

# SIR-Inspired Risk-Field-Guided Ant Colony Optimization For Static Fixed-Altitude UAV Path Planning

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Received: July 31, 2026; Accepted: September 14, 2026

Collision-free routing is not necessarily safe for unmanned aerial vehicles operating near spatially distributed hazards, because a geometrically short path may accumulate excessive exposure. This paper studies static fixed-altitude UAV path planning in known environments with non-blocking soft risks. An SIR-inspired risk-field-guided ant colony optimization framework, termed SIR-ACO, is proposed. A deterministic influence propagation surrogate based on susceptible–infected–removed states transforms sparse risk sources into a continuous horizontal risk field; the field is then coupled with ACO through path evaluation, transition guidance, and pheromone regulation. Experiments in three representative environments with 30 independent runs show that SIR-ACO reduces mean risk exposure by 64.2%, 74.1%, and 68.9% relative to basic ACO, and additional  $40 \times 40$  random-map tests show the same exposure-reduction trend against stochastic ACO baselines. Incremental component analysis identifies SIR-inspired risk-field evaluation as the primary source of exposure reduction, while mass-matched distance-decay and risk-weight-sweep comparisons show that the proposed representation changes the spatial safety–efficiency trade-off beyond merely adding a continuous distance penalty. Comparisons with A\*, Risk-A\*, and RRT\* are included as deterministic and stochastic references. The results support SIR-ACO as a safety-enhanced ACO framework for static global planning, while also showing that it is not a universal replacement for deterministic graph search when a fixed risk cost is directly available.

**Keywords:** Fixed-altitude UAV; Path planning; Ant colony optimization; Risk field; SIR model; Swarm intelligence

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[http://dx.doi.org/10.6180/jase.202701\\_36.018](http://dx.doi.org/10.6180/jase.202701_36.018)

## 1. Introduction

For unmanned aerial vehicles (UAVs), the safest route is not always the shortest collision-free route. In inspection, emergency response, environmental monitoring, and security-related missions, a UAV may have to fly through regions affected by radiation-like exposure, thermal hazards, smoke concentration, electromagnetic interference, surveillance intensity, or other non-contact threats. These threats may not be hard obstacles, but repeated exposure to them can compromise mission safety. This paper refers to such spatially distributed non-blocking hazards as soft risks. The planning problem is therefore not only to avoid obstacles, but

also to control accumulated exposure while maintaining an efficient and executable route.

UAV path planning has been reviewed from several complementary perspectives. General UAV-routing surveys commonly distinguish graph-search, sampling-based, potential-field, evolutionary or swarm-intelligence, learning-based, and hybrid families [1, 2]. Application-oriented reviews further emphasize obstacle avoidance and remote-sensing mission requirements [3, 4]. Recent surveys on multi-UAV and evolutionary planning also show that the field is moving from pure geometric feasibility toward multi-constraint and mission-aware route generation [5, 6]. However, many existing benchmarks still focus

on path length, smoothness, or dynamic obstacle avoidance. Less attention has been paid to the case where risk is spatially continuous, non-blocking, and accumulated along the route. This gap is important for mission-level UAV planning because a path that is free of collision may still be undesirable if it repeatedly traverses high-exposure regions.

Classical graph-search methods, including Dijkstra and A\*, are widely used because they are deterministic, computationally efficient, and easy to implement on discrete maps [7, 8]. Improved A\*-type planners have been used to enhance search direction, geometric efficiency, and obstacle avoidance in grid environments [9, 10]. Recent UAV studies further introduce learning acceleration, risk-aware cost design, or adaptive neighborhood strategies into A\*-based planning [11, 12]. Other A\*-based variants address high-obstacle-density or turning-constrained environments [13, 14]. When a risk penalty is inserted into the edge cost, risk-aware graph search can serve as a deterministic risk-cost reference. Its behavior, however, is largely governed by the predefined cost function, and a poorly tuned penalty may produce either risky shortcuts or overly conservative detours. Sampling-based planners such as RRT and RRT\* provide broad exploration capability in complex or dynamic spaces [15, 16]. Recent UAV studies have also extended sampling or hybrid planning to unknown three-dimensional environments [17]. Beyond route generation itself, UAV-swarm safety studies have also used federated intrusion detection to secure smart aerial-computing networks [18], indicating that path planning is increasingly considered together with risk-aware mission support. Sampling-based planners may nevertheless lead to unstable path quality on small mission grids unless a sufficient sampling budget and post-processing are used.

Evolutionary and swarm-intelligence planners provide another way to handle multi-factor planning objectives. Genetic and particle-swarm-based planners have been used to combine path length, smoothness, and other mission constraints in robot or UAV planning [19, 20]. Grey-wolf, artificial-bee-colony, and related population-based methods further illustrate the flexibility of meta-heuristic route optimization [21–23]. In disaster-response scenarios, communication-efficient federated learning has also been explored for post-flood risk assessment using UAV swarms [24], showing that risk estimation and route optimization can be coupled at the mission level. Among swarm-intelligence methods, ant colony optimization (ACO) is attractive for grid-based planning because a path can be constructed naturally as a sequence of cells and search experience can be accumulated through pheromone trails

[25]. ACO variants have improved convergence and robustness through adaptive evaporation, local update rules, and max–min pheromone bounds [26, 27]. Other studies enhance ACO by modifying heuristic functions, using multi-colony cooperation, or introducing path-pruning and learning-guided mechanisms [28, 29]. More recent ACO-based planners continue to combine global and local search or reinforcement-learning-driven guidance for robot and UAV applications [30, 31]. Additional improvements include island-type or trimming mechanisms for path planning in complex environments [32, 33]. Continuous and learning-guided ACO variants have also been explored for UAV path planning [34, 35]. Nevertheless, these improvements mainly address search efficiency, deadlock avoidance, or geometric path quality. In many ACO-based planners, the environment is still represented primarily as a binary obstacle map or as a predefined weighted cost map, so the gradual spatial influence of a soft-risk source is not explicitly modeled.

The key difficulty is therefore to give ACO a useful risk landscape, not merely an obstacle map. A sparse set of threat sources should be converted into a continuous and interpretable risk potential so that the colony can learn where pheromone should accumulate and where it should decay. Inspired by propagation processes, the susceptible–infected–removed (SIR) model provides a compact state-transition mechanism for representing how source influence spreads, overlaps, attenuates, and leaves residual influence in space [36]. In this paper, the SIR equations are used as a deterministic influence-propagation surrogate rather than as a calibrated epidemiological or physical hazard model. Compared with a Gaussian kernel, artificial potential field, or direct distance-decay penalty, the SIR-inspired risk-field propagation model maintains intermediate susceptible, infected, and removed influence states. These states provide local saturation, persistent source forcing, overlapping halos, and residual spatial memory before the final static field is frozen for planning. This field enables exposure to be evaluated as a path integral and can directly guide ant transitions and pheromone regulation.

This paper proposes SIR-ACO, a static SIR-inspired risk-field-guided ACO framework for fixed-altitude UAV path planning. The UAV is assumed to maintain a prescribed cruise altitude and is represented by its horizontal position on an eight-connected grid. The study therefore concerns global route generation in a known static horizontal plane rather than altitude selection, three-dimensional flight dynamics, or low-level real-time control. The main contributions are as follows:

1. A risk-aware problem formulation is established for

fixed-altitude UAV global path planning in known static environments with spatially distributed soft risks.

2. A deterministic SIR-inspired risk-field propagation model is formulated to map discrete soft-risk sources into a continuous and interpretable horizontal risk potential on a grid map.
3. An SIR-inspired risk-field-guided ACO framework is developed by coupling path evaluation, transition guidance, and pheromone regulation with propagation-based risk information.

The rest of this paper is organized as follows. Section 2 describes the problem formulation, the proposed SIR-ACO method, and the experimental protocol. Section 3 presents the results and discussion. Section 4 concludes the paper and discusses limitations.

## 2. Materials and methods

### 2.1. Problem Formulation

#### 2.1.1. Grid Environment and Mission Path

The UAV is assumed to fly at a prescribed constant altitude  $H_0$ , so its three-dimensional position along the planned route can be written as  $\mathbf{q}_k = (x_k, y_k, H_0)$ . The horizontal mission plane at  $H_0$  is discretized as

$$\mathcal{G} = \{(y, x) \mid y, x \in \{1, 2, \dots, N\}\}. \quad (1)$$

The obstacle set  $\mathcal{O} \subset \mathcal{G}$  contains the horizontal cross-sections of physical obstacles that intersect the selected altitude plane, and the traversable space is  $\mathcal{F} = \mathcal{G} \setminus \mathcal{O}$ . The start and goal cells are denoted by  $s \in \mathcal{F}$  and  $g \in \mathcal{F}$ , respectively. A feasible fixed-altitude path is an ordered cell sequence

$$P = \{p_1, p_2, \dots, p_K\}, \quad p_1 = s, \quad p_K = g, \quad (2)$$

where each transition satisfies  $p_{k+1} \in \mathcal{N}_8(p_k)$  and  $p_{k+1} \in \mathcal{F}$ . Here  $\mathcal{N}_8(\cdot)$  is the eight-neighbor set. The step cost between two adjacent cells is

$$d(p_k, p_{k+1}) = \begin{cases} 1, & \text{for horizontal or vertical motion,} \\ \sqrt{2}, & \text{for diagonal motion.} \end{cases} \quad (3)$$

The path length is therefore

$$L(P) = \sum_{k=1}^{K-1} d(p_k, p_{k+1}). \quad (4)$$

#### 2.1.2. Risk Field and Exposure Model

The environment contains a set of known static soft-risk sources

$$\mathcal{Q} = \{q_1, q_2, \dots, q_M\}, \quad q_m \in \mathcal{F}. \quad (5)$$

These sources do not necessarily block motion, but they induce risk in their surrounding cells. The normalized static risk field is defined as

$$R : \mathcal{G} \rightarrow [0, 1], \quad (6)$$

where  $R(p) = 0$  denotes negligible risk and  $R(p) = 1$  denotes the highest risk level. Obstacles are not traversable; for visualization and conservative evaluation, obstacle cells are assigned  $R(p) = 1$ , but they are excluded from feasible path construction.

For a path  $P$ , the accumulated risk exposure is defined as

$$E_R(P) = \sum_{k=1}^{K-1} R(p_{k+1}) d(p_k, p_{k+1}), \quad (7)$$

which is a discrete approximation of the line integral of the risk field along the path. The mean risk is

$$\bar{R}(P) = \frac{E_R(P)}{L(P) + \epsilon}, \quad (8)$$

where  $\epsilon$  is a small positive value for numerical stability.

In this paper, the abstract static risk field  $R(p)$  is instantiated by the deterministic SIR-inspired risk-field propagation model introduced in Section 2.2.1. Section 2.1 defines the mission-level risk-aware planning problem in a method-independent manner, whereas Section 2.2 specifies how the proposed framework constructs and exploits this field.

#### 2.1.3. Safety-Related Path Metrics

Besides length and risk exposure, two additional mission-level safety metrics are considered. First, the turn count  $T(P)$  is the number of heading changes along the path:

$$T(P) = \sum_{k=2}^{K-1} \mathbb{I}[(p_k - p_{k-1}) \neq (p_{k+1} - p_k)]. \quad (9)$$

Although this does not replace a full UAV dynamics model, it provides a reproducible proxy for the horizontal heading complexity of a fixed-altitude route. Second, the high-risk path length is defined as

$$H_R(P) = \sum_{k=1}^{K-1} \mathbb{I}[R(p_{k+1}) \geq R_{th}] d(p_k, p_{k+1}), \quad (10)$$

where  $R_{th}$  is a high-risk threshold, set to 0.60 in all experiments.

The planning objective is to find a feasible path that balances geometric efficiency, risk exposure, clearance, and

smoothness. In the proposed ACO search, candidate paths are ranked using the internal score

$$J(P) = L(P) + \lambda_R E_R(P) + \lambda_\theta \Theta(P), \quad (11)$$

where  $\Theta(P)$  is the accumulated turning angle,  $\lambda_R$  is the risk weight, and  $\lambda_\theta$  is the turning penalty. The score  $J(P)$  is an internal optimization score used only for path construction, path selection, and pheromone reinforcement within SIR-ACO. It is not used as a reported performance metric. All planners are evaluated by the same external metrics, including path length, risk exposure, mean risk, turn count, high-risk path length, clearance, and runtime.

## 2.2. Proposed SIR-ACO Method

The proposed method has two parts. The first part constructs a static risk field from known soft-risk sources. The second part embeds this field into ACO through risk-aware heuristics and risk-adaptive pheromone regulation.

### 2.2.1. SIR-Inspired Risk-Field Propagation Model

For each grid cell, three SIR-inspired influence states are maintained: susceptible intensity  $S_t(p)$ , infected influence intensity  $I_t(p)$ , and removed-state influence intensity  $Z_t(p)$ . The notation  $Z_t(p)$  is used only for this intermediate removed-state influence, whereas  $R(p)$  is reserved for the final normalized risk map used by the planner. Thus,  $Z_t(p)$  and  $R(p)$  have different meanings:  $Z_t(p)$  is an intermediate propagation state, while  $R(p)$  is the final static risk field. Initially, free cells are susceptible, and risk-source cells are initialized as infected cells. Obstacles are masked out from the propagation process.

Let the finite propagation support be

$$\mathcal{D}_{r_s} = \{(\Delta y, \Delta x) \mid \Delta y^2 + \Delta x^2 \leq r_s^2\}. \quad (12)$$

For  $(\Delta y, \Delta x) \in \mathcal{D}_{r_s}$ , an unnormalized distance-decaying kernel is defined as

$$\bar{K}(\Delta y, \Delta x) = \frac{\exp\left[-\frac{1}{2}\left(\frac{\sqrt{\Delta y^2 + \Delta x^2}}{\sigma}\right)^2\right]}{\max(\sqrt{\Delta y^2 + \Delta x^2}, 1)}. \quad (13)$$

The normalized propagation kernel is then

$$K(\Delta y, \Delta x) = \frac{\bar{K}(\Delta y, \Delta x)}{\sum_{(u,v) \in \mathcal{D}_{r_s}} \bar{K}(u,v) + \epsilon}, \quad (\Delta y, \Delta x) \in \mathcal{D}_{r_s}, \quad (14)$$

and  $K(\Delta y, \Delta x) = 0$  outside  $\mathcal{D}_{r_s}$ . This normalization ensures that  $\sum_{(\Delta y, \Delta x)} K(\Delta y, \Delta x) = 1$  up to the numerical stabilizer  $\epsilon$ .

Let  $Q_s(p)$  denote the static source-intensity map. Source forcing is consistently represented through  $Q_s(p)$ , with  $\kappa_I$  controlling pre-convolution source reinforcement and  $\kappa_Q$

controlling persistent source injection in the infected state update. At each propagation step,

$$\tilde{I}_t(p) = \text{clip}(I_t(p) + \kappa_I Q_s(p), 0, 1), \quad (15)$$

$$A_t(p) = (K * \tilde{I}_t)(p), \quad (16)$$

$$\Delta I_t(p) = \beta_s S_t(p) \text{clip}(A_t(p), 0, 1), \quad (17)$$

$$\Delta Z_t(p) = \gamma_s I_t(p), \quad (18)$$

where  $*$  denotes convolution,  $\beta_s$  is the infection parameter, and  $\gamma_s$  is the removal parameter. The state update is

$$I_{t+1}(p) = \text{clip}(I_t(p) + \Delta I_t(p) - \Delta Z_t(p) + \kappa_Q Q_s(p), 0, 1), \quad (19)$$

$$Z_{t+1}(p) = \text{clip}(0.96 Z_t(p) + \Delta Z_t(p), 0, 1), \quad (20)$$

$$S_{t+1}(p) = \text{clip}(1 - I_{t+1}(p) - Z_{t+1}(p), 0, 1). \quad (21)$$

In the implementation,  $\kappa_I$  corresponds to the source-gain term and  $\kappa_Q$  corresponds to the persistent source-injection term. After  $T_s$  propagation steps, the final normalized risk map is frozen as

$$R(p) = \text{clip}\left(I_{T_s}(p) + 0.65[K * (I_{T_s} + w_Z Z_{T_s})](p) + w_Z Z_{T_s}(p), 0, 1\right). \quad (22)$$

This construction converts sparse risk sources into a continuous mission-risk potential. The SIR-inspired risk-field propagation model is not intended to reproduce a particular physical diffusion law. Instead, it provides a compact engineering representation of soft-risk spread, overlap, attenuation, local saturation, and residual influence before a static planning field is obtained. The three static planning environments and their generated risk fields are shown in Fig. 1 and Fig. 2.

### 2.2.2. Risk-Field-Guided Transition Rule

In standard ACO, an ant selects the next node according to pheromone intensity and heuristic desirability. In SIR-ACO, the heuristic desirability of moving from the current cell  $i$  to a candidate cell  $j$  is defined as

$$\eta_{ij} = \eta_g(j) \eta_R(j) \eta_C(j) \eta_\theta(i, j), \quad (23)$$

where the goal-oriented factor is

$$\eta_g(j) = \left(\frac{1}{1 + D_{oct}(j, g)}\right)^{\beta_{eff}}, \quad (24)$$

and  $D_{oct}$  is the octile distance. The risk-repulsion factor is

$$\eta_R(j) = \frac{1}{1 + \rho_R R(j)}, \quad (25)$$

where  $\rho_R$  is the risk gain. The clearance factor is

$$\eta_C(j) = 1 + \rho_C \frac{C(j)}{C_{max} + \epsilon}, \quad (26)$$

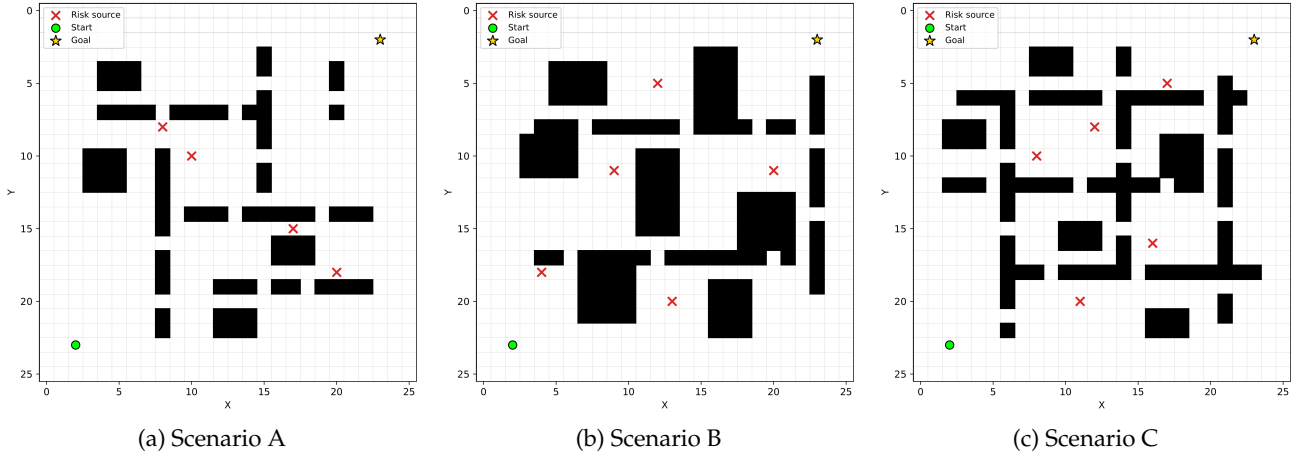


**Fig. 1.** Fixed-altitude horizontal planning environments used in the experiments. Each scenario contains obstacle cross-sections, a start cell, a goal cell, and static soft-risk sources.

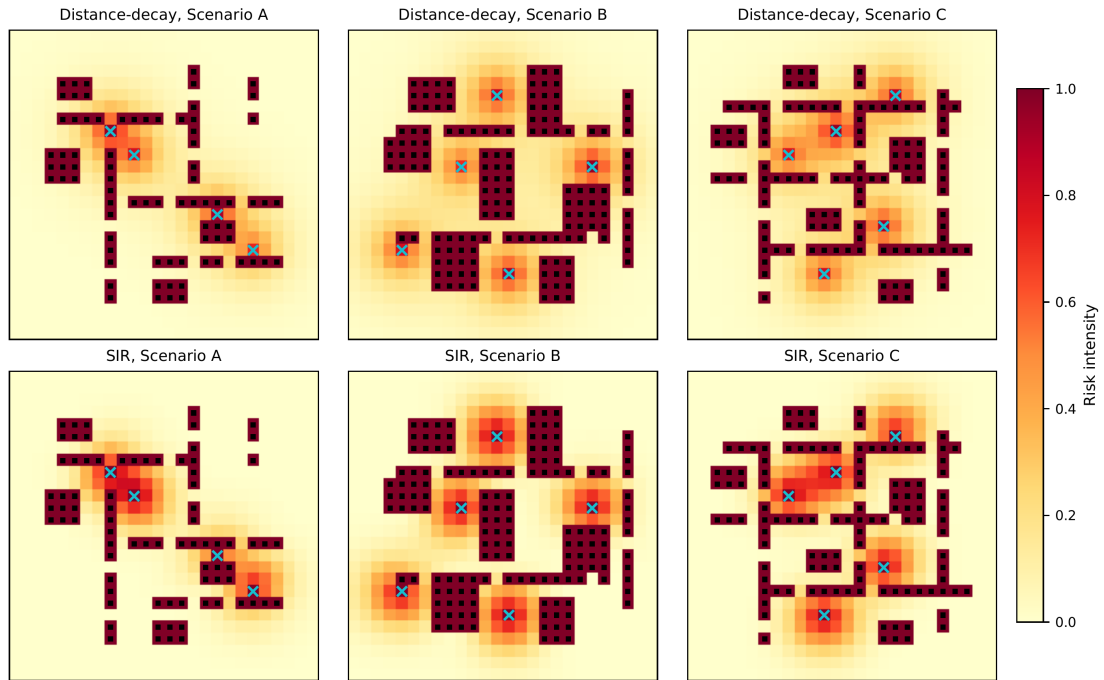


**Fig. 2.** Risk-field representations in the three scenarios. The top row shows direct distance-decay fields, and the bottom row shows SIR-inspired risk fields. For each scenario, the distance-decay scale is selected so that the total free-space risk mass equals that of the corresponding SIR-inspired risk field.

where  $C(j)$  is the distance from cell  $j$  to the nearest obstacle. The turn factor is

$$\eta_{\theta}(i, j) = \frac{1}{1 + \lambda_{\theta} \theta_{ij}}, \quad (27)$$

where  $\theta_{ij}$  is the turn angle induced by the previous, current, and candidate cells.

Let  $\mathcal{A}_t(i)$  denote the current feasible candidate set of ant  $t$  at cell  $i$ . This set is obtained from the eight-neighbor set after excluding obstacle cells, out-of-bound cells, ille-

gal diagonal moves, and nodes disallowed by the current visited-node exclusion and backtracking policy. The transition probability is defined only over this feasible set:

$$P_{ij} = \frac{\tau(j)^{\alpha} \eta_{ij}}{\sum_{l \in \mathcal{A}_t(i)} \tau(l)^{\alpha} \eta_{il}}, \quad j \in \mathcal{A}_t(i), \quad (28)$$

where  $\tau(j)$  is the pheromone value of cell  $j$  and  $\alpha$  controls the pheromone influence. If  $j \notin \mathcal{A}_t(i)$ , then  $P_{ij} = 0$ . The effective goal-guidance exponent  $\beta_{\text{eff}}$  is linearly increased

during iterations to encourage exploration in the early stage and exploitation in the later stage.

### 2.2.3. Risk-Adaptive Pheromone Regulation

SIR-ACO modifies both local and global pheromone updates. During path construction, the local update at the current cell  $i$  is

$$\tau(i) \leftarrow (1 - \phi_{\text{eff}})\tau(i) + \phi_{\text{eff}}\tau_{\min}, \quad (29)$$

where

$$\phi_{\text{eff}} = \min(0.5, \phi_0(1 + 0.5R(i))). \quad (30)$$

This rule weakens recently visited cells more strongly in high-risk areas and encourages subsequent ants to explore alternatives.

For global evaporation, SIR-ACO uses a risk-dependent decay:

$$\tau(p) \leftarrow \tau(p) [1 - \text{clip}(\rho(0.8 + 1.2R(p)), 0, 0.95)]. \quad (31)$$

Pheromone deposition is applied to both the iteration-best path and the global-best path. Let  $m \in \{\text{ib}, \text{gb}\}$  denote the deposition source, where ib is the iteration-best path and gb is the global-best path. The deposition weight is denoted by  $\omega_m$ ; in the experiments,  $\omega_{\text{ib}} = 0.45$  and  $\omega_{\text{gb}} = 1.0$ . For a cell  $p$  on path  $P_m$ , the deposited pheromone is

$$\Delta\tau_p^{(m)} = \omega_m \frac{Q}{J(P_m) + \epsilon} \left[ 1 + 0.60(1 - R(p)) + 0.25 \frac{C(p)}{C_{\max} + \epsilon} \right], \quad p \in P_m, \quad (32)$$

and  $\Delta\tau_p^{(m)} = 0$  for  $p \notin P_m$ . The final deposition update is

$$\tau(p) \leftarrow \text{clip} \left( \tau(p) + \sum_{m \in \{\text{ib}, \text{gb}\}} \Delta\tau_p^{(m)}, \tau_{\min}, \tau_{\max} \right). \quad (33)$$

Thus, low-risk cells with larger clearance receive stronger reinforcement, while high-risk cells evaporate faster.

## 2.3. Experimental Setup

### 2.3.1. Benchmark Scenarios and Compared Methods

Three static environments are used to evaluate the method: Scenario A is a structured corridor environment, Scenario B contains open risk clusters, and Scenario C combines maze-like obstacles with multiple risk regions. All maps represent horizontal slices at the prescribed flight altitude and contain known static obstacles and risk sources. Each stochastic algorithm is evaluated over 30 independent runs using seeds 1–30. A\* and Risk-A\* are deterministic: each produces one route per scenario, while repeated executions are used only to characterize runtime variability. These deterministic repetitions are not treated as independent solution samples.

### Algorithm 1. SIR-ACO for Static Fixed-Altitude Risk-Aware Mission Planning

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**Require:** Grid map  $\mathcal{G}$ , obstacle set  $\mathcal{O}$ , risk sources  $\mathcal{Q}$ , start  $s$ , goal  $g$

**Ensure:** Best feasible path  $P_{\text{best}}$

- 1: Construct the SIR-inspired risk-field propagation model and freeze  $R$  using Eqs. (14)–(22)
- 2: Initialize pheromone matrix  $\tau$  with risk and clearance priors
- 3: **for**  $t = 1$  to  $T_{\max}$  **do**
- 4:   Update  $\beta_{\text{eff}}$  according to the iteration index
- 5:   **for** each ant **do**
- 6:     Construct a feasible path using Eq. (28)
- 7:     Apply local risk-adaptive pheromone update along the path
- 8:     Evaluate the path by Eq. (11)
- 9:   Select the iteration-best and update the global-best path
- 10:   Apply risk-adaptive evaporation using Eq. (31)
- 11:   Deposit pheromone according to Eq. (32)
- 12: **return**  $P_{\text{best}}$

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The primary comparative target is the ACO family, because the main question is whether SIR-inspired risk-field guidance can improve the safety behavior of swarm-based route construction. Basic ACO is included as the ant-system reference [25]. ACS-ACO follows the ant-colony-system idea of local update and global-best-dominant reinforcement [37]. MMAS-ACO follows the max–min idea of bounded pheromone and global-best reinforcement [38]. EAS-ACO is implemented as an elitist global-best reinforcement variant, and IACO denotes the study’s non-risk geometric improvement baseline. Because all planners are embedded in one grid-path-construction code base, Table 1 states their exact operational definitions in this study. These configurations are controlled benchmark adaptations of the defining update mechanisms, not exact reproductions of every implementation detail from the canonical papers.

A progressive component-addition study then constructs the full framework from a common ACO backbone. All four stages use the same parameter settings, random seeds, goal factor, clearance factor, and turning factor; only the stated risk-related component is added at each stage:

- **A (Backbone):** uses risk-neutral path evaluation, transition, and pheromone regulation.
- **A+B (Risk-Field Evaluation):** adds SIR-inspired risk-field exposure to the path score used for solution selection and reinforcement magnitude.

**Table 1.** Operational definitions of the ACO-family benchmark configurations in the unified implementation.

All variants use the same scenario-specific ant and iteration budgets and the common numerical bounds

$$\tau_{\min} = 10^{-6} \text{ and } \tau_{\max} = 0.7.$$

| Method   | Local update | $\omega_{lb}$ | $\omega_{gb}$ | Init. prior | Distinguishing mechanism                           |
|----------|--------------|---------------|---------------|-------------|----------------------------------------------------|
| ACO      | No           | 1.00          | 0.20          | None        | Iteration-best-dominant ant-system update          |
| ACS-ACO  | Yes          | 0.25          | 1.20          | None        | Local decay and global-best-dominant update        |
| EAS-ACO  | No           | 0.30          | 2.00          | None        | Strong elitist reinforcement of the global best    |
| MMAS-ACO | No           | 0             | 1.00          | None        | Global-best-only deposition with bounded pheromone |
| IACO     | No           | 0.40          | 1.00          | Clearance   | Clearance and turning guidance without risk        |

- **A+B+C (Risk Transition):** additionally inserts the risk-field factor into the transition heuristic.
- **A+B+C+D (SIR-ACO):** additionally enables risk-aware pheromone initialization, local update, evaporation, and deposition.

To isolate the effect of the SIR-inspired risk-field propagation model from the effect of merely introducing a continuous source-distance penalty, the complete planner is also tested with a direct distance-decay field. For a free cell  $p$ , this baseline is

$$R_D(p) = 1 - \prod_{m=1}^M \left[ 1 - a_m \exp \left( -\frac{\|p - s_m\|_2}{\sigma_D} \right) \right], \quad (34)$$

where  $a_m$  and  $s_m$  are the intensity and position of source  $m$ . For each scenario,  $\sigma_D$  is determined before planning so that  $\sum_{p \in \mathcal{D}} R_D(p) = \sum_{p \in \mathcal{D}} R(p)$  over free cells. Thus, the comparison controls the total risk mass and changes only its spatial representation. Both planners use identical ACO parameters and random seeds. Every resulting path is cross-evaluated on both fields, producing distance-field exposure  $E_D$  and SIR-inspired risk-field exposure  $E_S$ .

Finally, cross-method comparisons are reported with A\*, Risk-A\*, RRT\*, basic ACO, IACO, and SIR-ACO. These comparisons are included as deterministic and stochastic references to clarify the applicability boundary of the proposed static planner rather than to define its primary optimization target.

To examine whether the observed behavior is limited to the three hand-designed maps, an additional random-map generalization experiment is conducted. Larger  $40 \times 40$  maps are generated with obstacle densities of 0.10, 0.20, and 0.30. For each density, five independently generated maps are used. A guaranteed feasible backbone between the start and goal is reserved before random obstacles are placed, and six non-blocking soft-risk sources are then sampled from the remaining free cells away from the endpoints.

**Table 2.** Scenario-dependent parameters and search budgets used in all formal experiments.

| Parameter              | Symbol or name       | Scenario A            | Scenario B            | Scenario C            |
|------------------------|----------------------|-----------------------|-----------------------|-----------------------|
| Number of ants         | $M$                  | 20                    | 22                    | 25                    |
| ACO iterations         | $I$                  | 50                    | 45                    | 50                    |
| Goal exponent schedule | $\beta_{\text{eff}}$ | $3.0 \rightarrow 5.0$ | $3.5 \rightarrow 5.5$ | $4.0 \rightarrow 6.0$ |
| Risk weight            | $\lambda_R$          | 4.0                   | 4.2                   | 4.6                   |
| Risk transition gain   | $\rho_R$             | 6.5                   | 6.0                   | 6.2                   |
| Clearance gain         | $\rho_C$             | 0.7                   | 0.3                   | 0.2                   |
| RRT* maximum samples   | $K_R$                | 2000                  | 1980                  | 2500                  |

On each random map, the stochastic planners are evaluated over five independent runs. The compared methods are Risk-A\*, basic ACO, IACO, and SIR-ACO. This experiment is intended as a supplementary generalization test rather than as a replacement for the controlled mechanism analyses on Scenarios A–C.

### 2.3.2. Parameter Settings, Computational Budgets, and Platform

Scenario-specific parameter presets were fixed before the formal 30-run evaluation and then shared by all ACO-family and progressive variants within each scenario. Consequently, a comparison within a scenario changes the stated algorithmic component rather than its search budget. Table 2 lists the scenario-dependent settings. Common settings are  $\alpha = 1.0$ ,  $\rho = 0.18$ ,  $Q = 1.0$ ,  $\phi_0 = 0.10$ ,  $\tau_{\min} = 10^{-6}$ ,  $\tau_{\max} = 0.7$ , and  $\lambda_\theta = 0.25$ . The SIR-inspired risk-field propagation model uses  $\beta_s = 0.42$ ,  $\gamma_s = 0.10$ , radius  $r = 2$ , and 10 propagation steps in every scenario. Risk-A\* uses the same scenario-specific  $\lambda_R$  and a clearance weight of 0.15. RRT\* uses goal-sampling probability 0.18, rewiring radius 3.0, and the sample budgets shown in Table 2. The comparison controls declared search budgets rather than equal wall-clock time because the algorithms have different computational structures.

The implementation was executed in Python 3.12 under 64-bit Windows 10 on an Intel Core i7-9750H CPU (6 cores, 12 logical processors) with 12 GB RAM. Runtime is the wall-clock time recorded inside each planner's `solve()` call; it excludes figure generation, file input and output, and the one-time construction of the static risk map. The same timing boundary is used for all methods.

### 2.3.3. External Evaluation Metrics and Statistical Protocol

All methods are evaluated using the same external metrics: path length  $L$ , risk exposure  $E_R$ , mean risk  $\bar{R}$ , turn count  $T$ , high-risk path length  $H_R$ , minimum clearance, success rate, and runtime. Lower values are preferred for all metrics except clearance and success rate. The primary discussion focuses on  $L$ ,  $E_R$ ,  $\bar{R}$ , and  $T$ , because these metrics provide the clearest discrimination for the present static mission-level maps. High-risk path length, minimum clearance, success rate, and runtime are retained as supplementary

**Table 3.** Alternative normalized composite-cost weight schemes used for convergence-ranking sensitivity analysis.

| Scheme             | $\hat{L}$ | $\hat{E}_R$ | $\hat{T}$ | $\hat{H}_R$ |
|--------------------|-----------|-------------|-----------|-------------|
| Balanced           | 0.35      | 0.35        | 0.15      | 0.15        |
| Risk emphasis      | 0.20      | 0.50        | 0.15      | 0.15        |
| Length emphasis    | 0.50      | 0.20        | 0.15      | 0.15        |
| Turn emphasis      | 0.25      | 0.30        | 0.30      | 0.15        |
| High-risk emphasis | 0.25      | 0.30        | 0.15      | 0.30        |

operational descriptors. These external metrics are independent of the method-specific internal score in Eq. (11). Comparisons between stochastic methods use seed-matched samples. Two-sided paired Wilcoxon signed-rank tests are conducted separately in each scenario, Holm correction is applied across the three scenarios for each comparison and metric, and the matched-pairs rank-biserial correlation  $r_{tb}$  is reported as an effect size. Positive  $r_{tb}$  means that the first listed method tends to have a larger metric value. Deterministic route values are descriptive references and are not included in stochastic significance tests. For convergence analysis, a unified normalized composite cost is used so that different ACO variants are evaluated on the same external scale:

$$J_N = 0.35\hat{L} + 0.35\hat{E}_R + 0.15\hat{T} + 0.15\hat{H}_R, \quad (35)$$

where each hatted term is min-max normalized over all compared curves in the same scenario. The two largest weights are assigned to path length and risk exposure because they represent the main efficiency and safety objectives, while turn count and high-risk path length are retained as secondary route-executability and severe-exposure descriptors. The plotted convergence curves are therefore not method-specific internal objective values, but a common external summary used only for visualization. To check whether the convergence interpretation depends on this particular balanced weighting scheme, the final rankings are also recomputed under the alternative schemes in Table 3. The solid convergence curve denotes the mean of 30 independent runs, and the shaded band denotes the 95% confidence interval.

### 3. Results and discussion

#### 3.1. Representative Path Characteristics in Static Scenarios

Figure 3 presents representative routes in the three static scenarios. The figure is intended to illustrate characteristic path behavior rather than to replace the 30-run statistical evaluation reported later. In these examples, the proposed

**Table 4.** Comparison of mass-matched distance-decay and SIR-inspired risk fields over 30 independent runs per scenario.  $E_D$  and  $E_S$  denote exposure evaluated on the distance-decay and SIR-inspired fields, respectively.

Values are mean  $\pm$  standard deviation.

| Scenario | Planning field | Length           | $E_D$           | $E_S$           | Turns            |
|----------|----------------|------------------|-----------------|-----------------|------------------|
| A        | Distance decay | 37.41 $\pm$ 3.58 | 1.55 $\pm$ 0.39 | 1.19 $\pm$ 0.61 | 13.97 $\pm$ 2.24 |
| A        | SIR-inspired   | 36.53 $\pm$ 2.20 | 1.64 $\pm$ 0.27 | 1.12 $\pm$ 0.34 | 13.87 $\pm$ 3.31 |
| B        | Distance decay | 45.08 $\pm$ 3.30 | 3.11 $\pm$ 1.20 | 2.16 $\pm$ 1.53 | 16.50 $\pm$ 4.95 |
| B        | SIR-inspired   | 44.59 $\pm$ 4.03 | 3.33 $\pm$ 1.29 | 2.15 $\pm$ 1.37 | 15.67 $\pm$ 4.47 |
| C        | Distance decay | 45.96 $\pm$ 3.03 | 1.94 $\pm$ 1.60 | 1.39 $\pm$ 1.63 | 17.83 $\pm$ 3.61 |
| C        | SIR-inspired   | 43.39 $\pm$ 4.20 | 3.10 $\pm$ 1.59 | 2.30 $\pm$ 1.69 | 15.97 $\pm$ 2.93 |

SIR-ACO planner bypasses concentrated soft-risk regions while maintaining feasible routes through the available corridors. By contrast, A\* tends to follow shorter geometric routes, Risk-A\* acts as a conservative deterministic low-risk reference, and the stochastic baselines exhibit broader variation in their response to the risk field. These examples indicate that SIR-inspired risk-field guidance can alter the search behavior of an ACO-style planner in known environments.

#### 3.2. Comparison of Risk-Field Representations and Trade-off Frontiers

Before comparing broader algorithm families, it is necessary to examine whether the proposed SIR-inspired risk-field propagation model provides a different planning signal from a simpler continuous source-distance penalty. For this reason, the complete planner is also tested with a mass-matched direct distance-decay field so that the total free-space risk mass is controlled while only the spatial shaping mechanism is changed. The visual difference between the mass-matched distance-decay field and the SIR-inspired risk field is shown in Fig. 2. This comparison isolates the contribution of the SIR-inspired risk-field propagation model itself rather than conflating it with the general benefit of using any continuous risk map.

Table 4 compares the complete planner using the SIR-inspired risk field and the mass-matched direct distance-decay field in Eq. (34). In Scenarios A and B, the two representations produce statistically indistinguishable path lengths and cross-field exposures after Holm correction. SIR-ACO is slightly shorter on average, while the exposure differences are small. This result indicates that both fields provide useful guidance when the source layout does not create a pronounced conflict between local risk avoidance and route compactness.

The nominal comparison in Table 4 shows that the difference becomes clearest in Scenario C. The SIR-inspired risk field produces a shorter mean path than direct distance

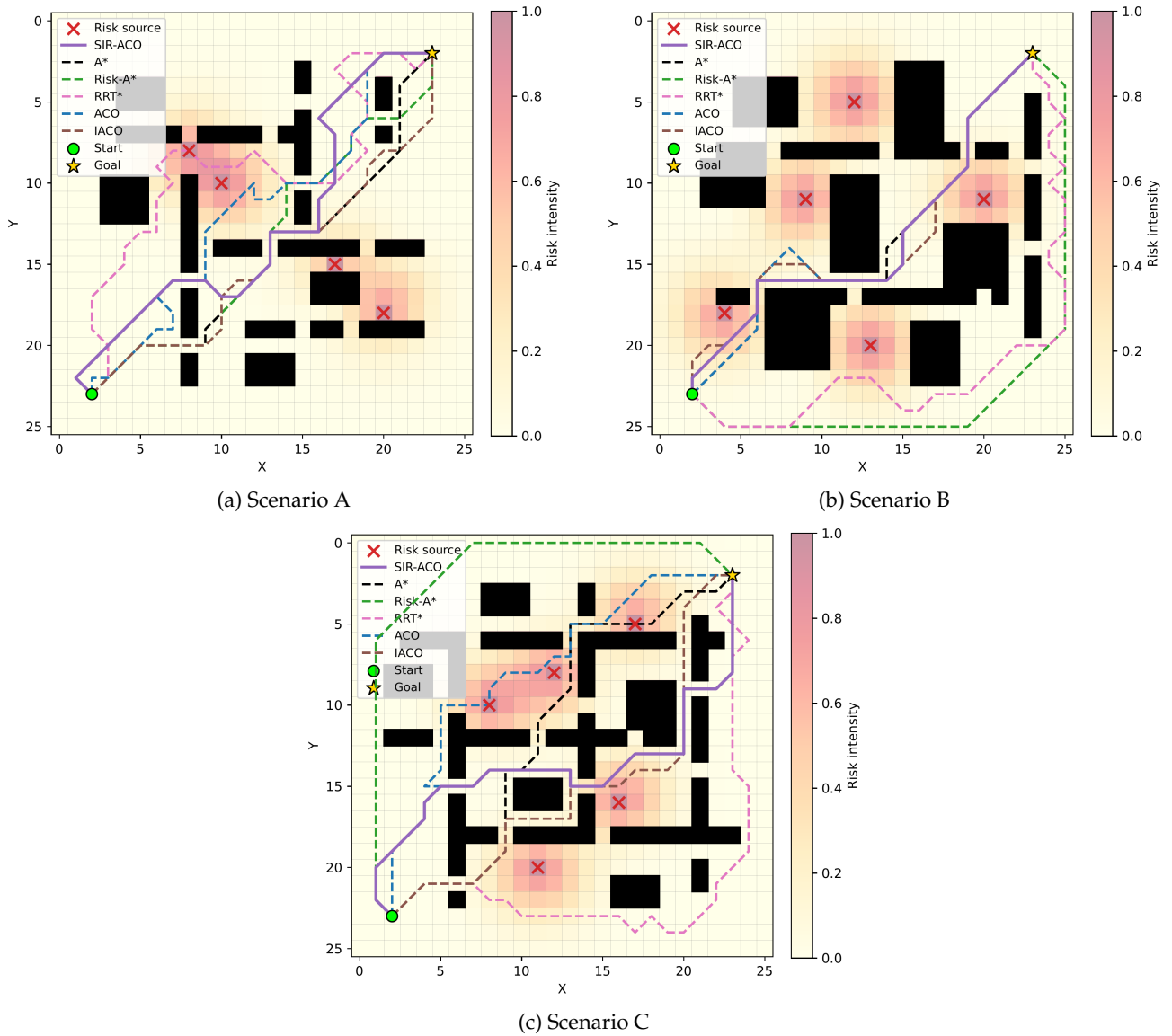


**Fig. 3.** Representative single-run path comparisons in the three static scenarios. The figure illustrates characteristic route behavior, while the quantitative conclusions are drawn from the 30-run statistical results reported later. SIR-ACO tends to avoid high-risk regions more actively than basic ACO, IACO, and RRT\*, while Risk-A\* provides a deterministic low-risk reference.

decay (43.39 versus 45.96,  $p_{\text{Holm}} = 0.021$ ,  $r_{\text{tb}} = -0.566$  for SIR-inspired minus distance-decay planning) and fewer mean turns (15.97 versus 17.83), although the turn-count difference is not significant after correction. Conversely, the distance-decay field produces lower exposure under both references:  $E_D$  decreases from 3.10 to 1.94 ( $p_{\text{Holm}} = 0.0061$ ,  $r_{\text{tb}} = 0.647$  for SIR-inspired minus distance-decay planning), and  $E_S$  decreases from 2.30 to 1.39 ( $p_{\text{Holm}} = 0.027$ ,  $r_{\text{tb}} = 0.548$ ). Therefore, the SIR-inspired representation should not be interpreted as universally minimizing exposure. Instead, it yields a less conservative and more com-

pact route in the tightly constrained hybrid environment, whereas direct distance decay favors a longer low-exposure detour.

To further avoid interpreting the representation comparison from a single risk-weight setting, Fig. 4 reports a risk-weight sweep in Scenario C for both the proposed SIR-inspired risk field and the mass-matched distance-decay field. The two representations are evaluated under the same set of risk weights  $\lambda_R$  and the same 30 random seeds, and every generated path is cross-evaluated on both risk fields. The resulting curves show that neither represen-

tation globally dominates the other. At low-to-moderate risk weights, the SIR-inspired risk field can produce lower exposure at comparable path lengths, whereas around the nominal setting  $\lambda_R = 4.6$  it yields a more compact route but higher exposure than the distance-decay field. At larger risk weights, both representations move toward low-exposure solutions, but the distance-decay field can still favor more conservative detours. Therefore, the role of the SIR-inspired risk-field propagation model is better understood as structured risk shaping that changes the length-exposure operating frontier, rather than as a uniformly superior exposure minimizer.

The cross-evaluation and risk-weight sweep demonstrate that the SIR-inspired risk-field propagation model changes the safety-efficiency trade-off rather than simply rescaling an ordinary distance penalty.

### 3.3. Comparison with ACO-Based Baselines

The primary comparative target of the proposed method is the family of ACO-style planners, because the present study aims to determine whether the SIR-inspired risk-field propagation model can improve the safety behavior of swarm-based route construction in static environments. Figure 5, Fig. 6, Fig. 7, and Table 5 show that SIR-ACO consistently produces much lower risk exposure and mean risk than the conventional ACO variants in all three scenarios. This pattern indicates that the proposed risk field does not serve merely as an external visualization layer; it actively reshapes colony search preference away from short but highly exposed corridors. The resulting paths are sometimes longer, especially in Scenarios B and C, but this reflects the intended safety-efficiency trade-off of mission-level planning rather than a failure of geometric optimization.

The exposure reduction is accompanied by increased path length and runtime in some cases. In Scenarios B and C, SIR-ACO produces longer paths than standard ACO variants because it deliberately bypasses high-risk regions. This is a mission-safety trade-off rather than a pure geometric improvement. The runtime of SIR-ACO is also higher than that of basic ACO and ACS-ACO, mainly because risk-aware heuristic computation, adaptive pheromone regulation, and safer path exploration increase the search cost. Therefore, the proposed planner is more appropriate for offline or mission-level global planning than for millisecond-level local control.

### 3.4. Incremental Component Analysis

To identify which part of the proposed framework is responsible for the observed safety gains, the full method is

decomposed into a sequence of incrementally enriched variants built on a common ACO backbone. Figure 8 and Table 6 show that the largest and most consistent reduction in exposure appears when SIR-inspired risk-field path evaluation is introduced. Adding risk-aware transition guidance provides an additional but scenario-dependent improvement, whereas the final risk-adaptive pheromone stage mainly improves path compactness and search regularity rather than uniformly driving exposure further downward. This analysis separates the contribution of each component and shows that the SIR-inspired risk-field evaluation term is the primary safety mechanism, while the remaining components play supporting roles.

Adding SIR-inspired risk-field evaluation ( $A \rightarrow A+B$ ) reduces the mean path exposure across runs from 2.45 to 1.53 in Scenario A, from 7.02 to 3.19 in Scenario B, and from 7.12 to 1.57 in Scenario C. The seed-matched reductions are significant after Holm correction in Scenarios B and C ( $p_{\text{Holm}} < 8 \times 10^{-6}$ ,  $r_{\text{tb}} = 0.987$  for A minus A+B), whereas Scenario A is borderline ( $p_{\text{Holm}} = 0.051$ ,  $r_{\text{tb}} = 0.411$ ). The reduction is accompanied by significantly longer paths in Scenarios B and C because the path score begins to reject short routes that cross strongly exposed regions.

Adding the risk-aware transition factor ( $A+B \rightarrow A+B+C$ ) further reduces mean exposure to 1.12, 2.07, and 1.51 in the three scenarios. After correction, this incremental reduction is significant in Scenario B ( $p_{\text{Holm}} = 0.012$ ,  $r_{\text{tb}} = 0.604$  for A+B minus A+B+C), but not in Scenarios A or C. Thus, transition-level risk guidance provides a scenario-dependent benefit beyond risk-aware path ranking rather than a uniform improvement. The final risk-adaptive pheromone stage shortens the mean path in all three scenarios, most visibly in Scenario C, where length decreases from 46.83 to 43.39 and turns decrease from 17.57 to 15.97. The path-length change is significant only in Scenario C ( $p_{\text{Holm}} = 0.012$ ,  $r_{\text{tb}} = 0.616$  for A+B+C minus A+B+C+D); no scenario shows a significant change in risk exposure after correction. The full method should therefore be interpreted as preserving the major risk reduction from SIR evaluation while improving path compactness in the most constrained environment, rather than as a uniformly superior single-metric risk minimizer.

### 3.5. Comparison with Graph-Search and Sampling-Based Baselines

This cross-method comparison is included to clarify the scope of the proposed static planner rather than to claim universal superiority over all planning paradigms. In the present setting, the risk field is known before planning and can be inserted directly into a deterministic graph-search

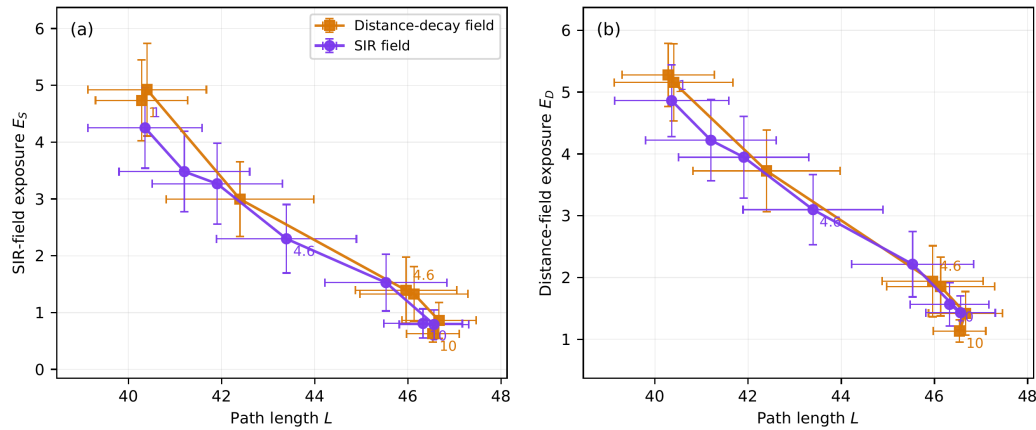


**Fig. 4.** Risk-weight sweep for the SIR-inspired risk field and the mass-matched distance-decay field in Scenario C. (a) Path length  $L$  versus SIR-inspired risk-field exposure  $E_S$ . (b) Path length  $L$  versus distance-field exposure  $E_D$ . Points denote mean values over 30 independent runs, and horizontal and vertical error bars denote 95% confidence intervals. Point labels indicate selected risk weights  $\lambda_R \in \{1, 4.6, 10\}$ .

**Table 5.** ACO-family comparison over 30 independent runs per scenario. Values are mean  $\pm$  standard deviation. The best stochastic result in each scenario is highlighted among the listed ACO-family planners.

| Scenario | Method   | Length                             | Risk exposure                     | Mean risk                           | Turns                              |
|----------|----------|------------------------------------|-----------------------------------|-------------------------------------|------------------------------------|
| A        | ACO      | 41.32 $\pm$ 3.59                   | 3.13 $\pm$ 1.53                   | 0.076 $\pm$ 0.036                   | 21.60 $\pm$ 4.77                   |
| A        | ACS-ACO  | 38.84 $\pm$ 2.52                   | 3.22 $\pm$ 1.76                   | 0.082 $\pm$ 0.043                   | 17.23 $\pm$ 3.68                   |
| A        | EAS-ACO  | 38.72 $\pm$ 2.56                   | 2.88 $\pm$ 1.48                   | 0.074 $\pm$ 0.037                   | 17.73 $\pm$ 3.02                   |
| A        | MMAS-ACO | 39.55 $\pm$ 3.34                   | 3.05 $\pm$ 1.54                   | 0.076 $\pm$ 0.036                   | 17.87 $\pm$ 4.11                   |
| A        | IACO     | 38.31 $\pm$ 2.65                   | 3.54 $\pm$ 1.19                   | 0.092 $\pm$ 0.028                   | 14.67 $\pm$ 3.77                   |
| A        | SIR-ACO  | <b>36.53 <math>\pm</math> 2.20</b> | <b>1.12 <math>\pm</math> 0.34</b> | <b>0.031 <math>\pm</math> 0.009</b> | <b>13.87 <math>\pm</math> 3.31</b> |
| B        | ACO      | 39.45 $\pm$ 3.38                   | 8.31 $\pm$ 1.85                   | 0.211 $\pm$ 0.043                   | 17.73 $\pm$ 4.86                   |
| B        | ACS-ACO  | 37.54 $\pm$ 2.46                   | 7.61 $\pm$ 1.56                   | 0.204 $\pm$ 0.044                   | 13.37 $\pm$ 3.15                   |
| B        | EAS-ACO  | 38.72 $\pm$ 3.07                   | 7.66 $\pm$ 1.79                   | 0.200 $\pm$ 0.049                   | 15.33 $\pm$ 3.44                   |
| B        | MMAS-ACO | 38.50 $\pm$ 2.99                   | 7.67 $\pm$ 1.83                   | 0.199 $\pm$ 0.043                   | 15.90 $\pm$ 4.07                   |
| B        | IACO     | 37.82 $\pm$ 2.45                   | 6.99 $\pm$ 1.46                   | 0.186 $\pm$ 0.040                   | <b>13.23 <math>\pm</math> 3.65</b> |
| B        | SIR-ACO  | 44.59 $\pm$ 4.03                   | <b>2.15 <math>\pm</math> 1.37</b> | <b>0.051 <math>\pm</math> 0.038</b> | 15.67 $\pm$ 4.47                   |
| C        | ACO      | 39.63 $\pm$ 1.97                   | 7.39 $\pm$ 2.74                   | 0.186 $\pm$ 0.066                   | 17.50 $\pm$ 4.18                   |
| C        | ACS-ACO  | 38.93 $\pm$ 2.11                   | 6.59 $\pm$ 2.18                   | 0.171 $\pm$ 0.059                   | 14.50 $\pm$ 2.73                   |
| C        | EAS-ACO  | 38.38 $\pm$ 1.90                   | 6.77 $\pm$ 2.42                   | 0.177 $\pm$ 0.064                   | 16.33 $\pm$ 2.59                   |
| C        | MMAS-ACO | 39.72 $\pm$ 2.33                   | 7.16 $\pm$ 2.22                   | 0.182 $\pm$ 0.060                   | 16.93 $\pm$ 2.69                   |
| C        | IACO     | <b>38.18 <math>\pm</math> 1.78</b> | 7.25 $\pm$ 2.01                   | 0.190 $\pm$ 0.052                   | <b>13.90 <math>\pm</math> 2.52</b> |
| C        | SIR-ACO  | 43.39 $\pm$ 4.20                   | <b>2.30 <math>\pm</math> 1.69</b> | <b>0.057 <math>\pm</math> 0.044</b> | 15.97 $\pm$ 2.93                   |

**Table 6.** Incremental component analysis over 30 independent runs per scenario. Values are mean  $\pm$  standard deviation.

| Scenario | Variant | Length           | Risk exposure   | Mean risk         | Turns            |
|----------|---------|------------------|-----------------|-------------------|------------------|
| A        | A       | 37.91 $\pm$ 2.76 | 2.45 $\pm$ 1.70 | 0.064 $\pm$ 0.042 | 14.17 $\pm$ 3.07 |
| A        | A+B     | 37.91 $\pm$ 2.70 | 1.53 $\pm$ 0.95 | 0.041 $\pm$ 0.026 | 14.83 $\pm$ 3.18 |
| A        | A+B+C   | 37.99 $\pm$ 3.53 | 1.12 $\pm$ 0.62 | 0.029 $\pm$ 0.015 | 14.73 $\pm$ 2.14 |
| A        | A+B+C+D | 36.53 $\pm$ 2.20 | 1.12 $\pm$ 0.34 | 0.031 $\pm$ 0.009 | 13.87 $\pm$ 3.31 |
| B        | A       | 37.82 $\pm$ 2.92 | 7.02 $\pm$ 1.70 | 0.187 $\pm$ 0.047 | 12.47 $\pm$ 3.34 |
| B        | A+B     | 43.40 $\pm$ 4.71 | 3.19 $\pm$ 1.82 | 0.078 $\pm$ 0.051 | 15.97 $\pm$ 4.58 |
| B        | A+B+C   | 44.68 $\pm$ 4.44 | 2.07 $\pm$ 1.51 | 0.050 $\pm$ 0.042 | 16.63 $\pm$ 4.62 |
| B        | A+B+C+D | 44.59 $\pm$ 4.03 | 2.15 $\pm$ 1.37 | 0.051 $\pm$ 0.038 | 15.67 $\pm$ 4.47 |
| C        | A       | 38.44 $\pm$ 2.75 | 7.12 $\pm$ 2.22 | 0.187 $\pm$ 0.060 | 14.40 $\pm$ 2.96 |
| C        | A+B     | 45.23 $\pm$ 4.73 | 1.57 $\pm$ 1.23 | 0.038 $\pm$ 0.033 | 17.27 $\pm$ 3.37 |
| C        | A+B+C   | 46.83 $\pm$ 3.79 | 1.51 $\pm$ 1.34 | 0.035 $\pm$ 0.034 | 17.57 $\pm$ 2.65 |
| C        | A+B+C+D | 43.39 $\pm$ 4.20 | 2.30 $\pm$ 1.69 | 0.057 $\pm$ 0.044 | 15.97 $\pm$ 2.93 |

cost, so A\* and Risk-A\* serve as deterministic references. Figure 9, Fig. 10, and Table 7 therefore should be interpreted with this role in mind. A\* provides the shortest routes but may cross hazardous regions because it ignores accumulated soft-risk exposure, whereas Risk-A\* gives a low-risk deterministic reference when a fixed scalar risk cost is suffi-

cient. Against this background, the main value of SIR-ACO is assessed relative to stochastic planners, where the proposed risk-field-guided mechanism reduces risk exposure in ACO-style and sampling-based search.

The seed-matched reductions in risk exposure are significant in every scenario for the comparisons with basic ACO,

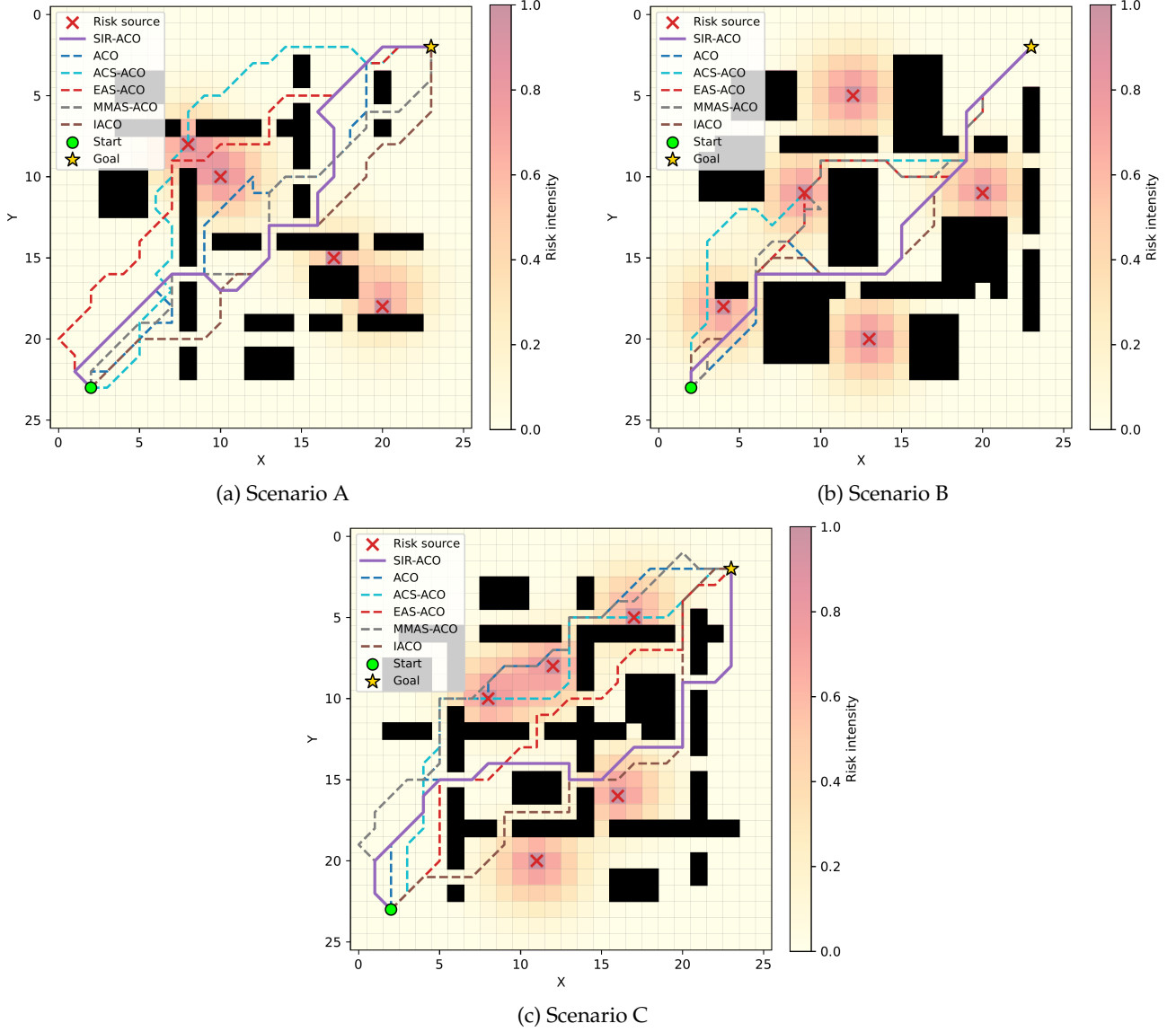


**Fig. 5.** Representative path comparison among ACO-family planners. SIR-ACO uses the SIR-inspired risk field to avoid high-risk regions more actively than the conventional ACO variants.

IACO, and RRT\* after Holm correction ( $p_{\text{Holm}} < 0.002$ ), and the corresponding rank-biserial effects have magnitude at least 0.665. In Scenario C, for example, SIR-ACO reduces mean exposure from 7.39 for basic ACO and 4.52 for RRT\* to 2.30. The length–risk trade-off in Fig. 10 further shows that SIR-ACO moves the stochastic solution distribution away from the high-risk region of the metric space. Together with the incremental study below, these results identify SIR-inspired risk-field evaluation as the principal safety contribution, while the other components refine the search behavior.

Table 8 reports the remaining external metrics declared in Section 2.3. Every method reaches the goal in all evalu-

ated cases. SIR-ACO nearly eliminates travel inside cells with  $R \geq 0.60$ , but its planning time is higher than graph search and RRT\*. Minimum clearance is mostly one grid cell because several maps contain narrow passages; it should therefore be interpreted as a map-resolution diagnostic rather than a certified vehicle-body clearance.

### 3.6. Random-Map Generalization Test

The additional random-map experiment examines whether the main stochastic-planner trends persist beyond the three hand-designed scenarios. All planners reached the goal in all 15 generated maps. Across the 75 stochastic runs, SIR-ACO reduced mean exposure from 8.17 for basic ACO

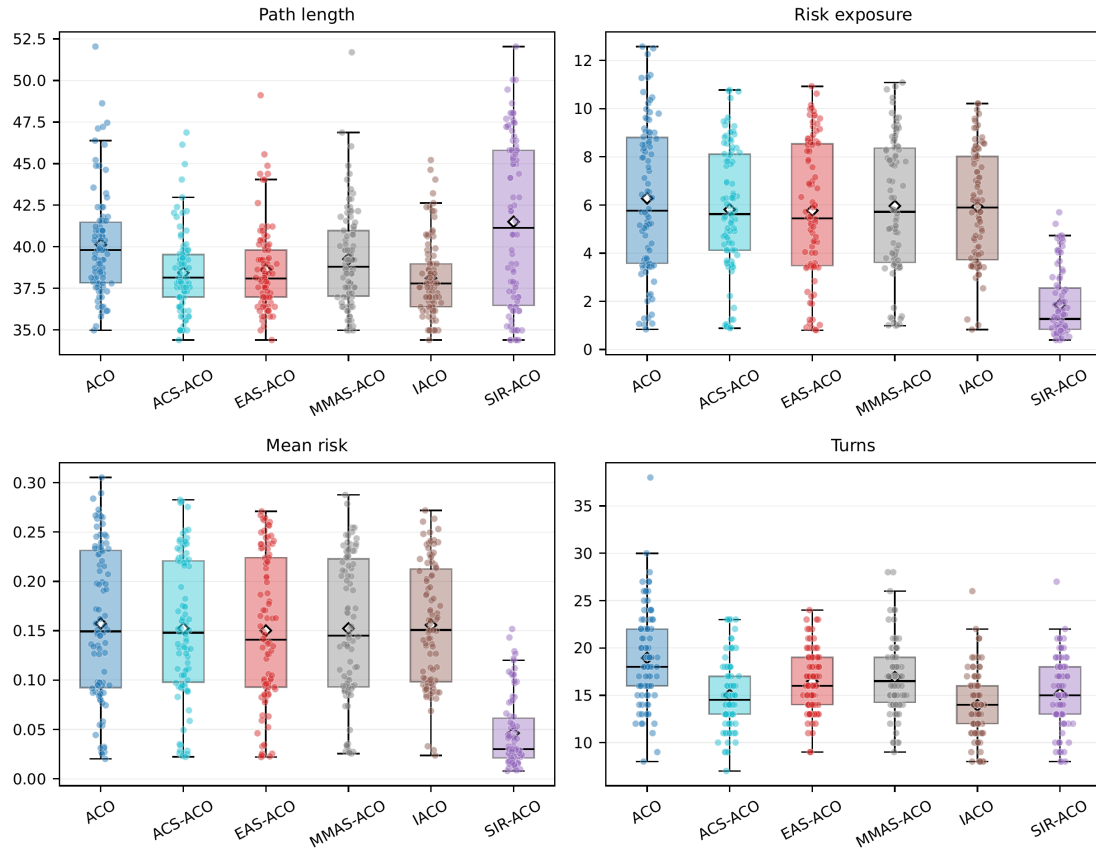


**Fig. 6.** ACO-family metric distributions pooled over the three scenarios, with 30 independent runs in each scenario. Boxes show distributions and scatter points show individual runs.

**Table 7.** Comparison with deterministic-reference and stochastic planning baselines. Stochastic results are mean  $\pm$  standard deviation over 30 independent runs per scenario, whereas deterministic A\* results are single-route values used as descriptive references under known static risk costs.

| Scenario | Method  | Length                             | Risk exposure                     | Mean risk                           | Turns                              |
|----------|---------|------------------------------------|-----------------------------------|-------------------------------------|------------------------------------|
| A        | A*      | 33.80                              | 1.01                              | 0.030                               | 8                                  |
| A        | Risk-A* | 34.38                              | 0.79                              | 0.023                               | 14                                 |
| A        | RRT*    | 43.38 $\pm$ 4.30                   | 4.11 $\pm$ 2.32                   | 0.097 $\pm$ 0.053                   | 17.80 $\pm$ 3.42                   |
| A        | ACO     | 41.32 $\pm$ 3.59                   | 3.13 $\pm$ 1.53                   | 0.076 $\pm$ 0.036                   | 21.60 $\pm$ 4.77                   |
| A        | IACO    | 38.31 $\pm$ 2.65                   | 3.54 $\pm$ 1.19                   | 0.092 $\pm$ 0.028                   | 14.67 $\pm$ 3.77                   |
| A        | SIR-ACO | <b>36.53 <math>\pm</math> 2.20</b> | <b>1.12 <math>\pm</math> 0.34</b> | <b>0.031 <math>\pm</math> 0.009</b> | <b>13.87 <math>\pm</math> 3.31</b> |
| B        | A*      | 34.38                              | 4.77                              | 0.139                               | 6                                  |
| B        | Risk-A* | 44.14                              | 0.47                              | 0.011                               | 4                                  |
| B        | RRT*    | 45.83 $\pm$ 3.88                   | 5.87 $\pm$ 2.75                   | 0.133 $\pm$ 0.072                   | 19.83 $\pm$ 3.87                   |
| B        | ACO     | 39.45 $\pm$ 3.38                   | 8.31 $\pm$ 1.85                   | 0.211 $\pm$ 0.043                   | 17.73 $\pm$ 4.86                   |
| B        | IACO    | 37.82 $\pm$ 2.45                   | 6.99 $\pm$ 1.46                   | 0.186 $\pm$ 0.040                   | 13.23 $\pm$ 3.65                   |
| B        | SIR-ACO | 44.59 $\pm$ 4.03                   | <b>2.15 <math>\pm</math> 1.37</b> | <b>0.051 <math>\pm</math> 0.038</b> | 15.67 $\pm$ 4.47                   |
| C        | A*      | 36.14                              | 8.52                              | 0.236                               | 12                                 |
| C        | Risk-A* | 42.73                              | 0.34                              | 0.008                               | 4                                  |
| C        | RRT*    | 44.65 $\pm$ 4.78                   | 4.52 $\pm$ 2.66                   | 0.108 $\pm$ 0.070                   | 19.00 $\pm$ 4.31                   |
| C        | ACO     | 39.63 $\pm$ 1.97                   | 7.39 $\pm$ 2.74                   | 0.186 $\pm$ 0.066                   | 17.50 $\pm$ 4.18                   |
| C        | IACO    | <b>38.18 <math>\pm</math> 1.78</b> | 7.25 $\pm$ 2.01                   | 0.190 $\pm$ 0.052                   | <b>13.90 <math>\pm</math> 2.52</b> |
| C        | SIR-ACO | 43.39 $\pm$ 4.20                   | <b>2.30 <math>\pm</math> 1.69</b> | <b>0.057 <math>\pm</math> 0.044</b> | 15.97 $\pm$ 2.93                   |

and 6.10 for IACO to 2.10, while also producing shorter and less tortuous routes than both stochastic ACO baselines. The seed-matched Wilcoxon tests remain significant after Holm correction for exposure, mean risk, turns, and high-risk path length when SIR-ACO is compared with basic ACO or IACO ( $p_{\text{Holm}} < 1.4 \times 10^{-8}$ ). Risk-A\* re-

mains the lowest-exposure deterministic reference in this known static setting, which is consistent with the intended interpretation of the proposed method: SIR-ACO mainly improves stochastic ACO-style route construction rather than replacing deterministic graph search when the risk cost is fixed and directly available.

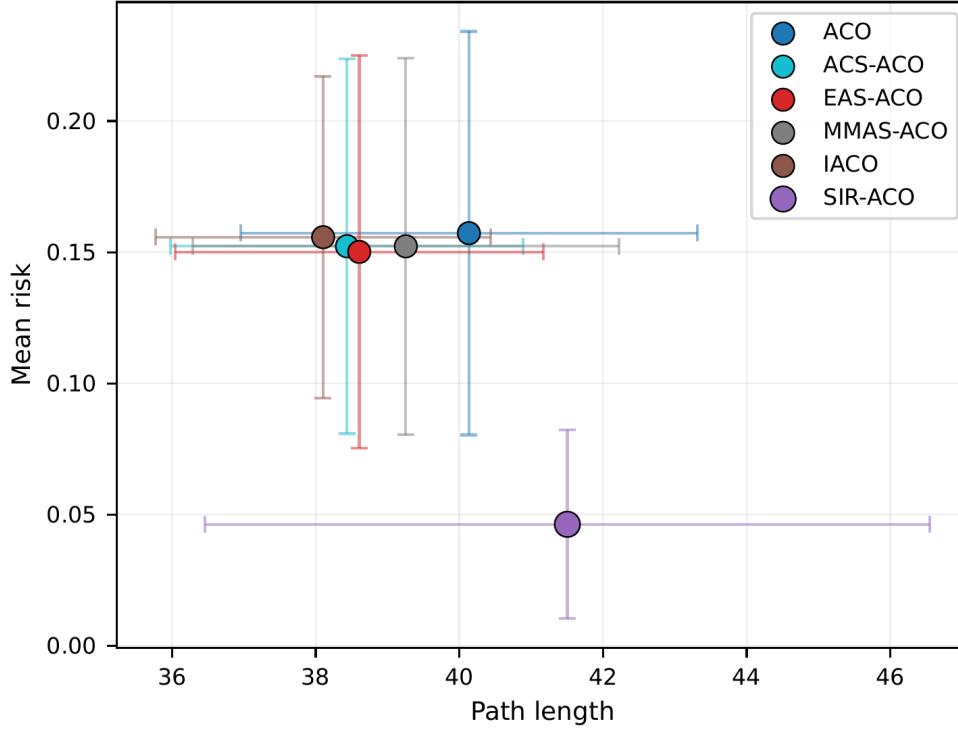


**Fig. 7.** Length-risk trade-off for ACO-family planners. Markers denote mean values, and horizontal and vertical error bars denote standard deviations over the scenario-run results.

**Table 8.** Supplementary operational metrics: success rate, high-risk path length, minimum clearance, and solver runtime. Stochastic values are mean  $\pm$  standard deviation over 30 runs. Deterministic route metrics are single values, whereas their runtimes are mean  $\pm$  standard deviation over 30 repeated timing measurements. Runtime is in seconds.

| Scenario | Method  | Success (%) | High-risk length | Min. clearance  | Runtime (s)        |
|----------|---------|-------------|------------------|-----------------|--------------------|
| A        | A*      | 100         | 0.00             | 1.00            | 0.010 $\pm$ 0.002  |
| A        | Risk-A* | 100         | 0.00             | 1.00            | 0.012 $\pm$ 0.002  |
| A        | RRT*    | 100         | 2.47 $\pm$ 2.24  | 1.00 $\pm$ 0.00 | 0.139 $\pm$ 0.094  |
| A        | ACO     | 100         | 1.13 $\pm$ 1.39  | 1.00 $\pm$ 0.00 | 3.735 $\pm$ 0.316  |
| A        | IACO    | 100         | 1.33 $\pm$ 1.12  | 1.00 $\pm$ 0.00 | 23.773 $\pm$ 1.699 |
| A        | SIR-ACO | 100         | 0.00 $\pm$ 0.00  | 1.00 $\pm$ 0.00 | 19.177 $\pm$ 1.856 |
| B        | A*      | 100         | 0.00             | 1.00            | 0.009 $\pm$ 0.002  |
| B        | Risk-A* | 100         | 0.00             | 1.41            | 0.019 $\pm$ 0.003  |
| B        | RRT*    | 100         | 1.90 $\pm$ 1.87  | 1.00 $\pm$ 0.00 | 0.228 $\pm$ 0.115  |
| B        | ACO     | 100         | 2.63 $\pm$ 1.84  | 1.00 $\pm$ 0.00 | 3.941 $\pm$ 0.153  |
| B        | IACO    | 100         | 2.18 $\pm$ 1.43  | 1.00 $\pm$ 0.00 | 23.646 $\pm$ 1.623 |
| B        | SIR-ACO | 100         | 0.11 $\pm$ 0.61  | 1.00 $\pm$ 0.00 | 20.866 $\pm$ 1.709 |
| C        | A*      | 100         | 2.00             | 1.00            | 0.013 $\pm$ 0.001  |
| C        | Risk-A* | 100         | 0.00             | 1.00            | 0.018 $\pm$ 0.003  |
| C        | RRT*    | 100         | 2.16 $\pm$ 2.29  | 1.00 $\pm$ 0.00 | 0.278 $\pm$ 0.108  |
| C        | ACO     | 100         | 3.58 $\pm$ 3.22  | 1.00 $\pm$ 0.00 | 4.598 $\pm$ 0.375  |
| C        | IACO    | 100         | 3.65 $\pm$ 2.68  | 1.00 $\pm$ 0.00 | 26.552 $\pm$ 1.442 |
| C        | SIR-ACO | 100         | 0.10 $\pm$ 0.30  | 1.00 $\pm$ 0.00 | 23.677 $\pm$ 3.608 |

### 3.7. Convergence Analysis of ACO Variants

Figure 12 compares the convergence behavior of the ACO-family planners using the unified normalized composite cost defined in Eq. (35). The plotted curves are based on external evaluation metrics rather than on method-specific internal objectives, allowing the compared variants to be judged on the same performance scale. Across the three scenarios, SIR-ACO converges rapidly in the early search stage and reaches the lowest final composite cost, while its

late-iteration confidence intervals remain relatively narrow. The result suggests that the proposed risk-guided mechanism is not only capable of finding safer routes, but also stabilizes the search process across independent random seeds.

At the final iteration, the mean normalized costs of SIR-ACO are 0.0373, 0.0706, and 0.0641 in Scenarios A, B, and C, respectively. The corresponding 95% confidence intervals are 0.0043, 0.0056, and 0.0038. The small late-iteration

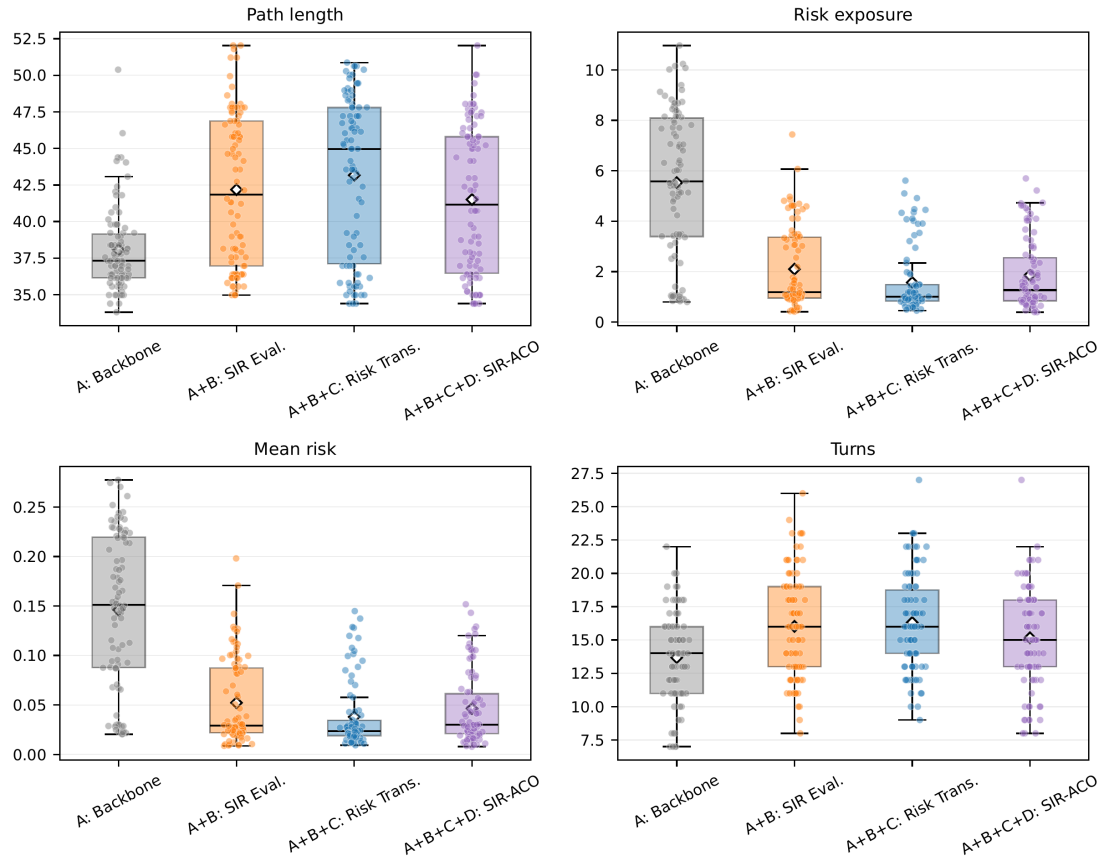


**Fig. 8.** Metric distributions for progressive component addition, pooled over the three scenarios with 30 independent runs in each scenario. B adds SIR-inspired risk-field evaluation, C adds risk-aware transition, and D adds risk-adaptive pheromone regulation.

**Table 9.** Random-map generalization results grouped by obstacle density. Values are mean  $\pm$  standard deviation. Risk-A\* is deterministic and contributes one path per generated map; the ACO-family methods contribute five independent runs per map.

| Obstacle density | Method  | Length                             | Risk exposure                     | Mean risk                           | Turns                              |
|------------------|---------|------------------------------------|-----------------------------------|-------------------------------------|------------------------------------|
| 0.10             | Risk-A* | 56.76 $\pm$ 1.84                   | <b>0.43 <math>\pm</math> 0.25</b> | <b>0.008 <math>\pm</math> 0.004</b> | <b>18.40 <math>\pm</math> 1.85</b> |
| 0.10             | ACO     | 103.27 $\pm$ 14.08                 | 8.71 $\pm$ 5.27                   | 0.086 $\pm$ 0.048                   | 69.00 $\pm$ 11.28                  |
| 0.10             | IACO    | 70.76 $\pm$ 6.40                   | 5.62 $\pm$ 3.64                   | 0.080 $\pm$ 0.051                   | 38.36 $\pm$ 7.72                   |
| 0.10             | SIR-ACO | 63.68 $\pm$ 4.03                   | 1.49 $\pm$ 1.52                   | 0.024 $\pm$ 0.025                   | 28.80 $\pm$ 4.33                   |
| 0.20             | Risk-A* | <b>57.16 <math>\pm</math> 1.89</b> | <b>0.79 <math>\pm</math> 0.69</b> | <b>0.014 <math>\pm</math> 0.012</b> | <b>19.80 <math>\pm</math> 3.49</b> |
| 0.20             | ACO     | 93.99 $\pm$ 6.38                   | 7.87 $\pm$ 6.63                   | 0.085 $\pm$ 0.071                   | 61.56 $\pm$ 5.10                   |
| 0.20             | IACO    | 72.03 $\pm$ 7.27                   | 5.78 $\pm$ 5.03                   | 0.083 $\pm$ 0.076                   | 37.56 $\pm$ 6.36                   |
| 0.20             | SIR-ACO | 63.51 $\pm$ 4.60                   | 1.38 $\pm$ 1.66                   | 0.022 $\pm$ 0.026                   | 28.04 $\pm$ 4.65                   |
| 0.30             | Risk-A* | <b>61.76 <math>\pm</math> 2.30</b> | <b>1.91 <math>\pm</math> 1.50</b> | <b>0.031 <math>\pm</math> 0.025</b> | <b>26.20 <math>\pm</math> 2.99</b> |
| 0.30             | ACO     | 101.35 $\pm$ 10.72                 | 7.93 $\pm$ 4.49                   | 0.078 $\pm$ 0.044                   | 66.68 $\pm$ 8.88                   |
| 0.30             | IACO    | 70.32 $\pm$ 6.19                   | 6.91 $\pm$ 2.73                   | 0.097 $\pm$ 0.032                   | 38.36 $\pm$ 7.52                   |
| 0.30             | SIR-ACO | 65.89 $\pm$ 6.05                   | 3.42 $\pm$ 1.89                   | 0.053 $\pm$ 0.032                   | 30.88 $\pm$ 5.20                   |

confidence intervals indicate that the reported convergence pattern is repeatable across independent random seeds rather than a favorable single run. In conjunction with the incremental analysis, the convergence curves support a narrower interpretation of the pheromone component: it stabilizes the risk-guided search and can improve path compactness while retaining the exposure reduction al-

ready produced by SIR-inspired risk-field evaluation and transition guidance.

The dependence of this convergence conclusion on the predefined composite-cost weights was further examined using the five schemes listed in Table 3. As summarized in Table 10, SIR-ACO retains the best overall rank under all five schemes when the three scenarios are pooled. It

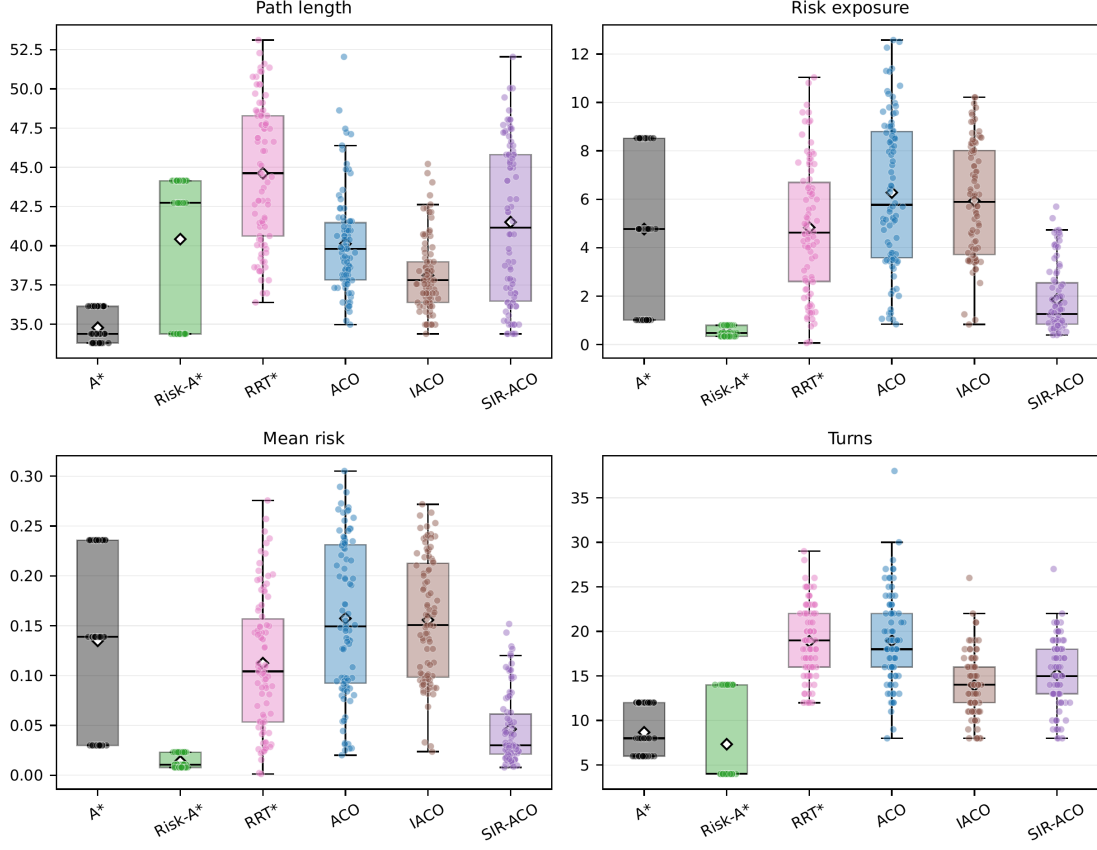


**Fig. 9.** Cross-algorithm metric distributions pooled over the three scenarios. Stochastic methods use 30 independent runs per scenario; A\* and Risk-A\* appear as invariant deterministic references.

**Table 10.** Rank of SIR-ACO under alternative normalized composite-cost weights. Rank 1 denotes the lowest mean final composite cost among the ACO-family planners.

| Weighting scheme   | Overall rank | Scenario A | Scenario B | Scenario C |
|--------------------|--------------|------------|------------|------------|
| Balanced           | 1            | 1          | 1          | 1          |
| Risk emphasis      | 1            | 1          | 1          | 1          |
| Length emphasis    | 1            | 1          | 5          | 4          |
| Turn emphasis      | 1            | 1          | 1          | 1          |
| High-risk emphasis | 1            | 1          | 1          | 1          |

also ranks first in every individual scenario under the balanced, risk-emphasis, turn-emphasis, and high-risk-emphasis schemes. The only exception occurs under the length-emphasis scheme, where IACO ranks ahead of SIR-ACO in Scenarios B and C because this scheme deliberately gives one half of the score to path length. Thus, the convergence ranking is stable for balanced or safety-oriented evaluations, while a length-dominated evaluation can favor shorter but more exposed routes.

### 3.8. Sensitivity Analysis of Risk-Related Parameters

Because the proposed framework is explicitly risk-aware, its behavior is examined under variations of the risk-related

parameters. Figure 13 studies the influence of the risk weight and the propagation radius in the SIR-inspired risk-field propagation model in Scenario C. The results show that neither parameter should be interpreted as monotonically beneficial. Increasing the risk weight or enlarging the propagation radius can reduce mean exposure in some settings, but may also produce longer and more conservative routes. This observation is consistent with the mission-level planning objective of the paper: the goal is not to minimize risk alone, but to obtain an acceptable balance between route efficiency and accumulated exposure.

### 3.9. Computational Cost and Applicability

The proposed SIR-ACO framework is computationally more expensive than deterministic graph-search baselines, and this difference should be interpreted explicitly rather than treated as a secondary detail. The SIR-inspired risk field must first be constructed, after which multiple ants repeatedly generate candidate paths and update pheromones over many iterations. Let  $n = N^2$  be the number of grid cells,  $K_S$  the number of propagation steps,  $r$  the propagation radius,  $M$  the number of ants,  $I$  the number of ACO

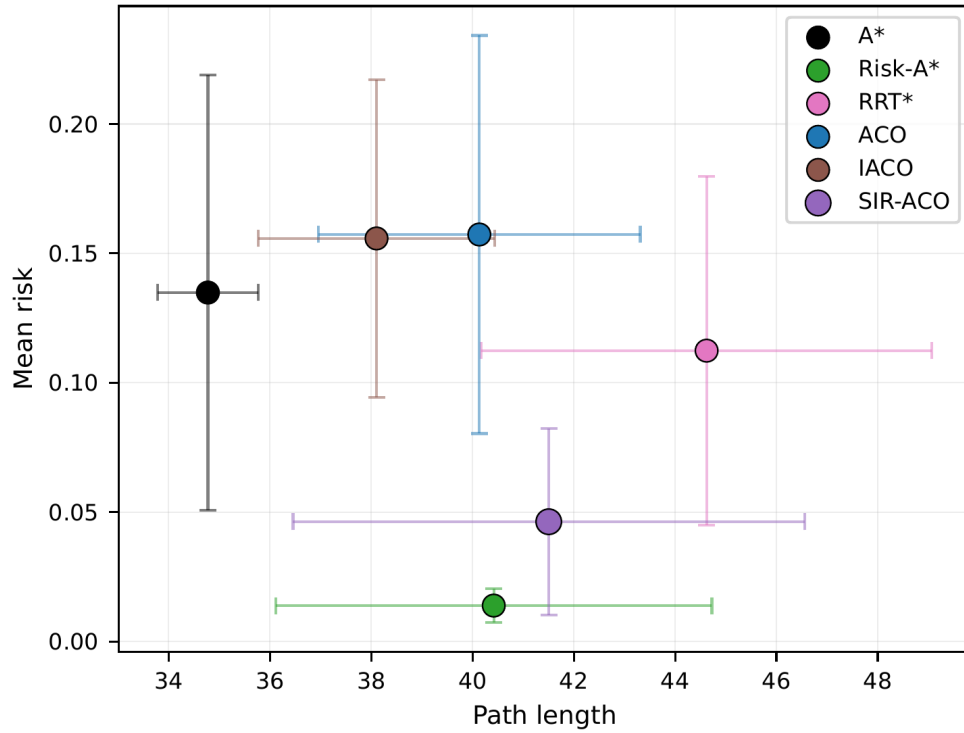


**Fig. 10.** Length-risk trade-off for the cross-algorithm comparison. Points closer to the lower-left region indicate shorter and safer paths.

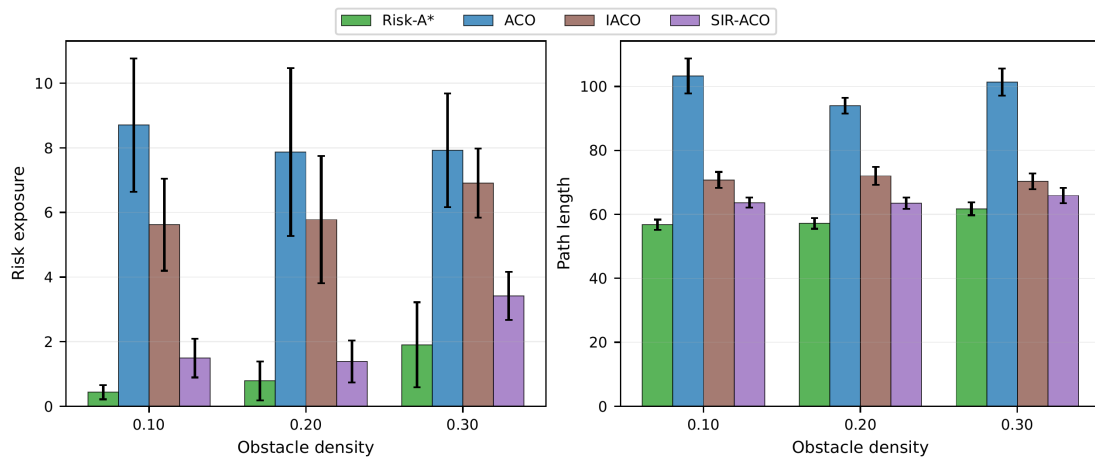


**Fig. 11.** Random-map generalization test on  $40 \times 40$  maps with obstacle densities of 0.10, 0.20, and 0.30. Each density contains five independently generated maps with six uniformly sampled soft-risk sources; stochastic planners use five independent runs per map.

iterations,  $S$  the maximum number of steps in one ant path, and  $b \leq 8$  the grid branching factor. Direct spatial propagation constructs the risk field in  $O(K_S n(2r + 1)^2)$  time and  $O(n)$  memory. SIR-ACO then requires  $O(IMSb + In)$  time: the first term covers path construction and the second covers grid-wide pheromone regulation. Because  $b$  is bounded, this is effectively  $O(IMS + In)$  for the present grid. Its

working memory is  $O(n + S + I)$ . By comparison, heap-based A\* requires  $O(n \log n)$  time in the worst case, while the implemented RRT\* baseline uses linear nearest-node and near-node scans and therefore has quadratic growth in its sample budget before accounting for occasional subtree cost propagation.

The measured runtimes in Table 8 report solver time af-

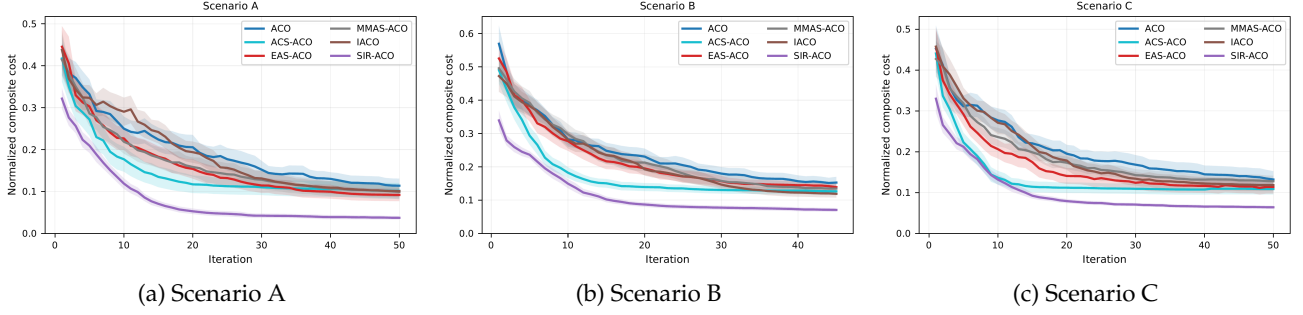


**Fig. 12.** Convergence comparison in the three scenarios. Solid curves represent the mean normalized composite cost over 30 independent runs, and shaded bands denote 95% confidence intervals. The plotted quantity is computed from external evaluation metrics rather than from variant-specific internal objective values.

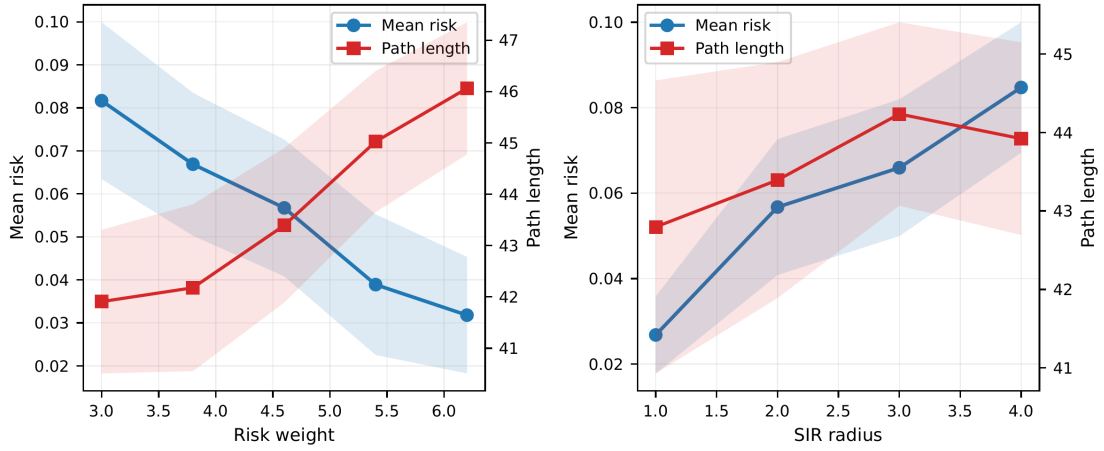


**Fig. 13.** Sensitivity analysis of risk weight and SIR radius in Scenario C. The figure illustrates the trade-off between mean risk and path length.

ter the static risk field is available; they therefore reflect the search-stage cost rather than the full one-time preprocessing pipeline. A\* and Risk-A\* complete within milliseconds, RRT\* within fractions of a second, and SIR-ACO requires approximately 19–24 seconds in the current Python implementation. SIR-ACO is faster than IACO in these experiments because its guided search often terminates before exhausting the iteration limit, but it remains slower than basic ACO and deterministic graph search. It is therefore not intended as a replacement for real-time low-level collision avoidance. Its appropriate scope is static mission-level global planning, with possible low-frequency replanning only when environmental changes are slow relative to the available computation time. For real-time dynamic planning, the static risk field and one-shot planning scheme should be extended with rolling re-planning and incremental risk-field updates.

#### 4. Conclusions

The main conclusions are summarized as follows:

1. A deterministic SIR-inspired risk-field-guided ACO framework for fixed-altitude UAV path planning was developed. The SIR-inspired risk-field propagation model transforms discrete soft-risk sources into a continuous horizontal risk field, which is embedded into ACO through risk-aware path evaluation, transition guidance, and pheromone regulation. The main contribution is the establishment and mechanism-level validation of a safety-enhanced ACO framework for known static environments rather than a claim of universal superiority over all planning paradigms.
2. Experiments in three static environments showed significant seed-matched reductions in risk exposure relative to basic ACO, IACO, and RRT\*, whereas Risk-A\* remained a deterministic low-risk reference when the risk field was known and a fixed cost function was sufficient. Additional  $40 \times 40$  random-map tests over three obstacle densities showed the same exposure-reduction trend relative to stochastic ACO

baselines. Incremental component analysis identified SIR-inspired risk-field path evaluation as the principal and most consistent source of exposure reduction; transition guidance provided an additional scenario-dependent benefit, while pheromone regulation primarily improved path compactness in the constrained scenario. A mass-matched distance-decay comparison further showed that the SIR-inspired risk-field propagation model changes the spatial safety–efficiency trade-off and can produce less conservative routes, but it is not universally superior in exposure minimization.

3. The main limitation is that the current study fixes the flight altitude and models only horizontal motion on an eight-connected grid. The UAV is represented as a point, and vehicle size, altitude changes, velocity, acceleration, energy consumption, wind, and six-degree-of-freedom flight dynamics are not considered. In addition, the method has higher computational cost than deterministic graph search and assumes that obstacles and risk sources are known before planning. Future work will extend the framework to time-varying risk fields, rolling re-planning, altitude selection, and higher-fidelity UAV motion constraints so that the second-stage dynamic setting and the later three-dimensional setting can be addressed on top of the static foundation established here.

## Acknowledgment

This work was supported by the Scientific Research Project of Higher Education Institutions of Hebei Province [grant numbers QN2026310, BJ2026037], the Regional Innovation Capability Improvement Project of Yanzhao Iron and Steel Laboratory [grant number YZISL2024014], and the Tangshan Talent Funding Project [grant number B202302009].

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