

1 Supporting information for: Wilson *et al.* 2023. The role of spatial
2 structure in at-risk metapopulation recoveries.

3 In: *Ecological Applications*

4 **Appendix S1:** Overview of metapopulation model description & detailed results

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6 31 May 2023

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28 **Section S1.1: Metapopulation model**

29 **Section S1.1.1: Local & metapopulation dynamics**

30 Our metapopulation was defined by a set of P local populations for a species with a one year generation time with
 31 time-dynamics that follows birth (i.e., recruitment R), immigration, death, and emigration processes typical to
 32 metapopulation theory and tested the role of multiple local and regional processes (Anderson et al. 2015; Fullerton
 33 et al. 2016; Zelnik et al. 2019; Bowlby & Gibson 2020; Okamoto et al. 2020):

$$N_{i,t} = (1 - d_{i,t})(R_{i,t} + \sum_{\substack{j=1 \\ j \neq i}}^P \omega p_{i,j} R_{j,t} - \omega R_{i,t}) \quad (\text{S.1})$$

34 where $N_{i,t}$ was the number of adults in patch i at time t , $R_{i,t}$ was the number of recruits at time t , $\sum_{\substack{j=1 \\ j \neq i}}^P \omega p_{i,j} R_{j,t}$ was
 35 the number of recruits immigrating into patch i from any other patch, ω was the proportion of local recruits to
 36 disperse, $p_{i,j}$ was a distance-dependent dispersal function, and $d_{i,t}$ was the proportion of post-dispersal recruits lost
 37 from the disturbance regime.

38 Figure S1 shows how local patch recruitment at time t depended on adult densities at $t-1$ and followed a
 39 reparameterized Beverton-Holt function based on compensation ratio (see Box 3.1 in Walters & Martell 2004) and
 40 ignoring age-structure to model adult-to-adult dynamics, i.e., setting $\phi_{E_0} = 1$, $\phi_{B_0} = 1$ and $R_0 = N_0$ (see Table 3 in
 41 Forrest et al. 2010):

$$R_{i,t} = \frac{\alpha_i N_{i,t-1}}{1 + \frac{\alpha_i - 1}{\beta_i} N_{i,t-1}} \epsilon_{i,t} \quad (\text{S.2})$$

42 where α_i was the recruitment compensation ratio, β_i was local patch carrying capacity, and $\epsilon_{i,t}$ was lognormally
 43 distributed deviates to introduce stochastic recruitment dynamics.

44 Resource monitoring often occurs at the scale of the whole metapopulation by sampling aggregate abundances from
 45 multiple local populations to (Anderson et al. 2015; Moore et al. 2021), hence we define metapopulation adults as:

$$A_t = \sum_{i=1}^P N_{i,t} \quad (\text{S.3})$$

46 with metapopulation recruits:

$$K_t = \sum_{i=1}^P R_{i,t} \quad (\text{S.4})$$

47 Monitoring at the scale of the whole metapopulation can produce productivity relationships that aggregates the
 48 population dynamics and productivity among all local populations. For example, take a two patch metapopulation
 49 model (Figure S1) that each vary in demographic shape parameters $\alpha_1 = 2$; $\alpha_2 = 4$ and $\beta_1 = 100$; $\beta_2 = 200$. Here,
 50 recruitment compensation from local patches α_i gets averaged across the metapopulation leading to an average
 51 compensation ratio $\bar{\alpha}$ of 3. Likewise, the total carrying capacity of the metapopulation $\bar{\beta}$ becomes the summation
 52 of local patch carrying capacities $\sum \beta_i$, which was 300. This scale of monitoring generates the following local patch
 53 and metapopulation dynamics:

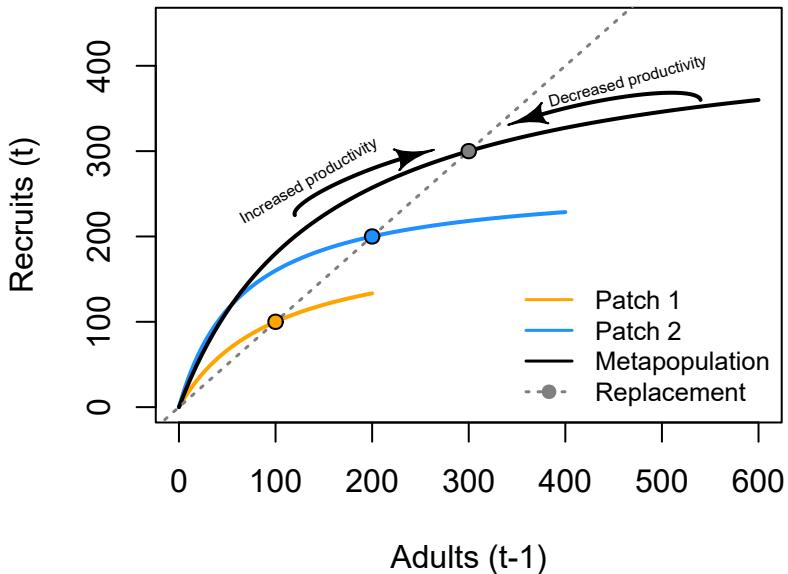


Figure S1: Density dependence in metapopulation and local patch recruitment dynamics. Dashed line indicates the line of replacement, with equilibrium indicated by points. When populations fall below equilibrium points, per-capita productivity improves driving populations back towards equilibrium. When populations exceed their capacity, per-capita productivity decreases driving populations back towards equilibrium. At each point of the x-axis, the distance between the solid and dashed lines indicates the amount of recruitment above replacement, i.e., the surplus recruitment produced via compensatory density dependence.

⁵⁴ **Section S1.1.2: Creating the spatial networks**

⁵⁵ The next aspect to developing our metapopulation model was connecting the set of patches to one another (Yeakel
⁵⁶ et al. 2014). We needed to specify the number of patches, their arrangements (i.e., connections), and how far apart
⁵⁷ they are from one another. We followed some classic metapopulation and source-sink arrangements to create four
⁵⁸ networks that generalize across a few real-world topologies: a linear habitat network (e.g., coastline), a dendritic or
⁵⁹ branching network (e.g., coastal rivers), a star network (e.g., mountain & valley, or lake with inlet tributaries), and
⁶⁰ a grid network (e.g., grasslands).

⁶¹ To make networks comparable, each spatial network type needs the same leading parameters (e.g., number of
⁶² patches P and mean distance between neighboring patches d). In this case, we set P to 16 and d to 1 unit
⁶³ (distance units are arbitrary). We used the `igraph` package (Csardi & Nepusz 2006) to arrange our spatial
⁶⁴ networks as the following:

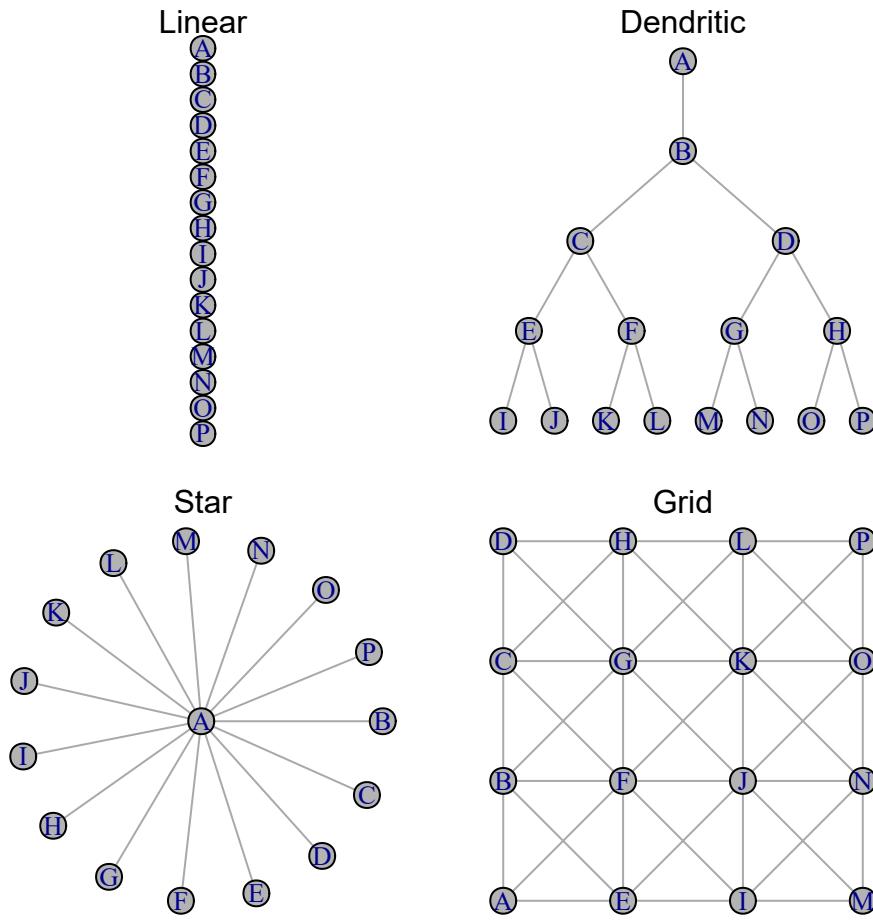


Figure S2: Four spatial network topologies.

65 Note that distances between neighbor patches in the above networks are equal. Table S1 shows an example
 66 dispersal matrix for a grid network.

67 Section S1.1.3: Dispersal

68 Dispersal from patch i into patch j depends on constant dispersal rate ω (defined as the proportion of total local
 69 recruits that will disperse) and an exponential distance-decay function between i and j with distance cost to
 70 dispersal m (Anderson et al. 2015; Fullerton et al. 2016):

$$E_{i,j,t} = \omega R_{i,t} p_{i,j} \quad (\text{S.5})$$

71 where $E_{i,j}$ was the total dispersing animals from patch i into patch j resulting from dispersal rate ω , total number
 72 of local recruits $R_{i,t}$, and probability of dispersal between patches $p_{i,j}$:

$$p_{i,j} = \frac{e^{-md_{i,j}}}{\sum_{\substack{j=1 \\ j \neq i}}^P e^{-md_{i,j}}} \quad (\text{S.6})$$

73 where $d_{i,j}$ was the pairwise distance between patches, m was the distance cost to dispersal. The summation term in
 74 the denominator normalizes the probability of moving to any patch to between 0 and 1 with the constraint that
 75 dispersers cannot move back into their home patch (i.e., $j \neq i$. With $\bar{d} = 1$, $m = 0.5$, $\omega = 0.1$, $R_{i,t} = 100$ in a linear
 76 network):

Table S1: Example distance matrix between 16 patches within a grid network to affect distance-dependent dispersal rates.

	A	B	E	F	C	G	D	H	I	J	K	L	M	N	O	P
A	0	1	1	1	2	2	3	3	2	2	2	3	3	3	3	3
B	1	0	1	1	1	1	2	2	2	2	2	2	3	3	3	3
E	1	1	0	1	2	2	3	3	1	1	2	3	2	2	2	3
F	1	1	1	0	1	1	2	2	1	1	1	2	2	2	2	2
C	2	1	2	1	0	1	1	1	2	2	2	2	3	3	3	3
G	2	1	2	1	1	0	1	1	2	1	1	1	2	2	2	2
D	3	2	3	2	1	1	0	1	3	2	2	2	3	3	3	3
H	3	2	3	2	1	1	1	0	3	2	1	1	3	2	2	2
I	2	2	1	1	2	2	3	3	0	1	2	3	1	1	2	3
J	2	2	1	1	2	1	2	2	1	0	1	2	1	1	1	2
K	2	2	2	1	2	1	2	1	2	1	0	1	2	1	1	1
L	3	2	3	2	2	1	2	1	3	2	1	0	3	2	1	1
M	3	3	2	2	3	2	3	3	1	1	2	3	0	1	2	3
N	3	3	2	2	3	2	3	2	1	1	1	2	1	0	1	2
O	3	3	2	2	3	2	3	2	2	1	1	1	2	1	0	1
P	3	3	3	2	3	2	3	2	3	2	1	1	3	2	1	0

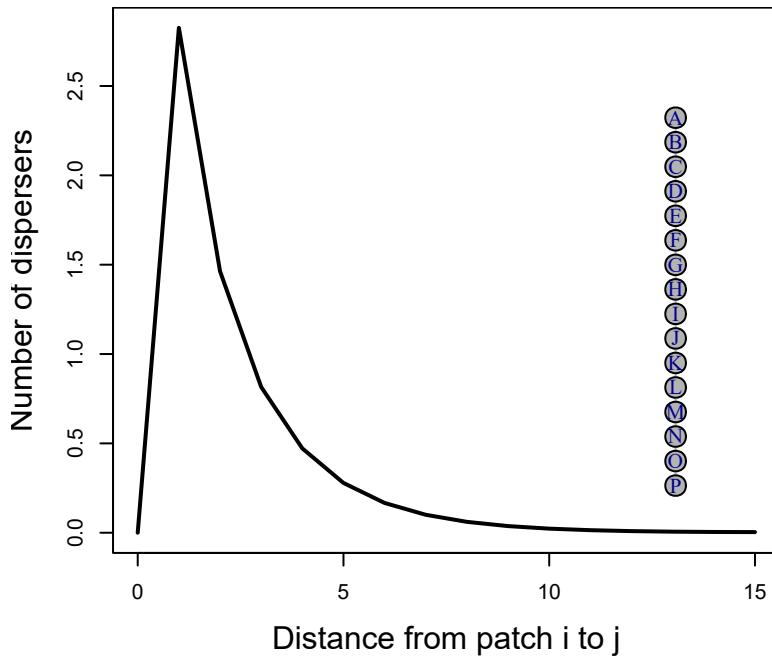


Figure S3: Example dispersal patterns across linear network.

77 Section S1.1.4: Disturbance regimes

78 In all scenarios, disturbance was applied after 50 years of equilibrating the metapopulation at pristine conditions.
 79 Initial conditions were defined as: at $t = 1$, each patch p had initial population abundance set to their local
 80 carrying capacity such that $N_1 = \beta_i$ before stochastic recruitment dynamics and dispersal could occur. To make
 81 each scenarios comparable, we set some constraints on the average recruitment productivity such that $\bar{\alpha} = 2$ and
 82 metapopulation carrying capacity $\sum \beta_i = 1600$ were always the same in each scenario. We then applied a pulsed
 83 disturbance regime at year 50 (the regime varied from *uniform*, *localized*, *even*, and *localized, uneven* - see *Scenarios*
 84 below). Disturbance immediately removed a fixed proportion of the metapopulation adults at that time (i.e., 0.9 of
 85 $A_{t=50}$). Once applied, the metapopulation was no longer disturbed and spatio-temporal recovery dynamics emerged

86 from these conditions given the ecological scenarios of network complexity, dispersal rate, spatio-temporal
 87 correlations, local patch demographies, and magnitude of stochastic variance.

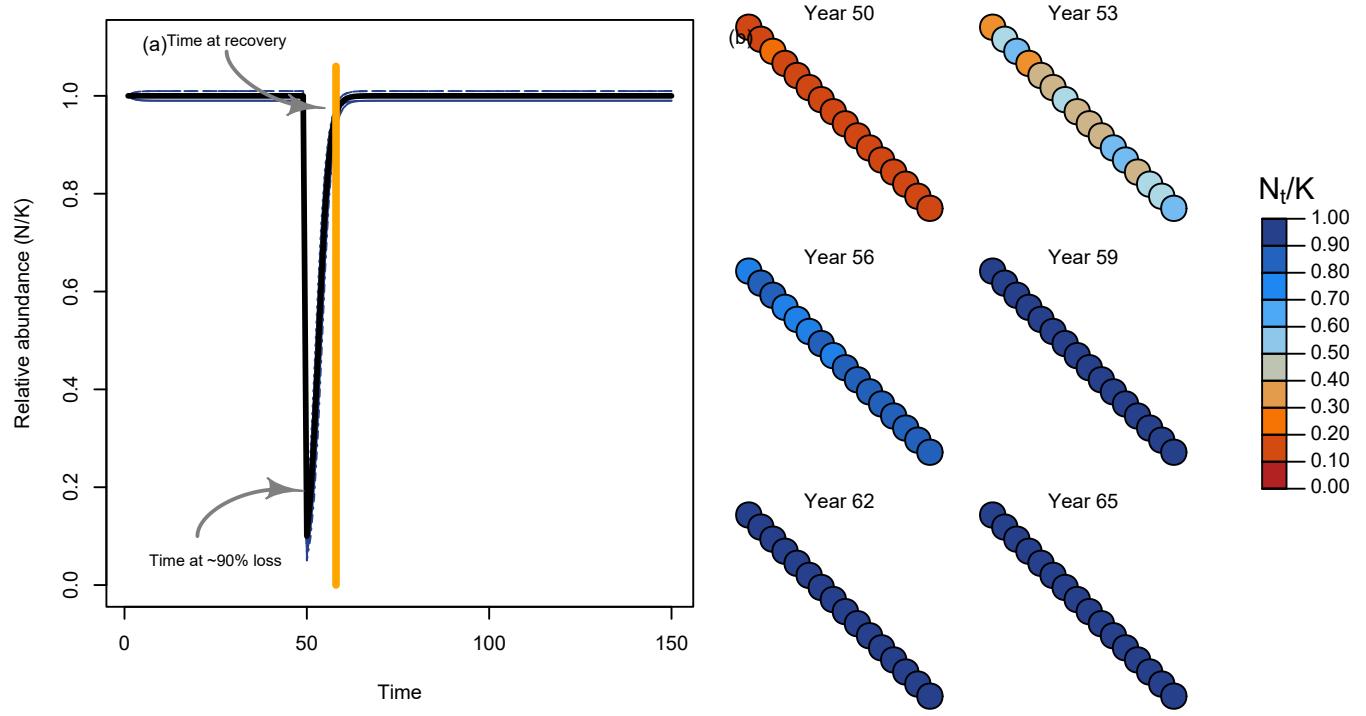


Figure S4: Recovery regime of metapopulation with linear topology through time (a) and space (b).

88 Section S1.1.5: Recruitment stochasticity

89 Our model allowed for stochastic recruitment that followed a lognormal distribution with average variation in
 90 recruitment of σ_R . In cases with stochastic recruitment, the deterministic recruitment in eq. S.4 becomes:

$$R_{i,t} = \frac{\alpha_i N_{i,t-1}}{1 + \frac{\alpha_i - 1}{\beta_i} N_{i,t-1}} e^{(\epsilon_{i,t} - \frac{\sigma_R^2}{2})} \quad (\text{S.7})$$

91 where lognormal deviates for each patch i at time t were drawn from a multivariate normal distribution (MVN)
 92 with bias correction $\frac{\sigma_R^2}{2}$. If σ_R was low, then metapopulation dynamics approach the deterministic case. In some
 93 scenarios, we evaluated the role of spatially and/or temporally correlated deviates among local patches to model
 94 potential common drivers affecting metapopulation dynamics (e.g., Moran effects). Expected recruitment deviates
 95 followed a first-order autoregression model such that:

$$\epsilon_{i,t} = \rho_T \epsilon_{t-1} + MVN(\mu = 0, \Sigma = \sigma_R^2(1 - \rho_T^2)e^{(-\rho_S D_{i,j})}) \quad (\text{S.8})$$

96 where ρ_T was temporal correlation (bounded $0 - 1$) and ρ_S was rate of distance-decay in spatial correlation
 97 (bounded $0 - \infty$ with higher values leading to independent patches). If ρ_T was 0 and ρ_S was high, then annual
 98 recruitment deviates were independent. We modelled the initial conditions for autoregressive recruitment deviates
 99 $\epsilon_{i,1}$ by drawing from a stationary normal distribution with mean $\mu = 0$ and variance σ_R^2 such that:

$$\epsilon_{i,1} \sim N(\mu = 0, \sigma = \sigma_R) \quad (\text{S.9})$$

100 We illustrate the effects of four kinds of recruitment deviates below using the same random number generator seed:

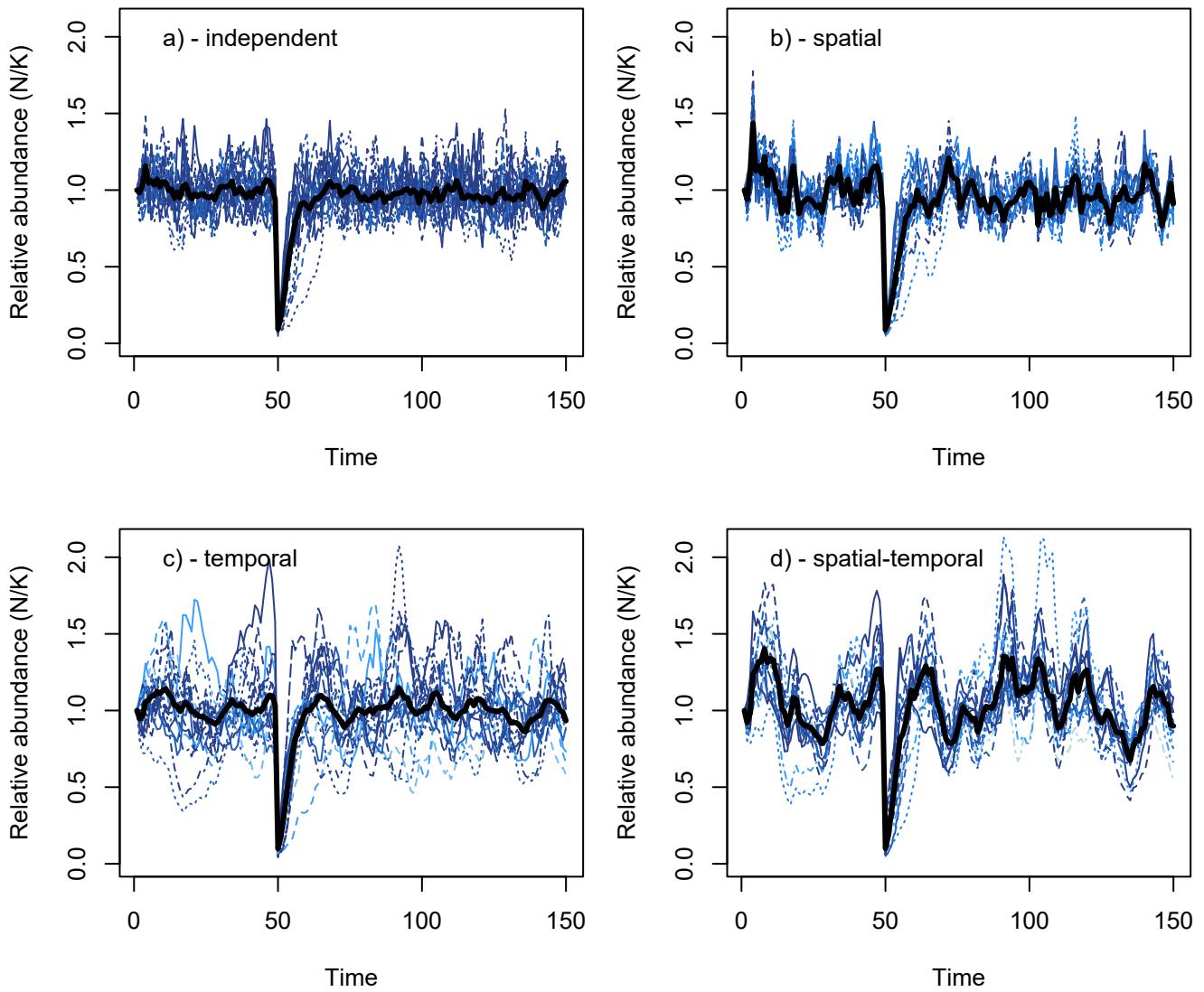


Figure S5: Metapopulation dynamics with independent (a), spatially correlated (b), temporally correlated (c), and spatio-temporally correlated (d) recruitment deviates. Black line indicates metapopulation, and dashed lines indicate local patches with red and blue relating to abundances after 100 years post-disturbance were less than or greater than 1.0 pre-disturbance, respectively.

¹⁰¹ **Section S1.2: Post-disturbance outcomes**

¹⁰² **Section S1.2.1: Monitoring & management at aggregate-scale**

¹⁰³ While true metapopulation dynamics emerge from local patch dynamics and dispersal in eq. S.1, natural resource
¹⁰⁴ managers often monitor and manage at the scale of the metapopulation. Hence, management at this scale
¹⁰⁵ inherently defines the stock-recruitment dynamics of the aggregate complex of patches (i.e., metapopulation) as:

$$\mathbb{E}(N_t) = \frac{\bar{\alpha}A_{t-1}}{1 + \frac{\bar{\alpha}-1}{\bar{\beta}}A_{t-1}} \quad (\text{S.10})$$

¹⁰⁶ where $\bar{\alpha}$ was the compensation ratio averaged across the metapopulation and $\bar{\beta}$ was the carrying capacity summed
¹⁰⁷ across the entire metapopulation.

108 **Section S1.2.2: Recovery metrics**

109 We measured the following post-disturbance outcomes to track the temporal and spatial recovery regime of the
 110 metapopulation.

- 111 1. Recovery rate after disturbance: Recovery rate represents the inverse proportion of the post-disturbance
 112 phase that the metapopulation took to recover. Recovery rate was calculated as $1 - T_{recovery}/T_{sim}$ where the
 113 recovery time, $T_{recovery}$, was the number of years/generations (1 year = 1 generation in our models) it took
 114 for the metapopulation to reach five consecutive years pre-disturbance abundance. Recovery rate captures
 115 how quickly the aggregate metapopulation recovers from disturbance but doesn't take into account whether
 116 any given local patches recover to their pre-disturbance capacity nor did it allow for any uncertainty around
 117 recovery criteria.
- 118 2. Patch occupancy: The number of patches with >0.1 local carrying capacity after disturbance in the
 119 short-term (5 years), medium-term (10 years), and long-term (25 years). This value characterizes the
 120 expected risk of spatial contractions or local patch collapses, and reflects how interactions between spatial
 121 structure, disturbance, and dispersal shape source-sink dynamics and the ability to provide (or not) rescue
 122 effects and recover local patches.
- 123 3. Relative production: The ratio between the empirical metapopulation adult abundances to the expected
 124 adult recruitment if the metapopulation were a single, contiguous population of equivalent size and
 125 productivity (i.e., carrying capacities and productivity were equal to the sum β and mean α among patches,
 126 respectively). We term Δ_N by calculating the stock-recruitment model to aggregate metapopulation adults
 127 (eq. S.10) such that:

$$\Delta_{N_t} = \frac{A_t}{\mathbb{E}(N_t)} \quad (\text{S.11})$$

128 A value of 1.0 would indicate that the disturbed metapopulation production was equal to a single, contiguous
 129 population such that source-sink dynamics were not consuming surplus recruits. In other words, this metric
 130 can describe whether the metapopulation acts more than ($\Delta_{N_t} > 1.0$), less than ($\Delta_{N_t} < 1.0$), or equal to the
 131 sum of its parts ($\Delta_{N_t} = 1.0$).

- 132 4. Risk of non-recovery after disturbance: Non-recovery rate was defined as the % of simulations where
 133 metapopulation abundance failed to recover to 1.0 of the average pre-disturbance abundance for 5
 134 consecutive years post-disturbance. This "non-recovery rate" reflects the risk of a long-term state shift in
 135 metapopulation dynamics after disturbance in the face of stochasticity.

136 **Section S1.3: Scenarios**

137 We tested all combinations of the following eight processes (below) and ran 100 stochastic iterations per scenario
 138 (see section on *Sensitivity test of mean recovery metrics* below) to estimate the mean outcome for each of the above
 139 recovery metrics:

- 140 1. Homogenous and spatially variable recruitment compensation ratio across patches, i.e. intrinsic rate of
 141 population growth (α_i).
- 142 a. when **variable**, $\alpha_i \sim TN(\mu = \bar{\alpha}, \sigma_\alpha = 0.3\bar{\alpha})$ with a truncation applied such that $5 \leq \alpha_i \geq 1$ to ensure
 143 that patches could, at minimum, could replace themselves but with an upper limit of a 5-fold
 144 improvement to per-capita productivity. By comparison, Myers et al. (1999) found that compensation
 145 ratio (their $\hat{\alpha}$) ranged 1-7 for most species evaluated. Since our focus was on at-risk species, we opted to
 146 truncate α_i towards the lower end of this range, with a mean of 2.0.
- 147 2. Homogenous and spatially variable local carrying capacity across patches, i.e. asymptote of expected recruits
 148 at high adult densities (β_i)
- 149 a. when **variable**, $\beta_i \sim multinomial(p_i, N)$ where $p_i = \frac{e^{\theta_i}}{\sum e^{\theta_i}}$, $\theta_i \sim uniform(0, 1)$, and $N = \bar{\beta}$, with the
 150 added constraint that $\beta_i < 0.1\bar{\beta}$ to ensure that no one patch exceed 10% of total metapopulation
 151 abundance (a necessary constraint when modelling *local, even* and *local, uneven* disturbances below).
 152 Note that, when local variation in demography rates occurred, the truncated normal in *Appendix S1: Section S1.3(1.a)* and truncated multinomial in *Appendix S1: Section S1.3(2.a)* above led compensation
 153 ratio and carrying capacity, respectively, to vary by the same magnitude ~28% coefficient of variation
 154 (Appendix S1: Figure S6).

- 156 3. Variation in the spatial distribution of disturbances where a proportion of individuals were removed from the
157 metapopulation (e.g., 0.90) occurs.
- 158 a. *uniform* - individuals randomly removed across all patches, with all individuals having equal
159 vulnerability to being removed.
- 160 b. *local, even* - randomly chosen individuals were removed from a random subset of patches (as long as 90%
161 of total metapopulation individuals can be removed from that subset)
- 162 i. Specifically, a numerical algorithm was used to search and find a set of disturbance conditions
163 whereby removing a random proportion of individuals from a random chosen portion of local
164 patches achieved both:
165 • a total loss that summed to a ~90% loss in abundance to the whole metapopulation, and
166 • left at least one local patch *undisturbed* to start metapopulation recoveries.
- 167 c. *local, uneven* - total extirpation of randomly selected subset of patches (as long as 90% of total
168 metapopulation individuals can be removed from that subset).
- 169 i. Specifically, a numerical algorithm was used to search and find a set of disturbance conditions
170 whereby extirpations to a random chosen portion of local patches achieved both:
171 • a total loss that summed to a ~90% loss in abundance to the whole metapopulation, and
172 • left at least one local patch *undisturbed* to start metapopulation recoveries.
- 173 4. Density-independent dispersal rates ω from 0 to 5% of individuals within a patch will disperse.
- 174 5. Topology of the spatial networks with linear, dendritic, star, and grid networks. Each network with $P = 16$
175 and distance between patches $\bar{d} = 1$.
- 176 6. Stochastic recruitment deviates with low, medium, and high standard deviation in lognormal error. Used to
177 generate stochastic population dynamics via random deviates from the expected recruitment relationship in
178 eq. S.2.
- 179 7. Temporal correlation in recruitment deviates from low, medium, and high correlation (i.e., good year at time
180 t begets good year at time $t+1$).
- 181 8. Spatial correlation in recruitment deviates among patches from low, medium, to high correlation (i.e.,
182 neighboring patches go up or down together).

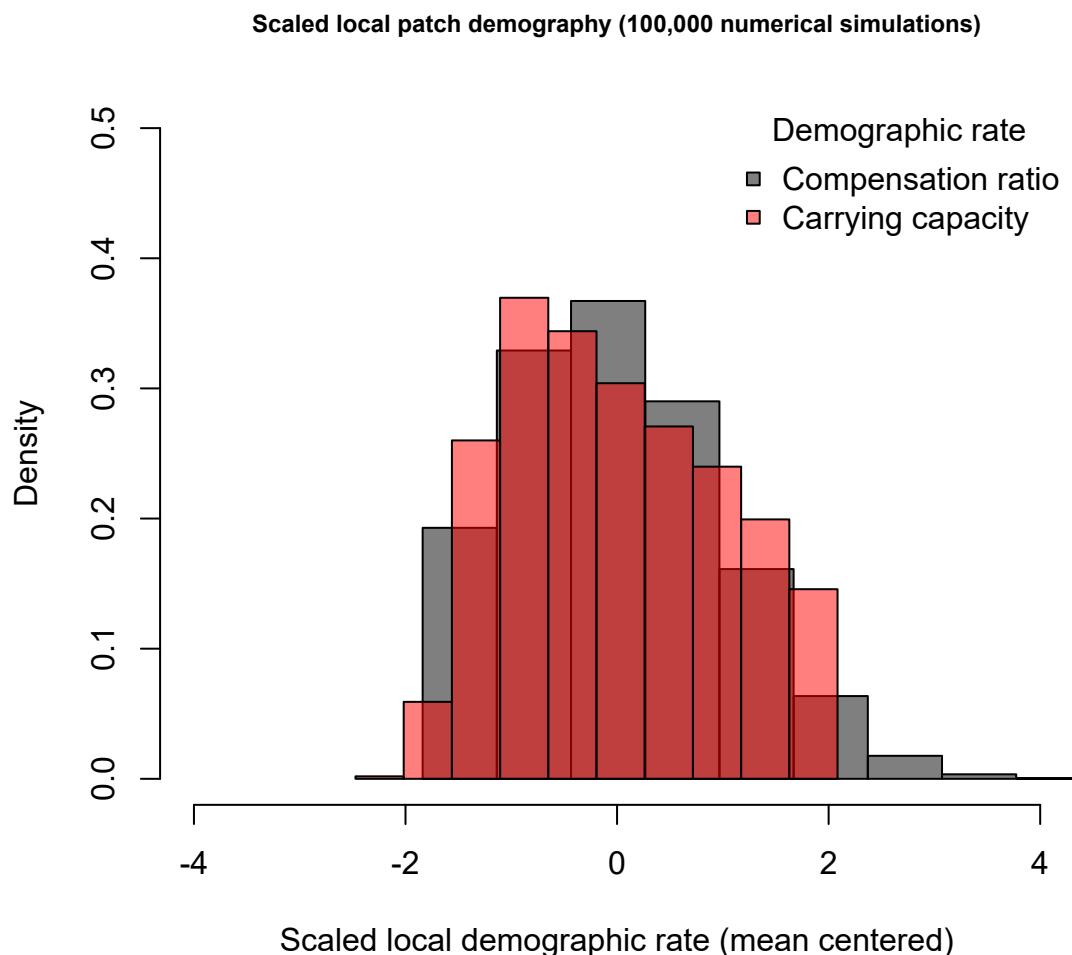


Figure S6: Histogram showing variation among demographic rates after simulating 100,000 local patches when using the truncated normal in Appendix S1: Section 1.3(1.a) and truncated multinomial in Appendix S1: Section 1.3(2.a) when modelling variation in local compensation ratio (grey) and carrying capacity (red).

183 **Section S1.3.1: Example disturbance regimes**

184 Below, we demonstrate how each of the above disturbance scenarios in *Section S1.3(3.a-c)* manifest as spatially
 185 distributed impacts to local patches among the metapopulation. Each figure below shows nine random iterations of
 186 a metapopulation with a set of 16 patches structured in a dendritic network at the time of a 90% loss in aggregate
 187 abundance, and how that aggregate loss is realized as impacts to local patches. Each patch is shown as a circle or
 188 node, and its abundance relative to its local carrying capacity is indicated in two ways: (1) with the numbers
 189 within the circle and (2) the colour of the circle itself (with the colour scale gradient indicated to the right). We
 190 begin with the *uniform* disturbance scenario.

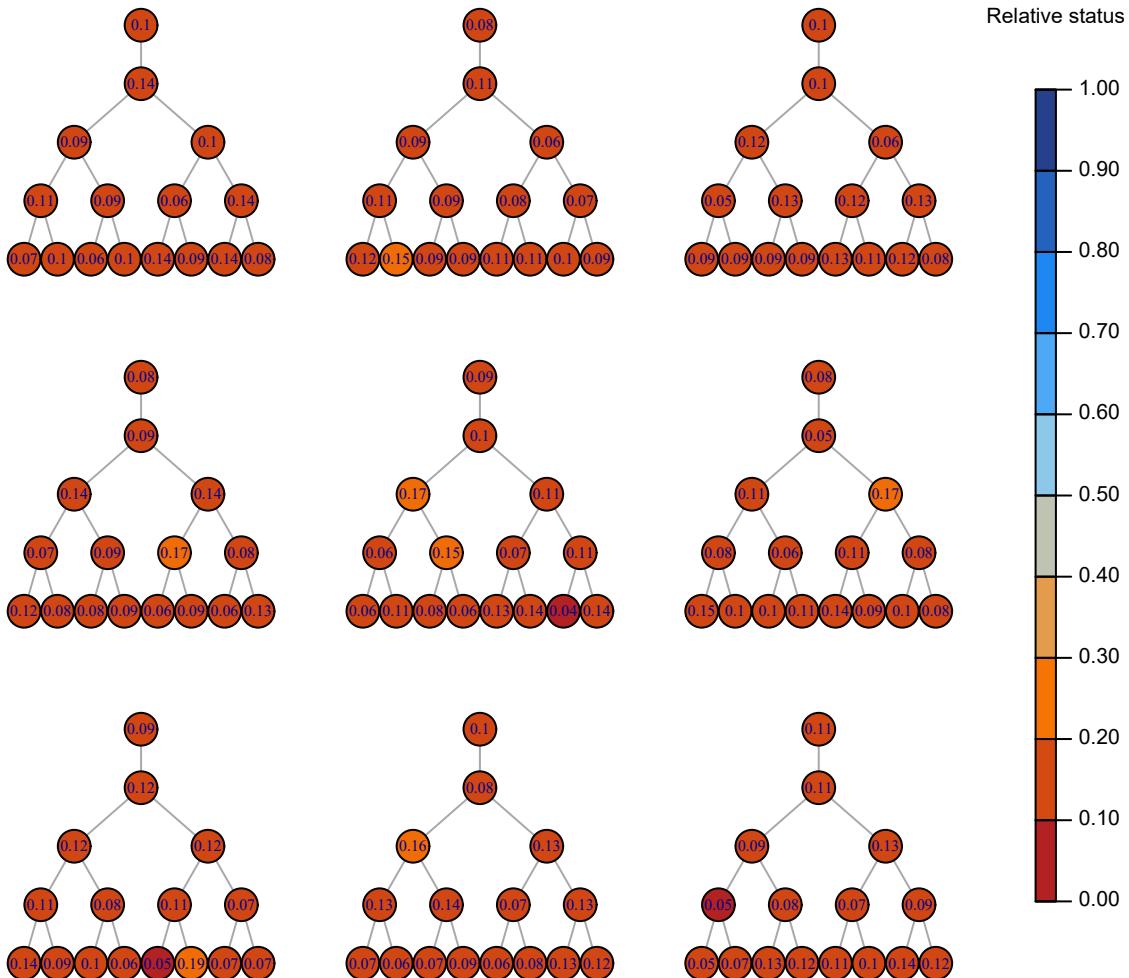


Figure S7: Nine example disturbance scenarios for uniform disturbance in a dendritic network. The relative population status at the time of disturbance (abundance relative to local carrying capacity) indicated by text labels and color gradient.

¹⁹¹ Next, we show how the 90% loss is applied to the dendritic network under the *local, even* disturbance scenario.

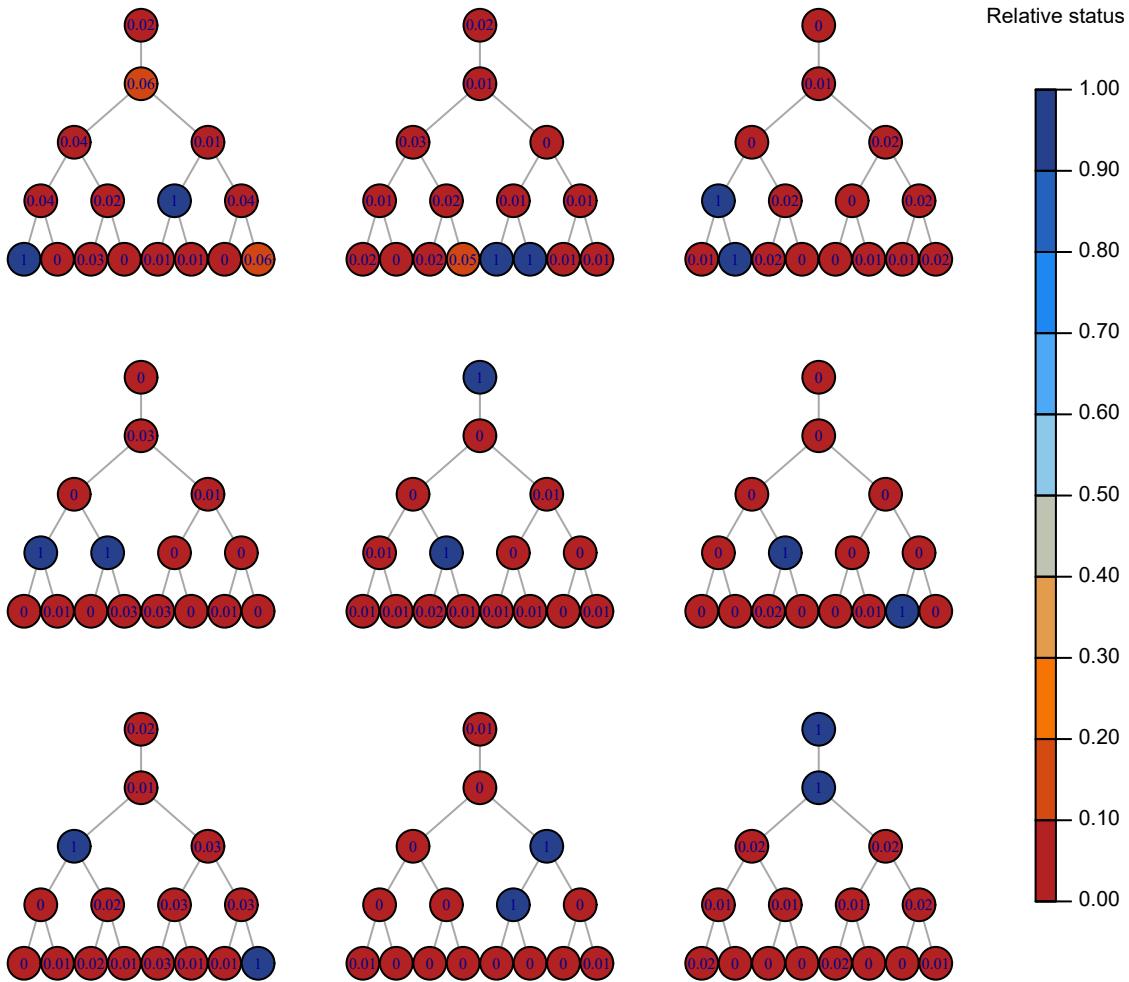


Figure S8: Nine example disturbance scenarios for local, even disturbance in a dendritic network. The relative population status at the time of disturbance (abundance relative to local carrying capacity) indicated by text labels and color gradient.

192 Last, we show how the 90% loss is applied to the dendritic network under the *local, uneven* disturbance scenario.

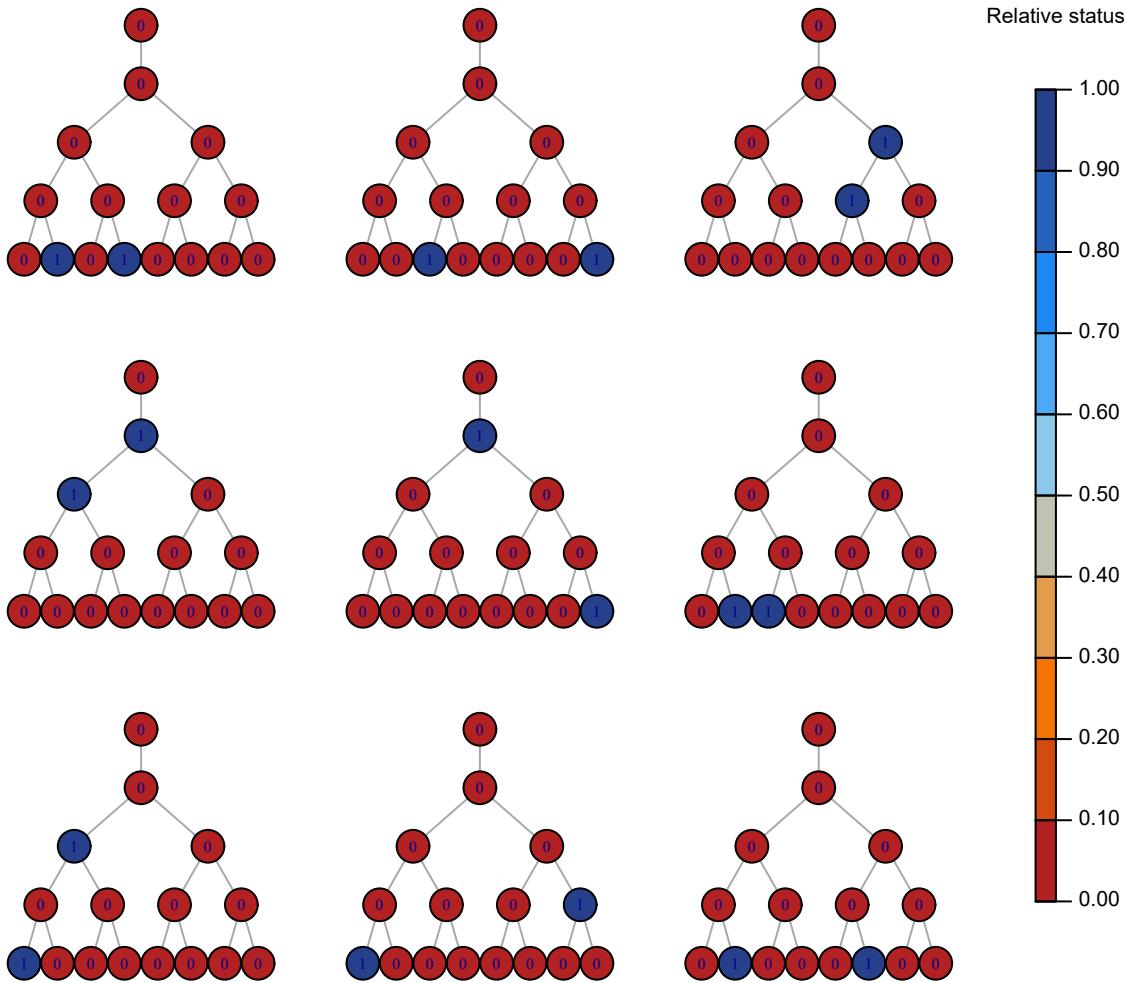


Figure S9: Nine example disturbance scenarios for local, uneven disturbances in a dendritic network. The relative population status at the time of disturbance (abundance relative to local carrying capacity) indicated by text labels and color gradient.

193 **Section S1.3.2: Walkthrough of example results**

194 We demonstrate our metapopulation model with an example outcome for a linear network composed of 16 patches,
 195 a dispersal rate of 0.01 and a high enough dispersal cost such that individuals are only willing to move to their
 196 closest neighboring patches. This limits the strength of potential rescue effects. For this example, patches varied in
 197 their productivity and carrying capacity but will have deterministic population dynamics.

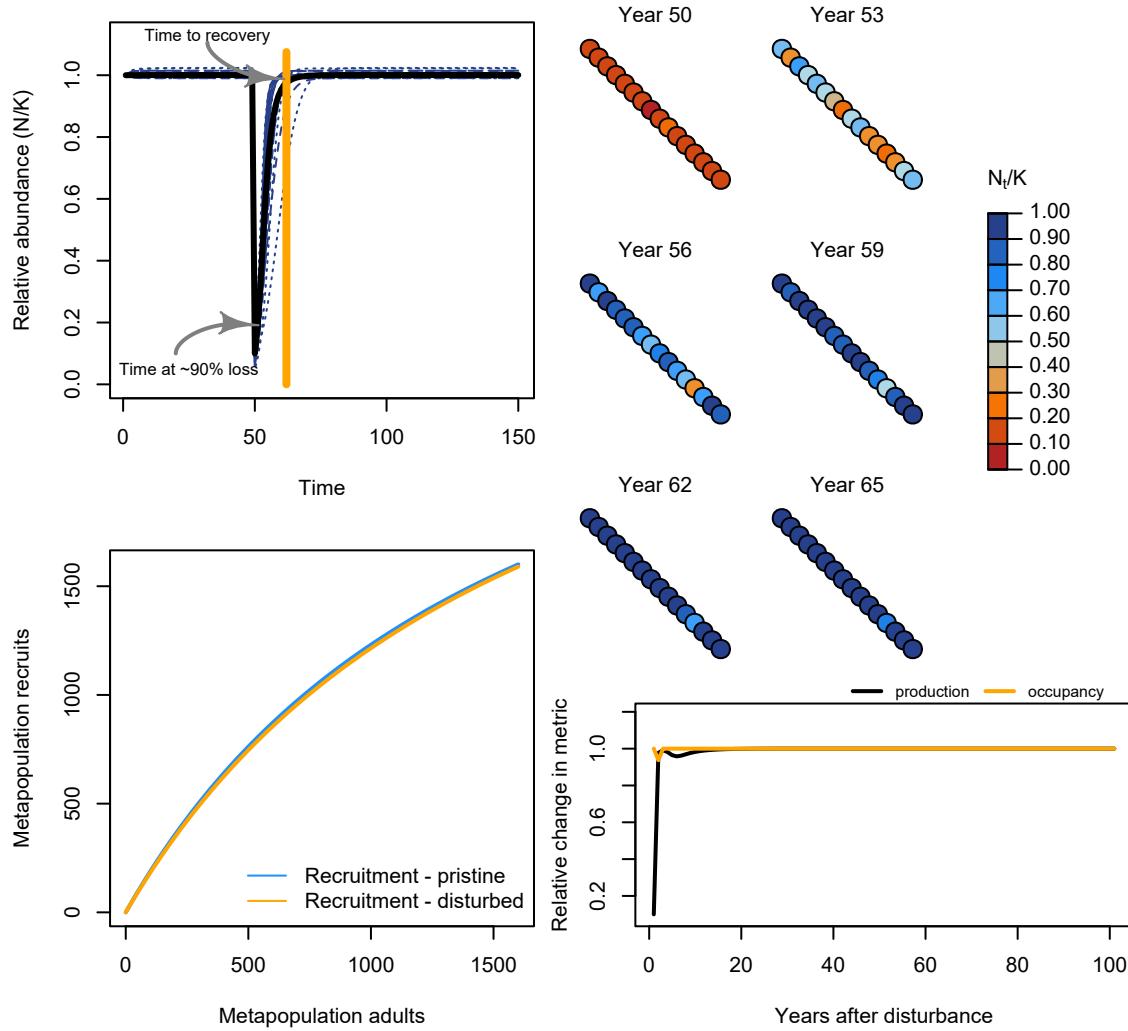


Figure S10: Example iteration of spatial recovery regime of metapopulation with linear topology through time (top left) and space (top right). Recruitment dynamics before and 10 years after disturbance (bottom left). Relative bias in aggregate-scale estimates of carrying capacity, compensation ratio, and recruitment production in recovery phase (bottom right).

¹⁹⁸ We can then contrast this with a different network shape, like a dendritic network.

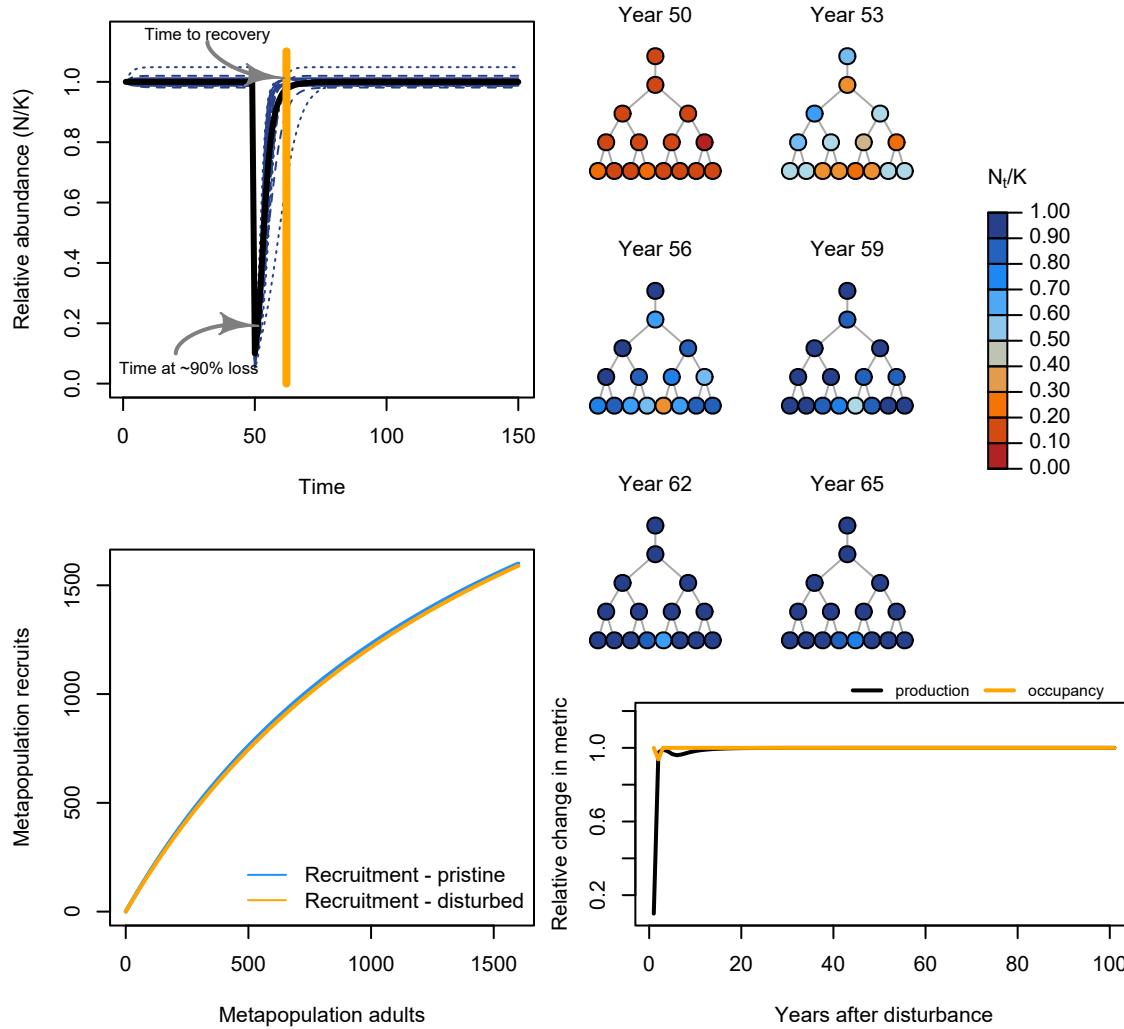


Figure S11: Example iteration of spatial recovery regime of metapopulation with dendritic topology.

¹⁹⁹ Now, let's add some stochasticity to recruitment and see how this affects the recovery regime.

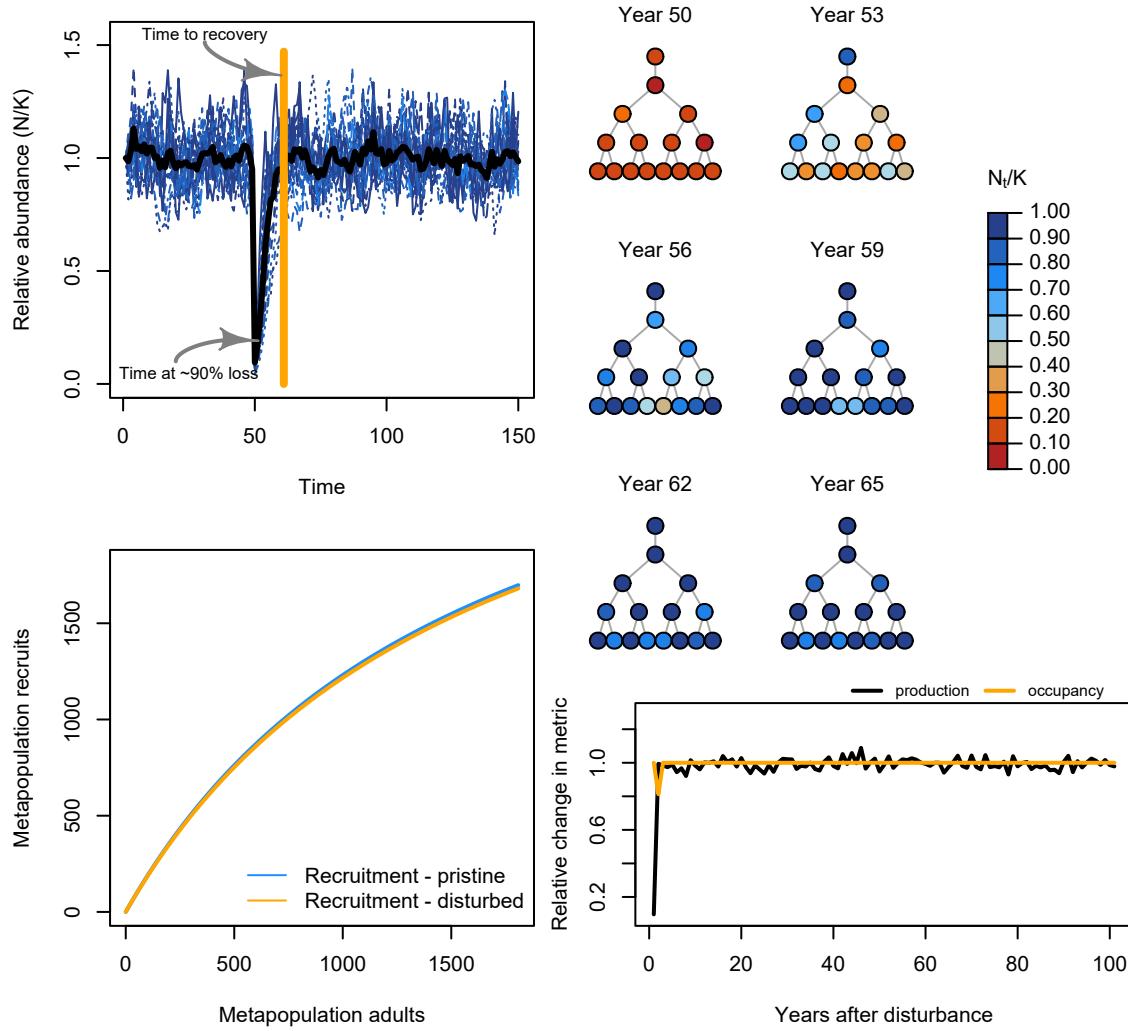


Figure S12: Example iteration of spatial recovery regime of stochastic metapopulation.

200 Next, we can contrast with a disturbance regime where the disturbance is locally even among a subset of local
 201 patches (rather than uniform across all patches or local extirpations).

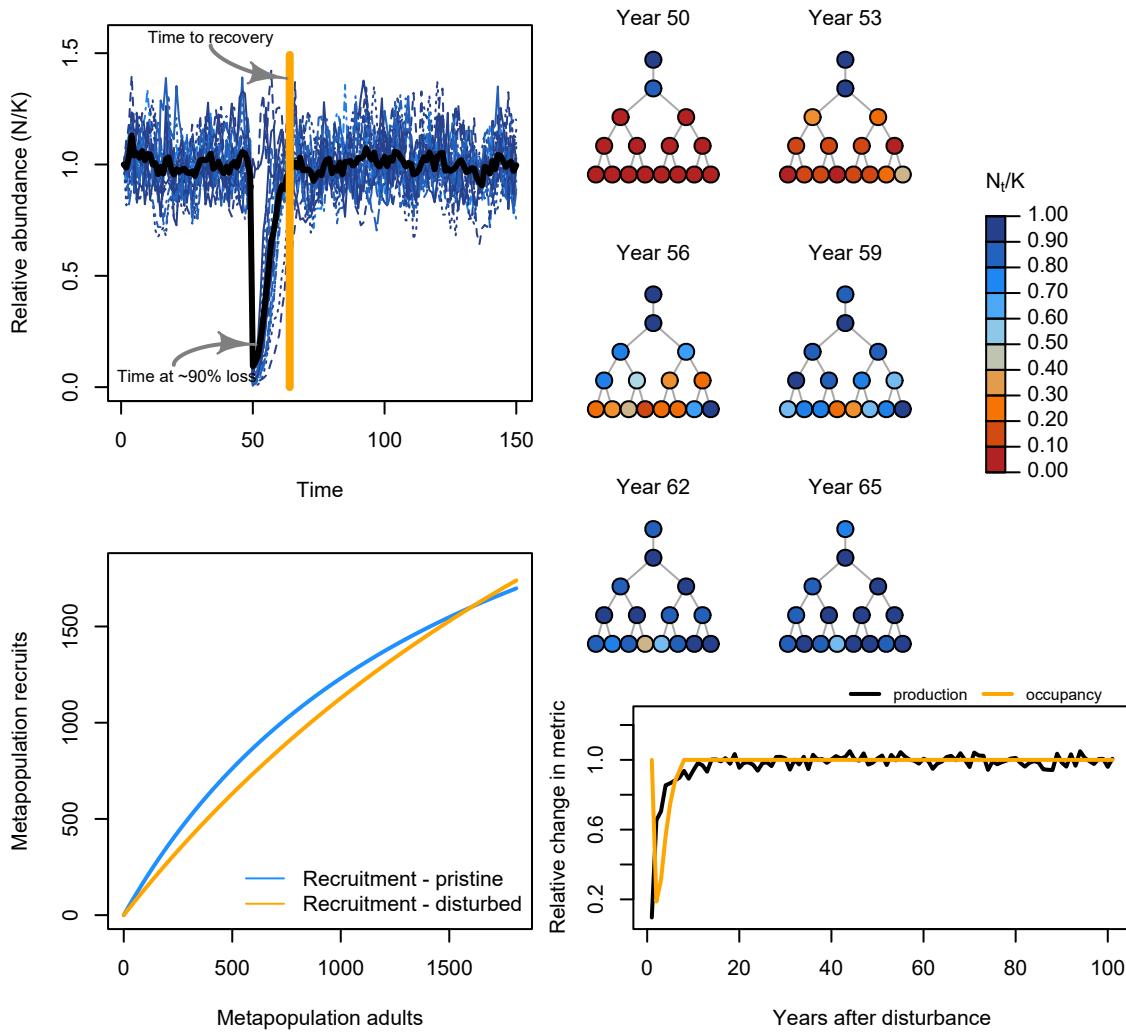


Figure S13: Example iteration of spatial recovery regime of stochastic metapopulation.

202 Next, we can contrast with a disturbance regime where the disturbance is concentrated on local patches that can
 203 be completely extirpated (rather than the disturbance being applied proportionally across all patches e.g., a
 204 mixed-stock fishery).

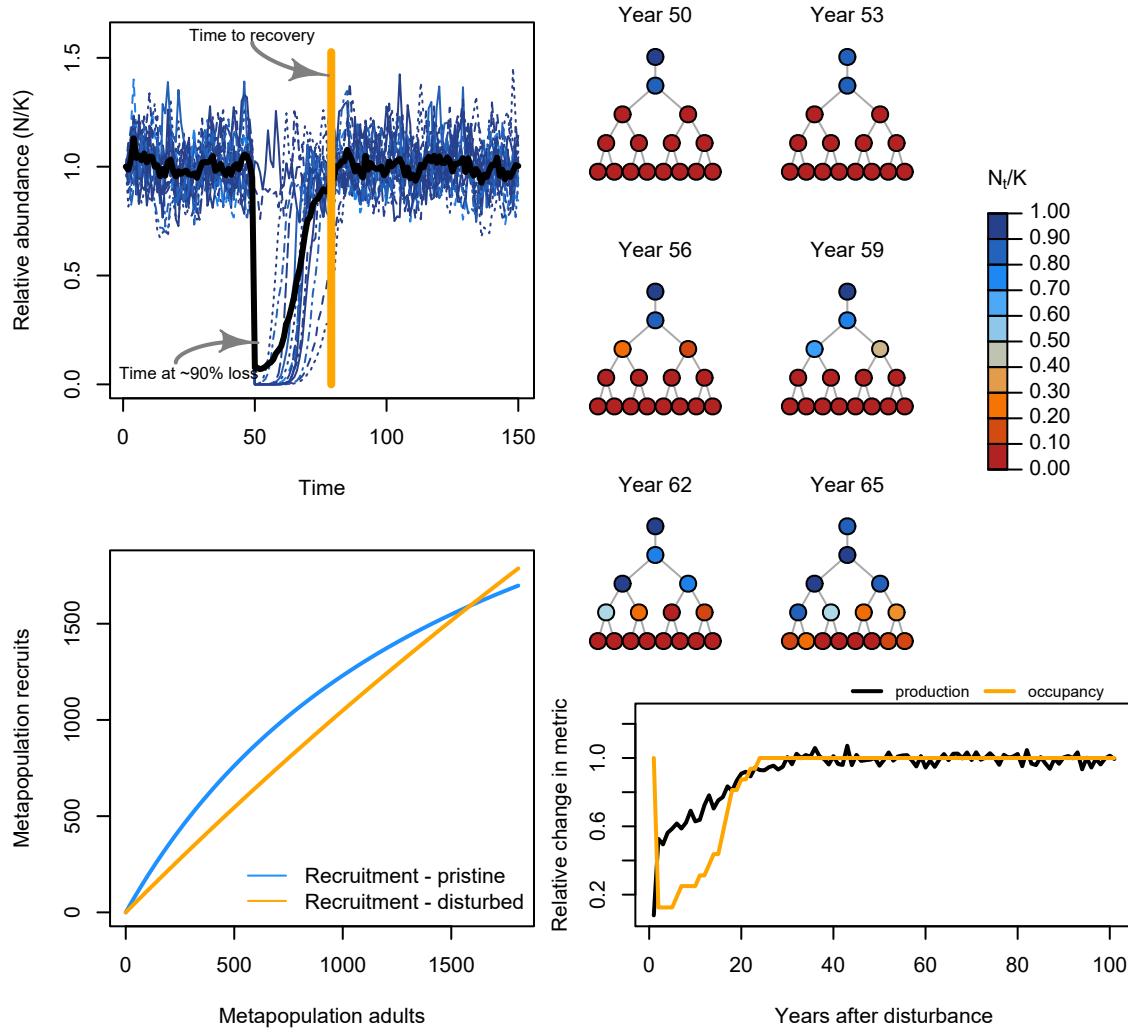


Figure S14: Example iteration of spatial recovery regime of stochastic metapopulation.

205 **Section S1.4: Sensitivity test of mean recovery metrics**

206 The total number of scenarios resulted in a long computation time to run all simulations a large number of times
207 necessary to evaluate how metapopulation responded, on average, to our ecological and disturbance scenarios. To
208 determine a sufficient number of bootstrap iterations to run, we ran a sensitivity test to explore the relative
209 sensitivity of the mean for a few recovery metrics of interest (recovery rate) to the number of stochastic simulations
210 ran per scenario. Below, we repeated the scenario for a metapopulation with a dendritic network, with high
211 stochasticity, locally uneven disturbances, large spatial-temporal correlations, variable patch productivities, and
212 variable patch capacities along gradients of 10, 100, 500, and 1,000 stochastic simulations. Based on these
213 preliminary results, we see that the mean for most metrics was relatively insensitive with at least 100 simulations.

Average recovery metrics

Sensitivity of mean recovery metrics to the number of stochastic simulations

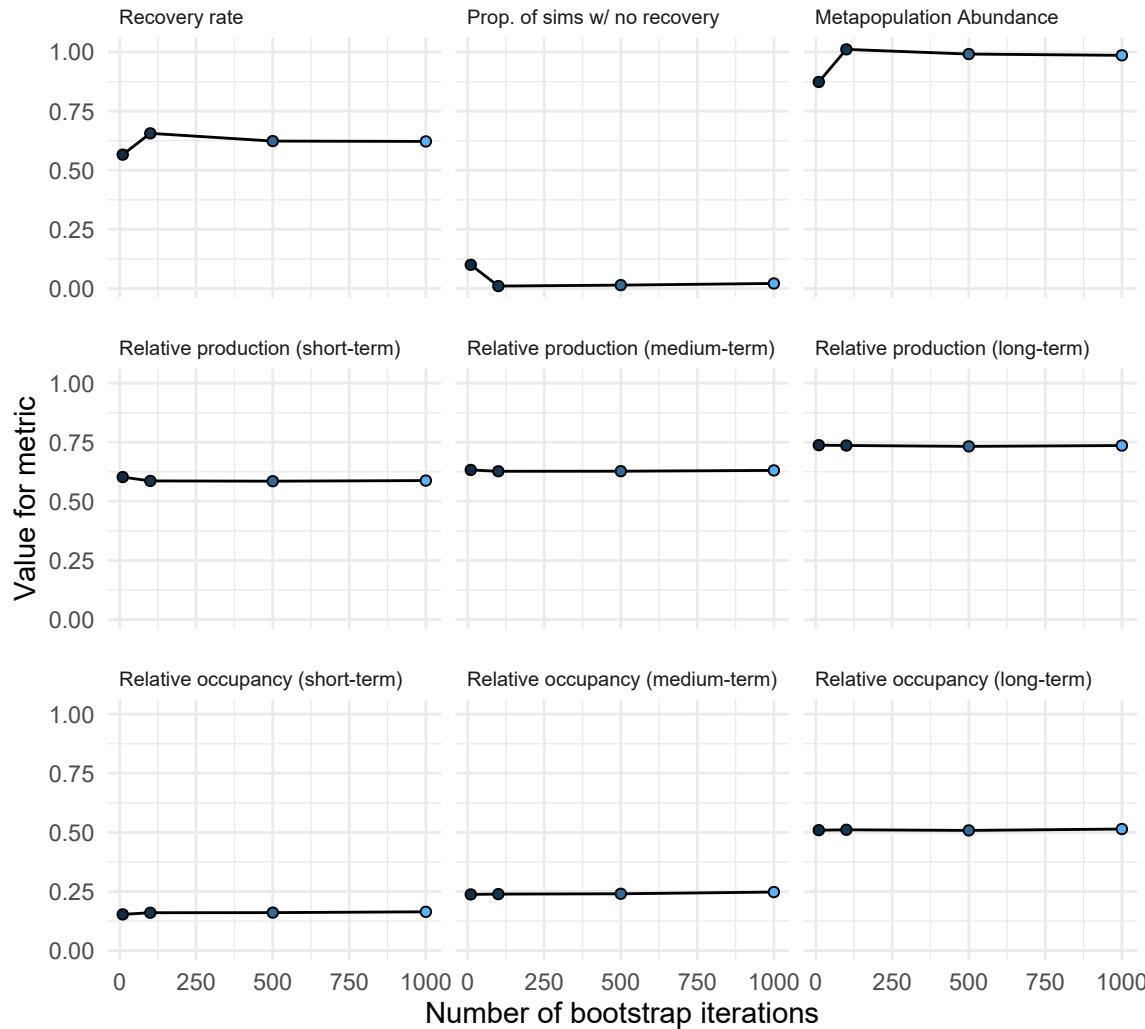


Figure S15: Sensitivity test of mean recovery metrics to number of iterations to bootstrap the stochastic simulations. Example metapopulation consisted of a dendritic network, high recruitment stochasticity, locally uneven disturbance regime, large spatial-temporal correlations, variable patch productivities, and variable patch capacities tested along gradients of 10, 100, 500, and 1,000 bootstrapped iterations.

214 **Section S1.5: General patterns**

215 **Section S1.5.1: Effects of disturbance regime**

216 The strongest lever influencing recovery in our simulated metapopulations was, by far, the characteristics of the
 217 disturbance regime. Specifically, the degree to how locally concentrated the disturbance was on the set of patches
 218 was more influential than variation in local demographic rates, dispersal rates, or network topology. Localized
 219 disturbances increased the risk of spatial contraction, reduced recovery rates and aggregate compensation, and
 220 increased the risk of non-recoveries. By altering aggregate compensation, localized disturbance reduced the relative
 221 production of the metapopulation. In other words, through changes in source-sink dynamics, metapopulations
 222 under localized disturbance acted less than the sum of their parts – the more localized the impacts, the worse these
 223 effects. Uniform disturbances generally left the metapopulation dynamics unaffected with few changes to recovery
 224 metrics outside of occasionally slower recoveries. These above spatial and temporal recovery processes also
 225 appeared tied to one another such that changes to any of them had feedbacks with other recovery metrics. Perhaps
 226 intuitively, for example, patch occupancy was highly correlated to the relative production of the metapopulation,
 227 such that the more patches occupied, the more that metapopulation dynamics resembled a contiguous population.

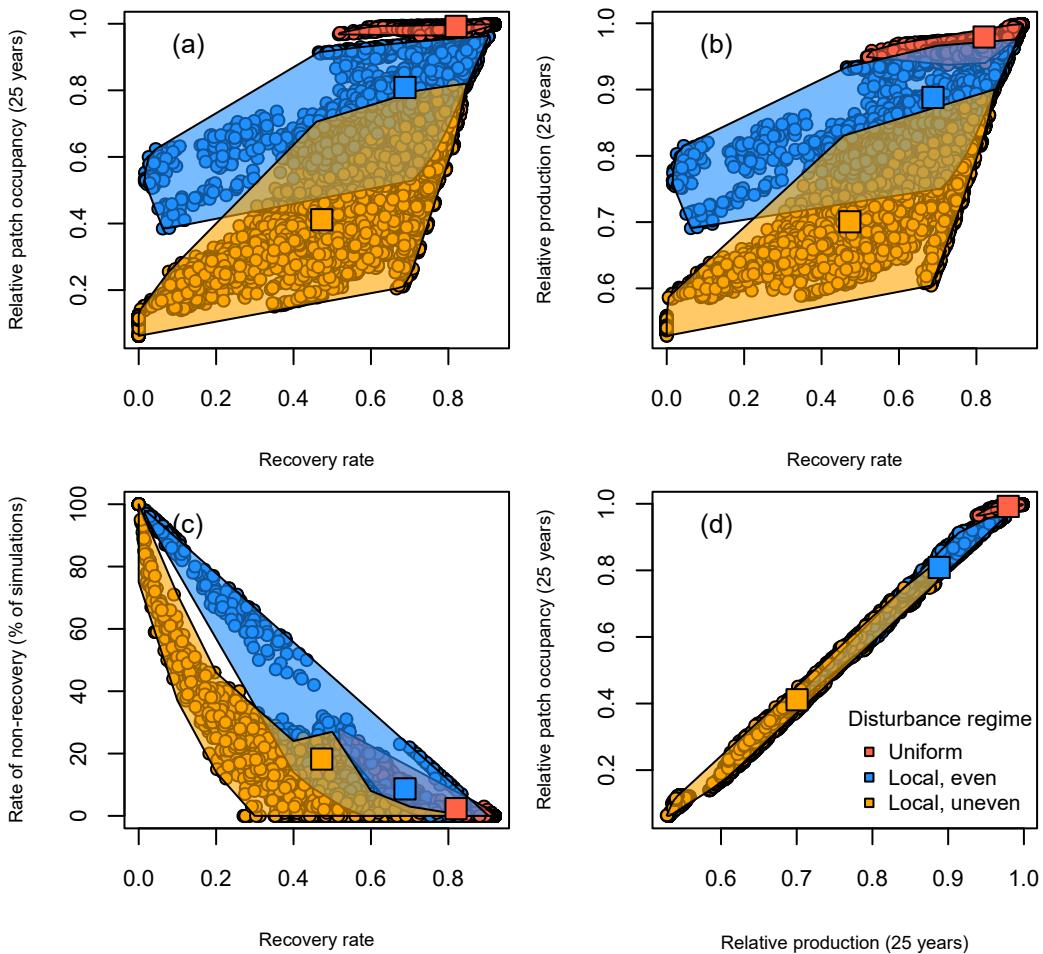


Figure S16: The role of spatial disturbance regimes on metapopulation recoveries and covariation among four recovery metrics: (a,b,c) recovery rate – the annual rate of metapopulation recovery; (a,d) relative patch occupancy – the mean proportion of patches occupied 25 years after disturbance; (b,d), relative production – the ratio between the summed abundances across all patches to the expected production of an equivalent single population 25 years after disturbance; and (c) rate of non-recovery – the percent of 100 stochastic simulations where the metapopulation failed to recover. Each point represents a single simulation for a metapopulation under a unique combination of local productivity, dispersal, spatial network, stochasticity, and disturbance (9,504 total simulations). Shaded regions describe the range in recovery metrics for all simulated metapopulations and are colored by disturbance regime. Square points represent the mean recovery metrics from all simulations within each disturbance regime.

²²⁸ **Section S1.5.2: Role of interplay in ecological and disturbance conditions on recovery patterns**

²²⁹ We now show some general patterns in how variable patch demographic rates, network structure, dispersal,
²³⁰ disturbance, recruitment stochasticity, and spatio-temporal correlations variation affects metapopulation *recovery*
²³¹ rates (shown in Figure 4 of the main text and Figure S16 & S18), *non-recovery rate* (i.e., the number of simulations
²³² where the metapopulation fails to recover; Figure S19), *patch occupancy* (i.e., number of patches with local
²³³ abundance <10% of pre-disturbance; Figure S20), and *relative production* (Figure S21).

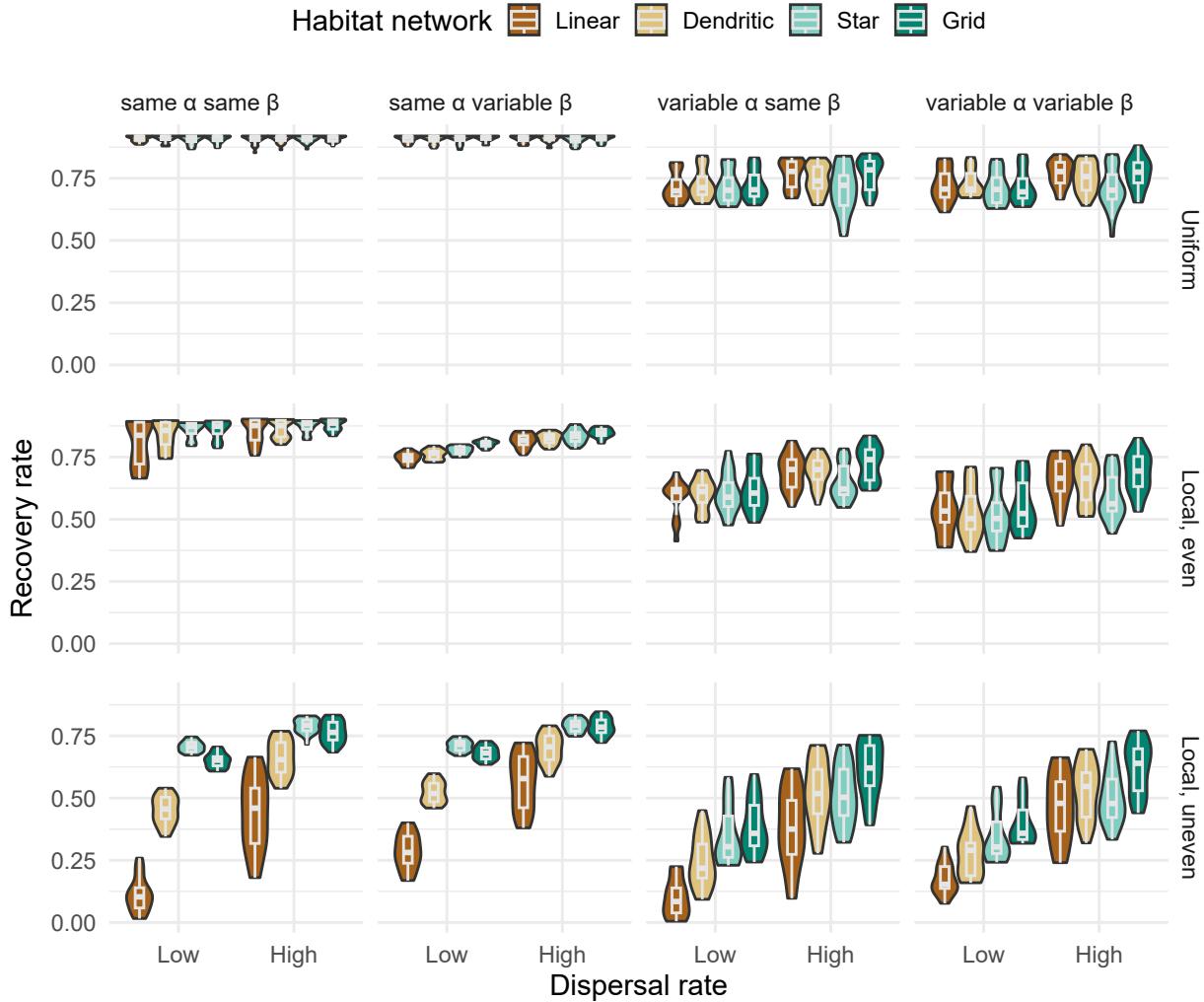


Figure S17: Violin plots showing marginal response of metapopulation recovery rates along gradients of network configuration, dispersal categories (low 0.001; high >0.001), heterogeneity in local demographic rates (α was local patch productivity and β was local patch carrying capacity in the Beverton-Holt model), and spatial distribution of disturbance.

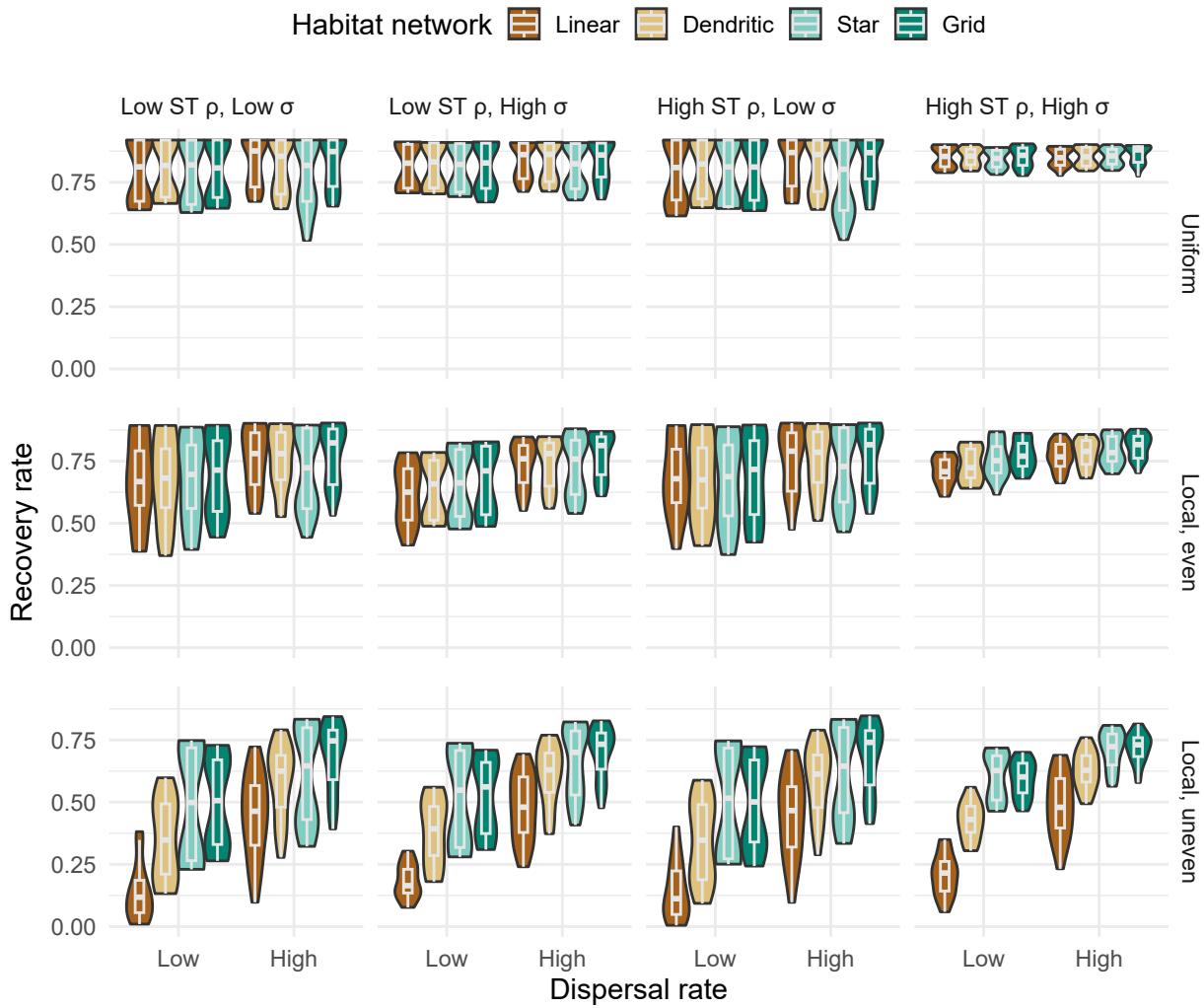


Figure S18: Violin plots showing marginal response of metapopulation recovery rates along gradients of network configuration, dispersal categories (low 0.001; high > 0.001), spatial-temporal (ST) correlations (low $\rho = 0$; high $\rho = 0.6$), scale of lognormal variance in recruitment (low $\sigma = 0.001$; high $\sigma = 0.1$), and spatial distribution of disturbance.

²³⁴ Next, we show violin plots demonstrating some of the modulating factors leading to variation in the risk of
²³⁵ non-recovery owing to stochastic recruitment dynamics.

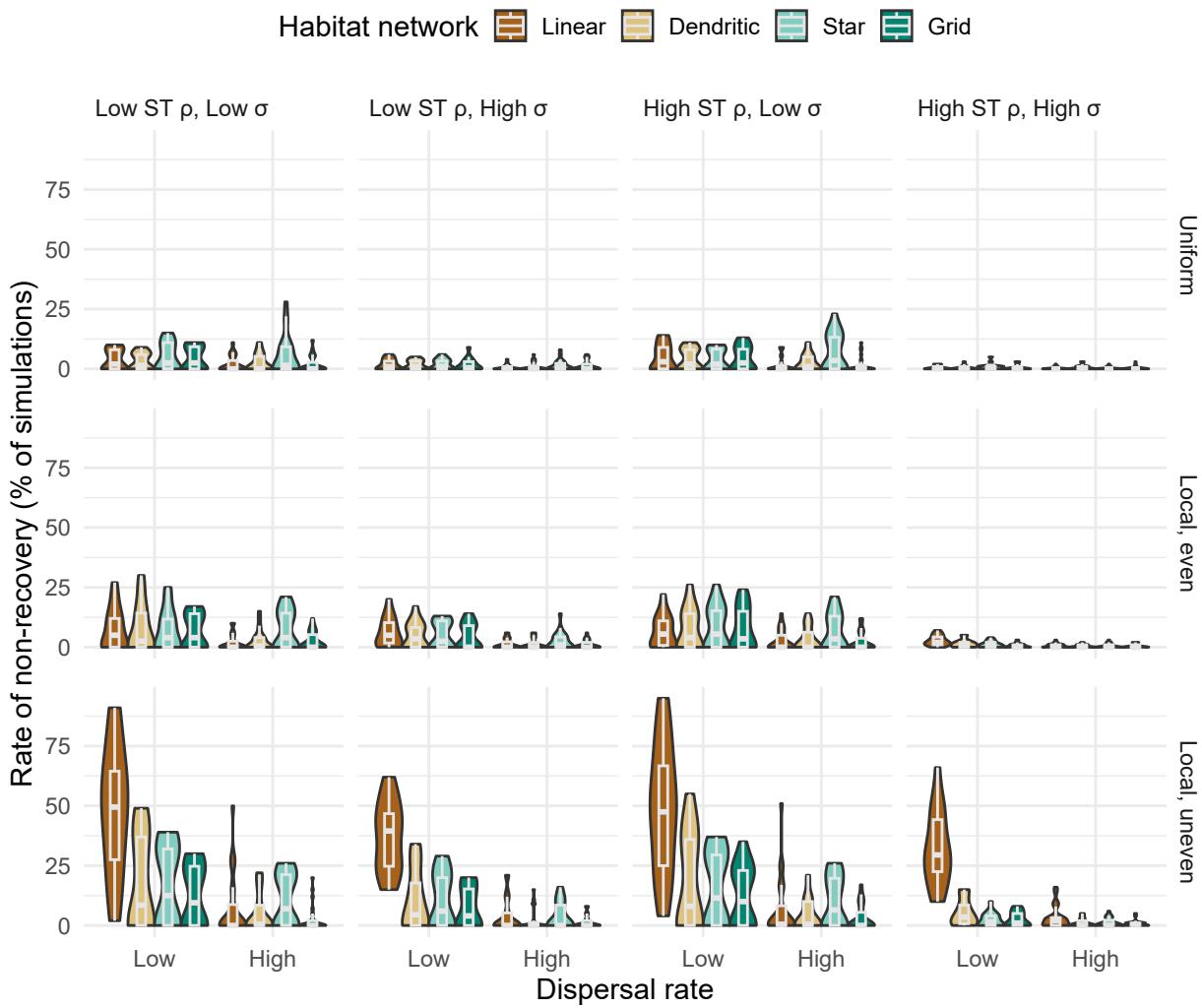


Figure S19: Violin plots showing marginal response of the stochastic risk of non-recovery in metapopulations along gradients of network configuration, dispersal categories (low 0.001; high > 0.001), spatial-temporal (ST) correlations (low $\rho = 0$; high $\rho = 0.6$), scale of lognormal variance in recruitment (low $\sigma = 0.001$; high $\sigma = 0.1$), and spatial distribution of disturbance.

236 Next, we show violin plots demonstrating some of the modulating factors leading to variation in long-term impacts
 237 to patch occupancy.

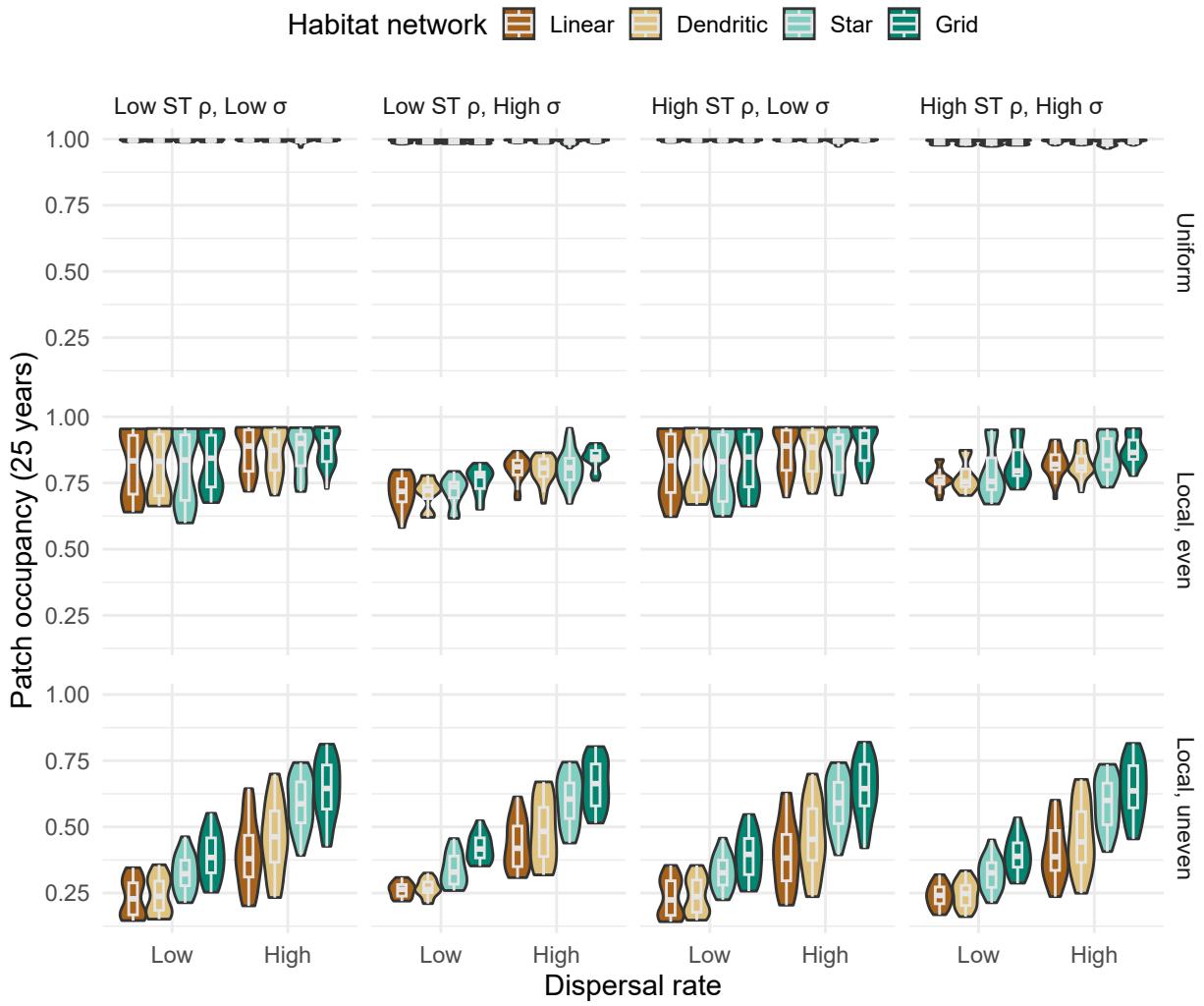


Figure S20: Violin plots showing marginal response of long-term patch occupancy in metapopulations along gradients of network configuration, dispersal categories (low 0.001; high > 0.001), spatial-temporal (ST) correlations (low $\rho = 0$; high $\rho = 0.6$), scale of lognormal variance in recruitment (low $\sigma = 0.001$; high $\sigma = 0.1$), and spatial distribution of disturbance.

²³⁸ Next, we show variation in relative production metrics. Figure S16 shows the tight correlation between patch
²³⁹ occupancy and relative production. Hence, Figure S20 and S21 look quite similar.

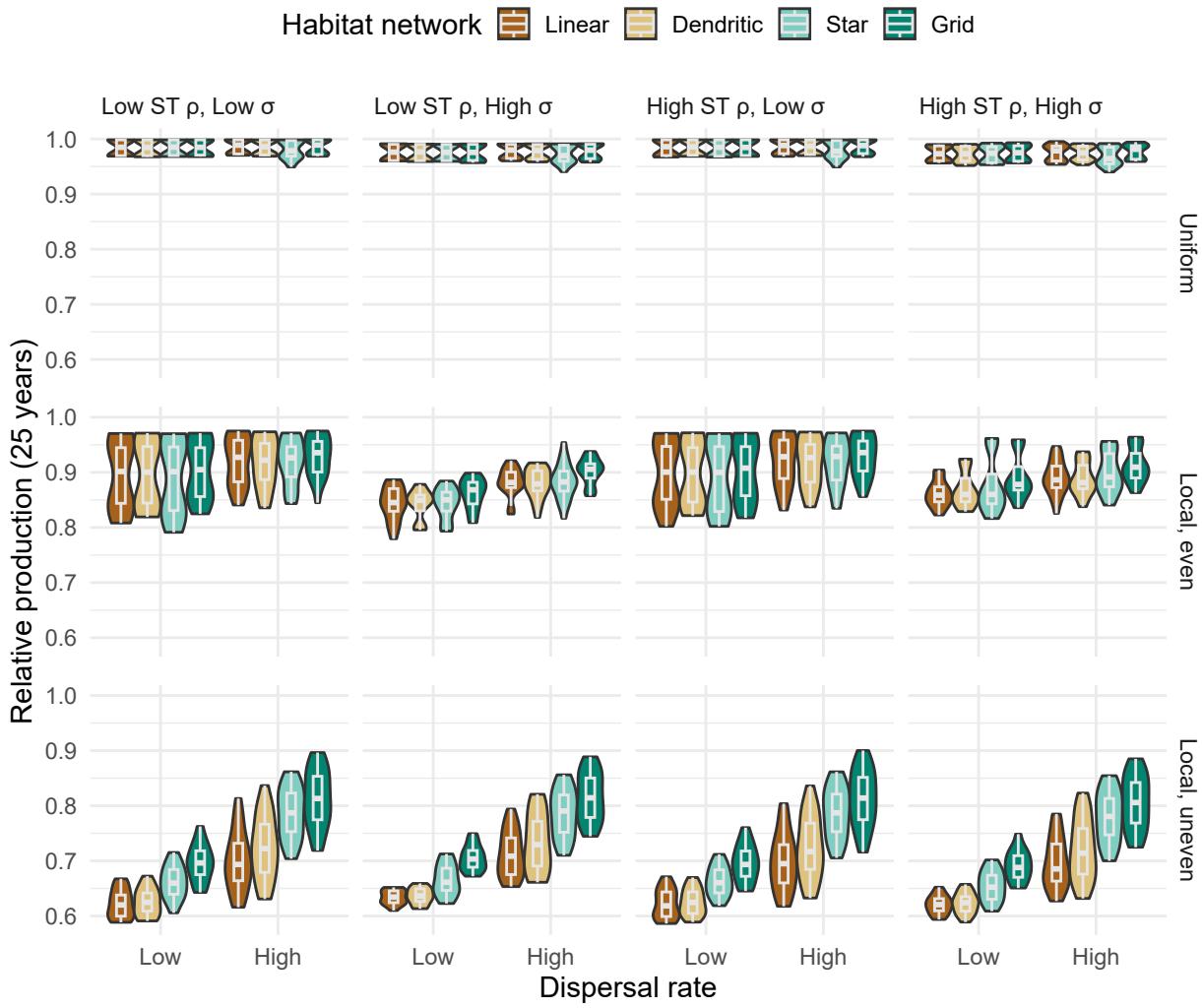


Figure S21: Violin plots showing marginal response of relative production for metapopulations along gradients of network configuration, dispersal categories (low 0.001; high >0.001), spatial-temporal (ST) correlations (low ρ 0; high $\rho=0.6$), scale of lognormal variance in recruitment (low $\sigma= 0.001$; high $\sigma=0.1$), and spatial distribution of disturbance.

240 Dispersal, network topology, variable local demography, spatial-temporal correlations, and recruitment stochasticity
 241 also affected metapopulation recovery patterns in three key ways, though to a lesser extent. First, recovery rates
 242 increased with increased dispersal. However, this effect was nonlinear with diminishing benefits of dispersal
 243 occurring at ~1-3%, depending on spatial structure and disturbance. Second, more linearized networks had slower
 244 recovery times than more connected networks suggesting that rescue effects take some time to cascade through the
 245 entire network of patches; but this interacted with the disturbance regime as only local, extirpation exhibited this
 246 change in any substantial manner. Last, diversity in local patch compensation and carrying capacities tended to
 247 slow metapopulation recoveries - this effect interacted with other factors like stochasticity.

248 Section S1.6: Clustering analyses

249 We used hierarchical clustering analyses (implementing Ward's criterion) of a dissimilarity matrix from our four
 250 recovery metrics to evaluate whether there was evidence for common recovery regimes among our simulation results
 251 across all ecological and disturbance scenarios (Murtagh & Legendre 2014). Based on advice laid out in Hennig
 252 (2014), we determined that the best number of unique clusters in metapopulation recoveries should satisfy the
 253 following statistical criteria:

- 254 1. recovery outcomes from within a cluster are closer to one another than to other clusters (i.e., the two Dunn
 255 indices are relatively high)
 256 2. the number of clusters explains much of the point variation within the dataset (i.e., diminishing returns in
 257 minimizing the sums-of-squared residuals)
 258 3. the point observations within clusters are relatively tight (i.e., both the average silhouette width and the
 259 widest within-cluster gap are relatively low)
 260 4. clusters are relatively unique and there is good separation between the clusters (i.e., the separation index is
 261 still high, while considering that low numbers of clusters should always have the highest separation)

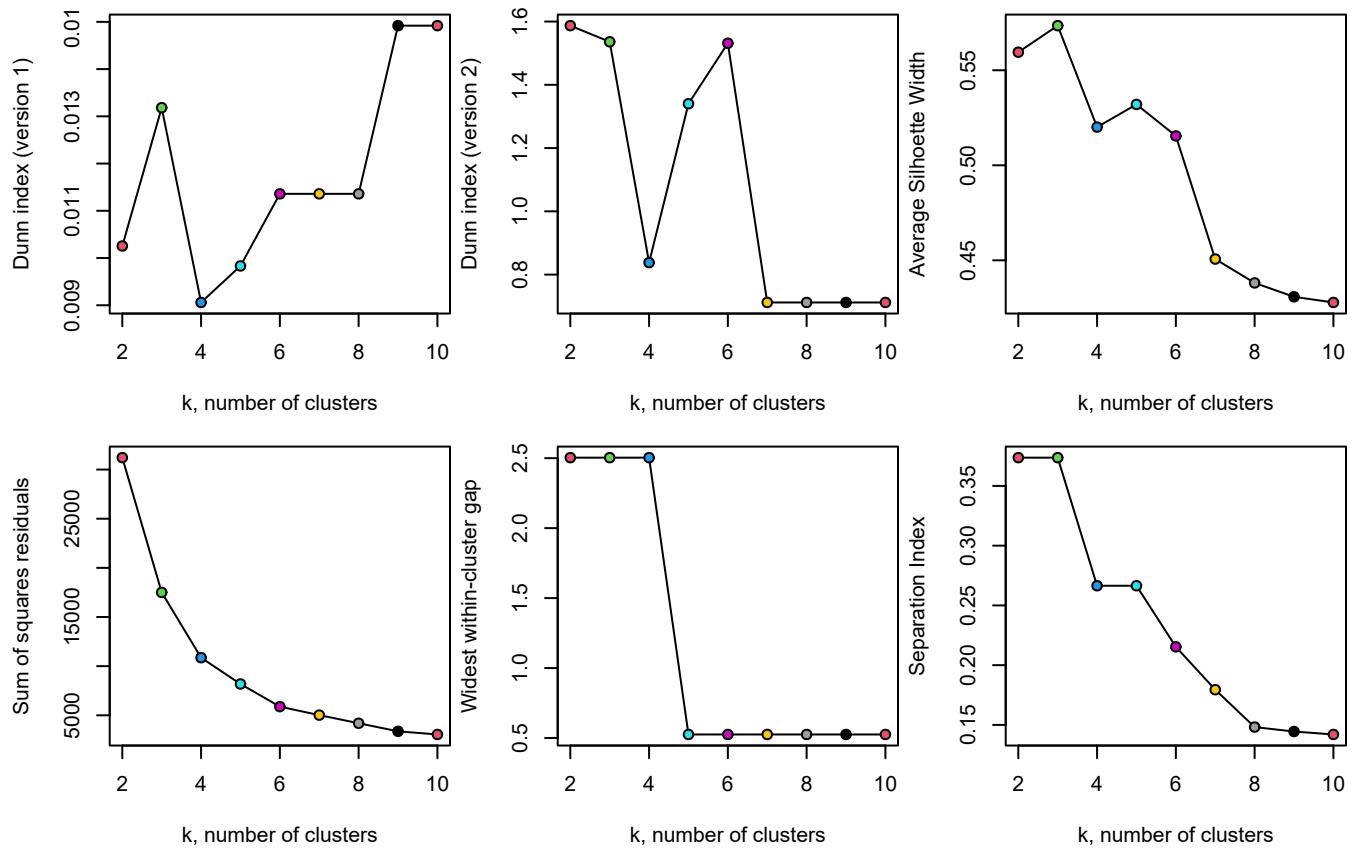


Figure S22: The relationships between number of potential clusters and multiple statistical criteria used to test support for the best number of clusters within the simulated recovery outcomes.

262 Based on the above criteria, we chose 5 unique clusters as satisfying most of the above criteria in the figure above,
 263 although there was good support for between 3 and 6 unique clusters. The principal components analysis indicates
 264 that five clusters has substantial explanatory power of metapopulation recovery metrics (explained ~89% of the
 265 point variation).

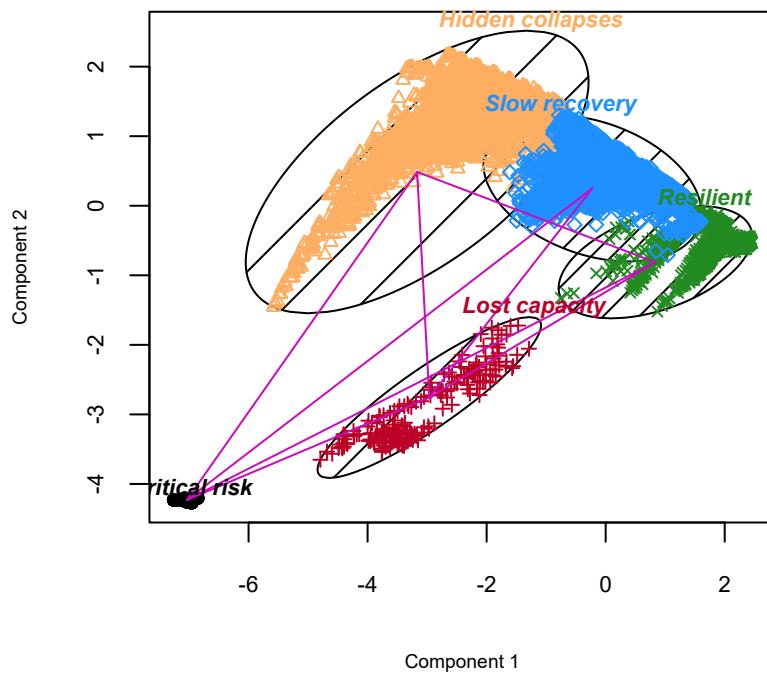


Figure S23: Bivariate cluster plot of the principal components explaining point variation in metapopulation recovery metrics across all simulated scenarios grouped into five distinct clusters.

266 Section S1.6.1: Emergent recovery outcomes

267 Overall, we used hierarchical clustering analyses to describe five common metapopulation recovery outcomes. These
 268 outcomes were: (1) resilient recovery – metapopulations recovered to pre-disturbance abundances quickly with all
 269 patches occupied, (2) slow recovery – were either slowed (compared to resilient recoveries), had reduced patch
 270 occupancy, or reduced relative production, (3) hidden collapses – metapopulations tended to recover and aggregate
 271 abundances were high, but many local patches remained unoccupied and recovery was slowed, (4) lost capacity –
 272 recovery rates were very slow, the risk of non-recovery was high, long-term production was low, and many local
 273 patches remained unoccupied and (5) critical risk – where metapopulations failed to recover, abundances remained
 274 low, and the risk of non-recovery was high.

Table S2: The mean recovery metrics, total sample size per regime (No.), and metapopulation abundance (N/K) for each of five common metapopulation recovery regimes supported by hierarchical clustering analyses across gradients in disturbance and network structure.

Regime	Network	Disturbance	No.	Recovery rate	% non-recovery	Occupancy	Relative production	Relative abundance
Resilient	Linear	Uniform	792	0.83	2	0.99	0.98	1.00
Resilient	Dendritic	Uniform	792	0.82	2	0.99	0.98	0.99
Resilient	Star	Uniform	792	0.81	3	0.99	0.98	0.99
Resilient	Grid	Uniform	792	0.82	2	0.99	0.98	1.00
Resilient	Linear	Local, even	205	0.78	5	0.94	0.95	0.99
Resilient	Dendritic	Local, even	201	0.78	5	0.94	0.96	0.99
Resilient	Star	Local, even	274	0.75	7	0.93	0.95	0.99
Resilient	Grid	Local, even	215	0.78	5	0.94	0.96	0.99
Slow recovery	Linear	Local, even	528	0.69	3	0.77	0.87	0.99
Slow recovery	Dendritic	Local, even	533	0.70	3	0.77	0.87	0.99
Slow recovery	Star	Local, even	466	0.68	5	0.75	0.86	0.99
Slow recovery	Grid	Local, even	529	0.73	3	0.81	0.89	0.99
Slow recovery	Linear	Local, uneven	11	0.72	0	0.64	0.81	1.00
Slow recovery	Dendritic	Local, uneven	69	0.73	0	0.66	0.81	0.99
Slow recovery	Star	Local, uneven	114	0.74	4	0.71	0.84	0.97
Slow recovery	Grid	Local, uneven	244	0.76	0	0.73	0.85	1.00
Hidden collapses	Linear	Local, even	9	0.61	3	0.59	0.79	0.99

Hidden collapses	Dendritic	Local, even	9	0.65	0	0.59	0.78	0.99
Hidden collapses	Star	Local, even	4	0.72	0	0.55	0.76	1.00
Hidden collapses	Linear	Local, uneven	709	0.34	21	0.34	0.67	0.97
Hidden collapses	Dendritic	Local, uneven	651	0.49	8	0.36	0.68	0.99
Hidden collapses	Star	Local, uneven	606	0.57	9	0.45	0.72	0.99
Hidden collapses	Grid	Local, uneven	476	0.56	7	0.46	0.73	0.99
Lost capacity	Linear	Local, even	50	0.17	77	0.58	0.79	0.66
Lost capacity	Dendritic	Local, even	49	0.16	78	0.58	0.78	0.65
Lost capacity	Star	Local, even	48	0.16	78	0.58	0.78	0.65
Lost capacity	Grid	Local, even	48	0.16	79	0.57	0.78	0.64
Critical risk	Linear	Local, uneven	72	0.00	100	0.10	0.54	0.09
Critical risk	Dendritic	Local, uneven	72	0.00	100	0.10	0.54	0.08
Critical risk	Star	Local, uneven	72	0.00	100	0.10	0.54	0.08
Critical risk	Grid	Local, uneven	72	0.00	100	0.10	0.54	0.08

275 In general, the five recovery regimes spanned a continuum of better (e.g., resilient) to worse recoveries (e.g.,
 276 long-term critical risks). Overall, the interplay between ecological and disturbance conditions appeared to structure
 277 the specific pathway for metapopulation recoveries (Figure S24; Table S2). For example, uniform disturbances
 278 always led to resilient recoveries. However, local, even disturbance regimes tended to lead to, at-best, a resilient
 279 recovery or, at worst, hidden collapses with the probability modulated by other ecological factors. Local, uneven
 280 disturbance regimes led to, at best, a slow recovery or, at worst, a long-term critical risk and non-recovery. The
 281 main text Figure 5 and 6 demonstrates the conditions that led to resilient recoveries compared to critical risks,
 282 while more intermediate outcomes, like slow recovery, hidden collapses, or lost capacity are shown here in Figures
 283 S25-S27.

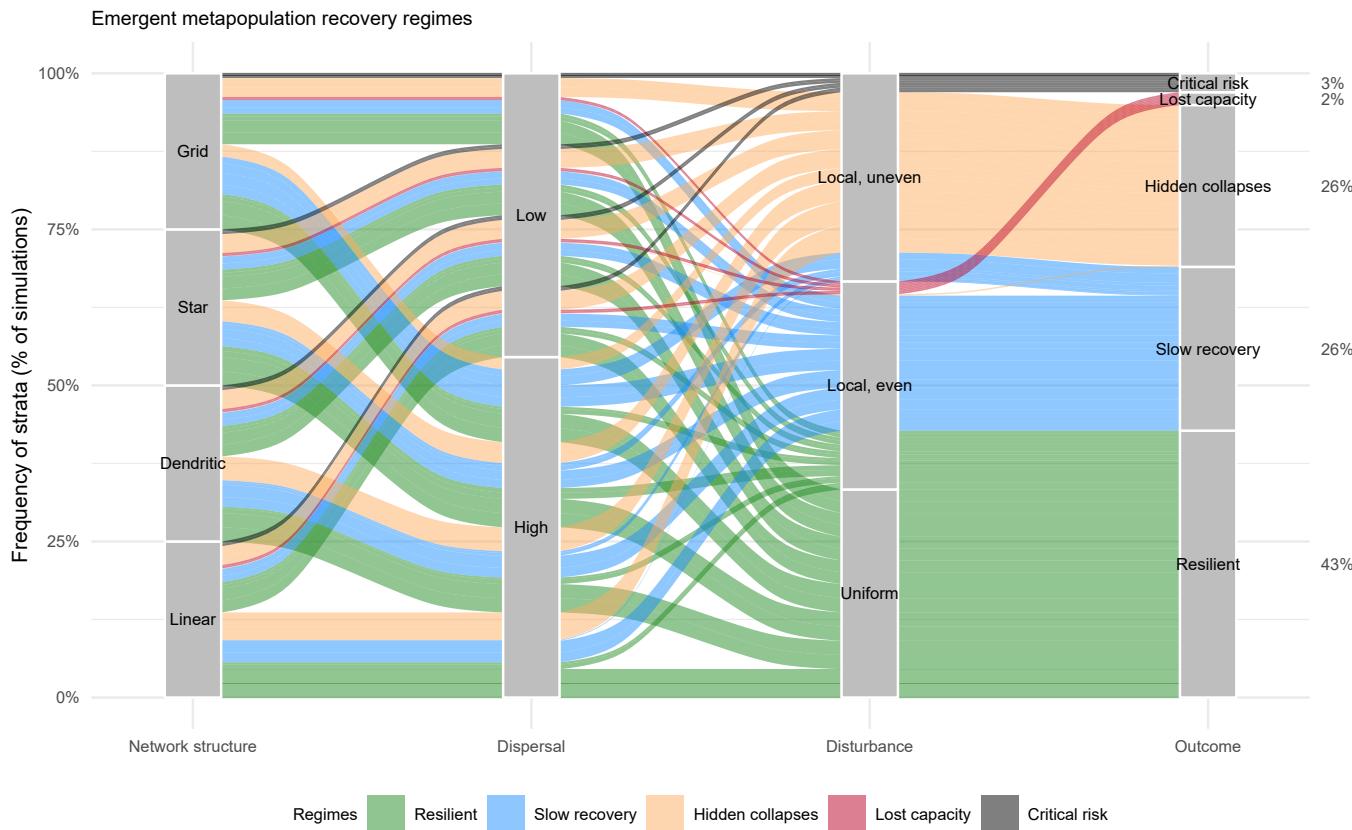


Figure S24: Frequency of emergent metapopulation recovery regimes can depend on a complex interplay between network structure, dispersal, and spatial disturbances. Ribbon colors denote a group of simulations that led to one of five common recovery outcomes. Frequency of regimes denoted by width of ribbons

284 Section S1.6.2: Role of ecological and disturbance conditions on recovery outcomes

285 Local patch demography, habitat network structure, dispersal, spatially and temporally correlated recruitment
 286 variation, and spatial disturbance regimes each had modulating effects on the probability for any particular

recovery regime (Figures 5 & 6 in the main text; and Figures S25-S27 here). There was a clear signal from any localized disturbances, which increased the probability for non-resilient recovery regimes. For habitat networks, metapopulations with linear networks tended to have increased probability for worse recoveries compared to gridded networks. For dispersal rates, metapopulations with low dispersal had increased probability for poor recoveries compared to high dispersal. For local demography, metapopulations with variable local patch demographic rates tended to increased probability for poor recoveries compared to metapopulations composed of homogeneous local patches. For recruitment stochasticity, metapopulations with both high recruitment variation and high spatial-temporal correlations led to increased probability for poor recoveries compared to low variation and low correlations.

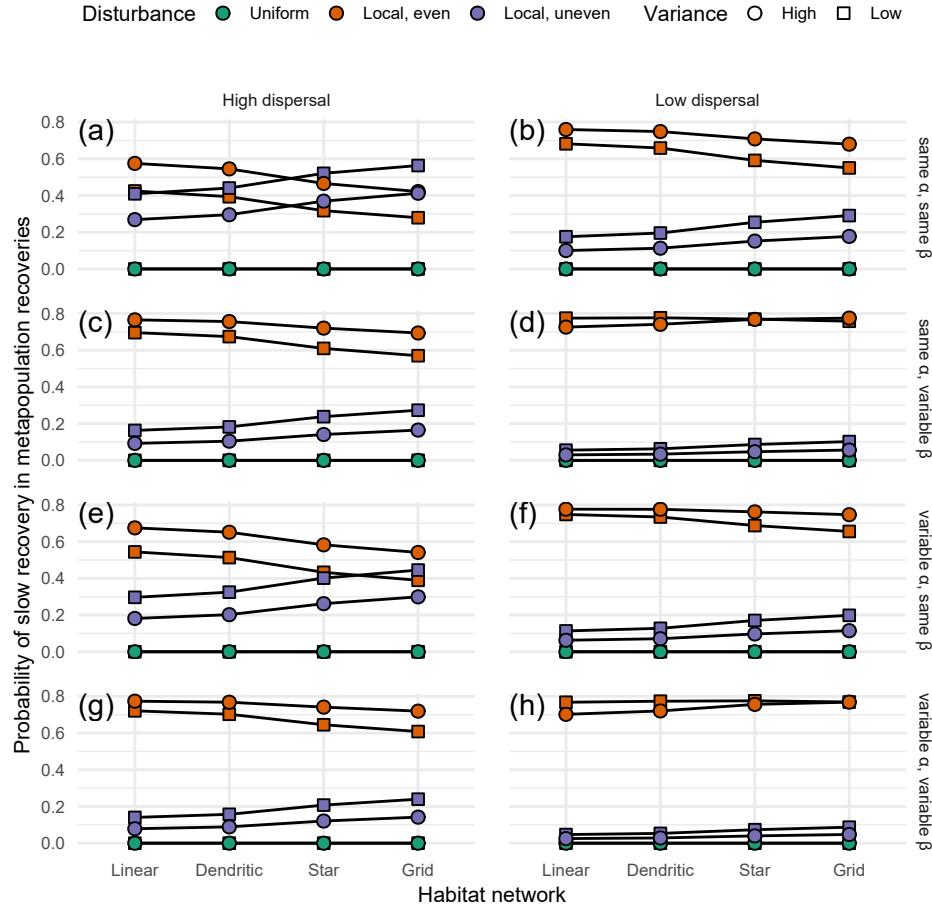


Figure S25: The probability of a slow recovery in metapopulation recoveries depended on the interplay between network structure, dispersal (low 0.001; high > 0.001), spatial disturbances, heterogeneity in local demographic rates (α is local patch productivity and β is local patch carrying capacity), and spatial-temporal recruitment variation (high = $\rho=0.6$ and $\sigma=0.1$; low = $\rho=0$ and $\sigma=0.001$) based on ordered logistic regression.

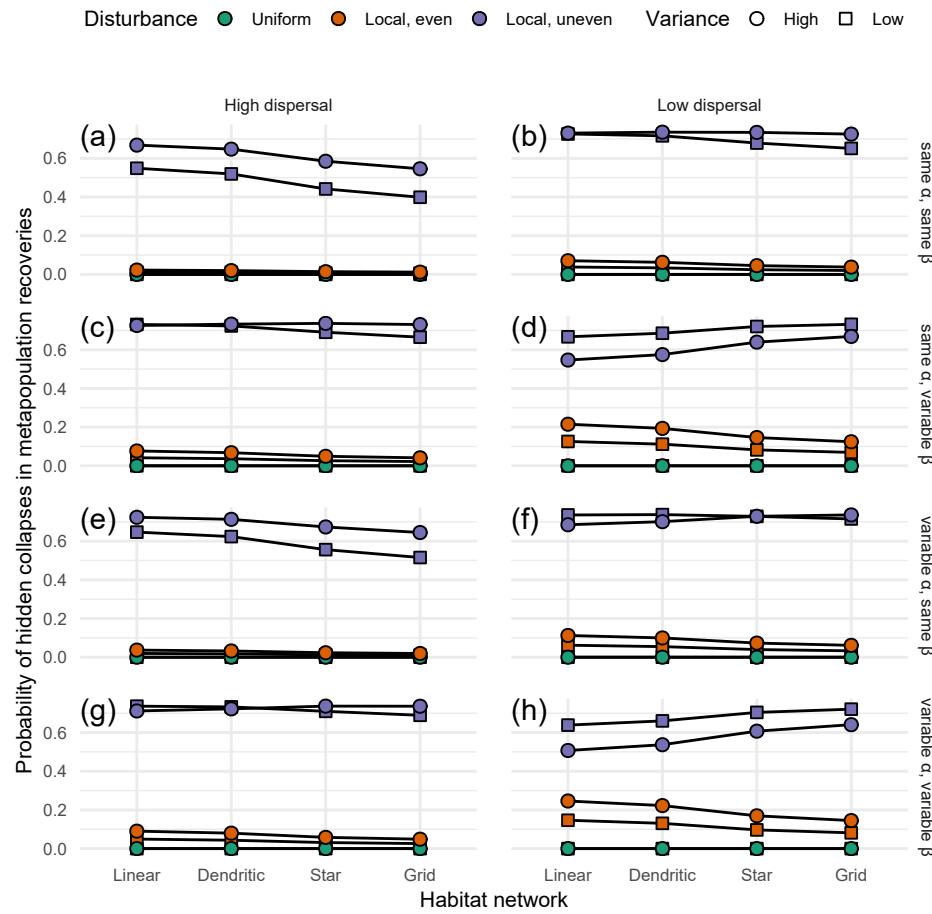


Figure S26: The probability of hidden local collapses in metapopulation recoveries depended on the interplay between network structure, dispersal (low 0.001; high > 0.001), spatial disturbances, heterogeneity in local demographic rates (α is local patch productivity and β is local patch carrying capacity), and spatial-temporal recruitment variation (high = $\rho=0.6$ and $\sigma=0.1$; low = $\rho=0$ and $\sigma=0.001$) based on ordered logistic regression.

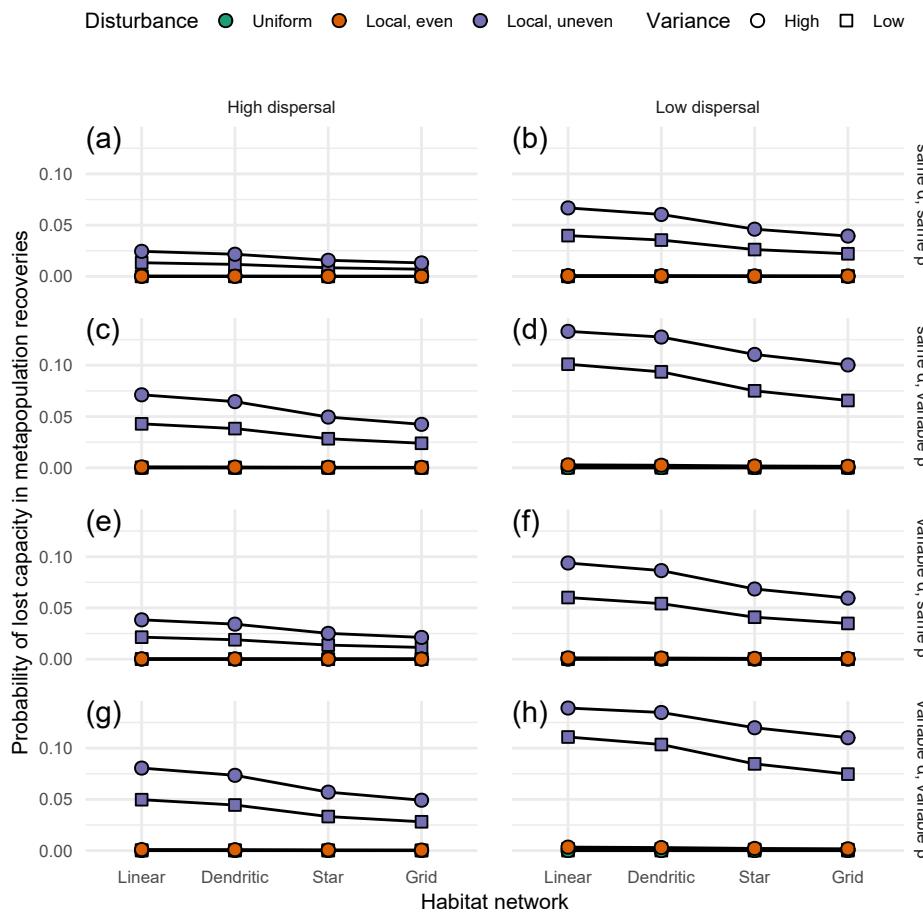


Figure S27: The probability of lost productive capacity in metapopulation recoveries depended on the interplay between network structure, dispersal (low 0.001; high > 0.001), spatial disturbances, heterogeneity in local demographic rates (α is local patch productivity and β is local patch carrying capacity), and spatial-temporal recruitment variation (high = $\rho=0.6$ and $\sigma=0.1$; low = $\rho=0$ and $\sigma=0.001$) based on ordered logistic regression.

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