Check for updates

FISHERIES

6.D(1)
153rd SSC

Stock assessment models overstate sustainability of the world's fisheries

Graham J. Edgar[1]*, Amanda E. Bates[2], Nils C. Krueck[1], Susan C. Baker[3], Rick D. Stuart-Smith[1], Christopher J. Brown[1,4]

Effective fisheries management requires accurate estimates of stock biomass and trends; yet, assumptions in stock assessment models generate high levels of uncertainty and error. For 230 fisheries worldwide, we contrasted stock biomass estimates at the time of assessment with updated hindcast estimates modeled for the same year in later assessments to evaluate systematic over- or underestimation. For stocks that were overfished, low value, or located in regions with rising temperatures, historical biomass estimates were generally overstated compared with updated assessments. Moreover, rising trends reported for overfished stocks were often inaccurate. With consideration of bias identified retrospectively, 85% more stocks than currently recognized have likely collapsed below 10% of maximum historical biomass. The high uncertainty and bias in modeled stock estimates warrants much greater precaution by managers.

Global assessments of the state of fisheries stocks consistently report that poorly managed fish populations are declining (*1*). Such declines contrast claims of widespread recovery for many highly managed stocks (*2*), including in the Food and Agriculture Organization of the United Nations (FAO)'s summary of the state of world fisheries (*1*). Nevertheless, conclusions that intensively managed stocks are generally improving depend on how information from different stocks is averaged to derive a global trend (*3*). Moreover, interpretation of stock trends is complicated by many factors influencing catch rates—e.g., the continuously improving technological efficiency of fishing fleets (*4*) can increase catch per unit effort even as stocks decline.

Best practice methods for assessing fisheries involve complex models integrating past catch data with biological and other information (*5*). Complex stock models can include more than 40 different parameters and settings related to fish life history (e.g., natural mortality, length and age at maturity, and growth rate), catch (e.g., landings, gear selectivity, and discards), effort (e.g., days fished and number of hooks), and management controls (e.g., fleet allocations and allowable catch) (*5*). The many estimated parameters and settings can lead to model overfitting, whereby uncertainty accumulates with each additional estimate. Accuracy of simpler stock assessment approaches is typically evaluated relative to complex models (*6*); however, the accuracy of complex stock models remains unknown because the true fish biomass is not directly observed.

[1]Institute for Marine and Antarctic Studies, University of Tasmania, Hobart, TAS 7001, Australia. [2]Biology Department, University of Victoria, Victoria, BC V8P 5C2, Canada. [3]School of Natural Sciences, University of Tasmania, Hobart, TAS 7001, Australia. [4]Centre for Marine Socioecology, University of Tasmania, Hobart, TAS 7001, Australia.
*Corresponding author. Email: g.edgar@utas.edu.au

In the absence of accurate biomass data, a retrospective analysis of differences in estimated stock biomass reported over time can indicate the magnitude of uncertainty and test for systematic bias. Previous retrospective analyses have generally considered variation in biomass estimates where modeled values for the same year were compared between stock assessments, with large variation noted (*7*–*9*). By contrast, we relate past stock assessments to the most recent assessment. Our reasoning is that modeled output of the most recent assessment should, on average, be the most accurate because estimates are hindcast using the longest time series and with the most knowledge for defining model structure. Our interest is primarily directed at whether systematic bias exists between past and most recent assessment estimates and how that bias varies with stock status. Bias matters because overfished stocks may not be identified for recovery actions if stock size is overestimated, or recovery actions may have unnecessary economic consequences if stock size is underestimated.

Our analysis considers depletion metrics that relate current stock biomass, B, to unfished biomass, B_0, because of their central role in fisheries management. Depletion metrics are important in rebuilding stocks through reduced quotas or fishery closures when stocks decline below particular limit reference points (*10*), which vary between jurisdictions and stocks but are often around $B/B_0 = 0.2$ (*11*). Overfished can be defined using a range of benchmarks related to stock modeling assumptions, estimated depletion, and estimated fishing mortality (*12*). These include $B/B_0 = 0.5$, the point of maximum sustainable yield according to classic stock models (*13*). To simplify discussion of depletion effects, we use $B/B_0 < 0.4$ to define overfished stocks, given that both catch and economic returns generally decline below 0.4 (*14*) and ecosystem impacts are larger than necessary [including reduced trophic [...] of target species (*15*)]. We distinguish collapsed stocks as the subset of overfished stocks with $B/B_0 < 0.1$ (*16*). An intermediate benchmark is the point where recruitment impairment commences, which has most frequently been characterized as $B/B_0 = 0.2$ (*17*, *18*). Although subjective, the choice of sustainability threshold had little impact on our study conclusions because our focus was not on estimating the proportion of overfished stocks but whether that proportion systematically changes between current and hindcast assessments. Notably, the set of stocks analyzed in this work includes stocks that are disproportionately well documented and managed and thus comprises a nonrepresentative subset of the stock assessment universe.

Because modeled B_0 was unavailable for most fisheries and is highly sensitive to input parameters, we approximated B_0 using spawning stock biomass in the historical year of maximum stock size (B_{max}) and thereby estimated depletion as B/B_{max} (*12*). For the 38 stocks with estimates of B_0 provided in the RAM Legacy Stock Assessment database, B_{max} tended to be similar to B_0 [coefficient of determination (R^2) = 0.97], albeit slightly higher on average (by 5.8%; fig. S1).

Depletion of fish stocks

Our retrospective analysis of spawning stock biomass (B; the combined biomass in tonnes of all mature females) included 230 stocks with 986 assessments that encompassed 128 species or species complexes, including most of the world's largest fisheries (table S1). Annual modeled estimates of B extended over an average of 47 years in time series. We compared 756 values of B reported in the final year of older stock assessments with the equivalent estimates of B (i.e., in the same year) provided as hindcast values in the most recent assessment.

Estimates of stock biomass in individual hindcast time series changed greatly from one year to the next (mean 1.12× change between successive years; maximum 2.10× change for Barents Sea capelin). Such instability unlikely reflects real-world population oscillations, given that most stocks are made up of multiple year classes that persist from year to year [e.g., >3 years for capelin (*19*)]. Modeled estimates of stock biomass for assessments released in different years showed even greater variability. For example, Pacific cod in the Gulf of Alaska varied by 1.49× in estimates of B for the same year between consecutive assessments (Fig. 1). This variability greatly exceeded uncertainty intervals described for individual stock models. Pacific cod variability was similar to mean change between assessments averaged across all 230 stocks (1.40×) and is thus typical of the variability in stocks considered in this work.

Downloaded from https://www.science.org on August 30, 2024

Such marked differences suggest that stock biomass estimates for any year were often far from the (unknown) true value.

Mean depletion in the most recent assessment averaged across stocks declined from an average of $0.50 \times B_{max}$ in 1980 to $0.35 \times B_{max}$ in 2006 and then rose to $0.47 \times B_{max}$ in 2017 (Fig. 2A, black curve), which suggests generalized stock recovery. The recent overall rise was driven by sustainable stocks (i.e., B/B_{max} in final year of most recent assessment > 0.4; Fig. 2B), whereas overfished stocks remained low in recent years on average (Fig. 2C). In general, older stock assessments were increasingly optimistic relative to the most recent assessment the further back in time they were produced (Fig. 2). Assessments released >8 years earlier than the most recent assessment showed a rise in mean B/B_{max} across stocks to $0.48 \times B_{max}$ by 2007—30% greater than the value of $0.35 \times B_{max}$ for the same year indicated by most recent assessments (Fig. 2A).

B/B_{max} plots for overfished stocks (Fig. 2C) generally featured upward slopes in the final 2 years of older assessments—suggesting improving stock size—that were no longer evident in the most recent assessments (Fig. 2C). Such phantom recoveries progressed across assessments as updated stock assessments were released.

Bias in old assessments

Hindcast stock biomass estimates for the 230 stocks spanned different year periods, with some stocks not assessed after 2010 (fig. S2). Consequently, differences in mean B/B_{max} for different sets of stocks may have influenced the general downward revisions in B/B_{max} from older to most recent assessments (Fig. 2). We considered this potential misrepresentation by standardizing biomass within stocks as the ratio relating stock biomass in the year of stock assessment to most recent assessment value for the same year before calculating the overall mean (fig. S3, A and B). Large downward revisions in stock biomass in later assessments, and a consistent tendency for phantom recoveries, typified overfished stocks (fig. S3B).

We investigated possible reasons for stock biomass downsizing in updated assessments by calculating a log response ratio to contrast old versus the most recent assessment values (Δ; stock biomass from the final year reported in older assessments relative to updated biomass for the same year in the most recent assessment; Fig. 1) for B/B_{max}, B, and B_{max}. Most older stock assessments overestimated B/B_{max} relative to later hindcast estimates for that year. A total of 152 of the 230 stocks (66%) had positive assessment bias, indicating that the full extent of biomass depletion was not known when management actions were considered. Biomass depletion estimates were negatively biased for 77 stocks (33%), in

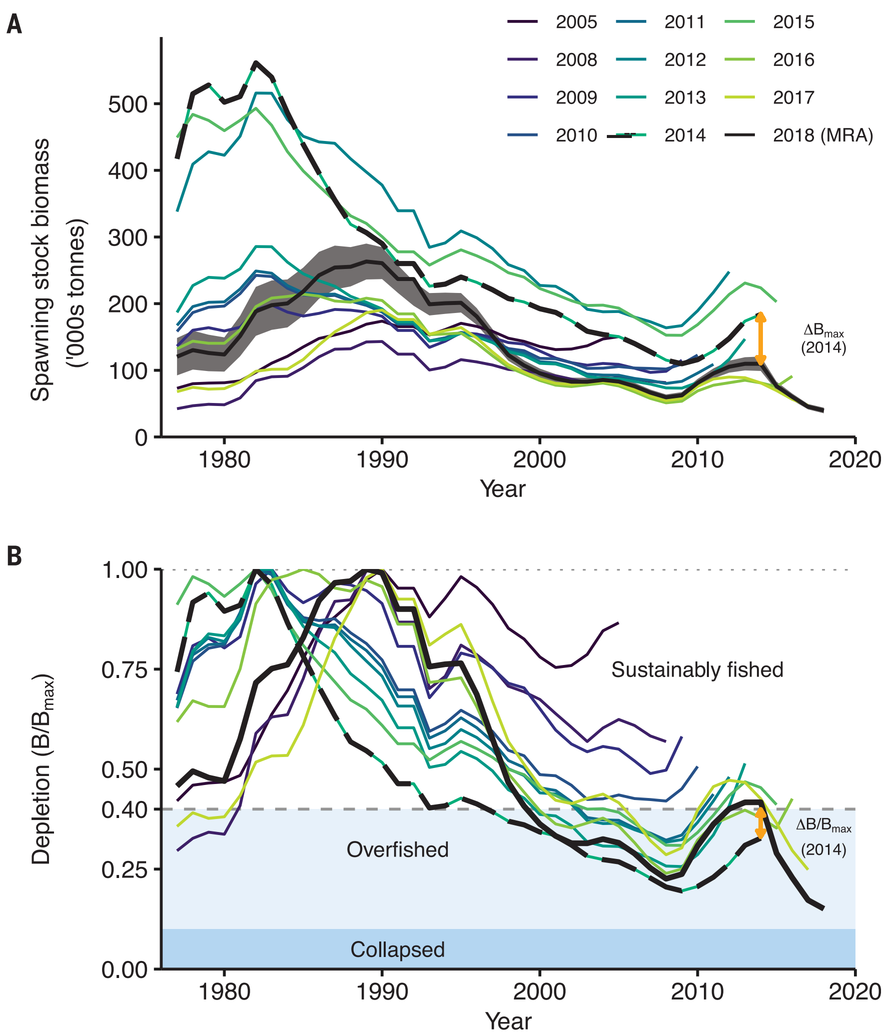

Fig. 1. Hindcast trends in stock biomass and depletion for Pacific cod (Gulf of Alaska). Stock models published in different years provided varying estimates of historical trends in stock biomass (B; tonnes) (*37*). Each colored curve connects best-fit modeled hindcast values. (**A**) Bias in spawning stock biomass. Orange arrows show the magnitude of bias in B (ΔB) calculated as the log ratio of B in the final year for the stock in an older assessment (2014 example) relative to the estimate of B in the same year as hindcast in the most recent assessment (MRA) (thick black curve). Shading indicates uncertainty (±1 SD) associated with modeled output in the most recent assessment. (**B**) Bias in stock depletion ($\Delta B/B_{max}$).

Downloaded from https://www.science.org on August 30, 2024

which case management decisions would have been precautionary. Calculated as a back-transformed geometric mean across all stocks, B/B_{max} was overestimated by an average of 11.5% (±2.3% SE) at the time of stock assessment release. Parsing of B/B_{max} into its two components indicated that positive bias in estimates of B (ΔB; 9.8 ± 3.3% SE) largely contributed to positive bias in B/B_{max}, whereas bias in B_{max} (ΔB_{max}; −1.6 ± 2.6% SE) had little effect.

Bias was extremely large for some stocks. Estimates of B/B_{max} in old assessments were more than 1.5× the most recent assessment values for 17% of assessments and more than 2× the most recent assessment values for 8.5% of assessments. Half of older estimates of B/B_{max} lay outside the range of 0.90× and 1.32× of the most recent estimate hindcast for the same year.

Clear patterns of overestimation of B/B_{max} were also observed for overfished stocks when bias in estimates at the time of stock assessment release was plotted against the number of years to most recent assessment (fig. S3D). More so than for sustainable stocks (fig. S3C), $\Delta B/B_{max}$ in the final assessment year for overfished stocks greatly exceeded the bias in earlier years (fig. S3D). In other words, overestimation bias was primarily a feature of depletion estimates for the year when the assessment was released and management decisions made rather than for earlier years in the modeled time series. This finding was not dependent on applying the criterion $B/B_{max} < 0.4$ to assess

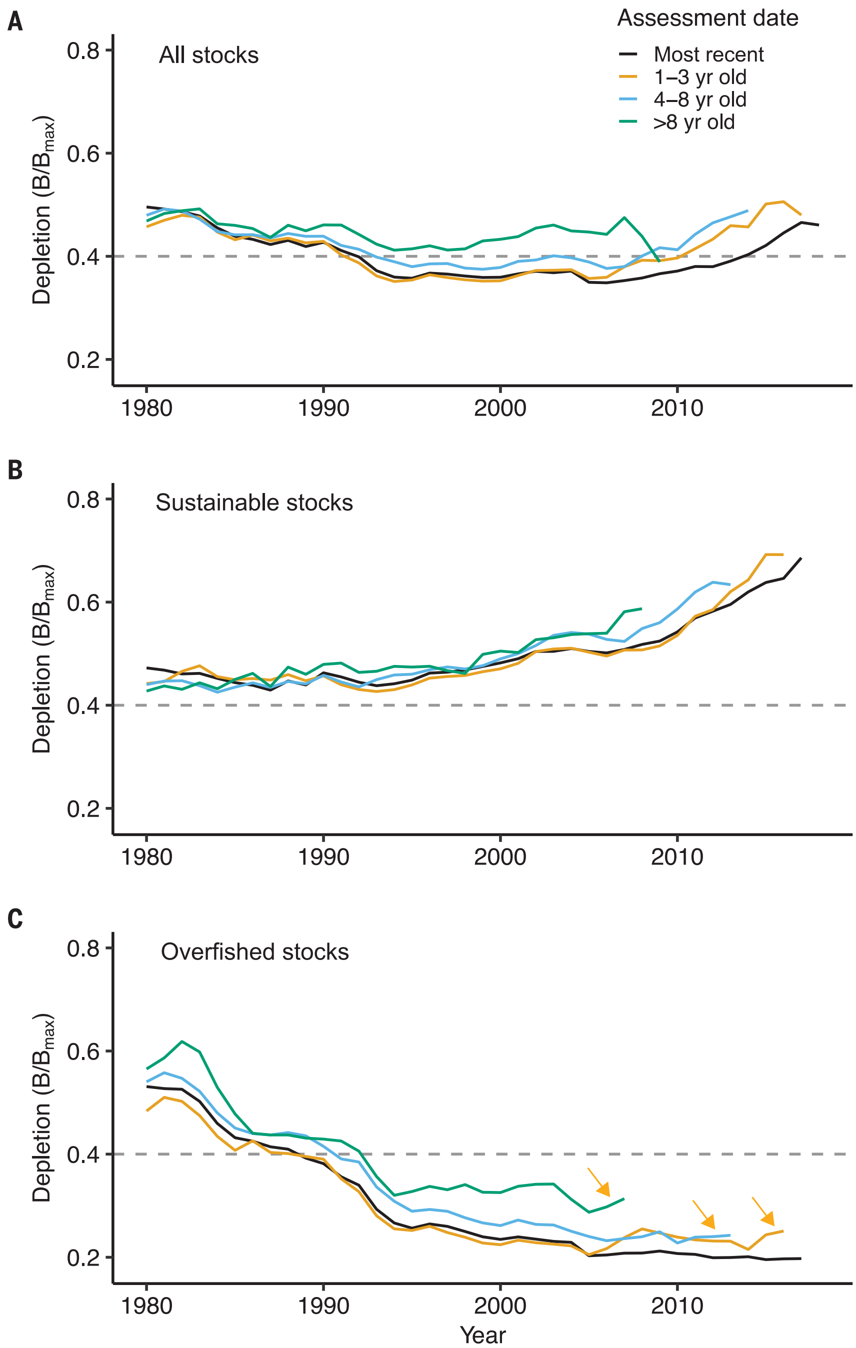

Fig. 2. Variation through time in estimates of mean depletion (B/B_{max}) between 1980 and 2018. (**A** to **C**) Variation is averaged for all 230 stocks (A), 137 sustainable stocks (B_{max} > 0.4) (B), and 93 overfished stocks (B_{max} < 0.4) (C). Curves depict the most recent assessment (black line) and older assessments completed 1 to 3 years, 4 to 8 years, or >8 years before the most recent assessment. Values for years with <10 stock assessments have been excluded because of high uncertainty. Sample sizes are shown in fig. S2. Arrows indicate phantom recoveries.

overfishing in the final assessment year. When overfished stocks were alternatively identified 5 years before the final stock assessment year, results changed little (fig. S4).

The existence of acute bias in the final year of assessments for overfished stocks led to positive bias in the final year of their modeled stock trends (fig. S3, E and F)—i.e., exaggerated stock recovery. For example, a stock trajectory that was truly flat would appear as a rising trend in the modeled time series—a phantom recovery—because B/B_{max} estimates were inflated in the most recent year but not early years. Managers of overfished stocks would thus be twice mistaken—first, by concluding that a stock is less overfished than reality and second, because an inaccurate trajectory suggesting stock recovery may signal little need for strong regulatory controls (*20*). The existence of phantom recoveries suggests that many highly managed stocks worldwide could be locked into an overfished state, regardless of an apparent rise in biomass in recent assessments.

We assessed the contributions of seven factors that potentially influenced biases in biomass estimates ($\Delta B/B_{max}$, ΔB, and ΔB_{max}) using generalized linear mixed-effects models (GLMMs) (Fig. 3): (i) Depletion. Depleted stocks may be more biased owing to fewer data for modeling or sociopolitical pressures to take nonconservative management options. (ii) Assessment age. Fewer years between old stock assessment and most recent assessment may reduce bias through greater overlap in time series or more similar model structure. (iii) Value. Fisheries with lower stock value may have more bias because few management resources are devoted to model development and data collection. (iv) Sea surface temperature (SST) trend. Rising regional SSTs may lead to greater bias through unpredictable interactions and ecosystem changes. (v) Mean SST. Tropical fisheries may have higher bias because prediction is increasingly difficult with high species richness, complex food webs, short-lived populations, or little fisheries data. (vi) Duration. Longer time series may have better calibrated models. (vii) Clupeoids. High interannual variability driven by climate cycles may increase unpredictability for small pelagic clupeoids (e.g., sardines and pilchards).

After initial testing of interaction strength between all factors and depletion (*10*), we included two interaction terms in the GLMMs—(i) assessment age × depletion and (ii) value × depletion—because these two parameters alone provided an improved model fit [lowest Watanabe-Akaike information criteria statistic (*21*); table S2]. We also tested whether GLMM results were consistent through the long term by deleting data for years after 2010, reassigning most recent assessments, and then rerunning models for $\Delta B/B_{max}$.

Biases in depletion estimates ($\Delta B/B_{max}$) were significantly affected by the assessment age × depletion interaction and also by the value × depletion interaction, SST trend, and duration [95% credible intervals (CIs) do not overlap 0; Fig. 3A]. The components ΔB and ΔB_{max} were influenced by the age × depletion interaction, depletion, age, and value covariates in the same direction as $\Delta B/B_{max}$, whereas other covariates displayed varying responses. Both ΔB and ΔB_{max} showed significant assessment age × depletion interactions (Fig. 3).

The value × depletion interaction for $\Delta B/B_{max}$ was driven by a tendency for bias among collapsed stocks to increase with stock value, whereas $\Delta B/B_{max}$ declined with value in sustainable stocks (fig. S5). Overfished high-value

Downloaded from https://www.science.org on August 30, 2024

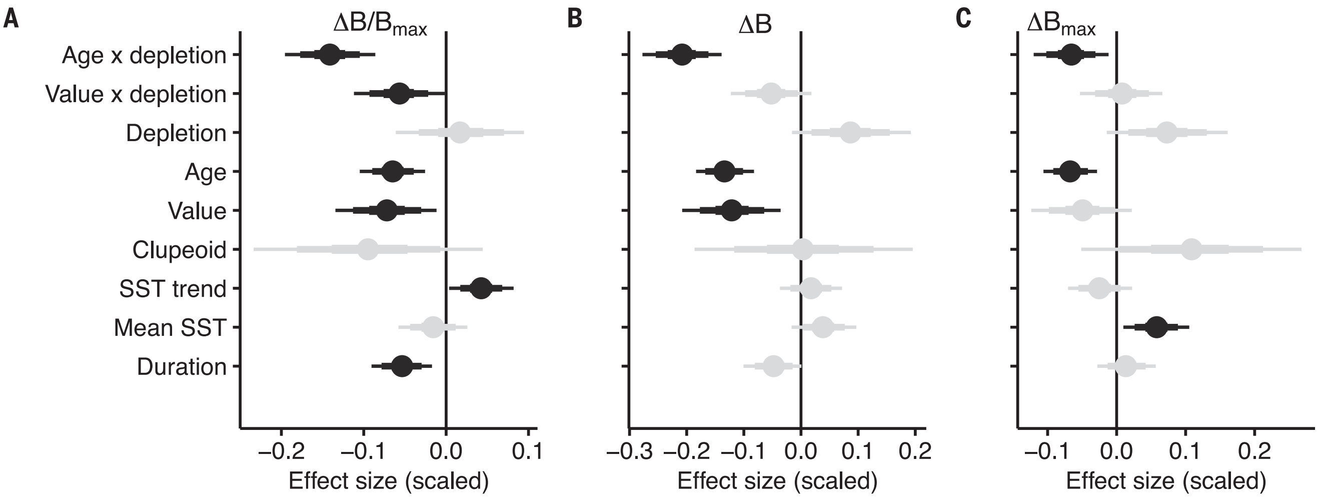

Fig. 3. Varying influences of covariates on bias in stock model output. Coefficient estimates were calculated from GLMMs relating bias Δ to seven covariates plus the interactions assessment age × depletion and value × depletion. (**A**) $\Delta B/B_{max}$. (**B**) ΔB. (**C**) ΔB_{max}. Error bars indicate 50%, 80%, and 95% CIs and are highlighted black when the 95% CIs do not overlap 0. Effect sizes were scaled by the SD of values. Negative effect sizes indicate that bias (historical overestimation of stock biomass) is less at high covariate values.

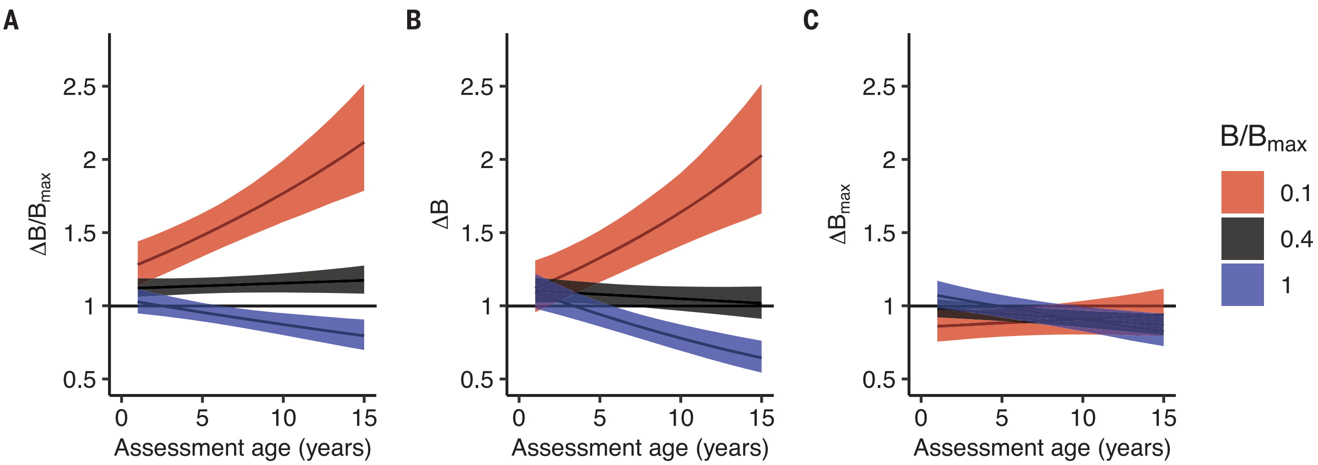

Fig. 4. Depletion bias rapidly increases with assessment age for overfished stocks. (**A** to **C**) Generalized log-linear mixed model output depicts relationships between bias and assessment age, with other covariates set to 0 for $\Delta B/B_{max}$ (A), ΔB (B), and ΔB_{max} (C). Separate curves are modeled for sustainable stocks with no depletion (B/B_{max} = 1; blue), stocks at the overfished threshold (B/B_{max} = 0.4; black), and collapsed threshold (B/B_{max} = 0.1; red). Shaded areas indicate 95% CIs. Positive values for bias indicate that older assessments overestimated stock size.

stocks showed less bias in both ΔB and ΔB_{max} compared with low-value stocks, indicating greater consistency in assessments for stocks with high value (fig. S5). Consistent with expectations, stock assessments calibrated with long time series (duration) had relatively low bias ($\Delta B/B_{max}$), and assessments for stocks in rapidly warming locations (SST trend) had relatively high bias (Fig. 3A).

The assessment age × depletion interaction exhibited the strongest and most robust effect, as underscored by a significant ($P < 0.05$) outcome in the GLMM consistency test where data after 2010 were deleted (fig. S6). By contrast, other factors, although generally having similar effect sizes as with the full dataset, were no longer significant after exclusion of years after 2010 owing to lower statistical power (fig. S6). The effect of assessment age (i.e., gap in years between stock assessment and most recent assessment) on $\Delta B/B_{max}$ diverged sharply between sustainable and overfished stocks (Fig. 4A), reflecting variability in ΔB (Fig. 4B) rather than ΔB_{max} (Fig. 4C). With 14 years of hindsight, estimates of $\Delta B/B_{max}$ had halved for collapsed stocks (i.e., 2× bias) while increasing by 23% (0.81× bias) for sustainable stocks (Fig. 4A).

Given the possibility that the strong assessment age × depletion effect may have been driven by improvements in the stock assessment approaches in recent calendar years leading to reduced bias, we reran GLMMs substituting year of most recent assessment for assessment age. We found no evidence of less bias in recent assessments for either overfished or sustainable stocks (fig. S7).

The extent to which bias varies with different stock modeling approaches was not evaluated in this work but is an important next step for reducing systematic errors. For example, the widely used Stock Synthesis assessment framework (*5*) allows for flexible modeling structure and parameterization but can yield optimistic assumptions about stock productivity and recovery potential versus empirical evidence (*12*).

Downloaded from https://www.science.org on August 30, 2024

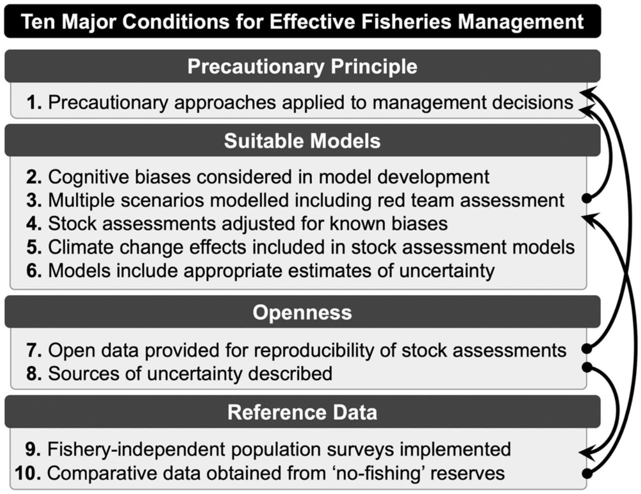

Fig. 5. Major conditions needed to improve the accuracy of fisheries stock assessment models and fisheries sustainability. (i) Precaution. Effective fisheries management requires appropriate precaution because of high uncertainty in stock assessments (*8*, *38*). Pressure to select the most optimistic scenario causes ratcheting, where stocks incrementally decline each time that a more pessimistic view was warranted. (ii) Consideration of bias. Modeling approaches require careful consideration to avoid possible cognitive biases. Simplification can reduce opaqueness, assisting decision-making. (iii) Multiple scenarios. Ensemble techniques that compare outputs of multiple models are generally needed, including an independent red team assessment where pessimistic scenarios are encouraged (*20*). (iv) Retrospective analyses. Assessments for overfished stocks should consider biases evident through retrospective analysis, given that systematic error likely persists. (v) Consideration of changing climate. Sea temperatures now fall above historical extremes in many regions, leading to rapid population changes among species (*39*). (vi) Independent parameter selection. Stock assessments should be conducted in a framework that uses the best scientific information and appropriately estimates uncertainty, such as a Bayesian framework. (vii) Open data. Online deposition of annotated modeling code and data allows independent validation and increases public confidence. (viii) Full consideration of uncertainty. All sources of stock assessment uncertainty should be explicitly described, including parameter selection, with sufficient detail for users to assess whether variation exceeds bounds fit for purpose. (ix) Fishery-independent surveys. Appropriately designed field surveys, particularly assessments of changing fish biomass, are necessary to test assumptions and to train and validate models. Data obtained during commercial fishery operations are generally insufficient because of biases associated with catch hyperstability (*22*), survey location, and improving technology. (x) Marine reserve surveys. Analysis of independent data from effective no-fishing reserves, where environmental change occurs in the absence of fishing, provides invaluable context for distinguishing fishing mortality from impacts of changing climate and pollution, for estimating benchmarks for unfished spawning stock biomass, and for greater assurance that adequate spawning stock persists long-term (*38*, *40*).

Future research priorities include examining how different assessment model types and inputs influence the magnitude of bias and uncertainty (*12*), the reliability of common model parameter inputs, and differences in bias between time series calibrated by standardized scientific survey versus fishery catch-per-unit-effort, which can be biased (*22*). Another important research avenue is the role of external factors that inhibit the rebuilding of highly overfished stocks, which can show little recovery even after fishing is greatly reduced (*23*, *24*), including reproductive failure when abundance drops below critical Allee thresholds (*25*). Such potential consequences of overfishing highlight the need for precaution to avoid reaching this state.

Consequences of observed bias for global assessments of fisheries sustainability

To illustrate consequences of observed bias for global fisheries status assessments, we adjusted B/B_{max} values for all 230 stocks using individual stock bias estimates to represent probable bias in each most recent assessment. Calculations were standardized using a retrospective analysis looking back from 10 years in the future because assessment age was an important predictor of bias. We assumed that $\Delta B/B_{max}$ remained unchanged in 10 years' time—an assumption supported by the stable relationship between bias and most recent assessment calendar year (fig. S7). By comparing current status from most recent assessments to status corrected for bias in 10 years' time, we estimate 1.29× more investigated stocks (53 versus 41) than presently indicated have passed below the B/B_{max} limit reference point of 0.2 [suggesting impaired recruitment (*18*)]. Moreover, 1.85× more assessed stocks (24 versus 13) have collapsed ($B/B_{max} < 0.1$) than currently recognized. Such distortions potentially affect conclusions from meta-analyses reliant on global assessment databases, including overly optimistic predictions for how well stock status can be managed. Meta-analyses of stock assessment databases have been used, for example, to infer the global status of fisheries (*16*), the role of management in stock recovery (*2*), the impact of climate change on fisheries production (*26*), and future scenario exploration for fisheries (*27*).

Dealing with uncertainty

Uncertainty associated with stock assessments includes interrelated process, observation, model, and estimation uncertainties (*28*). These uncertainties led to high interannual variability and consistent bias evident in our analyses, raising doubts about the accuracy of integrated stock assessment models regardless of sophistication. Bias erred toward stable stocks, with overestimation of biomass for overfished stocks and underestimation for sustainable stocks (Fig. 4).

The tendency for bias to inaccurately imply stable stock trajectories for both increasing and declining stocks suggests systematic technical issues or confirmation bias (*29*), where overfitted models align with modeler's expectations. Some modeled parameters are particularly relevant in this context, including natural mortality and the steepness of the stock-recruitment relationship (i.e., the extent that future stock replenishment depends on spawner biomass). Early investigations optimistically suggested that maximum productivity could be assumed with biomass reduced to only 0.2 B/B_0 (*30*). A subsequent meta-analysis found little association between recruitment and spawning biomass (*31*). A more recent study indicated that stock productivity declines when B/B_0 falls below 0.5 (*12*). Subjective decisions on such highly uncertain parameters provide a possible pathway for systematic bias and management failures (*32*, *33*). In particular, poor parameter choices can delay recognition of collapsing stocks, which become obvious only with subsequent data and hindsight (*34*).

Although some stock assessment reports candidly describe parameter adjustments needed to avoid projections of stock collapse (*35*), parameter tweaking is rarely well communicated to managers and policy-makers. Modeled output presented in reports typically depicts uncertainty generated through randomization routines included in model algorithms (Fig. 1A). By contrast, the much higher uncertainty contributed by model adjustment, choice of model structure (including spatial dynamics), input parameters, and inadequacy of input data is frequently overlooked. When older stock assessment trends (Fig. 1) are presented to decision-makers, rather than the most recent assessment alone, the scale of uncertainty is more obvious. Nevertheless, recognition of uncertainty by managers is not enough unless it also elicits precaution, such as reducing catch quotas to allow for assessment errors (*8*).

We concur with the many who argue that overexploitation can be avoided. We highlight 10 conditions which, combined, can fundamentally improve fisheries stock assessment modeling and policy interventions that secure the long-term sustainability of fisheries (Fig. 5).

Downloaded from https://www.science.org on August 30, 2024

Many of these conditions already apply in particular regions—the challenge is to ensure that all conditions are routinely considered in all regions, including appropriate precaution for fisheries where data and resource limitations prevent even the most basic stock assessments. Although inadequate precaution can generate short-term catch benefits, it erodes long-term societal interests through loss of species with immense economic, environmental, cultural, recreational, and spiritual value. Considering just the economic value, an inability to reverse decline when fish numbers are decreasing ultimately has far-reaching negative impacts on the fisheries workforce, ecosystems and their stability, and the world's capacity to provide protein to an increasing population (*36*).

REFERENCES AND NOTES

1. Food and Agriculture Organization of the United Nations (FAO), *The State of World Fisheries and Aquaculture 2020. Sustainability in Action* (FAO, 2020).
2. R. Hilborn *et al.*, *Proc. Natl. Acad. Sci. U.S.A.* **117**, 2218–2224 (2020).
3. G. L. Britten, C. M. Duarte, B. Worm, *Proc. Natl. Acad. Sci. U.S.A.* **118**, e2108532118 (2021).
4. Y. Rousseau, R. A. Watson, J. L. Blanchard, E. A. Fulton, *Proc. Natl. Acad. Sci. U.S.A.* **116**, 12238–12243 (2019).
5. R. D. Methot Jr., C. R. Wetzel, *Fish. Res.* **142**, 86–99 (2013).
6. R. Froese, N. Demirel, G. Coro, K. M. Kleisner, H. Winker, *Fish Fish.* **18**, 506–526 (2017).
7. A. E. Punt *et al.*, *Fish. Res.* **198**, 117–128 (2018).
8. S. Ralston, A. E. Punt, O. S. Hamel, J. D. DeVore, R. J. Conser, *Fish Bull.* **109**, 217–231 (2011).
9. R. Bi *et al.*, *Fish Fish.* **24**, 126–141 (2023).
10. Materials and methods are available as supplementary materials.
11. A. E. Punt, A. D. M. Smith, D. C. Smith, G. N. Tuck, N. L. Klaer, *ICES J. Mar. Sci.* **71**, 469–483 (2014).
12. R. Froese *et al.*, *Acta Ichthyol. Piscat.* **53**, 173–189 (2023).
13. M. B. Schaefer, *Inter-Am. Trop. Tuna Comm. Bull.* **1**, 23–56 (1954).
14. J. T. Thorson, J. M. Cope, T. A. Branch, O. P. Jensen, *Can. J. Fish. Aquat. Sci.* **69**, 1556–1568 (2012).
15. J. K. Baum, B. Worm, *J. Anim. Ecol.* **78**, 699–714 (2009).
16. B. Worm *et al.*, *Science* **325**, 578–585 (2009).
17. R. Hilborn, *Mar. Policy* **34**, 193–196 (2010).
18. R. A. Myers, A. A. Rosenberg, P. M. Mace, N. Barrowman, V. R. Restrepo, *ICES J. Mar. Sci.* **51**, 191–205 (1994).
19. H. Gjøsæter, P. Dalpadado, A. Hassel, *ICES J. Mar. Sci.* **59**, 959–967 (2002).
20. G. J. Edgar, T. J. Ward, R. D. Stuart-Smith, *Aquat. Conserv.* **28**, 1337–1350 (2018).
21. A. Vehtari, A. Gelman, J. Gabry, *Stat. Comput.* **27**, 1413–1432 (2017).
22. S. J. Harley, R. A. Myers, A. Dunn, *Can. J. Fish. Aquat. Sci.* **58**, 1760–1772 (2001).
23. D. P. Swain, H. P. Benoît, *Mar. Ecol. Prog. Ser.* **519**, 165–182 (2015).
24. G. M. Daskalov, A. N. Grishin, S. Rodionov, V. Mihneva, *Proc. Natl. Acad. Sci. U.S.A.* **104**, 10518–10523 (2007).
25. E. A. Aalto *et al.*, *Am. Nat.* **193**, 391–408 (2019).
26. C. M. Free *et al.*, *Science* **363**, 979–983 (2019).
27. C. Costello *et al.*, *Proc. Natl. Acad. Sci. U.S.A.* **113**, 5125–5129 (2016).
28. K. M. Privitera-Johnson, A. E. Punt, *ICES J. Mar. Sci.* **77**, 515–526 (2019).
29. E. A. Fulton, *Fish Fish.* **22**, 428–448 (2021).
30. R. A. Myers, K. G. Bowen, N. J. Barrowman, *Can. J. Fish. Aquat. Sci.* **56**, 2404–2419 (1999).
31. C. S. Szuwalski, K. A. Vert-Pre, A. E. Punt, T. A. Branch, R. Hilborn, *Fish Fish.* **16**, 633–648 (2015).
32. M. Mangel *et al.*, *Can. J. Fish. Aquat. Sci.* **70**, 930–940 (2013).
33. T. J. Miller, E. N. Brooks, *Fish Fish.* **22**, 634–645 (2021).
34. J. A. Hutchings, R. A. Myers, *Can. J. Fish. Aquat. Sci.* **51**, 2126–2146 (1994).
35. G. M. Leigh, M. F. O'Neill, J. Stewart, Stock assessment of the Australian east coast tailor (Pomatomus saltatrix) fishery, Technical Report, State of Queensland (2017); http://era.daf.qld.gov.au/id/eprint/5689/.
36. S. Coulthard, D. Johnson, J. A. McGregor, *Glob. Environ. Change* **21**, 453–463 (2011).
37. NOAA Fisheries, Stock SMART - Status, Management, Assessments & Resource Trends, Assessment Time Series Data (2020); https://www.st.nmfs.noaa.gov/stocksmart.
38. T. Lauck, C. W. Clark, M. Mangel, G. R. Munro, *Ecol. Appl.* **8**, S72–S78 (1998).
39. A. J. Pershing *et al.*, *Science* **350**, 809–812 (2015).
40. B. J. Hanns, T. Haggitt, N. T. Shears, *Biol. Conserv.* **276**, 109775 (2022).
41. C. Brown, cbrown5/fishery-retrospective-analysis: Stock assessment models overstate sustainability of the world's fisheries, v1.0.2, Zenodo (2024); https://doi.org/10.5281/zenodo.12043237.

ACKNOWLEDGMENTS

We thank C. Kuempel, C. Buelow, R. Methot, T. Ward, and anonymous reviewers for constructive comments and S. Barbeaux for data associated with Fig. 1. **Funding:** No external funding was received. **Author contributions:** G.J.E. conceived the study and wrote the initial draft; C.J.B., G.J.E., and A.E.B. analyzed data and organized figures; and all authors provided intellectual input and contributed to the text. **Competing interests:** The authors declare no competing interests. **Data and materials availability:** All data needed to evaluate the conclusions in the paper are present in the paper and/or the supplementary materials. Raw data and computations in R are available through Zenodo (*41*).

License information: Copyright © 2024 the authors, some rights reserved; exclusive licensee American Association for the Advancement of Science. No claim to original US government works. https://www.science.org/about/science-licenses-journal-article-reuse

SUPPLEMENTARY MATERIALS

science.org/doi/10.1126/science.adl6282
Materials and Methods
Figs. S1 to S8
Tables S1 and S2
References (*42–53*)
MDAR Reproducibility Checklist

Submitted 29 October 2023; accepted 25 June 2024
10.1126/science.adl6282

Downloaded from https://www.science.org on August 30, 2024