

Changing recruitment capacity in global fish stocks

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Marine fish and invertebrates are shifting their regional and global distributions in response to climate change, but it is unclear whether their productivity is being affected as well. Here we tested for time-varying trends in biological productivity parameters across 262 fish stocks of 127 species in 39 large marine ecosystems and high-seas areas (hereafter LMEs). This global meta-analysis revealed widespread changes in the relationship between spawning stock size and the production of juvenile offspring (recruitment), suggesting fundamental biological change in fish stock productivity at early life stages. Across regions, we estimate that average recruitment capacity has declined at a rate approximately equal to 3% of the historical maximum per decade. However, we observed large variability among stocks and regions; for example, highly negative trends in the North Atlantic contrast with more neutral patterns in the North Pacific. The extent of biological change in each LME was significantly related to observed changes in phytoplankton chlorophyll concentration and the intensity of historical overfishing in that ecosystem. We conclude that both environmental changes and chronic overfishing have already affected the productive capacity of many stocks at the recruitment stage of the life cycle. These results provide a baseline for ecosystem-based fisheries management and may help adjust expectations for future food production from the oceans.

fisheries | population dynamics | productivity | recruitment | nonstationary processes

Human well-being is closely linked with the productivity of marine fisheries, which provide a significant source of protein for more than half of the world's population (1). However, ongoing environmental and biological changes may impact productivity through a variety of mechanisms, including larger habitat areas for temperate species (2), altered body sizes (3), food availability (4), and increased exposure to oxygen-depleted and acidic waters (5). Recent research has documented marked changes in the distributional patterns of marine species that are consistent with climate forcing (6, 7). However, the net effect of these changes on global fish stock productivity is not clearly understood. In particular, documented environmental changes (4, 8, 9) and the long-term consequences of overfishing (10, 11) all impose relevant but poorly constrained effects. Here we help address this issue by evaluating the evidence for empirical trends in the relation between the size of the reproductively mature population (or “spawning stock”) and the annual production of juvenile offspring (“recruits”) using a recently synthesized global database of stock-recruit time series (12). We then test the relation between empirical recruitment trends and regional environmental variables associated with temperature, phytoplankton abundance, and historical overfishing.

Recruitment is modeled by relating the size of the spawning stock biomass to the annual production of recruits. The magnitude of annual recruitment is highly variable (13), yet it provides the basis for population growth and stock productivity by determining the initial number of fish that may grow, die, or be harvested by the fishery (14) (i.e., total productivity is the combination of recruitment, individual growth, and mortality). As such, the stock-recruit relationship has been identified as “the most important and generally most difficult problem in the biological

assessment of fisheries” (14). The simplest commonly used recruitment function is the Ricker model

$$R_t = \alpha B_{t-\tau} e^{-\beta B_{t-\tau}},$$

where recruitment R at time t is an increasing function of the spawning stock biomass B (lagged by the age of recruitment τ), with negative exponential density-dependent feedback. The two model parameters, α and β , characterize the magnitude of recruitment, where α is the maximum reproductive rate (or density-independent recruitment), and β gives the rate at which recruitment is reduced by density-dependent feedbacks. These two parameters combine to give the maximum recruitment capacity for an individual stock when $dR/dB = 0$ and $(d^2R)/(dB^2) < 0$, yielding

$$R_{\text{MAX}} = \frac{\alpha}{\beta} e^{-1},$$

where e is Euler's number. Note that R_{MAX} is a biomass-independent measure of maximum recruitment and does not depend on current stock size. This property of the measure is attractive as it allows comparison of both abundant and heavily depleted stocks, but it also means that R_{MAX} occasionally occurs at biomass levels larger than those observed today. Because R_{MAX} is highly correlated with alternative biomass-dependent measures of recruitment success (*SI Appendix*), we adopt it as a simple and comparable metric of fish stock productivity at the recruitment stage of their life cycle.

Results

When recruitment models are fitted to data (Fig. 1 *A–F*), there is often considerable structure in the residual variation (Fig. 1 *G–I*) that suggests that biological productivity may have changed significantly over time. Trends can be observed as directed declines (Fig. 1 *G*), threshold-like dynamics (Fig. 1 *H*), or regime shifts (Fig. 1 *I*; note that the observed shift coincided with the 1977 reversal of the Pacific Decadal Oscillation) (15). We evaluated evidence for

Significance

Marine fish stocks play an important role in marine ecosystems and provide a source of protein for billions of people worldwide. Recent environmental changes have affected the distribution of many stocks, but it is yet unclear whether their productivity is affected as well. We show that recruitment capacity (the ability of stocks to produce surviving offspring) has been significantly altered by both environmental changes and biological changes brought about by overfishing. In total, these effects have reduced recruitment capacity by 3% of the historical maximum per decade, on average. This paper helps us to understand and track previously unrecognized changes in fish stock productivity during the early stages of their life cycle.

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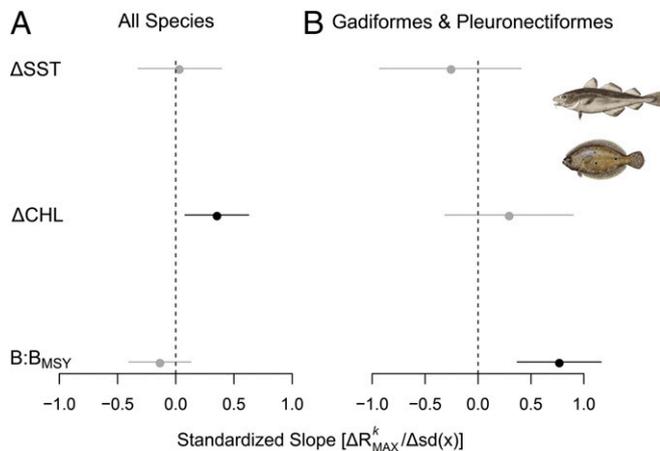


Fig. 3. Drivers of recruitment capacity. Relationships between LME-level ΔR_{MAX}^k and environmental and fisheries variables for all species (A) and orders Gadiformes and Pleuronectiformes (B) using multiple regression (weighted according to the number of stocks in the LME). The three LME-specific covariates tested include (i) observed changes in average sea surface temperature (ΔS_{ST}) and (ii) chlorophyll concentration (ΔCHL), as well as changes in overfishing indicated by the ratio of observed to target biomass ($B:B_{MSY}$). See Fig. 4 for spatial patterns. The regression slopes were normalized by transforming the regression variables to unit variance. Black symbols indicate statistical significance. See text and *SI Methods* for details.

biomass distribution and the productivity of individual stocks. We further note that the drivers of recruitment capacity identified here likely vary in importance among stocks and regions. Bottom-up changes in plankton concentration and top-down effects of overfishing are all known to affect recruitment in complex ways, including effects at both the adult (e.g., maternal effects on recruitment) (19) and larval stages (e.g., food availability) (20). Our results, however, make neither assumptions nor inferences regarding stock-specific mechanisms. Finally, correlations in recruitment may also be important for inferring long-term trends and patterns of shared responses to environmental changes and fishing at the regional scale. We emphasize that a more detailed hierarchical approach that accounts for recruitment correlations (21, 22) and species interactions is needed to fully resolve regional patterns and drivers and thus provide direct management guidance for individual stocks within individual LMEs.

At larger scales, the apparent divergence in productivity among the North Pacific and North Atlantic provides an interesting contrast, possibly linked to divergent ecological histories. The North Pacific experienced a large oceanographic regime shift in the 1970s (15), which resulted in relatively flat long-term environmental trends (Fig. 4). Observed patterns suggest that recruitment capacity may have tracked this variability (Fig. 1*I*), resulting in small ΔR_{MAX}^k values overall. Shorter histories of exploitation and lower exploitation rates (23) are also likely to have tempered declines in this region due to overfishing. In contrast, the North Atlantic is marked by strong directional environmental change and long-term over-exploitation (Fig. 4). Environmental and fishing-related trends in this region were among the most severe and were significantly related to observed changes in recruitment capacity. An exception for the North Atlantic trend is the positive ΔR_{MAX}^k value in the Gulf of Mexico [12 of 13 time series there predate the *Deepwater Horizon* (24) spill in 2010]. It is also important to note that the database is most representative of North American and European stocks due to the relative scarcity of stock assessments in tropical oceanic regions of the world (Fig. 4*C*) (12, 25) where earth system models predict that plankton productivity will decline more strongly than in the coastal and temperate regions that dominate the stock recruitment database (26). This historical bias in spatial

coverage limits our understanding of global fish populations as a whole (25).

In addition to impacting the productivity of marine fish stocks, observed changes in recruitment parameters may also have consequences for the stability of populations. Recent theoretical work has linked observed patterns of population stability (27) to changes in stock recruitment parameters (28) due to age-selective fishing. It was hypothesized that population stability has decreased in stocks due to increases in the mean and variance of the maximum reproductive rate α caused by the truncation of population age structure by fishing. Our results, however, suggest that such increases in α are not often observed in assessed fish populations, where α has generally trended downward. Rather, frequently observed increases in the magnitude of the density-dependent parameter β may provide an alternative explanation for reduced stability in exploited stocks based on the well-known destabilizing effects of strong density-dependent feedbacks (29). Testing this hypothesis should be a priority for follow-up research.

In summary, empirically estimated trends in recruitment capacity (Figs. 1 and 2) provide evidence for environmental- and fishing-related changes in the productivity of marine fish stocks (Fig. 3). Although far from uniform at the stock level, observed trends were significantly related to ongoing environmental and biological change at the ecosystem scale, specifically changes in phytoplankton biomass and the history of stock biomass depletion (Fig. 4*B* and *C*). The reality of time-varying biological parameters requires managers to revisit the common assumptions of fixed maximum sustainable yields (30) and emphasizes the need for ecosystem-based management strategies that investigate and account for observed environmental and fishing-related impacts on the long-term productive capacity of fish stocks. Such strategies are enabled by the methods presented here, in that the complex effects of environmental changes can be tracked within a reasonably simple assessment framework. Accounting for such changes is a prerequisite for the successful rebuilding and sustainable harvesting of fisheries resources in a rapidly changing environment.

Methods

The RAM Legacy Stock Assessment Database. All stock recruitment data were extracted from the RAM Legacy Stock Assessment Database (12), which is a global, quality-controlled database, available publicly at ramlegacy.org/. Stock assessments provide estimates of both spawning stock biomass (kilograms) and recruitment (no. individuals). We analyzed 262 of the ~420 time series available in the database based on (i) whether a recruitment relationship was already assumed in generating the stock assessment estimates (12) and (ii) whether the spawning stock biomass and recruitment time series were estimated directly, as opposed to indirect proxies such as spawner egg abundance. All series were then normalized to unit variance for easy comparison across stocks and regions. A list of species used in the analysis, along with their designated LME, can be found in Table S1. Frequency histograms of the start and end dates of the stock recruitment time series are shown in Fig. S1 and tabulated in Table S2.

Nonstationary Recruitment Model. The Ricker model can be linearized by reexpressing recruitment as log survival

$$\ln\left(\frac{R_t}{B_{t-\tau}}\right) = \ln \alpha - \beta B_{t-\tau}.$$

This model can be fitted to data as a linear regression. To model nonstationary recruitment relationships, we let the recruitment parameters vary in time (21, 31) by specifying the following linear Gaussian state space model

$$\ln\left(\frac{R_t}{B_{t-\tau}}\right) = \ln \alpha_t - \beta_t B_{t-\tau} + w_t, \quad w_t \sim N(0, \sigma_w^2),$$

$$\begin{bmatrix} \ln \alpha \\ \beta \end{bmatrix}_t = \begin{bmatrix} \ln \alpha \\ \beta \end{bmatrix}_{t-1} + \begin{bmatrix} v_1 \\ v_2 \end{bmatrix}_t, \quad \begin{bmatrix} v_1 \\ v_2 \end{bmatrix}_t \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \mathbf{Q} = \begin{bmatrix} \sigma_{\ln \alpha}^2 & 0 \\ 0 & \sigma_{\beta}^2 \end{bmatrix}\right),$$

where the recruitment parameters are treated as dynamic latent states. Note that w_t is the observation error with variance σ_w^2 and $[v_1 \ v_2]_t'$ is the process

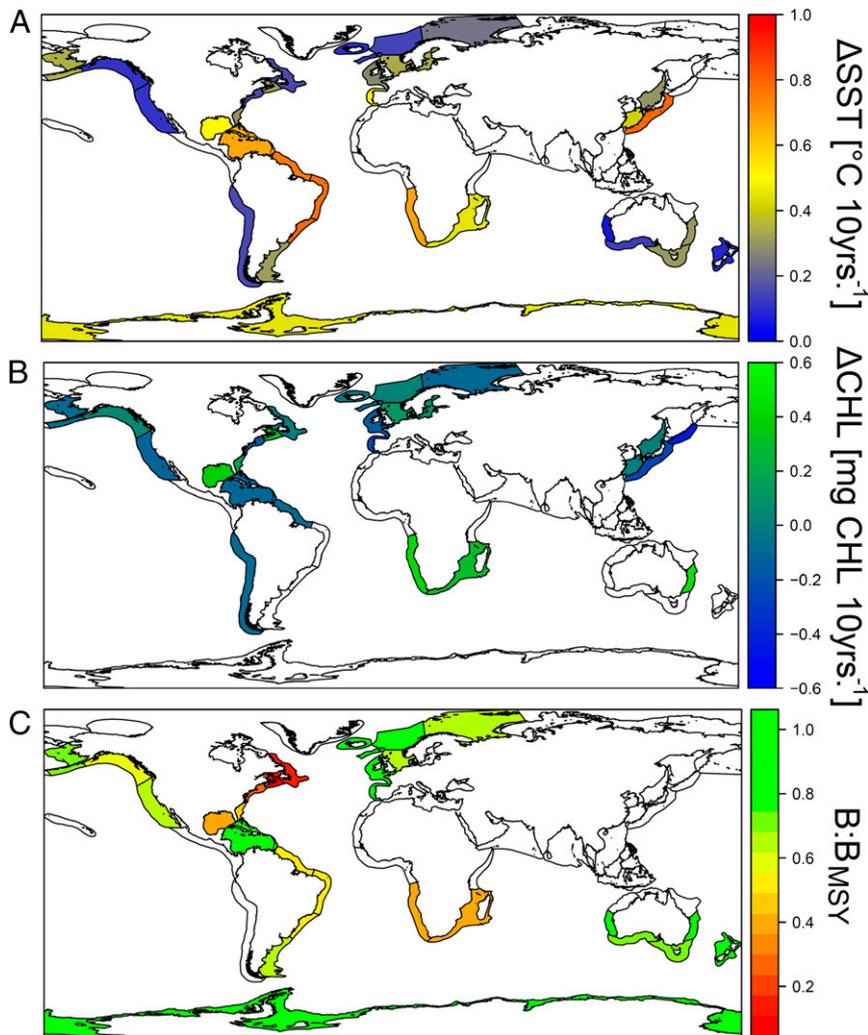


Fig. 4. Spatial distribution of environmental variables by LME. (A) Δ SST computed over the period covered by stock assessments in each LME. (B) Δ CHL (used as a common proxy for phytoplankton biomass). (C) $B:B_{MSY}$ (12).

error vector with covariance matrix \mathbf{Q} . The unknown parameters are σ_0^2 and the diagonal of the matrix \mathbf{Q} , which are estimated by the method of maximum likelihood. Details of the estimation can be found in *SI Methods*, including the model selection algorithm based on the Bayesian information criterion (BIC). Model selection was used to determine whether variance parameters should be zero or nonzero, thus determining whether the data support static or time-varying recruitment parameters (*SI Methods*). For stocks with at least one time-varying parameter, the trend in R_{MAX} was summarized by a linear slope (ΔR_{MAX}) standardized to have unit percent change per decade relative to the historical maximum. For stocks where both α and β were inferred as static, ΔR_{MAX} is zero. Results for the time-varying recruitment analysis for all stocks, along with statistical diagnostics, are displayed in *SI Appendix*. Model selection results are also given in *Table S3*.

Meta-Analysis. The nonstationary recruitment analysis and subsequent trend analysis were applied to each stock individually, and then regional and taxonomic patterns were summarized using a random effects meta-analysis model. The random effects model is written

$$\Delta R_{MAX}^i = \Delta R_{MAX}^k + \theta^i + \varphi^i,$$

where ΔR_{MAX}^i is the linear slope of R_{MAX} for stock i , ΔR_{MAX}^k is the overall mean across all stocks in group k , θ^i is the deviation of the observed ΔR_{MAX}^i from the "true" ΔR_{MAX}^k , and φ^i is the deviation of the true ΔR_{MAX}^i from ΔR_{MAX}^k . The random effects analysis assumes that a group trend can be described by an inverse-variance weighted average of trends across stocks and stock-specific deviations from the overall trend (*SI Methods*). The meta-analysis model was implemented

in the R package *rmeta* (32). All meta-analytic results for LMEs and taxa are given in the *SI Appendix*, which gives group-specific slopes and contributions from individual stocks. Three sensitivity analyses were also performed and are documented in *SI Methods*. These analyses included robustness tests against (i) alternative forms of density dependence (Figs. S2–S4); (ii) BIC model selection algorithm (Fig. S5); (iii) the choice of alternative metrics of recruitment success (Fig. S6); and (iv) the impact of variable time series length (Fig. S7).

Global Scale Correlates of Recruitment. To correlate recruitment trends to environmental change and overfishing intensity, we fit multiple regression models of the form

$$\Delta R_{MAX}^k = c_0 + c_1 \Delta SST + c_2 \Delta CHL + c_3 B : B_{MSY} + e_k,$$

where ΔR_{MAX}^k is the vector of ΔR_{MAX}^k estimated per LME, ΔSST is the linear trend in sea surface temperature in each LME, ΔCHL is the linear trend in chlorophyll concentration (a widely used proxy for phytoplankton biomass), $B:B_{MSY}$ is an index of historical overfishing, representing the mean historical ratio of annual biomass to target biomass levels as extracted from the stock assessments (12), c_0 is the intercept, c_1 , c_2 , c_3 are the partial slopes, and e_k is the LME-specific regression error. ΔSST and ΔCHL were computed according to the time window covered by stock assessments within individual LMEs. The frequency distributions of time series start and end dates are shown in Fig. S1. Historical SST data were extracted from the Simple Ocean Data Assimilation (33), and CHL data were taken from the in situ database provided in ref. 8. The trend model for CHL contained a seasonal term due to unequal seasonal sampling, whereas mean annual temperatures were extracted for SST. The

regression was weighted according to the number of stocks in each LME. We tested possible interactions but none were retained. All independent variables were standardized to unit variance to standardize the regression coefficients.

The multiple regression analysis was fit three times on three sets of species. The first included all species in each LME, and two more subsets (within LMEs) were made on the basis of taxonomic order. One taxonomic grouping included Gadiformes and Pleuronectiformes (generally bottom-associated species) and other included Clupeiformes and Perciformes (pelagic, open-water species). These orders do not occur in all LMEs; therefore, the regression analysis on

the subsets included fewer data points. The Gadiformes and Pleuronectiformes occurred in 21 LMEs and the Perciformes and Clupeiformes occurred in 23 LMEs.

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Supporting Information

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SI Methods

Here we provide additional detailed regarding the analysis. For compact description of the estimation, we define the recruitment parameter vector $\theta = [\ln \alpha, \beta]'$. Thus, the linear Gaussian state space models can be written

$$y_t = \mathbf{H}_t \theta_t + w_t \quad w_t \sim \mathcal{N}(0, \mathbf{R} = \sigma_w^2)$$

$$\theta_t = \theta_{t-1} + \mathbf{v}_t \quad \mathbf{v}_t \sim \mathcal{N}\left(0, \mathbf{Q} = \begin{bmatrix} \sigma_{\ln \alpha}^2 & 0 \\ 0 & \sigma_{\beta}^2 \end{bmatrix}\right),$$

where y_t is the observed log survival at time t , \mathbf{H}_t is the design matrix, w_t is a realization of the Gaussian observation error at time t with variance \mathbf{R} , and \mathbf{v}_t is a realization of the bivariate Gaussian process error at time t with covariance \mathbf{Q} . Conditional on \mathbf{R} and \mathbf{Q} and initial values for the state vector θ_0 , the optimal reconstruction for the latent time-varying recruitment parameters θ_t are estimated using the Kalman filter and smoother (34). Note that variance parameters \mathbf{R} and \mathbf{Q} are estimated by maximum likelihood, whereas the recruitment parameters (θ_t) are analytically determined by the forward-filter/backward smoother Kalman smoother algorithm, conditional on \mathbf{R} , \mathbf{Q} , and θ_0 (the latter assumed to take the form of a diffuse Gaussian).

Maximum Likelihood Estimation. Maximum likelihood estimation (MLE) is based on the normally distributed one-step ahead prediction errors of the filtering algorithm (34), termed the innovations. The innovations for the dynamic regression are given by

$$\delta_t = y_t - \mathbf{H}_t \hat{\theta}_t,$$

where $\hat{\theta}$ denotes an estimate. The error covariance of the innovations is defined by

$$\mathbf{F}_t = \mathbf{H}_t \mathbf{M}_t \mathbf{H}_t' + \mathbf{R},$$

where \mathbf{M}_t is the predictive covariance (34). The log likelihood of the innovations can then be written as

$$\text{Log } L(\mathbf{R}, \mathbf{Q}) = c - \frac{1}{2} \sum_{t=1}^T \ln |\mathbf{F}_t| - \frac{1}{2} \sum_{t=1}^T \delta_t' \mathbf{F}_t^{-1} \delta_t,$$

where c is a constant. Log L is maximized using standard nonlinear optimization, yielding MLE estimates of \mathbf{R} , \mathbf{Q} , and subsequently $\hat{\theta}_t$ (hat denotes the MLE estimate) by applying the Kalman filter/smoothing algorithm. All calculations were written in the R language (www.r-project.org), and the optimization was performed using the numerical routines within the R base package.

Model Selection. To determine whether individual recruitment time series have stationary or nonstationary parameters, we applied model selection using various parameterizations of the matrix \mathbf{Q} . We used the BIC for model selection, which is given as

$$\text{BIC} = -2 \widehat{\text{Log}} L + k \ln T,$$

where $\widehat{\text{Log}} L$ is the optimized value of the log likelihood, k is number of nonzero estimable variance parameters in the dynamic regression model, and T is the length (number of years) of an individual recruitment time series. We consider four

parameterizations of \mathbf{Q} which represent (i) static stock-recruit relationship (all elements of \mathbf{Q} equal to zero; $k = 1$); (ii) time-varying maximum reproductive rate, static density dependence [element (1,1) nonzero, all others zero; $k = 2$]; (iii) static maximum reproductive rate, time-varying density dependence [element (2,2) nonzero, all other zero; $k = 2$]; and (iv) time-varying maximum reproductive rate and density dependence [elements (1,1) and (2,2) nonzero, all others zero; $k = 3$]. Note we did not test the full covariance matrix with nonzero off-diagonal elements due to the inherent statistical dependency between the two stock-recruitment parameters (14). Under each parameterization, the Kalman filter/smoothing algorithm yields a likelihood that can be used to compute the BIC. {Note that we adopt the BIC over the more common AIC to be more conservative in model selection in the sense that BIC favors fewer parameters due to its stricter penalty term [i.e., for $n \geq 8$, the BIC penalty ($k \ln n$) is greater than the AIC penalty ($2k$)] and will thus discriminate more strongly against time-varying recruitment parameters.} The summarized results of the model selection procedure are given in Table S3.

ΔR_{MAX} and ΔR_{MAX}^k . The dynamic linear regression analysis yields time series of recruitment parameters R_{MAX}^i , and ΔR_{MAX}^i for 262 fish populations (now using i to denote an individual stock). We then summarize the trend using a linear slope based on least squares regression

$$R_{\text{MAX}}^i = b_0^i + b_1^i t + e_t^i,$$

where b_0^i is the intercept of the linear regression for stock i , b_1^i is the slope multiplied by time index t , and e_t^i is the regression error. To standardize the rate of change in recruitment, we define

$$\Delta R_{\text{MAX}}^i = \frac{b_1^i}{\max(R_{\text{MAX}}^i)} * 10 \text{ years.}$$

which represents the rate of change per decade (10 years) as a percent relative to the historical maximum of R_{MAX}^i . To estimate the uncertainty in ΔR_{MAX}^i according to the uncertainty in the estimated time-varying recruitment parameters, we used a bootstrap resampling scheme as follows. (i) Sample from the uncertainty distribution of the inferred time-varying recruitment parameters to compute bootstrapped time series of R_{MAX}^i . (ii) Compute the standardized linear slope ΔR_{MAX}^i from the bootstrapped R_{MAX}^i series. (iii) Repeat 500 times. This procedure yields bootstrapped distributions of ΔR_{MAX}^i with uncertainty determined by the uncertainty in the inferred recruitment parameters. Due to the nonlinearity in R_{MAX} , we use the median and median absolute deviation (MAD) as summary statistics for robustness.

To combine the results of the individual trend analyses, we perform a random effects meta-analysis at the taxonomic, regional, and global scales. For any particular grouping, the random-effects model is written

$$\Delta R_{\text{MAX}}^i = \Delta R_{\text{MAX}}^k + \vartheta^i + \varphi^i,$$

where ΔR_{MAX}^i is the estimated linear slope of R_{MAX} for stock i , ΔR_{MAX}^k is the overall mean ΔR_{MAX} for in the group, ϑ^i is the deviation of the observed ΔR_{MAX}^i from the true ΔR_{MAX}^i , and φ^i is the deviation of the true ΔR_{MAX}^i from ΔR_{MAX}^k . In the estimation, weights are applied according to the inverse variance of the

bootstrap distribution of ΔR_{MAX}^i . The meta-analysis model was implemented in the R package *rmeta* (32). All meta-analytic results for LMEs and taxa are given in *SI Appendix*.

Sensitivity Analyses.

Sensitivity of R_{MAX} trends to alternative forms of density dependence. The Ricker function is only one of several possible parameterizations for the recruitment function. Other common recruitment functions include the Beverton–Holt model, $R_t = \alpha[\beta/(1 + \beta B_{t-\tau})]$, or the more general three-parameter Shephard curve, $R_t = \alpha(1 - \gamma\beta B_{t-\tau})^{1/\gamma}$, both of which vary in their representation of density dependence. Several studies (35–37) have found that the Ricker model is most robust to biases introduced by both observation error and model misspecification. These results motivated our use of the Ricker function in the paper. However, we also tested the sensitivity of our results to the shape of density dependence by applying the generalized Ricker function (35), which approximates the behavior of the above models through the inclusion of the shape parameter γ

$$R_t = \alpha B_{t-\tau} e^{-(\beta B_{t-\tau})^\gamma}.$$

We set $\gamma = 0.5, 0.75, 1.25, 1.5$ to simulate the range of density-dependent behaviors from very weak ($\gamma = 0.5$) to highly overcompensatory ($\gamma = 1.5$). See Fig. S2 for depictions of the various forms of density dependence. Note that $\gamma = 1$ recovers the Ricker model. We found that the quantity ΔR_{MAX}^i was generally independent of the shape parameter γ (Figs. S3 and S4) and thus independent of the form of density dependence in the recruitment function. The individual recruitment parameters α and β changed in relative magnitude with γ (Fig. S3) in a way that resulted in α and β parameters closer to zero with increasing γ . However, the standardized slopes remained constant (Fig. S4) because as γ increases, the parameter is vertically translated on the y axis, altering the y intercept, but leaving the slope unchanged. This transformation resulted in constant ΔR_{MAX}^i across all values of γ .

Sensitivity of R_{MAX} trends to parameterization of Q . The BIC model selection algorithm was used to choose the appropriate structure

of the covariance matrix Q , which determined whether recruitment parameters varied in time. We tested the sensitivity of R_{MAX}^i and ΔR_{MAX}^i to the alternate parameterizations of Q by repeating the model selection two times under a restricted set of possible Q parameterizations: (i) static stock-recruit vs. time-varying α ; and (ii) static stock-recruit vs. time-varying β . We then took each set of results and repeated the estimation procedure for R_{MAX}^i and ΔR_{MAX}^i . Results indicated that the distribution of ΔR_{MAX}^i was relatively insensitive to whether Q was parameterized to represent time-varying α or β . The magnitudes and relative number of stationary vs. time-varying stock-recruit relationships also remained similar, as well as the magnitudes of ΔR_{MAX}^i . The main difference was that time-varying α tended to produce larger SEs for ΔR_{MAX}^i . The results of this analysis are presented in Fig. S5.

Sensitivity to an alternative definition of recruitment capacity. For some heavily depleted stocks, or those exhibiting extremely weak density dependence, the majority of the historically observed biomass may be below the biomass that produces maximum recruitment; therefore, R_{MAX} may not be a practical metric for management. To test the robustness of trends to the specific definition of recruitment capacity, we repeated the trend analysis with an alternative definition; specifically, recruitment evaluated at the median observed biomass, $R[B = \text{median}(B)]$ (Fig. S6). We found that $\Delta R[B = \text{median}(B)]$ correlated very strongly with ΔR_{MAX} at the regional and global scales, with correlations of 0.85 and 0.92, respectively. Magnitudes of $\Delta R[B = \text{median}(B)]$ were slightly smaller than ΔR_{MAX} but were generally estimated with smaller bootstrap resampled variances so resulting in very similar P values at the global and regional scales.

Analysis over the years 1980:2000. To test the sensitivity of our results to variable time series length, we repeated the time-varying recruitment analysis by subsetting time series for the period 1980:2000 and excluded stocks that do not cover this period. This subset excluded six stocks from the analysis. The scatterplot between ΔR_{MAX}^i using the full time series and ΔR_{MAX}^i calculated for the period 1980:2000 is given in Fig. S7. The results indicate a high correlation of 0.82 indicating a robustness in the overall trends that is not driven by the longer time series.

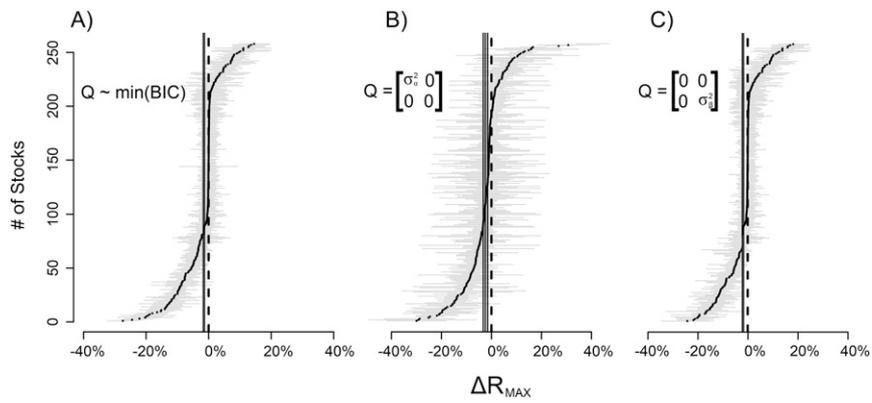


Fig. S5. Sensitivity of ΔR_{MAX} to model selection and specification. We tested the sensitivity of individual ΔR_{MAX} to the parameterization of the covariance matrix of the recruitment parameters Q . (A) Distribution of ΔR_{MAX} (and SE) when choosing the elements of Q according to BIC model selection. (B) Distribution ΔR_{MAX} when performing model selection between static stock-recruit vs. time-varying α . (C) ΔR_{MAX} for model selection between static stock-recruit and time-varying β . These results imply that maximum recruitment potential was relatively independent of whether we allowed α or β to vary.

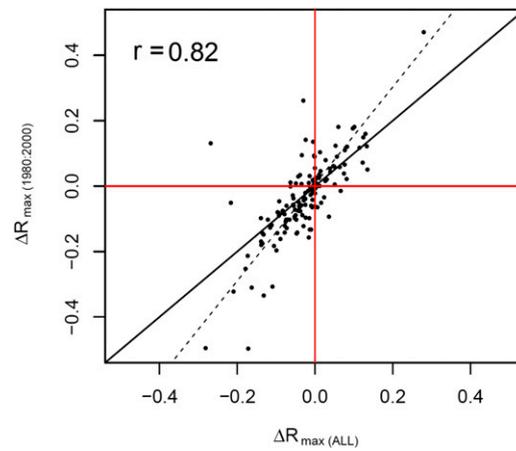


Fig. S7. Scatterplot between ΔR_{MAX} using the full time series (denoted $\Delta R_{\text{MAX(ALL)}}$) and ΔR_{MAX} calculated for the period 1980:2000 (denoted $\Delta R_{\text{MAX(1980:2000)}}$). The results indicate a high correlation indicating robustness in the trends to the length of the time series analyzed.

Other Supporting Information Files

[SI Appendix \(PDF\)](#)

[Table S1 \(DOCX\)](#)

[Table S2 \(DOCX\)](#)

[Table S3 \(DOCX\)](#)