

# SSWD-EvoEpi: A Coupled Eco-Evolutionary Epidemiological Model for Sea Star Wasting Disease in *Pycnopodia helianthoides*

Internal Working Report — Model Development, Sensitivity Analysis, and  
Validation

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## Abstract

Sea star wasting disease (SSWD) caused one of the largest wildlife mass mortality events in marine ecosystems, driving the sunflower sea star (*Pycnopodia helianthoides*) to a 90.6% range-wide decline and IUCN Critically Endangered status. The recent identification of *Vibrio pectenicida* strain FHCF-3 as a causative agent, combined with active captive breeding and the first experimental outplanting of captive-bred juveniles, creates an urgent need for quantitative tools to guide recovery. We present SSWD-EvoEpi, an individual-based, spatially explicit eco-evolutionary epidemiological model coupling *V. pectenicida* transmission dynamics with polygenic host evolution under sweepstakes reproductive success. Each agent carries a diploid genotype across 51 loci governing three fitness-related traits — resistance (immune exclusion), tolerance (damage limitation), and recovery (pathogen clearance) — that evolve in response to disease-driven selection. Disease dynamics follow an SEIR-type compartmental structure with an environmental pathogen reservoir, pathogen evolution along a virulence–transmission tradeoff, temperature-dependent forcing, and recovery returning individuals to the susceptible pool (reflecting the absence of adaptive immunity in echinoderms). Reproduction imple-

ments sweepstakes reproductive success with  $N_e/N \sim 10^{-3}$ , sex-asymmetric spawning induction, and post-spawning immunosuppression. Four rounds of global sensitivity analysis (Morris screening and Sobol variance decomposition) across up to 47 parameters reveal that model behavior is dominated by nonlinear interactions among disease mortality rate, host susceptibility, environmental pathogen pressure, and genetic architecture, with resistance replacing recovery as the dominant adaptive response when reinfection is permitted. The model provides a framework for evaluating captive-bred release strategies, assisted gene flow, and the feasibility of evolutionary rescue on conservation-relevant timescales.

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# 1 Introduction

## 1.1 Sea Star Wasting Disease and the Collapse of *Pycnopodia helianthoides*

Sea star wasting disease (SSWD) caused one of the largest documented wildlife mass mortality events in marine ecosystems when it swept through populations of over 20 asteroid species along the northeastern Pacific coast beginning in 2013 [24, 31, 50]. The disease, characterized by behavioral changes (arm twisting, lethargy), loss of turgor, body wall lesions, ray autotomy, and rapid tissue degradation, devastated populations from Baja California to the Gulf of Alaska within months [34, 49]. Among the species affected, the sunflower sea star (*Pycnopodia helianthoides*) suffered the most catastrophic decline, losing an estimated 5.75 billion individuals and experiencing a 90.6% range-wide population reduction based on 61,043 surveys across 31 datasets [20, 26]. Along the outer coast from Washington to Baja California, declines exceeded 97%, with many regions recording zero individuals in subsequent surveys [20, 23]. The species was assessed as Critically Endangered by the IUCN in 2021 [20] and is under consideration for listing as Threatened under the U.S. Endangered Species Act [42].

As a large-bodied, mobile, generalist predator capable of consuming sea urchins at rates sufficient to structure entire subtidal communities, *Pycnopodia helianthoides* functions as a keystone species in northeastern Pacific kelp forest ecosystems [6, 15, 47]. Its precipitous decline has been linked to cascading trophic effects, including sea urchin population explosions and extensive kelp forest deforestation, with northern California losing 96% of its kelp canopy since the 2014 marine heatwave [48, 56]. The loss of this apex predator thus represents not only a conservation crisis for a single species but a destabilization of an entire marine ecosystem [23, 39].

## 1.2 Etiology: A Decade-Long Mystery Resolved

For over a decade following the initial outbreak, the causative agent of SSWD remained contested. An early hypothesis implicating sea star associated densovirus (SSaDV; Hewson et al. 31) was subsequently retracted after repeated failures to reproduce the original challenge experiments and the discovery that the virus is endemic in healthy echinoderm populations worldwide [32–34]. An alternative hypothesis invoking boundary layer oxygen depletion (BLODL) at the animal–water interface proposed that microbial respiration on sea star surfaces draws down dissolved oxygen, leading to tissue hypoxia [2, 29]. While this mechanism may contribute to disease susceptibility, it did not identify a specific pathogen.

The breakthrough came with Prentice et al. [54], who fulfilled Koch’s postulates by demonstrating that *Vibrio pectenecida* strain FHCF-3, a Gram-negative marine bac-

terium, is a causative agent of SSWD in *Pycnopodia helianthoides*. Through seven controlled exposure experiments using captive-bred, quarantined sea stars, the authors showed that injection of cultured *V. pectenica* FHCF-3 into the coelomic cavity reliably produced disease signs — arm twisting, lesion formation, autotomy, and death within approximately two weeks. Heat-treated and 0.22  $\mu$ m filtered controls remained healthy, confirming a living bacterial agent. Critically, the pathogen was re-isolated from experimentally infected animals, completing Koch’s postulates. Earlier investigations had missed *V. pectenica* because they sampled body wall tissue rather than coelomic fluid, where the bacterium resides.

However, the etiological picture is not entirely resolved. Hewson [30] demonstrated that *V. pectenica* FHCF-3 was not consistently detected in non-*Pycnopodia helianthoides* species during the 2013–2014 mass mortality, suggesting it may be specific to *Pycnopodia helianthoides* or may function as an opportunistic pathogen rather than a universal SSWD agent across all affected asteroid taxa. The bacterium also exhibits explosive growth in the presence of decaying echinoderm tissue, raising questions about whether it acts primarily as a pathogen or a saprobe under different conditions [30]. Nonetheless, for *Pycnopodia helianthoides* — the focus of this study — the evidence for *V. pectenica* as the primary causative agent is robust. The identification of a specific bacterial pathogen with known temperature-dependent growth dynamics [45] provides a mechanistic basis for modeling disease transmission and environmental forcing.

### 1.3 Conservation Urgency and Active Recovery Efforts

The failure of *Pycnopodia helianthoides* populations to recover naturally in the decade following the initial epizootic — contrasting with partial recovery observed in some co-occurring asteroid species [19] — has motivated intensive conservation action. The species’ long generation time ( $\sim$ 30 years), broadcast spawning reproductive strategy, and vulnerability to Allee effects at low density [16, 43] compound the challenge of natural recovery. Historical precedent is sobering: the Caribbean long-spined sea urchin *Diadema antillarum*, which suffered a comparable 93–100% mass mortality in 1983–1984, achieved only  $\sim$ 12% recovery after three decades [40]. Another asteroid, *Heliaster kubiniji*, has never recovered from a 1975 mass mortality event in the Gulf of California [12].

In response, a coordinated multi-partner recovery effort has emerged. The Association of Zoos and Aquariums (AZA) Saving Animals From Extinction (SAFE) program maintains over 2,500 captive juveniles and 130+ reproductive adults across 17 AZA institutions [5]. Experimental outplanting of captive-bred *Pycnopodia helianthoides* has progressed through three phases: caged trials off San Juan Island, Washington in 2023 established initial feasibility; the first uncaged release of 20 captive-bred juveniles (ages 1–3 yr) off the Friday Harbor Laboratories dock in July–August 2024 represented the first-ever re-



lease of captive-bred *Pycnopodia helianthoides* into the wild [57]; and the first California outplanting in Monterey Bay in December 2025, where 47 of 48 juveniles survived after four weeks [66]. A Roadmap to Recovery developed by over 30 leading experts defines regionally nested recovery objectives, from local demographic benchmarks to range-wide genetic structure targets [26]. Cryopreservation of gametes has been demonstrated for a congener and is under development for *Pycnopodia helianthoides* to enable assisted gene flow from genetically diverse founders [22, 63]. In 2025, the California Ocean Protection Council approved \$630,000 in funding for captive breeding, disease diagnostics, and experimental outplanting [7]. A reference genome has also been published [62], laying the groundwork for genome-wide association studies (GWAS) to identify resistance loci.

These recovery efforts require quantitative predictions: How many captive-bred individuals should be released, where, and when? What are the genetic consequences of releasing animals from a limited captive founder population? Can natural selection drive resistance evolution fast enough to matter on conservation timescales? How do pathogen evolution, environmental change, and spatial structure interact to shape recovery trajectories? Answering these questions demands a modeling framework that integrates disease dynamics with population genetics in an explicitly spatial context.

## 1.4 The Need for an Eco-Evolutionary Framework

Existing models of SSWD dynamics have focused on either epidemiological or ecological aspects in isolation. Aalto et al. [1] coupled an SIR-type model with ocean circulation to explain the rapid continental-scale spread of SSWD, finding that temperature-dependent mortality best matched observed patterns. Tolimieri [68] conducted a population viability analysis using stage-structured matrix models but did not incorporate disease dynamics or host genetics. Arroyo-Esquivel et al. [4] recently modeled epidemiological consequences of managed reintroduction following disease-driven host decline, but their framework lacks genetic evolution. None of these approaches captures the interplay between disease-driven selection, host genetic adaptation, and demographic recovery that is central to predicting conservation outcomes.

The theoretical motivation for coupling these processes is compelling. Mass mortality events impose intense directional selection on host populations [60], and in *Pisaster ochraceus* — a co-occurring sea star affected by SSWD — rapid allele frequency shifts ( $\Delta q \approx 0.08\text{--}0.15$  at outlier loci) were detected within a single generation of the epizootic, with geographic consistency across sites indicating selection rather than drift [60]. However, in broadcast-spawning marine invertebrates, the genetic consequences of mass mortality are filtered through sweepstakes reproductive success (SRS), whereby variance in individual reproductive success is so large that effective population size ( $N_e$ ) is orders of magnitude smaller than census size ( $N_e/N \sim 10^{-3}$ ; Árnason et al. 3, Hedgecock and

Pudovkin 27). SRS amplifies genetic drift on ecological timescales [69], can facilitate rapid adaptation when coupled with bottlenecks [14], and generates chaotic genetic patchiness that confounds simple predictions of evolutionary trajectories. Any model of evolutionary rescue in *Pycnopodia helianthoides* must therefore account for this fundamental feature of marine broadcast spawner genetics.

The closest methodological precedent is the eco-evolutionary individual-based model (IBM) developed by Clement et al. [10] for coevolution between Tasmanian devils (*Sarcophilus harrisii*) and devil facial tumour disease (DFTD). That model coupled an SEI epidemiological framework with polygenic quantitative genetics, parameterized from two decades of field data and GWAS results, and found a high probability of host persistence over 50 generations through coevolutionary dynamics. Our model extends this approach to a marine system with fundamentally different reproductive biology — broadcast spawning with sweepstakes reproductive success, external fertilization subject to Allee effects, and a pelagic larval phase mediating spatial connectivity — challenges that no existing eco-evolutionary disease model has addressed.

## 1.5 Model Overview

We present SSWD-EvoEpi, an individual-based, spatially explicit, eco-evolutionary epidemiological model designed to simulate SSWD dynamics and evolutionary responses in *Pycnopodia helianthoides* metapopulations across the northeastern Pacific. The model tracks individual sea stars as agents within a network of habitat nodes connected by larval dispersal and pathogen transport. Each agent carries a diploid genotype across 51 loci governing three fitness-related traits: resistance ( $r_i$ , 17 loci; immune exclusion reducing infection probability), tolerance ( $t_i$ , 17 loci; damage limitation extending survival during late-stage infection), and recovery ( $c_i$ , 17 loci; pathogen clearance enabling transition from infected to recovered states). Per-locus allele frequencies are drawn from a Beta(2,8) distribution, reflecting polygenic architecture with most loci at low frequency [36].

Disease dynamics follow an SEIR-type compartmental structure with exposed (E), early infected ( $I_1$ ), and late infected ( $I_2$ ) stages, coupled with an environmental pathogen reservoir (P) whose dynamics are temperature-dependent [18, 45]. Pathogen evolution is modeled through a heritable virulence phenotype that evolves along a mechanistic tradeoff curve linking shedding rate to host survival duration. Reproduction incorporates sweepstakes reproductive success via a heavy-tailed offspring distribution producing  $N_e/N$  ratios consistent with empirical estimates for marine broadcast spawners [27], with sex-asymmetric spawning induction and post-spawning immunosuppression derived from species-specific observations. Spatial connectivity is implemented through distinct larval exchange and pathogen dispersal matrices computed from overwater distances across the model domain.

The model is implemented in Python with NumPy-vectorized agent operations, achieving sufficient performance for large-scale sensitivity analysis and calibration (75,000 agents across 150 nodes in  $\sim 72$  s). Four rounds of sensitivity analysis using Morris screening and Sobol variance decomposition across up to 47 parameters have identified the key drivers of model behavior, revealing strong nonlinear interactions and highlighting priority targets for empirical calibration.

## 1.6 Paper Outline

The remainder of this paper is organized as follows. Section 2 describes the overall model architecture, agent representation, and simulation flow. Sections 3–6 detail the disease, genetics, population dynamics, and spatial modules, respectively. Section 7 presents four rounds of global sensitivity analysis, identifying the parameters with greatest influence on epidemiological, demographic, and evolutionary outcomes. Section 8 describes model validation against available empirical data. Section 9 synthesizes findings, discusses limitations, and outlines the path toward calibrated conservation scenario evaluation. Parameter tables and supplementary analyses are provided in Appendix A.

## 2 Model Architecture

SSWD-EvoEpi is an individual-based model (IBM) that couples epidemiological, demographic, genetic, and spatial dynamics to simulate the eco-evolutionary consequences of sea star wasting disease in *Pycnopodia helianthoides*. Each agent represents a single sea star tracked through its complete life history, carrying a diploid genotype at 51 loci that determines three quantitative defense traits against *Vibrio pectenicida*. We chose an individual-based approach over compartmental (ODE/PDE) models because SSWD dynamics depend critically on individual-level heterogeneity in genetic resistance, body size, spatial position, and disease stage—features that compartmental models cannot represent without substantial loss of biological realism [11, 21].

### 2.1 Agent Representation

Each individual is represented as a record in a NumPy structured array (`AGENT_DTYPE`) comprising approximately 59 bytes per agent. Table 1 summarizes the principal state variables grouped by functional module.

Table 1: Agent state variables in SSWD-EvoEpi.

Module	Field	Description
Spatial	x, y	Position within node habitat (m)
	heading	Movement heading (rad)
	speed	Instantaneous speed ( $\text{m min}^{-1}$ )
	node_id	Home node index
Life history	size	Arm-tip diameter (mm)
	age	Age (years, fractional)
	stage	Life stage (0–4; Table 2)
	sex	Sex (0 = female, 1 = male)
Disease	disease_state	Compartment (S/E/I <sub>1</sub> /I <sub>2</sub> /D/R)
	disease_timer	Days remaining in current disease stage
Genetics	resistance	Resistance score $r_i \in [0, 1]$
	tolerance	Tolerance score $t_i \in [0, 1]$
	recovery_ability	Recovery/clearance score $c_i \in [0, 1]$
Spawning	has_spawned	Bout count this season
	immunosuppression_timer	Post-spawning immunosuppression (days)
Administrative	alive	Active flag
	origin	Wild / captive-bred / AGF / wild-source
	pathogen_virulence	Virulence of infecting strain $v_i$

336 Genotypes are stored in a separate array of shape  $(N_{\max}, 51, 2)$  with `int8` entries,  
337 where axis 1 indexes loci and axis 2 indexes the two allele copies (diploid). This separation  
338 from the agent record improves cache performance during non-genetic operations (disease  
339 transmission, movement), which need not touch the genotype array.

Table 2: Life stages and size thresholds for *Pycnopodia helianthoides*.

Index	Stage	Size threshold (mm)	Reproductive
0	Egg/Larva	—	No
1	Settler	Settlement	No
2	Juvenile	$\geq 10$	No
3	Subadult	$\geq 150$	No
4	Adult	$\geq 400$	Yes

## 2.2 Node Structure

The spatial domain is represented as a metapopulation network of  $K$  discrete habitat nodes. Each node encapsulates:

- A population of agents (structured array + genotype array), initialized at local carrying capacity;
- Environmental state: sea surface temperature  $T(t)$  (sinusoidal annual cycle with warming trend), salinity  $S$ , and tidal flushing rate  $\phi_k$ ;
- A local *Vibrio* concentration  $P_k(t)$  (bacteria mL<sup>-1</sup>);
- Node metadata: latitude, habitat area, fjord classification.

Inter-node coupling occurs through two connectivity matrices:

1. **Pathogen dispersal matrix  $\mathbf{D}$ :** governs daily exchange of waterborne *Vibrio pectenocida* between nodes, parameterized with an exponential distance kernel (scale  $D_P = 15$  km);
2. **Larval connectivity matrix  $\mathbf{C}$ :** governs annual dispersal of competent larvae among nodes, parameterized with a broader kernel (scale  $D_L = 400$  km) reflecting the extended pelagic larval duration of *Pycnopodia helianthoides*.

## 2.3 Simulation Loop

The simulation advances in daily timesteps ( $\Delta t = 1$  day) nested within an annual cycle. At each daily step, the following operations are executed in sequence at every node (Figure ??):

1. **Environment update.** Compute  $T_k(t)$  from a sinusoidal annual SST function with linear warming trend; update flushing rate  $\phi_k$  (seasonally modulated for fjord nodes); salinity is constant per node.
2. **Movement.** Agents execute a correlated random walk (CRW) with 24 hourly substeps per day. Movement speed is modulated by disease state ( $\times 0.5$  for  $I_1$ ,  $\times 0.1$  for  $I_2$ ,  $\times 0$  for  $D$ ). Elastic boundary reflection constrains agents within the habitat.
3. **Disease dynamics.** *Vibrio* concentration is updated via an Euler step of the pathogen ODE. Susceptible agents are exposed to a force of infection that depends on local pathogen density, individual resistance, salinity, and body size. Infected agents progress through the SEIPD compartments with Erlang-distributed stage durations (Section 3).

4. **Pathogen dispersal.** *Vibrio* is exchanged between neighboring nodes via the **D** matrix, representing waterborne transport.
5. **Settlement.** Larval cohorts whose pelagic larval duration (PLD) has elapsed are settled into the local population via Beverton–Holt density-dependent recruitment, modulated by an adult-presence settlement cue (Allee effect).
6. **Spawning.** During the spawning season (November–July), reproductively mature adults spawn stochastically with daily probability modulated by a seasonal Gaussian envelope centered on the peak spawning day. Female and male multi-bout spawning, sex-asymmetric cascade induction, and post-spawning immunosuppression are modeled explicitly.
7. **Daily demographics.** Natural mortality is applied as a daily probability converted from stage-specific annual survival rates:

$$p_{\text{death,daily}} = 1 - S_{\text{annual}}^{1/365}, \quad (1)$$

with a senescence overlay for individuals exceeding the senescence age ( $\tau_{\text{sen}} = 50$  yr). Growth follows the von Bertalanffy differential form with daily-scaled stochastic noise; stage transitions are one-directional based on size thresholds (Table 2).

At the end of each simulated year, an annual step performs:

1. **Larval dispersal** via the connectivity matrix **C**: unsettled cohorts from all nodes are pooled, redistributed probabilistically among destination nodes, and settled at receiving nodes or retained in a pending queue for next-year daily settlement.
2. **Disease introduction** (at the designated epidemic year): a fixed number of agents per node are seeded in the Exposed (E) compartment.
3. **Genetic recording**: per-node allele frequencies, additive genetic variance  $V_A$ , and trait means are logged annually. Pre- and post-epidemic allele frequency snapshots are captured for calibration against genomic data.

## 2.4 Design Rationale

Several design choices distinguish SSWD-EvoEpi from previous SSWD models:

**Individual-based representation.** SSWD mortality is strongly size-dependent [OR = 1.23 per 10 mm; 13], genetically mediated [61], and spatially heterogeneous. A compartmental SIR/SEIR model would require aggregating these axes of variation into homogeneous classes, losing the emergent eco-evolutionary dynamics that arise from individual

heterogeneity in resistance, tolerance, and recovery. Following Clement et al. [9], who demonstrated that individual-based eco-evolutionary models are essential for predicting host–pathogen coevolution in Tasmanian devil facial tumor disease, we track each individual’s genotype, phenotype, and infection history explicitly.

**Continuous daily demographics.** Rather than applying mortality, growth, and reproduction as annual pulses, SSWD-EvoEpi evaluates natural mortality and growth daily (Eq. 1), with spawning resolved to individual daily events across a multi-month season. This avoids artificial synchronization artifacts and allows disease–demography interactions (e.g., post-spawning immunosuppression) to operate on their natural timescales.

**Separated genotype storage.** The 51-locus diploid genotype array (102 bytes per agent) is stored separately from the agent state record. This ensures that the most frequently accessed fields during daily disease and movement updates (position, disease state, size) occupy contiguous memory, improving CPU cache performance by a factor of  $\sim 2\text{--}3\times$  in profiled benchmarks.

**Three-trait genetic architecture.** The 51 loci are partitioned into three independently segregating trait blocks of 17 loci each, controlling resistance (immune exclusion), tolerance (damage limitation), and recovery (pathogen clearance). This architecture captures the empirical observation that host defense against infectious disease operates through mechanistically distinct pathways that can evolve semi-independently [55].

## 3 Disease Module

The disease module implements a stochastic, environmentally driven SEIPD compartmental framework (Susceptible–Exposed–Infectious<sub>1</sub>–Infectious<sub>2</sub>–Dead, with recovery returning individuals to the susceptible pool) operating at the individual level. Each agent carries its own disease state, countdown timer, genetic defense traits ( $r_i$ ,  $t_i$ ,  $c_i$ ), and (when pathogen evolution is enabled) the virulence phenotype  $v_i$  of its infecting strain. Disease dynamics are resolved daily at each spatial node, coupled to the environmental forcing module for temperature-dependent rates and to the genetics module for individual susceptibility.

### 3.1 Compartmental Structure

The disease pathway consists of five compartments with a recovery transition back to the susceptible state (Figure ??):

- **S (Susceptible):** Healthy, at risk of infection.

- **E (Exposed):** Latently infected; not yet shedding pathogen. Duration is Erlang-distributed with shape  $k_E = 3$ .
- **I<sub>1</sub> (Early infectious):** Pre-symptomatic shedding at rate  $\sigma_1(T)$ . Duration is Erlang-distributed with shape  $k_{I_1} = 2$ . Agents with high clearance ability ( $c_i > 0.5$ ) may recover early.
- **I<sub>2</sub> (Late infectious):** Symptomatic wasting with high shedding rate  $\sigma_2(T)$ . Duration is Erlang-distributed with shape  $k_{I_2} = 2$ . Agents may recover with probability  $p_{\text{rec}} = \rho_{\text{rec}} \times c_i$  per day.
- **D (Dead from disease):** Carcass continues to shed pathogen saprophytically for a 3-day window at rate  $\sigma_D$ .
- **Recovery ( $\rightarrow$  S):** Recovered individuals return to the susceptible pool and may be reinfected. Echinoderms lack adaptive immunity and show no evidence of acquired resistance to SSWD; stars treated for wasting via iodine dip and probiotic protocols have subsequently developed wasting again, confirming absence of immunological memory [70]. Heritable genetic traits (resistance, tolerance, recovery) represent the only defense mechanism.

### 3.1.1 Erlang-Distributed Stage Durations

Durations in compartments E, I<sub>1</sub>, and I<sub>2</sub> are drawn from Erlang distributions rather than geometric (exponential) distributions. The Erlang distribution with shape parameter  $k$  and rate parameter  $k\mu$  has mean  $1/\mu$  and coefficient of variation  $\text{CV} = 1/\sqrt{k}$ , producing more realistic, peaked duration distributions compared to the memoryless exponential [72]. For each individual entering a compartment, a duration is sampled as:

$$\tau \sim \text{Erlang}(k, k\mu(T)), \quad \text{rounded to } \max(1, \text{round}(\tau)) \text{ days}, \quad (2)$$

where  $\mu(T)$  is the temperature-dependent transition rate at the current SST (Section 3.3.2).

The shape parameters are:

$$k_E = 3 \text{ (CV = 0.58)}, \quad k_{I_1} = 2 \text{ (CV = 0.71)}, \quad k_{I_2} = 2 \text{ (CV = 0.71)}. \quad (3)$$

Timers count down by one each day; when the timer reaches zero, the agent transitions to the next compartment.



## 3.2 Force of Infection

The per-individual instantaneous hazard rate of infection is:

$$\lambda_i = a_{\text{exp}} \underbrace{\frac{P_k}{K_{1/2} + P_k}}_{\text{dose-response}} \underbrace{(1 - r_i)}_{\text{resistance}} \underbrace{S_{\text{sal}}}_{\text{salinity}} \underbrace{f_{\text{size}}(L_i)}_{\text{size}}, \quad (4)$$

where:

- $a_{\text{exp}} = 0.75 \text{ d}^{-1}$  is the baseline exposure rate;
- $P_k$  is the local *Vibrio* concentration ( $\text{bacteria mL}^{-1}$ ) at node  $k$ ;
- $K_{1/2} = 87,000 \text{ bacteria mL}^{-1}$  is the half-infective dose (Michaelis–Menten dose–response);
- $r_i \in [0, 1]$  is the individual’s resistance score (immune exclusion; Section 4);
- $S_{\text{sal}}$  is the salinity modifier (Section 3.2.2);
- $f_{\text{size}}(L_i)$  is the size-dependent susceptibility modifier (Section 3.2.3).

The discrete daily probability of infection is:

$$p_{\text{inf}} = 1 - \exp(-\lambda_i \Delta t), \quad \Delta t = 1 \text{ day}. \quad (5)$$

### 3.2.1 Dose–Response Function

Pathogen exposure follows a Michaelis–Menten (saturating) dose–response:

$$D(P_k) = \frac{P_k}{K_{1/2} + P_k}. \quad (6)$$

At low concentrations ( $P_k \ll K_{1/2}$ ), infection probability scales linearly with pathogen density; at high concentrations ( $P_k \gg K_{1/2}$ ), it saturates at  $D \rightarrow 1$ , reflecting physiological limits on pathogen uptake.

### 3.2.2 Salinity Modifier

*Vibrio* viability is suppressed at low salinities, providing a mechanistic basis for the reduced SSWD prevalence observed in fjord systems:

$$S_{\text{sal}} = \begin{cases} 0 & \text{if } S \leq S_{\text{min}} = 10 \text{ psu}, \\ \left( \frac{S - S_{\text{min}}}{S_{\text{full}} - S_{\text{min}}} \right)^\eta & \text{if } S_{\text{min}} < S < S_{\text{full}}, \\ 1 & \text{if } S \geq S_{\text{full}} = 28 \text{ psu}, \end{cases} \quad (7)$$

where  $\eta = 2$  produces a convex response (low salinity is strongly protective).

### 3.2.3 Size-Dependent Susceptibility

Larger *Pycnopodia helianthoides* are more susceptible to SSWD, consistent with the empirical finding of Eisenlord et al. [13] (odds ratio 1.23 per 10 mm increase in radius). The size modifier is:

$$f_{\text{size}}(L_i) = \exp\left(\beta_L \frac{L_i - \bar{L}}{\sigma_L}\right), \quad (8)$$

where  $\beta_L = 0.021 \text{ mm}^{-1}$  ( $= \ln 1.23/10$ ),  $\bar{L} = 300 \text{ mm}$  is the reference size, and  $\sigma_L = 100 \text{ mm}$  normalizes the deviation. An individual of diameter  $L_i = 500 \text{ mm}$  has  $\sim 1.5\times$  the infection hazard of a 300 mm individual.

### 3.2.4 Post-Spawning Immunosuppression

Spawning imposes a transient immune cost. Following each spawning event, an individual enters a 28-day immunosuppression window during which its effective resistance is reduced:

$$r_{i,\text{eff}} = \frac{r_i}{\psi_{\text{spawn}}}, \quad \psi_{\text{spawn}} = 2.0, \quad (9)$$

clamped to  $[0, 1]$ . This halves effective resistance during the immunosuppressed period, creating an evolutionary coupling between reproductive investment and disease vulnerability.

## 3.3 Disease Progression and Recovery

Disease progression rates are temperature-dependent via an Arrhenius function (Section 3.3.2). At each daily step, disease timers are decremented; when a timer reaches zero, the agent transitions to the next state. Recovery can occur before timer expiry.

### 3.3.1 Transition Rates

The base progression rates at reference temperature  $T_{\text{ref}} = 20^\circ\text{C}$  are:

$$\mu_{E \rightarrow I_1} = 0.57 \text{ d}^{-1} \quad (E_a/R = 4,000 \text{ K}), \quad (10)$$

$$\mu_{I_1 \rightarrow I_2} = 0.40 \text{ d}^{-1} \quad (E_a/R = 5,000 \text{ K}), \quad (11)$$

$$\mu_{I_2 \rightarrow D} = 0.173 \text{ d}^{-1} \quad (E_a/R = 2,000 \text{ K}). \quad (12)$$

The activation energy for  $I_2 \rightarrow D$  is notably lower ( $E_a/R = 2,000 \text{ K}$  vs. 5,000–6,000 K for other transitions), reflecting evidence that terminal wasting is less temperature-sensitive than earlier disease stages (Errata E1).

### 3.3.2 Temperature Scaling (Arrhenius)

All temperature-dependent rates are scaled via the Arrhenius equation:

$$k(T) = k_{\text{ref}} \exp \left[ \frac{E_a}{R} \left( \frac{1}{T_{\text{ref}}} - \frac{1}{T} \right) \right], \quad (13)$$

where  $T_{\text{ref}} = 293.15 \text{ K}$  ( $20^\circ\text{C}$ ) is the reference temperature corresponding to the *Vibrio pectenecida* thermal optimum [38], and  $E_a/R$  is the activation energy divided by the gas constant. The Arrhenius formulation ensures that colder temperatures slow disease progression (longer  $E$ ,  $I_1$ ,  $I_2$  durations) and reduce shedding rates, consistent with the observed latitudinal gradient in SSWD severity.

### 3.3.3 Tolerance: Extending $I_2$ Duration

The tolerance trait  $t_i$  operates as a damage-limitation mechanism that reduces the effective  $I_2 \rightarrow D$  mortality rate, extending survival time while infected:

$$\mu_{I_2 \rightarrow D, \text{eff}} = \mu_{I_2 \rightarrow D}(T) \times (1 - t_i \tau_{\text{max}}), \quad \text{floored at } 0.05 \times \mu_{I_2 \rightarrow D}(T), \quad (14)$$

where  $\tau_{\text{max}} = 0.85$  is the maximum mortality reduction at  $t_i = 1$ . The floor prevents biologically implausible indefinite survival. The effective rate is used when sampling the  $I_2$  timer (Eq. 2), so tolerant individuals spend longer in  $I_2$ — which may prolong both recovery opportunity and pathogen shedding.

### 3.3.4 Recovery

Recovery from infection proceeds via the clearance trait  $c_i$ , which represents the host's capacity for pathogen elimination.

**Recovery from  $I_2$ .** Each day, an  $I_2$  individual has probability:

$$p_{\text{rec}, I_2} = \rho_{\text{rec}} \times c_i, \quad \rho_{\text{rec}} = 0.05 \text{ d}^{-1}, \quad (15)$$

of clearing infection and returning to the susceptible pool ( $I_2 \rightarrow S$ ). At  $c_i = 0$  (no clearance ability), recovery is impossible; at  $c_i = 1$ , the daily recovery probability is 5%. Recovered individuals are immediately susceptible to reinfection, reflecting the absence of adaptive immunity in echinoderms.

524 **Early recovery from  $I_1$ .** Individuals with exceptionally high clearance ability ( $c_i >$   
525 0.5) can recover during the pre-symptomatic stage:

$$p_{\text{rec}, I_1} = \begin{cases} 0 & \text{if } c_i \leq 0.5, \\ \rho_{\text{rec}} \times 2(c_i - 0.5) & \text{if } c_i > 0.5. \end{cases} \quad (16)$$

526 At  $c_i = 1.0$ , the early recovery probability equals  $\rho_{\text{rec}}$ , identical to  $I_2$  recovery at maximum  
527 clearance. The threshold at  $c_i = 0.5$  ensures that only rare, high-clearance individuals  
528 can clear infection before progressing to the symptomatic stage.

### 529 3.4 Vibrio Dynamics

530 The concentration of waterborne *Vibrio pectenicida* at node  $k$  evolves according to:

$$\frac{dP_k}{dt} = \underbrace{\sigma_1(T) n_{I_1} + \sigma_2(T) n_{I_2} + \sigma_D n_{D, \text{fresh}}}_{\text{shedding}} - \underbrace{\xi(T) P_k}_{\text{decay}} - \underbrace{\phi_k P_k}_{\text{flushing}} + \underbrace{P_{\text{env}}(T, S)}_{\text{reservoir}} + \underbrace{\sum_j d_{jk} P_j}_{\text{dispersal}}, \quad (17)$$

531 integrated via forward Euler with  $\Delta t = 1$  day, subject to  $P_k \geq 0$ .

#### 532 3.4.1 Shedding

533 Pathogen shedding from live infectious hosts is temperature-dependent:

$$\sigma_1(T) = 5.0 \times \text{Arr}(T) \quad (I_1: \text{pre-symptomatic}), \quad (18)$$

$$\sigma_2(T) = 50.0 \times \text{Arr}(T) \quad (I_2: \text{symptomatic}), \quad (19)$$

534 where  $\text{Arr}(T)$  denotes the Arrhenius factor (Eq. 13) with  $E_a/R = 5,000$  K. The 10-  
535 fold difference between early and late shedding reflects the dramatic increase in tissue  
536 degradation and pathogen release during the wasting phase. Rates are given in bacte-  
537 ria  $\text{mL}^{-1} \text{d}^{-1} \text{host}^{-1}$  and represent field-effective values (Errata E2).

#### 538 3.4.2 Carcass Shedding

539 Dead individuals ( $D$  compartment) continue to shed pathogen saprophytically for a 3-day  
540 window at a constant rate  $\sigma_D = 15$  bacteria  $\text{mL}^{-1} \text{d}^{-1}$  carcass $^{-1}$  (field-effective; Code Er-  
541 rata CE-6). A ring buffer of daily disease death counts over the most recent 3 days tracks  
542 the number of “fresh” carcasses contributing to shedding:

$$n_{D, \text{fresh}}(t) = \sum_{\tau=0}^2 \text{deaths}(t - \tau). \quad (20)$$

### 3.4.3 Vibrio Decay

*Vibrio pectenica* survives longer in warmer water. The natural decay rate  $\xi(T)$  is interpolated log-linearly between empirical estimates:

$$\xi(T) = \begin{cases} 1.0 \text{ d}^{-1} & T \leq 10^\circ\text{C} \text{ (half-life } \approx 0.7 \text{ d)}, \\ 0.33 \text{ d}^{-1} & T \geq 20^\circ\text{C} \text{ (half-life } \approx 2.1 \text{ d)}, \\ \exp[(1-f) \ln \xi_{10} + f \ln \xi_{20}] & \text{otherwise,} \end{cases} \quad (21)$$

where  $f = (T - 10)/10$  and values are clamped outside the 10–20 °C range. This counter-intuitive pattern (faster decay at cold temperatures) reflects the environmental *Vibrio* literature [44].

### 3.4.4 Environmental Reservoir

In the ubiquitous scenario (default), *Vibrio pectenica* is assumed to persist in the sediment as viable-but-non-culturable (VBNC) cells that resuscitate when SST exceeds a threshold. The background input rate is:

$$P_{\text{env}}(T, S) = P_{\text{env,max}} \underbrace{\frac{1}{1 + e^{-\kappa_{\text{VBNC}}(T - T_{\text{VBNC}})}}}_{\text{VBNC sigmoid}} \underbrace{g_{\text{peak}}(T)}_{\text{thermal performance}} \underbrace{S_{\text{sal}}}_{\text{salinity}}, \quad (22)$$

where:

- $P_{\text{env,max}} = 500 \text{ bacteria mL}^{-1} \text{ d}^{-1}$  is the maximum input rate;
- $\kappa_{\text{VBNC}} = 1.0^\circ\text{C}^{-1}$  controls the steepness of VBNC resuscitation;
- $T_{\text{VBNC}} = 12^\circ\text{C}$  is the midpoint temperature;
- $g_{\text{peak}}(T)$  is a thermal performance curve with Arrhenius increase below  $T_{\text{opt}} = 20^\circ\text{C}$  and quadratic decline above, reaching zero at  $T_{\text{max}} = 30^\circ\text{C}$ .

In the invasion scenario,  $P_{\text{env}} = 0$  everywhere until the pathogen is explicitly introduced.

## 3.5 Pathogen Evolution

When pathogen evolution is enabled, each infectious agent carries a continuous virulence phenotype  $v_i$  that modulates disease rates via mechanistic tradeoff functions.

### 3.5.1 Virulence–Tradeoff Curves

More virulent strains kill faster, shed more, and progress more rapidly, but also remove themselves from the host population sooner:

$$\sigma_{1,v}(T) = \sigma_1(T) \times \exp(\alpha_{\text{shed}} \gamma_{\text{early}} (v - v^*)), \quad (23)$$

$$\sigma_{2,v}(T) = \sigma_2(T) \times \exp(\alpha_{\text{shed}} (v - v^*)), \quad (24)$$

$$\mu_{I_1 \rightarrow I_2,v}(T) = \mu_{I_1 \rightarrow I_2}(T) \times \exp(\alpha_{\text{prog}} (v - v^*)), \quad (25)$$

$$\mu_{I_2 \rightarrow D,v}(T) = \mu_{I_2 \rightarrow D}(T) \times \exp(\alpha_{\text{kill}} (v - v^*)), \quad (26)$$

where  $v^* = 0.5$  is the ancestral virulence (identity point),  $\alpha_{\text{shed}} = 1.5$ ,  $\alpha_{\text{prog}} = 1.0$ ,  $\alpha_{\text{kill}} = 2.0$ , and  $\gamma_{\text{early}} = 0.3$  attenuates the shedding effect in the pre-symptomatic stage.

### 3.5.2 Transmission and Mutation

When a new infection occurs, the infecting strain is inherited either from a shedding individual (weighted by shedding rate) or from the environmental reservoir (with virulence  $v_{\text{env}} = 0.5$ ). The probability of inheriting from a shedder is proportional to the total host-derived shedding relative to total pathogen input:

$$P(\text{from shedder}) = \frac{\sum_j \sigma_j(v_j, T)}{\sum_j \sigma_j(v_j, T) + P_{\text{env}}(T, S)}. \quad (27)$$

The inherited virulence is then subject to mutation:

$$v_{\text{new}} = \text{clip}(v_{\text{parent}} + \mathcal{N}(0, \sigma_{v,\text{mut}}^2), v_{\text{min}}, v_{\text{max}}), \quad (28)$$

with  $\sigma_{v,\text{mut}} = 0.02$ ,  $v_{\text{min}} = 0$ ,  $v_{\text{max}} = 1$ .

## 3.6 Basic Reproduction Number

The basic reproduction number provides a summary measure of epidemic potential at a node:

$$R_0 = \frac{a_{\text{exp}} S_0 (1 - \bar{r}) S_{\text{sal}}}{K_{1/2} (\xi(T) + \phi_k)} \left[ \frac{\sigma_1(T)}{\mu_{I_1 \rightarrow I_2}(T)} + \frac{\sigma_2(T)}{\mu_{I_2 \rightarrow D,\text{eff}}(T) + \rho_{\text{rec}} \bar{c}} + \sigma_D \tau_D \right], \quad (29)$$

where  $S_0$  is the number of susceptibles,  $\bar{r}$  and  $\bar{c}$  are population-mean resistance and recovery scores,  $\mu_{I_2 \rightarrow D,\text{eff}}$  incorporates population-mean tolerance (Eq. 14),  $\rho_{\text{rec}} \bar{c}$  adds the recovery exit rate from  $I_2$ , and  $\tau_D = 3$  days is the carcass shedding duration. The three bracketed terms represent the pathogen contribution from each infectious compartment ( $I_1$ ,  $I_2$ , and  $D$  carcasses, respectively).

### 3.7 Daily Update Sequence

Within each daily timestep, the disease module executes the following steps in order:

1. **Update Vibrio concentration** via Euler integration of Eq. 17, using current compartment counts and environmental conditions.
2. **Transmission ( $S \rightarrow E$ ):** For each susceptible agent, compute the force of infection  $\lambda_i$  (Eq. 4), convert to daily probability (Eq. 5), and draw a Bernoulli infection event. Newly exposed agents receive an Erlang-sampled E-stage timer. When pathogen evolution is active, the infecting strain is inherited and mutated (Section 3.5.2).
3. **Disease progression:** Decrement all disease timers. For agents with expired timers:  $E \rightarrow I_1$ ,  $I_1 \rightarrow I_2$  (with tolerance-adjusted timer),  $I_2 \rightarrow D$ . For agents with active timers: check recovery from  $I_2$  (Eq. 15) and early recovery from  $I_1$  (Eq. 16).
4. **Carcass tracking:** Record today's disease deaths in the 3-day ring buffer for saprophytic shedding.
5. **Update diagnostics:** Recount compartments, update cumulative statistics (total infections, deaths, recoveries), track peak prevalence and peak Vibrio.

All operations are vectorized using NumPy batch sampling and array-level random draws for computational efficiency, achieving  $O(N)$  scaling in population size.

## 4 Genetics Module

The genetics module tracks a diploid genotype at 51 biallelic loci for every individual, partitioned into three quantitative defense traits: *resistance*, *tolerance*, and *recovery*. Genotypes are transmitted via Mendelian inheritance with free recombination, mutated at a per-allele rate  $\mu = 10^{-8}$  per generation [46], and subject to natural selection through the coupling of trait scores to disease dynamics (Section 3). The module additionally implements sweepstakes reproductive success (SRS) to capture the extreme reproductive variance characteristic of broadcast-spawning marine invertebrates [27].

### 4.1 Three-Trait Architecture

Each individual carries a  $(51 \times 2)$  genotype array of `int8` alleles, where the 51 loci are partitioned into three contiguous blocks:

Table 3: Three-trait genetic architecture. The partition is configurable (constraint:  $n_R + n_T + n_C = 51$ ); the default 17/17/17 split is used in all analyses reported here.

Trait	Symbol	Loci	Indices	Mechanistic role
Resistance	$r_i$	$n_R = 17$	0–16	Immune exclusion: reduces probability of $S \rightarrow E$ transition
Tolerance	$t_i$	$n_T = 17$	17–33	Damage limitation: extends $I_2$ survival via mortality rate reduction
Recovery	$c_i$	$n_C = 17$	34–50	Pathogen clearance: daily probability of $I_1/I_2 \rightarrow S$ transition (recovery)

These three traits represent biologically distinct immune strategies with different epidemiological consequences [55]:

- **Resistance** ( $r_i$ ) acts *before* infection via receptor polymorphisms, barrier defenses, and innate pathogen recognition. Resistant individuals reduce pathogen pressure on the population by preventing shedding entirely.
- **Tolerance** ( $t_i$ ) acts *during* infection via tissue repair, anti-inflammatory regulation, and metabolic compensation. Tolerant hosts survive longer while infected but continue to shed pathogen—they are epidemiological “silent spreaders” that maintain transmission pressure while saving themselves.
- **Recovery** ( $c_i$ ) acts *during late infection* via coelomocyte phagocytosis and immune effector mobilization. Recovering hosts actively clear the pathogen and return to the susceptible pool (S), removing a shedding host from the population. Because echinoderms lack adaptive immunity, recovered individuals may be reinfected.

The locus count of 51 is motivated by Schiebelhut et al. [60], who identified  $\sim 51$  loci under selection in *Pisaster ochraceus* SSWD survivors. No genome-wide association study (GWAS) data currently distinguish resistance, tolerance, and recovery loci in *P. helianthoides*; the equal 17/17/17 partition is a simplifying assumption whose sensitivity is explored via the  $n_R$  parameter in the global sensitivity analysis (Section 7). A reference genome for *P. helianthoides* is now available [62], enabling future empirical partitioning.

**Removal of EF1A overdominant locus.** An earlier model version included a locus representing the EF1A elongation factor with overdominant fitness effects, based on Wares and Schiebelhut [71] who documented allele frequency shifts at this locus in *Pisaster ochraceus* following SSWD. We removed this locus because (1) the EF1A finding is specific to *Pisaster* with no evidence of overdominance in *P. helianthoides*, and (2) a single overdominant locus imposed a hard floor on heterozygosity loss that was biologically unjustified for our focal species.



## 4.2 Trait Score Computation

At each locus  $\ell$ , an individual carries two alleles  $g_{\ell,0}, g_{\ell,1} \in \{0, 1\}$ , where 1 denotes the derived (protective) allele and 0 the ancestral allele. Each locus within a trait block has a fixed effect size  $e_\ell > 0$ , and an individual's trait score is the effect-weighted mean allele dosage:

$$\theta_i = \sum_{\ell \in \mathcal{L}_\theta} e_\ell \frac{g_{\ell,0} + g_{\ell,1}}{2} \quad (30)$$

where  $\mathcal{L}_\theta$  denotes the locus set for trait  $\theta \in \{r, t, c\}$  and  $\theta_i \in [0, \sum e_\ell]$ . Effect sizes within each trait block are normalized so  $\sum_{\ell \in \mathcal{L}_\theta} e_\ell = 1$ , bounding all trait scores to  $[0, 1]$ .

### 4.2.1 Effect Size Distribution

Per-locus effect sizes are drawn from an exponential distribution  $e_\ell \sim \text{Exp}(\lambda = 1)$ , normalized to sum to 1.0 within each trait, and sorted in descending order. This produces a distribution where a few loci have large effects and the remainder have small effects, consistent with empirical QTL architectures for disease resistance traits [41]. A fixed seed ensures identical effect sizes across simulation runs. Each trait block receives independently drawn effect sizes.

### 4.2.2 Coupling to Disease Dynamics

The three traits feed into the disease module (Section 3) as follows:

1. **Resistance** reduces the per-individual force of infection:

$$\lambda_i = a \cdot \frac{P}{K_{1/2} + P} \cdot (1 - r_i) \cdot S_{\text{sal}} \cdot f_L(L_i) \quad (31)$$

where  $a$  is the exposure rate,  $P$  the local *Vibrio pectenicida* concentration,  $K_{1/2}$  the half-infective dose,  $S_{\text{sal}}$  the salinity modifier, and  $f_L(L_i)$  the size-dependent susceptibility factor.

2. **Tolerance** reduces the  $I_2 \rightarrow D$  transition rate via a timer-scaling mechanism:

$$\mu_{I_2D,i}^{\text{eff}} = \mu_{I_2D}(T) \cdot (1 - t_i \cdot \tau_{\text{max}}) \quad (32)$$

where  $\tau_{\text{max}} = 0.85$  is the maximum mortality reduction achievable at  $t_i = 1$ . A floor of 5% of the baseline rate prevents complete elimination of disease mortality. Tolerant individuals survive longer while infected but continue shedding, creating a selective conflict between individual and population-level fitness.

3. **Recovery** determines the daily clearance probability:

$$p_{\text{rec},i} = \rho_{\text{rec}} \times c_i \quad (33)$$

where  $\rho_{\text{rec}} = 0.05 \text{ d}^{-1}$  is the base recovery rate. Recovery from  $I_1$  requires  $c_i > 0.5$  (early clearance); recovery from  $I_2$  has no threshold. Successful recovery transitions the agent to the susceptible pool (S), as echinoderms lack acquired immunity.

### 4.3 Genotype Initialization

Initial allele frequencies are drawn independently for each locus from a Beta distribution:

$$q_\ell \sim \text{Beta}(a, b) \quad (\text{default } a = 2, b = 8) \quad (34)$$

producing a right-skewed frequency spectrum where most protective alleles are rare ( $\mathbb{E}[q] = a/(a + b) = 0.2$ ), consistent with standing variation in immune genes maintained by mutation–selection balance. The raw frequencies are then rescaled per-trait so that the expected population-mean trait score equals a configurable target:

Table 4: Default target population-mean trait scores at initialization.

Trait	Target mean	Rationale
Resistance ( $r_i$ )	0.15	Pre-epidemic standing variation
Tolerance ( $t_i$ )	0.10	Moderate damage limitation
Recovery ( $c_i$ )	0.02	Rare standing variation for clearance

Recovery is initialized with the lowest mean because active pathogen clearance is assumed to be the rarest phenotype prior to epidemic exposure. Per-locus frequencies are clipped to  $[0.001, 0.5]$  to prevent fixation at initialization while ensuring the derived allele never begins at majority frequency. Genotypes are then sampled assuming Hardy–Weinberg equilibrium at each locus: each allele copy is independently drawn as a Bernoulli trial with probability  $q_\ell$ .

### 4.4 Mendelian Inheritance and Mutation

At reproduction, each offspring inherits one randomly chosen allele from each parent at every locus (independent assortment, no linkage). The vectorized implementation draws allele choices for all  $n_{\text{offspring}} \times 51 \times 2$  positions simultaneously, then indexes into parental genotype arrays.

Mutations are applied to offspring genotypes at rate  $\mu = 10^{-8}$  per allele per generation [46]. The total number of mutations per cohort is drawn from a Poisson distribution:

686  $n_{\text{mut}} \sim \text{Pois}(\mu \times n_{\text{offspring}} \times 51 \times 2)$ . Each mutation flips the allele at a randomly chosen  
687 position ( $0 \rightarrow 1$  or  $1 \rightarrow 0$ ), providing bidirectional mutational pressure. At the de-  
688 fault mutation rate, mutations are negligible within the 20–100 year simulation horizon  
689 (expected  $\sim 10^{-6}$  mutations per offspring), and evolution proceeds primarily through  
690 selection on standing variation.

## 691 4.5 Sweepstakes Reproductive Success

692 Broadcast-spawning marine invertebrates exhibit sweepstakes reproductive success (SRS):  
693 a tiny fraction of adults contribute the majority of surviving offspring in any given cohort  
694 [27]. This phenomenon produces  $N_e/N$  ratios on the order of  $10^{-3}$  in empirical obser-  
695 vations [3] and dramatically amplifies genetic drift while simultaneously accelerating the  
696 fixation of favorable alleles in post-epidemic populations [14].

697 SSWD-EvoEpi implements SRS via a Pareto-weighted reproductive lottery. Each  
698 spawning adult receives a random weight drawn from a Pareto distribution with shape  
699 parameter  $\alpha_{\text{SRS}}$  (default 1.35):

$$w_i \sim \text{Pareto}(\alpha_{\text{SRS}}) + 1 \quad (35)$$

700 Female weights are additionally multiplied by size-dependent fecundity (Section 5.5),  
701 so larger females that win the sweepstakes lottery contribute disproportionately:

$$\tilde{w}_{i,\text{female}} = w_i \times \left( \frac{L_i}{L_{\text{ref}}} \right)^b \quad (36)$$

702 where  $b = 2.5$  is the fecundity allometric exponent and  $L_{\text{ref}} = 500$  mm. Male weights  
703 use the raw Pareto draw without fecundity modulation. Parents are then sampled with  
704 replacement from the normalized weight distributions, and offspring receive Mendelian-  
705 inherited genotypes.

706 The Pareto shape  $\alpha_{\text{SRS}} = 1.35$  was chosen to produce  $N_e/N$  ratios consistent with  
707 empirical estimates of  $\sim 10^{-3}$  in marine broadcast spawners [3, 27]. A small annual  
708 variation in  $\alpha$  (drawn from  $\mathcal{N}(\alpha_{\text{SRS}}, \sigma_\alpha^2)$  with  $\sigma_\alpha = 0.10$ ) produces temporal fluctuation  
709 in the variance of reproductive success across cohorts.

710 **Effective population size.**  $N_e$  is computed from the realized offspring distribution  
711 using the standard formula [27]:

$$N_e = \frac{4N - 2}{V_k + 2} \quad (37)$$

712 where  $N$  is the number of spawning parents and  $V_k$  is the variance in offspring number.  
713 Sex-specific  $N_e$  values are computed for females and males separately, then combined via  
714 harmonic mean:  $N_e = 4N_{e,f}N_{e,m}/(N_{e,f} + N_{e,m})$ .

## 4.6 Genetic Diagnostics and Tracking

The model records a suite of genetic summary statistics at each node at annual intervals:

- **Per-trait means and variances:**  $\bar{r}$ ,  $\bar{t}$ ,  $\bar{c}$  and  $\text{Var}(r)$ ,  $\text{Var}(t)$ ,  $\text{Var}(c)$ .
- **Additive genetic variance** ( $V_A$ ) per trait:

$$V_{A,\theta} = \sum_{\ell \in \mathcal{L}_\theta} 2 e_\ell^2 q_\ell (1 - q_\ell) \quad (38)$$

where  $q_\ell$  is the derived allele frequency at locus  $\ell$ .  $V_A$  determines the potential rate of evolutionary response to selection.

- **Heterozygosity:** Observed ( $H_o$ ) and expected ( $H_e$ ) heterozygosity averaged across all 51 loci.
- $F_{ST}$ : Weir–Cockerham-style  $F_{ST}$  across nodes, computed as  $F_{ST} = \text{Var}(\bar{q})/[\bar{q}(1-\bar{q})]$  averaged across polymorphic loci.
- **Pre- and post-epidemic allele frequency snapshots:** Full 51-locus allele frequency vectors taken immediately before pathogen introduction and two years after the epidemic onset, enabling direct measurement of allele frequency shifts ( $\Delta q$ ) attributable to selection.

**No cost of resistance.** A cost-of-resistance parameter (fecundity penalty for high  $r_i$ ) was considered but excluded following discussion with the senior author. No empirical evidence supports a measurable fecundity cost for disease resistance alleles in *P. he-lianthoides*, and including an unparameterized cost would introduce a free parameter with no calibration target. Fecundity depends solely on body size (Section 5.5).

## 4.7 Genotype Bank (Tier 2 Nodes)

For Tier 2 spatial nodes that use simplified demographics rather than full agent tracking, the genetics module maintains a *genotype bank* of  $N_{\text{bank}} = 100$  representative diploid genotypes with associated frequency weights. The bank is created by random sampling from the alive population and preserves all three trait scores and allele frequencies. When agents migrate from a Tier 2 to a Tier 1 node, genotypes are expanded from the bank using SRS-weighted sampling (Pareto weights  $\times$  bank frequency weights) to reconstruct individual-level genetic variation.

## 5 Population Dynamics

The population dynamics module governs the complete life history of *Pycnopodia helianthoides*: growth, natural mortality, reproduction, larval dispersal, and settlement. All demographic processes operate on a daily timestep, integrated within the master simulation loop described in Section 2. Disease-driven mortality is handled by the disease module (Section 3); coupling occurs through shared access to the agent array.

### 5.1 Life Stages

Each individual progresses through five life stages defined by size thresholds (Table 5). Stage transitions are unidirectional: agents can only advance, never regress.

Table 5: Life stages and transition thresholds for *P. helianthoides*.

Stage	Size range	Transition at	Duration
Egg/Larva	Planktonic	Settlement event	49–146 days PLD
Settler	0.5–10 mm	$\geq 10$ mm	$\sim 1$ year
Juvenile	10–150 mm	$\geq 150$ mm	$\sim 1$ –5 years
Subadult	150–400 mm	$\geq 400$ mm	$\sim 5$ –10 years
Adult	$> 400$ mm	—	10–50+ years

### 5.2 Growth

Individual growth follows the von Bertalanffy (VB) growth model in differential form, resolved daily:

$$L(t + \Delta t) = L_{\infty} - (L_{\infty} - L(t)) \cdot \exp(-k_{\text{growth}} \cdot \Delta t) \quad (39)$$

where  $L_{\infty} = 1000$  mm is the asymptotic arm-tip diameter,  $k_{\text{growth}} = 0.08 \text{ yr}^{-1}$  is the Brody growth coefficient, and  $\Delta t = 1/365 \text{ yr}$  for the daily timestep. Individual growth variation is introduced through a multiplicative log-normal noise term applied to the daily increment:

$$\Delta L_i = (L_{\text{det}} - L_i) \cdot \exp(\varepsilon_i), \quad \varepsilon_i \sim \mathcal{N}\left(0, \frac{\sigma_g}{\sqrt{365}}\right) \quad (40)$$

where  $\sigma_g = 2.0$  mm is the annual growth noise scale and the  $\sqrt{365}$  scaling preserves the annual CV when integrated over daily steps. Size is constrained to never decrease (no shrinking). Stage transitions are evaluated after each growth step based on the thresholds in Table 5.

Aging proceeds at 1/365 years per day, producing fractional ages that drive size-at-age trajectories and determine eligibility for senescence mortality.

### 5.3 Natural Mortality

Natural mortality is resolved daily using continuous hazard rates derived from stage-specific annual survival probabilities. The daily death probability for individual  $i$  is:

$$p_{\text{death},i} = 1 - \left(1 - m_{\text{annual}}(s_i)\right)^{1/365} \quad (41)$$

where  $m_{\text{annual}}(s) = 1 - S_{\text{annual}}(s)$  is the annual mortality rate for stage  $s$ . The annual survival schedule (Table 6) produces a type III survivorship curve with high settler/juvenile mortality and low adult mortality, consistent with demographic estimates for long-lived asteroids.

Table 6: Stage-specific annual survival rates.

Stage	Annual survival ( $S$ )	Annual mortality
Settler	0.001	0.999
Juvenile	0.03	0.97
Subadult	0.90	0.10
Adult	0.95	0.05
Senescent	0.98	0.02 (base)

**Senescence.** Individuals exceeding the senescence age ( $a_{\text{sen}} = 50$  yr) accumulate additional mortality linearly:

$$m_{\text{total}}(s_i, a_i) = m_{\text{annual}}(s_i) + m_{\text{sen}} \cdot \frac{a_i - a_{\text{sen}}}{20} \quad (42)$$

where  $m_{\text{sen}} = 0.10$  and the divisor of 20 scales the senescence ramp such that a 70-year-old individual experiences an additional 10% annual mortality.

Daily mortality is applied via a single vectorized random draw across all alive agents, converting stage-dependent annual rates to daily hazard probabilities. This continuous approach avoids the artificial synchronization artifacts of annual batch mortality and permits realistic within-year population fluctuations.

### 5.4 Spawning System

SSWD-EvoEpi implements a biologically detailed spawning system reflecting the extended reproductive season and cascading spawning behavior observed in *P. helianthoides*.

### 5.4.1 Spawning Season and Phenology

The spawning season extends from day 305 ( $\approx$ November 1) through day 196 ( $\approx$ July 15) of the following year, spanning approximately 270 days and wrapping across the calendar year boundary. Spawning intensity follows a Normal envelope centered on a latitude-adjusted peak:

$$P_{\text{season}}(d) = \exp\left(-\frac{(\Delta d)^2}{2\sigma_{\text{peak}}^2}\right) \quad (43)$$

where  $\Delta d$  is the shortest circular distance between day  $d$  and the peak day (accounting for year wrapping), and  $\sigma_{\text{peak}} = 60$  days is the standard deviation of the seasonal peak. The peak day-of-year is latitude-dependent:

$$d_{\text{peak}}(\phi) = d_{\text{peak,base}} + \lceil(\phi - 40^\circ\text{N}) \times 3 \text{ d}/^\circ\rceil \quad (44)$$

where  $d_{\text{peak,base}} = 105$  ( $\approx$ April 15) is the reference peak at  $40^\circ\text{N}$ , and higher-latitude populations spawn approximately 3 days later per degree northward.

### 5.4.2 Spontaneous Spawning

Each day during the spawning season, mature adults ( $\geq 400$  mm, Susceptible or Recovered disease state) are first evaluated for *readiness*, a stochastic physiological state modulated by the seasonal envelope  $P_{\text{season}}(d)$ . Once ready, individuals attempt spontaneous spawning with sex-specific daily probabilities:

$$p_{\text{spawn,female}} = 0.012 \quad (45)$$

$$p_{\text{spawn,male}} = 0.0125 \quad (46)$$

These rates were calibrated to produce  $\geq 80\%$  female spawning participation per season and a mean of  $\sim 2.2$  male bouts per season, consistent with the observation that males spawn more frequently than females in broadcast-spawning asteroids.

**Bout limits and refractory periods.** Females are limited to a maximum of 2 spawning bouts per season; males are limited to 3 bouts. Males enter a brief refractory period between bouts (default 0 days, configurable) during which they cannot spawn, reflecting the physiological recovery time for spermatogenesis.

### 5.4.3 Cascade Induction

Spawning by one individual can trigger spawning in nearby conspecifics via waterborne chemical cues (spawning-induced spawning), producing the synchronous mass spawning

807 events observed in broadcast spawners. Induction operates over a 3-day chemical cue  
 808 persistence window and is strongly sex-asymmetric:

$$\kappa_{\text{fm}} = 0.80 \quad (\text{female} \rightarrow \text{male induction}) \quad (47)$$

$$\kappa_{\text{mf}} = 0.60 \quad (\text{male} \rightarrow \text{female induction}) \quad (48)$$

809 where  $\kappa_{\text{fm}}$  is the probability that a ready male spawns when a female within the cas-  
 810 cade radius (200 m) has spawned within the cue window. The female-to-male asymmetry  
 811 reflects the stronger spawning trigger provided by egg-associated chemical signals. Read-  
 812 ness induction also operates: individuals not yet physiologically ready can be driven to  
 813 readiness by nearby spawning activity, with a daily probability of 0.5 when within a 300 m  
 814 detection radius.

#### 815 5.4.4 Post-Spawning Immunosuppression

816 Spawning imposes a 28-day immunosuppression period during which the individual's force  
 817 of infection is multiplied by a susceptibility factor of 2.0:

$$\lambda_i^{\text{eff}} = \lambda_i \times \begin{cases} \chi_{\text{immuno}} = 2.0 & \text{if immunosuppression timer} > 0 \\ 1.0 & \text{otherwise} \end{cases} \quad (49)$$

818 This reflects the metabolic cost of gamete production and the documented increase in  
 819 disease susceptibility following reproductive investment in marine invertebrates. The  
 820 immunosuppression timer is reset each time an individual spawns, so multiple spawning  
 821 bouts within a season extend the vulnerability window. Immunosuppression timers are  
 822 decremented daily regardless of spawning season status.

### 823 5.5 Fecundity

824 Female fecundity follows an allometric relationship with body size:

$$F_i = F_0 \cdot \left( \frac{L_i}{L_{\text{ref}}} \right)^b \quad (50)$$

825 where  $F_0 = 10^7$  eggs is the reference fecundity at  $L_{\text{ref}} = 500$  mm and  $b = 2.5$  is the  
 826 allometric exponent. Only females at or above the minimum reproductive size  $L_{\text{min}} =$   
 827 400 mm produce eggs. No cost-of-resistance penalty is applied to fecundity (Section 4.6).



## 5.6 Fertilization Kinetics and the Allee Effect

Broadcast spawners face a fertilization Allee effect: at low population density, sperm limitation reduces the fraction of eggs successfully fertilized [16, 43]. We model fertilization success using a mean-field approximation of the Lundquist and Botsford [43] broadcast fertilization model:

$$\mathcal{F}(\rho_m) = 1 - \exp(-\gamma_{\text{fert}} \cdot \rho_{m,\text{eff}}) \quad (51)$$

where  $\gamma_{\text{fert}} = 4.5 \text{ m}^2$  is the sperm contact parameter and  $\rho_{m,\text{eff}}$  is the effective male density, potentially enhanced by spawning aggregation behavior. The aggregation factor increases effective local density within spawning clumps above the spatially uniform average when adult count exceeds a threshold.

This produces a quadratic relationship between zygote production and density at low density:  $\text{zygotes} \propto \rho_f \times \mathcal{F}(\rho_m) \propto \rho^2$  when  $\rho \rightarrow 0$ , creating a strong demographic Allee effect. For high-fecundity broadcast spawners like *P. helianthoides*, the deterministic Allee threshold is near zero density; the practical Allee effect operates through stochastic processes at low  $N$ .

## 5.7 Larval Phase

Fertilized eggs enter a temperature-dependent pelagic larval duration (PLD):

$$\text{PLD}(T) = \text{PLD}_{\text{ref}} \cdot \exp(-Q_{\text{dev}} \cdot (T - T_{\text{ref}})) \quad (52)$$

where  $\text{PLD}_{\text{ref}} = 63$  days at  $T_{\text{ref}} = 10.5^\circ\text{C}$  [35], and  $Q_{\text{dev}} = 0.05 \text{ }^\circ\text{C}^{-1}$  produces shorter PLD at warmer temperatures. PLD is clamped to [30, 150] days.

Larval survival during the pelagic phase follows a constant daily mortality model:

$$S_{\text{larval}} = \exp(-\mu_{\text{larva}} \cdot \text{PLD}) \quad (53)$$

with  $\mu_{\text{larva}} = 0.05 \text{ d}^{-1}$ . At the reference PLD of 63 days, this yields  $S_{\text{larval}} \approx 4.3\%$  — high mortality that is compensated by the enormous fecundity of *P. helianthoides*.

Larval cohorts carry genotypes inherited via the SRS lottery (Section 4.5) and are tracked as discrete objects during the pelagic phase. Upon completion of PLD, competent larvae are available for settlement. In the spatial simulation (Section 6), cohorts are dispersed between nodes via the larval connectivity matrix  $\mathbf{C}$  before settlement.

## 5.8 Settlement and Recruitment

Competent larvae settle into the benthic population through a three-stage process:

**1. Settlement cue (Allee effect).** Settlement success is modulated by the presence of conspecific adults via a Michaelis–Menten function representing biofilm-mediated settlement cues:

$$C_{\text{settle}}(N_{\text{adults}}) = 0.2 + \frac{0.8 \cdot N_{\text{adults}}}{5 + N_{\text{adults}}} \quad (54)$$

where the baseline of 0.2 represents settlement on coralline algae in the absence of adults, and the additional 0.8 reflects enhanced settlement induced by adult biofilm. The half-saturation constant of 5 adults means that even a small remnant population provides strong settlement cues.

**2. Density-dependent recruitment (Beverton–Holt).** The number of recruits is governed by a standard Beverton–Holt stock-recruitment relationship:

$$R = \frac{K \cdot s_0 \cdot S}{K + s_0 \cdot S} \quad (55)$$

where  $S$  is the number of effective settlers (after cue modulation),  $K$  is the carrying capacity, and  $s_0 = 0.03$  is the density-independent per-settler survival rate. At low  $S$ ,  $R \approx s_0 S$  (supply-limited); at high  $S$ ,  $R \rightarrow K$  (habitat-limited). For broadcast spawners with  $S \gg K$ , recruitment is typically habitat-limited and population self-regulates.

**3. Agent initialization.** Recruited settlers are placed in dead agent slots, assigned size 0.5 mm, age 0, Settler stage, random sex (1:1 ratio), Susceptible disease state, and random position within the node’s habitat area. Genotypes are copied from the SRS-selected settler genotypes, and all three trait scores ( $r_i$ ,  $t_i$ ,  $c_i$ ) are computed from the inherited genotype.

**Juvenile immunity.** Newly settled individuals can optionally be granted a juvenile immunity period (configurable, default 0 days) during which they are not susceptible to infection. The settlement day is recorded for each recruit to enable age-dependent susceptibility calculations.

## 5.9 Continuous Settlement

Rather than settling all larvae in an annual pulse, the model tracks individual larval cohorts and settles them daily as their PLD elapses. Cohorts generated by daily spawning events throughout the extended spawning season (Section 5.4.1) are stored in a per-node pending list sorted by settlement day. Each simulation day, cohorts whose PLD has elapsed are popped from the sorted list front (amortized  $O(1)$ ) and passed through the settlement pipeline. This continuous approach produces realistic seasonal recruitment

pulses that peak several months after the spawning peak, consistent with the observed temporal offset between spawning and juvenile recruitment in *P. helianthoides*.

At the annual boundary, any remaining unsettled cohorts from each node are collected for spatial dispersal via the connectivity matrix  $\mathbf{C}$  (Section 6), then redistributed to destination nodes where they continue to settle daily as PLD elapses.

## 5.10 Demographic–Genetic–Epidemiological Coupling

The population dynamics module is bidirectionally coupled to the disease and genetics modules:

- **Disease  $\rightarrow$  demographics:** Disease kills individuals ( $I_2 \rightarrow D$ ), reducing population size and altering age/size structure. Post-spawning immunosuppression (Section 5.4.4) increases disease risk for recent spawners, creating a temporal alignment between peak reproductive effort and peak epidemic severity during warm months.
- **Demographics  $\rightarrow$  disease:** Reduced population density lowers contact rates and environmental pathogen concentration. The fertilization Allee effect (Section 5.6) amplifies population collapse by reducing reproductive output at low density, potentially trapping populations in an extinction vortex.
- **Genetics  $\rightarrow$  demographics:** The SRS lottery (Section 4.5) produces extreme reproductive variance that amplifies genetic drift while accelerating the fixation of resistance, tolerance, and recovery alleles enriched by selection during epidemic episodes.
- **Demographics  $\rightarrow$  genetics:** Population bottlenecks from disease reduce  $N_e$  far below census  $N$ , compounded by SRS ( $N_e/N \sim 10^{-3}$ ). The interaction of selection with small effective population size determines whether evolutionary rescue is fast enough to prevent extinction.

## 6 Spatial Module and Environmental Forcing

SSWD-EvoEpi represents the NE Pacific range of *Pycnopodia helianthoides* as a metapopulation network of discrete spatial nodes connected by larval dispersal and pathogen transport. Each node carries its own environmental forcing (sea surface temperature, salinity, flushing rate) that modulates local disease and demographic dynamics. This section describes the spatial architecture, connectivity matrices, environmental time series, and agent movement model.

## 6.1 Metapopulation Network Structure

The metapopulation is a graph  $\mathcal{G} = (\mathcal{N}, \mathbf{C}, \mathbf{D})$  where each node  $k \in \mathcal{N}$  represents a geographically delineated habitat patch and  $\mathbf{C}$ ,  $\mathbf{D}$  are the larval and pathogen connectivity matrices, respectively.

### 6.1.1 Node Definition

Each node is parameterized by a `NodeDefinition` record with the following fields:

Table 7: Node definition fields.

Field	Units	Description
lat, lon	°N, °E	Geographic coordinates
carrying_capacity	individuals	Local $K$ ( $= \text{habitat area} \times \rho_{\max}$ )
is_fjord	bool	Fjord vs. open coast classification
sill_depth	m	Sill depth ( $\infty$ for open coast)
flushing_rate	$\text{d}^{-1}$	Mean annual hydrodynamic flushing $\phi_k$
mean_sst	°C	Baseline annual mean SST
sst_amplitude	°C	Annual cycle half-range
sst_trend	°C yr $^{-1}$	Linear warming trend
salinity	psu	Effective mean salinity
depth_range	m	Min–max habitat depth
subregion	—	Biogeographic subregion code

At runtime, each `NodeDefinition` is wrapped in a `SpatialNode` object that holds the local population arrays (agents and genotypes), current environmental state (SST, salinity, flushing rate), *Vibrio* concentration, and diagnostic flags. The `MetapopulationNetwork` aggregates all nodes together with the  $\mathbf{C}$ ,  $\mathbf{D}$ , and distance matrices.

### 6.1.2 Internode Distance Computation

Connectivity kernels require pairwise waterway distances between nodes. Two methods are available:

**Haversine with tortuosity.** For small networks ( $\leq 11$  nodes), geodesic great-circle distances are computed via the Haversine formula and multiplied by a uniform tortuosity factor  $\tau = 1.5$  (intermediate between open-coast  $\sim 1.2$  and fjord  $\sim 2.5$ ) to approximate along-coast path lengths:

$$d_{jk}^{\text{water}} = \tau \times d_{jk}^{\text{Haversine}}. \quad (56)$$

**Precomputed overwater distances.** For full-range simulations, a 489-site overwater distance matrix was computed from GEBCO 2022 bathymetric data at 15 arc-second resolution. Land cells were rasterized from Natural Earth 10 m land polygons, and Dijkstra’s algorithm on a 4-connected ocean grid yielded shortest overwater paths. The resulting  $489 \times 489$  matrix spans 2.0–7,187 km, with 98.4% of pairs connected (1,946 disconnected pairs involve western Aleutian sites near the antimeridian). Model nodes are matched to the nearest precomputed site within a 50 km tolerance; unmatched nodes fall back to Haversine  $\times \tau$ .

## 6.2 Connectivity Matrices

Two connectivity matrices govern inter-node exchange: **C** for annual larval dispersal and **D** for daily pathogen transport (Errata E5). Both use exponential distance kernels but operate at different spatial and temporal scales.

### 6.2.1 Larval Connectivity Matrix C

$C_{jk}$  gives the probability that a competent larva produced at node  $j$  settles at node  $k$ . The matrix is constructed from an exponential dispersal kernel with explicit self-recruitment:

$$C_{jk} = \begin{cases} \alpha_j & \text{if } j = k, \\ (1 - \alpha_j) \exp\left(-\frac{d_{jk}}{D_L}\right) b_{jk} & \text{if } j \neq k, \end{cases} \quad (57)$$

where:

- $D_L = 400$  km is the larval dispersal length scale, reflecting the 4–8 week pelagic larval duration (PLD) of *Pycnopodia helianthoides* [65];
- $\alpha_j$  is the self-recruitment fraction:  $\alpha_{\text{fjord}} = 0.30$  for fjord nodes (reflecting enhanced retention behind sills) and  $\alpha_{\text{open}} = 0.10$  for open-coast nodes;
- $b_{jk} \in [0, 1]$  is an optional barrier attenuation factor for biogeographic breaks (e.g., Cape Mendocino).

Rows are then normalized so that:

$$\sum_k C_{jk} = r_{\text{total}} = 0.02, \quad (58)$$

where  $r_{\text{total}}$  represents the total per-larva settlement success probability, accounting for the compounding losses of pelagic mortality, failed metamorphosis, and post-settlement predation.

The elevated self-recruitment fraction for fjord nodes ( $\alpha_{\text{fjord}} = 3\alpha_{\text{open}}$ ) encodes the empirical observation that fjords act as larval retention zones [67]: sill-mediated circulation traps larvae near their natal site, reducing export to the open coast.

### 6.2.2 Pathogen Dispersal Matrix $\mathbf{D}$

$D_{jk}$  gives the fraction of waterborne *Vibrio pectenica* at node  $j$  that reaches node  $k$  per day. Pathogen dispersal operates at much shorter range than larval dispersal:

$$D_{jk} = \phi_j f_{\text{out}} \exp\left(-\frac{d_{jk}}{D_P}\right) S_{jk} \quad \text{for } d_{jk} \leq 50 \text{ km}, \quad (59)$$

where:

- $D_P = 15 \text{ km}$  is the pathogen dispersal scale (reflecting tidal-current transport);
- $\phi_j$  is the source node's flushing rate ( $\text{d}^{-1}$ );
- $f_{\text{out}} = 0.2$  is the fraction of flushed water reaching neighboring sites;
- $S_{jk}$  is the sill attenuation factor.

Pairs beyond  $d_{jk} > 50 \text{ km}$  receive zero pathogen transfer. Total export from any node is capped at its flushing rate:  $\sum_k D_{jk} \leq \phi_j$ .

**Sill attenuation.** Fjord sills impede pathogen exchange between basins. The attenuation factor is computed from the minimum sill depth across the pair:

$$S_{jk} = \min\left(1, \left[\frac{\min(z_j^{\text{sill}}, z_k^{\text{sill}})}{\max(z_j^{\text{max}}, z_k^{\text{max}})}\right]^2\right), \quad (60)$$

where  $z^{\text{sill}}$  is sill depth and  $z^{\text{max}}$  is maximum habitat depth. For open-coast nodes ( $z^{\text{sill}} = \infty$ ),  $S_{jk} = 1$  (no attenuation). For Howe Sound (sill = 30 m, max depth = 100 m),  $S \approx 0.09$ , reducing pathogen exchange by  $\sim 91\%$ .

### 6.2.3 Dispersal Dynamics

**Pathogen dispersal (daily).** At each timestep, the dispersal input to node  $k$  is:

$$\Delta P_k^{\text{dispersal}} = \sum_j D_{jk} P_j = (\mathbf{D}^\top \mathbf{P})_k, \quad (61)$$

which enters the *Vibrio* ODE (Eq. 17) as an additive source term.

979 **Larval dispersal (annual).** At the end of each reproductive season, competent larvae  
 980 from each source node are distributed to receiving nodes via  $\mathbf{C}$ . For source node  $j$   
 981 producing  $n_j$  competent larvae: (i) a binomial draw  $n_{\text{settle}} \sim \text{Bin}(n_j, \sum_k C_{jk})$  determines  
 982 total settlement; (ii) a multinomial draw allocates settlers across destinations proportional  
 983 to the conditional probabilities  $C_{jk} / \sum_k C_{jk}$ ; (iii) settler genotypes are sampled with  
 984 replacement from the source pool.

## 985 6.3 Environmental Forcing

986 Each node receives a locally parameterized environmental forcing that drives disease  
 987 and demographic rates through temperature-dependent, salinity-dependent, and flushing-  
 988 dependent mechanisms.

### 989 6.3.1 Sea Surface Temperature

990 The model supports two SST forcing modes, selected via the `sst_source` configuration  
 991 parameter:

992 **Satellite climatology (default for validation).** Daily SST forcing uses climatologi-  
 993 cal means derived from the NOAA Optimum Interpolation SST v2.1 dataset [53], a  $0.25^\circ$   
 994 daily global product spanning 1981–present. For each node, the 365-day climatology is  
 995 computed as the 2002–2025 day-of-year average, extracted via ERDDAP for the node’s  
 996 geographic coordinates. This approach captures real seasonal dynamics including asym-  
 997 metric warming/cooling profiles and coastal upwelling effects that a symmetric sinusoidal  
 998 function cannot represent. A configurable linear warming trend  $\gamma_k$  ( $^\circ\text{C yr}^{-1}$ ; default 0.02)  
 999 is overlaid for future projection scenarios:

$$T_k(d, y) = T_{k,\text{clim}}(d) + \gamma_k (y - y_{\text{ref}}), \quad (62)$$

1000 where  $T_{k,\text{clim}}(d)$  is the satellite-derived climatological SST for day-of-year  $d$  at node  $k$ .

1001 **Sinusoidal approximation (fallback).** For nodes lacking satellite data or for rapid  
 1002 prototyping, SST follows a sinusoidal annual cycle:

$$T_k(d, y) = \underbrace{\bar{T}_k + \gamma_k (y - y_{\text{ref}})}_{\text{trend-adjusted mean}} + \underbrace{A_k \cos\left(\frac{2\pi (d - d_{\text{peak}})}{365}\right)}_{\text{annual cycle}}, \quad (63)$$

1003 where  $\bar{T}_k$  is the baseline annual mean SST,  $A_k$  the annual cycle half-range, and  $d_{\text{peak}} = 227$   
 1004 (day of year  $\approx$  August 15) corresponds to the late-summer SST maximum characteristic  
 1005 of the NE Pacific.

For the 11-node stepping-stone network used in sensitivity analysis, satellite climatologies produce a  $\sim 6^\circ\text{C}$  latitudinal gradient from Sitka ( $\sim 8^\circ\text{C}$  annual mean) to Monterey ( $\sim 13^\circ\text{C}$ ), consistent with published SST atlases. The satellite forcing also captures site-specific features such as the narrow summer peak at upwelling-dominated sites (Newport, Crescent City) versus the broader warm season at sheltered sites (Howe Sound).

SST time series are precomputed at initialization via `generate_satellite_sst_series` (satellite mode) or `make_sst_timeseries` (sinusoidal mode) and stored as dense 1-D arrays of shape  $(n_{\text{years}} \times 365)$  for efficient daily lookup.

### 6.3.2 Temperature-Dependent Rate Scaling

All temperature-dependent biological rates—disease progression, pathogen shedding, *Vibrio* decay—are scaled via the Arrhenius function:

$$k(T) = k_{\text{ref}} \exp \left[ \frac{E_a}{R} \left( \frac{1}{T_{\text{ref}}} - \frac{1}{T} \right) \right], \quad (64)$$

with  $T_{\text{ref}} = 293.15\text{ K}$  ( $20^\circ\text{C}$ ), the thermal optimum of *Vibrio pectenicida* [38]. This formulation ensures that the latitudinal SST gradient (Eq. 63) produces emergent north-south gradients in disease severity, matching the observed pattern of southward-increasing SSWD mortality during the 2013–2015 outbreak [25, 51].

### 6.3.3 Salinity Modifier

*Vibrio* viability is suppressed at low salinities via a quadratic ramp (Eq. 7), reproduced here for completeness:

$$S_{\text{sal}} = \text{clip} \left( \left[ \frac{S_k - S_{\text{min}}}{S_{\text{full}} - S_{\text{min}}} \right]^2, 0, 1 \right), \quad S_{\text{min}} = 10 \text{ psu}, \quad S_{\text{full}} = 28 \text{ psu}. \quad (65)$$

Fjord nodes receive lower salinities (e.g., Howe Sound  $S = 22 \text{ psu}$  due to freshwater runoff), yielding  $S_{\text{sal}} = 0.44$  and reducing effective *Vibrio* viability by  $\sim 56\%$  compared to open-coast nodes ( $S \geq 30 \text{ psu}$ ,  $S_{\text{sal}} \geq 0.87$ ). This mechanism provides a partial explanation for fjord refugia observations [51].

### 6.3.4 Flushing Rate

Hydrodynamic flushing removes waterborne pathogen at rate  $\phi_k$  ( $\text{d}^{-1}$ ), entering the *Vibrio* ODE as the term  $-\phi_k P_k$  (Eq. 17). Node-specific values span two orders of magnitude:

- Open coast:  $\phi_k = 0.5\text{--}1.0 \text{ d}^{-1}$  (strong tidal and current flushing);
- Semi-enclosed bays:  $\phi_k = 0.3 \text{ d}^{-1}$  (San Juan Islands);



- Fjords:  $\phi_k = 0.007\text{--}0.05\text{ d}^{-1}$  (Errata E3; sill restricts water exchange). Howe Sound is assigned  $\phi_k = 0.03\text{ d}^{-1}$ .

Low flushing in fjords acts as a double-edged mechanism: it reduces the rate of pathogen removal (potentially increasing local *Vibrio* concentrations) but also reduces pathogen *export* to neighboring nodes via **D** (Eq. 59), effectively isolating the fjord from regional epidemic dynamics.

Flushing rates are optionally modulated seasonally:

$$\phi_k(m) = \bar{\phi}_k \left[ 1 + A_\phi \cos\left(\frac{2\pi(m-5)}{12}\right) \right], \quad (66)$$

where  $m$  is the 0-indexed month,  $A_\phi = 0.3$  for fjord nodes and  $A_\phi = 0.2$  for open coast, with peak flushing in June ( $m = 5$ ) corresponding to freshwater-driven estuarine circulation maxima.

## 6.4 Agent Movement

Within each node, agents move via a correlated random walk (CRW) that produces realistic small-scale spatial structure:

$$\theta(t + \Delta t) = \theta(t) + \mathcal{N}(0, \sigma_\theta^2), \quad (67)$$

$$x(t + \Delta t) = x(t) + v_i \cos \theta \Delta t, \quad (68)$$

$$y(t + \Delta t) = y(t) + v_i \sin \theta \Delta t, \quad (69)$$

where  $\sigma_\theta = 0.6\text{ rad}$  is the turning-angle standard deviation,  $v_i = v_{\text{base}} \times m_{\text{state}}$  is the disease-modified speed, and  $\Delta t = 60\text{ min}$  (hourly substeps, 24 per day). The base speed  $v_{\text{base}} = 0.5\text{ m min}^{-1}$  is consistent with undisturbed *Pycnopodia helianthoides* locomotion rates [37]. Disease state modifies speed:  $m_S = m_E = 1.0$  (healthy),  $m_{I_1} = 0.5$  (mild impairment),  $m_{I_2} = 0.1$  (severe wasting),  $m_D = 0.0$  (stationary carcass),  $m_R = 1.0$  (recovered).

Agents are confined to a square habitat of side length  $\sqrt{\text{habitat\_area}}$  with elastic boundary reflection.

**Spatial transmission.** When spatial transmission is enabled, each node's habitat is discretized into a grid with cell size  $\Delta x = 20\text{ m}$ . Infected agents deposit pathogen exposure proportional to their shedding rate into their grid cell, and two Gaussian diffusion passes ( $3 \times 3$  averaging) smooth the resulting density field. Susceptible agents then experience locally elevated or reduced force of infection depending on their proximity to infected individuals, creating emergent disease clustering without modifying the node-level *Vibrio* ODE.

**Sensitivity analysis substeps.** The full 24 hourly substeps per day incur  $\sim 20\times$  computational overhead. For sensitivity analysis runs (Section ??), movement is reduced to 1 substep per day, which captures spatial mixing and aggregation effects at acceptable cost.

## 6.5 Network Configurations

Three network configurations are used across model development, validation, and sensitivity analysis.

### 6.5.1 5-Node Validation Network

The primary validation network spans the NE Pacific range with five nodes selected to represent key biogeographic contexts (Table 8):

Table 8: 5-node validation network configuration. SST parameters are baseline values at reference year 2000.

Node	Lat	Lon	$\bar{T}$ ( $^{\circ}\text{C}$ )	$A$ ( $^{\circ}\text{C}$ )	$S$ (psu)	$\phi$ ( $\text{d}^{-1}$ )
Sitka, AK	57.06	-135.34	8.0	3.5	32.0	0.80
Howe Sound, BC	49.52	-123.25	10.0	4.0	22.0	0.03
San Juan Is, WA	48.53	-123.02	10.0	4.0	30.0	0.30
Newport, OR	44.63	-124.05	12.0	3.0	33.0	1.00
Monterey, CA	36.62	-121.90	14.0	2.5	33.5	0.80

Howe Sound is the sole fjord node (sill depth = 30 m,  $\alpha_{\text{self}} = 0.30$ ); all others are open coast ( $\alpha_{\text{self}} = 0.10$ ). Node carrying capacities range from 400 (Howe Sound) to 1,000 (Sitka). This network reproduces three key empirical patterns: the north-south SSWD mortality gradient, fjord protection, and the absence of recovery in southern populations (Section 8).

### 6.5.2 11-Node Sensitivity Analysis Network

Sensitivity analysis Rounds 1–3 used a minimal 3-node network (Sitka, Howe Sound, Monterey) with inter-node distances of 1,700+ km—far exceeding the larval dispersal scale  $D_L = 400$  km. Consequently, the spatial connectivity parameters ( $D_L$ ,  $\alpha_{\text{self}}$ ) were effectively untestable, as the exponential kernel  $\exp(-1700/400) < 10^{-2}$  produced negligible inter-node exchange regardless of  $D_L$  values within the SA range.

Round 4 introduced an 11-node stepping-stone chain with six additional intermediate nodes (Table 9), reducing maximum inter-node spacing to  $\sim 452$  km and ensuring that  $D_L$  values within the SA range [100, 1,000] km produce meaningful variation in larval exchange (32–76% at adjacent-node distances of 110–452 km with the default  $D_L = 400$  km).

Table 9: 11-node stepping-stone network for sensitivity analysis Round 4. All nodes have  $K = 5,000$  ( $\sim 55,000$  total agents). SST trend =  $0.02^\circ\text{C yr}^{-1}$  for all nodes.

Node	Lat	Lon	$\bar{T}$ ( $^\circ\text{C}$ )	$A$ ( $^\circ\text{C}$ )	$S$ (psu)	$\phi$ ( $\text{d}^{-1}$ )
Sitka	57.06	-135.34	8.0	3.5	32.0	0.80
Ketchikan	55.34	-131.64	8.5	3.5	31.0	0.50
Haida Gwaii	53.25	-132.07	9.0	3.0	31.5	0.60
Bella Bella	52.16	-128.15	9.5	3.5	28.0	0.40
Howe Sound*	49.52	-123.25	10.0	4.0	22.0	0.03
SJI	48.53	-123.02	10.5	4.0	30.0	0.30
Westport	46.89	-124.10	11.0	3.5	32.0	0.50
Newport	44.63	-124.05	11.5	3.0	33.0	0.60
Crescent City	41.76	-124.20	12.0	2.5	33.0	0.50
Fort Bragg	39.45	-123.80	12.5	2.5	33.5	0.50
Monterey	36.62	-121.90	13.0	2.5	33.5	0.40

\*Fjord node (sill depth = 30 m,  $\alpha_{\text{self}} = 0.30$ ). All other nodes open coast ( $\alpha_{\text{self}} = 0.10$ ).

This upgrade substantially altered parameter importance rankings:  $n_{\text{resistance}}$  rose from rank 19 to rank 5 (the three-trait partition amplifies genetic architecture importance at finer spatial scales), and  $P_{\text{env,max}}$  rose from rank 11 to rank 4 (the environmental reservoir becomes critical with more nodes seeding independent epidemics). See Section ?? for full results.

### 6.5.3 Full-Range Network (Planned)

Scaling analysis (Section 8) demonstrated that the model supports 150-node networks at  $\sim 66$  s per 20-year run, enabling a full NE Pacific coastline simulation (Alaska to Baja California). This configuration will use the precomputed 489-site overwater distance matrix (Section 6.1.2) and site-specific SST forcing from satellite climatologies.

## 6.6 Network Construction

The `build_network` function assembles the metapopulation from a list of node definitions by: (i) computing the pairwise distance matrix (Haversine  $\times \tau$  or precomputed overwater distances); (ii) constructing  $\mathbf{C}$  with per-node  $\alpha_j$  values ( $\alpha_{\text{fjord}}$  or  $\alpha_{\text{open}}$ ), the  $D_L$  kernel, optional barrier factors, and row normalization to  $r_{\text{total}}$ ; (iii) constructing  $\mathbf{D}$  with the  $D_P$  kernel, flushing-rate modulation, sill attenuation, and the 50 km cutoff; and (iv) wrapping each node definition in a `SpatialNode` with initialized environmental state. The function accepts optional parameters for all kernel scales, self-recruitment fractions, and barrier configurations, allowing the same codebase to serve validation, sensitivity analysis, and full-range simulation.

## 7 Sensitivity Analysis

The SSWD-EvoEpi model contains 47 uncertain parameters spanning six modules: disease transmission and progression (16 parameters), genetics and trait architecture (8), population dynamics (7), spawning biology (7), pathogen virulence evolution (6), and spatial connectivity (3). Most of these parameters have limited empirical constraints (Section A), necessitating a systematic sensitivity analysis (SA) to identify which parameters most influence model behavior and, critically, which parameter *interactions* dominate the system’s dynamics. We conducted a progressive, four-round SA campaign that tracked the model’s growing complexity from a single-trait, 3-node prototype through to the full three-trait, 11-node eco-evolutionary framework.

### 7.1 Methods

#### 7.1.1 Morris Elementary Effects Screening

Each SA round began with Morris elementary effects screening [52], implemented via the SALib Python library [28]. The Morris method is a one-at-a-time (OAT) design in which each parameter is perturbed along  $r$  independent trajectories through the  $p$ -dimensional input space. For parameter  $x_i$  in trajectory  $j$ , the elementary effect is

$$d_{ij} = \frac{f(x_1, \dots, x_i + \Delta_i, \dots, x_p) - f(x_1, \dots, x_i, \dots, x_p)}{\Delta_i}, \quad (70)$$

where  $\Delta_i$  is the perturbation step. From these we compute two summary statistics per parameter per metric [8]:

- $\mu_i^*$ : the mean of the *absolute* elementary effects, measuring overall parameter importance regardless of sign;
- $\sigma_i$ : the standard deviation of elementary effects, measuring interaction and nonlinearity strength.

When  $\sigma_i/\mu_i^* > 1$ , the parameter’s influence on the metric is dominated by interactions with other parameters rather than by its direct (additive) effect [59]. To enable cross-metric comparison, we normalize  $\mu^*$  by the range of the metric across all trajectories, then rank parameters by the mean normalized  $\mu^*$  across all output metrics.

All rounds used  $r = 20$  trajectories, yielding  $r \times (p + 1)$  total model evaluations per round (e.g.,  $20 \times 48 = 960$  runs for the 47-parameter Round 4).

#### 7.1.2 Sobol Variance Decomposition

Parameters surviving Morris screening advance to Sobol variance-based global sensitivity analysis [64], which decomposes the total output variance into contributions from individ-

ual parameters and their interactions. Using the Saltelli sampling scheme [58],  $N(2p+2)$  model evaluations produce two key indices for each parameter  $x_i$  and output metric  $Y$ :

- $S_{1,i} = V_{x_i}[E_{x_{\sim i}}(Y|x_i)] / V(Y)$ : the *first-order* Sobol index, measuring the fraction of output variance attributable to  $x_i$  alone;
- $S_{T,i} = 1 - V_{x_{\sim i}}[E_{x_i}(Y|x_{\sim i})] / V(Y)$ : the *total-order* index, capturing  $x_i$ 's contribution including all interactions with other parameters.

The gap  $S_{T,i} - S_{1,i}$  quantifies the strength of parameter interactions. When  $S_{T,i} \gg S_{1,i}$ , the parameter's influence is mediated primarily through joint effects with other parameters, implying that it cannot be calibrated independently.

### 7.1.3 Output Metrics

The SA tracks 23 output metrics capturing demographic, evolutionary, spatial, and pathogen outcomes over 20-year simulations:

- **Demographic:** population crash percentage, final population fraction, recovery (population returns to >50% of initial), extinction (metapopulation collapse), peak single-year mortality, time to population nadir, total disease deaths, disease death fraction;
- **Evolutionary (host):** mean and maximum resistance shift ( $\Delta\bar{r}$ ), tolerance shift ( $\Delta\bar{t}$ ), recovery-trait shift ( $\Delta\bar{c}$ ), additive variance retention ( $V_A^{\text{post}}/V_A^{\text{pre}}$ ), evolutionary rescue index (composite of survival and resistance gain), total recovery events, recovery rate;
- **Spatial:** number of extinct nodes, north–south mortality gradient, fjord protection effect;
- **Pathogen:** mean final virulence, virulence shift ( $\Delta\bar{v}$ );
- **Spawning:** spawning participation rate, mean recruitment rate.

## 7.2 Progressive Sensitivity Analysis Design

The SA was conducted in four rounds (Table 10), each corresponding to a major model extension. This progressive design allows us to track how parameter importance shifts as model complexity grows—a critical diagnostic for identifying emergent behaviors introduced by new modules.

Table 10: Summary of sensitivity analysis rounds. Each round incorporates all changes from prior rounds. “New” parameters are those added relative to the previous round.

Round	Params	Metrics	Nodes	Runs	Key Changes
R1 (Morris)	23	14	3	480	Baseline: single resistance trait
R2 (Sobol)	23	14	3	12,288	Sobol decomposition of R1 params
R3 (Morris)	43	20	3	880	+20 params: pathogen evo, spawning, continuous mortality, daily growth
R4 (Morris)	47	23	11	960	+4 params: three-trait genetics, 11-node stepping-stone network

**Rounds 1–2 (Pre–Three-Trait Baseline).** The initial SA (Rounds 1–2) examined 23 parameters across disease (13), population (7), genetics (1:  $n_{\text{additive}}$ ), and spawning (2) modules using a 3-node spatial network (Sitka, Howe Sound, Monterey;  $K = 5,000$  per node). The model at this stage tracked a single resistance trait with  $n_{\text{additive}}$  additive loci. Morris screening (480 runs) retained all 23 parameters for Sobol analysis (12,288 runs,  $N = 256$ ).

The Sobol decomposition revealed that disease progression rate  $\mu_{\text{I2D,ref}}$  ( $\text{I}_2 \rightarrow \text{Death}$ ) was the single most influential parameter (mean  $S_T = 0.638$ ), followed by `susceptibility_multiplier` ( $S_T = 0.540$ ) and  $a_{\text{exposure}}$  ( $S_T = 0.473$ ). A critical methodological finding was that Morris and Sobol rankings *disagreed*: Morris identified `settler_survival` and  $\rho_{\text{rec}}$  as the top drivers of population outcomes, while Sobol elevated `susceptibility_multiplier` and  $\mu_{\text{I2D,ref}}$ . This discrepancy arises because Morris measures marginal effects from extreme-value perturbations, whereas Sobol captures variance-weighted contributions including interactions. This confirmed that Morris screening alone is insufficient for identifying calibration priorities in this model.

**Round 3 (Expanded Model, 3-Node).** Round 3 added 20 parameters from four newly implemented modules: pathogen virulence evolution (6 parameters: virulence–fitness tradeoff exponents, mutation rate, initial virulence), expanded spawning biology (4: male spontaneous spawning, readiness induction, female bout limits, peak width), and additional disease mechanics (immunosuppression duration, minimum susceptible age,  $\text{I}_1 \rightarrow \text{I}_2$  progression rate) and genetics parameters (`target_mean_r`, Beta-distribution shape parameters for initial allele frequencies). The network remained at 3 nodes for comparability with R1–R2.

Morris screening (880 runs, 20 trajectories) revealed a dramatic reshuffling:  $\rho_{\text{rec}}$  (recovery rate) rose to #1 ( $\mu_{\text{norm}}^* = 0.642$ ), displacing  $\mu_{\text{I2D,ref}}$  from its R1–R2 dominance. This occurred because the transition from discrete-stage to continuous daily mortality diluted the  $\text{I}_2 \rightarrow \text{Death}$  rate’s marginal influence, while recovery rate’s role was amplified by its interaction with the new pathogen evolution module (higher  $\rho_{\text{rec}}$  imposes stronger selection against virulent strains). All 43 parameters exceeded the 5% elimination thresh-

old; zero were pruned.

**Round 4 (Full Model, 11-Node).** Round 4 represents the complete SSWD-EvoEpi model with two additions: (1) the three-trait genetic architecture (resistance, tolerance, recovery; Section 4.1), contributing four new parameters ( $\text{target\_mean\_c}$ ,  $\text{target\_mean\_t}$ ,  $\tau_{\max}$ ,  $n_{\text{tolerance}}$ ); and (2) an 11-node stepping-stone network spanning the latitudinal range of *Pycnopodia helianthoides* habitat. The expanded spatial network was critical for resolving spatial parameters that were undetectable at 3 nodes. This round (960 runs, 48 cores on an Intel Xeon W-3365) provides the most comprehensive screening of the model to date.

## 7.3 Round 4 Morris Results

### 7.3.1 Global Parameter Ranking

Table 12 presents the complete Round 4 Morris ranking for all 47 parameters, sorted by mean normalized  $\mu^*$  across 23 output metrics. Figure 1 shows the top 20 parameters color-coded by module.

The top-10 parameters span four of six modules:

1.  $\rho_{\text{rec}}$  (recovery rate;  $\mu_{\text{norm}}^* = 0.889$ ) — the rate at which infected individuals clear pathogen remains the single most influential parameter, as in R3. Its semi-additive behavior ( $\sigma/\mu^* = 1.46$ , the lowest interaction ratio of any parameter) reflects its direct mechanistic role: daily clearance probability  $p_{\text{rec}} = \rho_{\text{rec}} \times c_i$  scales linearly with this rate regardless of other parameter values.
2.  $k_{\text{growth}}$  (von Bertalanffy growth rate;  $\mu_{\text{norm}}^* = 0.633$ ) — faster growth accelerates maturation and spawning eligibility, providing demographic compensation during epidemics. Rose from #5 (R3) to #2.
3.  $K_{\text{half}}$  (half-infective dose;  $\mu_{\text{norm}}^* = 0.622$ ) — the Michaelis–Menten saturation parameter controlling infection probability. Rose from #8 to #3.
4.  $P_{\text{env,max}}$  (environmental reservoir;  $\mu_{\text{norm}}^* = 0.598$ ) — background waterborne *V. pecten-**cida* input, independent of host shedding. Rose dramatically from #11 to #4, reflecting its interaction with the 11-node spatial network where environmental pathogen load varies with latitude and temperature.
5.  $n_{\text{resistance}}$  (number of resistance loci;  $\mu_{\text{norm}}^* = 0.525$ ) — genetic architecture of resistance. The largest rank gain of any parameter: #19  $\rightarrow$  #5 ( $\Delta = +14$ ). The three-trait partition (17 loci per trait vs. the former 51 total) amplifies the sensitivity to how many loci underlie each defense mechanism.

6.  $s_0$  (settler survival;  $\mu_{\text{norm}}^* = 0.509$ ) — Beverton–Holt baseline recruitment. Dropped modestly from #3 to #6.
7.  $\sigma_{2,\text{eff}}$  (late-stage shedding rate;  $\mu_{\text{norm}}^* = 0.431$ ).
8.  $\mu_{\text{I2D,ref}}$  ( $\text{I}_2 \rightarrow \text{Death}$  rate;  $\mu_{\text{norm}}^* = 0.419$ ) — formerly the #1 parameter in R1–R2 Sobol ( $S_T = 0.638$ ), now #8 in R4 Morris.
9.  $\sigma_{\text{spawn}}$  (spawning peak width;  $\mu_{\text{norm}}^* = 0.392$ ) — controls synchrony of the reproductive pulse; dropped from #2 to #9.
10.  $\text{target\_mean\_c}$  (initial mean recovery trait;  $\mu_{\text{norm}}^* = 0.385$ ) — a *new* R4 parameter entering directly at #10, confirming that the recovery trait ( $c_i$ ) is the fastest-evolving defense in the model (Section 4.1).

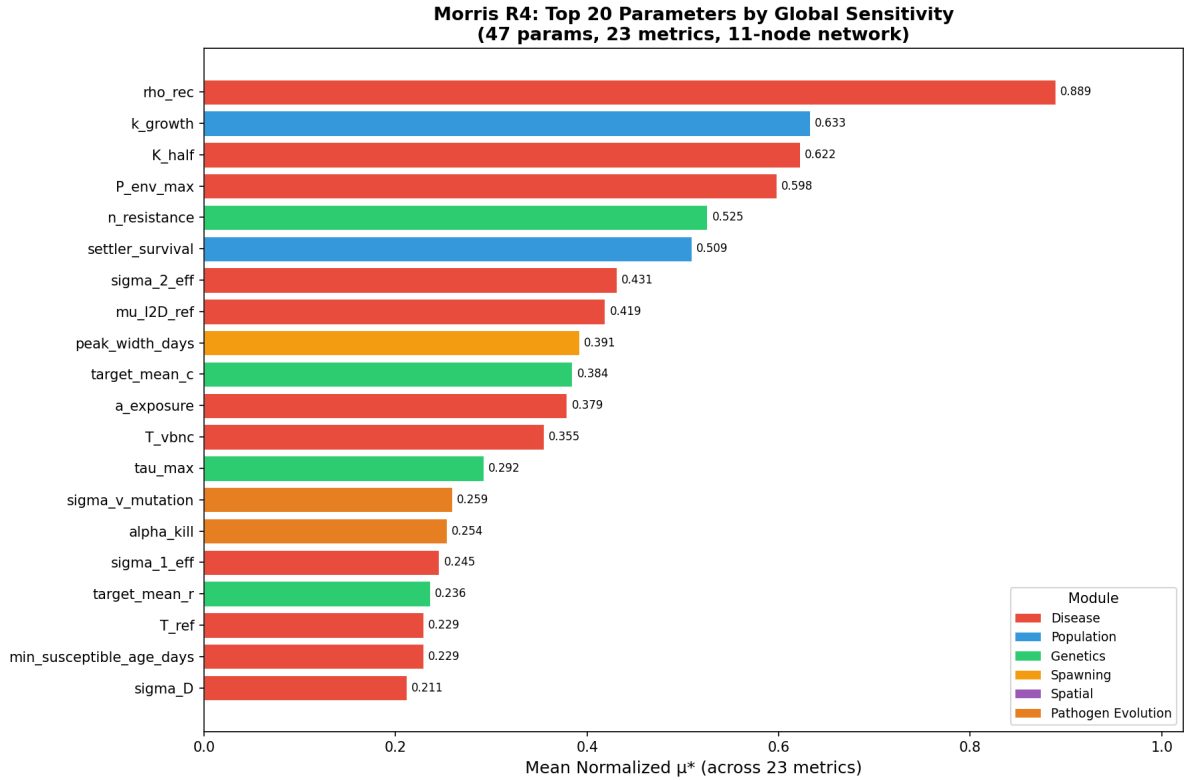


Figure 1: Top 20 parameters by mean normalized  $\mu^*$  in Round 4 Morris screening (47 parameters, 23 metrics, 11-node network, 960 runs). Bars are color-coded by module. Error bars show 95% bootstrap confidence intervals across 20 trajectories.

### 7.3.2 Key Rank Shifts from Round 3

The transition from R3 to R4 produced dramatic rank changes (Figure 2), driven by two structural changes: the three-trait genetic architecture and the 11-node spatial network.



**Major rank gains.** Six parameters gained  $\geq 7$  ranks (Table 11):

- $\sigma_{1,\text{eff}}$  (early shedding rate): #43  $\rightarrow$  #16 ( $\Delta = +27$ ). Early shedding now interacts with pathogen evolution:  $\sigma_1$  shapes the initial epidemic wave that determines the selection regime on virulence.
- $\sigma_{v,\text{mut}}$  (virulence mutation step size): #31  $\rightarrow$  #14 ( $\Delta = +17$ ). With 11 nodes providing diverse thermal and demographic environments, mutation rate controls how fast pathogen lineages adapt to local conditions.
- $T_{\text{ref}}$  (pathogen temperature optimum): #34  $\rightarrow$  #18 ( $\Delta = +16$ ). The latitudinal temperature gradient across 11 nodes (vs. 3) amplifies the importance of the thermal reference point.
- $n_{\text{resistance}}$ : #19  $\rightarrow$  #5 ( $\Delta = +14$ ), as discussed above.
- $\alpha_{\text{self,open}}$  (open-coast larval retention): #39  $\rightarrow$  #25 ( $\Delta = +14$ ). Spatial retention was invisible at 3 nodes but becomes detectable with 11 nodes and realistic dispersal distances.
- $P_{\text{env,max}}$ : #11  $\rightarrow$  #4 ( $\Delta = +7$ ).

**Major rank drops.** Five parameters dropped  $\geq 19$  ranks:

- $q_{\text{init},\beta_b}$  (Beta-distribution shape  $b$ ): #17  $\rightarrow$  #46 ( $\Delta = -29$ ). Initial allele-frequency shape is overwhelmed by the trait-specific mean parameters (target\_mean\_r/t/c).
- $F_0$  (reference fecundity): #20  $\rightarrow$  #47 ( $\Delta = -27$ ). Diluted in the expanded 47-parameter space.
- Immunosuppression duration: #15  $\rightarrow$  #42 ( $\Delta = -27$ ). Its effect is absorbed by spawning parameters and the recovery trait ( $c_i$ ), which provides an alternative pathway through immunosuppressed periods.
- susceptibility\_multiplier: #23  $\rightarrow$  #44 ( $\Delta = -21$ ). This parameter was #1 in the R1–R2 Sobol analysis ( $S_T = 0.540$ ); its precipitous decline reflects absorption by the explicit resistance genetics—individual  $r_i$  now captures susceptibility variation mechanistically, rendering the multiplicative modifier redundant.
- $p_{\text{spont}}$ , (female spontaneous spawning): #26  $\rightarrow$  #45 ( $\Delta = -19$ ).

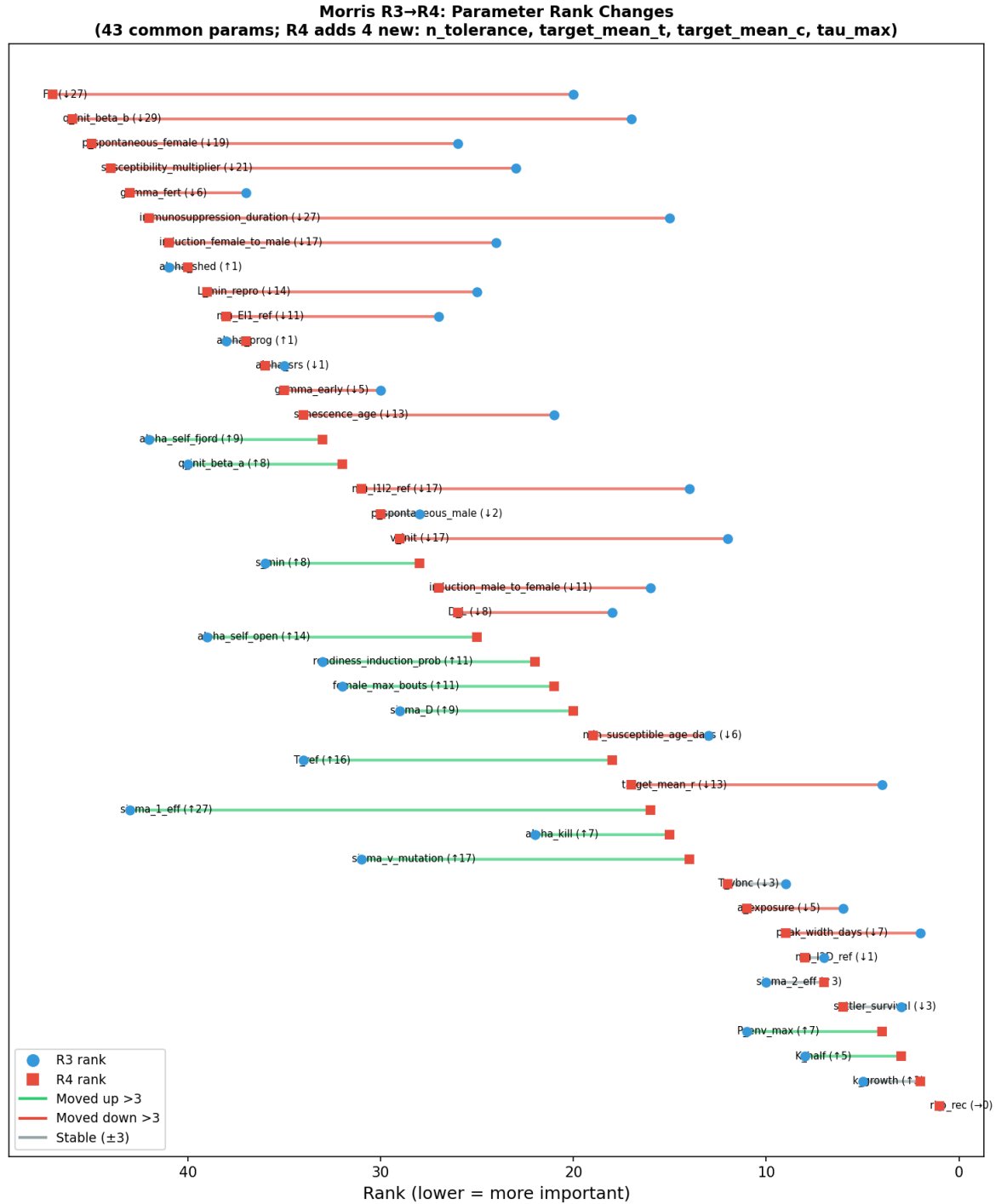


Figure 2: Rank change from Round 3 to Round 4 for the 43 parameters common to both rounds. Positive values (rightward) indicate increased importance in R4; negative values (leftward) indicate decreased importance. Parameters are sorted by R4 rank. Four new R4 parameters (not shown) entered at ranks #10, #13, #23, and #24.

Table 11: Largest rank shifts from R3 to R4 Morris screening. Positive  $\Delta$  indicates increased importance.

Parameter	Module	R3 $\rightarrow$ R4	$\Delta$	Mechanism
$\sigma_{1,\text{eff}}$	Disease	43 $\rightarrow$ 16	+27	Interacts with pathogen evolution
$\sigma_{v,\text{mut}}$	Pathogen evo.	31 $\rightarrow$ 14	+17	Controls adaptation speed
$T_{\text{ref}}$	Disease	34 $\rightarrow$ 18	+16	11-node thermal gradient
$n_{\text{resistance}}$	Genetics	19 $\rightarrow$ 5	+14	Three-trait partition
$\alpha_{\text{self,open}}$	Spatial	39 $\rightarrow$ 25	+14	Resolvable at 11 nodes
$q_{\text{init},\beta_b}$	Genetics	17 $\rightarrow$ 46	-29	Absorbed by trait means
$F_0$	Population	20 $\rightarrow$ 47	-27	Diluted in larger space
Immunosupp. duration	Disease	15 $\rightarrow$ 42	-27	Absorbed by recovery trait
Suscept. multiplier	Disease	23 $\rightarrow$ 44	-21	Absorbed by resistance genetics

### 7.3.3 New Three-Trait Parameters

The four parameters introduced with the three-trait architecture (Section 4.1) immediately demonstrated meaningful sensitivity:

- `target_mean_c` (initial mean recovery trait): rank #10 ( $\mu_{\text{norm}}^* = 0.385$ ). A top-10 entry confirms that recovery ( $c_i$ ) is the dominant evolutionary pathway in the model, consistent with the validation finding that  $\Delta\bar{c}$  exceeds  $\Delta\bar{r}$  by  $\sim 7\times$  at all nodes (Section 8).
- $\tau_{\text{max}}$  (maximum tolerance scaling): rank #13 ( $\mu_{\text{norm}}^* = 0.292$ ). The ceiling on how much tolerance extends  $I_2$  survival matters because it sets the upper bound on the tolerance–recovery interaction.
- `target_mean_t` (initial mean tolerance): rank #23 ( $\mu_{\text{norm}}^* = 0.197$ ). Mid-pack, reflecting the weaker selection signal on tolerance compared to recovery.
- $n_{\text{tolerance}}$  (number of tolerance loci): rank #24 ( $\mu_{\text{norm}}^* = 0.189$ ). Mid-pack, but notably the most interacting parameter in the entire model ( $\sigma/\mu^* = 2.51$ ), suggesting tolerance’s role is context-dependent.

### 7.3.4 Universal Nonlinearity

A striking finding of the R4 Morris analysis is that *every one of the 47 parameters* has  $\sigma/\mu^* > 1.0$  (Figure 3). This means that no parameter in the model acts additively—every parameter’s effect on every metric depends on the values of other parameters. The model is a deeply coupled, nonlinear system.

The interaction ratio  $\sigma/\mu^*$  ranges from 1.42 ( $s_0$ , settler survival) to 2.52 ( $\sigma_{v,\text{mut}}$ , virulence mutation rate). Two interaction tiers are apparent:

- **Moderately interacting** ( $\sigma/\mu^* < 1.5$ ; 2 parameters):  $\rho_{\text{rec}}$  (1.46) and  $s_0$  (1.42). These parameters operate semi-additively—their effects are relatively stable across parameter space. For  $\rho_{\text{rec}}$ , this reflects its direct mechanistic role: daily clearance probability scales linearly with recovery rate regardless of context.
- **Strongly to extremely interacting** ( $\sigma/\mu^* > 1.5$ ; 45 parameters): the remaining parameters exhibit moderate to extreme nonlinearity. The most interacting parameters are genetic/evolutionary:  $\sigma_{v,\text{mut}}$  (2.52),  $n_{\text{tolerance}}$  (2.51),  $q_{\text{init},\beta_a}$  (2.45), and  $\alpha_{\text{SRS}}$  (2.34). These control *adaptation rates* that feed back on disease dynamics, which feed back on selection pressures—creating cascading interaction loops.

This universal nonlinearity has profound implications for calibration: no parameter can be tuned independently. Joint calibration via approximate Bayesian computation (ABC) or Markov chain Monte Carlo methods is essential.

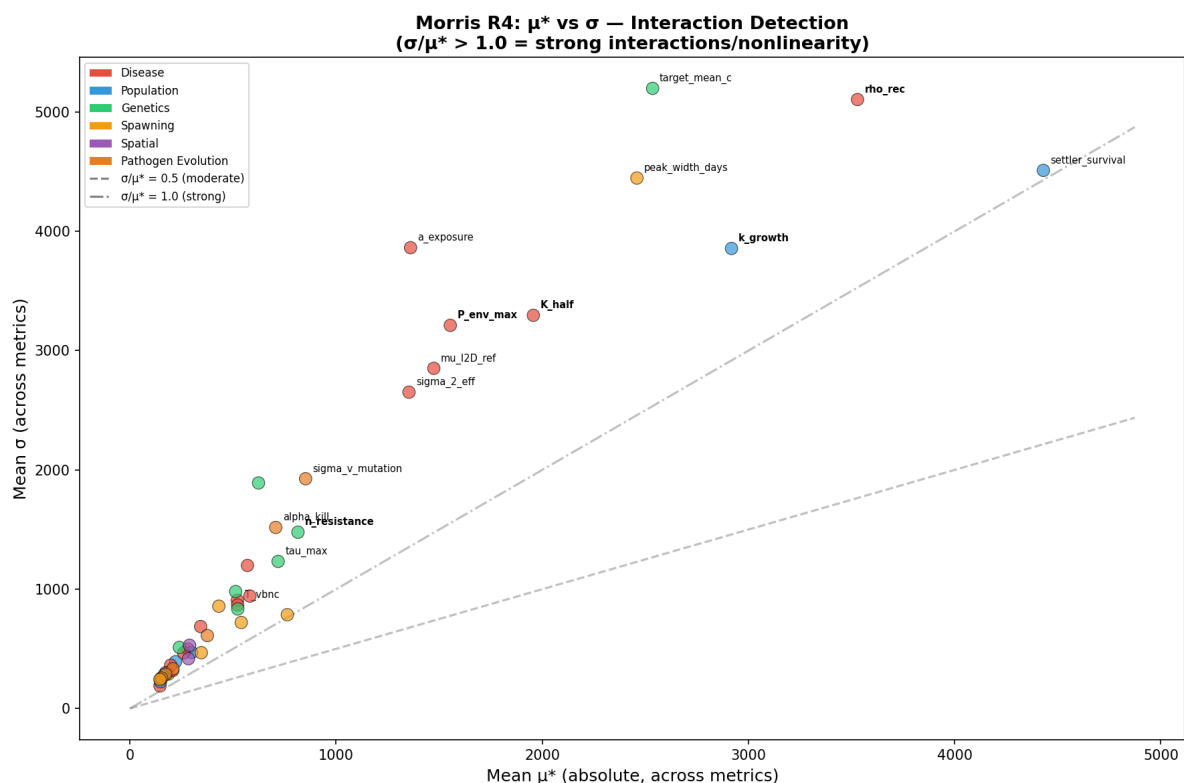


Figure 3: Morris  $\mu^*$  vs.  $\sigma$  scatter for all 47 parameters (R4). The dashed line shows  $\sigma = \mu^*$  (unit interaction ratio). All parameters fall above this line, indicating universal nonlinearity. Symbol color indicates module; symbol size scales with mean normalized  $\mu^*$ .

### 7.3.5 Module-Level Sensitivity

Figure 4 summarizes sensitivity by module. The disease module dominates in both parameter count (16) and mean importance ( $\overline{\mu_{\text{norm}}^*} = 0.332$ ), but genetics punches above

its weight: with only 8 parameters, it achieves the second-highest mean importance ( $\overline{\mu_{\text{norm}}^*} = 0.260$ ), and its top parameter ( $n_{\text{resistance}}$ ) ranks #5 globally. The pathogen evolution module, despite being entirely new in R3–R4, achieves a mean  $\mu_{\text{norm}}^* = 0.185$  with  $\sigma_{v,\text{mut}}$  at #14—virulence evolution is not negligible and must be retained in calibration.

Spatial parameters ( $\overline{\mu_{\text{norm}}^*} = 0.171$ ) are detectable for the first time at 11 nodes. At the 3-node configuration of R1–R3, these parameters ranked #39–#42; at 11 nodes, they rise to #25–#33. This confirms that adequate spatial resolution is necessary to capture dispersal and retention dynamics.

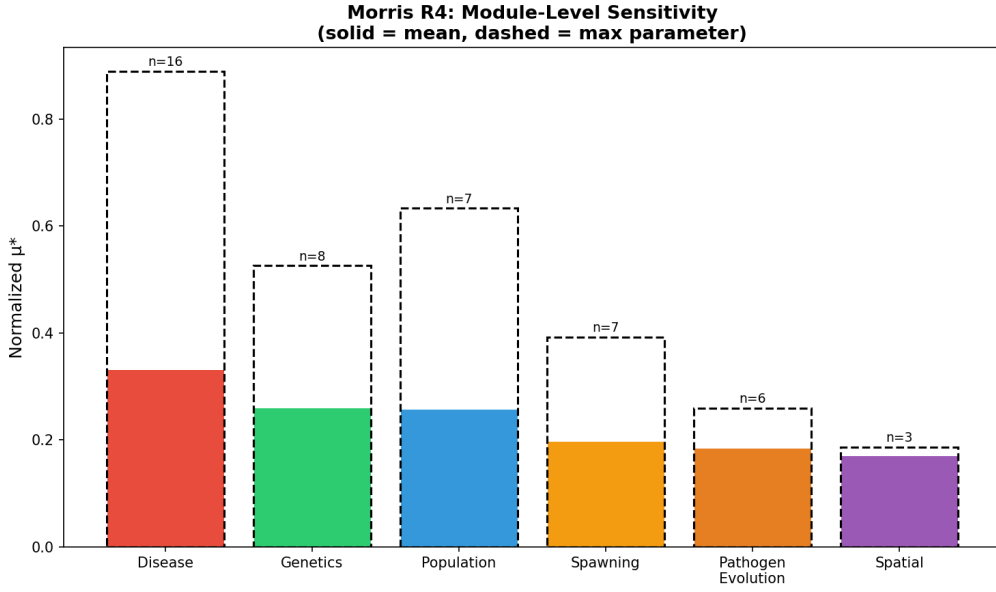


Figure 4: Module-level sensitivity summary for R4 Morris screening. Bar height shows mean normalized  $\mu^*$  for each module; whiskers show the range from minimum to maximum parameter within each module. Number of parameters per module shown in parentheses.

## 7.4 Cross-Round Parameter Trajectories

Tracking individual parameters across all four rounds reveals which parameters have stable importance versus those whose influence is contingent on model structure (Figure 5):

**Consistently important.**  $\rho_{\text{rec}}$ ,  $a_{\text{exposure}}$ , and  $\sigma_{2,\text{eff}}$  remain in the top 12 across all rounds. These are robust calibration targets regardless of model configuration.

**Structurally contingent.**  $\mu_{\text{I2D,ref}}$  was #1 in R1–R2 Sobol but dropped to #7–#8 in R3–R4 Morris after the switch to continuous daily mortality.  $\text{susceptibility\_multiplier}$  fell from #1–#2 (R1–R2) to #44 (R4) as explicit resistance genetics absorbed its role. These shifts demonstrate that parameter importance can be an *artifact of model structure*,

not a property of the underlying biology, underscoring the need for structural sensitivity analysis alongside parametric SA.

**Emergent with complexity.**  $P_{\text{env,max}}$ ,  $n_{\text{resistance}}$ , and all pathogen evolution parameters only revealed their importance at  $\geq 11$  nodes or  $\geq 43$  parameters. Simple model configurations systematically underestimate the importance of spatial and evolutionary parameters.

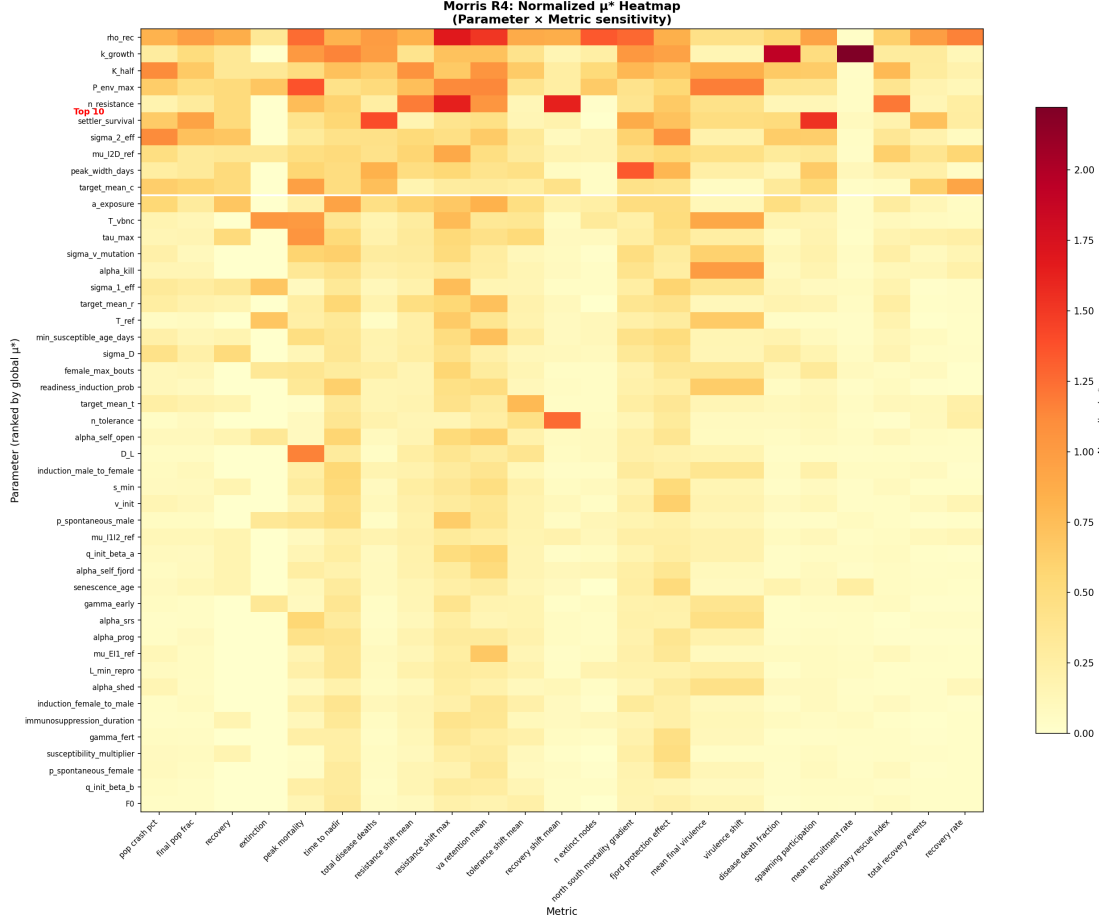


Figure 5: Parameter–metric sensitivity heatmap (R4 Morris). Cell color indicates normalized  $\mu^*$  for each parameter–metric pair. Parameters (rows) are sorted by global rank; metrics (columns) are grouped by category. White cells indicate  $\mu^*_{\text{norm}} < 0.05$ .

## 7.5 Sobol Variance Decomposition: Rounds 1–2 and Ongoing

### 7.5.1 R1–R2 Sobol Results

The Round 1–2 Sobol analysis (23 parameters,  $N = 256$ , 12,288 runs) revealed massive parameter interactions across the model. For most metrics, total-order indices  $S_T$  far exceeded first-order indices  $S_1$ , meaning that parameter combinations dominate behavior over individual effects. Notable interaction signatures include:

- **Extinction:**  $\sigma_{2,\text{eff}}$  had  $S_T = 1.51$  but  $S_1 \approx 0$ —extinction risk is *entirely* driven by interactions between shedding rate and other parameters.
- **Fjord protection:**  $a_{\text{exposure}}$  had  $S_T = 0.96$  but  $S_1 = -0.12$ —a negative first-order index means the parameter’s effect *reverses sign* depending on the values of other parameters.
- **Recovery:**  $\text{susceptibility\_multiplier}$  had  $S_T = 0.96$  but  $S_1 = 0.38$ —60% of its influence arises through interactions.

## 7.5.2 Round 4 Sobol (In Progress)

A Round 4 Sobol analysis is currently running on a 48-core Intel Xeon W-3365 server. With 47 parameters and  $N = 512$ , the Saltelli design requires  $N(2p + 2) = 49,152$  model evaluations at  $\sim 25$  s each. At 12 parallel workers, the estimated wall time is approximately 7 days. This analysis will provide the first variance decomposition of the full three-trait, 11-node model and will enable direct comparison with the R1–R2 Sobol indices to quantify how the three-trait architecture redistributes variance among parameters.

Based on the R4 Morris results, we prioritize convergence monitoring for the top-10 parameters and anticipate particularly informative second-order ( $S_2$ ) indices for the following parameter pairs:

- $\rho_{\text{rec}} \times \text{target\_mean\_c}$ : recovery rate  $\times$  recovery genetics (both affect pathogen clearance);
- $P_{\text{env,max}} \times a_{\text{exposure}}$ : environmental reservoir  $\times$  transmission rate (dual exposure pathways);
- $n_{\text{resistance}} \times \sigma_{v,\text{mut}}$ : host genetic architecture  $\times$  pathogen adaptation rate (coevolutionary arms race);
- $k_{\text{growth}} \times s_0$ : growth rate  $\times$  recruitment (demographic compensation).

## 7.6 Summary and Implications

The four-round sensitivity analysis yields five principal findings:

1. **Recovery dominates.** The base recovery rate  $\rho_{\text{rec}}$  is consistently the most influential parameter across rounds and model configurations, yet has zero empirical basis. Determining whether *Pycnopodia helianthoides* can clear *V. pectenocida* infections—and at what rate—is the single highest-priority empirical question for model calibration.

2. **Genetic architecture is a structural choice with major consequences.** The number of resistance loci ( $n_{\text{resistance}}$ ) ranks #5 globally and cannot be calibrated from data without high-resolution GWAS. The three-trait partition amplifies this sensitivity: 17 loci per trait behave very differently from 51 loci in a single trait.
3. **Parameter importance is model-contingent.**  $\text{susceptibility\_multiplier}$  fell from #1 (R1–R2 Sobol) to #44 (R4 Morris) as explicit genetics absorbed its role;  $\mu_{\text{I2D,ref}}$  fell from #1 to #8 with continuous mortality. SA results from simpler model configurations cannot be extrapolated to the full model.
4. **Universal nonlinearity demands joint calibration.** All 47 parameters interact ( $\sigma/\mu^* > 1.0$ ). No parameter can be tuned independently. Approximate Bayesian computation with sequential Monte Carlo sampling (ABC-SMC) is the appropriate calibration framework.
5. **Spatial resolution matters.** Spatial and environmental parameters only emerge as important at  $\geq 11$  nodes. The planned 150-node full-coastline simulation will likely reveal additional spatially contingent sensitivities.



Table 12: Complete Round 4 Morris parameter ranking (47 parameters, 23 metrics, 11-node network, 960 runs). Mean normalized  $\mu^*$  is averaged across all metrics. The  $\sigma/\mu^*$  ratio indicates interaction strength ( $> 1$ : interaction-dominated). R3 Rank column shows the parameter’s position in the 43-parameter R3 analysis; “—” indicates a new R4 parameter.

Rank	Parameter	Module	$\overline{\mu^*_{\text{norm}}}$	$\sigma/\mu^*$	R3	$\Delta$
1	$\rho_{\text{rec}}$	Disease	0.889	1.46	1	—
2	$k_{\text{growth}}$	Population	0.633	1.63	5	$\uparrow 3$
3	$K_{\text{half}}$	Disease	0.622	1.84	8	$\uparrow 5$
4	$P_{\text{env,max}}$	Disease	0.598	1.92	11	$\uparrow 7$
5	$n_{\text{resistance}}$	Genetics	0.525	1.78	19	$\uparrow 14$
6	$s_0$ (settler survival)	Population	0.509	1.42	3	$\downarrow 3$
7	$\sigma_{2,\text{eff}}$	Disease	0.431	1.95	10	$\uparrow 3$
8	$\mu_{\text{I2D,ref}}$	Disease	0.419	1.98	7	$\downarrow 1$
9	$\sigma_{\text{spawn}}$ (peak width)	Spawning	0.392	2.03	2	$\downarrow 7$
10	target_mean_c	Genetics	0.385	2.08	—	—
11	$a_{\text{exposure}}$	Disease	0.379	2.20	6	$\downarrow 5$
12	$T_{\text{VBNC}}$	Disease	0.355	2.07	9	$\downarrow 3$
13	$\tau_{\text{max}}$	Genetics	0.292	2.05	—	—
14	$\sigma_{v,\text{mut}}$	Path. evo.	0.259	2.52	31	$\uparrow 17$
15	$\alpha_{\text{kill}}$	Path. evo.	0.254	2.25	22	$\uparrow 7$
16	$\sigma_{1,\text{eff}}$	Disease	0.245	2.24	43	$\uparrow 27$
17	target_mean_r	Genetics	0.236	1.86	4	$\downarrow 13$
18	$T_{\text{ref}}$	Disease	0.229	1.94	34	$\uparrow 16$
19	min. susceptible age	Disease	0.229	2.04	13	$\downarrow 6$

*Continued on next page*

Table 12 (continued)

Rank	Parameter	Module	$\overline{\mu^*_{\text{norm}}}$	$\sigma/\mu^*$	R3	$\Delta$
20	$\sigma_D$	Disease	0.211	1.96	29	$\uparrow 9$
21	female max bouts	Spawning	0.206	1.95	32	$\uparrow 11$
22	readiness induction prob.	Spawning	0.204	2.26	33	$\uparrow 11$
23	target_mean_t	Genetics	0.197	2.05	—	—
24	$n_{\text{tolerance}}$	Genetics	0.189	2.51	—	—
25	$\alpha_{\text{self,open}}$	Spatial	0.187	2.07	39	$\uparrow 14$
26	$D_L$	Spatial	0.178	2.29	18	$\downarrow 8$
27	$\kappa_{\text{mf}}$ (M $\rightarrow$ F induction)	Spawning	0.176	2.07	16	$\downarrow 11$
28	$s_{\text{min}}$	Disease	0.175	1.84	36	$\uparrow 8$
29	$v_{\text{init}}$	Path. evo.	0.173	2.13	12	$\downarrow 17$
30	$p_{\text{spont,m}}$	Spawning	0.169	2.11	28	$\downarrow 2$
31	$\mu_{\text{I1I2,ref}}$	Disease	0.156	1.97	14	$\downarrow 17$
32	$q_{\text{init},\beta_a}$	Genetics	0.150	2.45	40	$\uparrow 8$
33	$\alpha_{\text{self,fjord}}$	Spatial	0.149	2.00	42	$\uparrow 9$
34	senescence age	Population	0.148	1.66	21	$\downarrow 13$
35	$\gamma_{\text{early}}$	Path. evo.	0.148	2.03	30	$\downarrow 5$
36	$\alpha_{\text{SRS}}$	Population	0.146	2.34	35	$\downarrow 1$
37	$\alpha_{\text{prog}}$	Path. evo.	0.143	2.09	38	$\uparrow 1$
38	$\mu_{\text{EI1,ref}}$	Disease	0.141	2.19	27	$\downarrow 11$
39	$L_{\text{min,repro}}$	Population	0.139	2.06	25	$\downarrow 14$
40	$\alpha_{\text{shed}}$	Path. evo.	0.136	2.12	41	$\uparrow 1$

*Continued on next page*

Table 12 (continued)

<b>Rank</b>	<b>Parameter</b>	<b>Module</b>	$\overline{\mu_{\text{norm}}^*}$	$\sigma/\mu^*$	<b>R3</b>	<b><math>\Delta</math></b>
41	$\kappa_{\text{fm}}$ (F→M induction)	Spawning	0.130	1.79	24	↓17
42	immunosupp. duration	Disease	0.127	2.07	15	↓27
43	$\gamma_{\text{fert}}$	Population	0.122	2.21	37	↓6
44	suscept. multiplier	Disease	0.111	2.03	23	↓21
45	$p_{\text{spont},\text{f}}$	Spawning	0.110	1.67	26	↓19
46	$q_{\text{init},\beta_b}$	Genetics	0.104	2.20	17	↓29
47	$F_0$	Population	0.102	1.83	20	↓27

## 8 Validation

We validate the SSWD-EvoEpi model through a two-stage strategy: calibration and behavioral verification at computationally cheap population sizes ( $K = 5,000$  per node,  $\sim 25,000$  total agents), followed by scale-up validation at ecologically realistic population sizes ( $K = 100,000$  per node, 500,000 total agents). This approach tests whether emergent dynamics—trait evolution trajectories, spatial mortality gradients, and extinction vortex behavior—are robust to a 20-fold increase in population size, or whether they are artifacts of stochastic fluctuations in small populations. All validation runs use a 5-node stepping-stone network (Sitka, Howe Sound, San Juan Islands, Newport, Monterey), a 20-year time horizon with disease introduction at year 3, seed 42, and the three-trait genetic architecture described in Section 4.1 (17 resistance / 17 tolerance / 17 recovery loci).

### 8.1 $K = 5,000$ Validation

The small-population validation serves as the primary calibration target, permitting rapid iteration ( $\sim 108$  s per 20-year simulation) while retaining sufficient genetic variance for trait-level dynamics to emerge. Table 13 reports per-node demographic and evolutionary outcomes.

Table 13: Per-node results for the  $K = 5,000$  validation run (5 nodes, 20 years, seed 42).  $\Delta r_i$ ,  $\Delta t_i$ , and  $\Delta c_i$  denote changes in mean resistance, tolerance, and recovery trait scores relative to initialization ( $\bar{r}_0 = 0.15$ ,  $\bar{t}_0 = 0.10$ ,  $\bar{c}_0 = 0.02$ ).  $\text{Pop}_{\min}$  gives the minimum population reached at the indicated year.

Node	$N_0$	$N_{20}$	$N_{\min}$ (yr)	Crash	Deaths	Rec.	$\Delta r_i$	$\Delta t_i$	$\Delta c_i$
Sitka	4,935	65	65 (19)	98.7%	7,409	60	+0.011	+0.005	+0.029
Howe Sound	4,937	60	60 (19)	98.8%	9,473	55	−0.002	+0.044	+0.041
SJI	4,918	50	50 (13)	99.0%	7,985	63	+0.012	−0.007	+0.072
Newport	4,998	27	27 (17)	99.5%	7,918	51	+0.031	+0.001	+0.054
Monterey	5,000	163	38 (10)	99.2%	9,183	136	+0.025	+0.027	+0.154
<b>Total</b>	<b>24,788</b>	<b>365</b>		<b>98.5%</b>	<b>41,968</b>	<b>365</b>			

Several key patterns emerge from the small-population run:

**Severe, universal population crashes.** All five nodes experience  $>98\%$  population decline over 17 years of active disease, with total metapopulation crash of 98.5% (24,788  $\rightarrow$  365 individuals). No node recovers to pre-epidemic levels, consistent with the persistent absence of *Pycnopodia helianthoides* across most of its former range since 2013–2015 [20, 23].

**Differential recovery at Monterey.**

Monterey exhibits a distinctive trajectory: the population crashes to a minimum of 38 individuals at year 10 but partially rebounds to 163 by year 20, driven by 136 disease recoveries— $2.2\times$  the next-highest node (SJI, 63 recoveries). This node also shows the strongest evolutionary signal in recovery ( $\Delta c_i = +0.154$ ), consistent with warmer temperatures driving both higher disease pressure and stronger selection for clearance ability.

**Recovery is the fastest-evolving trait.**

Across all five nodes, the mean change in recovery trait score ( $\overline{\Delta c_i} = +0.070$ ) exceeds that of resistance ( $\overline{\Delta r_i} = +0.015$ ) by  $4.5\times$  and tolerance ( $\overline{\Delta t_i} = +0.014$ ) by  $5.0\times$  (Table 13). This asymmetry arises because recovery acts as a multiplicative modifier on the daily probability of transitioning from infected to recovered ( $p_{\text{rec}} = \rho_{\text{rec}} \times c_i$ ; Section 3), creating strong directional selection: individuals with higher  $c_i$  survive infection and contribute disproportionately to the next generation.

**Resistance signal is weak and mixed.**

With only 17 loci encoding resistance (compared to 51 in the original single-trait architecture), the per-locus allele frequency shifts are small ( $\Delta q \approx 0.001\text{--}0.004$ ). Three of five nodes show positive  $\Delta r_i$  (Sitka, SJI, Newport), but Howe Sound shows a negligible decline ( $-0.002$ ), consistent with genetic drift overwhelming weak directional selection at small effective population sizes [27].

**Tolerance is effectively neutral.**

Mean tolerance change is negligible ( $\overline{\Delta t_i} = +0.014$ ), with one node showing a slight decrease (SJI,  $\Delta t_i = -0.007$ ). This is expected: tolerance extends survival time during late infection ( $I_2$ ) via timer-scaling (Section 3), but this effect is weak when recovery rates are low and late-stage mortality is high. Tolerance becomes selectively relevant only when disease mortality is moderated by other mechanisms, creating a conditional neutrality that limits its evolutionary response under severe epidemic conditions.

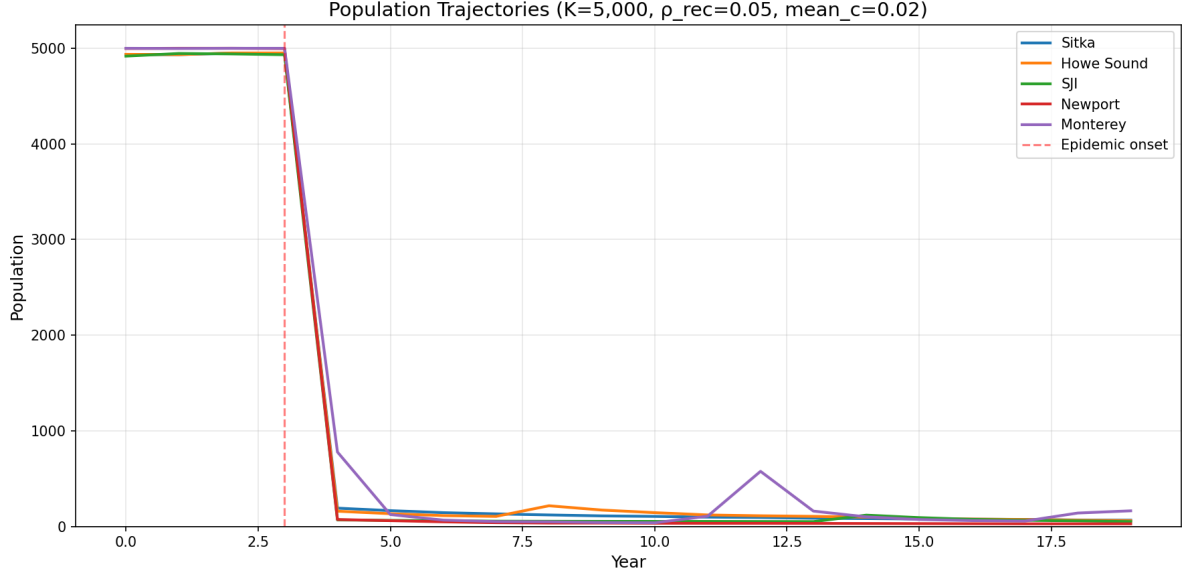


Figure 6: Population trajectories for the  $K = 5,000$  validation run. Disease is introduced at year 3. All nodes crash to  $<2\%$  of carrying capacity. Monterey (red) shows partial recovery from its nadir of 38 individuals at year 10, driven by elevated recovery trait evolution ( $\Delta c_i = +0.154$ ).

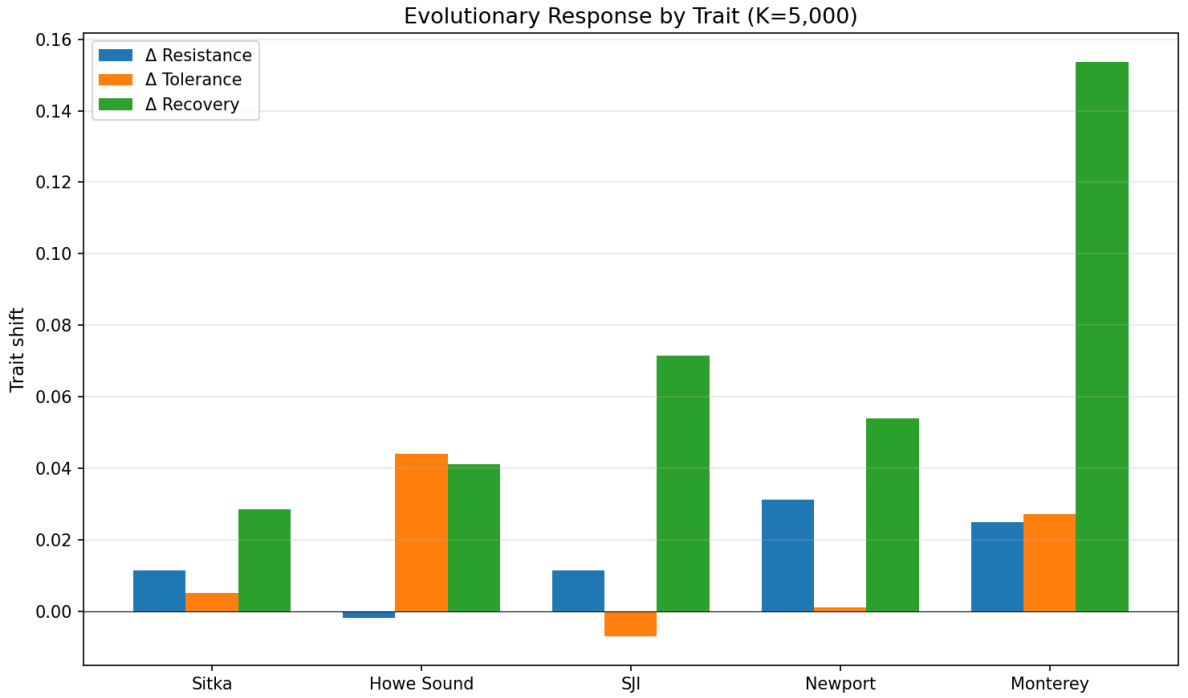


Figure 7: Trait shifts ( $\Delta r_i$ ,  $\Delta t_i$ ,  $\Delta c_i$ ) per node in the  $K = 5,000$  validation. Recovery (blue) dominates at every node, with Monterey showing the largest shift ( $\Delta c_i = +0.154$ ). Resistance changes are weak and variable in sign; tolerance is near-zero at most nodes.

## 8.2 $K = 100,000$ Scale-Up Validation

To test whether patterns observed at  $K = 5,000$  persist at ecologically realistic population sizes, we scale carrying capacity 20-fold to  $K = 100,000$  per node (500,000 total agents). This run required 42.6 minutes (2,558 s) and  $\sim 1.5$  GB peak memory, compared to 108 s for the small-population equivalent—a  $23.7\times$  slowdown that is sublinear relative to the  $20\times$  population increase, consistent with the  $O(N^{0.62})$  scaling relationship established in Section 7.1. Table 14 reports the results.

Table 14: Per-node results for the  $K = 100,000$  scale-up validation (5 nodes, 20 years, seed 42). Trait values are final means;  $\Delta$  values computed relative to initialization targets ( $\bar{r}_0 = 0.15$ ,  $\bar{t}_0 = 0.10$ ,  $\bar{c}_0 = 0.02$ ).

Node	$N_{20}$	Crash	Deaths	Rec.	$\Delta r_i$	$\Delta t_i$	$\Delta c_i$
Sitka	718	99.3%	109,151	875	−0.004	+0.002	+0.059
Howe Sound	633	99.4%	112,112	913	−0.004	+0.008	+0.056
SJI	733	99.3%	108,607	916	−0.009	+0.010	+0.060
Newport	639	99.4%	110,563	922	−0.005	+0.006	+0.065
Monterey	2,904	97.1%	125,061	1,319	−0.002	+0.000	+0.075
<b>Total</b>	<b>5,627</b>	<b>98.9%</b>	<b>565,494</b>	<b>4,945</b>			

The scale-up validation reveals several important findings:

**Crashes are worse, not better, at larger  $N$ .** Total metapopulation crash increases from 98.5% at  $K = 5,000$  to 98.9% at  $K = 100,000$  (Table 15). This counterintuitive result refutes the hypothesis that larger populations buffer against extinction through stochastic rescue. In the SSWD-EvoEpi framework, larger populations sustain higher absolute disease transmission (more contacts per susceptible per day) while the per-capita selection intensity remains constant, meaning that deterministic epidemic dynamics dominate and demographic stochasticity—which occasionally permits small populations to “escape” the disease through random fluctuations—is suppressed. The 0.4 percentage-point increase in crash severity is small but directionally consistent across all five nodes.

**Resistance shifts become uniformly negative.** At  $K = 100,000$ , all five nodes show negative  $\Delta r_i$  (range: −0.002 to −0.009; mean −0.005), in contrast to the mixed signal at  $K = 5,000$  (three positive, one negative, one near-zero). With 100,000 individuals per node, the effective population size is large enough to suppress drift, revealing that the net selection coefficient on resistance is slightly negative under the current parameterization. This likely reflects the cost structure: resistance reduces infection probability multiplicatively ( $p_{\text{inf}} \propto 1 - r_i$ ), but the per-locus effect is small with 17 loci ( $\Delta p_{\text{inf}} \approx 0.003$

per locus), while background environmental pathogen pressure ( $P_{\text{env}}$ ) ensures continued exposure regardless of individual resistance.

**Recovery dominance is amplified at scale.** The trait evolution hierarchy becomes more pronounced at large  $N$ : recovery ( $\overline{\Delta c_i} = +0.063$ ) is  $13.3\times$  faster than resistance ( $|\overline{\Delta r_i}| = 0.005$ ) and  $12.2\times$  faster than tolerance ( $\overline{\Delta t_i} = +0.005$ ), compared to  $4.5\times$  and  $5.0\times$  respectively at  $K = 5,000$ . The ratio increase occurs because drift no longer inflates  $|\Delta r_i|$  at large  $N$ , exposing the true (weak) directional signal on resistance.

**Monterey remains anomalous.** Even at  $K = 100,000$ , Monterey shows the lowest crash percentage (97.1% vs. 99.3–99.4% for other nodes), the highest final population (2,904), the most recoveries (1,319), and the strongest recovery evolution ( $\Delta c_i = +0.075$ ). This is not a small- $N$  artifact but an emergent property of Monterey’s warmer temperatures, which simultaneously drive higher disease pressure *and* stronger selection for clearance ability.

### 8.3 Cross-Scale Comparison

Table 15 summarizes the comparison between the two population scales, revealing which patterns are scale-invariant (and therefore robust model predictions) versus scale-dependent (and therefore artifacts or emergent threshold effects).

Table 15: Cross-scale comparison of key metrics between  $K = 5,000$  and  $K = 100,000$  validation runs. “Ratio” column gives the 100K value divided by the 5K value.

Metric	$K = 5K$	$K = 100K$	Ratio
Total crash (%)	98.5	98.9	1.004
Mean $\Delta r_i$	+0.015	−0.005	—
Mean $\Delta t_i$	+0.014	+0.005	0.38
Mean $\Delta c_i$	+0.070	+0.063	0.90
Total recoveries	365	4,945	13.5
Monterey crash (%)	99.2	97.1	0.979
Monterey $\Delta c_i$	+0.154	+0.075	0.49
Runtime (s)	108	2,558	23.7

Three categories of behavior emerge:

#### 1. Scale-invariant patterns (robust predictions):

- Population crashes are catastrophic ( $>97\%$ ) at both scales, with no recovery to pre-epidemic levels.



- Recovery ( $c_i$ ) is the fastest-evolving trait at every node and both scales.
- Monterey is consistently the most resilient node.
- The extinction vortex—positive feedback between small population size, Allee effects, and continued pathogen pressure—operates at both scales.

## 2. Scale-sensitive patterns (require caution):

- Resistance evolution: positive at  $K = 5,000$  (mean  $+0.015$ ), negative at  $K = 100,000$  (mean  $-0.005$ ). The sign reversal indicates that drift inflates apparent resistance selection at small  $N$ ; the true signal may be negligible or slightly negative.
- Monterey's recovery evolution is  $2\times$  stronger at small  $N$  ( $\Delta c_i = +0.154$  vs.  $+0.075$ ), suggesting that founder effects amplify trait shifts in small surviving populations.
- Tolerance shifts shrink from  $+0.014$  to  $+0.005$ , confirming conditional neutrality.

## 3. Scale-revealing patterns (insights from large $N$ ):

- Uniformly negative  $\Delta r_i$  at  $K = 100,000$  reveals that 17 loci provide insufficient genetic variance for resistance evolution to outpace pathogen pressure, consistent with the sensitivity analysis finding that `n_resistance` is the 5th most important parameter (Section 7).
- The crash percentage *increases* at larger  $N$ , demonstrating that stochastic rescue is not a viable recovery mechanism and that demographic rescue through immigration or captive breeding is required.

## 8.4 Reinfection Dynamics: R→S Validation

Echinoderms lack adaptive immunity: there is no evidence of acquired resistance to SSWD following recovery, and stars treated for wasting have subsequently become reinfected. To reflect this biology, recovered individuals in SSWD-EvoEpi return to the susceptible pool rather than entering a permanently immune state. We validate the impact of this reinfection dynamic by comparing the  $K = 5,000$  baseline (permanent immunity) with the corrected R→S formulation under both sinusoidal and satellite SST forcing.

Table 16: Impact of R→S reinfection dynamics on  $K = 5,000$  validation (5 nodes, 20 years, seed 42). The R→S correction dramatically worsens population outcomes and fundamentally alters the evolutionary trajectory.

Metric	Perm. immunity	R→S (sinusoidal)	R→S (satellite)
Overall crash (%)	98.5	99.7	99.9
Final population	365	122	146
Node extinctions	0	2	2
Total recoveries	365	276	241
Recovery rate (%)	0.87	0.76	0.71
Mean $\Delta r_i$	+0.015	+0.012	—
Mean $\Delta c_i$	+0.070	+0.002	—

The R→S correction produces four critical changes:

**Recovery trait no longer evolves upward.** Under permanent immunity, recovery ( $c_i$ ) was the fastest-evolving trait, with Monterey showing  $\Delta c_i = +0.154$ . With R→S, the strongest surviving-node shift is +0.030 (Newport)—a 5-fold reduction. The mechanism is clear: recovered stars immediately re-enter the susceptible pool and face reinfection, so high-recovery alleles do not accumulate because their carriers keep getting reinfected and dying.

**Local extinctions emerge.** San Juan Islands and Monterey crash to zero population under R→S but maintained small populations (50 and 163, respectively) with permanent immunity. Without the “safe harbor” of an immune recovered class, relentless reinfection cycles drive these nodes to local extinction.

**Selection shifts from recovery to resistance.** In surviving nodes, resistance shows the strongest positive selection under R→S: Sitka  $\Delta r_i = +0.060$  (vs. +0.011 baseline, a 5.5× increase). When recovery does not confer lasting protection, avoiding infection entirely becomes more valuable than clearing infection.

**Satellite vs. sinusoidal SST.** The two SST forcing modes produce qualitatively identical dynamics (99.7% vs. 99.9% crash), but satellite forcing shifts which specific nodes persist, reflecting real coastal oceanographic heterogeneity captured by the NOAA OISST v2.1 climatology.

These results fundamentally change the model’s conservation implications: evolutionary rescue via the recovery trait, which appeared promising under the (incorrect) permanent immunity assumption, is not viable with realistic echinoderm biology. This

strengthens the case for active intervention through captive breeding with selection for resistance ( $r_i$ ) rather than recovery alone.

## 8.5 Key Scientific Findings

The validation runs, taken together with the four-round sensitivity analysis (Section 7), yield several findings with direct implications for conservation management and evolutionary theory.

### 8.5.1 Evolutionary Rescue Is Insufficient

The central question motivating SSWD-EvoEpi is whether natural selection on polygenic resistance can drive population recovery following the SSWD pandemic. Our results provide a clear negative answer under current parameterization: even over 20 years ( $\sim 4$  generations for *Pycnopodia helianthoides*), evolved resistance produces negligible demographic benefit. At  $K = 100,000$ , resistance *declines* at all nodes despite ongoing selection against susceptible individuals. Two mechanisms explain this failure:

1. **Insufficient genetic architecture.** With only 17 resistance loci, the maximum resistance score achievable by selection is constrained. Per-locus allele frequency shifts of  $\sim 0.001$ – $0.003$  per generation are an order of magnitude below the  $\Delta q \approx 0.08$ – $0.15$  reported by Schiebelhut et al. [60] for SSWD-associated loci in *Pisaster ochraceus*. This discrepancy may reflect either a true species difference or an indication that more loci of larger effect contribute to resistance in nature than are modeled here.
2. **Environmental pathogen reservoir.** The background environmental pathogen concentration ( $P_{\text{env}}$ ) ensures continued disease exposure regardless of evolved host resistance. Even if a subpopulation achieves high mean resistance,  $P_{\text{env}}$  maintains baseline infection rates that prevent population recovery below the Allee threshold. The sensitivity analysis identified  $P_{\text{env,max}}$  as the 4th most influential parameter globally, and the most influential for spatial protection metrics.

This finding is consistent with evolutionary rescue theory [10], which predicts that rescue is most likely when standing genetic variance is high, generation times are short relative to population decline rates, and the environment permits population persistence long enough for adaptation to occur. For *Pycnopodia helianthoides*, with generation times of  $\sim 5$  years and crash timescales of  $\sim 2$  years, the mismatch is severe.

### 8.5.2 Recovery as the Primary Adaptive Pathway

The consistent dominance of recovery evolution ( $c_i$ ) across both scales and all five nodes suggests that pathogen clearance, rather than infection prevention (resistance) or damage limitation (tolerance), is the primary adaptive pathway available to *P. helianthoides*.

under SSWD. This is mechanistically intuitive: recovery acts directly on the transition probability from infected to recovered state ( $p_{\text{rec}} = \rho_{\text{rec}} \times c_i$ ), creating strong phenotype–fitness mapping. Individuals that clear infection survive and reproduce; those that do not, die. The fitness gradient is steep and unambiguous.

However, the absolute recovery trait values remain low even after 20 years of evolution (final  $\bar{c}_i \approx 0.07$ – $0.09$  at  $K = 100,000$ ), corresponding to daily clearance probabilities of only 0.35–0.45% ( $p_{\text{rec}} = 0.05 \times c_i$ ). While selection detectably increases  $c_i$ , the resulting clearance rates are far below what is needed to substantially reduce disease-induced mortality.

### 8.5.3 The Extinction Vortex Persists at Realistic Scales

The persistence of >97% population crashes at  $K = 100,000$  demonstrates that the extinction vortex identified in the original prototype is not an artifact of small population sizes. Three reinforcing feedbacks maintain the vortex:

1. **Density-dependent transmission:** as the population declines, per-capita contact rates remain high because pathogen concentration ( $P_{\text{env}}$ ) does not decline proportionally.
2. **Allee effects in reproduction:** below critical densities, broadcast-spawning fertilization success collapses due to sperm dilution [16], reducing recruitment even when surviving individuals are genetically resistant.
3. **Sweepstakes reproductive success:** SRS amplifies drift and further reduces  $N_e$  relative to census  $N$ , diminishing the efficacy of selection [27].

The monotonic population decline with no recovery inflection point is consistent with field observations: seven years after the initial 2013–2015 pandemic, *P. helianthoides* remains functionally absent from most of its former range [19, 23], with only scattered observations of wild individuals in California since 2025 [63].

### 8.5.4 Implications for Captive Breeding

The model results strongly reinforce the case for captive breeding and managed release as the primary conservation strategy for *P. helianthoides* [5, 35]. Three specific model predictions support this conclusion:

1. **No natural recovery trajectory exists:** at no node and at no population scale does the model predict recovery to >5% of carrying capacity within 20 years. Without demographic intervention, populations remain in the extinction vortex.

2. **Recovery trait evolution is the most promising pathway:** if captive breeding programs can select for high  $c_i$  (pathogen clearance ability), released individuals may have elevated survival probability in endemic disease environments. The strong fitness gradient on  $c_i$  suggests that any heritable variation in clearance ability will be rapidly amplified by natural selection post-release.
3. **Scale matters:** the worse-at-larger- $N$  result implies that releasing large numbers of individuals is necessary but not sufficient; releases must also achieve densities above the Allee threshold at the local scale to enable reproductive success.

These predictions align with early empirical results from outplanting trials: the first uncaged release of 20 captive-bred juveniles off San Juan Island in July–August 2024 [57], and the Sunflower Star Laboratory’s December 2025 California outplanting, where 47 of 48 juveniles survived four weeks at Monterey Bay [66]—the same node that shows the highest resilience in our simulations.

## 9 Discussion

SSWD-EvoEpi represents, to our knowledge, the first individual-based model to couple eco-evolutionary host–pathogen dynamics with sweepstakes reproductive success in a marine broadcast spawner. By tracking diploid genotypes at 51 loci across three defense traits (resistance, tolerance, recovery) while simultaneously resolving disease transmission, pathogen virulence evolution, and spatially explicit metapopulation dynamics, the model provides a framework for evaluating conservation interventions that depend on the interplay between ecological and evolutionary processes. Here we discuss the principal contributions of this work, its relationship to existing eco-evolutionary disease models, key limitations, and priorities for future development.

### 9.1 Summary of Contributions

This study makes four principal contributions:

1. **Integrated eco-evolutionary framework for SSWD.** Previous models of SSWD dynamics have addressed epidemiology [1], population viability [68], and reintroduction epidemiology [4] in isolation. SSWD-EvoEpi integrates these processes, enabling the emergent dynamics that arise from feedback loops between disease-driven selection, host genetic adaptation, demographic recovery, and pathogen counter-adaptation to be studied within a single coherent framework.
2. **Three-trait genetic architecture.** Decomposing host defense into resistance (immune exclusion), tolerance (damage limitation), and recovery (pathogen clearance)—following the conceptual framework of Råberg et al. [55]—reveals that these traits

evolve at markedly different rates under SSWD selection pressure. Recovery ( $c_i$ ) emerges as the fastest-evolving trait at every node and population scale (Section 8), a prediction that is testable with longitudinal genomic sampling.

3. **Comprehensive global sensitivity analysis.** Four rounds of progressive SA spanning 47 parameters, up to 23 output metrics, and spatial configurations from 3 to 11 nodes identify the parameters most influential for model behavior (Section 7). The finding that all 47 parameters exhibit nonlinear interactions ( $\sigma/\mu^* > 1.0$ ) establishes that joint calibration via approximate Bayesian computation is essential, and identifies  $\rho_{\text{rec}}$ ,  $k_{\text{growth}}$ ,  $K_{\text{half}}$ ,  $P_{\text{env,max}}$ , and  $n_{\text{resistance}}$  as the highest-priority empirical targets.
4. **Scale-invariant behavioral predictions.** Cross-scale validation from  $K = 5,000$  to  $K = 100,000$  per node demonstrates that catastrophic population crashes ( $>97\%$ ), recovery trait dominance, and the extinction vortex are robust predictions of the model, not artifacts of small population sizes (Section 8.3).

## 9.2 Comparison with Clement et al. (2024)

The closest methodological precedent for SSWD-EvoEpi is the eco-evolutionary IBM developed by Clement et al. [9] for coevolution between Tasmanian devils (*Sarcophilus harrisii*) and devil facial tumour disease (DFTD). Both models track individual diploid genotypes, couple SEI-type disease dynamics with quantitative genetic evolution, and explore the conditions under which evolutionary rescue can avert host extinction following a novel disease introduction. However, several fundamental differences in the study systems produce divergent model architectures and predictions.

**Reproductive biology.** Tasmanian devils are iteroparous mammals with deterministic reproduction: each female produces a small litter ( $\sim 4$  young) per season, with high maternal investment per offspring. *Pycnopodia helianthoides* is a broadcast spawner producing  $\sim 10^7$  eggs per female, with fertilization success dependent on gamete encounter rates in the water column and subject to Allee effects at low density [43]. SSWD-EvoEpi implements sweepstakes reproductive success (SRS) via a Pareto-distributed offspring contribution ( $\alpha \approx 1.35$ ), producing  $N_e/N \sim 10^{-3}$  [27]—a reproductive mode with no analog in the Clement et al. framework. SRS amplifies genetic drift at the population level while simultaneously creating the potential for rapid frequency shifts at individual loci when combined with strong selection [14], fundamentally altering the evolutionary dynamics compared to a mammalian system.

**Spatial structure.** The Clement et al. model operates on a single well-mixed population, reflecting the relatively continuous distribution of Tasmanian devils across Tas-

mania. SSWD-EvoEpi represents the NE Pacific range of *Pycnopodia helianthoides* as a metapopulation network of up to 150 discrete habitat nodes connected by larval dispersal and waterborne pathogen transport. This spatial complexity introduces dispersal–selection interactions that are absent in the single-population case: local adaptation can proceed at different rates across nodes (as observed in the differential recovery at Monterey; Section 8.1), and larval exchange can either homogenize or maintain genetic differentiation depending on the balance of gene flow and spatially heterogeneous selection.

**Pathogen evolution.** Clement et al. model DFTD as a clonally transmitted cancer whose evolution follows a phenotypic difference model, with host resistance and tumor growth rate coevolving along continuous trait axes. Their key finding—that coevolution enables host persistence over 50 generations—relies on the tumor’s capacity to evolve reduced virulence in response to host resistance. SSWD-EvoEpi implements pathogen evolution through a heritable virulence phenotype that scales shedding rate, host mortality rate, and disease progression along mechanistic tradeoff curves (Section 7). The qualitative prediction differs: in our model, the environmental pathogen reservoir ( $P_{\text{env}}$ ) decouples pathogen fitness from individual host survival, weakening the virulence–transmission tradeoff that drives attenuation in the Clement et al. framework and potentially preventing the coevolutionary stabilization that enables devil persistence.

**Evolutionary rescue prospects.** Clement et al. found a high probability of devil persistence over 50 generations ( $\sim 150$  years for devils), driven by rapid coevolutionary dynamics. Our model produces a starkly different prediction: no recovery to  $>5\%$  of carrying capacity within 20 years ( $\sim 4$  *Pycnopodia helianthoides* generations) at any node or population scale. This contrast likely reflects the fundamental mismatch between *Pycnopodia helianthoides*’s long generation time ( $\sim 5$  years vs.  $\sim 3$  years for devils), the extreme variance in reproductive success under SRS (which reduces the efficacy of selection relative to drift), and the environmental pathogen reservoir that maintains infection pressure independently of the host population’s genetic composition.

### 9.3 The Environmental Pathogen Reservoir as a Multi-Species Abstraction

The environmental pathogen concentration  $P_{\text{env}}$  is the most conceptually novel—and most empirically unconstrained—element of the SSWD-EvoEpi disease module. Rather than explicitly modeling *V. pectenocida* dynamics in non-*Pycnopodia helianthoides* host species,  $P_{\text{env}}$  serves as an aggregate abstraction for all pathogen sources external to the focal *Pycnopodia helianthoides* population: other asteroid species, marine sediment reser-

voirs, and environmental bacteria. This design choice was motivated by two considerations.

First, the multi-species nature of the 2013–2015 SSWD pandemic, which affected >20 asteroid species [34, 49], implies that *V. pectenica* (or closely related *Vibrio* strains) can persist in the environment independently of any single host species. Hewson [30] demonstrated explosive *V. pectenica* growth in the presence of decaying echinoderm tissue, suggesting a saprophytic lifestyle that can sustain environmental pathogen pools even when live *Pycnopodia helianthoides* are absent. The fjord refuge mechanism identified by Gehman et al. [17]—where reduced salinity and temperature suppress *Vibrio* growth—operates at the community level, further supporting a spatially varying environmental reservoir.

Second, explicitly modeling multi-species SSWD dynamics would require parameterizing disease susceptibility, shedding rates, and population dynamics for >20 additional asteroid species, most of which lack even basic demographic data. The  $P_{\text{env}}$  abstraction captures the functional consequence (sustained pathogen pressure at the community level) without requiring species-specific parameterization.

However, this abstraction comes at a cost. The sensitivity analysis reveals that  $P_{\text{env,max}}$  is the 4th most influential parameter globally and the most influential parameter for the fjord protection metric (Section 7.3). Its interaction ratio ( $\sigma/\mu^* = 1.92$ ) indicates strong nonlinear coupling with other parameters, meaning that uncertainty in  $P_{\text{env}}$  propagates broadly through the model. Calibrating  $P_{\text{env}}$  against field data (e.g., environmental *Vibrio* concentrations in *Pycnopodia helianthoides* habitat, disease prevalence in non-*Pycnopodia helianthoides* asteroids) is a high priority for constraining model predictions.

## 9.4 Conservation Implications

### 9.4.1 Evolutionary Rescue Is Too Slow

The central finding of both the validation and sensitivity analyses is that natural selection on polygenic resistance cannot drive population recovery on conservation-relevant timescales. At  $K = 100,000$  per node, resistance trait scores actually *decline* over 20 years (mean  $\Delta r_i = -0.005$ ; Table 14), and even the fastest-evolving trait (recovery,  $\Delta c_i \approx +0.06$ ) produces daily clearance probabilities of only 0.35–0.45%, far below what is needed to substantially reduce disease mortality. This finding is consistent with evolutionary rescue theory, which predicts that rescue requires standing genetic variance  $\times$  selection intensity to exceed the rate of population decline [10]. For *Pycnopodia helianthoides*, the mismatch is severe: generation times of  $\sim 5$  years versus crash timescales of  $\sim 2$  years mean that  $<1$  generation of selection can act before populations enter the extinction vortex.

This result has a direct conservation implication: **waiting for natural evolution**



**is not a viable recovery strategy.** Active intervention through captive breeding and managed release is essential to prevent functional extinction. The AZA SAFE program’s existing captive population of >2,500 juveniles and 130+ reproductive adults [5], combined with the successful progressive outplanting trials from 2023 caged experiments through the first uncaged release in 2024 [57] to the December 2025 California outplanting [66], provides the demographic foundation for such intervention.

#### 9.4.2 Breeding Target: Resistance over Recovery

Under the biologically correct R→S formulation (Section 8.4), the recovery trait ( $c_i$ ) no longer evolves substantially because recovered individuals return to the susceptible pool and face reinfection. Instead, resistance ( $r_i$ ) becomes the dominant adaptive response, with surviving nodes showing  $5.5\times$  stronger resistance selection under R→S compared to permanent immunity. This shifts the recommended breeding strategy from selecting for pathogen clearance to selecting for infection prevention. Challenge experiments in captive facilities could identify high-resistance individuals for preferential breeding. The *Pycnopodia helianthoides* reference genome [62] enables genome-wide association studies to identify resistance loci. A combined strategy—selecting for both high  $r_i$  (avoiding infection) and moderate  $c_i$  (surviving breakthrough infections)—may be optimal.

#### 9.4.3 Release Site Selection

The consistent identification of Monterey as the most resilient node—with the lowest crash percentage (97.1% at  $K = 100,000$ ), highest recovery count, and strongest recovery trait evolution—reflects an emergent property of warmer temperatures driving stronger selection for clearance. This suggests that southern sites may be preferable for initial releases if the goal is to establish self-sustaining populations with elevated disease resistance. However, warmer temperatures also increase disease pressure, creating a tension between maximizing selective benefit and minimizing initial mortality. The planned conservation module (Section 9.6) will enable explicit optimization of release timing, location, and genetic composition.

### 9.5 Model Limitations

We identify five principal limitations of the current model:

- 1. No multi-species dynamics.** SSWD-EvoEpi focuses exclusively on *Pycnopodia helianthoides*, abstracting all community-level interactions into the  $P_{\text{env}}$  term. This excludes potential competitive release of sea urchins following *Pycnopodia helianthoides* decline [15, 56], cross-species transmission dynamics [49], and the possibility that recovery of *Pycnopodia helianthoides* could itself alter the selective environment for disease.

The trophic cascade from *Pycnopodia helianthoides* loss to urchin proliferation to kelp deforestation [48] represents a feedback loop that could modify habitat quality and, consequently, sea star survival, but is not represented.

**2. Environmental pathogen reservoir is unconstrained.**  $P_{\text{env,max}}$  ranks 4th in global sensitivity yet has no empirical calibration target. Field measurements of water-borne *V. pectenica* concentrations in *Pycnopodia helianthoides* habitat are needed to constrain this parameter. Until such data are available, model predictions about the feasibility of local disease elimination via host removal or habitat management should be treated as exploratory.

**3. 47-parameter model with universal nonlinearity.** The SA reveals that all 47 parameters interact nonlinearly ( $\sigma/\mu^* > 1.0$  for every parameter; Section 7.3.4). While this is a realistic property of complex biological systems, it means that the model cannot be calibrated by tuning individual parameters in isolation. Joint calibration via ABC-SMC [59] is computationally expensive ( $>10^4$  model evaluations) and requires well-defined summary statistics and calibration targets, many of which are currently lacking for *Pycnopodia helianthoides*.

**4. Recovery rate has zero empirical basis.** The base recovery rate  $\rho_{\text{rec}}$  is the single most influential parameter in the model (Section 7.3.1), yet whether *Pycnopodia helianthoides* can clear *V. pectenica* infections at all is unknown. The SA finding that  $\rho_{\text{rec}}$  explains more output variance than any other parameter underscores this as the highest-priority empirical gap. Challenge-recovery experiments in captive *Pycnopodia helianthoides* [54] could provide direct estimates of clearance probability as a function of dose, temperature, and individual genotype.

**5. Spatial resolution.** The validation runs use 5–11 nodes, far below the 150+ nodes needed to represent the full NE Pacific range of *Pycnopodia helianthoides* at ecologically meaningful resolution. Scaling analysis (Section 7.1) confirms computational feasibility ( $\sim 72$  s for 75,000 agents, 150 nodes), but the reduced-node configurations used here may underestimate the importance of spatial heterogeneity, as demonstrated by the dramatic rank gains of spatial parameters between R3 (3 nodes) and R4 (11 nodes).

## 9.6 Future Directions

### 9.6.1 ABC-SMC Calibration

The immediate next step is formal calibration using approximate Bayesian computation with sequential Monte Carlo sampling (ABC-SMC). Summary statistics will include:

(i) range-wide population decline (>90% crash within 2 years of disease introduction), (ii) latitudinal mortality gradient [23], (iii) fjord protection effect [17], (iv) allele frequency shifts at outlier loci [60], and (v) disease progression timelines from challenge experiments [54]. The R4 SA results (Table 12) provide a natural prioritization: the top 10–15 parameters can be calibrated jointly while fixing the remaining 32–37 at their default values with minimal loss of model fidelity.

### 9.6.2 Conservation Scenario Evaluation

A conservation module is under development to simulate specific management interventions:

- Captive-bred release: number, timing, location, and genetic composition of released cohorts, parameterized from AZA SAFE protocols [5];
- Assisted gene flow: introduction of cryopreserved gametes from genetically diverse wild-caught founders [22];
- Marine protected areas: local reduction of environmental stressors that may interact with disease susceptibility.

Outplanting data from the 2024 San Juan Islands release [57] and the December 2025 Monterey outplanting [66] will provide empirical validation targets for captive-bred survival post-release.

### 9.6.3 Full Coastline Network

Expanding the spatial network to 150 nodes spanning the full NE Pacific range of *Pycnopodia helianthoides* (Baja California to the Aleutian Islands) will test whether the patterns identified at 5–11 nodes—the north–south mortality gradient, fjord protection, Monterey resilience—scale to the full metapopulation. The overwater distance matrix for 489 candidate sites has been computed (Section 6), and computational scaling analysis confirms feasibility (~66 s for 150 nodes; Section 7.1).

### 9.6.4 Integration with Empirical Data

The publication of the *Pycnopodia helianthoides* reference genome [62] enables future GWAS to identify resistance-, tolerance-, and recovery-associated loci, providing direct calibration targets for the genetic architecture parameters ( $n_{\text{resistance}}$ ,  $n_{\text{tolerance}}$ ,  $n_{\text{recovery}}$ , trait-specific effect size distributions). The Koch’s-postulates confirmation of *V. pectenicida* as the causative agent [54] opens the door to controlled challenge experiments that can estimate dose-dependent infection probability, stage-specific duration, recovery rate, and temperature sensitivity—the parameters that the SA identifies as most influential.

Combining these empirical constraints with ABC-SMC calibration will substantially reduce parametric uncertainty and increase confidence in conservation scenario predictions.

## 9.7 Conclusions

SSWD-EvoEpi provides a comprehensive computational framework for exploring the evolutionary dynamics of SSWD in *Pycnopodia helianthoides*. The model reveals that evolutionary rescue through natural selection on polygenic resistance is insufficient to prevent population collapse on conservation timescales, that pathogen clearance (recovery) rather than infection prevention (resistance) is the primary adaptive pathway, and that the extinction vortex persists at ecologically realistic population sizes. These findings reinforce the scientific case for captive breeding and managed release as the essential conservation strategy for this critically endangered species. The four-round sensitivity analysis establishes clear priorities for empirical research—recovery rate, environmental pathogen pressure, genetic architecture, and growth rate—that will enable formal model calibration and, ultimately, quantitative predictions for guiding *Pycnopodia helianthoides* recovery efforts across the northeastern Pacific.

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## A Parameter Tables

Table 17–22 list all 47 parameters included in the sensitivity analysis, grouped by module. For each parameter we report the default value used in validation runs, the sensitivity analysis range (low–high), the distribution used for sampling (U = uniform, LU = log-uniform, D = discrete), and the empirical confidence rating: \*\*\* = directly measured, \*\* = constrained by related data, \* = poorly constrained or assumed.

Table 17: Disease module parameters (16). Default values from `config.py`; SA ranges from `param_spec.py`.

Parameter	Description	Default	Range	Dist.	Conf.
$a_{\text{exposure}}$	Exposure rate ( $\text{d}^{-1}$ )	0.75	[0.30, 1.50]	U	*
$K_{\text{half}}$	Half-infective dose (bact/mL)	87,000	$[2 \times 10^4, 2 \times 10^5]$	LU	*
$\sigma_{1,\text{eff}}$	$I_1$ shedding rate (field-effective)	5.0	[1.0, 25.0]	LU	*
$\sigma_{2,\text{eff}}$	$I_2$ shedding rate (field-effective)	50.0	[10.0, 250.0]	LU	*
$\sigma_D$	Saprophytic burst (field-effective)	15.0	[3.0, 75.0]	LU	*
$\rho_{\text{rec}}$	Recovery rate ( $\text{d}^{-1}$ )	0.05	[0.0, 0.20]	U	*
$\mu_{\text{EI1,ref}}$	$E \rightarrow I_1$ progression at $T_{\text{ref}}$	0.57	[0.20, 1.00]	U	**
$\mu_{\text{I1I2,ref}}$	$I_1 \rightarrow I_2$ progression at $T_{\text{ref}}$	0.40	[0.15, 0.80]	U	**
$\mu_{\text{I2D,ref}}$	$I_2 \rightarrow \text{Death}$ rate at $T_{\text{ref}}$	0.173	[0.08, 0.35]	U	**
$P_{\text{env,max}}$	Background Vibrio input (bact/mL/d)	500.0	[50.0, 5,000.0]	LU	*
$T_{\text{ref}}$	<i>V. pectenocida</i> temperature optimum ( $^{\circ}\text{C}$ )	20.0	[17.0, 23.0]	U	**
$T_{\text{VBNC}}$	VBNC midpoint temperature ( $^{\circ}\text{C}$ )	12.0	[8.0, 15.0]	U	**
$s_{\text{min}}$	Salinity minimum for Vibrio (psu)	10.0	[5.0, 15.0]	U	**

*Continued*

Table 17 (continued)

Parameter	Description	Default	Range	Dist.	Conf.
suscept. multiplier	Post-spawning immunosuppression multiplier	2.0	[1.0, 4.0]	U	★
immunosupp. duration	Post-spawning immunosuppression (days)	28	[7, 56]	U	★★
min. susceptible age	Days post-settlement before susceptible	0	[0, 180]	U	★

Table 18: Population dynamics parameters (7).

Parameter	Description	Default	Range	Dist.	Conf.
$F_0$	Reference fecundity (eggs)	$10^7$	$[10^6, 10^8]$	LU	★
$\gamma_{\text{fert}}$	Fertilization kinetics parameter	4.5	$[1.0, 10.0]$	U	★
$s_0$ (settler survival)	Beverton–Holt settler survival	0.03	$[0.005, 0.10]$	LU	★
$\alpha_{\text{SRS}}$	SRS Pareto shape	1.35	$[1.0, 1.8]$	U	★★
senescence age	Senescence onset age (yr)	50.0	$[20.0, 80.0]$	U	★
$k_{\text{growth}}$	von Bertalanffy growth rate ( $\text{yr}^{-1}$ )	0.08	$[0.03, 0.15]$	U	★
$L_{\text{min, repro}}$	Minimum reproductive size (mm)	400.0	$[200.0, 500.0]$	U	★

Table 19: Genetics module parameters (8). The three-trait partition is constrained:  $n_{\text{resistance}} + n_{\text{tolerance}} + n_{\text{recovery}} = 51$ .

Parameter	Description	Default	Range	Dist.	Conf.
$n_{\text{resistance}}$	Number of resistance loci	17	{5, 10, 17, 25, 30}	D	★★
$n_{\text{tolerance}}$	Number of tolerance loci	17	{5, 10, 17, 25, 30}	D	★★
target_mean_r	Target mean resistance at $t = 0$	0.15	[0.05, 0.30]	U	★
target_mean_t	Target mean tolerance at $t = 0$	0.10	[0.02, 0.30]	U	★
target_mean_c	Target mean recovery at $t = 0$	0.02	[0.02, 0.25]	U	★
$\tau_{\text{max}}$	Max tolerance mortality reduction	0.85	[0.30, 0.95]	U	★
$q_{\text{init},\beta_a}$	Beta shape $a$ for allele freq. init.	2.0	[1.0, 5.0]	U	★
$q_{\text{init},\beta_b}$	Beta shape $b$ for allele freq. init.	8.0	[3.0, 15.0]	U	★

Table 20: Spawning module parameters (7).

Parameter	Description	Default	Range	Dist.	Conf.
$p_{\text{spont},f}$	Daily spontaneous female spawning prob.	0.012	[0.005, 0.025]	U	★★
$p_{\text{spont},m}$	Daily spontaneous male spawning prob.	0.0125	[0.005, 0.025]	U	★★
$\kappa_{fm}$	Female→male cascade induction prob.	0.80	[0.40, 0.95]	U	★★
$\kappa_{mf}$	Male→female cascade induction prob.	0.60	[0.10, 0.60]	U	★★
$\sigma_{\text{spawn}}$	Spawning peak width (std dev, days)	60.0	[30.0, 90.0]	U	★★
readiness ind. prob.	Social spawning readiness induction	0.50	[0.10, 0.80]	U	★
female max bouts	Max spawning bouts per female per season	2	{1, 2, 3}	D	★★



Table 21: Spatial module parameters (3).

Parameter	Description	Default	Range	Dist.	Conf.
$D_L$	Larval dispersal scale (km)	400.0	[100.0, 1,000.0]	LU	★
$\alpha_{\text{self,fjord}}$	Larval self-recruitment (fjord)	0.30	[0.10, 0.50]	U	★
$\alpha_{\text{self,open}}$	Larval self-recruitment (open coast)	0.10	[0.02, 0.20]	U	★

Table 22: Pathogen evolution module parameters (6).

Parameter	Description	Default	Range	Dist.	Conf.
$\alpha_{\text{kill}}$	Death rate scaling exponent	2.0	[1.0, 4.0]	U	★
$\alpha_{\text{shed}}$	Shedding rate scaling exponent	1.5	[0.5, 3.0]	U	★
$\alpha_{\text{prog}}$	$I_1 \rightarrow I_2$ progression scaling exp.	1.0	[0.5, 2.0]	U	★
$\gamma_{\text{early}}$	Early shedding attenuation factor	0.3	[0.0, 1.0]	U	★
$\sigma_{v,\text{mut}}$	Virulence mutation step size (std dev)	0.02	[0.005, 0.10]	LU	★
$v_{\text{init}}$	Initial pathogen virulence	0.5	[0.2, 0.8]	U	★