A large-scale study of competition of two temperate reef fishes: temperature, functional diversity, and regional differences in dynamics

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Supplement 1: A direct test of the effects of water temperature on competition

The goal of this analysis was to test whether temperature had an effect on competition above and beyond the observed, regional differences in competition. Specifically, we tested for associations between average water temperature and estimates of the strength of competition. Competition was measured at the scale of the survey site, and given the structure of the data (time-series observations of densities at many locations), we have spatially-replicated estimates the strength of competition. Temperature data were not available for the exact survey locations, but we were able to obtain records of sea surface temperature from nearby weather buoys during the survey period. Data from the survey period (2006-2016) were accessed from the Coastal Data Information Program at Scripps Institution of Oceanography (http://cdip.ucsd.edu). Temperature data are available from 25 stations located throughout California. For sites located between two buoys, we used the average temperature weighted by the distance to each buoy. Although distances from the temperature stations to the sites were on the order of 10's of kilometers, the survey sites covered over 1000km of coastline, and we believe this analysis captured most of the spatial variation in water temperatures.

To measure spatial variation in the strength of competition, we modeled per capita growth of each species (equation 2 in the main text) as a function of its own density, and the density of its competitor. We used linear, mixed effects models in which the intercepts and competition coefficients had both fixed and random components. The fixed effects provided the overall estimate of the growth and competition coefficients, and the random effects varied by site. The random effects thus provided an estimate of the relative strength of competition at each site. We conducted these analyses for both Northern California and Southern California, and with the growth of each surfperch species as the response. All analyses were conducted using the *lme4* package in R (Bolker and the R Development Core Team, 2017).

To summarize variation in the strength of competition, we used the Best Linear Unbiased Predictors for the random effects at each site. These values summarize whether competition was stronger or weaker than expected (positive and negative values, respectively). We then used correlation analyses to test whether the various forms of competition were significantly related to temperature. Random effect BLUPs from both the Northern California and Southern California analyses were pooled to examine overall effects of temperature.

There were no significant relationships between temperature the estimated strength of competition (Fig. S1). Correlation coefficients ranged from -0.12 to 0.07, and P-values ranged from 0.31 to 0.78. Because we found no evidence of an effect of temperature on either intraspecific or interspecific competition, we proceeded with our main analyses that focused on regional variation in competition.
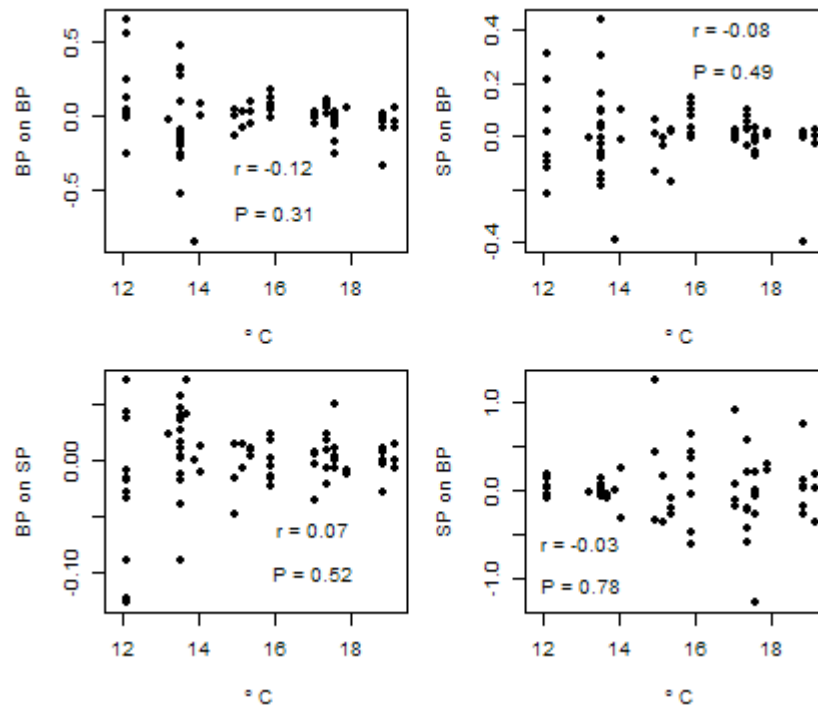

Figure S1. Relationships between the relative strength of competition, and average sea surface temperature. BP on BP (top left panel) indicates effects of black perch density on the per capita growth of black perch (intraspecific competition). SP on BP (top right panel) indicates the effects of black perch density on the per capita growth of black perch (interspecific competition). BP on SP (bottom left panel) indicates the effects of black perch density on the per capita growth of striped perch. SP on SP (bottom right panel) indicates the effects of black perch density on the per capita growth of striped perch.

Supplement 2: Correcting for the effects of observation error on estimates of intraspecific competition

Estimating observation error

Surveys were conducted by counting fish on 18 transects per site. To estimate observation error per survey, we used a resampling procedure where we measured how variable the estimates of density would be if different subsets of the 18 transects were used to estimate density. Because transects were located in different areas of the reef, and because transects were conducted by separate observers, this procedure estimated the observation error associated with transect placement, and among-observer variability. These factors are believed to be the major sources of observation error when using visual transect surveys to estimate population density of reef fishes (Thompson and Mapstone 2002, McClanahan et al. 2007, Irigoyen et al. 2013).

It is useful to represent observation error as a multiplier that is a lognormally-distributed random variable with mean of zero and a standard deviation of σ_{obs} (both parameters are on the log scale). In this way, the median multiplier is 1, and because observation error is a random variable, sometimes the observed value of N_t is a fraction of the true value; other times the observed value is a multiple of N_t greater than 1.

To calculate σ_{obs}, we used the following procedure. For each of the n = 18 transects, we calculated mean density when that transect was excluded from the set of 18. We then took the natural log (x + 0.1) of mean density (hereafter referred to as $lm1$), and compared the degree to which $lm1$ varied among the 18 cases. Specifically, σ_{obs} was calculated as:

$$\sigma_{obs} = \left(\frac{n-1}{n} \sum_{i=1}^{n} \left(lm1_i - \overline{lm1} \right)^2 \right)^{1/2} \qquad \text{(S1)}$$

This formula is the jackknife resampling estimate of the standard error of the natural log of mean density (Dixon 2001). By examining variability of the log of the mean, it allowed us to express observation error on a multiplicative, rather than additive scale. In this case, it describes the degree to which an estimate of mean density may have varied in response to transect placement. This quantity provides a good estimate of measurement error for a particular survey.

Observation errors were estimated for both species and for all surveys in which mean density was greater than zero (n = 266 for black surfperch in the north, n = 622 for black surfperch in the south, n = 337 for striped perch in the north, n = 532 for striped perch in the south). Log-scale observation error declined sharply with mean density, indicating that when densities were low, observation error was proportionately higher. As an example, Fig. S2 displays the relationship for black surfperch in Southern California. Patterns were similar for the remaining species and location combinations (data summarized in Table S1). These patterns reflect the fact that when fish densities are low, few transects encounter fish. Random placement of transects can therefore result in proportionately large differences in density estimates. In contrast, when densities are high, fish such as surfperch are spread more evenly throughout the reef (Johnson et al. 2016), and random transect placement results in similar estimates of density. For example, based on the curve in Fig. S2, if the true density was 0.1 fish per 60m^2 transect, 95% of the time we would expect the observed density to be within a

factor of 4.2. In contrast, if the true density were 5 fish per 60m^2, 95% of the time we would expect the observed density to be within a factor of 1.6.
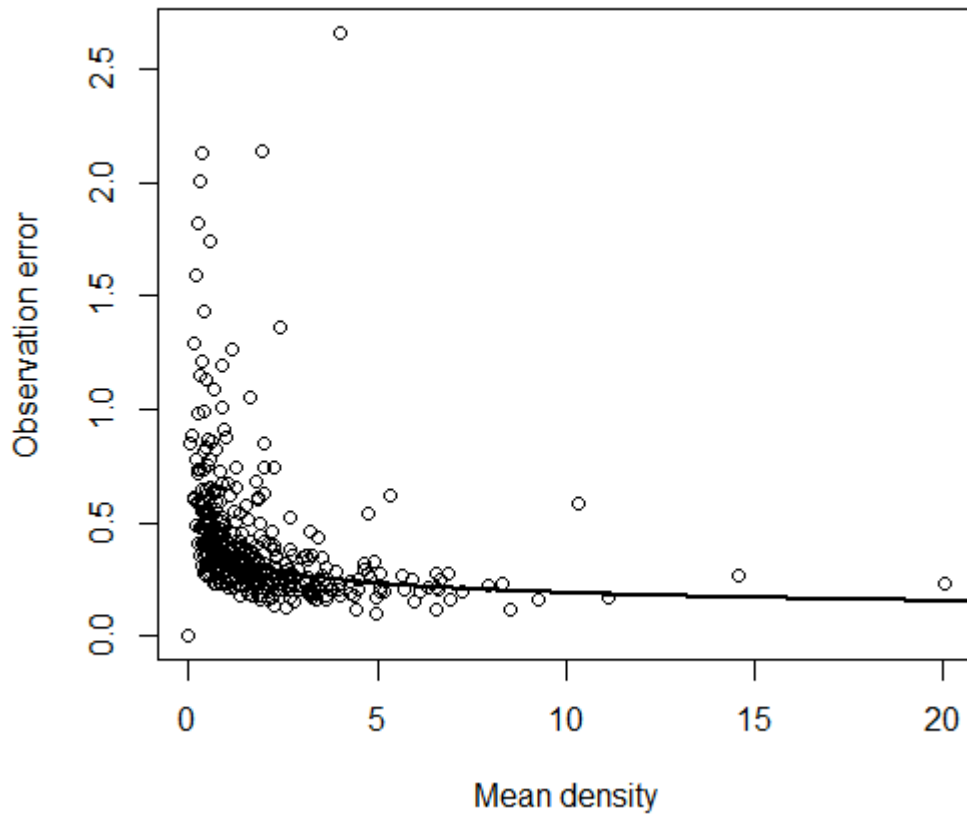

Fig. S2. Relationship between observation error and mean density of black surfperch. Data are from sites in Northern California. Density is expressed as fish per 60m^2 transect, and observation error is expressed as the standard error of a lognormal distribution describing an error multiplier.

Table S1. Estimates of parameters describing the relationships between observation error and mean density.   In all cases, mean observation error was described as a power function, $\sigma_{Obs} = aN_t^b$, where N_t = mean density, and a and b are scaling parameters.

Species	Region	a	SE	b	SE
Black perch	North	0.410	0.015	-0.240	0.023
	South	0.375	0.006	-0.293	0.012
Striped perch	North	0.358	0.008	-0.321	0.021
	South	0.406	0.007	-0.311	0.017

Correcting for bias when estimating coefficients of intraspecific competition

When population density (N_t) is estimated with uncertainty, our estimates of intraspecific competition coefficients can be biased. Because N_t appears in both the response (population growth, $\ln(\frac{N_{t+1}}{N_t})$, and the predictor (N_t), overestimates of N_t will result in underestimates of population growth (where N_t is in the denominator) and underestimates of N_t will result in overestimates of population growth. Observation error will therefore bias this relationship downward, and inflate estimates of intraspecific competition. To correct for this bias, we conducted simulations where we added measurement error to each of our observed densities and calculated the expected relationship between apparent density and apparent population growth if the true rate of population growth was zero. For each species and region, we added observation error according to the functions described in Table S1. That is, to generate apparent values of N_t, we multiplied our known values of N_t by exp(ε) where ε is a random variable with mean 0 and sd = aN_t^b. To generate apparent values of N_{t+1}, we multiplied N_t by exp(γ) where γ is also a random variable with mean 0 and sd = aN_t^b. This procedure simulated a population that did not grow ($r = 0$), but densities in year 1 and year 2 were estimated, and subject to observation error.

For each of 1000 iterations, we simulated measurement error at random and then estimated the slope of the relationship between apparent growth and apparent density as described above. We used the average values of slope and intercept parameters to estimate bias due to observation error. Because the population did not grow in these simulations, the true slope and intercept values are zero. The mean values of the apparent slope and apparent intercept provided our estimates of bias due to observation error. To correct for bias in our main analyses, these values were subtracted from the competition parameters estimated from the actual, observed growth rates (see equation 3 in the main text).

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