

Article

Truck–Drone Collaborative Location-Routing Optimization for Emergency Supplies Considering Flood Impact Evolution and Stage-Specific Response

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Abstract

Flood disasters evolve through distinct stages, and emergency supply demand shifts accordingly, rendering static post-disaster distribution plans inadequate for stage-specific rescue needs. This study develops a multi-stage location-routing optimization model that integrates flood impact evolution with truck–drone collaborative delivery. A flood impact evolution model is first established to describe population transitions among the normal, mildly affected, severely affected, and recovery states. The emergency response period is accordingly divided into the initial, middle, and late stages. Stage-specific time–cost coefficients are then introduced to convert delivery time into equivalent cost, reflecting the varying urgency across stages. To handle the model’s dynamic nature, model predictive control is embedded into an improved salp swarm algorithm (MPC-ISSA), enabling rolling updates of distribution decisions as flood conditions change. A case study of the 2021 Zhengzhou urban flood reveals that center activation and routing patterns differ markedly across stages, with all four distribution centers activated during the high-impact middle stage. The MPC-ISSA outperforms GA, PSO, DE, and RCGA in all three stages, lowering the total objective value by an average of 6.87%, 13.82%, and 10.45%, respectively. Relative to truck-only delivery, the collaborative mode trims total delivery time by 51.58%, 10.75%, and 10.71% across the three stages. Sensitivity analysis further verifies that the stage division holds stable under $\pm 10\%$ parameter perturbations, and the rolling framework absorbs minor boundary shifts without degrading plan reliability. These findings confirm the model’s effectiveness and the value of truck–drone collaboration for time-critical flood emergency response.



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Keywords: flood impact evolution; stage-specific response; emergency supply distribution; truck–drone collaborative distribution; location-routing optimization; improved salp swarm algorithm

1. Introduction

Frequent flood disasters are among the major threats facing human society today. Examples include the severe and persistent flooding in the Yangtze River and Huai River basins in 2016, the extreme rainstorm and flood disasters in southern China in 2020, the Zhengzhou 20 July extreme rainstorm and flood disaster in 2021, and the Doksuri-induced extreme rainstorm and flooding in the Beijing–Tianjin–Hebei region in 2023. Such events

not only cause severe losses to life and property but also substantially disrupt social and economic development. Flood disasters are characterized by urgency, uncertainty, wide spatial coverage, and long duration. After an event occurs, emergency response activities such as rescue and medical assistance require large quantities of relief supplies. Rationally selecting and establishing emergency supply distribution centers and planning efficient distribution schemes are therefore key issues in logistics decision-making.

In recent years, extensive research has been conducted on emergency logistics optimization under sudden-onset events, mainly involving the facility location problem (FLP) and the vehicle-routing problem (VRP). Feng et al. considered the uncapacitated multi-product facility location problem with submodular penalties and proposed a $(2k + 2)$ -approximation algorithm based on LP rounding to minimize total cost [1]. Tanti et al. integrated distribution center location, demand-point prediction, prohibited-route mapping, and efficient relief-supply distribution into a unified post-disaster logistics management framework [2]. Liu et al. developed a mathematical model considering both total cost minimization and carbon emission minimization, and used an improved particle swarm optimization algorithm with chaotic mapping to obtain a more uniform initial distribution and random perturbations, thereby enhancing global search capability [3]. Štádlarová et al. proposed a multi-stage mixed-integer programming formulation to characterize dynamic adjustments such as facility expansion, contraction, and closure [4]. Bideq et al. combined a swarm learning algorithm with a multi-armed bandit mechanism to solve the capacitated vehicle-routing problem [5]. In addition, Cooper proposed the location-routing problem (LRP), which integrates facility location and vehicle routing by simultaneously determining the locations of candidate facilities and vehicle routes [6]. Mao proposed an LRP with pickup facilities and heterogeneous demand (LRP-PFHD), formulated a mixed-integer linear programming (MILP) model to minimize total cost, and solved it using an adaptive large-neighborhood decomposition search algorithm [7]. Yu et al. considered the interaction among facility vulnerability, road degradation, and cascading failures, and constructed a multi-objective location-routing model for the joint optimization of system reliability, response time, and rescue cost [8]. Jiao et al. considered cooperation between transport platforms and rescue vehicles after disasters, proposed a variant of the LRP involving interdependent mobile vehicle segment operations, and designed an improved heuristic memetic algorithm (IMA-NH) [9]. Hu et al. studied a multi-period emergency facility location-routing problem that accounts for uncertainty in material demand and transportation time, as well as dynamic inventory replenishment in a multi-level emergency logistics network [10]. Temiz et al. proposed a fuel-consumption-estimation-based decision-support model for slot selection and distribution operations in humanitarian logistics [11]. Wang et al. formulated a cost-effectiveness objective for the post-disaster rescue LRP and compared cost-effectiveness maximization with social cost minimization through mathematical programming and numerical experiments [12].

Disasters may cause various forms of transport infrastructure damage, including road destruction and bridge collapse. The occurrence of such damage is highly uncertain, making normal vehicle travel difficult and obstructing post-disaster relief supply distribution. Compared with trucks, drones offer flexible aerial dispatch, are less affected by road damage, and can deliver supplies more rapidly. With continued technological progress, drones have been widely used in flood rescue scenarios. However, because of performance constraints, drones still have clear limitations in payload capacity, endurance, and operating radius, and they can hardly complete heavy-load and long-distance emergency supply delivery alone. Against this background, truck–drone collaborative distribution has become an effective way to improve the efficiency of post-flood relief supply delivery. The concept of truck–drone collaborative distribution was first proposed by Murray: the truck acts

as a mobile base and battery replacement station for drones, carries drones closer to demand points to extend their operating radius, and simultaneously undertakes ground transportation tasks [13]. Trucks are suitable for large-scale and long-distance material transport, whereas drones excel in rapid last-mile delivery. Their integration combines the advantages of ground and aerial transportation. This collaborative mode can effectively respond to road interruptions, improve distribution flexibility and regional accessibility, shorten delivery time, and strengthen emergency rescue capability. A typical operating mode is as follows: after the truck reaches a designated node, it releases a drone to perform an independent delivery task; the truck may either wait at the launch node or continue travelling, and the drone returns to the truck after completing delivery.

Regarding truck–drone collaborative distribution, Dukkanci et al. systematically reviewed studies on facility location for drone delivery systems [14]. Shi introduced the concept of drone stations for truck–drone collaborative distribution in densely populated urban areas and extended the parallel drone scheduling travelling salesman problem (PDSTSP) [15]. Faiz constructed a two-echelon delivery model in which trucks transport supplies from distribution centers to satellite stations in the first stage, and drones serve customers from the satellite stations in the second stage [16]. Wang developed a truck–drone collaborative routing framework with stochastic demand, proposed a truck–drone synchronous replenishment strategy (TDS), and analyzed its monotonicity [17]. Zhao et al. studied a dynamic truck–drone routing problem with stochastic demand and wind conditions, modeled the problem as a Markov decision process, and designed an approximate dynamic programming (ADP) algorithm [18]. Cui et al. developed a reinforcement learning-enhanced cascade-based adaptive large-neighborhood search algorithm that effectively explores tightly coupled ground–air decisions in a two-stage truck–van–drone collaborative transportation problem with transshipment [19]. For post-disaster emergency scenarios, Chen et al. proposed a customer priority post-disaster truck–drone routing and scheduling problem, considered heterogeneous urgency levels, and designed a two-stage adaptive large-neighborhood search algorithm for customer assignment [20]. Shi et al. modeled the dynamic allocation of post-disaster emergency supplies using truck–drone collaboration with the dual objectives of minimizing road risk and total waiting time at affected sites, and designed a bi-objective optimization algorithm combining a non-dominated sorting genetic algorithm and Q-learning [21]. Shen et al. constructed a mixed-integer programming model for a synchronized truck–drone system with heterogeneous monitoring tasks, deciding the number and type of drones assigned to trucks and the corresponding routes [22]. Li et al. investigated multi-drone vehicle parallel scheduling in post-disaster humanitarian logistics, formulated a mixed-integer linear programming model, and considered the effects of undeliverable nodes, dominance paths, and node priorities [23]. Kong et al. identified key challenges and emerging trends in vehicle and drone routing, integrated existing models and solution methods, and provided new insights into the interaction between vehicle and drone functions in last-mile delivery [24].

Routing optimization in emergency supply distribution is a typical combinatorial optimization problem. Genetic algorithms can search for near-optimal delivery routes through mechanisms such as selection, crossover, and mutation, thereby shortening response time and improving relief delivery efficiency. Holland introduced genetic algorithms and a general adaptation framework, showing how selection, crossover, and mutation solve complex optimization problems in natural and artificial systems [25]. Makarov et al. proposes a hybrid agent-based/discrete-event simulation digital twin for a TV plant, implemented in AnyLogic and optimized via genetic algorithm across three production scenarios [26]. Tasoglu et al. propose a simulation-based genetic algorithm to jointly optimize reverse logistics network design, disassembly line balancing, and sequencing under stochastic times,

improving cost, throughput, and satisfaction [27]. Besides genetic algorithms, many other evolutionary algorithms have been applied to simulation-based routing optimization, including PSO (particle swarm optimization), DE (differential evolution), RCGA (real-coded genetic algorithm), RCGA-PSO (combination of RCGA and PSO), hybrid multi-swarm particle swarm optimization algorithm (HMSPSO), ACO (ant colony optimization), and WOA (whale optimization algorithm).

Post-disaster rescue also exhibits clear stage-specific features. Most existing studies on emergency material rescue in disaster events focus on a particular stage of the event. However, as the event evolves, material demand and urgency differ substantially across stages. Emergency rescue is therefore a multi-stage decision-making process that must satisfy dynamic demand. Barbarosoğlu et al. used a two-stage stochastic programming framework to describe emergency material transportation in post-disaster response, distinguishing the initial rescue stage, when disaster information is unclear, from the remedial stage, when information becomes clearer [28]. Xin et al. studied a truck–drone-based humanitarian relief network design problem and proposed a two-stage distributionally robust optimization model [29]. Ali et al. considered pre-disaster and post-disaster activities, developed a bi-objective mixed-integer linear programming model, and described it as an integrated location-allocation-routing problem under uncertain parameters [30]. Rahmani et al. established a mixed-integer mathematical model for a two-stage stochastic green location-routing problem with uncertain customer demand, while considering speed, travel time, and fuel consumption [31]. Tran et al. addressed a two-stage location problem under flood disaster impacts, minimized the total expected interruption-risk cost, and developed a probability-chain-based solution technique [32]. Zang et al. studied a two-stage adaptive robust hub location problem with multiple assignments under uncertain demand and developed a column-and-constraint generation method integrated with Benders decomposition [33]. Gao et al. focused on post-disaster humanitarian relief in a drone-supported two-stage capacitated facility location problem, combining first-stage facility location and drone assignment with second-stage delivery of relief supplies, and used a two-stage distributionally robust optimization framework to handle post-disaster demand uncertainty [34]. Han et al. studied an electric-vehicle-routing problem with fuzzy demand, established a chance-constrained model based on credibility theory to minimize the total distance travelled by all vehicles, and designed a two-stage adaptive variable neighborhood search algorithm [35].

Overall, existing studies have achieved substantial progress in emergency facility location, vehicle routing, and truck–drone collaborative delivery. However, most of them still treat post-disaster demand as static or focus on a single response stage, while the dynamic evolution of flood impact and the resulting stage-specific changes in emergency supply demand have received relatively limited attention. A fixed distribution center activation scheme or a static routing plan may therefore fail to match the rescue requirements of different stages. Therefore, how to incorporate flood impact evolution into emergency supply location-routing decisions and dynamically adjust truck–drone collaborative distribution plans across response stages constitutes the primary focus of this study.

The main contributions of this study are summarized as follows:

- (1) A flood impact evolution model is established to describe population transitions among the normal, mildly affected, severely affected, and recovery states. Based on the predicted evolution of flood impact, the emergency response horizon is divided into the initial, middle, and late stages, providing a quantitative basis for stage-specific emergency supply distribution.

- (2) A multi-stage emergency supply location-routing optimization model is developed for collaborative truck–drone distribution under flood disasters. By introducing time–cost

coefficients, the model incorporates delivery time into the total distribution cost. As the flood impact evolves, the model determines when distribution centers should be activated or closed and coordinates parallel truck and drone deliveries, thereby improving both distribution efficiency and overall cost-effectiveness.

(3) A dynamic solution framework is developed by embedding model predictive control into an improved salp swarm algorithm (MPC-ISSA). The proposed method updates distribution decisions on a rolling basis as flood conditions evolve, and its effectiveness is verified through a case study based on the July 2021 severe urban flood in Zhengzhou, together with algorithm comparison and distribution mode comparison.

Finally, the remainder of this paper is organized as follows. Section 2 presents the flood impact evolution model and the stage division of the emergency response process. Section 3 formulates the multi-stage truck–drone collaborative emergency supply location-routing optimization model and introduces the MPC-based rolling decision strategy. Section 4 describes the improved salp swarm algorithm embedded with MPC. Section 5 reports the case analysis, algorithm comparison, sensitivity analysis and distribution mode comparison. Section 6 concludes the paper and discusses future research directions.

2. Evolution of Flood Impact and Stage Division

Drawing on the idea of state transition modeling, this study classifies the population and material demand in the study area into four states according to the degree of disaster impact: normal state (N), mildly affected state (F), severely affected state (S), and recovery state (R). Flood impact intensity is introduced to characterize the external driving force of the disaster. Each state corresponds to a different emergency supply demand pattern, and affected populations transfer from one state to another as flood impact evolves. Figure 1 shows the mechanism of flood impact evolution, and Table 1 reports the state variables and material demand under different flood impact states.

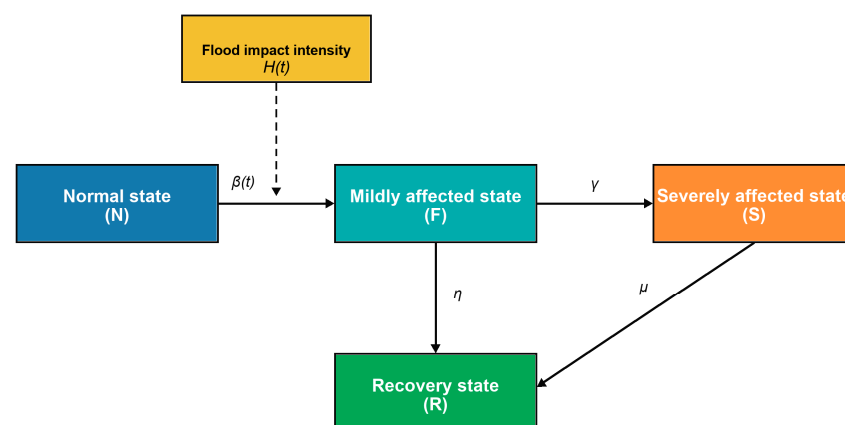


Figure 1. State transition mechanism of flood impact evolution.

Table 1. State variables and material demand under flood impact states.

State Variable	Description	Main Material Demand
$N(t)$	Number of people in the normal state at time t	No additional emergency supply demand
$F(t)$	Number of people in the mildly affected state at time t	Simple medical equipment and basic rescue supplies
$S(t)$	Number of people in the severely affected state at time t	Food, drinking water, and medicine
$R(t)$	Number of people in the recovery state at time t	Disinfection supplies, cleaning supplies, and recovery materials

In the normal state, people are not obviously affected by flooding and no additional emergency supplies are required. In the mildly affected state, simple medical equipment and basic rescue supplies are mainly needed. In the severely affected state, the degree of disaster impact further increases, and priority must be given to food, drinking water, medicine, and other emergency supplies. In the recovery state, the flood impact gradually weakens, and demand is mainly for disinfection supplies, cleaning supplies, and other recovery-related materials. Parameters and variables are shown in Table 2.

Table 2. Parameters of the flood impact evolution model.

Parameter	Description
$I(t)$	Input intensity of rainfall or upstream inflow at time t
$H(t)$	Flood impact intensity at time t
α	Flood enhancement coefficient, representing the strengthening effect of rainfall or inflow on flood impact intensity
δ	Flood attenuation coefficient, representing the weakening effect of drainage and flood recession on flood impact intensity
$\beta(t)$	Transition rate from the normal state to the mildly affected state at time t
β_0	Basic disaster impact transition rate
β_1	Influence coefficient of flood impact intensity on the state transition rate
γ	Transition rate from the mildly affected state to the severely affected state at time t
η	Recovery rate of the mildly affected population at time t
μ	Recovery rate of the severely affected population at time t

Based on the above assumptions, the following system of ordinary differential equations is established:

$$\frac{dH(t)}{dt} = \alpha I(t) - \delta H(t) \quad (1)$$

$$\beta(t) = \beta_0 + \beta_1 H(t) \quad (2)$$

$$\frac{dN(t)}{dt} = -\beta(t)N(t) \quad (3)$$

$$\frac{dF(t)}{dt} = \beta(t)N(t) - \gamma F(t) - \eta F(t) \quad (4)$$

$$\frac{dS(t)}{dt} = \gamma F(t) - \mu S(t) \quad (5)$$

$$\frac{dR(t)}{dt} = \eta F(t) + \mu S(t) \quad (6)$$

Equation (1) indicates that flood impact intensity increases under rainfall or upstream inflow and gradually decays with drainage, flood recession, and engineering measures. Equation (2) indicates that the flood impact diffusion rate is jointly determined by the basic diffusion level and flood impact intensity. Equation (3) indicates that the normal-state population transfers to the mildly affected state under flood impact. Equation (4) indicates that the mildly affected population increases because of inflow from the normal state and decreases because of disaster aggravation or rescue recovery. Equation (5) indicates that the mildly affected population further transfers to the severely affected state and decreases after rescue and transfer. Equation (6) indicates that mildly and severely affected populations enter the recovery state after rescue, transfer, or environmental recovery.

Given the initial values of each state and the relevant parameters, the model can be used to analyze the evolution of flood impact and predict the number of affected people in

each state. Moreover, flood impact evolves over time in a stage-specific manner and often exhibits different characteristics at different stages. To divide the flood disaster process into stages, the degree of flood impact is defined by the proportion of affected population:

$$Z(t) = \frac{F(t) + S(t)}{P} \quad (7)$$

Accordingly, the complex evolution of flood impact can be divided into three stages, as shown in Figure 2. $T_0 - T_1$ is the initial rapid development stage, in which flood impact intensity continues to rise, the affected population increases rapidly, and material demand grows quickly. $T_1 - T_2$ is the middle high-level stable stage, in which the flood-affected area remains at a high level, the proportion of severely affected population is relatively large, and material demand remains high. $T_2 - T_3$ is the late recession and recovery stage, in which flood impact intensity decreases, the recovery-state population gradually increases, and emergency supply demand gradually declines to zero.

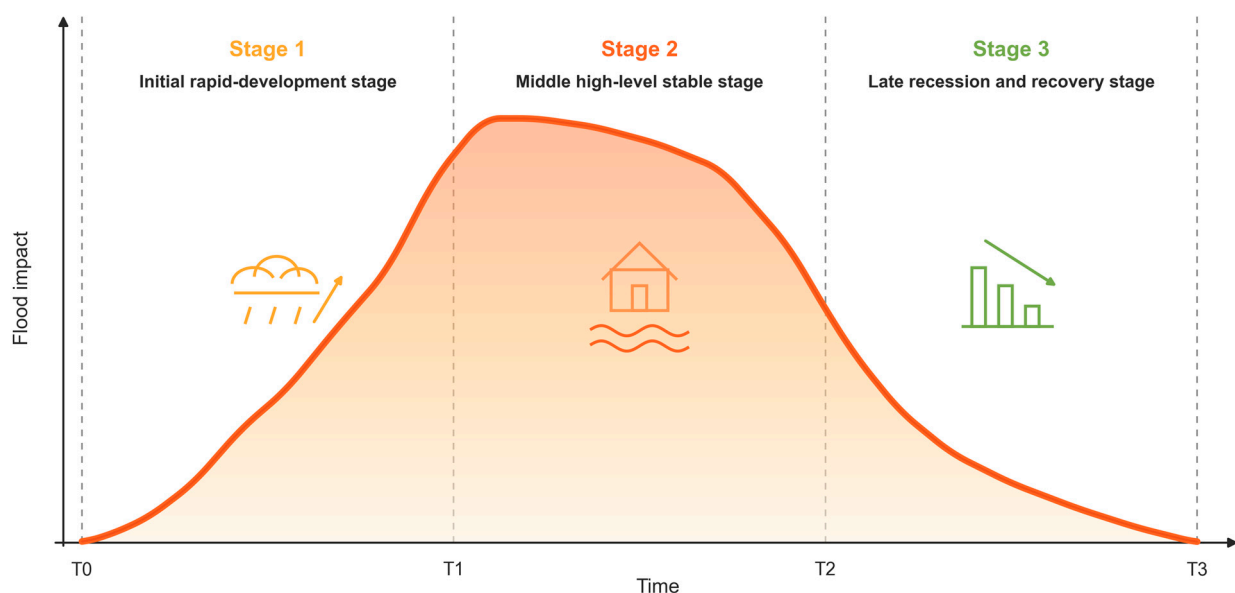


Figure 2. Stage division of flood impact evolution.

3. Emergency Supply Distribution LRP Model

3.1. Problem Description and Model Assumptions

After a flood disaster, location selection and route optimization for emergency medical supply distribution are important decision-making tasks in rescue organization. Decision-makers should comprehensively consider multiple objectives and constraints, including economic efficiency and timeliness, and develop efficient and reasonable distribution schemes according to actual conditions. Each distribution problem can be described as follows: several demand points are distributed in a region, and n distribution centers must be selected and activated from m known candidate distribution centers to organize truck-drone collaborative delivery of emergency medical supplies. Trucks depart from activated distribution centers, undertake large-volume material transport tasks, and can release drones at safe stopping points or near demand points. Drones complete last-mile delivery and then return to the original truck or to a designated recovery point.

Based on the above analysis of flood evolution stages, the emergency medical supply distribution LRP is divided into initial, middle, and late stages. The distribution characteristics of each stage are as follows:

The initial stage is a period in which the flood disaster develops rapidly and its destructive impact continues to expand. As the flood level keeps rising, the inundated area and the degree of damage expand rapidly, and traffic accessibility in some areas is restricted. Emergency supply distribution centers must therefore be added in a timely manner, and trucks and drones must be rationally dispatched to deliver various emergency supplies quickly to affected demand points, as shown in Figure 3a.

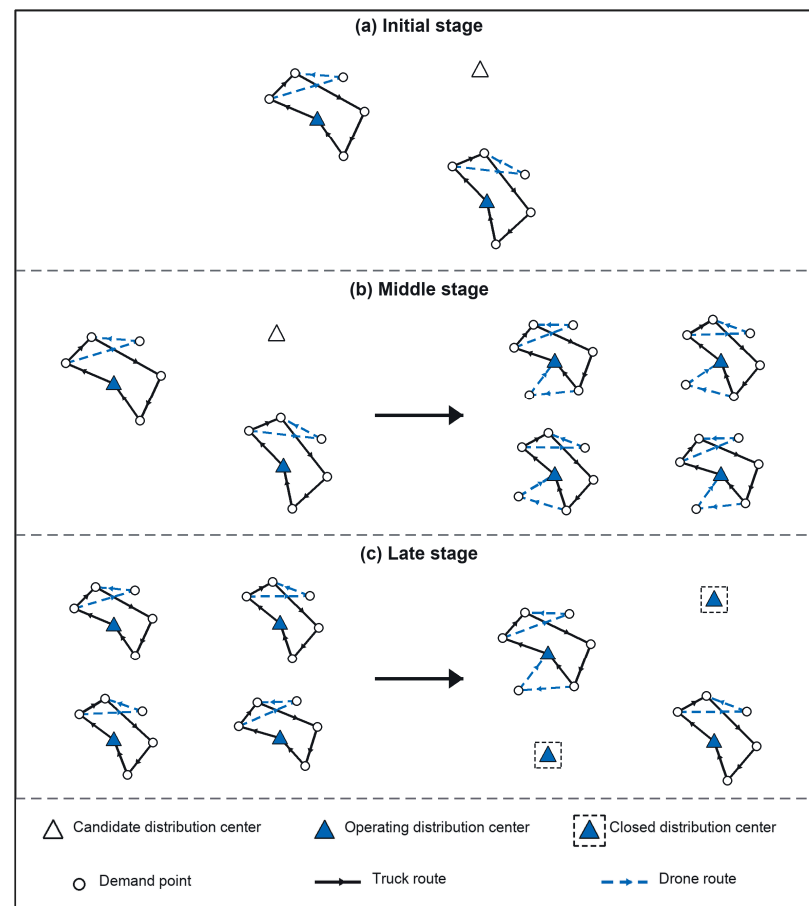


Figure 3. Truck–drone collaborative distribution strategies at different flood disaster stages.

In the middle stage, the flood gradually reaches its peak and is controlled within a relatively stable range, but the disaster remains at a high-impact level. The number of activated distribution centers can generally meet the distribution demand of each demand point. It is therefore necessary to continuously strengthen the allocation of emergency supplies and distribution resources, make full use of truck–drone collaborative delivery capacity, and ensure timely supply to affected areas, as shown in Figure 3b.

In the late stage, the flood gradually recedes, and both the affected area and the degree of damage begin to decline. Emergency supply demand at demand points decreases accordingly, and the capacity of activated distribution centers gradually becomes redundant. To avoid unnecessary resource waste, some distribution centers activated in earlier stages should be gradually closed according to changes in the actual affected area and material demand, and truck and drone delivery tasks should be adjusted, as shown in Figure 3c.

To highlight the research focus and ensure model solvability, the following assumptions are made:

(1) Emergency supply distribution centers can only be selected from several candidate distribution centers, and each activated distribution center can meet the supply demand within its service area.

- (2) The locations of all candidate distribution centers and demand points are known.
- (3) The performance parameters of trucks and drones, including load capacity, endurance, and driving or flight speed, are constant.
- (4) The time required for drone loading and unloading and battery replacement is ignored, and the stopping time of trucks and drones at demand nodes is not considered.
- (5) Each demand point can be served by only one distribution center, and the required emergency supplies can be delivered by only one truck or one drone and cannot be split into multiple deliveries.
- (6) Each drone can serve only one demand node in a single mission.
- (7) After completing service, each vehicle must return to the distribution center, forming a closed-loop distribution network.
- (8) Road accessibility is not considered, and all road links used by trucks are assumed to be passable throughout the distribution process.

3.2. Notation

The set of flood disaster stages is defined as $S = \{1, 2, 3\}$, representing the initial, middle, and late stages, respectively; the set of delivery periods is defined as $T = \{1, 2, \dots, t\}$; the set of candidate distribution centers is denoted as $D = \{1, 2, \dots, d\}$; the set of demand nodes is denoted as $N = \{1, 2, \dots, n\}$, where $i, j \in N$; the set of trucks is denoted as $K = \{1, 2, \dots, k\}$; and the set of drones is denoted as $U = \{1, 2, \dots, u\}$. Other parameters and variables are defined as shown in Tables 3 and 4.

Table 3. Parameter descriptions.

Parameter	Description
v_k	The average speed of truck k
v_u	The average speed of drone u
d_{ij}	The distance between nodes i and j
Q^u	The maximum load capacity of the drone
L^u	The maximum flight range of the drone
E^u	The maximum flight endurance of the drone
t_{ij}^u	The flight time of drone u from node i to j
t_{ij}^k	The travel time of truck k from node i to j
C^k	The unit transportation cost of the truck per unit load
C^u	The unit flight cost of the drone per unit load
O_t	The operating cost of a single distribution center per period
F_t	The activation cost of a single distribution center
g_i^k	The visiting order of demand nodes in the truck route
g_i^u	The visiting order of demand nodes in the drone route
M	A sufficiently large positive constant
λ	The time–cost coefficient

Table 4. Description of the decision variables.

Decision Variable	Description
x_{ij}^k	Binary decision variable indicating whether truck k travels from node i to node j
x_{ij}^u	Binary decision variable indicating whether drone u flies from node i to node j
y_i^k	Binary decision variable indicating whether demand node i is served by truck k
y_i^u	Binary decision variable indicating whether demand node i is served by drone u
z_t^d	Binary decision variable indicating whether distribution center d is activated in period t
h_i^L	Binary decision variable indicating whether demand node i is the launch node of drone u
h_i^R	Binary decision variable indicating whether demand node i is the recovery node of drone u

3.3. Mathematical Model

Based on the above assumptions and notation, the multi-stage truck–drone collaborative emergency supply distribution model under flood disasters is formulated as follows:

$$\min Z_1 = \max_{t \in T} \left\{ \sum_{k \in K} \sum_{i \in N} \sum_{j \in N} t_{ij}^k x_{ij}^k, \sum_{u \in U} \sum_{i \in N} \sum_{j \in N} t_{ij}^u x_{ij}^u \right\} \quad (8)$$

$$\min Z_2 = \sum_{t \in T} \sum_{d \in D} (F_t + O_t) z_d^t + \sum_{t \in T} \sum_{k \in K} \sum_{i \in N} \sum_{j \in N} C^k d_{ij} x_{ij}^k + \sum_{t \in T} \sum_{u \in U} \sum_{i \in N} \sum_{j \in N} C^u d_{ij} x_{ij}^u \quad (9)$$

Objective function Z_1 minimizes the total collaborative emergency supply delivery time for the whole distribution process under the parallel truck–drone collaboration mode. Since trucks and drones perform their delivery tasks concurrently, summing their route durations would overestimate the completion time, while a weighted average would not accurately reflect the synchronized operation; therefore, the maximum of the two time terms is adopted to represent the actual completion time of the collaborative distribution mission. Objective function Z_2 minimizes the total emergency response cost, including distribution center activation cost, operating cost, and truck and drone transportation costs. For the multi-objective functions, this study introduces the time–cost coefficient λ and treats time as part of cost, thereby converting the multi-objective formulation into a single-objective function as follows:

$$\min Z = \lambda Z_1 + Z_2 = \lambda \max_{t \in T} \left\{ \sum_{k \in K} \sum_{i \in N} \sum_{j \in N} t_{ij}^k x_{ij}^k, \sum_{u \in U} \sum_{i \in N} \sum_{j \in N} t_{ij}^u x_{ij}^u \right\} + \sum_{t \in T} \sum_{d \in D} (F_t + O_t) z_d^t + \sum_{t \in T} \sum_{k \in K} \sum_{i \in N} \sum_{j \in N} C^k d_{ij} x_{ij}^k + \sum_{t \in T} \sum_{u \in U} \sum_{i \in N} \sum_{j \in N} C^u d_{ij} x_{ij}^u \quad (10)$$

$$\sum_{k \in K} y_i^k + \sum_{u \in U} y_i^u = 1, \forall i \in N \quad (11)$$

$$\sum_{j \in N} x_{ij}^k = y_i^k, \forall i \in N, k \in K \quad (12)$$

$$\sum_{j \in N} x_{ij}^u = y_i^u, \forall i \in N, u \in U \quad (13)$$

$$\sum_{j \in N} x_{ji}^k - \sum_{j \in N} x_{ij}^k = 0, \forall i \in N, k \in K \quad (14)$$

$$\sum_{j \in N} x_{ji}^u - \sum_{j \in N} x_{ij}^u = 0, \forall i \in N, u \in U \quad (15)$$

$$x_{ij}^k \leq y_i^k, \forall i, j \in N, k \in K \quad (16)$$

$$x_{ij}^u \leq y_i^u, \forall i, j \in N, u \in U \quad (17)$$

$$x_{ii}^k = 0, \forall i \in N, k \in K \quad (18)$$

$$x_{ii}^u = 0, \forall i \in N, u \in U \quad (19)$$

$$\sum_{i \in N} y_i^u \leq Q^u, \forall u \in U \quad (20)$$

$$g_i^k - g_j^k + n x_{ij}^k \leq n - 1, \forall i, j \in N, i \neq j, k \in K \quad (21)$$

$$g_i^u - g_j^u + n x_{ij}^u \leq n - 1, \forall i, j \in N, i \neq j, u \in U \quad (22)$$

$$d_{ij} x_{ij}^u \leq L^u, \forall i, j \in N, i \neq j, u \in U \quad (23)$$

$$t_{ij}^u x_{ij}^u \leq E^u, \forall i, j \in N, i \neq j, u \in U \quad (24)$$

$$\sum_{d \in D} z_d^t \geq 1, \forall t \in T \quad (25)$$

$$h_i^L \leq \sum_{k \in K} y_i^k, \forall i \in N \quad (26)$$

$$h_i^R \leq \sum_{k \in K} y_i^k, \forall i \in N \quad (27)$$

$$\sum_{i \in N} h_i^L = \sum_{i \in N} h_i^R \quad (28)$$

Constraint (11) states that each demand point can be visited only once by either a truck or a drone. Constraint (12) prevents a truck from returning directly from a node to itself. Constraint (13) prevents a drone from returning directly from a node to itself. Constraints (14) and (15) enforce flow conservation for trucks and drones entering and leaving demand points. Constraint (16) states that truck k can enter node i only when it serves node i . Constraint (17) states that drone u can fly into node i only when it serves node i . Constraints (18) and (19) prohibit self-loops at the same node for trucks and drones. Constraint (20) ensures that a drone does not exceed its maximum payload. Constraints (21) and (22) eliminate truck and drone subtours. Constraints (23) and (24) require each drone flight to remain within the maximum flight range and maximum flight endurance. Constraint (25) ensures that at least one distribution center is activated in each delivery period. Constraints (26) and (27) require drone launch and recovery nodes to be visited by a truck. Constraint (28) ensures that the number of drone launch nodes is equal to the number of drone recovery nodes.

3.4. Mpc-Based Emergency Supply Distribution Strategy

Emergency supply distribution under flood disasters is a typical dynamic decision-making problem. Uncertainty regarding flood intensity and dynamic changes in the affected population require distribution schemes to be adjusted continuously according to actual disaster conditions. To address this problem, this study uses model predictive control (MPC) to solve the dynamic location-routing optimization problem for emergency supply distribution [36]. By rolling forward and updating affected-population information in each decision period, the distribution scheme is continuously optimized so that truck and drone delivery tasks can be adjusted dynamically as the flood evolves. The specific implementation is shown in Figure 4. In the current decision period (DP), the latest disaster information is used to predict subsequent periods and determine the corresponding distribution scheme. After the current-period scheme is executed, that period becomes an executed period (EP), and subsequent periods are treated as forecast periods (FPs). As new actual information becomes available, affected-population prediction and distribution optimization are conducted again in the next decision period, and a new decision scheme is implemented. This rolling process enables dynamic adjustment of the emergency supply distribution strategy.

Define τ as the index of the current rolling decision moment. Let $\mathcal{T}_\tau = \{\tau, \tau + 1, \dots, T\}$ denote the predictive time horizon starting from decision moment τ . Under the MPC rolling framework, only the decision variables corresponding to the current moment τ are implemented physically; variables for periods $t > \tau$ are predictive intermediate variables, which will be re-optimized in subsequent rolling iterations. Denote the decision variables solved at rolling moment τ as $x_{ij}^{k,\tau}, x_{ij}^{u,\tau}, z_d^{t,\tau}$. The time–cost trade-off coefficient is dynamically updated to λ^τ according to real-time disaster severity at moment τ .

The rolling optimization problem is subject to all original model Constraints (11)–(28), with all time indices restricted to the predictive horizon $t \in \mathcal{T}_\tau$. Based on the known

disaster information, the time–cost weight and decision variables λ , x_{ij}^k , x_{ij}^u are updated to λ^τ , $x_{ij}^{k,\tau}$, $x_{ij}^{u,\tau}$. The objective function for decision period τ can then be expressed as:

$$\begin{aligned} \min Z^\tau &= \lambda^\tau Z_1^\tau + Z_2^\tau \\ &= \lambda^\tau \max_{t=\tau, \dots, T} \left(\sum_{k \in K} \sum_{i \in N} \sum_{j \in N} t_{ij}^k x_{ij}^{k,\tau}, \sum_{u \in U} \sum_{i \in N} \sum_{j \in N} t_{ij}^u x_{ij}^{u,\tau} \right) \\ &\quad + \sum_{t=\tau}^T \sum_{d \in D} (F_t + O_t) z_d^{t,\tau} + \sum_{t=\tau}^T \sum_{k \in K} \sum_{i \in N} \sum_{j \in N} C^k d_{ij} x_{ij}^{k,\tau} + \sum_{t=\tau}^T \sum_{u \in U} \sum_{i \in N} \sum_{j \in N} C^u d_{ij} x_{ij}^{u,\tau} \end{aligned} \quad (29)$$

λ^τ adapts the weight of delivery completion time in the composite objective at each rolling step according to real-time flood disaster severity. Z_1^τ represents the predicted maximum task completion time of truck–drone collaborative distribution over the future predictive horizon starting from moment τ . Z_2^τ aggregates the predicted activation operation cost of distribution centers and the transportation cost of trucks and drones. Only the optimization results corresponding to current time τ are executed; when new disaster observation data arrive, τ is updated to $\tau + 1$, the predictive window slides forward, and the rolling optimization problem is reconstructed and solved again.

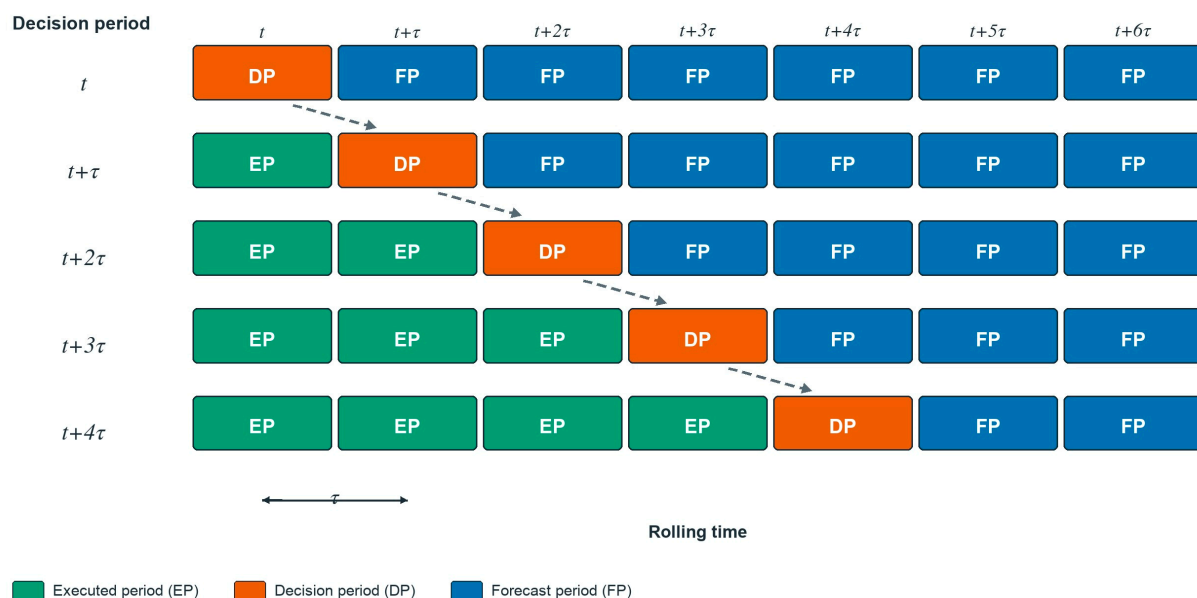


Figure 4. Rolling optimization process of the MPC-based emergency supply distribution strategy.

4. Algorithm Design

The multi-stage truck–drone collaborative emergency supply location-routing optimization model under flood disasters involves multiple distribution centers and multiple demand points, and simultaneously determines truck routes and drone tasks over multiple periods. It is therefore an NP-hard large-scale combinatorial optimization problem. To solve this model, an improved salp swarm algorithm embedded with MPC (ISSA) and based on period and stage-specific decoding is designed [37].

4.1. Population Initialization

In the salp swarm algorithm, each salp represents one solution of the model. This study adopts a natural number encoding scheme, and each salp consists of 4T substrings. The four substrings represent distribution center operating decisions, distribution center assignment of demand points, demand point service sequence, and service mode, respectively. The first substring uses 0–1 encoding with length M, where M is the number of distribution centers; values 0 and 1 indicate whether a distribution center operates in period t. The

second substring uses natural number encoding with length N , where N is the number of demand points; its values are the identifiers of operating distribution centers, indicating the distribution center serving each demand point. The third substring is a random permutation of natural numbers and represents the demand point service sequence. The fourth substring uses 0–1 encoding with length N , representing the service mode of demand points: 0 indicates truck service, and 1 indicates drone service. For example, the salp encoding in the period when there are four distribution centers and 15 demand points is shown in Figure 5.

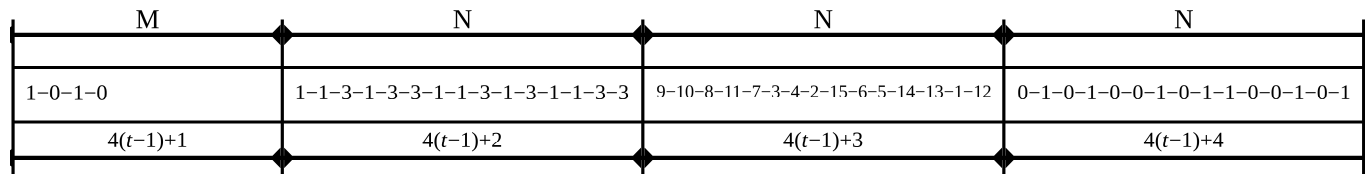


Figure 5. Schematic of the population initialization structure.

4.2. Salp Position Updating

During salp position updating, the three individuals with the best fitness values in the leader group are first selected as candidate food sources and denoted by F_α , F_β , and F_δ . The search mechanism in Equation (30) is designed for other leader individuals. A random number $rand$ in the interval $[0, 1]$ is generated, and according to its value, each leader individual other than the three candidate food sources in generation t performs LOX (linear order crossover) with F_α , F_β , or F_δ . Figure 6 presents a specific example of LOX.

$$F_i(t+1) = \begin{cases} \text{LOX}(F_i(t), F_\alpha(t)), & rand < \frac{1}{3} \\ \text{LOX}(F_i(t), F_\beta(t)), & \frac{1}{3} \leq rand < \frac{2}{3} \\ \text{LOX}(F_i(t), F_\delta(t)), & \text{otherwise} \end{cases} \quad (30)$$

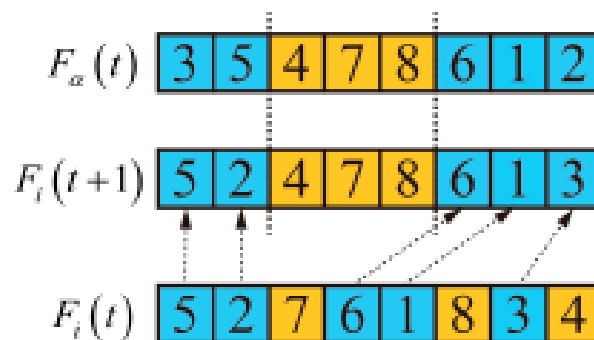


Figure 6. LOX operation for salp position updating.

In Equation (30), $F_i(t)$ denotes the i -th individual in generation t , and $F_i(t+1)$ denotes the updated individual. Because the service sequence of affected demand points is permutation-coded, the LOX operator can inherit high-quality local route structures while preserving the legality of the demand point sequence, making it suitable for route optimization decoding in flood disaster emergency distribution.

A front-insertion mutation operator is adopted. Two different gene positions, $pos1$ and $pos2$, are randomly selected, and the gene at $pos2$ is inserted before $pos1$; the genes at and after $pos1$ are shifted backward in sequence. This operation mainly acts on the affected demand point service sequence substring and can change the local delivery sequence without destroying the legality of permutation encoding, thereby generating new truck and drone service routes. The insertion mutation operation is shown in Figure 7.

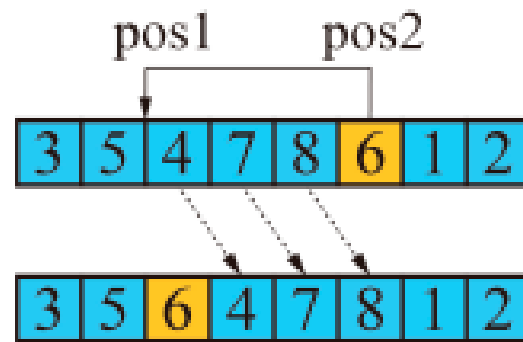


Figure 7. Front-insertion mutation operation.

To further enhance global search capability, a learning perturbation mechanism is introduced for candidate food source positions. Specifically, two positions are randomly selected within each chromosome segment of a candidate food source, and the gene fragment between the two positions is copied to the corresponding position of the new food source. The remaining left-side gene fragment is shuffled and copied to the left side of the new food source, and the remaining right-side gene fragment is shuffled and copied to the right side. The operation process is shown in Figure 8. This mechanism preserves the core structure of high-quality distribution schemes while expanding the search range, thereby reducing the possibility that the algorithm falls into a local optimum.

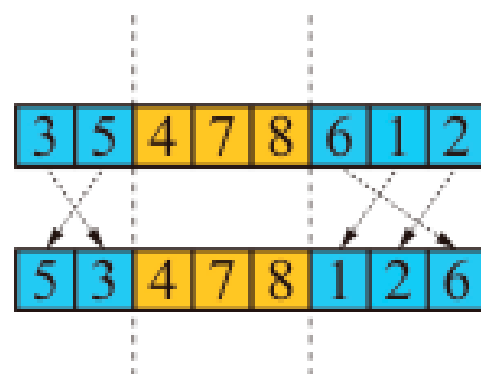


Figure 8. Learning perturbation operation for candidate food source positions.

4.3. Salp Swarm Algorithm Embedded with Mpc

For the multi-stage and multi-period emergency supply location-routing decision model under flood disasters, this study embeds the MPC method into the improved salp swarm algorithm (MPC-ISSA) and divides each decision-making process into three parts. (1) Flood impact prediction. At the beginning of each decision period, the trend of affected population over subsequent periods is predicted and the flood impact stage is updated. (2) Distribution decision planning and implementation. Based on known information and predicted data, the hybrid salp swarm algorithm is used to solve the current-period distribution center activation and truck–drone route-planning scheme. (3) Data updating and dynamic adjustment. After the current-period distribution task is completed, relevant data are collected and the distribution center status is updated before entering the next optimization period. Unlike a multi-period model that directly uses disaster prediction results over the entire planning horizon as input, the proposed method can adjust the emergency scheme according to real-time information. The algorithmic procedure after embedding MPC is shown in Figure 9.

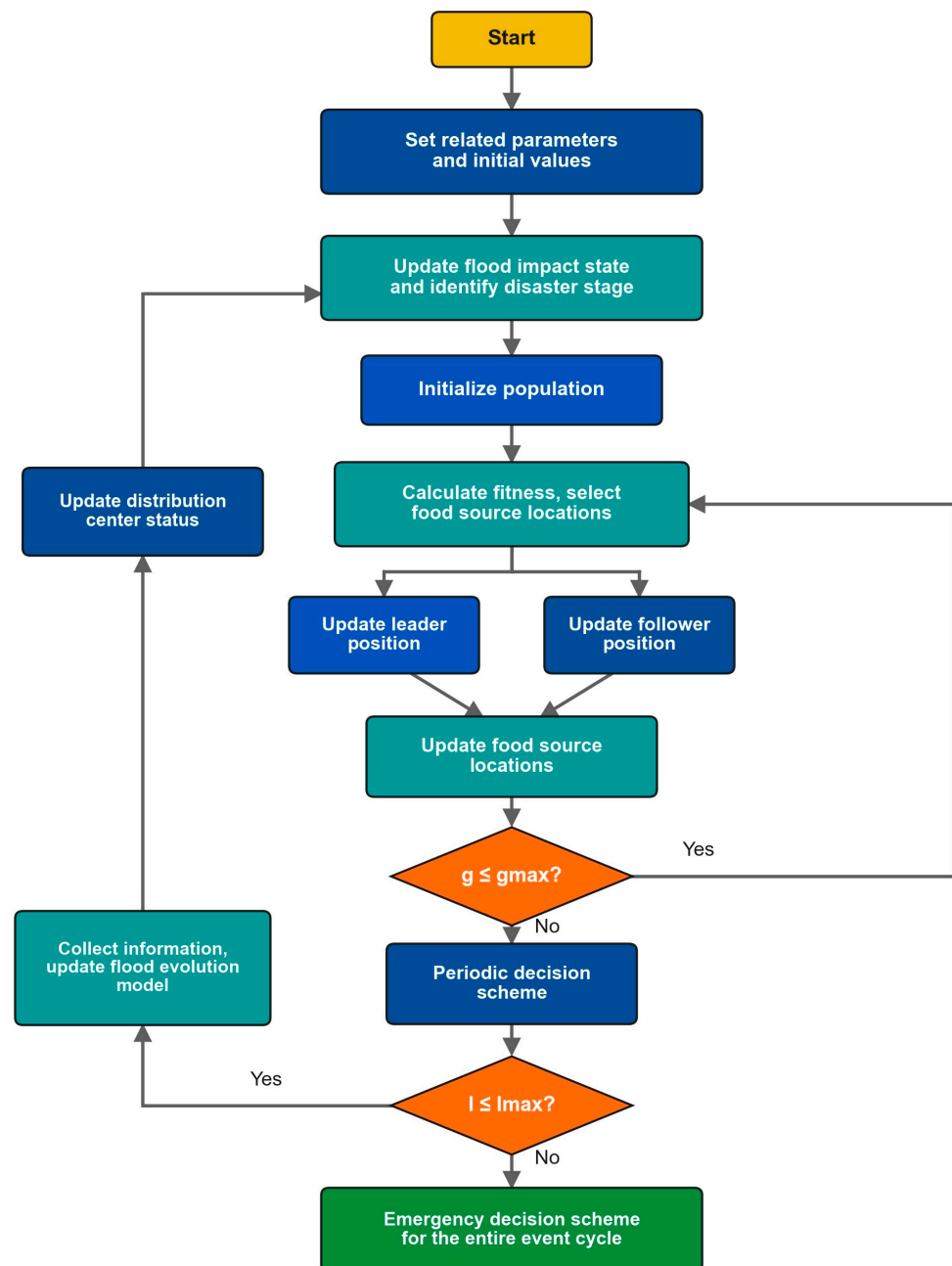


Figure 9. Flowchart of the MPC-ISSA.

Let G denote the current iteration, $G_{\max}$ denote the maximum iteration number, S denote the rolling decision counter, $S_{\max}$ denote the maximum rolling times of MPC, and N_{leader} denote the number of leader salps within the population. Each salp individual encodes distribution center status, demand point assignment, service sequence and service mode. For leader salps, three elite food sources, F_{α} , F_{β} , F_{δ} , are selected by fitness sorting. Except for the three elites, the leader position update adopts a LOX crossover operator:

$$F_i(G+1) = \begin{cases} \text{LOX}(F_i(G), F_{\alpha}(G)), & \text{rand} < \frac{1}{3} \\ \text{LOX}(F_i(G), F_{\beta}(G)), & \frac{1}{3} \leq \text{rand} < \frac{2}{3} \\ \text{LOX}(F_i(G), F_{\delta}(G)), & \text{otherwise} \end{cases} \quad (31)$$

Follower salps follow the elite leader with front-insertion mutation. Let pos_1, pos_2 be randomly selected gene positions; the follower update rule is:

$$F_j(G+1) = \text{InsertMutate}(F_j(G), pos_1, pos_2), j > N_{\text{leader}} \quad (32)$$

Learning perturbation acts on elite food sources to escape the local optimum:

$$\tilde{F}_s = \text{LearnPerturb}(F_s(G)), s \in \{\alpha, \beta, \delta\} \quad (33)$$

Under MPC rolling logic, the fitness evaluation of each salp individual is based on the MPC objective function at current rolling moment τ :

$$\text{Fitness}(F) = Z^\tau(F) \quad (34)$$

where $Z^\tau(F)$ is the objective value in Equation (29) decoded from salp individual F . When $G \geq G_{\max}$, the optimal solution for current rolling moment τ is output; then, the disaster observation data is updated, $\tau = \tau + 1$ is set, and the population iteration is restarted for the next rolling optimization until $S \geq S_{\max}$.

5. Simulation Analysis

To validate the effectiveness of the proposed model and algorithm in emergency relief material distribution under real flood disasters, a simulation study is conducted based on the severe urban flooding event that occurred in Zhengzhou, China, in July 2021. The disaster began with continuous rainfall on 17 July, which reached its precipitation peak on 20 July, and the main rainfall process ended on 23 July. By 28 July, urban waterlogging was largely eliminated, marking the completion of the emergency material distribution task.

The entire emergency distribution period is divided into twelve delivery periods, with each period lasting one day. Four candidate distribution centers and fifteen demand points are considered in the simulation area. Their specific geographical locations are presented in Table 5 and Figure 10.

Table 5. Locations of distribution centers and demand points.

Node Type	Node ID	Longitude (°E)	Latitude (°N)
Candidate distribution center	C1	113.2633	34.7684
	C2	113.3833	34.4761
	C3	113.6100	34.7055
	C4	113.7300	34.4798
Demand point	D1	112.9166	34.6204
	D2	113.1833	34.5279
	D3	113.2846	34.7943
	D4	113.2980	34.7055
	D5	113.3220	34.5982
	D6	113.5220	34.6833
	D7	113.6366	34.5427
	D8	113.6686	34.9682
	D9	113.6900	34.6500
	D10	113.7353	34.7980
	D11	113.7700	34.6204
	D12	113.8046	34.6537
	D13	113.8500	34.4428
	D14	113.9566	34.6981
	D15	113.5033	34.3133

Based on government-released disaster information and hydrological data, the total population in the study area is set to 10,000. The parameters of the flood impact evolution model are listed in Table 6. The flood impact evolution model is then used to predict the number of people in each impact state over the full planning horizon, as shown in Table 7. The flood impact rate $Z(t)$ in each delivery period is calculated, as shown in Table 8.

Table 6. Parameter settings of the flood impact evolution model.

α	δ	β_0	β_1	γ
0.90	0.75	0.002	0.06	0.16

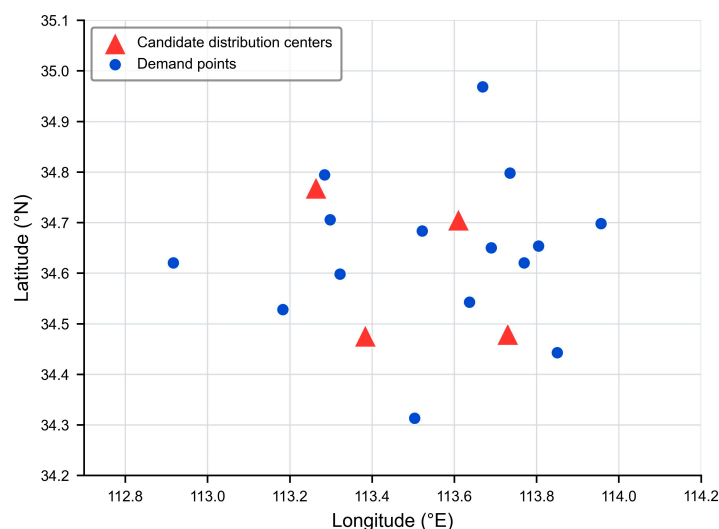


Figure 10. The spatial distribution of all nodes.

Table 7. Predicted population in each flood impact state.

Period	I(t)	H(t)	$\beta(t)$	η	μ	N(t)	F(t)	S(t)	R(t)
1	0.15	0.0947	0.0077	0.06	0.08	9948	48	3	1
2	0.40	0.2973	0.0198	0.06	0.08	9804	170	18	8
3	0.75	0.6142	0.0389	0.06	0.08	9508	405	59	28
4	1.00	0.9223	0.0573	0.06	0.08	9050	739	142	69
5	0.70	0.8790	0.0547	0.30	0.40	8558	859	202	381
6	0.40	0.6692	0.0422	0.30	0.40	8160	857	251	732
7	0	0.3173	0.0210	0.80	1.00	7918	474	155	1453
8	0	0.1504	0.0110	0.80	1.00	7797	255	91	1857
9	0	0.0713	0.0063	0.80	1.00	7732	137	52	2079
10	0	0.0338	0.0040	0.80	1.00	7694	77	29	2201
11	0	0.0160	0.0030	0.80	1.00	7668	46	16	2270
12	0	0.0076	0.0025	0.80	1.00	7647	31	10	2313

Table 8. Flood impact rate in each delivery period.

Period	1	2	3	4	5	6	7	8	9	10	11	12
$Z(t)(\%)$	0.51	1.88	4.64	8.81	10.61	11.08	6.29	3.46	1.89	1.06	0.62	0.40

Taking 8% as the threshold, the emergency supply distribution horizon is divided into the initial, middle, and late stages, as shown in Figure 11. Periods 1–3 are classified as the initial stage, periods 4–6 as the middle stage, and periods 7–12 as the late stage.

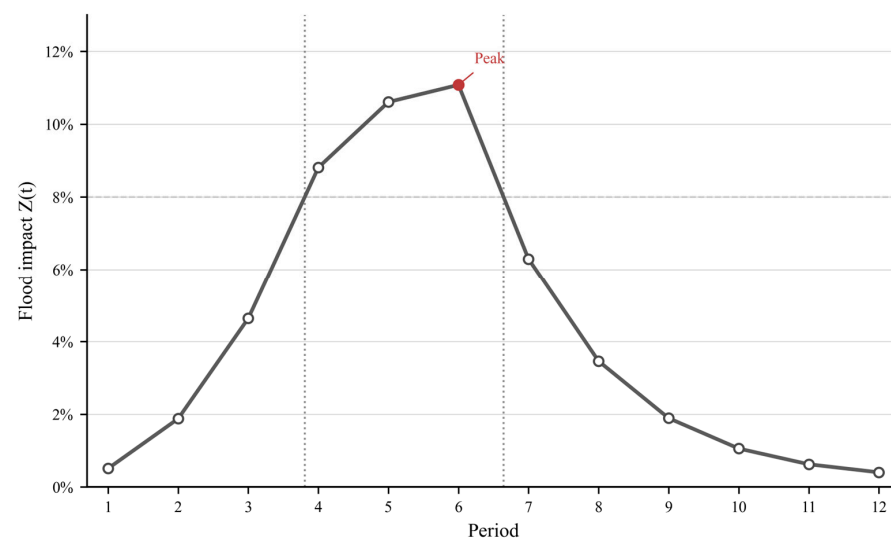


Figure 11. The stage division based on the flood impact rate.

Because the delivery time objective Z_1 and the operating cost objective Z_2 differ substantially in both units and numerical magnitude, the time–cost coefficient λ is introduced to convert delivery time into its equivalent monetary cost and to prevent Z_2 from dominating the integrated objective function. The value of λ is determined by considering both the numerical balance between Z_1 and Z_2 and the stage-specific urgency of emergency delivery. In the initial stage, the disaster impact and emergency demand remain relatively limited, resulting in a lower time penalty. During the middle stage, flood impacts and relief demand reach their highest levels, making delivery delays substantially more consequential and therefore requiring the largest time–cost coefficient. In the late stage, the overall emergency pressure decreases as the disaster subsides, although the remaining relief and recovery activities still require timely delivery; thus, its time–cost coefficient is lower than that in the middle stage but higher than that in the initial stage. Accordingly, λ is assumed to be 120, 1600, and 350 for the initial, middle, and late stages, respectively. Given that these values are set through qualitative reasoning rather than strict data fitting, a sensitivity analysis is presented in Section 5.2. The remaining model parameters are listed in Table 9.

Table 9. Parameters settings of the emergency supply distribution model.

Parameter	Description	Value
v_k	The average speed of truck k	30 km/h
v_u	The average speed of drone u	60 km/h
Q^u	The maximum load capacity of the drone	20 kg
L^u	The maximum flight range of the drone	30 km
E^u	The maximum flight endurance of the drone	0.5 h
C^k	The unit transportation cost of the truck per unit load	10 CNY/km
C^u	The unit flight cost of the drone per unit load	1.5 CNY/km
O_t	The operating cost of a single distribution center per period	150 CNY
F_t	The activation cost of a single distribution center	450 CNY

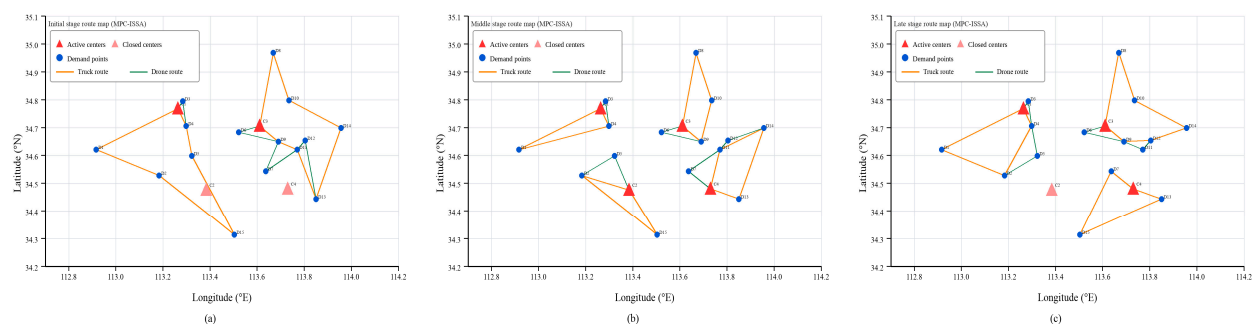
All numerical experiments are performed on a MacBook Air (2025) (Apple Inc., Cupertino, CA, USA), equipped with the Apple M4 chip and 16 GB unified memory. The simulation is coded in Python 3.13.7. The basic algorithm parameters are set as follows: population size of 100, and 300 maximum iterations. The routing decisions are reported in Table 10.

Table 10. Center activation and routing plans of MPC-ISSA.

Stage	Activated Centers	Closed Centers	Truck Route	Drone Route
Initial	C1, C3	C2, C4	C1-D4-D5-D15-D2-D1-C1; C3-D9-D11-D13-D14-D10-D8-C3	C1-D3-D4; C3-D6-D9, D9-D7-D11, D11-D12-D13
Middle	C1, C2, C3, C4	-	C1-D1-D4-C1; C2-D15-D2-C2; C3-D9-D10-D8-C3; C4-D11-D14-D13-C4	D4-D3-C1; D2-D5-C2, C3-D6-D9; C4-D7-D11, D11-D12-D14
Late	C1, C3, C4	C2	C1-D1-D2-D4-C1; C3-D8-D10-D14-D12-D9-C3; C4-D13-D15-D7-C4	D2-D5-D4; D4-D3-C1; D12-D11-D9, D9-D6-C3

The optimized results show clear stage-specific differences in emergency supply distribution. In the initial stage, only C1 and C3 are activated, which reduces fixed operating cost while maintaining service coverage through truck–drone collaboration. In the middle stage, all four candidate distribution centers are activated because demand urgency and flood impact are both at relatively high levels, leading to the highest total cost among the three stages. In the late stage, C2 is closed again as the flood impact weakens and the number of affected people declines. This adjustment indicates that the proposed model can adapt center activation and routing decisions to disaster evolution rather than using a fixed distribution scheme.

The distribution routes for the three stages are shown in Figure 12. In the initial stage, the delivery network is mainly organized around C1 and C3, and the truck routes cover the major demand clusters through closed-loop tours, while drones are used to serve selected nearby demand points such as D3, D6, D7 and D12. This arrangement reduces the need to activate all candidate centers at the beginning of the disaster and uses drones to perform parallel delivery tasks with trucks, thereby improving distribution efficiency and shortening the overall response time. In the middle stage, all four distribution centers are activated to shorten service distances and share the distribution workload, and the routes become more decentralized. In the late stage, as the flood impact weakens, C2 is no longer activated, and the distribution network is reorganized around C1, C3 and C4. Truck routes continue to undertake the main delivery tasks, whereas drone routes are mainly embedded within local service areas to connect demand points that are spatially close or less efficiently served by truck.

**Figure 12.** Distribution routes of MPC-ISSA at different stages: (a) initial stage, (b) middle stage, and (c) final stage.

Overall, the distribution routes show that the proposed model can adjust both center activation and truck–drone route allocation according to flood impact evolution. The collaborative structure combines the load capacity of trucks with the flexibility of drones,

thereby improving the adaptability and response efficiency of the emergency distribution network across different disaster stages.

5.1. Algorithm Comparison

To verify the effectiveness of the MPC-ISSA, a genetic algorithm (GA), particle swarm optimization (PSO), differential evolution (DE), and a real-coded genetic algorithm (RCGA) are selected to solve the proposed model. For a fair comparison, the population size and maximum number of iterations are uniformly set to 100 and 300 across all algorithms. These settings are consistent with those used in MPC-ISSA. Specifically, GA uses a crossover probability of 0.8 and a mutation probability of 0.15; PSO adopts an inertia weight of 0.5, with cognitive and social coefficients both set to 1.0 under the global best topology; DE uses the DE/rand/1/bin variant, with a differential weight of 0.5 and a crossover probability of 0.9; RCGA employs simulated binary crossover (distribution index 15), polynomial mutate on (distribution index 20, probability 1/49), a tournament selection of size 2, and an elite size of 1.

Each algorithm runs independently 20 times, and the mean values are adopted for the results. The Wilcoxon signed-rank test ($\alpha = 0.05$) is applied to the total cost Z between MPC-ISSA and each competitor. All p -values in Table 11 are below 0.05, confirming the statistical significance of MPC-ISSA's superiority.

Table 11. Objective values obtained by all algorithms.

Algorithm	Stage	Z_1 (h)	Z_2 (CNY)	Z (Mean $\pm$ SD)	p -Value
MPC-ISSA	Initial	5.1875	4310.7783	4933.2783 $\pm$ 108.6502	-
	Middle	2.6511	5677.6480	9919.6208 $\pm$ 803.2625	-
	Late	3.6665	4773.5864	6056.8614 $\pm$ 270.9823	-
GA	Initial	7.0317	4350.0024	5193.8064 $\pm$ 197.3015	0.0002
	Middle	3.5352	6001.0153	11657.3353 $\pm$ 981.6902	0.0004
	Late	5.9204	4483.0624	6555.2024 $\pm$ 293.6527	0.0196
PSO	Initial	6.3931	4470.5314	5237.7034 $\pm$ 284.2530	0.0001
	Middle	3.6714	4773.5944	10647.8344 $\pm$ 1343.7731	0.0013
	Late	4.3562	5337.6524	6862.3224 $\pm$ 425.3930	0.0023
DE	Initial	4.4117	5091.2103	5620.6143 $\pm$ 178.0105	0.0000
	Middle	3.6934	6154.9025	12064.3425 $\pm$ 672.0071	0.0192
	Late	4.4206	5118.4834	6665.6934 $\pm$ 308.8069	0.0000
RCGA	Initial	10.8573	3857.7754	5160.6514 $\pm$ 155.3985	0.0007
	Middle	3.4832	6201.6485	11774.7685 $\pm$ 1177.8903	0.0073
	Late	5.0846	5207.1436	6986.7536 $\pm$ 454.5769	0.0266

Table 12 presents the optimal solutions obtained by each algorithm. Figures 13–16 show the distribution routes for three stages of GA, PSO, DE, and RCGA.

Table 12. Center activation and routing plans obtained by GA, PSO, DE, and RCGA.

Algorithm	Stage	Active Centers	Closed Centers	Truck Route	Drone Route
GA	Initial	C1, C3	C2, C4	C1-D4-D2-D1-D3-C1; C3-D7-D15-D13-D11-D12-D14-D8-D10-D9-C3	D4-D5-D2; D9-D6-C3
	Middle	C1, C2, C3, C4	-	C1-D1-D2-D4-C1; C2-D15-D5-C2; C3-D12-D14-D10-D8-C3; C4-D7-D6-D9-D13-C4	D4-D3-C1; C3-D11-D12
	Late	C2, C4	C1, C3	C2-D15-D2-D1-D4-D3-D5-C2; C4-D13-D14-D12-D11-D9-D10-D8-C4	C2-D5-D2; D9-D6-D10; D11-D7-D9

Table 12. Cont.

Algorithm	Stage	Active Centers	Closed Centers	Truck Route	Drone Route
PSO	Initial	C3, C4	C1, C2	C3-D6-D5-D2-D1-D4-D3-D8-D10-C3; C4-D15-D7-D11-D12-D14-D13-C4	D11-D9-D12
	Middle	C1, C3, C4	C2	C1-D4-D2-D1-C1; C3-D8-D10-D14-D12-D9-C3; C4-D13-D15-D7-C4	C1-D3-D4, D4-D5-D2; D12-D11-D9, D9-D6-C3
	Late	C1, C2, C3	C4	C1-D3-D8-C1; C2-D15-D1-D2-C2; C3-D7-D13-D12-D14-D10-C3	C1-D4-D3; D2-D5-C2; C3-D6-D7, D12-D11-D14, D10-D9-C3
DE	Initial	C1, C3, C4	C2	C1-D5-D4-D2-D1-D3-C1; C3-D10-D8-D12-D14-D11-D9-C3; C4-D15-D13-C4	D11-D7-D9, D9-D6-C3
	Middle	C1, C2, C3, C4	-	C1-D4-D2-D1-C1; C2-D5-D15-C2; C3-D10-D9-D8-D6-C3; C4-D13-D12-D14-D7-C4	C1-D3-D4; D12-D11-D14
	Late	C1, C3, C4	C2	C1-D4-D2-D1-C1; C3-D9-D10-D8-D12-D14-C3; C4-D7-D13-D15-C4	C1-D3-D4, D4-D5-D2; C3-D6-D9, D12-D11-D14
RCGA	Initial	C1	C2, C3, C4	C1-D8-D10-D9-D11-D12-D14-D13- D15-D6-D5-D2-D1-D4-C1	D9-D7-D11, D4-D3-C1
	Middle	C1, C2, C3, C4	-	C1-D4-D2-D1-C1; C2-D7-D6-C2; C3-D8-D10-D14-C3; C4-D11-D13-D15-C4	C1-D3-D4, D4-D5-D2; D7-D9-D6; C4-D12-D11
	Late	C1, C2, C3	C4	C1-D4-D6-C1; C2-D2-D1-D15-C2; C3-D8-D10-D14-D13-D11-D9-C3	C1-D3-D4; C2-D5-D2; D11-D7-D9, D9-D12-C3

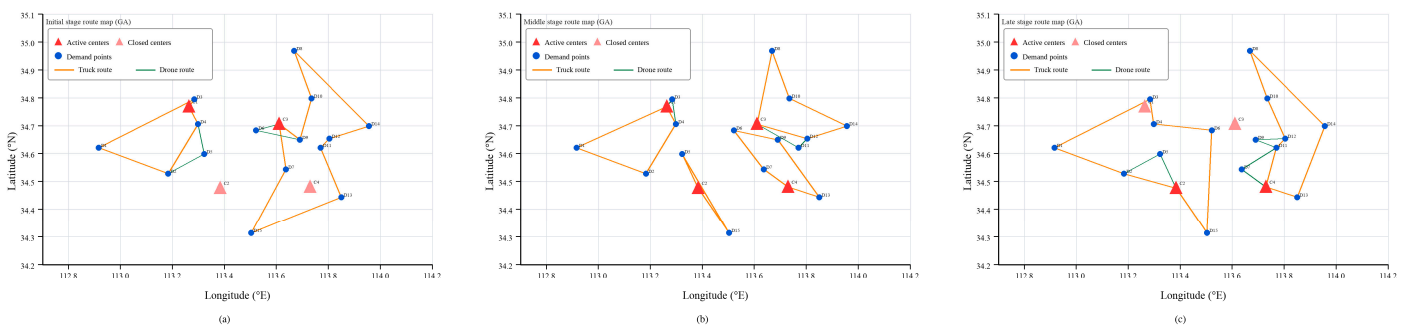


Figure 13. Distribution routes of GA at different stages: (a) initial stage, (b) middle stage, and (c) final stage.

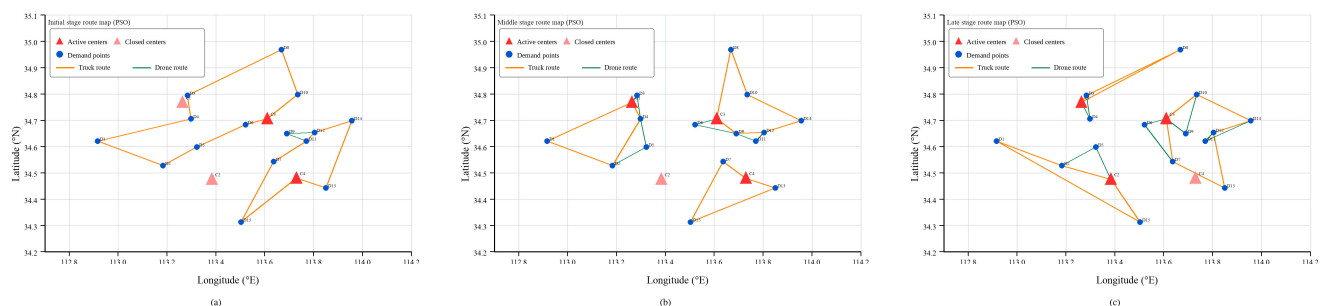


Figure 14. Distribution routes of PSO at different stages: (a) initial stage, (b) middle stage, and (c) final stage.

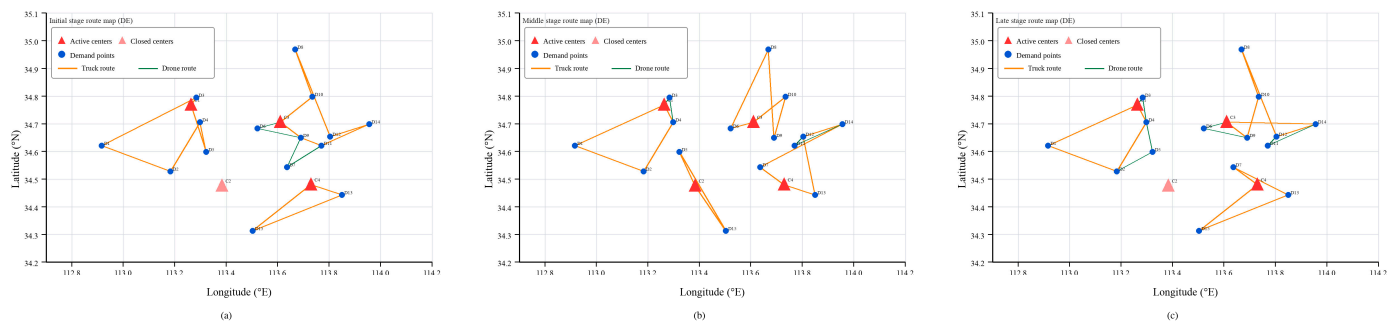


Figure 15. Distribution routes of DE at different stages: (a) initial stage, (b) middle stage, and (c) final stage.

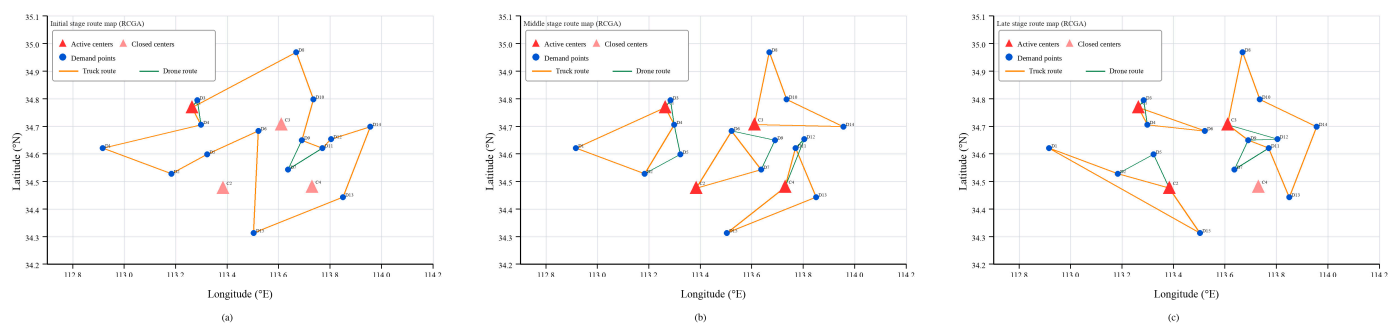


Figure 16. Distribution routes of RCGA at different stages: (a) initial stage, (b) middle stage, and (c) final stage.

Compared with GA, PSO, DE and RCGA, the proposed MPC-ISSA obtains the lowest total objective values in all three stages, with average reductions of 6.87%, 13.82%, and 10.45% relative to the four benchmark algorithms in the initial, middle, and late stages, respectively. In the initial stage, MPC-ISSA produces a lower total objective value than all benchmark algorithms (up to 12.23% lower than DE), and its delivery time is shorter than that of GA, PSO, and RCGA. In the middle stage under severe flood conditions, MPC-ISSA significantly reduces delivery time by an average of 26.2% while keeping competitive distribution cost, resulting in an average total objective reduction of 13.82%. In the late stage, it still outperforms other algorithms in both delivery time (up to 38.1% faster than GA) and total objective value (up to 13.3% lower than RCGA).

5.2. Sensitivity Analysis

To verify the reliability of the calibrated parameters and the effect of parameter perturbations on the stage division of flood impact evolution, a one-at-a-time (OAT) sensitivity analysis is conducted on the five key parameters: α , δ , β_0 , β_1 , and γ . Each is perturbed within $\pm 20\%$ of its baseline value. The system of ordinary differential equations (Equations (1)–(6)) is resolved to obtain the evolution curves of the flood impact rate $Z(t)$, as shown in Figure 17. The results indicate that α and β_1 exert the most significant influence on $Z(t)$: under $\pm 20\%$ perturbation, the peak flood impact rate ranges from 9.18% to 12.92%. δ has a moderate effect, whereas β_0 and γ are nearly insensitive, with the curves before and after perturbation almost overlapping. In terms of stage division, $Z(t)$ maintains a three-stage pattern of “rise–peak–recession” across all scenarios. Within $\pm 10\%$ perturbation, the period-level stage classification remains entirely unchanged. Even under $\pm 20\%$ perturbation, only the extreme low values of α and β_1 cause a slight delay in T_1 , while the overall three-stage structure remains essentially unaltered. This demonstrates that the stage division proposed in this study is robust to parameter uncertainty, and the MPC

rolling optimization mechanism can automatically adapt to minor shifts in stage boundaries without compromising the reliability of subsequent distribution plans.

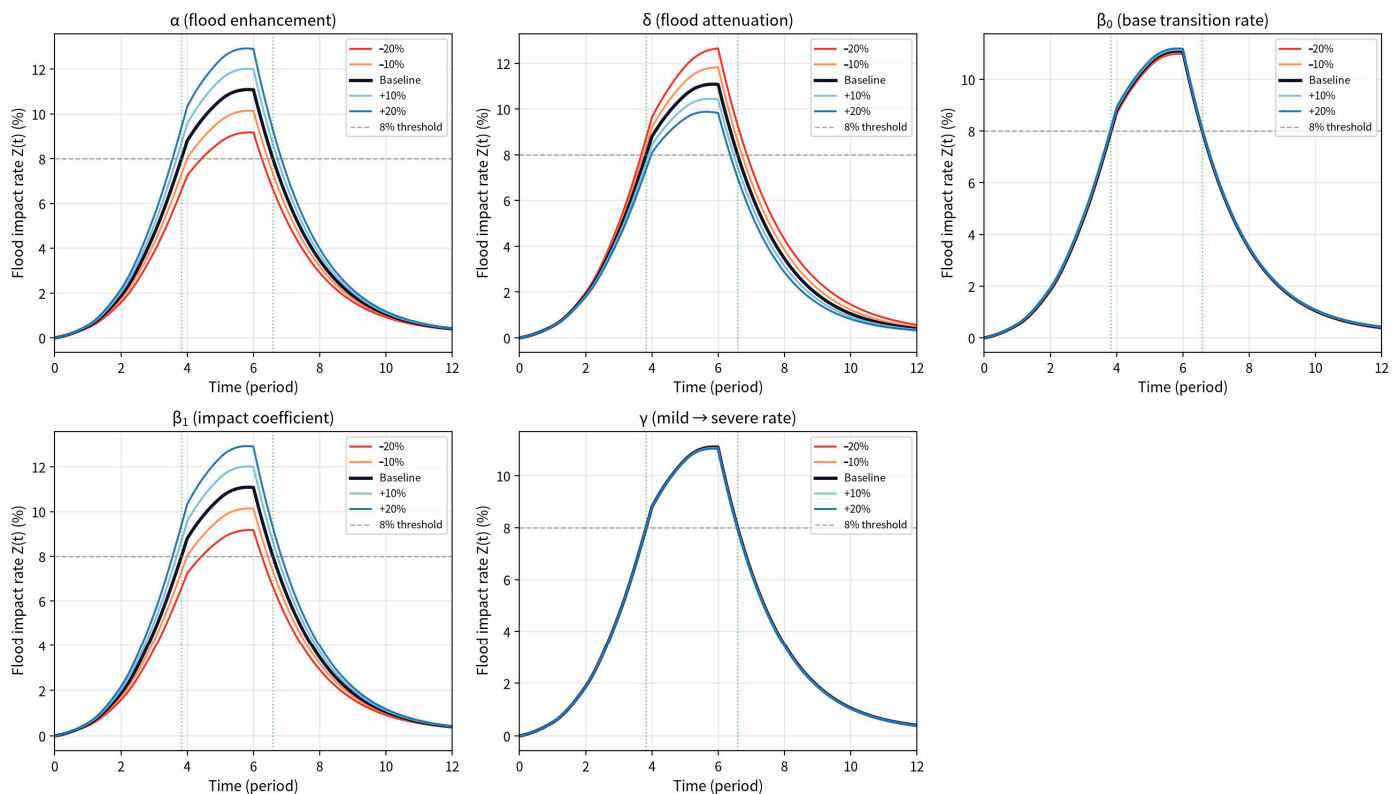


Figure 17. Sensitivity of the flood impact rate $Z(t)$ to $\pm 20\%$ perturbations of the key parameters.

5.3. Comparison Between the Tsp-D and Tsp Modes

To further evaluate the advantage of truck–drone collaborative distribution, the proposed model is also solved under a truck-only transportation mode, namely the TSP mode. The comparison with the TSP-D mode is shown in Table 13. Relative to the truck-only mode, the TSP-D mode reduces total delivery time by 51.58%, 10.75%, and 10.71% in the initial, middle, and late stages, respectively. Although drone use increases the transportation cost component in the initial stage, the substantial reduction in delivery time still lowers the total objective value by 3.26%. In the middle and late stages, the TSP-D mode reduces both delivery time and total cost. These results confirm that truck–drone collaboration is particularly valuable when emergency response time is constrained by flood conditions.

Table 13. Distribution results under the TSP mode.

Stage	Active Centers	Closed Centers	Z_1 (h)	Z_2 (CNY)	Z	Truck Route
Initial	C4	C1, C2, C3	10.7132	3814.0735	5099.6575	C4-D13-D15-D2-D1-D3-D4-D5-D6-D8-D10-D14-D12-D11-D9-D7-C4
Middle	C1, C2, C3, C4	-	2.9703	5905.2824	10,657.7624	C1-D3-D4-D1-C1; C2-D5-D2-D15-C2; C3-D9-D10-D8-D6-C3; C4-D7-D11-D12-D14-D13-C4
Late	C1, C3, C4	C2	4.1064	4916.6218	6353.8618	C1-D3-D4-D5-D2-D1-C1; C3-D9-D11-D12-D14-D10-D8-D6-C3; C4-D7-D15-D13-C4

In this study, the road network was assumed to remain accessible during the simulation period. However, actual flood disasters may cause road disruptions and accessibility

degradation, which could further increase truck travel time and operational costs. Since drones are less affected by ground infrastructure failures, considering dynamic road accessibility constraints may further highlight the advantages of truck–drone collaborative delivery.

6. Conclusions

This paper develops a multi-stage emergency supply location-routing optimization model to address time-varying flood impact, stage-specific relief demand, and restricted road accessibility. A flood impact evolution model describes population transitions among the normal, mildly affected, severely affected, and recovery states, and divides the response horizon into initial, middle, and late stages. On this basis, a truck–drone collaborative mode with stage-specific time–cost coefficients is introduced, and model predictive control is embedded into an improved salp swarm algorithm (MPC-ISSA) for rolling optimization. A case study of the 2021 Zhengzhou flood, together with algorithm comparison, sensitivity analysis, and distribution mode comparison, verifies the effectiveness of the model and algorithm. The main conclusions are as follows:

(1) Flood impact evolution significantly affects emergency supply distribution decisions, and distribution center activation and vehicle-routing decisions are adjusted differently across stages. In the middle stage, flood impact is stronger and demand is more concentrated and urgent, so more distribution centers need to be activated to improve response efficiency.

(2) The MPC-ISSA obtains the lowest total objective values among all tested algorithms in all three stages. Compared with GA, PSO, DE, and RCGA, the average reductions in total objective value reach 6.87%, 13.82%, and 10.45% in the initial, middle, and late stages, respectively. In the middle stage under severe flood conditions, MPC-ISSA reduces delivery time by an average of 26.2% while maintaining competitive distribution cost; in the late stage, delivery time is up to 38.1% faster than that of GA.

(3) Compared with truck-only delivery, the truck–drone collaborative distribution mode significantly shortens delivery time and reduces the overall objective value. Relative to the TSP mode, the TSP-D mode reduces total delivery time by 51.58%, 10.75%, and 10.71% in the initial, middle, and late stages, respectively. By combining trunk transportation by trucks with rapid supplementary delivery by drones, this mode improves the flexibility and timeliness of emergency supply distribution under flood disasters.

(4) The sensitivity analysis confirms that the three-stage division is robust to parameter uncertainty. The MPC-based rolling optimization mechanism updates affected-population predictions and re-optimizes center activation and routing decisions at each period, automatically adapting to minor stage boundary shifts and keeping the distribution scheme aligned with real-time conditions without compromising reliability.

Several directions remain for future research. First, this paper mainly develops the model under deterministic parameter settings, whereas actual flood disaster scenarios involve uncertainty in rainfall intensity, road damage, demand scale, and drone operating conditions. Future studies may introduce stochastic programming or robust optimization to improve the applicability of the model under uncertain environments. Second, this paper considers only trucks and drones as delivery vehicles. Future research may further incorporate rescue boats, helicopters, and other emergency equipment to build a multi-modal collaborative distribution model that is closer to real rescue operations. In addition, the scale of the case study is relatively limited. Future work can use larger real-world road networks and real-time disaster data to further test the computational efficiency and practical applicability of the proposed model and algorithm.

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