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ARTICLE

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Abstract

Single-species surplus production models are often used to assess multispecies assemblages in data-poor situations where catch and effort data are insufficient to perform individual species assessments. We examined the performance of single-species surplus production models applied to aggregated multispecies assemblages and explored the incorporation of time-varying parameters to improve model estimates. We simulated the dynamics of three species with different intrinsic growth rates and survey catchabilities over 50 years in the presence of fishing and a single fishery-independent survey. Schaefer surplus production models with and without time-varying growth rate and catchability were fitted to simulated data. We then compared the ability of each model to accurately estimate multispecies maximum sustainable yield and terminal year biomass and to accurately reflect overall trends in individual component stocks. All models produced biased estimates, but the accuracy of multispecies assemblage maximum sustainable yield was improved with the incorporation of time-varying parameters. The terminal biomass of the assemblage was best estimated by a basic production model in two of three scenarios. Multispecies assemblage trends were not reflective of all individual component species, resulting in situations in which some species were overexploited and others underexploited. Although the incorporation of time-varying parameters improved the accuracy of some estimates in this application, the direction and magnitude of bias may not be predictable unless the relative differences in growth rate and catchability among species in the assemblage are known. If single-species surplus production models are the only viable option for modeling assemblages, precautionary reference points should be adopted. Scaling the level of precaution to the range of growth rates among species in the assemblage is recommended.

Determining the status of data-poor fish species is an important challenge facing many fisheries management agencies. Interest in assessing data-poor fish stocks has increased in recent years in the USA following the reauthorization of the Magnuson–Stevens Act of 2006, which required catch limits for all marine and anadromous species with federal fishery management plans. However, many data-poor species lack the catch, effort, and life history information necessary to conduct single-species assessments for specifying catch limits either because several species in the same region are difficult to distinguish or collecting species-specific data is cost prohibitive. In such circumstances, one approach is to aggregate and assess multiple species using a single-species surplus production model (SSPM; Pauly 1984; Sparre and Venema 1998). Single-species surplus production models have been applied to many multispecies assemblages, including tropical fishes (Ralston and Polovina 1982), sharks (McAllister et al. 2001; SEDAR 2006, 2007; Jiao et al. 2009), demersal fishes (Brander 1977; Mueter and Megrey

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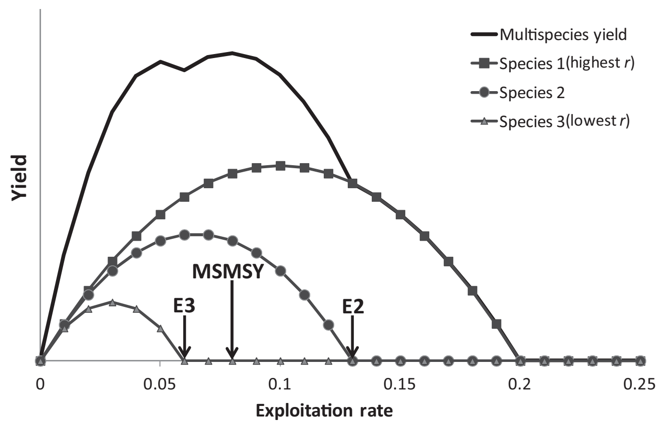

FIGURE 1. Hypothetical example of single-species and multispecies yields as a function of exploitation rate when the intrinsic growth rate (*r*) differs among species and all species are subject to the same exploitation rate. MSMSY is the maximum sustainable yield for the multispecies assemblage; E3 is the exploitation rate at which species 3 is extirpated, and E2 is the exploitation rate at which species 2 is extirpated.

2006), Northwest Atlantic finfish (Brown et al. 1976), and multispecies fisheries in developing countries (Koslow et al. 1994; Gascuel and Ménard 1997; Ould Dedah et al. 1999; Halls et al. 2006; Lachica-Aliño et al. 2006).

The ability to assess data-poor stocks with SSPMs is appealing in its simplicity. However, such assessments are likely to violate the underlying assumption that the data used in an SSPM come from a homogeneous stock (Prager 1994; Quinn and Deriso 1999). This assumption will almost always be violated because catchability, life history, and fishing pressure likely differ among the individual species in an assemblage (Fox 1974; Brander 1977; Pauly 1984; Sparre and Venema 1998). In the extreme case, managing according to the results of an assessment in which the assumption of stock homogeneity is violated has the potential to functionally extirpate one or more species within the assemblage because the parabolic yield curve underlying an SSPM may not be reversible (Kirkwood 1982; Pauly 1984; Sparre and Venema 1998). Consider a hypothetical example in which growth rates differ among the species in an assemblage and management is aimed at achieving multispecies maximum sustainable yield (MSMSY; Figure 1). Species 1 would be extirpated if exploitation was sustained above level E3, and species 2 would be extirpated above level E2. In this example, exploitation levels above MSMSY cannot necessarily be reduced with the expectation that yields will return to MSMSY.

Although the theoretical implications of applying SSPMs to multispecies assemblages have been explored (Brown et al. 1976; Pope 1976a, 1979; Kirkwood 1982; Pauly 1984), the performance of statistically fitted, nonequilibrium SSPMs in assessing heterogeneous multispecies assemblages has not been rigorously evaluated. Kleiber and Maunder (2008) demonstrated the consequences of pooling catch-per-unit-effort (CPUE) data across multiple species to form a single index of abundance. The resulting index was found to be reflective of the changes in true abundance only in the unlikely event that all species have the same catchability. Aggregate CPUE did not track aggregate abundance even in situations where the component single-species indices were accurate. Although aggregating CPUE may be a convenient way to treat data, aggregate CPUE is likely to provide misleading trends in relative abundance and should not be relied upon for management (Maunder et al. 2006; Kleiber and Maunder 2008).

One potential method of implicitly accounting for changes in the aggregate catchability or life history parameters of a multispecies assemblage is to allow parameters to vary over time. If individual biomass trends differ among species in an assemblage as a result of variation in life history characteristics (e.g., growth or availability to survey gear), the aggregate parameters describing multispecies assemblage dynamics (e.g., assemblage growth rate or catchability) will change over time. For example, if an assemblage such as the hypothetical example in Figure 1 is managed to achieve MSMSY, species 3 will decline over time and become a smaller proportion of the assemblage; as a result, the average aggregate growth rate will increase. If an SSPM is used to assess a heterogeneous multispecies assemblage, the incorporation of time-varying growth or catchability parameters may help account for the resulting changes in aggregate dynamics and improve model performance. Wilberg et al. (2010) reviewed the estimation of time-varying catchability in SSPMs and suggested the use of such parameters to account for multiple known or unknown causes of changing catchability when assessing a single stock; however, to our knowledge, time-varying parameters have not been applied to SSPMs in multispecies assemblage assessments.

In this study we examined the implications of using SSPMs to assess multispecies assemblages when growth rate and catchability differ among species. The goals of our study were to (1) evaluate the ability of traditional SSPMs to assess multispecies dynamics, (2) determine whether SSPMs with time-varying parameters improve model performance, and (3) assess the potential ramifications of using SSPM-based assemblage reference points when conservation of individual species within the assemblage is desired. We were specifically interested in the ability of SSPMs to provide accurate stock status information for management of a multispecies assemblage and to monitor its component stocks. Therefore, we compared the relative errors in MSMSY and terminal biomass estimates generated by SSPMs with and without time-varying parameters. We also explored the use of SSPMs to monitor individual stocks by comparing the overall estimated trend in total multispecies assemblage biomass with that of its individual component stocks.

METHODS

We conducted a simulation study to evaluate the ability of SSPMs to estimate the dynamics of multispecies assemblages. We simulated the dynamics of an assemblage of three noninteracting species with different intrinsic growth rates and catchabilities over 50 years in the presence of fishing and a single fishery-independent survey. Three SSPMs were fitted to the simulated data: a traditional SSPM, an SSPM with a time-varying intrinsic growth rate, and an SSPM with time-varying catchability. We then compared the ability of each model to accurately estimate MSMSY and terminal assemblage biomass and to reflect the changes over time in the relative biomass of individual component stocks. The simulations were performed in AD Model Builder (Fournier et al. 2012).

Simulation model.—We simulated the population dynamics of three species individually using an independent, discrete-time, deterministic, logistic population model, namely,

$$B_{s,t+1} = \left[B_{s,t} + r_s B_{s,t}\left(1 - \frac{B_{s,t}}{K_s}\right)\right](1 - U_t), \tag{1}$$

where $B_{s,t}$ was the biomass in year t for species s, r_s was the intrinsic rate of increase for species s, K_s was carrying capacity for species s, and U_t was the fishery exploitation rate in year t. We assumed that $B_{s,0}$ was equal to K_s in the first year and that the fishery occurred at the end of each year. To avoid complications that arise when SSPMs are confronted with uninformative time series, we simulated fisheries dynamics in which U varied over time. The exploitation rate of the simulated fishery increased from 2.5% in year 1 to a peak of 20% in year 15. The exploitation rate then decreased to 10% for years 16–24 and to 5% for years 25–50. This exploitation rate time series avoided the generation of unidirectional trends in biomass that would prevent independent estimation of the r and K parameters (i.e., one-way trips; Hilborn and Walters 1992). The same time series of U_t was applied to each species in a given year. We summed catch across all three species in each year to generate total fishery catch (C) for input into the estimation model, that is,

$$C_t = \sum_{s=1}^{3}\left[B_{s,t} + r_s B_{s,t}\left(1 - \frac{B_{s,t}}{K_s}\right)\right]U_t. \tag{2}$$

We generated an index of biomass (I) for the multispecies assemblage from a simulated survey that encountered all three species, namely,

$$I_t = \left(\sum_{s=1}^{3} q_s B_{s,t}\right)e^{\epsilon_t}, \tag{3}$$

where q_s was the catchability of species s and ε_t were observation errors from a normal distribution with a mean of zero and a standard deviation (SD) of 0.2. We also considered observation errors with an SD of 0.5. All assessment models exhibited wider variability in their estimates, but the overall performance was similar to the results with an SD of 0.2; therefore, we only present results with the lower observation error.

Estimation model.—We fit a Schaefer surplus production model (Quinn and Deriso 1999) to aggregate catch and an index of biomass. Assemblage biomass followed the logistic growth model

$$\hat{B}_{t+1} = \hat{B}_t + \hat{r}_t\hat{B}_t\left(1 - \frac{\hat{B}_t}{\hat{K}}\right) - C_t. \tag{4}$$

where $\hat{B}_t$, $\hat{r}_t$, and $\hat{K}$ were the estimated assemblage biomass at time t, the intrinsic growth rate at time t, and carrying capacity, respectively. The estimated index of biomass, $\hat{I}_t$, was the product of catchability and assemblage biomass, that is,

$$\hat{I}_t = \hat{q}_t\hat{B}_t, \tag{5}$$

where $\hat{q}_t$ was survey catchability at time t. The estimation model assumed that total catch was known without error. For models with time-varying parameters, either $\hat{r}$ or $\hat{q}$ was allowed to vary according to a random walk on the log scale, that is,

$$\log_e \hat{q}_{t+1} = \log_e \hat{q}_t + \omega_t, \quad \text{or} \tag{6}$$

$$\log_e \hat{r}_{t+1} = \log_e \hat{r}_t + \omega_t, \tag{7}$$

with annual deviations (ω_t) from a normal distribution with a mean of zero and a standard deviation of 0.1. Although larger standard deviation values are typically used when modeling time-varying parameters as random walks (e.g., Wilberg and Bence 2006; Fenske et al. 2011), we found that SSPMs would not converge to unique solutions if the random walk was allowed too much flexibility. Assuming a small standard deviation implies that r and q should not exhibit large interannual fluctuations, which is to be expected given that these parameters reflect changes due to gradual shifts in species composition. Assemblage growth rate or survey catchability in the first year was an estimated parameter.

We obtained parameter estimates by minimizing the concentrated negative log-likelihood function

$$-LL_1 = \frac{n}{2}\log_e\left(\sum(\log_e(I_t) - \log_e(\hat{I}_t))^2\right). \tag{8}$$

We assumed multiplicative lognormal observation errors for the index of biomass. For models with time-varying growth or catchability, an additional likelihood term, $-LL_2$, defined as

$$-LL_2 = \frac{1}{2\sigma^2}\sum\omega_t^2, \tag{9}$$

was included for the random walk deviations.

We generated starting parameter values for the multispecies assemblage r and q by calculating the biomass-weighted r and q averaged across all species and years. The starting value for the multispecies assemblage K was simply the sum of individual species' Ks. We assumed that $\hat{B}_0$ was equal to K.

TABLE 1. Intrinsic growth rates (r) and catchabilities (q) used in the three simulation model scenarios.

	r			q		
Scenario	Species 1	Species 2	Species 3	Species 1	Species 2	Species 3
A	0.2	0.13	0.06	0.13	0.13	0.13
B	0.2	0.13	0.06	0.2	0.13	0.06
C	0.2	0.13	0.06	0.06	0.13	0.2

Scenarios.—We developed three scenarios that differed in relative survey catchability for each species (Table 1). For all scenarios, we simulated population growth assuming intrinsic growth rates of 0.2, 0.13, and 0.06 for the three species, reflecting a realistic range of estimated rates found among members of the small coastal shark complex (blacknose shark *Carcharhinus acronotus*, finetooth shark *Carcharhinus isodon*, Atlantic sharpnose shark *Rhizoprionodon terraenovae*, and bonnethead *Sphyrna tiburo*; SEDAR 2007). Survey catchability was either (A) the same for all species, (B) higher for species with faster growth rates, or (C) lower for species with faster growth rates (Table 1). We chose these scenarios to reflect simplified cases in which the assumption of constant catchability would be met for the index of abundance, the index would overweight the most productive species, or the index would overweight the least productive species. We set carrying capacity at the same value (1,000,000) for all three species. For each scenario, 1,000 data sets were generated assuming the log-scale standard deviation (SD) of observation error in the survey was 0.2.

Model performance evaluation.—Our evaluation of the SSPMs applied to multispecies assemblage data concentrated on three characteristics important to fisheries management, namely, the models' ability to (1) estimate the true MSMSY, (2) estimate the terminal biomass of the multispecies assemblage, and (3) reflect overall trends in single-species dynamics.

The estimate of MSMSY for the assemblage was calculated as the peak yield from the logistic model (Quinn and Deriso 1999), that is,

$$\widehat{\mathrm{MSMSY}} = \frac{(\hat{K}\hat{r})}{4}. \tag{10}$$

Because current conditions are often of greatest interest in fisheries management, we used the terminal year estimates of $\hat{r}$ to calculate $\widehat{\mathrm{MSMSY}}$ for models with time-varying parameters.

We calculated the relative error (RE) in MSMSY and terminal biomass as

$$\mathrm{RE} = \frac{\text{estimated} - \text{true}}{\text{true}} \times 100. \tag{11}$$

Positive values of RE indicated overestimation, whereas negative values indicated underestimation. We used the median of the absolute values of the relative errors as a measure of accuracy.

The change in assemblage biomass relative to the change in the biomass of each species across the time series was used as an indicator of the overall direction and magnitude of biomass trends. The change in assemblage biomass (i.e., relative biomass [RB]) was calculated as the proportion of biomass in the last year relative to that in the first year, namely,

$$\widehat{RB} = \frac{\hat{B}_{t=50}}{\hat{B}_{t=1}}, \tag{12}$$

and single-species relative biomass was estimated as

$$RB_s = \frac{B_{s,t=50}}{B_{s,t=1}}. \tag{13}$$

The relative difference (RD) between multispecies change in biomass and single-species change in biomass was represented as

$$\mathrm{RD_s} = \frac{D_\mathrm{s} - \hat{D}}{D_\mathrm{s}} \times 100. \tag{14}$$

Positive values of RD indicated overestimation, whereas negative values indicated underestimation.

RESULTS

Simulated Population Dynamics

Total biomass and species composition changed throughout the simulation (Figure 2). As the exploitation rate increased from 2.5% to 20% over the first 15 years, the biomass of each species declined steadily. With the decrease in the exploitation rate to 10% in years 16–24, the rate of decline in assemblage biomass decreased. In the last 25 years of the simulation, the assemblage biomass began to increase again at an exploitation rate of 5%. The species with the highest growth rate (species 1) gradually became the most abundant species in the assemblage. The species with the lowest growth rate (species 3) followed the same biomass trend as the other two species, but eventually comprised only 12% of the biomass. The relative biomass was 0.72, 0.51, and 0.16 for species 1, 2, and 3, respectively.

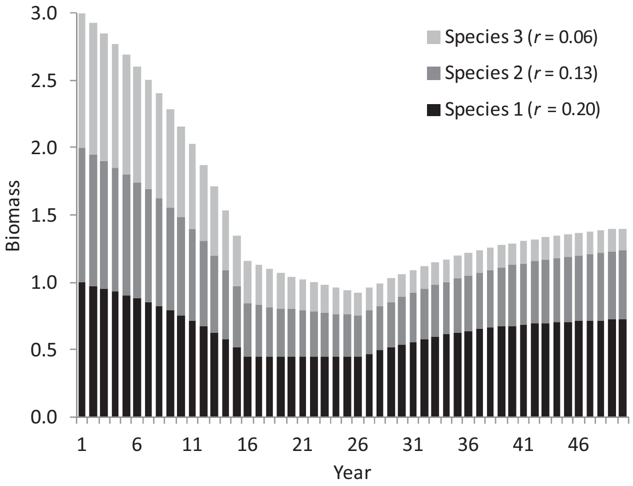

FIGURE 2. Trends in the relative biomass of three species with different intrinsic growth rates being managed as a multispecies assemblage.

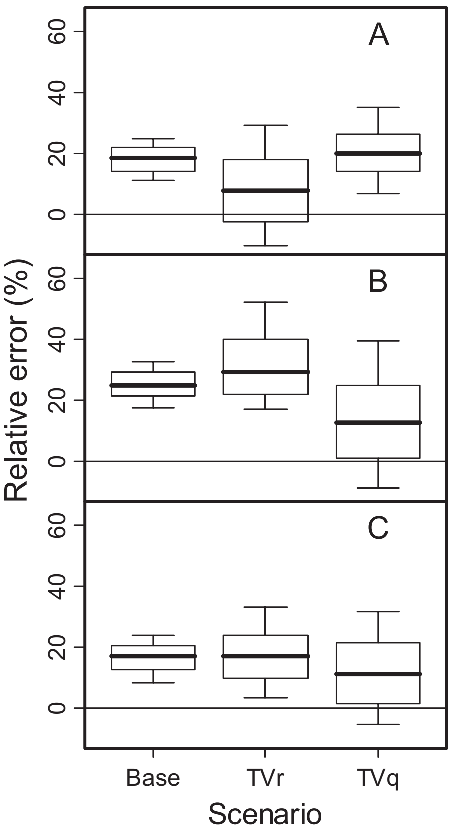

FIGURE 3. Comparison of the relative errors (REs) in estimating multispecies maximum sustainable yield among three alternative single-species surplus production models (base = the Schaefer model, TVr = the Schaefer model with a time-varying intrinsic growth rate, and TVq = the Schaefer model with time-varying catchability). Panel **(A)** compares REs when the growth rate differs among species in a multispecies assemblage. In panels **(B)** and **(C)**, both growth rate and catchability differ; in panel B catchability is higher for species with faster growth rates, whereas in panel C catchability is higher for species with slower growth rates. The lower and upper boundaries of the boxes indicate the 25th and 75th percentiles, the dark horizontal lines indicate the medians, and the whiskers indicate the 10th and 90th percentiles. Positive values of RE indicate overestimation and negative values indicate underestimation.

Estimation Model Performance

Both the basic SSPMs and models with time-varying parameters produced positively biased estimates of MSMSY in all scenarios; however, the most accurate model in each scenario was either the time-varying r or q model (Figure 3). The median relative errors for MSMSY were positively biased by 7–29% across scenarios. Although the time-varying models produced more variable estimates than the basic SSPM, their estimates of MSMSY were more accurate (Table 2). The time-varying r model produced the most accurate estimates of MSMSY when catchability was constant across species. The time-varying q model produced the most accurate estimates of MSMSY when both r and q varied among species.

The median relative errors of terminal assemblage biomass were positively biased by 12–41% (Figure 4). However, some scenarios resulted in median estimates of terminal biomass that were negatively biased by 4–29%, particularly scenario C. As with MSMSY, the estimates from the basic SSPM produced the lowest variation in relative error across scenarios. The basic SSPM produced the most accurate estimates of terminal assemblage biomass for scenarios A and C (Table 2). Time-varying models exhibited more variability within a scenario, but the amount of bias depended on the scenario. The time-varying q model was most accurate when the species with the lowest q also had the lowest r.

TABLE 2. Medians of the absolute values of the relative errors for estimates of multispecies maximum sustainable yield (MSMSY) and terminal assemblage biomass. The scenarios are described more fully in Table 1. Model types include the base (Schaefer) model, TVr (Schaefer model with time-varying intrinsic growth rate), and TVq (Schaefer model with time-varying catchability).

Variable	Scenario	Base	TVr	TVq
MSMSY	A	18	11	20
	B	25	29	15
	C	17	17	13
Terminal biomass	A	12	16	19
	B	38	41	24
	C	18	20	29

Multispecies assemblage trends were not reflective of all individual component species such that relative biomass was overestimated for some species and underestimated for others. All of the assessment models produced biased estimates of relative biomass for individual species in almost all scenarios (Figure 5). The relative difference between multispecies and single-species change in biomass was generally overestimated for species 1 (ranging from 12% to 49%), was scenario and model dependent for species 2 (ranging from −23% to +28%), and was grossly underestimated for species 3 (ranging from −291% to

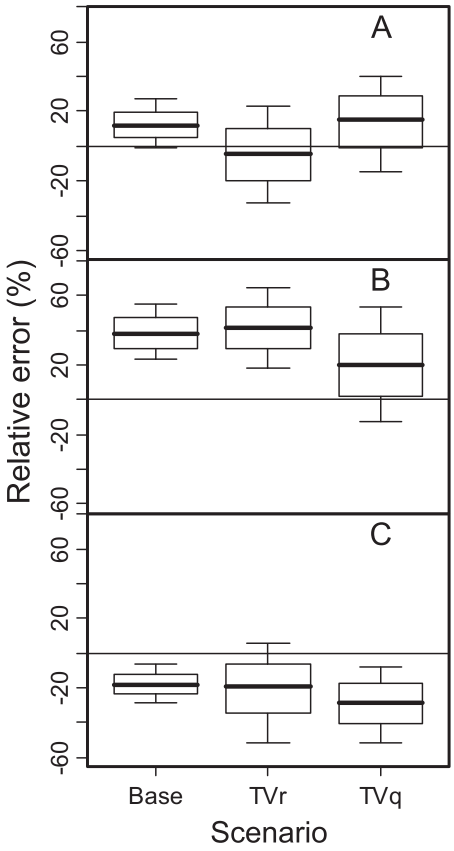

FIGURE 4. Comparison of the relative errors in estimating the terminal biomass of a multispecies assemblage among three alternative single-species surplus production models. See Figure 3 for additional details.

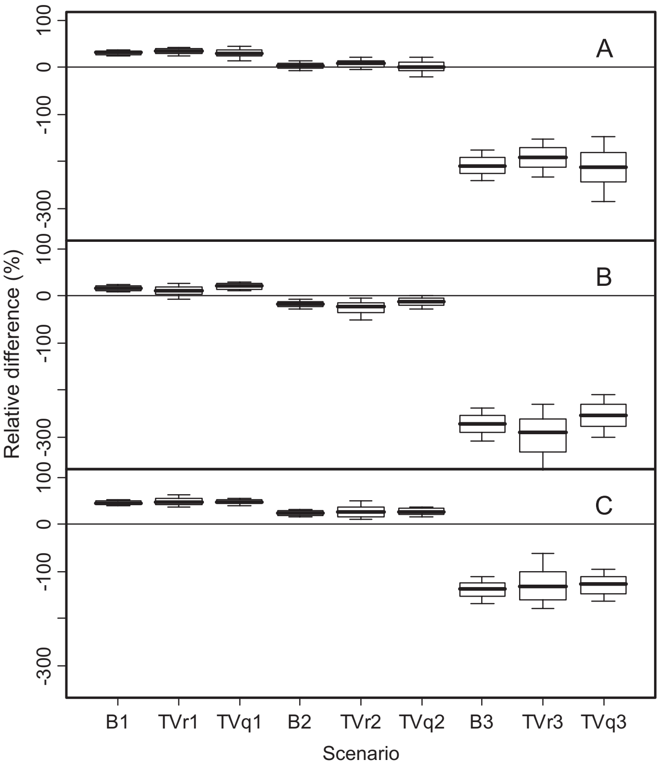

FIGURE 5. Comparison of the relative differences (RDs) between multispecies assemblage and individual component species changes in biomass over time among three alternative single-species surplus production models. The models are designated as in Figures 3 and 4 except that the base model is now denoted by the letter B; the numbers 1–3 indicate the three species. Positive values of RD indicate that the relative biomass of the assemblage was greater than that of the individual species; negative values of RD indicate that the relative biomass of the assemblage was less than that of the individual species.

−127%). The relative biomass of species 2, the species with average values of *r* and *q*, was most similar to that of the entire assemblage; such an averaging effect would be expected in circumstances where a single model used to represent multiple species returns estimates of the average species conditions. The relative biomass of species 2 was slightly lower than that of the assemblage when the species with the lowest *q* also had the lowest *r* (Figure 5B) and slightly higher than that of the assemblage when the species with the highest *q* had the lowest *r* (Figure 5C). In contrast, assemblage relative biomass was almost always higher than that of species 1 (highest *r*), resulting in positive RDs for most simulations. The relative biomass of species 3 (lowest *r*) was always much higher than that of the assemblage, resulting in extremely large negative RD values for all simulations. The incorporation of time-varying parameters did not substantially improve RD.

DISCUSSION

Our simulation study showed how the estimates of important management quantities such as MSMSY and terminal biomass generated by SSPMs are biased if the assemblage being assessed is heterogeneous with regard to intrinsic growth rate and catchability. Kleiber and Maunder (2008) demonstrated how multistock-aggregated CPUE is not an acceptable index of abundance unless catchability is the same among all stocks. Our study expands upon their work by fitting SSPMs with and without time-varying parameters to aggregated multispecies data and showing that, even when catchabilities are the same, model estimates will still be biased if growth rates differ among stocks. In all of our scenarios, MSMSY was overestimated, while the direction and magnitude of the bias in assemblage biomass depended on the growth rates and catchabilities of the individual species within the assemblage and the parameter chosen to vary over time. In many data-poor situations, too little information is available on individual species' life histories and relative catchability to confidently select which parameter (if any) to vary over time. Although intrinsic growth rate can be estimated using known life history characteristics, catchability is likely to be unknown in most data-poor situations.

Our results underestimate the potential bias in SSPM estimates because model-fitting conditions were simplified in several ways: (1) the correct assessment model was used given the logistic growth pattern used to simulate population dynamics for each species, (2) fishery catch was provided to the model without error, (3) the parameters for each species were constant over time (i.e., there was no process error), and (4) all species were subject to the same highly informative pattern of fishing mortality. These simplifications were chosen so that the evaluation of SSPM performance in regard to multispecies assemblages could be evaluated separately from more general production model performance issues that have been thoroughly examined already (Prager 1994). The incorporation of more realistic modeling situations (e.g., errors in catch, one-way trip time series) would decrease model performance.

Several simplifying assumptions were also made when simulating multispecies dynamics: (1) fishing mortality was assumed to be the same across all species, (2) all species had the same carrying capacity, (3) species did not interact, and (4) the fishery did not switch target species, as is often observed in developing fisheries (e.g., Regier and Loftus 1972). Real-world assemblages experience some or all of these complicating factors and may have more complicated and potentially unpredictable dynamics (Pope 1976b; Ralston and Polovina 1982; Sparre and Venema 1998). However, it is unlikely that these more complicated situations would result in better model performance than that of the simplified situations presented in this study. Therefore, biased estimates of MSMSY and terminal biomass should be anticipated when SSPMs are used to assess multispecies assemblages.

We encourage stock assessment scientists to carefully consider the assumptions that will be violated and how those violations will affect the management advice provided by an SSPM (Schnute and Richards 2001). The application of single-species surplus production models to multispecies assemblages has been shown to produce more precise results than single-species assessments (Pope 1979; Ralston and Polovina 1982), but we have shown in this study that SSPMs also tend to produce biased results. Increased precision should not be achieved at the expense of decreased accuracy. Both precision and accuracy should be considered when weighing the relative benefits of adopting a single versus a multispecies approach.

We found that the incorporation of time-varying growth and catchability parameters using random walks could improve the accuracy of MSMSY and terminal biomass estimates. We caution that time-varying parameters may not be estimable in many real-world situations because times series data tend to be less informative than those we simulated. In four out of six scenarios, models with time-varying parameters produced the most accurate results (Table 2; Figures 4B, 5B); however, the basic SSPM produced more accurate estimates of terminal biomass, whereas models with time-varying parameters tended to produce the most accurate estimates of MSMSY. When faced with a data-poor situation in which an SSPM is the only viable modeling option, the incorporation of time-varying parameters may be the most reasonable approach if MSMSY is the management goal. However, the best choice of parameters to vary over time and the direction and magnitude of the resulting bias may not be predictable unless the relative difference in r and q among species in the assemblage is known. Another advantage of incorporating time-varying parameters may be that estimates of uncertainty are more realistically represented; in our study, models with time-varying parameters produced a wider range of estimates (i.e., wider confidence intervals) than traditional SSPMs.

Bayesian estimation of SSPM parameters has been suggested as a better method for assessing multispecies assemblages (McAllister et al. 2001; Jiao et al. 2009). Bayesian estimation methods that assume constant r and q will also produce biased estimates if the composition of the multispecies complex changes over time due to overexploitation of some species and underexploitation of others. Bayesian estimation techniques may, however, provide a workable solution in one-way trip situations if credible informative priors can be developed for some or all of the parameters. Likewise, strongly informative priors that are accurately specified may reduce the bias in estimates.

Even if less biased estimates could be generated with the use of time-varying parameters in SSPMs, severe overexploitation of species within the assemblage and the potential loss of yield may still occur. Fishing at a rate to achieve a target biomass of a multispecies assemblage may be a risky management strategy if all components of the assemblage are valued enough to be conserved (May et al. 1979; Larkin 1982). As shown in Figure 1, if MSMSY target estimates are biased, one or more component species could be functionally extirpated while total yield for the assemblage remains high (Paulik et al. 1967; Pauly 1984; Jensen 1991). We found the species with the lowest r was severely depleted by the end of the time series even though the biomass of the multispecies assemblage as a whole was increasing (Figure 2). In contrast, the species with the highest r was underexploited, resulting in lost yield and a missed opportunity for the fishery. Several authors have argued that a fishery cannot be optimized for more than one species at a time and that, ultimately, some species in a multispecies fishery will be overexploited while others are underexploited (Jensen 1991, 1999; Dichmont et al. 2006). Pope (1974) showed theoretically how a multispecies fishery MSMSY could be attained only though a set of complicated catch quotas. Jensen (1999) simulated the population and fishery dynamics of eight Great Lakes cisco species *Coregonus* spp. caught in the same multispecies fishery and with the same gear and assessed them using a two-species surplus production model with no interspecific interactions; extinction of up to half of the species was a common result in his simulations. Using a similar model for two species, Jensen (1991) showed that fishing at the multispecies fishing mortality rate that produces the maximum sustainable yield (F_{msy}) would lead to the extirpation of lake trout *Salvelinus namaycush* if managed and assessed jointly with lake whitefish *Coregonus clupeaformis*. Dichmont et al. (2006) performed a management strategy evaluation on a two-species tiger prawn *Penaeus esculentus* and *P. semisulcatus* fishery and determined that none of the proposed management strategies allowed the stock size of both species to remain above the spawning stock size at maximum sustainable yield. Preventing overfishing of some members of a multispecies assemblage may be impossible if life histories or catchabilities differ or the multispecies fishery uses unselective gear (Pope 1976b, 1979; Pauly 1984).

For U.S. marine fisheries, the 2006 reauthorization of the Magnuson–Stevens Fishery Conservation and Management Act requires the management of individual fish stocks as a unit throughout their range; if that is not practical, a group of interrelated fish stocks may be managed as a unit. Due to the lack of species-specific data collection and the logistical challenges of assessing numerous species, many regional fisheries management councils have moved toward assessing some groups of species as stock complexes (Carmichael and Fenske 2011). For this approach to be successful, the life history and fishery characteristics of the species in the complex must be homogeneous (Cope et al. 2011). Defining appropriate stock complexes that, when assessed as a group, will not result in overexploitation of component stocks will be a serious challenge in regions with limited life history research and data collection programs (Carmichael and Fenske 2011). For management of stock complexes to be effective, stocks must be grouped into assemblages based on their productivity and catchability, with the groupings being as similar as possible. In many cases, though, species have been grouped together based on the similarity of appearance or taxonomy, which may not correspond to the similarity in productivity or catchability (e.g., sharks).

When adequate data are available, species should be assessed individually, jointly (Punt et al. 2011), or as a multispecies assemblage using stock assessment models that specifically account for interspecific or fishery gear interactions among component stocks (Hollowed et al. 2000), such as multispecies configurations of the surplus production model (Pope 1976b; Arreguin-Sanchez et al. 1992; Spencer and Collie 1997; Gamble and Link 2009), yield-per-recruit model (Pikitch 1987), or multispecies age-structured stock assessment methods (Helgason and Gislason 1979; Gislason and Helgason 1985; Jurado-Molina et al. 2005). We acknowledge that data limitations prohibit the use of multispecies models in many cases. If a few years of recent species-specific catch or survey data are available, the performance of production models may be improved if they can be modified to incorporate species-specific data at the end of the time series. However, if species-specific data are not available and SSPMs are the only viable modeling option, precautionary reference points should be adopted. More precaution than is typically considered reasonable for single-species fisheries may be needed to account for the expected bias in SSPM estimates of MSMSY. A reasonable ad hoc approach may be to scale the level of precaution to the range of growth rates among species in the assemblage, such that more precautionary management is adopted as the range in r increases among species in the assemblage.

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