of staging nodes selected in sector s , and C_{ih} is the three-dimensional inter-site cost between candidate vertiport i and staging node candidate h . After the staging node set was obtained, each candidate vertiport $i \in \mathcal{S}_s$ was assigned to the nearest staging node $h \in H_s^*$ that minimized C_{ih} . This produced a sector-based vertiport support structure for resource replenishment, energy supply, and local operational coordination.

2.11. Operational Validation Design

After the vertiport suitability evaluation and staging node selection, an operational validation was conducted. The purpose of this step was to test whether the selected vertiports and staging nodes could improve fire-suppression sortie efficiency. This validation did not change the vertiport ranking results. It was used only to compare different operational modes.

The V2000CGF was selected as the reference platform. The aircraft was treated as a fire-suppression UAV. Each sortie was assumed to carry four fire-extinguishing bombs. The operational parameters used in this validation are listed in Table 4. These values were used as scenario assumptions. They can be replaced by measured operational data in future work.

The fire point operation was simplified as a three-dimensional target-access problem. For each facility or vertiport point, the three-dimensional distance to the fire point was calculated as

$$D_{i,f}^{3D} = \sqrt{d_{i,f}^2 + \Delta h_{i,f}^2}, \quad (13)$$

where $D_{i,f}^{3D}$ is the three-dimensional distance between point i and the fire point f , $d_{i,f}$ is the horizontal distance, and $\Delta h_{i,f}$ is the elevation difference.

Table 4. Operational assumptions used in the fire-suppression validation.

Parameter	Value	Unit
UAV type	V2000CGF	–
Fire-extinguishing bombs per sortie	4	bombs
Loaded cruise speed	30	m/s
Empty return speed	50	m/s
Bomb release time	1	min
Reload time at fire station	5	min
Reload time at ordinary vertiport	10	min
Reload time at staging node	2.5	min
Fire point elevation	2200	m

Three operational modes were considered. The first mode was the fire-station closed-loop mode. In this mode, a UAV departs from an existing fire station, flies to the fire point, releases four fire-extinguishing bombs, and returns to the same fire station for reloading. The cycle time, expressed in minutes, is

$$T_i^{FS} = \frac{D_{i,f}^{3D}}{60v_{\text{loaded}}} + t_{\text{drop}} + \frac{D_{i,f}^{3D}}{60v_{\text{empty}}} + t_{\text{reload}}^{FS}, \quad (14)$$

where v_{loaded} is the loaded cruise speed, v_{empty} is the empty return speed, t_{drop} is the bomb release time, and t_{reload}^{FS} is the reload time at a fire station.

The second mode was the ordinary vertiport closed-loop mode. In this mode, a UAV departs from a vertiport candidate, flies to the fire point, releases four fire-extinguishing bombs, and returns to the same vertiport for reloading. The cycle time, expressed in minutes, is

$$T_i^{\text{vertiport}} = \frac{D_{i,f}^{3D}}{60v_{\text{loaded}}} + t_{\text{drop}} + \frac{D_{i,f}^{3D}}{60v_{\text{empty}}} + t_{\text{reload}}^{\text{vertiport}}, \quad (15)$$

where $t_{\text{reload}}^{\text{vertiport}}$ is the reload time at an ordinary vertiport.

The third mode was the staging node mode. This mode was divided into two stages. The first stage was a transition cycle. A UAV departs from an ordinary vertiport, flies to the fire point, and then returns to its assigned staging node. This cycle describes the transfer from a distributed vertiport point into the staging node system. The cycle time, expressed in minutes, is

$$T_i^{SN,trans} = \frac{D_{i,f}^{3D}}{60v_{\text{loaded}}} + t_{\text{drop}} + \frac{D_{h(i),f}^{3D}}{60v_{\text{empty}}} + t_{\text{reload}}^{SN}, \quad (16)$$

where $h(i)$ is the assigned staging node of vertiport candidate i , and t_{reload}^{SN} is the reload time at a staging node.

After the UAV returns to the staging node, later sorties are assumed to follow a staging node closed loop. In this steady cycle, the UAV departs from the staging node, flies to the fire point, releases four fire-extinguishing bombs, and returns to the same staging node for reloading. The cycle time, expressed in minutes, is

$$T_h^{SN} = \frac{D_{h,f}^{3D}}{60v_{\text{loaded}}} + t_{\text{drop}} + \frac{D_{h,f}^{3D}}{60v_{\text{empty}}} + t_{\text{reload}}^{SN}. \quad (17)$$

For each mode, the sortie rate and bomb-delivery rate were calculated as

$$R_{\text{sortie}} = \frac{60}{T}, \quad (18)$$

$$Q = qR_{\text{sortie}}, \quad (19)$$

where R_{sortie} is the sortie rate in sorties per hour per UAV, Q is the bomb-delivery rate in bombs per hour per UAV, and q is the number of fire-extinguishing bombs carried per sortie. In this study, $q = 4$.

3. Results

3.1. Vertiport Suitability Ranking Based on MCDM

3.1.1. Indicator Weighting Results

Using the min–max normalized suitability matrix, CRITIC-derived indicator weights, and the TOPSIS ranking model, the 847 feasible vertiport candidates retained after GIS-based constraint screening were evaluated to obtain their suitability scores and priority rankings. Table 5 summarizes the indicator weights used in the primary MinMax CRITIC–TOPSIS evaluation, the rank–percentile CRITIC–TOPSIS comparison scheme, and the entropy-weight comparison scheme.

Table 5. Indicator weights used in the MCDM evaluation and comparison.

Indicator	CRITIC	Rank-Percentile CRITIC	Entropy
Slope suitability	0.2654	0.2015	0.2184
Local-relief suitability	0.1287	0.1971	0.0220
Fire-distance suitability	0.2450	0.1950	0.2148
Road-distance suitability	0.1817	0.1790	0.0626
Elevation-difference suitability	0.1792	0.2273	0.4822

The primary min–max CRITIC weighting scheme assigned the highest weights to slope suitability and fire-distance suitability. This result indicates that slope suitability and fire-distance suitability provide relatively strong objective information in the CRITIC weighting stage, while the final TOPSIS ranking integrates all five criteria to determine overall suitability. This scheme was used as the primary method because CRITIC weights depend on both indicator variation and inter-indicator conflict. Applying CRITIC to the min–max normalized matrix preserves the relative differences among candidates and the correlation structure among indicators.

The rank–percentile CRITIC scheme was retained only as a comparison. The rank transformation changes the original value intervals into relative ranks. This can reduce the variation information used by CRITIC and weaken the original correlation structure. In this study, it produced more balanced weights across the five indicators. The entropy-weight method was also used as a sensitivity reference. It mainly reflects single-indicator dispersion and does not explicitly consider inter-indicator conflict. As a result, elevation-difference suitability received a dominant weight, whereas local-relief suitability received a very small weight. Therefore, the min–max CRITIC–TOPSIS result was used as the primary basis for subsequent staging node deployment, while the rank–percentile CRITIC–TOPSIS and entropy-weight results were used for sensitivity analysis.

3.1.2. Top-Ranked Candidate Characteristics

The primary ranking was obtained using the min–max normalized suitability matrix, CRITIC weights, and TOPSIS. The top 100 and top 200 candidates were extracted from this ranking. Table 6 compares the mean indicator values of all candidates, the top 100 candidates, and the top 200 candidates.

Table 6. Mean indicator values of all candidates, top 100 candidates, and top 200 candidates.

Indicator	All Candidates	Top 100	Top 200
Slope (°)	9.81	11.19	9.97
Local relief (m)	7.37	10.71	9.04
Fire distance (m)	3589.29	2517.18	2717.19
Road distance (m)	186.99	96.87	142.06
Elevation difference (m)	590.28	341.83	451.39
Primary score	0.3978	0.5743	0.5164

The higher mean slope and local relief values of the Top 100 candidates reflect the trade-off mechanism of the multi-criteria ranking. The CRITIC weight represents the information contrast and conflict of an indicator, whereas the TOPSIS closeness coefficient aggregates all five indicators simultaneously. Compared with the full candidate set, the Top 100 candidates show clear advantages in fire distance, road distance, and elevation difference. These advantages offset the moderately higher slope and local relief values. In addition, all candidates had already passed the prior slope screening threshold of 20°, indicating that they remained within the predefined terrain-safety constraint. Therefore, the final ranking reflects overall operational suitability under terrain-safety constraints, rather than superiority on any single indicator.

The top-ranked candidates had higher overall suitability scores than the full candidate set. The mean primary score increased from 0.3978 for all candidates to 0.5743 for the top 100 candidates and 0.5164 for the top 200 candidates. Compared with the full candidate set, the top 100 and top 200 groups were closer to the wildfire area, closer to roads, and had lower elevation differences. The mean fire distance decreased from 3589.29 m for all candidates to 2517.18 m for the top 100 candidates and 2717.19 m for the top 200 candidates. The mean road distance decreased from 186.99 m to 96.87 m and 142.06 m, respectively. The mean elevation difference decreased from 590.28 m to 341.83 m and 451.39 m, respectively.

The top 100 candidates represent the core high-suitability candidate set. The top 200 candidates represent an extended high-suitability set for spatial inspection and staging node deployment. These candidates are planning-level results and still require site-level verification before actual deployment.

3.1.3. Sensitivity of Top Candidate Sets

A sensitivity comparison was conducted among three ranking results: the primary MinMax CRITIC–TOPSIS result, the rank-percentile CRITIC–TOPSIS result, and the entropy-weight ranking result. The overlap of the top 100 and top 200 candidate sets was measured using the Jaccard index. The results are shown in Table 7.

Table 7. Overlap of top candidate sets under different normalization and weighting schemes.

Comparison	Top Set	Intersection	Jaccard Index
Primary vs. rank-percentile CRITIC	Top 100	50	0.3333
Primary vs. entropy weight	Top 100	72	0.5625
Rank-percentile CRITIC vs. entropy weight	Top 100	36	0.2195
All three methods	Top 100	34	0.1932
Primary vs. rank-percentile CRITIC	Top 200	130	0.4815
Primary vs. entropy weight	Top 200	137	0.5209
Rank-percentile CRITIC vs. entropy weight	Top 200	98	0.3245
All three methods	Top 200	85	0.2656

As shown in Table 7, several high-suitability candidates were supported by different objective weighting schemes when the min–max normalized suitability matrix was used. By contrast, the rank–percentile CRITIC result showed lower overlap with the other methods. This is because rank transformation changes continuous indicator values into relative positions and may weaken the variation and correlation information used by CRITIC.

Across all three methods, 34 candidates were shared in the top 100 group and 85 candidates were shared in the top 200 group. These common candidates represent relatively stable high-suitability locations under different assumptions. Overall, the sensitivity comparison indicates that the min–max CRITIC–TOPSIS result can be used as the primary planning-level input for subsequent staging node deployment.

3.1.4. Staging Node Selection Results

The selected staging nodes based on the primary MinMax CRITIC–TOPSIS ranking are listed in Table 8. For the top 100 subset, six staging nodes were selected. For the top 200 subset, nine effective staging nodes were used in the final assignment. All selected staging nodes were real vertiport candidates retained after the GIS-based screening and MCDM ranking process.

Table 8. Selected staging nodes in the top 100 and top 200 candidate subsets.

Subset	Sector	Staging Node Rank	Node ID	X	Y
Top 100	1	1	341	818,516	3,080,437
Top 100	2	1	571	819,216	3,085,057
Top 100	3	1	412	821,316	3,081,097
Top 100	3	2	292	820,476	3,079,997
Top 100	4	1	465	821,176	3,082,527
Top 100	4	2	519	820,476	3,084,397
Top 200	1	1	315	818,096	3,080,217
Top 200	1	2	233	819,356	3,079,557
Top 200	2	1	408	817,256	3,081,097
Top 200	2	2	585	818,796	3,085,167
Top 200	3	1	387	820,896	3,080,767
Top 200	3	2	389	822,436	3,080,767
Top 200	3	3	320	819,636	3,080,217
Top 200	4	1	468	821,176	3,082,747
Top 200	4	2	561	820,196	3,084,947

The assignment results are summarized in Table 9. For the top 100 subset, the mean cost to the assigned staging node was 659.34 m, and the maximum cost was 2342.00 m. For the top 200 subset, the mean cost was 670.58 m, and the maximum cost was 2264.68 m. Although the mean assignment cost of the top 200 subset was slightly higher than that of the top 100 subset, the maximum assignment cost decreased, indicating that the expanded candidate set improved the coverage of distant candidates and reduced the most unfavorable local-support distance.

Table 9. Summary of staging node assignment costs.

Candidate Subset	Staging Nodes	Mean Cost (m)	Max. Cost (m)
Top 100	6	659.34	2342.00
Top 200	9	670.58	2264.68

The sector-level results are shown in Table 10. In the top 100 subset, Sector 1 had the highest mean assignment cost, with a value of 912.07 m, whereas Sector 3 had the

lowest mean assignment cost, with a value of 478.14 m. The maximum assignment cost occurred in Sector 2, reaching 2342.00 m. In the top 200 subset, Sector 2 had the highest mean assignment cost, with a value of 901.85 m, and also had the largest maximum cost of 2264.68 m. Sector 3 had the lowest mean assignment cost, with a value of 504.26 m. These results indicate that the spatial dispersion and terrain-related assignment burden differed among sectors, and that increasing the candidate pool mainly reduced the extreme assignment cost rather than uniformly reducing the mean cost in every sector.

Table 10. Sector-level staging node assignment results.

Subset	Sector	Candidates	Staging Nodes	Mean Cost (m)	Maximum Cost (m)
Top 100	1	23	1	912.07	1739.59
Top 100	2	25	1	789.17	2342.00
Top 100	3	26	2	478.14	1184.00
Top 100	4	26	2	492.15	1087.24
Top 200	1	50	2	575.40	1182.76
Top 200	2	50	2	901.85	2264.68
Top 200	3	52	3	504.26	1667.78
Top 200	4	48	2	709.02	1718.65

Figure 7 shows the staging node selection results for the two candidate subsets. The assignment links indicate the assigned local staging node for each candidate vertiport. The selected staging nodes provide representative support points within each deployment sector, while all staging node locations remain within the feasible vertiport candidate set.

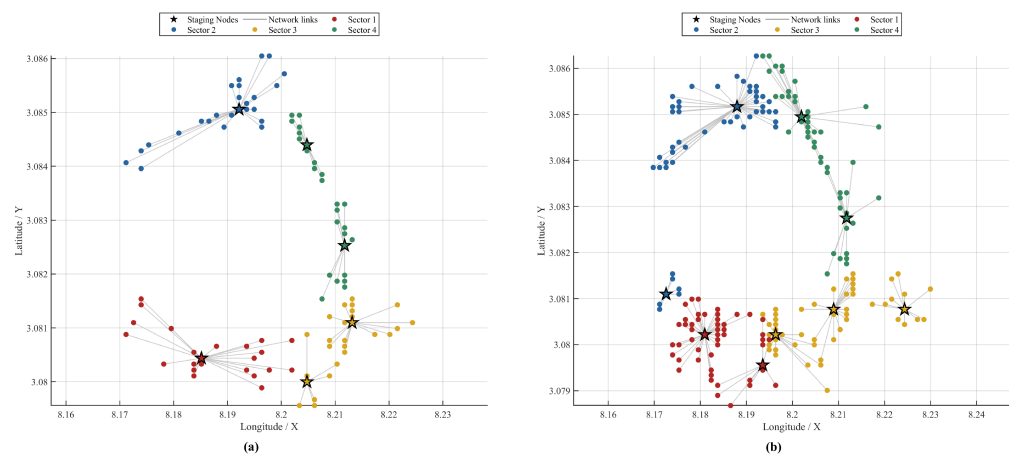


Figure 7. Staging node selection results based on the primary MinMax CRITIC-TOPSIS ranking: (a) top 100 candidate vertiports; (b) top 200 candidate vertiports.

3.2. Operational Validation of Deployment Modes

The validation results are shown in Table 11. Seven scenarios were evaluated. The fire-station mode used nine existing fire stations. The ordinary vertiport mode used the Top 100 and Top 200 candidate sets. The staging node mode included a transition cycle and a steady closed-loop cycle.

Table 11. Fire-suppression sortie efficiency under different operational modes.

Dataset	Operational Mode	N	First Arrival (min)	Cycle Time (min)	Bombs (/h/UAV)	Reload (min)
Fire stations	Closed loop	9	4.9495	13.919	17	5
Top 100	vertiport closed loop	100	1.4159	13.265	18	10
Top 100	vertiport to staging node	100	1.4159	5.7368	41	2.5
Top 100	staging node closed loop	6	1.3897	5.7236	42	2.5
Top 200	vertiport closed loop	200	1.5342	13.455	17	10
Top 200	vertiport to staging node	200	1.5342	5.927	40	2.5
Top 200	staging node closed loop	9	1.5306	5.949	40	2.5

Table 12 compares the staging node closed-loop mode with the ordinary vertiport closed-loop mode.

Table 12. Cycle-time reduction of the staging node closed-loop mode under differentiated reload-time assumptions.

Dataset	Vertiport Cycle (min)	Staging Node Cycle (min)	Cycle Reduction (%)
Top 100	13.265	5.7236	56.85
Top 200	13.455	5.949	55.78

Under the differentiated reload-time assumptions, the staging node closed-loop mode clearly improved the repeated sortie efficiency of the vertiport network. For the Top 100 set, the mean cycle time was reduced by 56.85% compared with the ordinary vertiport closed-loop mode. The bomb-delivery rate increased by 132.15%. For the Top 200 set, the mean cycle time was reduced by 55.78%, and the bomb-delivery rate increased by 127.01%.

The Top 100 staging nodes produced a slightly shorter cycle time than the Top 200 staging nodes. This indicates that the Top 100 set formed a more compact core deployment area. The Top 200 set provided a larger candidate pool, but it also included more peripheral sites. Therefore, its mean staging node cycle time was slightly longer.

To further distinguish the spatial-layout effect from the logistical-resource effect, an additional equal-reload-time test was conducted. In this controlled test, the reload time was uniformly set to 5 min for all operational modes. The results are shown in Table 13.

Table 13. Cycle-time comparison under the equal-reload-time setting.

Dataset	Operational Mode	N	First Arrival (min)	Cycle Time (min)
Fire stations	Closed loop	9	4.9495	13.919
Top 100	Vertiport closed loop	100	1.4159	8.2655
Top 100	Staging node closed loop	6	1.3897	8.2236
Top 200	Vertiport closed loop	200	1.5342	8.4547
Top 200	Staging node closed loop	9	1.5306	8.4490

Under the equal-reload-time setting, the selected vertiport candidates shortened the sortie cycle time compared with the fire-station baseline. This indicates that the main spatial-siting benefit comes from deploying UAVs at high-suitability vertiport candidates closer to the wildfire area, rather than relying on existing fire stations. Meanwhile, because the UAV cruise speed used in this study is relatively high, and both ordinary vertiports and staging nodes are selected from high-suitability candidates near the fire point, the distance difference between the two modes is compressed in the total cycle time. Therefore, under equal reload conditions, the staging node closed-loop mode further slightly shortened

the sortie cycle time compared with the ordinary vertiport closed-loop mode. This result indicates that the staging node configuration has a spatial layout optimization effect.

In practical emergency operations, it is usually unrealistic and costly to equip all ordinary vertiport candidates with the same level of personnel, fire-extinguishing materials, energy supply, and reload equipment. Therefore, this study uses the selected staging nodes as resource assembly points and assigns reload times consistent with their support function. This setting reduces the pressure of fully distributed resource preparation. It also reflects the advantage of networked deployment in resource organization, centralized reloading, and continuous operational support.

4. Discussion

The proposed framework integrates GIS-based vertiport selection and staging node deployment to address mountainous wildfire operations. Traditional emergency response relies solely on existing fire stations. Firefighters arrive randomly at fire zones. They conduct hurried operations. This approach typically leads to delayed first-arrival times. In contrast, the present study explicitly organizes optimal vertiport candidates into sector-based staging nodes. This organization substantially shortens the operational cycle time. It also increases the fire-extinguishing bomb-delivery rate. Effective UAV deployment must move beyond the evaluation of isolated vertiports. It must use a systematically organized local support network within spatially coherent deployment sectors.

Previous studies on UAV site-selection have largely focused on urban environments. Complex environments such as plateaus and mountainous regions remain largely underexplored. Mountainous wildfires are difficult to control. They frequently result in catastrophic ecological damage and property losses. Traditional suppression relies heavily on manual ground personnel and manned aviation. This conventional approach incurs prohibitive economic costs. It also exposes responders to extreme, life-threatening risks. In contrast, this study integrates MCDM and clustering approaches for mountainous topography. The proposed framework first pre-selects feasible landing zones. It then identifies resource assembly points within these zones to minimize logistical costs.

The limited overlap among the three ranking schemes is mainly related to their different treatments of indicator information. In the min–max CRITIC–TOPSIS scheme, the original value ranges and the correlations among indicators are retained. Therefore, the ranking is affected by both indicator contrast and inter-indicator conflict. In the entropy-weight scheme, the weights are mainly determined by the dispersion of each individual indicator. This may increase the influence of indicators with larger numerical variation. In contrast, the rank-percentile transformation converts the original indicator values into ordinal positions. This reduces the influence of absolute value differences among candidates. These differences indicate that the identification of highly suitable vertiport candidates is affected by the choice of normalization and weighting methods. Therefore, the selected candidates should be regarded as planning-level guidance. Site-level verification is still required before practical implementation.

At the same time, several limitations should be acknowledged. The current framework focuses only on the initial fire outbreak stage to demonstrate rapid deployment. It does not fully consider stochastic fire-spread dynamics. It also does not explicitly quantify other operational factors that may affect practical deployment, such as local obstacles, microclimatic conditions, and related site-specific constraints. In addition, because the ALOS PALSAR DEM has a spatial resolution of 12.5 m, local terrain relief was not used as a strict exclusion factor. It was instead included as a soft criterion in the suitability evaluation. Therefore, the results should be interpreted as planning-level guidance and should be

supplemented with UAV photogrammetry, field inspection, qualitative judgment, and necessary ground leveling or obstacle clearance before actual deployment.

Although the numerical results obtained from the 2020 Xichang wildfire and the V2000CGF platform are case-specific, the proposed framework was not developed solely based on this case. Its factor system is derived from general vertiport planning considerations and wildfire emergency-response requirements. Future research will focus on expanding this planning-level static framework into dynamic operational models and examining additional representative wildfire scenarios to further evaluate the transferability and robustness of the proposed framework. Site-specific operational constraints, such as microclimatic conditions, local obstacles, and fine-scale terrain conditions, should also be incorporated. Further sensitivity analysis of different normalization, weighting, and ranking schemes could be conducted to assess the robustness of site-selection results. Extending the framework to support real-time vertiport redeployment in extreme environments is a promising direction. Such extensions would support safer and more efficient wildfire suppression.

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Abbreviations

AAM	Advanced Air Mobility
AHP	Analytic Hierarchy Process
ALOS	Advanced Land Observing Satellite
ASTM	American Society for Testing and Materials
CAAC	Civil Aviation Administration of China
CRITIC	CRiteria Importance Through Intercriteria Correlation
DEM	Digital Elevation Model
EASA	European Union Aviation Safety Agency
ESA	European Space Agency
EWM	Entropy Weight Method
eVTOL	Electric Vertical Take-Off and Landing
FAA	Federal Aviation Administration

FATO	Final Approach and Takeoff Area
FIRMS	Fire Information for Resource Management System
FRP	Fire Radiative Power
GIS	Geographic Information System
GIS-MCDA	Geographic Information System-based Multi-Criteria Decision Analysis
ISO	International Organization for Standardization
LANCE	Land, Atmosphere Near real-time Capability for Earth observation
MCDM	Multi-Criteria Decision-Making
NASA	National Aeronautics and Space Administration
PALSAR	Phased Array type L-band Synthetic Aperture Radar
PTS-VPT-DSN	Prototype Technical Specifications for the Design of VFR Vertiports
RLG	Robot Landing Gear
S-NPP	Suomi National Polar-orbiting Partnership
TLOF	Touchdown and Lift-Off Area
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
UAS	Unmanned Aircraft System
UAV	Unmanned Aerial Vehicle
UTC	Coordinated Universal Time
UTM	Universal Transverse Mercator
VFR	Visual Flight Rules
VIIRS	Visible Infrared Imaging Radiometer Suite
VTOL	Vertical Take-Off and Landing
WGS	World Geodetic System

Appendix A. Dimensional Basis for Vertiport Discretization

This appendix provides the reference basis and calculation process used to determine the spatial discretization scale of candidate UAV vertiports. Since there is currently no dedicated standard for UAV vertiports in mountainous wildfire emergency scenarios, this study reviews relevant standards, guidelines, and research on UAV landing areas, eVTOL vertiports, helicopter landing pads, and advanced air mobility (AAM) takeoff and landing facilities. The objective is not to design a certified vertiport or heliport, but to justify the GIS-level spatial unit used for preliminary vertiport screening.

Appendix A.1. Supplementary Comparison of UAV Platform Dimensions

Table A1. Dimensional information of reviewed UAV platforms.

UAV Platform	Officially Reported Aircraft Dimensions
Wing Loong-2H	Wing Loong II base platform: length 11.0 m; height 4.1 m; wingspan 20.5 m
CW-15	Fuselage length 2.06 m; wingspan 3.54 m
DJI Matrice 30T	Unfolded: 470 mm × 585 mm × 215 mm, excluding propellers
DJI Matrice 350 RTK	Unfolded: 810 mm × 670 mm × 430 mm, excluding propellers
Autel EVO II Dual 640T	unfolded: 506 mm × 620 mm × 111 mm; wheelbase: 427 mm
Autel EVO II Dual 640T V3	unfolded: 457 mm × 558 mm × 108 mm
DJI FlyCart 30	Arms and propellers unfolded: 2800 mm × 3085 mm × 947 mm
EHang EH216F	Length 7.33 m; width 5.61 m; height 2.13 m
EHM-2000	Unfolded: 2659 × 2659 × 730 mm; folded: 982 × 692 × 447 mm
EHM-2600	Unfolded: 3650 × 3650 × 870 mm
EHM-3600	Unfolded: 4930 × 4930 × 900 mm; folded: 1950 × 1250 × 600 mm
BRINC LEMUR S	324 × 386 × 96 mm
Skydio X10	Unfolded with propellers: 79.0 cm × 65.0 cm × 14.5 cm
Zipline Platform 2 (P2)	Length: approximately 8 ft/2.44 m; wingspan: approximately 7.8 ft/2.38 m; height: approximately 1.8 ft/0.55 m
A2Z RDST Longtail	maximum external dimensions including blades and prop guards: 2100 × 2100 × 850 mm

Table A1. Cont.

UAV Platform	Officially Reported Aircraft Dimensions
Volocopter VoloDrone	Diameter 9.15 m; height 2.15 m
Lockheed Martin Indago 4	Flight configuration: 108.6 cm × 110.5 cm × 31.8 cm
DJI Matrice 600 Pro	Unfolded: 1668 mm × 1518 mm × 727 mm; folded: 437 mm × 402 mm × 553 mm
DJI Matrice 400 RTK	Unfolded: 980 mm × 760 mm × 480 mm, with landing gear and excluding propellers
DJI FlyCart 100	Arms and propellers unfolded: 3220 mm × 3224 mm × 975 mm
Freefly Alta X	unfolded diameter including propellers: 2273 mm; folded diameter: 877 mm; height: 387 mm
Inspired Flight IF1200A	Diagonal size: 1025 mm; unfolded size, flight ready, W×L×H: 165.5 cm × 154 cm × 76.5 cm
Inspired Flight IF800 Tomcat	Diagonal size: 905 mm; unfolded size, W×L×H: 132 cm × 114 cm × 52 cm; folded size, W×L×H: 36 cm × 44 cm × 20 cm
Acecore Zoe	Frame dimensions: 693 mm × 682 mm × 524 mm
JOUAV CW-30E	Fuselage length: 2.4 m; wingspan: 4.4 m
Watts Innovations PRISM Sky	Motor-to-motor diameter: 1100 mm; maximum diameter from propeller tip to propeller tip: 1817 mm; height: 500 mm
AutoFlight V2000CG CarryAll/V2000CGF	Wingspan 14.5 m; length 11.6 m; height 2.6 m
DJI Mavic 3T	unfolded: 347.5 mm × 283 mm × 107.7 mm; diagonal length: 380.1 mm
Parrot ANAFI USA	unfolded: 282 mm × 373 mm × 82 mm
LIFT Aircraft HEXA	Overall diameter/length: approximately 4.5 m; height: approximately 2.4 m
AOSSCI XC-150	3300 × 6900 × 1000 mm
AR500C	Length: approximately 7.2 m; rotor diameter: approximately 6.3 m; height: approximately 2.4 m
H300/Spider-i H300	Unfolded: 4605 mm × 4605 mm × 990 mm
CH-4	Length: 8.5 m; wingspan: 18 m; height: approximately 2.5 m
V750	Length: 8.53 m; width: 2.08 m; height: 2.11 m
TD550	Fuselage dimensions: 4.2 × 1.54 × 1.983 m; rotor diameter: 6.4 m
Yamaha RMAX/FAZER R G2	overall length 3908 mm; width 734 mm; height 1226 mm; main rotor diameter 3600 mm; tail rotor diameter 550 mm
CAMCOPTER S-100	Length 3110 mm; width 1240 mm; height 1120 mm; main rotor diameter 3400 mm
MQ-8 Fire Scout	MQ-8C: overall length 34.7 ft; height 10.6 ft; rotor diameter 35.0 ft
Flyability Elios 3	Fits in a 400 mm sphere

Note: The dimensional information in this table was compiled and standardized by the authors from manufacturer-published specifications, official government or regulatory documents, and other authoritative public or project-level materials, including sources such as FAA, USAF, CAAC, Janes, and publicly available product documentation.

Appendix A.2. Reference Standards and Applicability

The reference documents used for the dimensional analysis are summarized in Table A2.

Table A2. Reference documents used for candidate vertiport dimensional analysis.

Document Type	Source	Year
AAM vertiport planning report	NASA AAM vertiport considerations [40]	2022
Vertiport design guidance	FAA EB 105A, [41]	2024
VFR vertiports technical specifications	EASA PTS-VPT-DSN [42]	2022
Low-altitude VTOL facility guidelines	Guangzhou Municipal Government, [55]	2025
Civil VTOL site technical requirement	Civil vertical takeoff and landing site technical requirements [58]	2024
UAS vertiport infrastructure standard	ISO 5491:2023 [59]	2023
eVTOL infrastructure feasibility	São Paulo eVTOL infrastructure feasibility study [60]	2025
Vertiport design specification	ASTM F3423-22, [61]	2022

Appendix A.3. Verification of the 50 m Grid Size

The V2000CGF firefighting eVTOL UAV was used as the reference platform for grid-size verification. Public information for the V2000CGF series reports a wingspan of about 14.5 m. Therefore, this study used a rounded design dimension of

$$D_U = 15.0 \text{ m.} \quad (\text{A1})$$

This value was used only for GIS-level planning. Detailed engineering design would require manufacturer data, including landing-gear layout, rotor or propeller envelope, obstacle clearance, and site survey results.

According to FAA EB 105A, the touchdown and lift-off area (TLOF), final approach and takeoff area (FATO), and safety area can be expressed in terms of the controlling aircraft dimension as

$$L_{\text{TLOF}} = 1.0RD_U, \quad (\text{A2})$$

$$L_{\text{FATO}} = 2.0RD_U, \quad (\text{A3})$$

and

$$L_{\text{SA}} = 2.5RD_U. \quad (\text{A4})$$

Because the detailed propulsion-unit diameter of the V2000CGF is not publicly available, this study adopted a conservative approximation:

$$RD_U \approx D_U = 15.0 \text{ m}. \quad (\text{A5})$$

The corresponding FAA-based dimensions are therefore 15.0 m for the TLOF, 30.0 m for the FATO, and 37.5 m for the overall safety area.

A conservative domestic reference was also considered. The TLOF should contain a circle of at least $1.0D_U$, the FATO should contain a circle or square of at least $2.0D_U$, and the safety area should extend at least 5 m or $0.5D_U$ beyond the FATO boundary. With $D_U = 15.0$ m, the minimum TLOF and FATO dimensions are 15.0 m and 30.0 m, respectively. The one-side safety extension is 7.5 m. Thus, the overall vertiport dimension is

$$S_{\text{vertiport},U}^{\text{CN}} = 30.0 + 2 \times 7.5 = 45.0 \text{ m}. \quad (\text{A6})$$

The adopted grid size is

$$S_{\text{grid}} = 50.0 \text{ m}. \quad (\text{A7})$$

It is larger than both the FAA-based envelope of 37.5 m and the conservative domestic envelope of 45.0 m. Therefore, the 50 m $\times$ 50 m grid can be used as a GIS-level functional vertiport planning unit. It should not be interpreted as the exact touchdown surface. The extra space can support terrain preparation, equipment placement, loading and unloading, personnel movement, drainage, access, and safety buffering in mountainous wildfire operations.

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