An integrated Data-Driven-Simulation-Optimization model: Insights into controlling invasive plants in China

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Abstract: The rapid spread of invasive plants such as Spartina alterniflora has emerged as a major ecological and economic threats to coastal wetlands, while existing management strategies often fail to adapt to dynamic invasion processes and limited financial resources. To address this challenge, this study develops a novel data-driven-simulation-optimization (DDSO) framework that enables dynamic and spatially explicit management of biological invasions. The core innovation lies in coupling data-driven ecological parameterization based on multi-source observations with a simulation model that captures life-cycle transitions and spatial dispersal, and a mixed-integer optimization module that allocates control budgets and intervention intensities across space and time. By integrating heterogeneous environmental, biological, and management data, the framework constructs time-varying ecological parameters that reflect evolving invasion conditions and underlying ecological processes. The optimization component then generates cost-effective intervention schedules under fixed budget constraints. Comparative evaluation against system dynamics (SD) and simulation-optimization (SO) models shows that DDSO outperforms conventional approaches not only in budget efficiency, but also by revealing counterintuitive management logics: management effectiveness hinges more on the presence of a coordinated optimization framework than on investment scale, and economically efficient strategies inherently favor highly uneven spatial resource allocation. These mechanism-level insights underscore the importance of early intervention and cross-regional coordination, establishing DDSO as a policy-relevant framework for adaptive invasive species management.

Keywords: Invasive species management, Resources allocation, Evolutionary dynamics, Scenarios-based optimization, Mixed-integer programming

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1. Introduction

Biological invasions by non-native species are a major driver of global ecological degradation and biodiversity loss, while also imposing substantial economic and social costs through ecosystem service decline and rising management expenditures (Chen et al., 2016). The dynamic, uncertain, and spatially heterogeneous nature of invasion processes, combined with limited control resources, poses significant challenges for effective and cost-efficient management. Developing decision frameworks that can adapt to changing ecological conditions and support optimal resource allocation has therefore become a central issue in invasion management and environmental decision science.

Spartina alterniflora (S. alterniflora) is among the most destructive invasive plants in coastal wetlands. Originally introduced for shoreline stabilization because of its tolerance to salinity and flooding, it has spread rapidly through vigorous clonal growth and high seed production, displacing native vegetation, altering hydrological processes, and degrading habitats for benthic organisms and migratory birds. Owing to these severe ecological impacts, S. alterniflora is listed among the world's 100 worst invasive alien species, highlighting the urgent need for effective, adaptive, and resource-efficient management strategies. The Yancheng coastal wetlands along the central Yellow Sea provide a representative case for studying this invasion. As the largest mudflat ecosystem on the western Pacific coast and a core component of the UNESCO-listed Yellow (Bohai) Sea Migratory Bird Habitats, Yancheng supports high biodiversity and critical ecosystem services, yet its flat terrain and dynamic sedimentary environment make it particularly vulnerable to S. alterniflora expansion, offering an ideal setting for developing and validating adaptive, system-based management models for invasive species control.

Managing invasive species is a complex decision problem involving resource allocation, intervention design, and cost-effectiveness. Operations research and management science offer valuable tools for addressing these challenges by integrating biological characteristics, invasion intensity, treatment costs, and expected effectiveness into optimization-based decision models. Previous studies have applied optimal control and mathematical programming models to analyze population dynamics and dispersal processes (Baker et al., 2019), identify effective intervention timing and strategies (Haight et al., 2023), and allocate limited resources to maximize ecological benefits under budget constraints (Howerton et al., 2024). Scenario-based modeling has further been used to assess the long-term performance of alternative management strategies, supporting evidence-based policy decisions (Kıbış et al., 2021).

Despite substantial advances in invasion ecology and management modeling, important gaps remain. Most studies do not integrate real-time data with dynamic dispersal and adaptive control, and key ecological parameters are typically assumed constant despite pronounced spatiotemporal variability. In addition, feedbacks between species dynamics and management actions are often underrepresented, and optimal spatiotemporal allocation of limited control resources remains insufficiently explored. Recent advances in data-driven offer new opportunities to address these challenges by extracting dynamic ecological parameters from multi-source data and coupling them with simulation-optimization models, thereby enhancing adaptability, realism, and decision support for invasive species management.

To overcome these limitations, we develop a Data-Driven-Simulation-Optimization (DDSO) framework that integrates time-varying parameter estimation, ecological simulation, and optimization-based control. The framework is validated through a case study in the Yancheng coastal wetlands, integrating multi-source environmental data to simulate invasion dynamics and to optimize spatial resource allocation for Spartina alterniflora management. Scenario analyses with different budget levels and invasion intensities are further conducted to evaluate management effectiveness.

The remainder of this paper is organized as follows: Section 2 reviews related work on optimization-based invasive species management. Section 3 presents the problem formulation and DDSO framework. Section 4 reports computational experiments and scenario analyses. Section 5 discusses key insights and management implications, and Section 6 concludes the paper.

2. Literature review

Recent advances in invasive species research reflect a growing integration of field ecology, remote sensing, and computational modeling. Traditional field surveys rely on capture-recapture techniques, isotopic and genetic tracing, and GPS-based monitoring to estimate population size and spatial distribution (Fancourt et al., 2021). Complementing these efforts, remote sensing and UAV-based image analysis have enabled large-scale monitoring using machine learning algorithms such as Random Forest, Support Vector Machines, and Convolutional Neural Networks (Aota et al., 2021; Wang et al., 2025; Luo et al., 2026). Recent studies further combine these algorithms with GIS and Google Earth Engine platforms to map invasion dynamics with high spatial and temporal resolution (Wu & Wu, 2023; Min et al., 2023).

Beyond monitoring, ecological modeling has evolved from static niche-based approaches (e.g., BIOCLIM, CLIMEX, GARP, MAXENT) toward dynamic, scenario-driven frameworks that explicitly represent population processes and spatial spread (Tanga et al., 2021). Methods such as cellular automata, integro-difference equation models, reaction-diffusion and competition systems, Markov decision processes, Bayesian inference models, and agent-based simulations have been used to reconstruct invasion trajectories, simulate population transitions, and evaluate control strategies (Hudgins et al., 2020; Eppinga et al., 2021; Barnes et al., 2023). Compared with traditional niche-based models, scenario-driven dynamic approaches, such as system dynamics (Bushaj et al., 2022), can not only reproduce invasion trajectories (Yemshanov et al., 2017) but also simulate population changes (Carrillo et al., 2023), construct dynamic control processes (Rosso & Venturino, 2023), and describe population variations through mathematical formulations (Dia et al., 2020). These models provide quantitative insights into invasion extent and speed, offering a theoretical foundation for designing effective management and control strategies.

Given the complexity and heterogeneity of biological invasions, optimization has emerged as a promising tool for allocating limited management resources. Scholars have applied multi-objective optimization (Büyüktahtakın et al., 2014), robust optimization (Jafari et al., 2018), stochastic dynamic programming (Kumar et al., 2022), Bayesian hierarchical models (Nishimoto et al., 2021), scenario simulations (Liu et al., 2023), and various mathematical programming approaches-including linear programming (Zhang et al., 2025), 0-1 integer programming (Hultberg et al., 2020), mixed-integer programming (Haight et al., 2021), mixed-integer linear programming (Kıbış & Büyüktahtakın, 2017) and mixed-integer nonlinear programming to allocate limited management resources effectively (Marangi et al., 2023). These models typically incorporate management costs and budget constraints to allocate resources across prevention, monitoring, and control actions, aiming to reduce ecological and economic losses or enhance post-control benefits (Yemshanov et al., 2019). Notably, Onal et al. (2020) and Yemshanov et al. (2020a) have integrated simulation with optimization to address spatiotemporal decision-making under uncertainty, demonstrating the advantages of coordinated, time-phased, and spatially explicit control strategies.

Recent years have witnessed a growing interest in integrating big data, simulation, and optimization to address complex resource-constrained decision problems. In invasive species management, spatial optimization under fixed budgets has been used to identify cost-effective surveillance and control strategies across heterogeneous landscapes, with budget constraints and spatial heterogeneity shown to strongly affect marginal management returns (Yemshanov et al., 2020b; Lampert & Liebhold, 2023). Reviews of operations research approaches further highlight budget-constrained, spatiotemporal resource allocation as a core analytical paradigm (Büyüktahtakın & Haight, 2018). More recent work applies cost, benefit optimization and dynamic threat, response models to prioritize spatial control under limited funding (Salgado-Rojas et al., 2025). Together, these studies demonstrate the potential of combining data-driven estimation with simulation-optimization under budget constraints. However, existing approaches have not yet integrated time-varying ecological parameters estimation, dynamic invasion simulation, and mixed-integer optimization within a unified Data-Driven-Simulation-Optimization (DDSO) framework for ecological invasion management. This study addresses this gap.

Despite these advances, important gaps remain. Most studies rely on single data sources or standalone algorithms, with limited integration of multi-source monitoring data into intelligent decision-support frameworks. Although multi-sensor time-series imagery (e.g., Sentinel-2 and

GF-1) has improved monitoring of S. alterniflora, its potential to inform adaptive, optimization-based resource allocation remains underexplored. In addition, ecological niche models often assume static or simplified environmental conditions, limiting their ability to capture dynamic invasion processes. Existing optimization approaches likewise tend to adopt static parameter settings and rarely incorporate time-varying ecological information derived from real observations. Given that invasion dynamics and environmental conditions evolve continuously, there is a clear need for integrated frameworks that can assimilate updated ecological data to enhance the realism and effectiveness of management decisions.

Building on these insights, our study makes the following key innovations:

(1) Multi-source data integration and intelligent processing: Satellite remote sensing is combined with image recognition and Random Forest and K-Nearest Neighbors methods on platforms such as Google Earth Engine and Python to quantify the spatiotemporal spread of S. alterniflora, improving monitoring accuracy and efficiency through data fusion.

(2) Environmental parameter learning and environmental response functions: Data-driven models based on KNN and RF are used to estimate key ecological parameters and construct dispersal and migration rates, capturing the interactions between environmental conditions and interregional spread dynamics.

(3) Explicit coupling of ecological process simulation and optimization: By integrating spatial dispersal mechanisms with optimization-driven control decisions within an ecological simulation, this study overcomes the conventional separation between process-based modeling and resource allocation. The framework provides a coherent representation of invasion dynamics, spanning life-cycle transitions and interregional spread pathways, and supplies a dynamic foundation for spatiotemporally explicit optimization.

(4) Integrated data-driven-simulation-optimization framework: To address the key challenges of invasive plant management–namely data scarcity, latent ecological parameters, and complex decision-making–we propose a systematic framework spanning the entire DDSO chain. The framework achieves full-link integration from constrained latent parameter inference, through stage-structured ecological simulation, to spatiotemporally explicit optimization.

(5) An extensive case study for real-world management: Scenario-based analyses across varying budgets, invasion intensities, intervention timings, and other key parameters are conducted to assess management performance beyond static or single-scenario approaches.

3. Data-Driven-Simulation-Optimization model (DDSO model)

3.1 Modeling framework

This study establishes an integrated modeling framework that quantitatively links multi-source environmental information with optimal management strategies for controlling Spartina alterniflora invasions in coastal wetlands. Decision granularity is defined at the site-year level, where the optimizer determines when and where to implement control, and treatment costs are determined by current infestation abundance. Accordingly, the study area is divided into spatial units $r \in R$, time is discretized into decision periods $t \in T$, and $k \in K$ represents the life cycle stage.

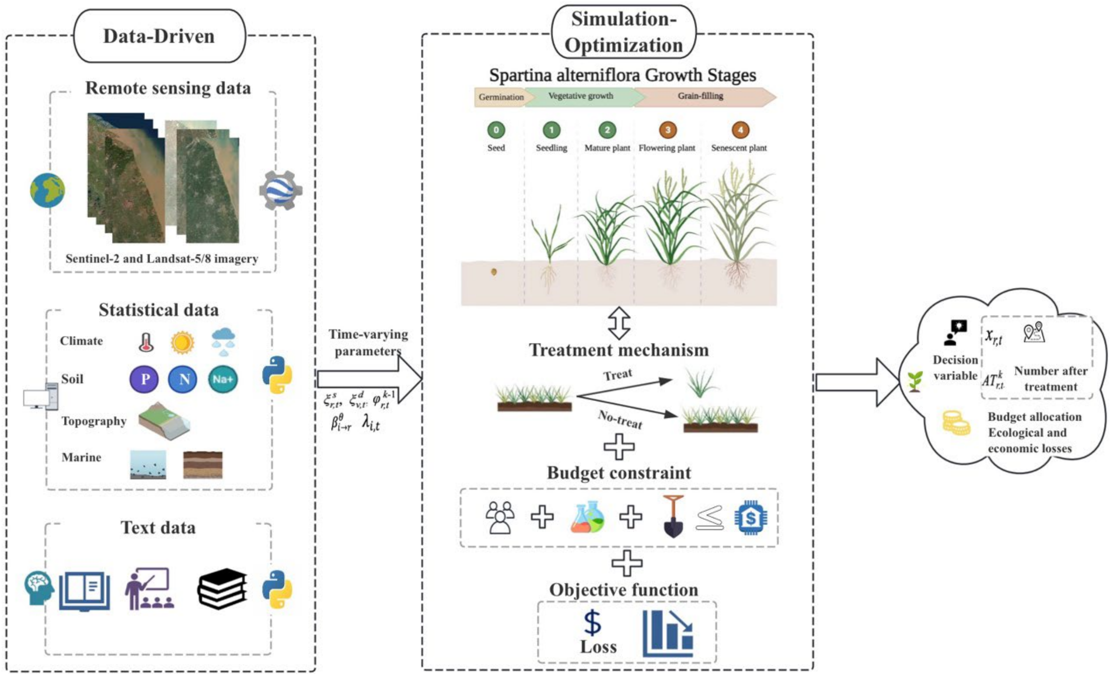

Figure 1. Schematic framework of the Data-Driven-Simulation-Optimization model

As illustrated in Figure 1, the framework consists of two major components: (i) a data-driven-based ecological parameterization module and (ii) a simulation-optimization module. The data-driven module integrates heterogeneous data sources, including remote sensing imagery (Sentinel-2, Landsat-5/8), and statistical datasets covering climate, soil, topography, and hydrodynamic conditions. By applying RF and KNN algorithms, this module extracts distribution data and estimates key ecological and dispersal parameters, such as reproduction rate $\xi^{s}_{r,t}$, $\xi^{d}_{v,t}$, natural mortality rate $\varphi^{k\text{-}1}_{r,t}$ and dispersal coefficient $\beta^{\theta}_{i\to r}$, interregional migration rate $\lambda_{r,t}$. The integration of these time-varying parameters captures the spatial and temporal heterogeneity of species growth, dispersal, and environmental conditions, thereby enhancing the realism of subsequent simulation and optimization analyses.

The simulation-optimization module integrates a plant growth and dispersal simulator with a resource allocation optimization model to characterize the dynamic invasion trends of S. alterniflora under multiple scenarios. The simulation component is formulated as a stage-structured system dynamics model, in which key ecological parameters estimated by data-driven are incorporated as exogenous drivers. Through biologically informed transition dynamics, the model represents the full life cycle of S. alterniflora, including seed bank dynamics, growth, reproduction, dispersal, and migration. Based on the simulated ecological evolution, the optimization component identifies the most cost-effective spatial and temporal allocation of control resources under budget constraints. The binary decision variable $x_{r,t}$ represents whether control is implemented in region r at time t, while $AT_{r,t}^{k}$ denotes the remaining S. alterniflora population in stage k after intervention. Notably, $AT_{r,t}^{k}$ functions as a coupling variable linking the simulation and optimization modules, serving simultaneously as the output of ecological dynamics and a constraint input for treatment decisions (see Eq. (9)).

Through the integration of data-driven parameter estimation, system dynamics simulation, and optimization-based decision analysis, this framework provides a unified platform for evaluating where and when to implement control measures, thereby supporting evidence-based and cost-effective management of coastal invasive species.

3.2 S. alterniflora control optimization model

Building on the framework in Section 3.1, this section formalizes the S. alterniflora control optimization model by specifying the key ecological processes, management actions, and decision constraints that link population dynamics with management interventions:

(1) Simulation of the growth and diffusion

1) Dispersal dynamics

Seeds of S. alterniflora can disperse over long distances via waves and tides. For any region r, the quantity of seeds migrating from neighboring regions $i \in M(r)$ to region r at time $t+1$ can be expressed as:

$$AD_{r,t+1} = \sum_{k=1}^{N} \sum_{i \in M(r)} \lambda_{i,t+1} \beta_{i \to r}^{\theta} AT_{i,t}^{k} S_{i}^{k} \qquad \forall\, r,\, t \tag{1}$$

Here, $\lambda_{i,t+1}$ denotes the proportion of seeds leaving region i at time $t+1$ via waterborne dispersal (migration rate). $\beta_{i \to r}^{\theta}$ represents the probability of seeds from neighboring region $i \in M(r)$ dispersing to region r in wave direction θ, and $M(r)$ is the set of all neighboring regions of r. $AT_{i,t}^{k}$ denotes the post-control number of plants in stage k in region i at time t, and S_{i}^{k} represents the number of seeds produced by stage-k plants in region i.

Some seeds remain within region r rather than dispersing outward due to hydrodynamic conditions, expressed as:

$$AR_{r,t+1} = \omega_{r,t+1} \sum_{k=1}^{K} AT_{r,t}^{k} S_{r}^{k} \qquad \forall\, r,\, t \tag{2}$$

where $\omega_{r,t+1}$ is the proportion of seeds retained in region r after dispersal at time $t+1$.

2) Seed bank dynamics

The retained seeds in region r, together with seeds dispersed from neighboring regions, form the seed bank. The constraint for the seed bank is thus defined as:

$$AB_{r,t+1}=AD_{r,t+1}+AR_{r,t+1} \quad \forall\, r,t \tag{3}$$

3) Population transition dynamics

S. alterniflora reproduces both sexually (via seeds) and asexually (via rhizomes and plant fragments). Seeds in the seed bank and asexually propagated rhizomes germinate into seedlings at specific rates. As seedlings grow, natural mortality occurs at each stage. Mature plants then produce seeds. The state transition equations are:

$$AP^{k}_{r,t+1}=\sigma\pi_r\xi^{s}_{r,t+1}AB_{r,t+1}+\tau(1\text{-}\varphi^{k\text{-}1}_{r,t+1})AT^{k\text{-}1}_{r,t}P^{k}\xi^{d}_{r,t+1} \quad k=1 \; and \; \forall\, r,t \tag{4}$$

$$AP^{k}_{r,t+1}=\left(1\text{-}\varphi^{k\text{-}1}_{r,t+1}\right)AT^{k\text{-}1}_{r,t+1}+\tau(1\text{-}\varphi^{k\text{-}1}_{r,t+1})AT^{k\text{-}1}_{r,t+1}P^{k}\xi^{d}_{r,t+1} \quad k=2 \; and \; \forall\, r,t \tag{5}$$

$$AP^{k}_{r,t+1}=\left(1\text{-}\varphi^{k\text{-}1}_{r,t+1}\right)AT^{k\text{-}1}_{r,t+1} \quad k=3,\ldots,K \; and \; \forall\, r,t \tag{6}$$

Here, $AP^{k}_{r,t+1}$ denotes the number of stage-k plants in region r at time t+1, $\xi^{s}_{r,t+1}$ is the seed survival rate. π_r is the seed germination rate, σ is the seed-to-seedling transition rate, τ is the vegetative propagation rate from rhizomes. P^{k} is the number of rhizomes produced by stage-k plants. $\xi^{d}_{r,t+1}$ is the rhizome survival rate, and $\varphi^{k\text{-}1}_{r,t+1}$ represents the natural attrition during the transition from stage k-1 to stage k.

4) Carrying capacity and actual population

Since each region r contains S. alterniflora at different life stages, plants compete for limited resources such as soil and living space. The carrying capacity L_r specifies the maximum population that region r can sustain, and is estimated from field survey data reported in Liu et al. (2017). As the population approaches L_r, survival and growth become increasingly suppressed. Thus, the pre-control population of stage-k plants in region r, $BT^{k}_{r,t}$, is defined as:

$$BT^{k}_{r,t+1}=min\left\{AP^{k}_{r,t+1},L_r\right\} \quad k=K \; and \; \forall\, r,t \tag{7}$$

$$BT^{k}_{r,t+1}=min\left\{AP^{k}_{r,t+1},N^{k}_{r,t+1}\right\} \quad k=1,\ldots,K\text{-}1 \; and \; \forall\, r,t \tag{8}$$

We adopt a Lotka-Volterra competition framework to model inter-stage suppression, where the population dynamics $N^{k}_{r,t+1}$ detailed in the supplementary (see supplementary material S1).

(2) Treatment mechanism

To mitigate the damage caused by invasive species, government agencies periodically implement control measures against S. alterniflora. In this study, based on the local context, we adopt combined physical and chemical control method to control for region r. After treatment, the population of stage-k plants in region r at time t+1, $AT^{k}_{r,t+1}$, can be expressed as:

$$AT^{k}_{r,t+1}=BT^{k}_{r,t+1}\times\left(1\text{-}\gamma x_{r,t+1}\right) \quad \forall\, r,t,k \tag{9}$$

Here, γ is the effective control rate, and $x_{r,t}$ is a binary decision variable indicating whether control is applied to region r at time t.

(3) Budget constraint

Since the budget for controlling S. alterniflora is limited, the total expenditure across the planning horizon must satisfy:

$$\sum_{t=1}^{T}\sum_{r=1}^{R} C * SA_{r,t} * x_{r,t} \leq B \tag{10}$$

where C includes labor and machinery costs, $SA_{r,t}$ is the area of S. alterniflora in region r at time t, obtained from GEE and machine-learning-based monitoring, and B is the total budget.

(4) Objective function

The goal of the model is to minimize the total damage caused by S. alterniflora across all regions and time periods within the planning horizon (obstruct waterways, destroy habitats, etc.). Let $E_{r,t}$ denote the expected economic benefits of region r at time t. The objective function thus minimizes invasion-induced economic losses subject to budget constraints through optimized control strategies, and is formulated as follows:

$$Min \sum_{r}^{R}\sum_{t}^{T} E_{r,t}\left(\sum_{k=1}^{K} AT_{r,t}^{k}\right)/L_r \tag{11}$$

3.3 Data-driven parameterization for invasion dynamics simulation

To address the limitations of conventional field- and laboratory-based monitoring, this study adopts a data-driven parameterization framework that integrates multi-source observations with a process-based dispersal-control model. Specifically, the data-driven approach serves two purposes: (i) reconstructing the spatiotemporal distribution of Spartina alterniflora from historical environmental and remote-sensing data, and (ii) inferring environmentally driven, time-varying invasion parameters by learning nonlinear relationships between environmental factors and biological processes. These data-derived parameters are then embedded into the process-based simulation model, providing dynamically updated inputs that enhance the realism and adaptability of invasion dynamics representation (see Supplementary Material S2).

3.3.1 Remote sensing-based data extraction using GEE and Python

Using multi-source data, including remote sensing, climate records, and statistical surveys, this study examined the dynamic evolution of S. alterniflora in the coastal areas of Yancheng from 1990 to 2022. On the Google Earth Engine (GEE) platform, we extracted vegetation and water indices from Sentinel-2 and Landsat-5/8 imagery, including Normalized Difference Vegetation Index, Enhanced Vegetation Index, and Normalized Difference Water Index. Random Forest classifiers was then employed to identify different growth stages of S. alterniflora and to derive the initial invasion maps (Figure 2).

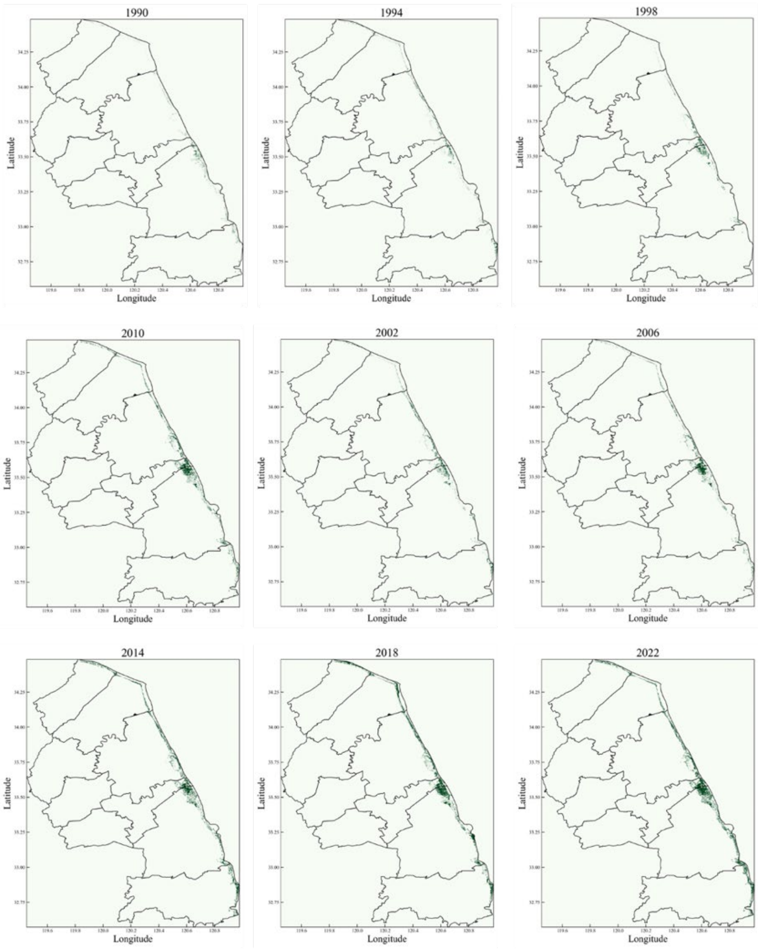

Figure 2. Spatial distribution of S. alterniflora in selected years from 1990 to 2022

3.3.2 Ecological environmental parameters inference

Because direct observation of seed survival, vegetative sprouting, and natural mortality is challenging, corresponding dispersal parameters were represented as latent process variables. These are jointly driven by multi-source environmental predictors and bounded by ecological constraints informed by prior studies (Liu et al., 2017; Wang et al., 2021). To appropriately capture the distinct ecological processes represented by each parameter, we implemented tailored strategies. Cross-validation results indicate that the data-driven parameterization achieves consistently high explanatory power (mean R^2 ranging from approximately 0.79 to 0.88) with low prediction errors, supporting the internal consistency and stability of the inferred spatiotemporal patterns (Table S1). All models operate under strict ecological boundary constraints and are intended to represent the relative structure and spatiotemporal heterogeneity of parameter responses to environmental change, rather than to estimate unobservable true parameter values. The resulting outputs provide ecologically plausible, time-varying inputs for the simulation-optimization framework (see supplementary material S3).

(1) Reproductive rate of S. alterniflora

Let the proportional contribution of seed-based reproduction be f_s and that of rhizome-based reproduction be f_d, satisfying f_s+f_d=1.

The seed survival rate $\xi^s_{r,t}$ is regulated by an environmental adaptability coefficient $\alpha_{r,t}$:

$$\xi^s_{r,t}=\alpha^s_{r,t}f_s \quad \forall\ r,t \tag{12}$$

$$\alpha^s_{r,t}=g(T,S,Na_{soil},P,\Delta T) \quad \forall\ r,t \tag{13}$$

Here, $g(\cdot)$ denotes a K-Nearest Neighbor (KNN) regression model based on temperature (T), salinity (S), soil exchangeable sodium (Na_{soil}), precipitation (P), and temperature variability (ΔT), with its output normalized to [0, 1].

$$\xi^d_{r,t}=\alpha^d_{r,t}f_vA_{new}(t) \quad \forall\ r,t \tag{14}$$

The rhizome survival rate $\xi^d_{v,t}$ is also governed by an environmental adaptability coefficient $\alpha_{v,t}$, with key drivers including silt content ($Silt$), seawater flow velocity (U), and PH.

$$\xi^d_{v,t}=\alpha^d_{r,t}f_v \quad \forall\ r,t \tag{15}$$

$$\alpha^d_{r,t}=h(Silt,S,U,Na_{soil},PH,P) \quad \forall\ r,t \tag{16}$$

(2) Natural attrition rate

The attrition rate at growth stage k, $\varphi^k_{r,t}$, is modeled as a function of environmental factors. Using Random Forest models for stage-specific estimation, we impose the constraint $\sum_{k=1}^{K}\varphi^k_{r,t}\leq 1$.

$$\varphi^k_{r,t}=a(T,S,Na_{soil},\Delta T,PH,P) \quad \forall\ r,t \tag{17}$$

3.3.3 Quantification of migration and dispersal dynamics

(1) Migration rate

Hydrodynamic conditions are the primary drivers of long-distance seed dispersal for S. alterniflora in coastal regions. We introduce a hydrodynamic index to characterize seed migration probability, incorporating both water flow velocity and wind strength (see Eq. 18). To standardize migration rates, the hydrodynamic index is normalized (Eq. 19) to derive seed migration rates for each region:

$$MP_{r,t}=\sum_{k=1}^{K}\frac{WS_{r,t}(k)\cdot WV_{r,t}(k)}{K} \quad \forall\ r,t \tag{18}$$

$$\lambda_{r,t}=\frac{MP_{max,t}-MP_{r,t}}{MP_{max,t}-MP_{min,t}} \quad \forall\ r,t \tag{19}$$

Here, MP_r denotes the average hydrodynamic intensity in region r over the planning horizon T. $WS_{r,t}$ and $WV_{r,t}$ are the average wind speed and water flow velocity in region r at time t, respectively, and MP_{max} and MP_{min} are the maximum and minimum average hydrodynamic intensities across all regions. λ_r is the normalized hydrodynamic index representing the seed migration rate in region r. A larger λ_r indicates weaker hydrodynamic conditions and thus a lower probability of seed movement from region i to region r.

(2) Diffusion rate

Beyond hydrodynamic intensity, water flow direction and the spatial distance between neighboring regions also influence seed dispersal. We define $\beta^{\theta}_{i\to r}$ as the probability of S. alterniflora seeds dispersing from region i to region r along migration direction θ, given by:

$$\mu_{i\to r}=\frac{1}{1+(\frac{\sqrt{S_i}d_{i\to r}}{\varepsilon})^2} \tag{20}$$

$$\beta^{\theta}_{i\to r}=\frac{\mu_{i\to r}}{\sum_{i\in M(r)}\mu_{i\to r}} \tag{21}$$

Here, S_i represents the mudflat area of region i. $d_{i\to r}$ denotes the distance between the geographic centers of mudflats in regions i and r, and ε is the diffusion coefficient. As expressed in Eq. (20), larger mudflat areas and greater interregional distances both reduce the proportion of seeds migrating from region i to region r.

3.4 Linearization of the DDSO model

Because constraints (7) and (8) contain minimum operators, we employed Big-M formulations with binary variables to linearize the constraints, transforming them into a mixed-integer programming (MIP) model ((7a)-(7d) and (8a)-(8d)). Likewise, constraint (9) was linearized into equivalent sub-constraints (9a-9d). The auxiliary upper bounds used in these linearizations are defined as $U^1_r=1.5L_r$ and $U^2_r=1.5N^k_r$. These values provide biologically plausible, conservative bounds that improve the conditioning of the MIP. Thus, the DDSO model is expressed by equations (1)-(6), (7a)-(7d), (8a)-(8d), (9a)-(9e), and (10)-(11).

(DDSO) Obj (11)

s.t.:

$$BT^k_{r,t+1}\leq AP^k_{r,t+1} \quad k=K \text{ and } \forall\, r,t \tag{7a}$$

$$BT^k_{r,t+1}\leq L_r \quad k=K \text{ and } \forall\, r,t \tag{7b}$$

$$BT^k_{r,t+1}\geq AP^k_{r,t+1}-U^1_r(1-z^1_{r,t+1}) \quad k=K \text{ and } \forall\, r,t \tag{7c}$$

$$BT^k_{r,t+1}\geq L_r-U^1_r z^1_{r,t+1} \quad k=K \text{ and } \forall\, r,t \tag{7d}$$

$$BT^k_{r,t+1}\leq AP^k_{r,t+1} \quad k=1,\ldots,K\text{-}1 \text{ and } \forall\, r,t \tag{8a}$$

$$BT^k_{r,t+1}\leq N^k_{r,t+1} \quad k=1,\ldots,K\text{-}1 \text{ and } \forall\, r,t \tag{8b}$$

$$BT^k_{r,t+1}\geq AP^k_{r,t+1}-U^1_r(1-z^1_{r,t+1}) \quad k=1,\ldots,K\text{-}1 \text{ and } \forall\, r,t \tag{8c}$$

$$BT^k_{r,t+1}\geq N^k_{r,t+1}-U^1_r z^1_{r,t+1} \quad k=1,\ldots,K\text{-}1 \text{ and } \forall\, r,t \tag{8d}$$

$$w^k_{r,t+1}\leq \gamma BT^k_{r,t+1} \quad \forall\, r,t,k \tag{9a}$$

$$w^k_{r,t+1}\leq \gamma U^2_r x_{r,t} \quad \forall\, r,t,k \tag{9b}$$

$$w^k_{r,t+1}\geq \gamma BT^k_{r,t+1}-\gamma U^2_r(1-x_{r,t}) \quad \forall\, r,t,k \tag{9c}$$

$$w_{r,t+1}^{k} \geq 0 \quad \forall\, r,t,k \tag{9d}$$

$$AT_{r,t}^{k} = BT_{r,t+1}^{k} - w_{r,t+1}^{k} \quad \forall\, r,t,k \tag{9e}$$

(1)-(6), (10).

By incorporating data-driven, time-varying parameters estimated from multi-source observations and remote-sensing inversions as exogenous inputs, the proposed DDSO framework tightly integrates a mechanistic stage-structured simulation with a rigorously linearized deterministic MIP formulation. This integration enhances ecological realism while preserving computational robustness and model reproducibility. In the following section, we apply this framework to a case study of S. alterniflora invasion control across six severely affected coastal areas of Yancheng, Jiangsu Province, China, where a scenario-based analysis is conducted to examine optimal control strategies under alternative invasion and budget conditions.

4. Case study

4.1 Parameter settings

This study focuses on six coastal regions in Yancheng, Jiangsu Province–Xiangshui (XS), Binhai (BH), Sheyang (SY), Tinghu (TH), Dafeng (DF), and Dongtai (DT)–to validate the computational feasibility and rationality of the proposed DDSO model. Drawing upon peer-reviewed literature, government reports, and expert consultation, and integrating Yancheng's regional environmental characteristics with multi-source datasets, key parameters governing population dynamics and management interventions were calibrated. Table 1 summarizes the initial population structure and model parameters, while Figure 3 illustrates the growth dynamics parameters derived from multi-source data.

We adopt a scenario-based comparative framework to assess management performance across a range of plausible invasion conditions, using alternative invasion scenarios to examine how management outcomes vary with invasion intensity and spatial extent. Invasion scenarios are defined according to the severity of S. alterniflora infestation, characterized by two key ecological dimensions: invasion frequency (spatial distribution proportion) and invasion abundance (initial population per region). Each dimension is specified at three levels: Low (L), Medium (M), and High (H). The M-M scenario, which represents the observed S. alterniflora distribution derived from GEE-based mapping and machine-learning analysis, is used as the baseline ecological scenario. Building upon this reference condition, nine hypothetical invasion scenarios are constructed by systematically adjusting invasion frequency (-20%, baseline, +25%) and invasion abundance (-10%, baseline, +5%), thereby generating a spectrum of ecological conditions for model evaluation (see supplementary material S4).

Table 1. Initial population structure and model parameters

Description	Notations	Unit	Value	Reference
Initial frequency	L, M, H	-	-20%, Based, +25%	-
Initial abundance	L, M, H	-	-10%, Based, +5%	-
Seed-to-seedling transition rate	σ	-	0.15	Hayasaka et al., 2020; Liu et al., 2017; Xu et al., 2014
Seed germination rate	π_r	-	0.225, 0.2, 0.175, 0.25, 0.21, 0.19	
Vegetative propagation rate from rhizomes	τ	-	0.3	An et al., 2007; Trilla et al., 2009
The number of rhizomes produced by stage-k plants	P^k	-	5, 15	
The effective control rate	γ	-	0.85	Wang et al., 2016
Labor and machinery costs	C	CNY	2400	An et al., 2024
Proportional contribution of seed-based reproduction	f_s	-	25%	Hayasaka et al., 2020
Proportional contribution of rhizome-based reproduction	f_v	-	75%	Hayasaka et al., 2020

Figure 3. Survival and attrition rates of S. alterniflora

We solved the mixed-integer programming model proposed in Section 3 using IBM ILOG CPLEX Optimization Studio 22.1 to identify optimal S. alterniflora control strategies under varying scenarios. All computations were performed on a personal computer equipped with an Apple M1 processor (8-core CPU) and 8 GB RAM. The full-scale model covers 33 time steps × 6 regions × 5 growth stages, all tested instances were solved within 180 seconds. Scalability experiments for extended time horizons indicate that computational effort grows approximately linearly with the number of periods, and the model remains tractable under default solver configurations.

4.2 Comparative analysis of models

To evaluate the benefits of optimization-based management, three models–System Dynamics (SD), Simulation-Optimization (SO, i.e., simulation optimization model with fixed parameters), and Data-Driven-Simulation-Optimization (DDSO)–were compared under a fixed budget of CNY 300 million (Table 2). First, the contrast between the SD and control-based models (SO and DDSO) demonstrates that the inclusion of optimized control decisions fundamentally determines the order of magnitude of economic losses, reducing total damage by nearly two orders of magnitude. This finding implies that, once invasion reaches a regional scale, the critical policy question is no longer the precise tuning of control intensity, but whether coordinated, forward-looking control is embedded in the decision framework at all. Second, the optimal solutions consistently favor highly uneven spatial allocation of budgets and treatment intensity, concentrating resources in Sheyang, Dafeng, and Dongtai. This pattern indicates that economically efficient management prioritizes regions with high marginal control returns and strong roles in invasion propagation, rather than pursuing uniform loss reduction across space. Such results quantitatively support a node-based or leverage-oriented control strategy in invasive species management. Third, comparing SO and DDSO shows that incorporating finer ecological or life-stage structure does not increase overall costs or losses, but instead produces more temporally distributed and less extreme control pathways. This suggests that greater ecological realism enhances the robustness and sustainability of management strategies by reducing reliance on short-term, high-intensity interventions.

Overall, this scenario analysis reveals a fundamental decision logic: the existence of control decisions determines the magnitude of economic losses, the spatial-temporal allocation of control resources determines management efficiency, and the depth of ecological process representation influences the robustness and sustainability of control pathways. These insights not only provide strategic guidance for S. alterniflora management but also offer a transferable decision framework for the coordinated regional control of other coastal invasive species.

Table 2. Optimal budget allocation, treatment capacity, and associated economic losses under different models

Model	Time Sec.	Gap %	Objective CNY	City	Regional Economic Loss	OptBudget Million CNY	Control Year	Treatment Intensity
SD	0.08	-	521595663	Xiangshui	18329916	-	-	-
				Binhai	37397940	-	-	-
				Sheyang	281920608	-	-	-
				Tinghu	63024022	-	-	-
				Dafeng	59517669	-	-	-
				Dongtai	61405508	-	-	-
				Total	**521595663**	**-**	**-**	**-**
SO	2.81	0.08	5651560	Xiangshui	133244	8.82	6	1097693
				Binhai	345837	15.49	6	622944
				Sheyang	1749445	58.69	7	9345237
				Tinghu	382216	41.11	5	26915933
				Dafeng	2361063	82.14	5	26376299
				Dongtai	679754	93.74	5	15770451
				Total	**5651560**	**299.99**	**34**	**80128557**
DDSO	3.49	0.07	5705480	Xiangshui	144472	11.50	7	1201357
				Binhai	368399	20.02	7	668732
				Sheyang	1802625	58.69	7	9676748
				Tinghu	374991	55.54	6	26605569
				Dafeng	2479850	82.14	5	27903752
				Dongtai	535143	69.55	4	12277739
				Total	**5705480**	**297.44**	**36**	**78338967**

4.3 Effects of different budget levels

Using the medium invasion abundance-frequency scenario as a baseline, the optimization results under different budget scenarios reveal three interrelated decision insights concerning marginal returns, budget thresholds, and the evolution of control pathways (Table 3). First, under the zero-budget scenario, total economic losses exceed CNY 774 million, indicating that without intervention the invasion system evolves toward severe and cumulative regional damage. When the budget increases to CNY 100 million, losses drop by more than two orders of magnitude, demonstrating a pronounced initial leverage effect whereby relatively modest but coordinated investments fundamentally alter invasion dynamics. Second, as the budget rises from CNY 100 to 200 million, total losses continue to decline but at a markedly diminishing rate; beyond the CNY 200-400 million range, further budget increases yield almost no additional reduction in economic losses, which stabilize at approximately CNY 5.7 million. This pattern reveals a clear budget threshold and diminishing marginal returns, identifying an economically efficient investment interval beyond which additional funding primarily enhances coverage and persistence rather than outcome effectiveness. Third, higher budgets do not change the spatial prioritization of control but are absorbed through longer control horizons and greater continuity of treatment, rather than intensified short-term interventions. This indicates a strategic shift from rapid suppression toward maintenance-oriented and stabilization-focused control pathways as financial constraints are relaxed.

Table 3. Optimal budget allocation, treatment capacity, and associated economic losses under different budgets

Budget Million yuan	Time Sec.	Gap %	Objective	City	Regional Economic Loss	OptBudget Million CNY	Control Plan	Treatment Intensity
0	0.07	-	774420984	Xiangshui	168428929	-	-	-
				Binhai	241206722	-	-	-
				Sheyang	166152008	-	-	-
				Tinghu	69569053	-	-	-
				Dafeng	118213723	-	-	-
				Dongtai	10850549	-	-	-
				Total	**774420984**	-	-	-
100	8.14	5.97	9575297	Xiangshui	157022	6.60	5	1201151
				Binhai	386122	11.68	5	668607
				Sheyang	2273848	20.23	3	9631804
				Tinghu	591040	20.29	3	26472003
				Dafeng	4539683	26.50	2	27102211
				Dongtai	1627582	14.08	1	10644558
				Total	**9575297**	**99.38**	**19**	**75720334**
200	5.24	0.19	5808421	Xiangshui	157022	6.60	5	1201151
				Binhai	371045	15.50	6	668710
				Sheyang	1812367	37.75	5	9675381
				Tinghu	406200	29.59	4	26582104
				Dafeng	2514243	61.04	4	27886137
				Dongtai	547544	48.47	3	12248167
				Total	**5808421**	**198.95**	**27**	**78261650**
400	0.5	0.01	5697889	Xiangshui	144481	8.82	6	1201373
				Binhai	368401	20.02	7	668734
				Sheyang	1802677	59.87	7	9676812
				Tinghu	374308	73.66	7	26606187
				Dafeng	2474265	137.67	7	27907578
				Dongtai	533757	93.74	5	12282151
				Total	**5697889**	**393.78**	**39**	**78342835**
500	0.12	0.00	5697488	Xiangshui	144472	11.50	7	1201357
				Binhai	368399	20.02	7	668732
				Sheyang	1802617	58.69	7	9676731
				Tinghu	374292	73.66	7	26606193
				Dafeng	2474122	133.82	7	27907597
				Dongtai	533586	153.13	7	12282806
				Total	**5697488**	**450.82**	**42**	**78343416**

Overall, the analysis suggests a hierarchical budget logic: budget availability determines whether system trajectories can be reversed, threshold levels define efficiency limits, and post-threshold allocations shape long-term stability rather than immediate loss reduction. This framework provides a concise and transferable basis for investment planning in invasive species management under fiscal constraints.

4.4 Effects of different invasion frequencies and abundances

Under a fixed budget of CNY 300 million, increasing invasion frequency and abundance fundamentally alters the control mechanism rather than proportionally increasing losses (Figures 4 and 5).

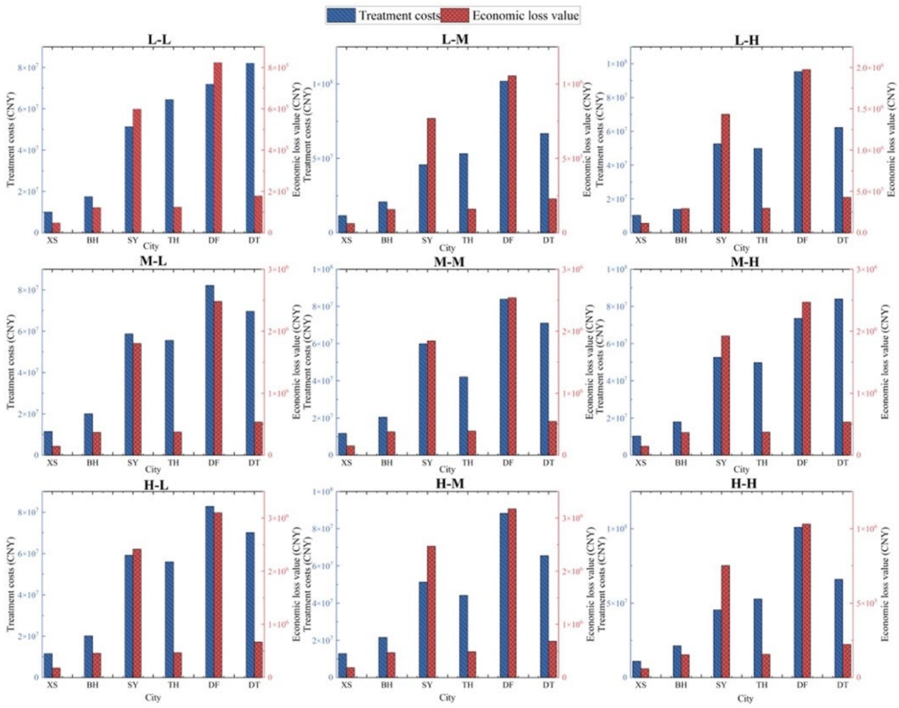

Figure 4. Budget allocation and economic losses across different invasion scenarios

Note: The left vertical axis in the figure represents the treatment costs, and the right vertical axis represents the economic loss value. Scenarios are categorized as follows: Low frequency and low abundance (L-L), Low frequency and medium abundance (L-M), Low frequency and high abundance (L-H), Medium frequency and low abundance (M-L), Medium frequency and medium abundance (M-M), Medium frequency and high abundance (M-H), High frequency and low abundance (H-L), High frequency and medium abundance (H-M), and High frequency and high abundance (H-H).).

First, total economic losses escalate sharply with increasing invasion severity, yet governance costs remain relatively constrained, indicating a nonlinear sensitivity of the system to invasion levels. This divergence indicates that, once control coverage and timing approach saturation, residual losses are driven primarily by exogenous risk intensity rather than insufficient management effort. Under high-risk conditions, budgets and control capacity therefore function more as loss buffers than as instruments of loss elimination. Second, the optimal temporal structure is remarkably stable across scenarios, characterized by early and persistent control beginning at the initial period and maintained throughout the planning horizon. As scenario severity increases, the model responds not by shifting control timing, but by scaling treatment intensity within existing time windows. This reflects a strategic transition from timing-based intervention to scale-based risk hedging under elevated invasion pressure. Third, spatial prioritization remains largely invariant across all scenarios: Sheyang, Dafeng, and Tinghu consistently dominate control effort and residual losses, while Xiangshui and

Binhai play secondary roles. This stability suggests that regional priorities are determined by structural ecological and diffusion characteristics, rather than by budget or capacity assumptions. Scenario escalation thus affects the cost of maintaining a given spatial control pattern, not the pattern itself.

Overall, these results imply a hierarchical decision logic: management resources determine the system's capacity to absorb risk, whereas scenario severity determines the irreducible loss floor. Under high-risk regimes, the objective of control shifts from minimizing losses to preventing systemic loss escalation, underscoring the importance of integrating routine management with risk-tiered and scenario-responsive strategies in long-term invasive species control.

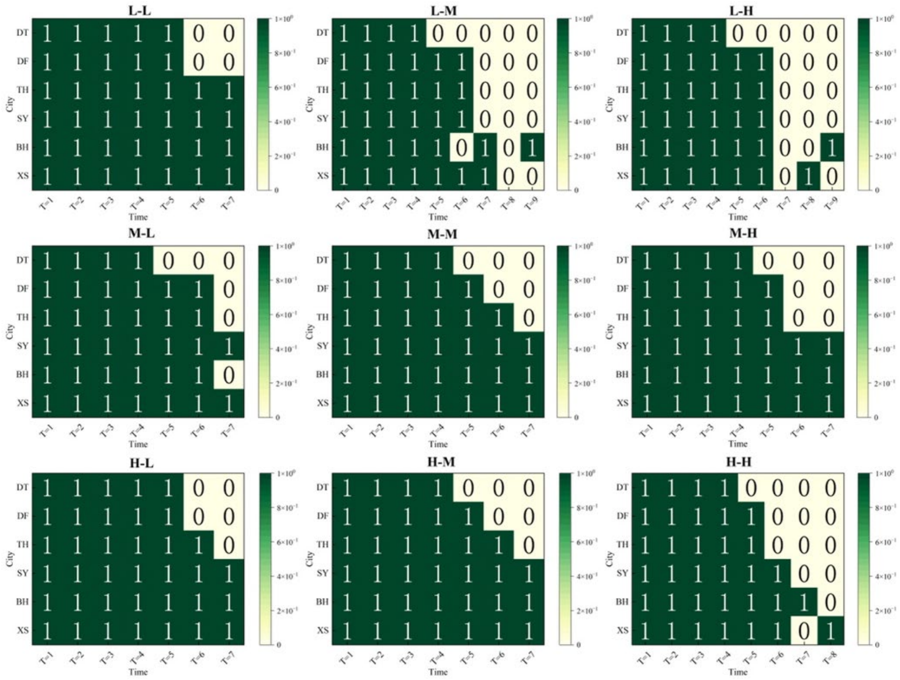

Figure 5. Distribution of treatment decisions across different invasion scenarios

Note: The left vertical axis in the figure represents the six research areas, and the horizontal axis at the bottom represents the time at which the treatment measures were implemented. 0 = no treatment, 1 = treatment implemented

4.5 Effects of different intervention timings

Under a fixed budget of CNY 300 million, delaying eradication leads to a strongly nonlinear deterioration in outcomes (Figure 6). First, the timing of control implementation is highly determinant of economic outcomes. Early intervention (e.g., Delay 1) limits total losses to approximately CNY 1.08×10^8, whereas delayed intervention (e.g., Delay 3 or Delay 5) leads to dramatic increases, up to CNY 7.14×10^8. This highlights a pronounced early-action leverage, where timely, coordinated interventions maximize marginal returns before invasion expansion amplifies system-wide risks. Second, delayed interventions induce resource concentration: under late scenarios, critical regions such as Sheyang, Dafeng, and Tinghu bear the majority of control effort, while peripheral regions receive minimal treatment. This demonstrates that when invasion pressure is high or intervention is postponed, the optimal strategy shifts from balanced coverage to risk-focused allocation, concentrating resources in areas of greatest influence to prevent systemic loss escalation. Third, spatial prioritization remains largely invariant across scenarios. Despite differences in timing and budget absorption, the ranking of key regions is stable, indicating that underlying ecological and dispersal structures drive spatial control priorities, while intervention timing primarily affects the intensity and cost of management rather than the spatial configuration.

Overall, these findings suggest a hierarchical logic: early interventions determine the magnitude of system-wide losses, delayed interventions necessitate concentrated risk-based resource allocation, and spatial priorities are structurally determined by ecological and dispersal characteristics. Integrating intervention timing with spatial structure and budget allocation is therefore critical for designing robust, long-term invasive species management strategies.

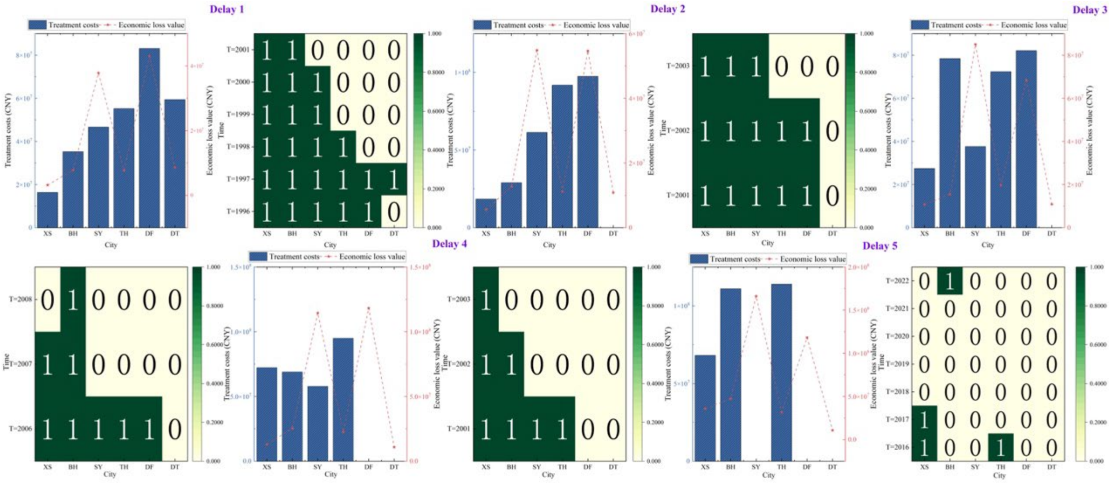

Figure 6. Regional budget allocations, economic losses, and management decisions under different intervention timing scenarios

Note: The bar charts represent treatment costs, while the line charts depict economic loss values. The heat map illustrates the management scheduling, where 0 = no treatment and 1 = treatment implemented. “Delay1”-“Delay5” indicate interventions commencing 5, 10, 15, 20, and 25 years later, respectively.

4.6 Effects of migration

Under a fixed budget of CNY 300 million, incorporating migration mainly alters the spatial-temporal deployment of control rather than total cost (Figures 7 and 8). Comparing no-migration and migration scenarios highlights the critical influence of dispersal on invasive species management. Migration amplifies economic losses across all invasion intensities, emphasizing that connectivity drives both regional vulnerability and required control effort.

In no-migration scenarios, interventions are consistently applied across all regions, reflecting the localized and predictable spread of the invasion. With migration, control efforts concentrate on high-risk regions, demonstrating that resource allocation must adapt to dispersal pathways rather than static regional risk. Intervention timing and intensity also interact with invasion severity: high-intensity invasions demand larger budgets and prolonged treatment, whereas lower-intensity invasions achieve effective control with moderate, shorter interventions.

These findings suggest three strategic implications: Incorporate dispersal dynamics into spatial prioritization to optimize resource allocation; Adjust intervention intensity to invasion severity, balancing coverage and efficiency; And prioritize early and sustained interventions under low-connectivity scenarios, while targeting key dispersal nodes under high connectivity.

Overall, both invasion intensity and ecological connectivity critically shape optimal governance strategies, and neglecting migration can lead to under-resourced interventions and higher cumulative losses.

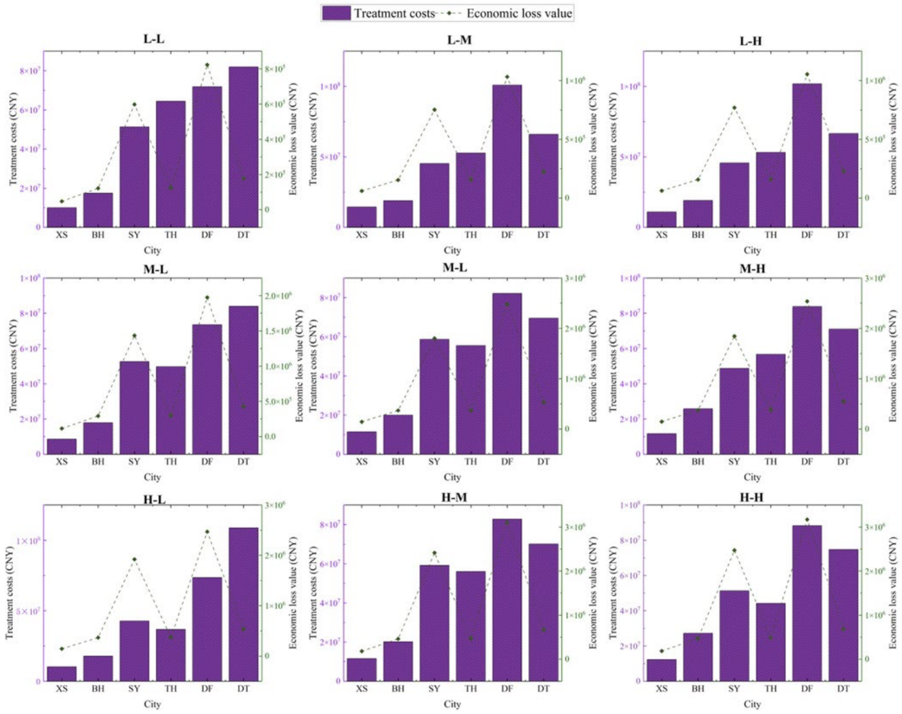

Figure 7. Regional budget allocations and economic losses under non-migration scenarios across different invasion levels

Note: The left vertical axis in the figure represents the treatment costs, and the right vertical axis represents the economic loss value.

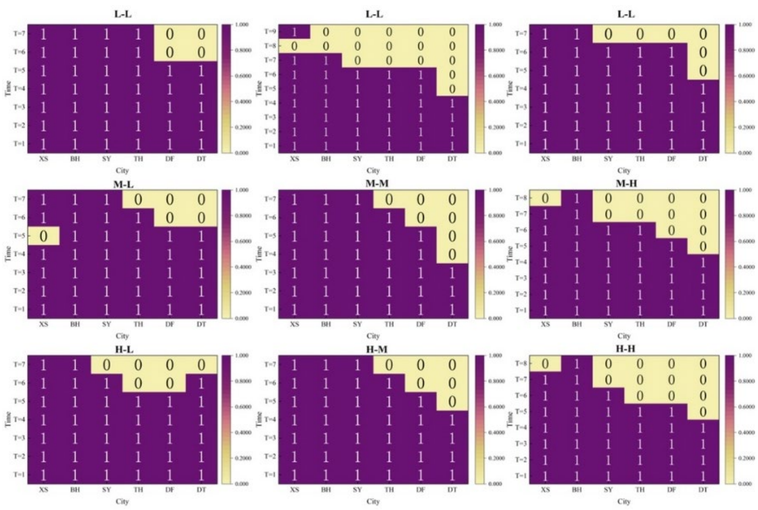

Figure 8. Regional management decisions under non-migration scenarios across different invasion levels

Note: The left vertical axis in the figure represents the time at which the treatment measures were implemented, and the horizontal axis at the bottom represents the six research areas. 0 = no treatment, 1 = treatment implemented.

4.7 Sensitivity analysis of other key parameters

To assess the model's sensitivity to key biological parameters, we conducted perturbation tests on lifecycle attributes of S. alterniflora, including the number of seeds produced (S_i^k), the seed-to-seedling transition rate (σ), and the number of rhizomes produced by vegetative reproduction at different stages (P^k), adjusting each by ±10% or ±1% (Figure 9 and Table 4, see supplementary material S8).

Results show a clear hierarchy of parameter influence. Seed production exhibits the strongest sensitivity: a 10% decrease reduces total losses to 5.13×10^6 CNY, whereas a 10% increase raises losses to 6.35×10^6 CNY and markedly increases treatment demand, particularly in high-density regions such as Sheyang and Dafeng. In contrast, perturbations in σ produce only minor changes in aggregate outcomes, indicating effective buffering by density regulation and optimized control. Vegetative propagation has intermediate, stage-dependent effects, with increased late-stage rhizome production modestly elevating control effort and losses in later periods (T = 5-8), while early-stage propagation remains less influential.

Across all scenarios, the model consistently prioritizes regions with high invasion potential, indicating that spatial heterogeneity and local population dynamics are primary drivers of budget allocation decisions. These results suggest that management strategies should account for the potential impacts of variations in critical ecological parameters to optimize intervention timing, intensity, and regional allocation while minimizing cumulative economic losses.

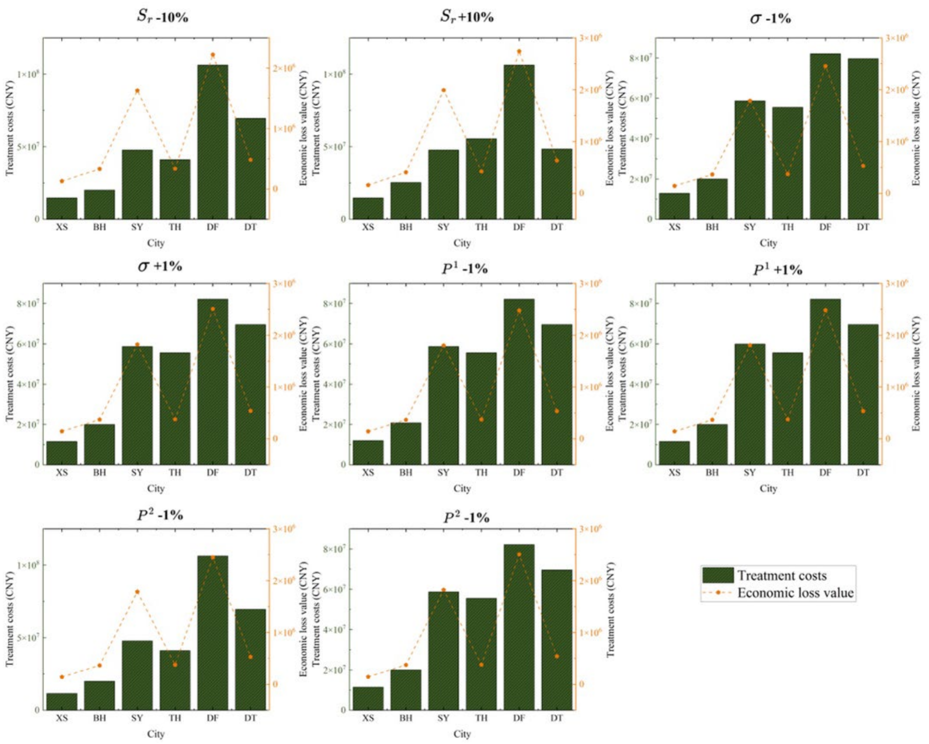

Figure 9. Regional budget allocations and economic losses under other parameter-sensitivity analyses

Table 4. Decision outcomes from other parameter-sensitivity analyses

S_r-10%	**XS**	**BH**	**SY**	**TH**	**DF**	**DT**	**S_r+10%**	**XS**	**BH**	**SY**	**TH**	**DF**	**DT**	**σ-1%**	**XS**	**BH**	**SY**	**TH**	**DF**	**DT**
T=1	✓	✓	✓	✓	✓	✓	T=1	✓	✓	✓	✓	✓	✓	T=1	✓	✓	✓	✓	✓	✓
T=2	✓	✓	✓	✓	✓	✓	T=2	✓	✓	✓	✓	✓	✓	T=2	✓	✓	✓	✓	✓	✓
T=3	✓	✓	✓	✓	✓	✓	T=3	✓	✓	✓	✓	✓	✓	T=3	✓	✓	✓	✓	✓	✓
T=4	✓	✓	✓	✓	✓	✓	T=4	✓	✓	✓	✓	✓		T=4	✓	✓	✓	✓	✓	✓
T=5	✓	✓	✓	✓	✓		T=5	✓	✓	✓	✓	✓		T=5	✓	✓	✓	✓	✓	
T=6	✓	✓	✓		✓		T=6	✓	✓	✓	✓	✓		T=6	✓	✓	✓	✓		
T=7	✓	✓					T=7	✓	✓					T=7	✓	✓	✓			
T=8	✓						T=8	✓	✓					T=8	✓					
σ+1%	**XS**	**BH**	**SY**	**TH**	**DF**	**DT**	**P^1+1%**	**XS**	**BH**	**SY**	**TH**	**DF**	**DT**	**P^1+1%**	**XS**	**BH**	**SY**	**TH**	**DF**	**DT**
T=1	✓	✓	✓	✓	✓	✓	T=1	✓	✓	✓	✓	✓	✓	T=1	✓	✓	✓	✓	✓	✓
T=2	✓	✓	✓	✓	✓	✓	T=2	✓	✓	✓	✓	✓	✓	T=2	✓	✓	✓	✓	✓	✓
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T=4	✓	✓	✓	✓	✓	✓	T=4	✓	✓	✓	✓	✓	✓	T=4	✓	✓	✓	✓	✓	✓
T=5	✓	✓	✓	✓	✓		T=5	✓	✓	✓	✓	✓		T=5	✓	✓	✓	✓	✓	
T=6	✓	✓	✓	✓			T=6	✓	✓	✓	✓			T=6	✓	✓	✓	✓		
T=7	✓	✓	✓				T=7			✓				T=7	✓	✓				
T=8							T=8	✓	✓					T=8			✓			
P^2-1%	**XS**	**BH**	**SY**	**TH**	**DF**	**DT**	**P^2+1%**	**XS**	**BH**	**SY**	**TH**	**DF**	**DT**							
T=1	✓	✓	✓	✓	✓	✓	T=1	✓	✓	✓	✓	✓	✓							
T=2	✓	✓	✓	✓	✓	✓	T=2	✓	✓	✓	✓	✓	✓							
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T=4	✓	✓	✓	✓	✓	✓	T=4	✓	✓	✓	✓	✓	✓							
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T=7	✓	✓					T=7	✓	✓	✓										

5. Discussion

This study develops an integrated Data-Driven-Simulation-Optimization (DDSO) framework to dynamically design and evaluate invasive species management under ecological and economic constraints. By coupling data-driven parameter estimation with a life-cycle-based time-varying dynamic simulation and a mixed-integer optimization model, the framework links ecological processes with operational decision-making, enabling systematic evaluation of management strategies across heterogeneous regions and intervention schedules. Across all experimental dimensions, a set of consistent and non-trivial decision insights emerges that transcends individual scenarios.

Framework precedence over intensity. Once biological invasions reach a regional scale, the order of magnitude of economic losses is determined primarily by whether an optimized control framework is in place, rather than by marginal adjustments in control intensity. This underscores that, in complex ecological systems, establishing coordinated and forward-looking decision structures is more fundamental than localized optimization of effort.

Unevenness as efficiency. Economically efficient management naturally entails highly uneven spatial allocation of resources, with investments concentrated in key transmission or leverage nodes (e.g., Sheyang and Dafeng in this study). Pursuing spatially uniform loss reduction can, counterintuitively, undermine overall budget efficiency, challenging the intuitive association between equitable allocation and effective management.

Ecological complexity enhances robustness, not cost. Incorporating finer ecological process representations (e.g., life-history structure) does not increase total costs or aggregate losses. Instead, it improves strategy robustness by generating smoother and more sustainable control trajectories. This challenges the common concern that greater model complexity necessarily entails higher management costs, highlighting ecological realism as a mechanism for avoiding short-term, high-intensity interventions and achieving long-term stability.

Budget saturation and regime shifts. The marginal effectiveness of budget increases exhibits a clear threshold effect. Beyond this threshold, additional investments primarily translate into greater persistence and spatial coverage of control, rather than further loss reduction. This indicates a qualitative shift in allocation logic: pre-threshold investments aim to reverse system trajectories, whereas post-threshold investments focus on maintaining long-term stability.

Risk levels reshape management objectives. Under high invasion pressure, management resources shift from instruments of loss minimization to buffers against systemic loss escalation. In such contexts, the primary objective should move away from reducing absolute losses toward preventing cascading and system-wide amplification, emphasizing the integration of routine management with risk-tiered response strategies.

Timing shapes intensity, not spatial priority. While intervention timing critically affects loss magnitude and the degree of resource concentration, optimal spatial priorities remain structurally determined by underlying ecological and dispersal processes and are largely invariant to budget or timing assumptions. Effective strategies therefore require early initiation to secure system-wide benefits, alongside a stable anchoring of structurally critical regions.

Allocation must track dynamic connectivity, not static risk. In the presence of migration, optimal control must shift from responding to static regional risks toward targeting dynamic dispersal pathways. Ignoring ecological connectivity leads to systematic misallocation of resources and higher cumulative losses, even under identical budget constraints.

Overall, this study advances a hierarchical decision logic: control frameworks determine loss magnitude, spatiotemporal allocation determines management efficiency, and the depth of ecological representation determines pathway robustness. Strategically, invasive species governance should prioritize coordinated optimization architectures, deliberately adopt uneven leverage-based interventions, and recognize how budgets, risks, and timing jointly trigger fundamental shifts in management objectives to balance resilience and efficiency in dynamic environments.

6. Conclusion and future work

This study proposes and implements an integrated Data-Driven-Simulation-Optimization (DDSO) framework to support spatiotemporal management of coastal S. alterniflora under constrained public budgets. By integrating heterogeneous multi-source observations, the framework constructs time-varying ecological parameters that characterize evolving invasion dynamics. These parameters are embedded within a stage-structured population simulation and a mixed-integer optimization model to determine cost-effective intervention timings, intensities, and regional budget allocations. Extensive scenario experiments–covering variations in budget levels, invasion intensity, intervention timing, dispersal conditions, and key ecological parameters–demonstrate the practical value of the DDSO framework in generating actionable, data-informed management strategies.

Despite establishing this multi-source DDSO framework and conducting systematic analyses across diverse budgets, invasion intensities, and intervention scenarios, several limitations remain. First, many model parameters are derived from historical monitoring data and expert assumptions, without fully incorporating randomness and uncertainty, which may underestimate management needs under extreme conditions. Second, this study focuses primarily on minimizing economic losses as a single objective, without fully accounting for ecosystem services, social acceptance, or multi-stakeholder trade-offs. Third, the mixed-integer optimization model faces computational challenges in large-scale scenarios, requiring dedicated algorithms and high-performance computing resources.

Future research can be expanded in several directions: First, although the present study adopts economic loss minimization to maintain a transparent and tractable core structure, the model can be naturally extended to multi-objective formulations that incorporate ecosystem services, ecological resilience, and social considerations, thereby enabling explicit trade-off analysis in real-world management. Second, uncertainty-aware decision-making can be strengthened by integrating multi-stage stochastic or robust optimization approaches, enabling management strategies to remain effective under environmental variability and parameter uncertainty. Third, further advances in computational efficiency, including decomposition techniques, heuristic or approximate dynamic programming methods, and GIS-based decision-support interfaces, would enhance scalability and facilitate practical implementation by management agencies. Collectively, these extensions would improve the ecological realism, policy relevance, and operational robustness of the proposed framework, supporting adaptive and sustainable long-term management of coastal invasive species.

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Data availability

The authors declare that all data supporting the findings of this study are available within the article.

Disclosure of interest

There are no relevant financial or non-financial competing interests to report.

References

An, Y. T., Chen, Z. Z., Chen, G. Y., Yin, P., Gao, Z. D., & Li, C. R. (2024). Current status and eradication strategy of invasive alien plants Spartina alterniflora in coastal zones of Jiangsu

Province. *Journal of Jiangsu Forestry Science & Technology*, 51(2), 43-47.

An, S. Q., Gu, B. H., Zhou, C. F., Wang, Z. S., Deng, Z. F., Zhi, Y. B., ... & Liu, Y. H. (2007). Spartina invasion in China: implications for invasive species management and future research. *Weed Research*, 47(3), 183-191.

Aota, T., Ashizawa, K., Mori, H., Toda, M., & Chiba, S. (2021). Detection of Anolis carolinensis using drone images and a deep neural network: an effective tool for controlling invasive species. *Biological Invasions*, 23(5), 1321-1327.

Baker, C. M., Diele, F., Lacitignola, D., Marangi, C., & Martiradonna, A. (2019). Optimal control of invasive species through a dynamical systems approach. *Nonlinear Analysis: Real World Applications*, 49, 45-70.

Barnes, B., Parsa, M., Giannini, F., & Ramsey, D. (2023). Analytical Bayesian approach for the design of surveillance and control programs to assess pest-eradication success. *Theoretical Population Biology*, 149, 1-11.

Bushaj, S., Büyüktahtakın, I. E., & Haight, R. G. (2022). Risk-averse multi-stage stochastic optimization for surveillance and operations planning of a forest insect infestation. *European Journal of Operational Research*, 299(3), 1094-1110.

Büyüktahtakın, İ. E., Feng, Z., & Szidarovszky, F. (2014). A multi-objective optimization approach for invasive species control. *Journal of the Operational Research Society*, 65(11), 1625-1635.

Büyüktahtakın, I. E., & Haight, R. G. (2018). A review of operations research models in invasive species management: state of the art, challenges, and future directions. *Annals of Operations Research*, 271(2), 357-403.

Carrillo, C. C., Charbonneau, B. R., Altman, S., Keele, J. A., Pucherelli, S. F., Passamaneck, Y. J., ... & Swannack, T. M. (2023). Patterns of dreissenid mussel invasions in western US lakes within an integrated gravity model framework. *Journal of Environmental Management*, 332, 117383.

Chen, B. M., Peng, S. L., Wu, X. P., Wang, P. L., & Ma, J. X. (2016). A bibliometric analysis of researches on topics related to the ecological damage caused by and risk assessments of exotic invasive species from 1995 to 2014. *Acta Ecologica Sinica*, 36(20), 6677-6685.

Dia, B. M., Diagne, M. L., & Goudiaby, M. S. (2020). Optimal control of invasive species with economic benefits: Application to the Typha proliferation. *Natural Resource Modeling*, 33(2), e12268.

Eppinga, M. B., Baudena, M., Haber, E. A., Rietkerk, M., Wassen, M. J., & Santos, M. J. (2021). Spatially explicit removal strategies increase the efficiency of invasive plant species control. *Ecological Applications*, 31(3), e02257.

Fancourt, B. A., Augusteyn, J., Cremasco, P., Nolan, B., Richards, S., Speed, J., ... & Gentle, M. N. (2021). Measuring, evaluating and improving the effectiveness of invasive predator control programs: Feral cat baiting as a case study. *Journal of Environmental Management*, 280, 111691.

Haight, R. G., Kinsley, A. C., Kao, S. Y., Yemshanov, D., & Phelps, N. B. (2021). Optimizing the location of watercraft inspection stations to slow the spread of aquatic invasive species. *Biological Invasions*, 23(12), 3907-3919.

Haight, R. G., Yemshanov, D., Kao, S. Y., Phelps, N. B., & Kinsley, A. C. (2023). A bi-level model for state and county aquatic invasive species prevention decisions. *Journal of Environmental Management*, 327, 116855.

Hayasaka, D., Nakagawa, M., Maebara, Y., Kurazono, T., & Hashimoto, K. (2020). Seed germination characteristics of invasive Spartina alterniflora Loisel in Japan: implications for its effective management. *Scientific Reports*, 10(1), 2116.

Howerton, E., Langkilde, T., & Shea, K. (2024). Misapplied management makes matters worse: Spatially explicit control leverages biotic interactions to slow invasion. *Ecological Applications*, 34(4), e2974.

Hudgins, E. J., Liebhold, A. M., & Leung, B. (2020). Comparing generalized and customized spread models for nonnative forest pests. *Ecological Applications*, 30(1), e01988.

Hultberg, T., Sandström, J., Felton, A., Öhman, K., Rönnberg, J., Witzell, J., & Cleary, M. (2020). Ash dieback risks an extinction cascade. *Biological Conservation*, 244, 108516.

Jafari, N., Phillips, A., & Pardalos, P. M. (2018). A robust optimization model for an invasive species management problem. *Environmental Modeling & Assessment*, 23(6), 743-752.

Kıbış, E. Y., & Büyüktahtakın, İ. E. (2017). Optimizing invasive species management: A mixed-integer linear programming approach. *European Journal of Operational Research*, 259(1), 308-321.

Kıbış, E. Y., Büyüktahtakın, İ. E., Haight, R. G., Akhundov, N., Knight, K., & Flower, C. E. (2021). A multistage stochastic programming approach to the optimal surveillance and control of the emerald ash borer in cities. *INFORMS Journal on Computing*, 33(2), 808-834.

Kumar, V., Nunez, A., Brown, K., Agarwal, K., Hall, S., & Bode, M. (2022). Prioritising the eradication of invasive species from island archipelagos with high reinvasion risk. *Journal of Applied Ecology*, 59(12), 3003-3013.

Lampert, A., & Liebhold, A. M. (2023). Optimizing the use of suppression zones for containment of invasive species. *Ecological Applications*, 33(2), e2797.

Liu, H., Lin, Z., Zhang, M., & Qi, X. (2017). Relative importance of sexual and asexual reproduction for range expansion of Spartina alterniflora in different tidal zones on Chinese coast. *Estuarine, Coastal and Shelf Science*, 185, 22-30.

Liu, M., Wu, J., Zhang, S., & Liang, J. (2023). Cyanobacterial blooms management: A modified optimization model for interdisciplinary research. *Ecological Modelling*, 484, 110480.

Luo W.D., Zhang X. Y., Chen Z. B., Huo G. Y., Zhang R., & Mu L. P. (2026) Invader Defender:

Multimodal recognition of invasive alien species via a large language model with vision-guided targeted RAG. *Expert Systems with Applications*, 302, 130478.

Marangi, C., Martiradonna, A., & Ragni, S. (2023). Optimal resource allocation for spatiotemporal control of invasive species. *Applied Mathematics and Computation*, 439, 127614.

Min, Y. K., Ke, Y. H., Han, Y., Yin, X. L., & Zhou, D. M. (2023). Dynamic monitoring of invasive Spartina alterniflora clearance via fusion of Sentinel-2 and GF-1 time series images. *National Remote Sensing Bulletin*, 27(6), 1467-1479.

Nishimoto, M., Miyashita, T., Yokomizo, H., Matsuda, H., Imazu, T., Takahashi, H., ... & Fukasawa, K. (2021). Spatial optimization of invasive species control informed by management practices. *Ecological Applications*, 31(3), e02261.

Onal, S., Akhundov, N., Büyüktahtakın, İ. E., Smith, J., & Houseman, G. R. (2020). An integrated simulation-optimization framework to optimize search and treatment path for controlling a biological invader. *International Journal of Production Economics*, 222, 107507.

Rosso, A., & Venturino, E. (2023). A dynamic programming approach to ecosystem management. *Algorithms*, 16(3), 139.

Salgado-Rojas, J., Hermoso, V., & Álvarez-Miranda, E. (2025). Optimising management against dynamic threats: A spatially explicit approach based on integer programming. *Methods in Ecology and Evolution*, 16(8), 1868-1885.

Tanga, C. M., Ghemoh, C. J., Tonnang, H. E., Suresh, S., Kimathi, E. K., Mohamed, S. A., ... & Ekesi, S. (2021). Eco-climatic matching to guide foreign exploration and optimal release strategies for biological control agents of Rastrococcus iceryoides in Africa and Asia. *Biological Control*, 158, 104603.

Trilla, G. G., Kandus, P., Negrin, V., Vicari, R., & Marcovecchio, J. (2009). Tiller dynamic and production on a SW Atlantic Spartina alterniflora marsh. *Estuarine, Coastal and Shelf Science*, 85(1), 126-133.

Wang, N., Li, W. F., Zhou, B., & Yan, X. H. (2016). Invasiveness, clonal form and geographical origin of invasive clonal plant species in China. *Biodiversity Science*, 24, 12.

Wang G. X., Yu J. X., Xu W. K., Muhammad A., & Li, D. L. (2025). Automated fish counting system based on instance segmentation in aquaculture. *Expert Systems with Applications*, 259, 125318.

Wang, X. Y., Zhou, Y. P., Xue, Y. F., Cheng, J. Y., Liu, W. W., & Zhang, Y. H. (2021). Seed germination characteristics of Spartina alterniflora from high and low latitude populations in relation to temperature. *Chinese Journal Ecology*, 40(9), 2763-2772.

Wu, L., & Wu, W. T. (2023). The optimum time window for Spartina alterniflora classification based on the filtering algorithm and vegetation phonology using GEE. *Journal of Geo-information Science*, 25(3), 606-624.

Xu, W. W., Wang, G. X., Liu, J. E., Chen, Z. Y., Hang, Z. Q., & Wang, H. (2014). Two reproductive mode of Spartina alterniflora on coastal wetland of North Jiangsu. *Acta Ecologica Sinica*, 34(14), 3839-3847.

Yemshanov, D., Haight, R. G., Koch, F. H., Lu, B., Venette, R., Fournier, R. E., & Turgeon, J. J. (2017). Robust surveillance and control of invasive species using a scenario optimization approach. *Ecological Economics*, 133, 86-98.

Yemshanov, D., Haight, R. G., Koch, F. H., Venette, R. C., Swystun, T., Fournier, R. E., ... & Turgeon, J. J. (2019). Optimizing surveillance strategies for early detection of invasive alien species. *Ecological Economics*, 162, 87-99.

Yemshanov, D., Haight, R. G., Liu, N., Chen, C., MacQuarrie, C. J., Ryall, K., ... & Koch, F. H. (2020b). Acceptance sampling for cost-effective surveillance of emerald ash borer in urban environments. *Forestry: An International Journal of Forest Research*, 93(2), 280-296.

Yemshanov, D., Haight, R. G., MacQuarrie, C. J., Koch, F. H., Liu, N., Venette, R., & Ryall, K. (2020a). Optimal planning of multi-day invasive species surveillance campaigns. *Ecological Solutions and Evidence*, 1(2), e12029.

Zhang, S., Liu, M., & Wang, P. (2025). Resource allocation for Hyphantria cunea invasive management: A novel simulation-based optimization model. *Applied Mathematical Modelling*, 138, 115771.