Electronic supplementary material for:

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Siegel, D. A., & Simons, R. D. Fluctuations in population fecundity drive variation in

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Appendix S1: Supplementary methods

Estimation of giant kelp fecundity. We estimated giant kelp patch fecundity from canopy

biomass by calibrating a relationship between the density of spore-bearing tissue (measured as

sorus area per unit area of reef) and Landsat estimates of canopy biomass density at the San

Clemente Artificial Reef (SCAR), located offshore of San Clemente, California, USA. Briefly,

from March to June in each year from 2000 to 2004 at 7 artificial reef sites at SCAR, divers

measured the mean sorus area of sporophytes (mean number of plants measured per site per year

$= 276 \pm 230$ [SD]; range $= 10$–933; data and detailed methods in ref. 1). We estimated canopy

biomass density using Landsat 5 Thematic Mapper and Landsat 7 Enhanced Thematic Mapper

Plus imagery collected from the same locations and similar dates (the average of all observations

within one month before and after the diver measurement date). We estimated the relationship

between pixel fecundity (cm^2 sorus per m^2) and the square root of pixel canopy biomass density

(kg wet per m^2) in the first semester of the year (January–June) using a zero intercept regression

as *fecundity density* $= 1463 \times \sqrt{}$ *canopy biomass density* (electronic supplementary material,

figure 2; 95% CI of model coefficient $= 1234$–1865). To accommodate the possibility of spore

production in pixels lacking canopy biomass (due to measurement error or the presence of

subsurface adult kelp), we also fit a linear regression with a nonzero intercept as *fecundity*

density = 12.14 + 1596 × $\sqrt{}$ *canopy biomass density*. We fit these relationships in R 3.2.5 [2]

using generalized least squares (GLS) linear regression with heterogeneous, first-order

autoregressive covariance structure because ordinary linear regression residuals showed serial

autocorrelation and heteroscedasticity [3,4]. Sample autocorrelation function analysis showed no

evidence for temporal autocorrelation of GLS standardized residuals [3–5]. Semi-variograms and

bubble plots showed no evidence of spatial autocorrelation of GLS standardized residuals

[3,4,6].

Data to parameterize the relationship between canopy biomass density and fecundity

were available at SCAR from the first semester of the year only. To adjust fecundity estimates

for seasonality in biomass-specific fecundity, we used field data collected by Reed *et al.* [7].

Briefly, divers sampled giant kelp monthly from November 1990 to September 1994 at three

sites in the Santa Barbara Channel, California, USA (7–14 m depth). During each sampling,

divers measured the fecundity (i.e., sorus area per individual) and number of fronds of the first

30 mature giant kelp sporophytes (with ≥ 8 fronds and holdfast diameter ≥ 30 cm) encountered

along each transect. We estimated biomass-specific fecundity as sorus area per frond because the

density of fronds from mature sporophytes is a strong predictor of canopy biomass density [8].

Our analysis revealed that average giant kelp biomass-specific fecundity is 2.4 (95% CI = 1.73–

2.96) times greater during the first half of the year than during the second half of the year

(Welch's unequal variances *t*-test; $t_{38} = 4.42$, $P < 0.001$; January–June = 119.2 ± 84.9 [SD] cm^2

per frond; July–December = 50.1 ± 29.7 cm^2 per frond). Therefore, to estimate the relationship

between patch fecundity and canopy biomass density in the second semester of the year, we

adjusted the relationship from the first semester by dividing the model coefficient by 2.4 (hence,

for July–December, *fecundity density* = 609.6 × $\sqrt{}$ *canopy biomass density*).

Estimations of giant kelp spore dispersal. Because the giant kelp patches in the study

region are smaller than the ROMS connectivity cells (nominal alongshore distance = 8 km;

electronic supplementary material, figure 1), minimum transport times between any two giant

kelp patches cannot be calculated without making assumptions. Thus, for cases where two giant

kelp patches were located in different ROMS cells, we assumed that for each semester, t, the

transport time from kelp patch i to patch j ($d_{ij,t}$) was proportional to the minimum transport time

between the two ROMS cells x and y ($D_{xy,t}$), respectively:

$$\frac{D_{xy,t}}{L_{xy}} = \frac{d_{ij,t}}{l_{ij}}$$

where L_{xy} is the alongshore distance between the centroids of ROMS cells x and y, and l_{ij} is the

alongshore distance between the centroids of giant kelp patches i and j. For cases where two

giant kelp patches were located within the same ROMS cell (y), we assumed that $d_{ij,t}$ could be

estimated using the minimum transport times between the adjacent ROMS cells (x and z):

$$\frac{(D_{xy,t} + D_{yz,t})}{(L_{xy} + L_{yz})} = \frac{d_{ij,t}}{l_{ij}}$$

Assessment of model assumptions. Prior to all analyses, we ensured that data conformed

to model assumptions. To prevent extrapolation to extreme connectivity values with very few

observed cases, we recoded the highest 0.1% of values to the 99.9% value for each connectivity

measure. To directly compare regression coefficients of binary and continuous predictors within

and among models as a measure of effect size, we centered (i.e., subtracted the mean from) all

predictors and standardized continuous predictors by dividing by two standard deviations [9]. To

assess data linearity, we examined the relationship between the log odds of patch occupancy and

each continuous predictor using locally weighted scatterplot smoothing (bandwidth = 0.6–0.9;

ref. 10). To determine multicollinearity, we measured the variance inflation factor (VIF = 1/[1−

R^2]) among predictors within each model [3]; in all cases multicollinearity was very low (VIF <

1.27). We examined Pearson residuals for temporal and spatial autocorrelation using sample

autocorrelation function analysis and spline correlograms (with bootstrapped 95% confidence

intervals; n = 1000 randomizations), respectively. Temporal or spatial autocorrelation was not

detected in any models (electronic supplementary material, figures S3 and S4).

References

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