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The Economic and Ecological Benefits of the Optimal Control Measures for Pine Wood Nematode Disease in Weihai City, China

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Abstract

Pine wilt disease poses a significant threat to forest ecosystems. This study evaluates the efficacy and economic–ecological benefits of its control measures in Weihai City, China, from 2019 to 2022. Employing disaster economics theory and a simultaneous equation model, we analyzed control performance, influencing factors, and optimal strategies, estimating costs and losses under actual, optimal, and no-control scenarios. The results show that the optimal investment is 70.63 CNY per dead tree. Each additional treated hectare averts 119.6 tree deaths, and every 10,000 CNY invested prevents 88.5 mortalities. Economic benefits increased sharply from 2.169 to 94.749 billion CNY, while ecological benefits also grew substantially. However, control inputs in 2019 were insufficient, and subsequent years revealed opportunities for more efficient allocation, despite persistent constraints like limited funding and personnel. We recommend implementing a precision budgeting model with dynamic adjustment model and an integrated township-level management system to optimize control outcomes.

Keywords: pine wood nematode disease; optimal prevention and control strategy; expected cost; economic benefits; ecological benefits

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1. Introduction

The pine wood nematode (*Bursaphelenchus xylophilus*), identified as the primary exotic forestry quarantine pest in China, presents a grave threat owing to its high pathogenicity and destructiveness. First detected in Nanjing in 1982, the disease has gradually disseminated across the country. By 1999, it had spread to 53 counties in five provinces, resulting in 5.57 million dead trees, marking the first historical peak [1]. Research from Zhejiang Province indicates that from 1991 to 2005, the disease devastated over 340,000 hectares of pine forest, leading to the death of more than 33 million trees and the degradation of 3400 hectares of forestland, demonstrating its significant destructive potential [1]. By the end of 2020, the number of dead pine trees had escalated to 19.47 million, and the affected area reached 1.81 million hectares [2]. Infection causes rapid tree mortality, typically within

40 days, and can lead to the destruction of entire pine forests within 3–5 years. Consequently, it has been termed "pine cancer" and is listed among the national key targets for prevention and control [3–5]. Natural dispersal is primarily mediated by vector longhorn beetles (*Monochamus* spp.), while human activities, particularly the transportation of infested wood, account for approximately 75% of spread incidents [6]. Coupled with climate changes, the pathogen has gradually expanded northward and westward, rendering most regions in China potentially suitable habitats and significantly intensifying the nationwide prevention and control pressure [7,8]. The economic impact is substantial, with losses in 2020 alone estimated at 19.5 billion Chinese yuan, affecting national ecological security and socio-economic development [9–11].

Weihai City is chosen as a key case study owing to its substantial ecological significance, its position as a pilot area designated by the Disease Control Center of the National Forestry and Grassland Administration, and the exemplary value of its control practices for nationwide dissemination. Situated at the easternmost tip of the Shandong Peninsula, Weihai City boasts rich pine forest resources that act as vital ecological barriers, offering coastal protection, landscape tourism, and other irreplaceable functions. Similar to Zhoushan in Zhejiang, Weihai's pine forests play a vital role in "water conservation, soil preservation, windbreak and sand fixation, and national defense" [3], and their ecological value often surpasses direct economic value. Therefore, the prevention and control of Pine Wood Disease (PWD) in Weihai not only pertains to forestry production but also relates to the maintenance of regional ecological security. Currently, Weihai faces control challenges common to many infected areas: continuously increasing infection sites, expanding epidemic ranges, and persistently high numbers of dead pine trees [12].

The Chinese government has long attached great importance to this issue. As early as 1989, relevant regulations were promulgated, and PWD was included in national key research projects [2]. Through years of practice, an integrated control technology system has been established [12]. For instance, the application of microwave treatment technology can reduce the processing costs while offering environmental advantages [13]. The successful practice in Jiangshan City, which combined measures such as enhancing prevention levels and stimulating market vitality, achieved a significant reduction in disease severity [14]. Since the 14th Five-Year Plan period, the state has further strengthened systemic construction. The implementation of measures such as the Five-Year Action Plan for National Pine Wilt Disease Prevention and Control (2021–2025) has achieved phased results, effectively curbing the rapid spread of the epidemic [2]. However, research and surveys indicate that the current system still confronts significant challenges. A national questionnaire survey revealed severe shortages in personnel and funding as critical constraints [2,5]. Therefore, merely increasing workloads and financial inputs indefinitely does not guarantee optimal outcomes [15]. Given limited resources, it is essential to identify the optimal level of prevention and control investment and evaluate the economic and ecological benefits generated by different strategies.

Regarding optimal resource allocation, disaster economics theory posits that minimizing the total risk cost (the sum of expected loss and mitigation investment) represents the optimal strategy [16]. A non-linear relationship often exists between mitigation measures and outcomes. The optimal investment corresponds to the point where the marginal cost of prevention equals the marginal benefit of loss avoidance [17,18]. Scholars have employed various frameworks, such as econometric and meta-analytical models, to establish non-linear cost–benefit relationships and measure the returns of disaster prevention investments [19–21]. In the context of benefit evaluation, methods have been developed to assess efficiency based on risk and loss indicators [22]. Scenario analyses and integrated

assessments have been conducted to estimate losses from PWD and evaluate management impacts on forest ecosystem services [23–25].

The existing literature provides a valuable foundation in theoretical frameworks and empirical case studies [1,26]. However, a significant research gap remains: few studies have applied systematic economic principles to determine the optimal investment threshold specifically for PWD control at a regional scale. Most assessments focus on quantifying losses or reporting the benefits of single measures. There is scarce dedicated research that compares the cost-effectiveness of different strategy combinations under regional constraints and evaluates the comprehensive economic and ecological benefits generated by optimized control strategies. Therefore, this study aims to address this gap. Taking Weihai City as a case study, we construct a comprehensive analytical framework based on its specific context. The objective is to analyze potential optimal prevention and control strategy combinations and subsequently evaluate and compare the economic and ecological benefits arising from both current measures and theoretically optimal strategies. This will provide evidence-based insights for improving resource allocation and enhancing prevention and control efficacy in practice.

2. Materials and Methods

2.1. Theoretical Analysis and Evaluation Indicator System Construction

2.1.1. Disaster Economics Theory of PWD

In accordance with the principles of disaster economics, which aim to minimize the sum of expected losses and mitigation investments, this research utilizes its framework to conduct an analysis of PWD—a diffusible and continuously managed biological disaster that poses a central challenge of optimal resource allocation. By means of cost–benefit analysis, it endeavors to determine the economic equilibrium point at which the marginal cost of control is equivalent to the marginal reduction in losses, thus offering a foundation for formulating cost-effective and sustainable control strategies [16]. Let the horizontal axis (R) denote the response capacity and the vertical axis (L) represent the expected losses. In Figure 1, curve L depicts the projected disaster losses amount (presented positively for the convenience of analysis). This curve slopes downward to the right, indicating that losses exhibit a continuous decline as the response capacity improves. When the response capacity is initially at a low level, the expected losses decline rapidly with an increase in capacity. Nevertheless, after reaching a certain threshold, the rate of decrease in expected losses decelerates. This implies that at this stage, further enhancements in response capacity result in relatively smaller reductions in disaster losses, causing the expected loss curve L to become increasingly flat.

Curve C represents the disaster-mitigation investment amount, which is defined as the cost required to attain any given level of response capacity (also presented positively). It is an upward-sloping curve, signifying that a higher level of response capacity necessitates higher investment costs. In the initial stages (when the response capacity is low), the cost increases gradually, suggesting that disaster-mitigation investments can significantly augment the response capability. Conversely, when the response capacity is already at a high level, the cost rises more steeply. This indicates that beyond a certain point, achieving further improvements in response capacity becomes more arduous and demands substantially larger investment, as reflected in the increasingly steep slope of the mitigation investment curve C.

The L+C curve employs capital volume as the verification unit. This curve depicts the aggregate of expected loss and mitigation investment, and its configuration initially declines and subsequently ascends. This demonstrates that as response capacity improves, the value of (L+C) continuously declines until it reaches a minimum point, after which it starts to rise

again. It is shown that point A denotes the inflection point of risk minimization, which is the point where the disaster caused by the minimum investment of funds is minimized at any specific time.

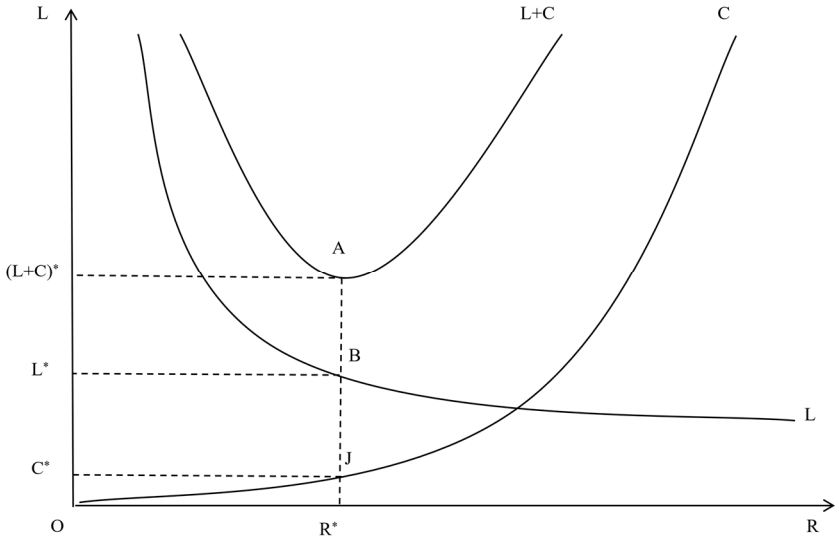


Figure 1. Analysis diagram of the optimal control strategy for disaster losses. R: response capacity; L: expected losses; C: disaster-mitigation investment; L+C: sum of expected losses and mitigation investments; A: optimal point for mitigation investment; C*: optimal investment level; L*: expected loss at optimal point; (L+C)* is the optimal prevention and control strategy, with point A corresponding to the lowest point on the L+C curve; B is the intersection point of the optimal strategy on curve L; J is the intersection point of the optimal strategy on curve C; R* is the intersection point of the optimal strategy on the horizontal axis R.

As illustrated in Figure 1, Point *A* represents the minimum of the *L+C* curve. The point B on the L curve corresponding to point A denotes the relative equilibrium of disaster loss under the optimal measure, with a value of L*. The point J on the C curve corresponding to point A represents the optimal level of capital input at the equilibrium point, with a value of C*.

To the left of Point *A*, the response capability is relatively limited. Although the requisite mitigation investment is also minimal, the resultant loss is substantial, leading to a total that has not yet attained its minimum value. Therefore, it is imperative to augment the mitigation investment further to improve the response capability and, in turn, diminish the disaster losses.

To the right of Point *A*, the loss is relatively smaller; however, the corresponding cost is relatively higher. The risk cost has not reached its minimum, suggesting an excessive investment in risk mitigation. The cost incurred for loss avoidance at this stage is excessively high, thus necessitating a reduction in risk-mitigation investment [16].

2.1.2. Indicator System, Data Sources, and Characteristics

From 2019 to 2022, data related to 23 indicators associated with the occurrence, control, and economic investment of PWD were collected from the Huancui, Wendeng, Rongcheng, Rushan, Gaogu, Jingqu, and Lingang districts in Weihai City, as shown in Table 1. On average across the city's districts and counties, the number of dead trees reached 324,000, the affected area was 7614 hectares, and the area of host tree species was 11,445.23 hectares on average annually. The incidence rate reached 71.42%, with an average of 33.08 dead trees per hectare. The control area covered average 13,958.21 hectares, corresponding to a control rate of 188.29%, while the monitoring area extended to average 29,463.88 hectares per year. Control measures were implemented 2 to 3 times on average annually, involving approx-

imately 209 personnel and 241 work-days. Technical training sessions were organized 224 times, and publicity activities were conducted 9 to 10 times per year on average.

Table 1. Indicator construction and explanation.

Indicator Name	Unit	Indicator Explanation	Mean
Dead Pine Trees	tree	Number of pine trees completely withered due to PWD	324,044.9
Affected Area	hectare	Total area of pine forest affected by PWD	7614.392
Host Tree Species Area	hectare	Total area of pine forest (host species)	11,445.23
Incidence Rate	%	Affected area/host tree species area	71.42%
Control Area	hectare	Total area where control measures were implemented	13,958.21
Monitoring Area	hectare	Total area monitored annually for PWD	29,463.88
Number of Control Applications	time	Total number of control applications per year	2786
Number of Control Personnel	person	Total number of personnel involved in control measures per year	208.893
Workdays for Control	day	Total number of workdays invested in control measures per year	240.786
Technical Training Participants	person	Total number of participants in technical training within the region	223.964
Publicity Campaigns	time	Total number of organized publicity campaigns	9571
Chemical Control Area	hectare	Total area sprayed with efficient, low-toxicity, and environmentally friendly pesticides during the vector beetle emergence period	12,343.86
Silvicultural Control Area	hectare	Area treated with infected wood removal measures such as selective cutting, clear-cutting, and stump treatment	7650.198
Aerial Control Area	hectare	Annual area treated with aerial pesticide application for vector insect control	14,826.04
Outsourced Control Area	hectare	Total annual area controlled by hired specialized companies	10,143.19
Cost of Hiring Specialized Companies	10^4 CNY	Annual investment in hiring specialized control companies	2034.688
Total Investment	10^4 CNY	Sum of eradication, preventive, and management investments	2331.158
Eradication Investment	10^4 CNY	Costs used for removing and disposing of dead pine trees	1741.017
Preventive Investment	10^4 CNY	Costs used for monitoring, prevention, and trapping of vector insects	477.779
Management Investment	10^4 CNY	Costs used for personnel wages, organizational operations, etc.	11.797
Fiscal Allocation	10^4 CNY	Annual central fiscal appropriation	345.355
Locally Raised Funds	10^4 CNY	Annual investment funds raised locally	1874.991
Revenue from Infected Wood Sales	10^4 CNY	Total annual revenue from selling infected wood within the region	101.298
Annual Output Value of Disposal Co.	10^4 CNY	Total annual revenue of enterprises specializing in infected wood disposal	968.731
Number of Disposal Enterprises	company	Total number of infected wood disposal companies	9.643

Note: the "Mean" values are averages across the studied districts and years (2019–2022).

Regarding specific control measures, the area subjected to chemical control amounted to 12,343.86 hectares, silvicultural measures were implemented on 7650.20 hectares, aerial control covered an area of 14,826.04 hectares, and the area for which control was outsourced to specialized companies was 10,143.19 hectares. The average cost of engaging these specialized control companies was 20.347 million yuan. The total average annual

investment reached 23.312 million yuan, which encompassed 17.410 million yuan for eradication measures, 4778 million yuan for preventive measures, and 0.118 million yuan for management expenses.

Regarding funding sources, the average annual fiscal appropriation amounted to 3454 million yuan, whereas the average amount of locally-raised funds reached 18.750 million yuan. The average annual income from the sale of infected wood was 1013 million yuan. The average annual output value of enterprises specialized in infected wood disposal stood at 9687 million yuan, and there were approximately 9 to 10 such enterprises operating within the region.

2.2. Research Methodology and Model Specification

2.2.1. Simultaneous Equation Model

The correlation functions among the control measures (R), financial input (C), and the quantity of dead trees (L) were fitted, as presented in Figures 2–4. A quadratic correlation exists between the control area and both the quantity of dead trees and the financial input. To conduct an analysis of extreme scenarios, a quadratic term was incorporated into the equations for these relationships. In contrast, the relationship between financial input and the quantity of dead trees is linear. Based on these findings, the research equations were formulated accordingly.

$$C = \beta_1 R + \beta_2 R^2 + \beta_3 L + Z_1 \quad (1)$$

$$L = \delta_1 R + \delta_2 R^2 + \delta_3 C + Z_2 \quad (2)$$

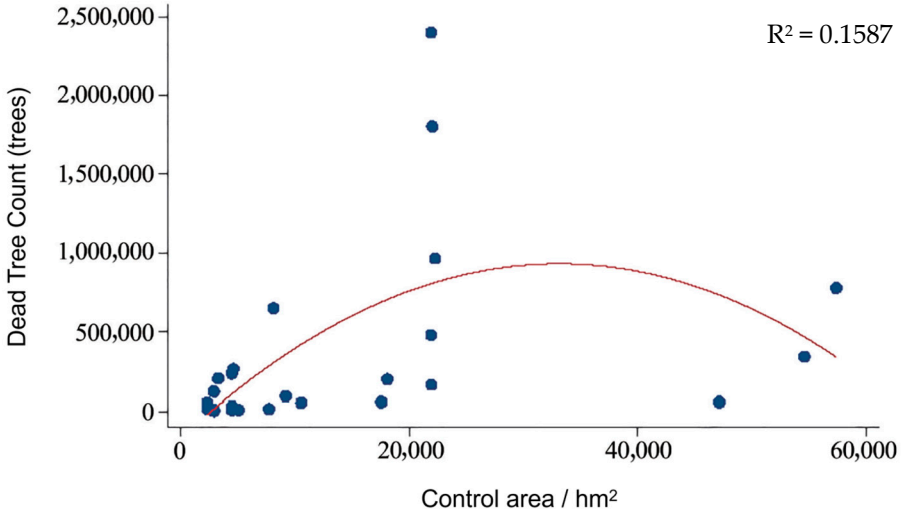


Figure 2. Relationship between control area and dead tree count. The red line is the fitted curve corresponding to the reduction in dead trees caused by diseases after the implementation of prevention and control measures, and the blue points are the fitted points corresponding to different scenarios.

Bivariate relationships were respectively established between control measures and the quantity of dead trees, as well as between control measures and financial investment. In Equation (1), the control measure (R) serves as the explained variable, which is also influenced by factors such as the frequency of control implementation, the number of personnel, and working days [27]. Meanwhile, monitoring measures rely on preventive funds, the income of control personnel depends on management funds, and funding sources are constrained by factors such as local self-raised funds and central fiscal allocations [28]. Concerning Equation (2), the quantity of dead trees is affected not only by the overall level of financial investment and control measures but also differentially influenced by specific control methods, including aerial control, outsourced control, chemical control, and

silvicultural measures [29]. To address potential endogeneity issues between the models, a simultaneous equation model was constructed to improve regression efficiency.

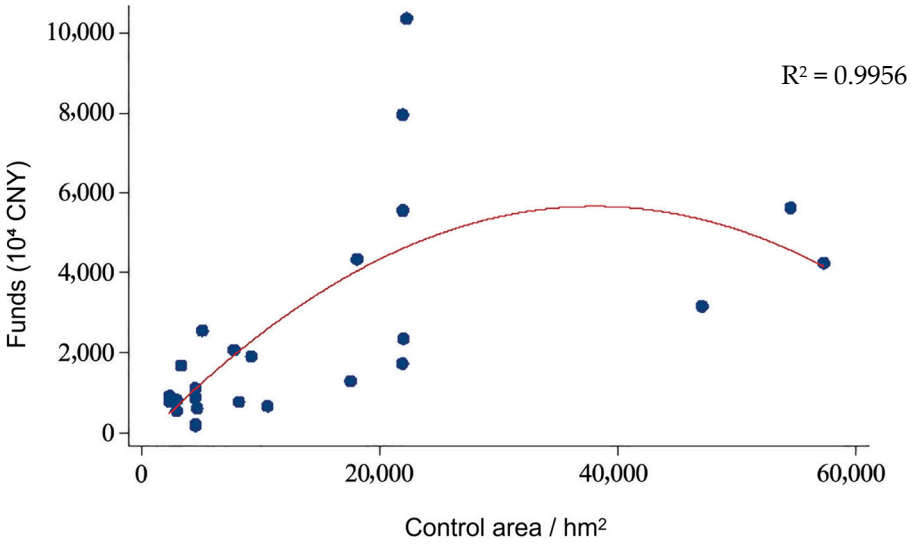


Figure 3. Relationship between control area and financial investment. The red line is the fitted curve corresponding to the amount of funds invested in prevention and control measures, and the blue points are the fitted points corresponding to different scenarios.

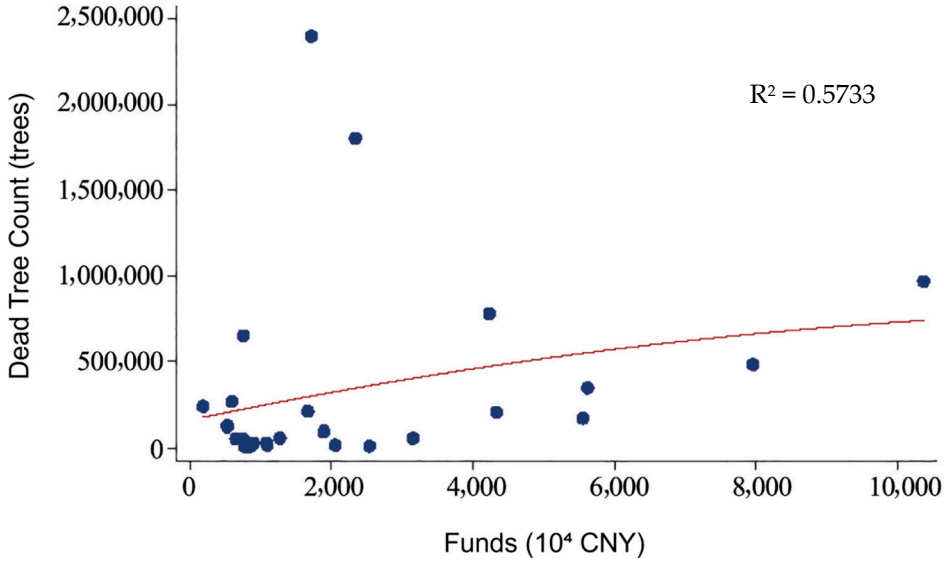


Figure 4. Relationship between financial investment and dead tree count. The red line is the fitted curve corresponding to the amount of funds invested and the number of dead trees treated, and the blue points are the fitted points corresponding to different scenarios.

Based on the theoretical foundation of disaster economics, identifying the minimum point involves

$$\frac{\partial(C+L)}{\partial R} = \frac{\partial\left(\beta_1 R + \beta_2 R^2 + \beta_3 L + Z_1 + \delta_1 R + \delta_2 R^2 + \delta_3 C + Z_2\right)}{\partial R} = \beta_1 + 2\beta_2 R + \delta_1 + 2\delta_2 R = 0 \quad (3)$$

$$R = -\frac{\beta_1 + \delta_1}{2\beta_2 + 2\delta_2} \quad (4)$$

2.2.2. Economic Cost and Benefit Evaluation Model

(1) Game Analysis of Prevention and Control Economic Costs

$$Measures\ Expected\ cost\ =\ E(C)\ =\ \sum_{j=1}^{n} P_j C_j \quad (5)$$

Reference is made to the decision-tree structure for pest control projects presented in the research on forestry uncertainty and risk by [30] to construct Figure 5. Within this framework, the variable j represents distinct regions, and the probability P corresponds to the incidence rate X of PWD. The cost C in this study incorporates both the actual input and the optimal input funds. The optimal input fund is estimated as the product of the quantity of dead trees (D) and the calculated optimal input per tree (C_Y). The probability of successful spray application is defined as the control effectiveness (R_e). D_w denotes the fitted quantity of anticipated pine tree deaths in the absence of any control measures.

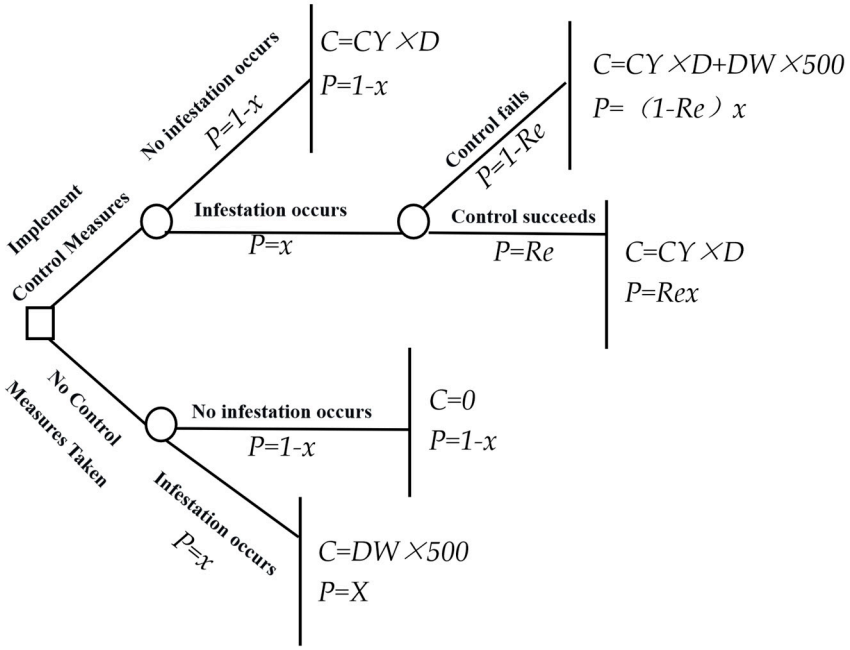


Figure 5. Decision game analysis diagram of prevention and control. In accordance with the technical specifications for pine forest management, when the planting spacings are 1.5 m × 2.0 m or 1.5 m × 1.5 m, the number of trees that can be planted per mu ranges from approximately 222 (sparse planting) to 297 (dense planting). Given that the pine forests in Weihai City are mainly natural and relatively dense, a median value of approximately 260 trees per mu is adopted, which is equivalent to 3900 trees per hectare.

Based on market prices, the costs of pine tree seedlings with soil balls are as follows: seedlings of 1.5 m in height cost 183 CNY, 2 m seedlings cost 414 CNY, 2.5 m seedlings cost 747 CNY, 3 m seedlings cost 1297 CNY, and 3.5 m seedlings cost 2427 CNY. Considering that Weihai is an epidemic area of PWD, which has an impact on forest value, a compromised mean price of 500 CNY per tree is used for calculation [31]. The expected cost is the product of price and quantity. Therefore, the expected cost in the "no-control" scenario is the product of the quantity of dead trees without control (D_w), the incidence rate (X), and the tree price. The expected cost in the "implement control" scenario is the sum of the cost invested when no infestation occurs and the total costs (including both investment and loss) for scenarios where infestation occurs with either successful or failed control outcomes.

$$\begin{gathered} E(C_{control}) = C_Y \times D \times (1 - X) + (1 - R_e)x \times (C_Y \times D + D_W \times 500) + R_e \times X \times C_Y \times D \\ E(C_{not\text{-}control}) = (1 - X) \times 0 + D_W \times 500 \times X \end{gathered} \quad (6)$$

(2) Fitting Analysis of Dead Trees under No Control Measures (D_w)

The literature suggests that PWD has the potential to cause the complete destruction of a forest within a period of 3 to 5 years [5]. By taking the median value, it is assumed that the complete loss of a forest occurs over a 4-year period. Based on the data from the initial year (2019), under the scenario where no control measures are implemented in Weihai City, assuming a constant annual forest loss rate H, the formula is as Table 2.

Table 2. Annual number of dead trees under no control measures.

Year	Formula for Cumulative Dead Trees	
Initial Year (2019)	$Number\ of\ dead\ trees\ (2019) = D$	(7)
Year 2	$D \times H + D$	
Year 3	$(D \times H + D) \times H + D \times H + D$	

Given that the analysis presupposes the non-implementation of any control measures, the annual tally of dead trees is cumulative. This indicates that it is hypothesized that dead trees from the preceding year remain unremoved, and the infestation propagates at an annual rate (H) in the subsequent year, gradually amassing over time. By the fourth year, the entire pine forest is utterly devastated. The total quantity of destroyed pine trees is computed as the ratio of the area of the host tree species to the estimated number of pine trees per unit area.

According to Formula (5), the overall forest destruction rate for Weihai City is calculated to be 2.796. This indicates that if a single tree is infected in the first year, and no control measures are implemented, the infected and dead pine tree may lead to approximately three additional pine trees in the surrounding area becoming infected and dying. Based on this destruction rate, the annual number of dead trees in a non-control scenario is fitted.

(3) Control Effectiveness Analysis (R_e)

The extant quantity of deceased trees denotes the annual fresh data under the implemented control measures. In contrast, the quantity of deceased trees in the non-control scenario (D_w) represents the annual cumulative data, assuming that infected trees are not eliminated. To facilitate comparative analysis, the quantity of deceased trees under the existing control measures is also converted into cumulative data (D_X). Consequently, the formula for control efficacy is derived as follows:

$$R_e = (D_W - D_X)/D_W \tag{8}$$

Given that the year 2019 is designated as the baseline period, the calculated control effectiveness corresponds to the time span from 2020 to 2022. Simultaneously, the data for 2019 utilize the annual average value of that particular year.

(4) Economic Benefits of Control Measures

The formula for calculating the economic benefits of implementing PWD control measures is as follows:

$$ES_i = E(C)_{\mathrm{wi}} - E(C)_{\mathrm{si}} \tag{9}$$

where

ES_i denotes the actual economic benefits in year i;

$E(C)_{wi}$ represents the expected cost in the absence of control measures in year i;

$E(C)_{si}$ represents the expected cost under the actual control input scenario in year i;

i represents the year, corresponding to the data from 2019 to 2022.

2.2.3. Ecological Benefits of Control Measures

The ecological benefits of the control measures were assessed by adopting the methodology formulated by [32]. A standard equivalent factor for the value of ecosystem services (hereafter denoted as the standard equivalent) is defined as the economic value of the annual natural grain output per hectare (hm^2) of the nationally average cropland. This value is mainly calculated based on three staple grain crops, namely rice, wheat, and corn. The calculation formula is presented as follows:

$$E = S_r \times F_r + S_w \times F_w + S_c \times F_c \quad (10)$$

where

E represents the monetary value of ecosystem services per standard equivalent factor (CNY/hm^2);

S_r, S_w, and S_c denote the percentages of the sown area of rice, wheat, and corn, respectively, in the total sown area of these three crops in a specific year (%);

F_r, F_w, and F_c respectively signify the average net profit per unit area of rice, wheat, and corn in that year (CNY/hm^2).

As per the Weihai Statistical Yearbook (2023) [33] and the China Agricultural Product Price Survey Yearbook (2023) [34], the main crops in Weihai City are wheat and corn. The calculated annual values of E from 2019 to 2022 are 13,747.85 CNY/hm^2, 16,750.43 CNY/hm^2, and 17,704.92 CNY/hm^2, respectively.

Based on the unit-area ecosystem service value equivalent for different biomes established by [32], the coefficients of coniferous forests relative to E can be obtained, as shown in Table 3. Thus,

$$EL_i = EV \times DA_i \times E_i \quad (11)$$

where

EL denotes the ecological value loss attributable to dead pine trees;

EV signifies the ecosystem service value equivalent per unit area of pine forest (coniferous forest);

D represents the area impacted by dead trees (hm^2).

Subsequently, the actual ecological benefit derived from implementing control measures is calculated as follows:

$$ES_i = EL_{DWi} - EL_{Di} \quad (12)$$

where

ES denotes the actual ecological benefit engendered by the control measures;

EL_{DWi} represents the ecological value loss in the absence of control measures;

EL_{Di} signifies the actual ecological value loss attributable to dead trees.

Furthermore, the expected quantity of dead trees under the optimal control scenario—specifically, the values acquired by substituting the optimal control measures and financial inputs derived from Formulas (1)–(4) into Formula (2)—represents the absolute quantity of dead trees that can be avoided in Weihai City under optimal control. Substituting this preventable quantity of dead trees into Equation (11) yields the ecological benefit generated by the implementation of the optimal control strategy.

In the process of preparing this manuscript, the author(s) employed Deepseek for the objectives of proof-reading the translation, refining the language, and obtaining revision suggestions. The authors have reviewed and edited the output and assume full responsibility for the content of this publication.

Table 3. Ecosystem service value equivalents per unit area by forest type.

Ecosystem Classification	Provisioning Services			Regulating Services				Supporting Services			Cultural Services
	Food Production	Raw Material Production	Water Supply	Gas Regulation	Climate Regulation	Environmental Purification	Hydrological Regulation	Soil Retention	Nutrient Cycling Maintenance	Biodiversity	Aesthetic Landscape
Coniferous Forest	0.22	0.52	0.27	1.7	5.07	1.49	3.34	2.06	0.16	1.88	0.82
Mixed Coniferous–Broadleaf Forest	0.31	0.71	0.37	2.35	7.03	1.99	3.51	2.86	0.22	2.6	1.14
Broadleaf Forest	0.29	0.66	0.34	2.17	6.5	1.93	4.74	2.65	0.2	2.41	1.06
Shrubland	0.19	0.43	0.22	1.41	4.23	1.28	3.35	1.72	0.13	1.57	0.69

3. Results

3.1. Evaluation of Optimal Prevention and Control Measures

3.1.1. Results of the Simultaneous Equation Model

In relation to the influence of control measures on the quantity of dead trees, data from diverse districts in Weihai City were analyzed via a simultaneous equation model. The outcomes, presented in Table 4, demonstrate that both the control area and control funds have passed the significance test. As illustrated in Figure 2 used by software of Stata 13.0, the correlation between the control area and the number of dead trees is quadratic, featuring a downward-opening curve. At the present stage, as control measures are intensified, the number of dead trees also rises concurrently. Specifically, for every additional hectare under control measures, 119.64 additional pine trees can be removed. Nevertheless, the existing control measures have not yet exerted a constraining effect on the number of dead trees. Figure 4 depicts a linear relationship between control funds and the number of dead trees, where an increase of 10,000 CNY leads to a reduction of 88.52 in the number of dead trees.

Table 4. Analysis of the inhibitory effect of control measures on the number of dead trees.

Model for Number of Dead Trees	Coefficient	Std. Err.	Z-Value
Control Area	119.639 ***	22.023	5.43
Control Area^2	−0.002 ***	0.0004	−5.05
Control Funds	−88.516 **	42.749	−2.07
Constant	−367,812.2 **	147,178.1	−2.50
Model Fit	R^2 = 0.297		χ^2 = 35.15
Model for Control Area	**Coefficient**	**Std. Err.**	**Z-Value**
Number of Dead Trees	0.006 *	0.003	1.88
Eradication Funds	3.909 ***	0.937	4.17
Number of Control Rounds	1332.57	1074.012	1.24
Number of Control Personnel	−43.015	28.976	−1.48
Workdays for Control	−67.930	56.295	−1.21
Technical Trainees	18.953	30.852	0.61
Publicity Campaigns	−128.825	601.148	−0.21
Constant	23,833.68 **	11,241.63	2.12
Model Fit	R^2 = 0.627		χ^2 = 48.49
Model for Control Funds	**Coefficient**	**Std. Err.**	**Z-Value**
Fiscal Allocation	0.612 ***	0.197	3.11
Locally Raised Funds	0.928 ***	0.173	5.36
Cost of Hiring Specialized Co.	0.131 *	0.068	1.92
Revenue from Infected Wood Sales	0.545	0.817	0.67
Output of Disposal Enterprises	−0.134	0.128	−1.04
Constant	189.569	201.112	0.94
Model Fit	R^2 = 0.918		χ^2 = 318.07
Model for Number of Control Personnel	**Coefficient**	**Std. Err.**	**Z-Value**
Management Funds	−1607 ***	0.440	−3.66
Constant	227.851 ***	19.142	11.90
Model Fit	R^2 = 0.151		χ^2=13.36
Model for Monitoring Area	**Coefficient**	**Std. Err.**	**Z-Value**
Preventive Funds	−18.561	25.051	−0.74
Constant	38,331.79 **	15,872.54	2.41
Model Fit	R^2 = 0.011		χ^2 = 0.55

Note: *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Regarding the factors influencing the control area, only the number of dead trees and eradication funds have passed the significance test. For each additional dead tree, the control area expands by 0.006 hectares. An increase of 10,000 CNY in eradication funds results in an expansion of the control area by 3.91 hectares. Management funds had a significant impact on the number of control personnel but not a positive influence, indicating that the current management funds are inadequate to support the efficient implementation of control work by the personnel.

Concerning the factors affecting control funds, an increase of 10,000 CNY in fiscal allocation significantly elevates the control funds by 6120 CNY. An increase of 10,000 CNY in locally raised funds raises the control funds by 9280 CNY. An increase of 10,000 CNY in the cost of hiring specialized control companies increases the control funds by 1310 CNY.

A more comprehensive analysis employing the simultaneous equation model was conducted to examine the responsiveness of funds to the control system, and the results are presented in Table 5. The relationship between control measures and control funds also takes on a quadratic form characterized by a downward-opening curve, as shown in Figure 3. For each additional hectare of the control area, the control funds increase by 0.41 ten thousand CNY, indicating that the current level of financial input has not yet attained an optimal state. The negative coefficient of the squared control area implies diminishing returns to scale. Given that the current investment level is below the optimal point, additional funding for the expansion of the control area is economically justifiable. The threshold is relatively high, and as the quantity of dead trees rises, the control funds display a decreasing trend. This suggests that the marginal input potential of the existing control funds is constrained.

Table 5. Responsiveness of control funds to the control system.

Model for Control Funds	Coefficient	Std. Err.	Z-Value
Control Area	0.410 ***	0.089	4.58
Control Area^2	-5.80×10^{-6} ***	1.52×10^{-6}	−3.81
Number of Dead Trees	−0.001 *	0.001	−1.78
Constant	−484.310	617.898	−0.78
Model Fit	$R^2 = 0.511$		$\chi^2 = 30.20$
Model for Control Area	**Coefficient**	**Std. Err.**	**Z-Value**
Number of Control Rounds	4438.674 ***	1673.897	2.65
Number of Control Personnel	−73.043 *	43.391	−1.68
Workdays for Control	−168.132 **	83.964	−2.00
Technical Trainees	40.929	47.419	0.86
Publicity Campaigns	607.387	862.559	0.70
Constant	42,355.03 **	16,540.67	2.56
Model Fit	$R^2 = 0.888$		$\chi^2 = 232.42$
Model for Number of Dead Trees	**Coefficient**	**Std. Err.**	**Z-Value**
Monitoring Area	−3197 *	1.919	−1.67
Aerial Control Area	−22.945 ***	5.565	−4.12
Outsourced Control Area	−19.184 *	10.435	−1.84
Number of Disposal Enterprises	−21,603.82 ***	6447.378	−3.35
Chemical Control Area	14.723 *	8455	1.74
Silvicultural Control Area	119.272 ***	10.768	11.08
Constant	67,149.34	61,654.45	1.09
Model Fit	$R^2 = 0.408$		$\chi^2 = 21.38$

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Given that factors such as the number of control rounds, personnel, and workdays did not demonstrate significant characteristics in Table 4, a more in-depth analysis in Table 5 explores the influencing factors of the control measures. The results indicate that each additional control round can expand the control area by 4438 hectares. However, the number of control personnel and workdays did not generate significant incentive effects on the control area. This implies that within the existing control system, the number of personnel is inadequate, the workdays are relatively brief, and the large area covered per control round results in high-pressure workloads.

A further investigation of the inhibitory effects of specific control measures on dead trees reveals that all indicators passed the significance test. Among them, the monitoring area, aerial control, outsourced control, and infected wood disposal enterprises had significant inhibitory effects on the quantity of dead trees. For each unit increase in these measures, the number of dead trees decreased by 3, 23, 19, and 21,603 trees, respectively. In contrast, the currently predominant chemical and silvicultural measures led to the removal of an additional 15 and 119 dead trees per hectare increase, respectively.

3.1.2. Calculation of Optimal Prevention and Control Measures

Substituting the regression results from Tables 4 and 5 into Equations (1) and (2) yields

$$C = 0.410R - 5.80 \times 10^{-6}R^2 - 0.001L - 484.310$$

$$L = 119.639R - 0.002R^2 - 88.516C - 367,812.2$$

$$\text{As } R = -\frac{0.410 + 119.639}{2(-5.80 \times 10^{-6}) + 2(-0.002)} = 33,397.04$$

$$C = 6739.375 - 0.001L$$

$$L = 1,629,604.743 - 88.516C = 1,033,062.479 + 0.113L$$

$$L = -1,164,611.414$$

$$C = 8225.536$$

Consequently, the threshold for prevention and control measures that minimizes disaster losses is achieved when the control area reaches 33,400 hectares and the financial investment amounts to 82.255 million CNY. In this scenario, the quantity of dead trees can be decreased by 1.165 million. This corresponds to an optimal control area per dead tree (*R*/*L*) of 0.029 hectares and an optimal investment per dead tree (*C*/*L*) of 70.63 CNY.

Based on the obtained optimal coefficients of control measures and using the actual quantity of dead trees as a reference, the theoretically optimal control area (R_Y) and investment funds (C_Y) were calculated, as shown in Figure 6. A comparison with the actual annual averages spanning from 2019 to 2022 demonstrates that the theoretically optimal control area (33,400 hectares) constitutes merely 56.6% of the actual average area (59,034 hectares). Concurrently, the optimal investment (82.255 million CNY) accounts for a mere 10.3% of the actual average funding (800 million CNY). This phenomenon suggests that recent overall input levels have exceeded the theoretically optimal requirements.

On an annual scale, in 2019, the actual control area and funding reached only 41.0% and 68.5% of their respective optimal values for that year, which underscores a distinct under-investment during the initial outbreak stage. Conversely, from 2020 to 2022, the actual inputs consistently exceeded the annual optimal levels, implying the potential for resource optimization in subsequent years.

When the optimal control measures are substituted into the model to estimate the preventable number of dead trees, it is revealed that the theoretical control capacity in 2019

was notably higher than the actual outcome, slightly lower than the actual results during 2020–2021, and marginally higher in 2022, with negligible differences in all instances.

These research findings indicate that adopting a dynamic adjustment strategy grounded in the optimal model—specifically, increasing investment in 2019 to more efficiently contain the epidemic outbreak and moderately decreasing inputs from 2020 to 2022—can sustain comparable control efficacy while notably improving the overall efficiency of resource allocation.

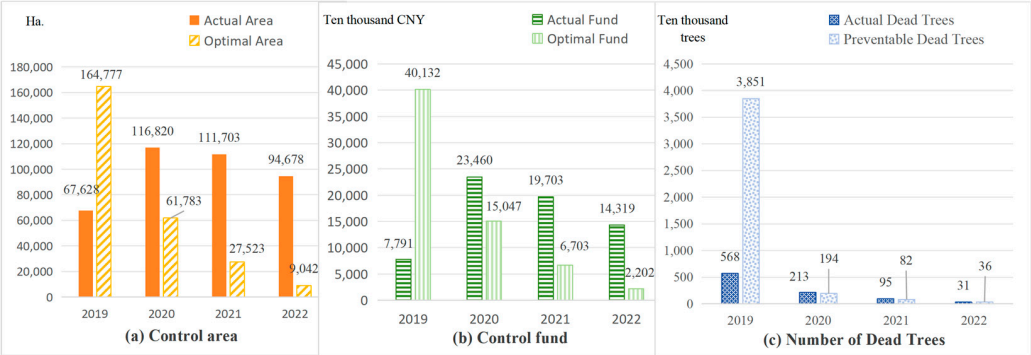


Figure 6. Comparison of actual versus theoretically optimal control measures against PWD in Weihai City (2019–2022). (**a**) Control area implemented versus the model-derived optimal control area. (**b**) Actual control funds invested versus the optimal financial input calculated by the model. (**c**) Trend of the actual number of dead trees versus the number of dead trees that could have been prevented under the optimal control strategy. The data indicate a substantial under-investment in both operational scale and funding during the initial outbreak year (2019). In contrast, during 2020–2021, actual inputs exceeded the theoretically sufficient levels, suggesting potential for more efficient resource allocation in subsequent years while maintaining similar control effectiveness.

3.2. Analysis of the Economic Benefits of Control Measures

Under the existing control measures, as of the end of 2022, the cumulative number of dead trees reached 9.073 million. In the absence of any control measures, assuming an annual forest devastation rate of 2.796, it is estimated that 311 million pine trees would have perished by 2022. The control effectiveness, calculated using Formula (8), indicates the increasing necessity of implementing control measures on an annual basis. The incidence rate presented in Figure 7 represents the proportion of the area affected by PWD to the area of the host tree species. With the value of each pine tree set at 500 CNY, the expected control cost is derived from Formula (6). Except for the year 2019, the optimal expected control costs for the remaining years are lower than the actual expected costs. This suggests that the adoption of optimal control measures can reduce the expected costs while achieving effects comparable to those of the current control measures. The expected cost in the non-control scenario is significantly higher than that in both the actual and optimal control scenarios, emphasizing the economic necessity of implementing control measures. Based on the annual average, the expected cost at the optimal point amounts to 6.608 billion CNY. According to Formula (9), the actual economic benefits generated have increased significantly year by year, rising from 1.717 billion CNY in 2019 to 91.909 billion CNY in 2022, with the economic benefit at the optimal point reaching 26.667 billion CNY.

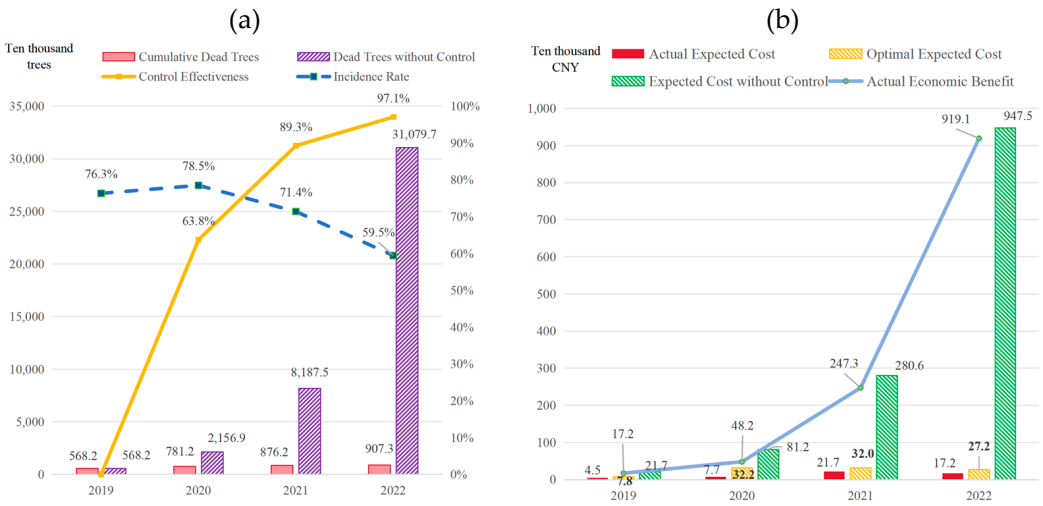


Figure 7. Estimation of economic costs and benefits for PWD control measures in Weihai City (2019–2022) (**a**) Trends in cumulative dead trees and control efficacy. This figure compares the cumulative number of actual dead trees with the simulated number of dead trees expected in the absence of control measures and simultaneously presents the annual control efficacy rate. The data indicate that during the initial outbreak year (2019), the actual number of dead trees was considerable, and the control efficacy was relatively low. In the subsequent years (2020–2022), the control efficacy improved significantly, effectively curbing the upward trend of tree mortality. (**b**) Comparison of actual versus optimal economic input and benefit. This figure compares the actual funds invested, the expected economic loss without control, the optimal control cost calculated by the model, and the actual economic benefit achieved. The data suggest that in 2019, the actual investment was lower than the optimal funds required for control. Conversely, during 2020–2021, the actual inputs exceeded the theoretically adequate levels, indicating the potential for more efficient resource allocation in subsequent years while maintaining comparable control efficacy.

3.3. Analysis of the Ecological Benefits of Control Measures

Based on Formulas (10) and (11), the ecological value losses caused by dead trees were calculated under both the current control measures and the scenario without any measures. Meanwhile, the ecological benefits obtained after the implementation of control measures were also computed (Figure 8). Figure 8a shows a comparison of the ecological value losses between the current measures and the optimal measures. At the optimal combination of control measures and investment, 1.165 million dead trees can be avoided, with an equivalent ecological value of 77.269 million CNY. Under the optimal control strategy, the achievable ecological value reached its maximum in 2019, amounting to 1.876 billion CNY (Figure 8d). Subsequently, It exhibited a year-on-year decline., with values of 120.030 million CNY, 61.486 million CNY, and 28.292 million CNY from 2020 to 2022, gradually reaching a stable state. This trend is consistent with the reduction in the ecological value loss due to dead trees under the current measures (Figure 8a). Figure 8b indicates that in the absence of control measures, the ecological value loss would increase significantly, reaching 24.734 billion CNY by 2022, highlighting the necessity of implementing control measures.

Moreover, the ecological benefits under both the actual and optimal measures were calculated based on Formula (12) (Figure 8c,d). From 2020 to 2022, the ecological benefits realized through the implementation of the existing control measures were 1201 billion CNY, 6093 billion CNY, and 24.709 billion CNY, respectively, demonstrating a notable year-on-year upward trend (Figure 8c). Meanwhile, under the optimal control strategy, the achievable ecological benefits for each year also followed a similar growth trajectory, further validating the crucial role of scientific resource allocation in augmenting ecological benefits (Figure 8d). In conclusion, the ecological benefits conferred by control measures

increase substantially over time, and the optimization of strategies is anticipated to yield more significant ecological returns while effectively managing costs.

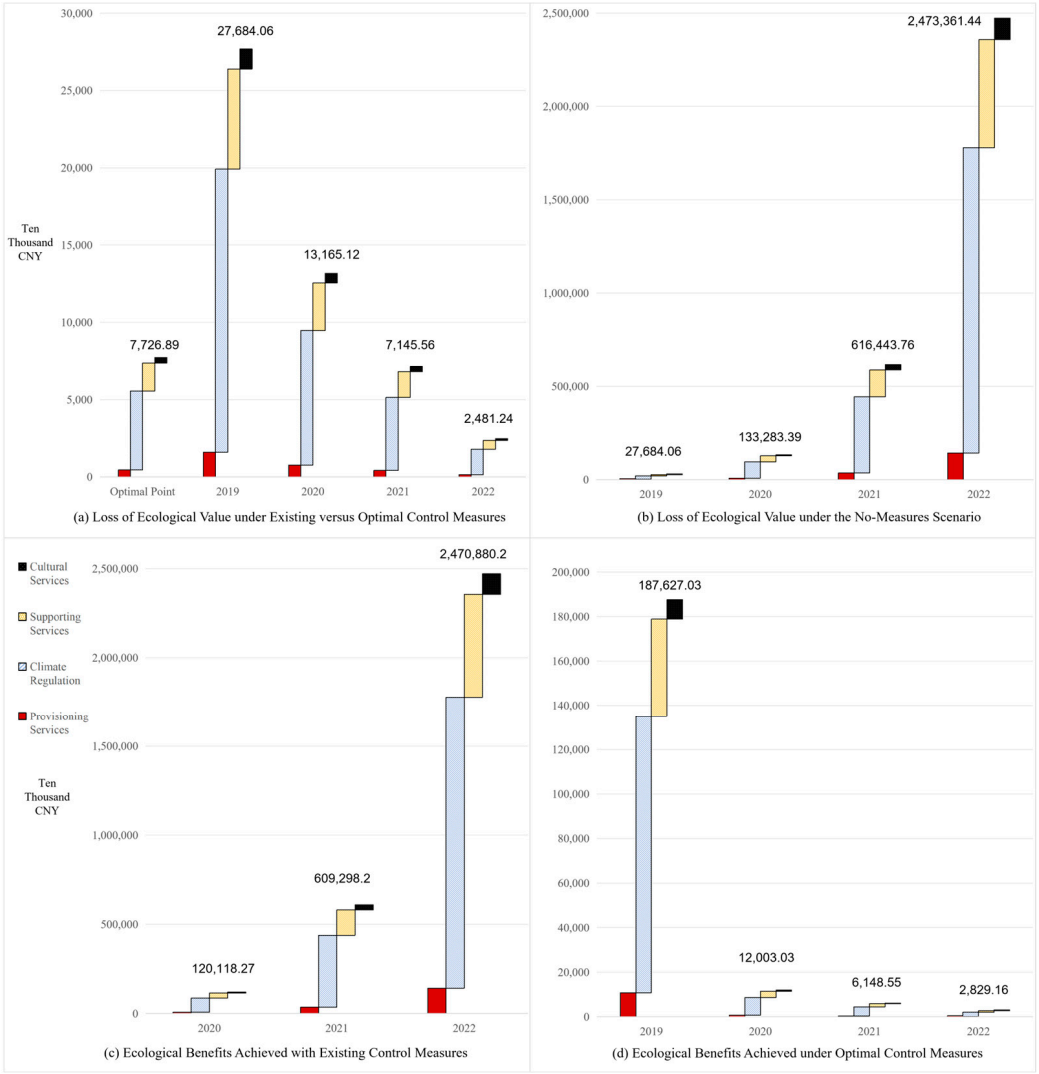


Figure 8. Ecological losses and benefits of pine wilt disease control in Weihai City (2019–2022). (**a**) Ecological value loss under existing vs. optimal measures. The optimal point (preventing 1.165 million trees) saves 77.27 million CNY. (**b**) Ecological value loss without control, showing a sharp rise to 24.73 billion CNY by 2022. (**c**) Ecological benefits from existing measures, calculated as avoided losses, increasing from 1.20 to 24.71 billion CNY. (**d**) Potential ecological benefits under the optimal strategy, following a similar growth trend.

4. Discussion

This study conducted a systematic quantitative analysis of the prevention and control practices for PWD in Weihai City during the period from 2019 to 2022, based on the theory of disaster economics. By constructing a simultaneous equation model, it evaluated the effectiveness and influencing factors of the existing control measures, assessed the efficiency of resource investment, and simulated the potential benefits of an optimal control strategy. The subsequent discussion integrates these research results with broader theoretical frameworks, international comparisons, and forward-looking policy and scientific considerations, while addressing the complexities associated with the management of this "slow-moving" ecological disaster.

4.1. Effectiveness of Control Measures, Structural Bottlenecks, and Cross-Regional Comparison

The diversified control measures for PWD implemented in Weihai City exhibit general efficacy. Specifically, for each additional hectare of the control area, there is an approximate reduction of 120 dead trees. Socialized prevention and control play a crucial role, as each additional hectare of the market-based control area leads to a decrease of about 19 dead trees. This validates the rationality of the "precision monitoring + integrated management" technical approach, which is in line with the globally recognized principle of early surveillance and rapid intervention for invasive species management [18].

However, econometric analysis reveals that the increase in management funding has not effectively improved personnel performance. For every additional 10,000 CNY in management funds, the corresponding "number of control personnel" significantly decreases by approximately 1.6 individuals. This counter-intuitive outcome implies that the current funds may mainly be utilized to maintain basic subsidies for existing personnel, rather than being allocated to systematic skills training, equipment upgrades, or the development of a career system appealing to younger professionals [35]. This has directly resulted in an aging workforce, outdated knowledge, and difficulties in recruiting new personnel [27]. Relying on elderly forest rangers to undertake high-intensity and technically demanding tasks poses a systemic risk to the sustainability of the control system [36]. In disaster prevention and control, when financial investment is divorced from strategic investment in "human capital", its marginal benefits may decline or even yield negative effects [29].

In contrast, European countries such as Portugal and Spain deeply integrate forest health management into their Integrated Pest Management (IPM) framework. Their fund allocation explicitly prioritizes supporting a professionalized and younger technical workforce, focusing on higher education, international training, the operation of smart equipment, and providing clear career pathways [37]. This ensures that financial inputs are efficiently translated into on the ground control capabilities [38]. Therefore, reforming China's grassroots control system depends on reconstructing the logic of management fund utilization, shifting from "maintaining scale" to "investing in human capital".

4.2. Sustainability of Funding Mechanisms, Incentive Structures, and Multi-Level Fiscal Coordination

Funding constitutes a fundamental cornerstone for effective control endeavors. This research reveals that for every 10,000 Chinese Yuan invested, approximately 88.5 pine tree mortalities can be prevented, indicating an efficient utilization of resources and corroborating the principle of marginal benefit in mitigation investment [16]. Nevertheless, the current funding structure remains highly reliant on locally sourced funds, rendering it susceptible to macro-economic fluctuations and disparities in local fiscal capabilities, causing some townships to encounter substantial budgetary deficits [28]. This underscores the structural challenges within China's fiscal system regarding the delineation of forestry administrative responsibilities and corresponding expenditure obligations [29].

From the perspective of public economics, the control of PWD generates substantial positive ecological externalities across regions, which frequently results in sub-optimal investment by local governments acting autonomously [18]. The significant stimulatory impact of central and provincial fiscal allocations in this realm highlights the crucial role of higher-level financial intervention in rectifying this market inefficiency. In the future, there is an urgent necessity to develop more innovative and sustainable financing mechanisms [39]. This encompasses the implementation of performance-based fiscal transfers and the adoption of market-oriented instruments such as green finance, ecological insurance, and green bonds for long-term resilience projects. Collectively, these tools can cultivate a diversified and sustainable funding ecosystem [40].

Specific and context-appropriate market mechanisms can be devised for the forestry sector. For example, cross-regional watershed eco-compensation agreements could be formulated, enabling downstream beneficiaries (e.g., municipal governments, water utilities) to remunerate upstream townships for preserving the health of pine forests—a service that directly improves water quality and security [41]. Another innovative approach is the "Control + Carbon Sink" project, which would incorporate certified carbon sequestration from activities such as infected wood removal and forest management into national voluntary emission reduction schemes [42]. Revenue from carbon credit sales could then be reinvested in control operations [43]. For long-term infrastructure requirements, such as the establishment of township-level wood disposal centers, the issuance of project revenue-based green bonds could be explored, with future income from eco-compensation or carbon credits serving as a repayment source [44].

4.3. Significance of Control Benefits, Implications of the Optimal Strategy, and Dynamic Adjustment Mechanisms

The benefit assessment firmly corroborates the necessity of control. Simulations indicate that in the absence of control measures, the quantity of dead trees by 2022 would have reached 34 times the actual amount. From 2019 to 2022, there was a notable increase in the economic and ecological benefits attained, highlighting the considerable value and long-term returns of early intervention and continuous investment, which far surpass the cost of post-disaster recovery [22]. This quantifies the substantial "cost of non-action".

The calculation of the optimal control strategy provides a scientific foundation for optimizing resource allocation. The results suggest that there is a specific investment threshold, at which an optimal balance between cost and benefit is achieved. A comparative analysis demonstrates that the actual investment in 2019 was lower than the optimal requirement, indicating a potential risk of insufficiency. In the following years, it remained higher than the optimal level, implying possible resource redundancy [19,20]. This suggests a strategic transition from "sustained high-intensity investment" to "adaptive, precision management" based on epidemic dynamics. This concept aligns with the internationally advocated "adaptive management" framework, which involves continuously adjusting strategies based on monitoring feedback to enhance resource efficiency [15,45].

4.4. Methodological Value, Limitations, and Future Research Directions

This study establishes an integrated analytical framework of "status evaluation–optimization calculation–benefit simulation", which synthesizes disaster economics theory, econometric modeling, and ecosystem service valuation. This framework addresses a notable research gap by enabling the quantitative optimization and comprehensive benefit assessment of PWD control, offering a transferable model for evidence-based phytosanitary policy in other epidemic regions.

Several limitations highlight avenues for future research. First, the relatively short time series (2019–2022) and the high heterogeneity of data from the initial outbreak year may affect the model stability. The overlap of this period with the COVID-19 pandemic should also be considered, as related disruptions could have influenced data collection consistency, field operations, and funding flows—even if such impacts were ultimately deemed negligible in this analysis [46]. Extending the observation period is necessary to account for long-term effects, threshold dynamics, and system resilience [47]. Second, the reliance on data from Weihai City means that regional variations in ecology, economics, and management may affect the generalizability of the optimal thresholds. Future work should expand to comparative regional studies to distinguish universal patterns from local specificities [48]. Third, while the unit-value equivalent factor method provides a robust macroscopic valuation of ecosystem services, future assessments could be refined by

integrating localized ecological process models (e.g., InVEST for spatially explicit services) or employing non-market valuation methods (e.g., choice experiments) for more context-sensitive estimates [49].

Accordingly, future research should prioritize the following: (1) extending the data time-series to improve longitudinal robustness; (2) conducting inter-regional comparative analyses to test the transferability of optimization models; (3) performing more granular cost–benefit evaluations of individual and combined control measures; and (4) investigating the influence of external drivers such as climate change on epidemic spread and control efficacy [50–52]. The integration of mechanistic epidemiological models with advanced remote sensing and "Precision Forest Health" technologies also represents a promising direction for dynamic risk forecasting and management [53,54]. These efforts will collectively enhance the scientific foundation for adaptive evidence-based decision-support systems in PWD control.

5. Conclusions

This study conducted a quantitative analysis of the control practices for PWD in Weihai City, utilizing the theoretical framework of disaster economics and a simultaneous equation model. The primary findings and implications are presented as follows:

5.1. Summary

(1) Weihai City has established an effective integrated control system for PWD. All the implemented measures have yielded quantifiable positive results, leading to a "dual decline" in both the affected area and the number of dead trees.
(2) Financial investment is a core variable influencing control effectiveness. Nevertheless, the current investment mechanism confronts sustainability risks, manifested by excessive reliance on a single funding source and inadequate incentives for personnel.
(3) The control measures have generated remarkably significant economic and ecological benefits, averting large-scale forest destruction and associated value losses.
(4) There exists a distinct "optimal control threshold". Scientifically adjusting the intensity of inputs in accordance with epidemic dynamics can ensure effectiveness while reducing costs and alleviating control pressure.

5.2. Policy Recommendations

Based on the aforementioned conclusions, the following recommendations are put forward:

(1) Implement a "Precision Budgeting and Dynamic Adjustment" management model: Fully integrate the "National Forest–Grassland Ecological Network Perception System". Establish a "PWD Monitoring and Control Platform" to achieve real-time and precise positioning of dead trees and conduct dynamic epidemic risk assessment. This data should serve as the core basis for formulating and adjusting the control budget, shifting resource allocation from a "fixed-quota" model to an "on-demand, flexible" one.
(2) Establish an "Integrated and Professional" township-level control system: Thoroughly advance the township-level "Characteristic Forest Farm" management mode to integrate resources and develop a younger and more professional control workforce. This can be achieved through measures such as setting up training funds, providing skill allowances, and implementing customized training programs via school–enterprise cooperation. Implement a grid- and parcel-based responsibility system, supported by standardized equipment and centralized management, to improve the professionalism and operational efficiency of control operations.

(3) Improve a "Multi-level and Sustainable" funding guarantee mechanism: While ensuring the allocation of special fiscal funds from all levels of government, actively explore market-oriented instruments such as forestry disaster insurance and ecological compensation. This will diversify funding sources, alleviate local fiscal pressure, optimize the fund structure, and strengthen performance-based incentives for frontline control personnel.

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