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Developing an intermediate-complexity projection model for China's fisheries: A case study of small yellow croaker (*Larimichthys polyactis*) in the Haizhou Bay, China

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Abstract

Projection models are commonly used to evaluate the impacts of fishing. However, previously developed projection tools were not suitable for China's fisheries as they are either overly complex and data-demanding or too simple to reflect the realistic management measures. Herein, an intermediate-complexity projection model was developed that could adequately describe fish population dynamics and account for management measures including mesh size limits, summer closure, and spatial closure. A two-patch operating model was outlined for the projection model and applied to the heavily depleted but commercially important small yellow croaker (*Larimichthys polyactis*) fishery in the Haizhou Bay, China, as a case study. The model was calibrated to realistically capture the fisheries dynamics with hindcasting. Three simulation scenarios featuring different fishing intensities based on status quo and maximum sustainable yield (MSY) were proposed and evaluated with projections. Stochastic projections were additionally performed to investigate the influence of uncertainty associated with recruitment strengths and the implementation of control targets. It was found that fishing at F_{MSY} level could effectively rebuild the depleted stock biomass, while the stock collapsed rapidly in the status quo scenario. Uncertainty in recruitment and implementation could result in variabilities in management effects; but they did not much alter the management effects of the F_{MSY} scenario. These results indicate that the lack of science-based control targets in fishing mortality or catch limits has hindered the achievement of sustainable fisheries in China. Overall, the presented work highlights that the developed projection model can promote the understanding of the possible consequences of fishing under uncertainty and is applicable to other fisheries in China.

Key words: two-patch operating model, simulation, maximum sustainable yield, control targets, uncertainty

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1 Introduction

Fisheries projection models play an important role in evaluating fisheries stock assessment for its ability to forecast trends in stock status and catch under different candidate exploitation options (Brodziak et al., 1998; Coro et al., 2016; Matson et al., 2017). Such ability is particularly useful when uncertainties associated with natural and human dimensions are present and threaten the sustainability of fisheries (Punt and Donovan, 2007; Sethi, 2010; Memarzadeh et al., 2019). Projection models can also be collectively implemented with fisheries management strategy, stock assessment, and survey to constitute a tool known as management strategy evaluation, which is prosperously growing into a research hotspot in recent years (De Oliveira et al., 2008; Holland, 2010; Punt et al., 2016; Goethel et al., 2019).

Contrasting this strong worldwide momentum, applications of fisheries projection model remain limited in China. As the biggest player of the global capture fisheries, China's fisheries have a significant impact on the well-being of the global marine ecosystem and food supply (Worm, 2016; Su et al., 2020). The achievement of sustainable fisheries in China is impeded by a suite of challenges including data limitation, lack of scientific support, and uniform management approaches (Cao et al., 2017; Su et al., 2020). Most commercial species in China exhibit a unique form of data scarcity: the long time-series of fishery-dependent data are not available, rendering the application of data-rich stock assessment infeasible and leaving only data-limited

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methods based on sporadic fishery-independent data as viable assessment tools (Sun et al., 2018a; Zhang et al., 2018; Guan et al., 2020). Estimating stock status and maximum sustainable yield (MSY) are extremely difficult in this situation. Thus, scientific evidences are rarely used to establish fisheries management targets based on fishing mortality or catch limits. Developing fisheries projection models would be tricky under such circumstance. Another issue impeding the implementation of projection approach is how to realistically incorporate the fisheries management measures into projection models. Management measures currently employed in China include the summer closure, mesh size limits, total vessel (horsepower) limits, and regional spatial closure. These measures are indiscriminately imposed on all fisheries as a uniform sustainability solution. Many questions have been raised concerning the effectiveness of these measures, including the ambiguity of compliance levels, ignorance of stock-specific status, and lack of quantitative evaluations (Shen and Heino, 2014; Su et al., 2020). Incorporating these measures into projection models require relatively high spatio-temporal resolutions and detailed stock structure, while ignoring them will result in considerable biases in stock assessment and management (Sun et al., 2020).

In fact, previous modeling efforts in developing dynamics projection tools of various complexity are not rare, ranging from end-to-end ecosystem model to the simple unvalidated population dynamic model (Han et al., 2017; Xing et al., 2017; Chen et al., 2018; Sun et al., 2018a; Lee et al., 2020; Li et al., 2020). However, some deficiencies in these models disqualified them as appropriate projection models to evaluate fisheries in China. For example, the Object-oriented Simulator of Marine ecoSystem Exploitation developed by Xing et al. (2017) can comprehensively simulate the marine ecosystem dynamics in Jiaozhou Bay, China, with a fine spatio-temporal scale; however, the data-demanding nature undermines its large scale applicability in China. Similar issue is observed with the implementation of the food web model-Ecopath with Ecosim (Han et al., 2017). The spatial-explicit population model developed by Li et al. (2020) has plausible configurations of fish population dynamics and fleet dynamics. But it is overly complicated in spatial design and more suitable for marine conservation planning. Population models inherent to DLMtool are used to evaluate data-limited methods (Chen et al., 2018; Sun et al., 2018a). They tend to maintain a minimum complexity by using empirical assumptions or simplified population dynamics, therefore lacking the necessary validations to ensure their representativeness. The operating model developed by Lee et al. (2020) is by far the most appropriate model. It resembles the classic fish population model used in stock assessment and has the potential to be widely applied. Unfortunately, this model fails to consider the management measures used in China in the operating model configuration, making it a less meaningful tool in the context of China. Recent studies indicated that this inconsistency may lead to biases in projections and make the too less reliable in supporting management strategy evaluation (Carruthers and Hordyk, 2019). Furthermore, by neglecting the management measures, uncertainty caused by ineffective implementation is completely excluded, which has been pointed out as one of the most impactive factors resulting in management failures (Punt and Donovan, 2007).

Overall, an appropriate fisheries projection model for China should be of intermediate complexity. Here the intermediate complexity is defined as: moderate data demands to adequately describe population dynamics, minimum sufficient temporal-spatio resolutions, and realistic management reflections. The present study aims to develop and implement such a projection model. In this projection model, the major management measures currently used in China were considered including summer closure, mesh size limits, and regional spatial closure, and downscaled them onto a local level. A two-patch operating model was outlined with an adequate spatio-temporal resolution to accommodate the implementation of the considered management measures. Additionally three possible future exploitation scenarios of different fishing intensities were simulated based on status quo and MSY. Two sources of uncertainty were specifically incorporated from both natural and human dimensions and investigated their influences with the Monte-Carlo method. This model was expected to be widely used to promote the understanding of the possible consequence of fishing under uncertainty and ultimately support the achievement of sustainable fisheries.

2 Materials and methods

2.1 *Projection framework*

The framework followed the classic conceptual structure that has been developed and implemented for other fisheries (Punt et al., 2016; Sun et al., 2019). Three major models were established and connected to form a closed loop, including operating model, observation model, and management model (Fig. 1). Each model was able to emulate certain components of the realistic fishery while also being able to function on its own. These models were linked by the one-way data flow as the output data from the preceding model would be fed to the subsequent model as input data. The simulation program was written in R with the version of 3.5.3 (R Core Team, 2019).

2.1.1 *Operating model*

The operating model was dedicated to simulating the population dynamics of the small yellow croaker stock. To simulate the effects of the spatial closure measure, a two-patch structure was designed with one patch open to fishing and the other one closed patch closed to fishing. The patch sizes were determined from the size of the spatial closure area in the region (Table 1). The two patches were assumed identical in terms of habitat suitability and environmental sensitivity according to the earlier model (Li et al., 2019). Under this design, the stock became a meta-population consisting of two sub-populations differing in their exposure to fishing. Both sub-populations were age-structured with age one and six as the recruited group and plus-group, respectively. The time step for the operating model was one month, during which the meta-population could undergo a complete loop within the operating model.

Variations in population size were influenced by key processes including recruitment, growth, mortality, migration entering or leaving the meta-population, and movement between the sub-populations (parameterization and details can be found in Table 1). Given that certain processes only occurred periodically, a definitive looping path was nested with several conditional components. Immigration and emigration would occur during the migration season in May and November, respectively. The amounts of migrating fish were determined by multiplying the stock abundance with a constant migration factor for both sub-populations (Zhong et al., 2011). Age-one recruitment would be generated during the spawning season in May. The stock recruitment relationship of small yellow croaker followed the Beverton-Holt model (Liu et al., 2015; Li et al., 2020):

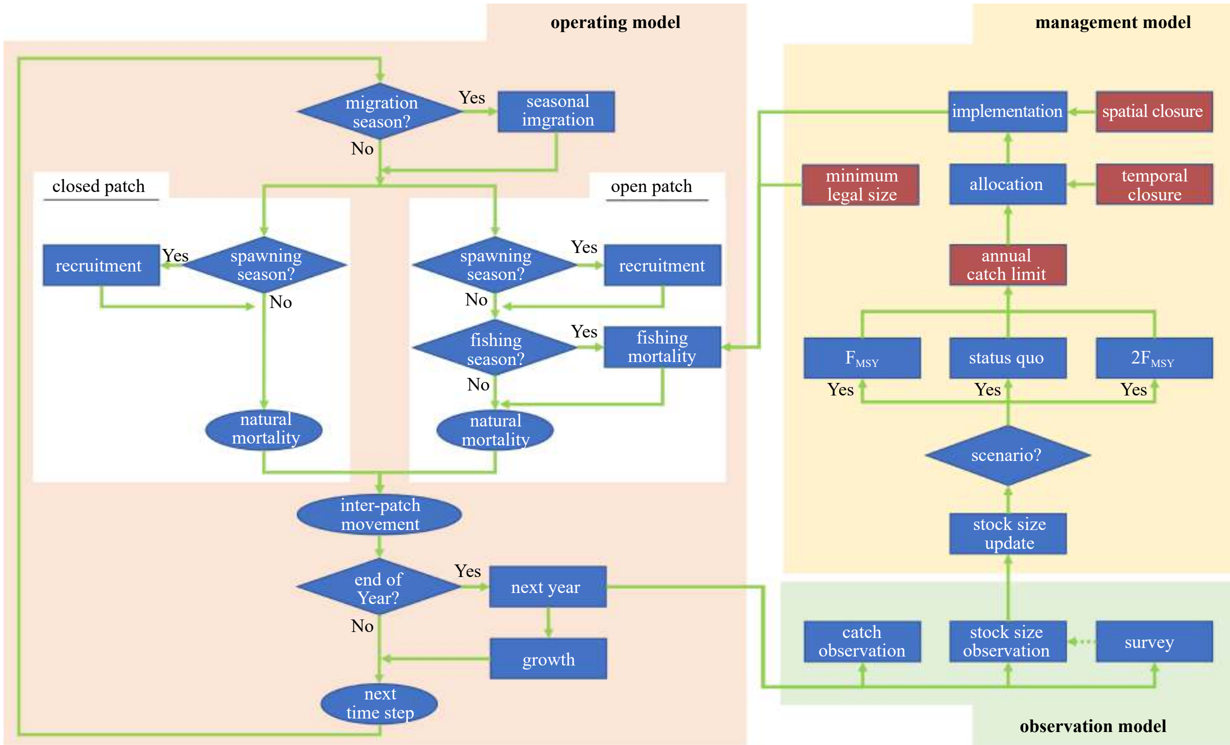

Fig. 1. Flowchart of the projection framework developed in this study. The framework is connected by three models and the components under them. The diamond-shaped components represent decision nodes where judgements need to be made. The rectangle-shaped components represent conditional processes that only happen in certain time steps. The circle-shaped components represent definitive processes that happen in each time step. The red-colored components under management model represent the management measures considered in this study.

Table 1. Technical description of operating model components

Components	Details	Sources
Patch structure	Two patches are spatially homogenous and differ only in size. The size of the open and closed patches account for 95.66% and 4.34% of the study region, respectively	Li et al. (2019)
Migration	Immigration occurs in May; immigration factor equals to 1.613 3. Emigration occurs in November; emigration factor equals 0.464 9	Zhong et al. (2011); Li et al. (2020)
Recruitment	Recruitment dynamics follows the Beverton-Holt stock recruitment model, whose parameters are: α=0.142 7; β=2.56×10^{-9}	Liu et al. (2015); Li et al. (2020)
Fishing mortality	Fishing mortality for each age group is obtained by multiplying target fishing mortality to selectivity at age: $F_{ts,i,a}=F_{\text{target }ts}\times \text{sel}_a$. Selectivity for age one fish is 0.45. Other age groups are fully selected	Sun et al. (2018a)
Natural mortality	Natural mortality is set constantly at 0.2 for each year. This value is determined following the common practice in stock assessment and is only subject to change when data are available to support a precise estimation.	Li et al. (2020)
Inter-patch movement	The dynamics for inter-patch movement is based on density-dependent diffusion. The maximum movement rate $T_{\max}$ assumed to be 1 when calculating the basic movement rate $T^b_{ts,i}$. The logistic function parameter A is 9. The values of carrying capacity for the open and closed patches are obtained by partitioning the total carrying capacity based on the patches size, end up with 1 460.75 mt and 65.62 mt, respectively	Goethel et al. (2015)
Growth	Weight-at-age data are obtained by fitting survey samples to von Bertalanffy growth function and assumed to be certain values without any variations. Weights for fish from age one to six are 10.08 g, 29.66 g, 52.67 g, 74.21 g, 92.18 g, and 106.07 g, respectively	Sun et al. (2018a)
Maturity	Maturity-at-age data are obtained by fitting survey samples to formulate a maturation ogive and assumed to be certain values without any variations. Maturity rates for fish from age one to six are 37%, 74%, 90%, 95%, 97%, and 100%, respectively	Sun et al. (2018a)

$$R=\frac{\alpha\times S}{1+\beta\times S}\times\varepsilon, \tag{1}$$

where S indicates spawning stock biomass (SSB) in weight, R indicates the number of recruits, ε indicates the error term, and α and β are model parameters. In this operating model, recruitment was a localized event subject to density-dependency within each sub-population, therefore recruits were to be calculated separately for two patches. Mortality arose from both natural causes and fishing. Natural mortality were set as a constant for both patches with no age effects, while fishing mortality would only occur during the fishing season in the open patch. The mortality was calculated as:

$$Z_{ts,i,a}=M_{ts,i,a}+F_{ts,i,a}, \tag{2}$$

where $Z_{ts,i,a}$ indicates total mortality for fish from patch i in time step ts of age group a, $M_{ts,i,a}$ indicates natural mortality, and $F_{ts,i,a}$ indicates fishing mortality (i must correspond to the open patch), which hinges on target fishing mortality and selectivity-at-age (Table 1). Variation in stock abundance caused by mortality was realized as:

$$N_{ts+1,i,a} = N_{ts,i,a} \times \mathrm{e}^{-Z_{ts,i,a}}, \tag{3}$$

where $N_{ts,i,a}$ indicates the abundance of fish. Note that age would only increase at each 12th time step. The amount fish caught in each time step was obtained by summing up catches from all age groups:

$$C_{ts} = \sum_{a=1}^{6} \frac{N_{ts,a} \times F_{ts,a}\left[1 - \exp\left(-Z_{ts,a}\right)\right]}{Z_{ts,a}}, \tag{4}$$

where C indicates the catch in amounts. Note that the patch was not subscripted in the Eq. (4) because fishing only occurred at the open patch. The mechanism of inter-patch movement was built on a dynamic density-dependent diffusive algorithm. The principle was that the movement rate out of one patch was subject primarily to the extent of local saturation, and secondarily to the relative density difference between two patches. Specifically, the basic movement rate was firstly determined with a logistic function assuming density-dependency (Goethel et al., 2015):

$$T^b_{ts,i} = \frac{T_{\max}}{1 + A\mathrm{e}^{-\frac{\ln(A)}{B^*_i} \times S_{ts,i}}}, \tag{5}$$

where $T^b_{ts,i}$ indicates the basic movement rate, $T_{\max}$ indicates the maximum movement rate which is to be tuned based on validation (theoretically ranges from 0 to 1), A indicates the logistic function parameter, B^*_i indicates the carrying capacity of patch i measured with biomass determined from a fishing-free projection, and $S_{ts,i}$ indicates the SSB (parameterization in Table 1). The obtained basic movement rate was then adjusted by the diffusive factor considering the relative SSB density in both patches following:

$$T_{ts,i} = T^b_{ts,i} \times \frac{\frac{S_{ts,i}}{P_i}}{\sum \frac{S_{ts,i}}{P_i}} \times 2, \tag{6}$$

where $T_{ts,i}$ indicates the final movement rate, P_i indicates the size of patch i. According to Eq. (6), if there was no difference in SSB density between two patches, the basic movement rate would be taken as the final value; otherwise, the movement rate from the patch with higher SSB density would be slightly increased, resulting in more fish moving out of the patch. The last event of each time step was to pass the stock information to the next time step. Here an extra but vital judgement must be made: if the current time step marked the end of the management year, all fish would enter the next age group and gain the corresponding growth in weight (fish of the plus group stayed in the same age group and did not grow). If not, the simulation would loop back to the first step to initialize the next time step and skip growing.

2.1.2 *Observation model*

The observation model was activated only at the end of the year. Its task was to extract certain data from the operating model to simulate the data observation process. Three components were simulated in the observation model, including the catch observation, the survey, and the stock size observation. For the catch observation process, age-specific catch data in number were captured and then used to calculate age-specific catch and total catch in weight. Due to the lack of formal stock assessment in this system, catch data were only stored for the follow-up statistical analysis. For the survey process, the Haizhou Bay bottom trawl survey in May and September and derived abundance indices were simulated with catch-per-unit-efforts based on the survey time assuming static catchability-at-age (Xu et al., 2015). The selectivity of survey was identical to that of the fishery. Catchability of small yellow croaker was set constantly at 0.5 (Sun et al., 2018b). In reality, stock size was estimated with survey abundance data using swept-area methods. But since the spatial structure of survey design was omitted, stock size estimation was only achievable through direct observation. Through simplified stock size observation, the abundance-at-age data for the corresponding year were obtained and passed on to the management model.

2.1.3 *Management model*

The management model was where management decisions were made to regulate fishing for the next year. Similar to the observation model, the management model was also activated once a year. Four management measures were accounted for under this model. Temporal closure, spatial closure, and minimum legal size are incorporated based on the realistic setting in the Haizhou Bay, while catch limits were tested here as a potential management tool. The current temporal closure measure functioned as a national management policy and stipulated a four-month summer moratorium for all fisheries in the study region from the beginning of May to the end of August. The temporal catch allocation pattern was strongly shaped by temporal closure, which has been observed from fisheries monitoring and could be readily included in the study (Fig. S2). The spatial closure measures in this region mainly took the form of no-take marine reserves, accounting for 4.3% of the study area by the end of 2019 (Table 1). The closed patch in the operating model was used to reflect this measure. The minimum legal size measure specified the mesh size and consequently, the smallest retainable fish. Its effect was reflected in the selectivity-at-age pattern determined from a length-based analysis (Sun et al., 2018a).

Catch control measure simulated in this study was a single species catch limit system. Since stock assessment was not incorporated, the catch limits should be calculated with the updated stock size data generated from the preceding observation model. In this study, three representative management scenarios were considered featuring different fishing mortality levels to deduce catch limits. The status quo scenario represented the current exploitation level as severe overfishing. The $\mathrm{F_{MSY}}$ scenario represented a well-managed fishing intensity aiming for maximum sustainable yield. The $2\mathrm{F_{MSY}}$ scenario represented a compromise between the other two scenarios, using two-fold of $\mathrm{F_{MSY}}$ as the target fishing mortality, which was also approximately the median value of $\mathrm{F_{MSY}}$ and the status quo F. These targets were then used to derive the corresponding annual catch limits with a one-year deterministic projection. In order to accommodate the temporal closure measure and make the annual catch limits executable in the month-based operating model, an allocation pattern was used to allocate the annual catch between fishable months (Fig. S2). The obtained month-specific catch limits were then implemented to the patch open to fishing as regulated by the spatial closure measure. Ultimately, catch removed from each age group was determined based on the age-specific fishing mortality, which was shaped by the minimum legal size regulation.

2.1.4 *Stochasticity*

As other evaluation frameworks used to perform projections, a variety of uncertainty could be incorporated into this framework as stochasticity processes. Uncertainty could arise from both human dimensions (implementation, target misspecification, fishing behavior, etc.) and natural dimensions (recruitment, mortality, growth, etc.). In this study, only the most representative sources of uncertainty were considered for the two dimensions-errors in implementation and recruitment. Their influences were accounted for with iterative simulation using Monte Carlo methods. Specifically, implementation error was associated with catch limits and occurred at all time steps during fish seasons; recruitment error was associated with the calculation of recruitment abundance and occurred at only the time steps of spawning season (Eq. (1)). The values of error terms for recruitment were generated from a uniform distribution U(0.5,1.5) and used to adjust the fitting results of stock recruitment relationship. Implementation uncertainty was also sampled from an identical distribution to produce a comparable level of implementation bias. Despite this, the two sources of uncertainty were mutually independent and incorporated as two individual processes. In this case, both uncertainties could adversely affect management success: a positive implementation error could lead to a fishing mortality higher than that of the target, while a negative recruitment error could lead to a lower recruitment strength.

2.2 *Case study data source*

The small yellow croaker (*Larimichthys polyactis*) is one of the most iconic commercial species in China's domestic fisheries. Despite its wide distribution and formerly prosperous productivity, small yellow croaker fisheries in China have suffered from multiple stressors, including overfishing and changes in environment, and have thus been considerably depleted in recent years (Shan et al., 2017; Lee et al., 2020). Meanwhile, Haizhou Bay is also a major fishing ground and fish habitat in northern China, where sustainability in fisheries not only has economic significance but also ecological merits (Zhang et al., 2016). Currently, the small yellow croaker in the Haizhou Bay is managed with a combination of management measures including summer closure, regional spatial closure, and mesh size limits. The summer closure starts from 1 May and lasted until 31 August. The scale of regional spatial closure was determined based on the existing marine protected area, which accounted for 4.34% of the region in terms of size (Table 1, Fig. S1) (Li et al., 2019). The mesh size limits were transformed into selectivity-at-age (see the following sections and Table 1). No formal stock assessment has been conducted for the small yellow croaker fishery in the Haizhou Bay to support management. No target fishing mortality or catch limits were defined as control targets. Some estimations of biological reference points are available based on data-limited length-based methods (Liu et al., 2012; Sun et al., 2018a). However, these estimations were not used to develop management strategies. The status of the small yellow croaker in the Haizhou Bay has been monitored by long-term fisheries-independent surveys and evaluated by substantial quantitative studies since 2011 (Liu et al., 2012; Xu et al., 2015; Sun et al., 2018a, 2018b). The survey data were used to estimate standardized stock biomass and life-history traits, which were used in this study to develop the projection model. The used data included the size frequency and abundance of small yellow croaker caught by the survey. Age-structure and age-specific life-history traits were estimated using length-based methods (Sun et al., 2018a; Li et al., 2020), such as growth function, maturity-at-age, and selectivity-at-age (Table 1).

2.3 *Model validation*

A hindcast simulation was conducted to examine how well this framework could reproduce the stock development from 2011 to 2018. The survey index of small yellow croaker derived from a local fisheries-independent survey was used as a reference due to lack of available data and stock assessment (Xu et al., 2015). All historical data were deemed as perfectly available in the hindcasting, including the initial stock status of 2011 and the yearly-specific fishing mortality. The simulation was deterministic using the observed yearly-specific recruitment error from the residual of stock recruitment relationship fitting (Supplementary information). Management measures applied to the hindcasting were the three realistically implemented measures including temporal closure, spatial closure, and minimum legal size. Over the past few years, the first two measures underwent several modifications in scales, which were also accounted for in the hindcasting (Supplementary information). Based on these data and settings, hindcasting simulation was performed using the proposed projection framework, strictly following the population dynamics in the operating model under the considered management measures. The simulated biomass for each year was validated against the observed biomass derived from survey. The relative goodness of fitting was quantified with the root mean squared error (RMSE) (Stow et al., 2009):

$$\mathrm{RMSE}=\sqrt{\sum_{i=1}^{n}\left(P_i-O_i\right)^2/n}, \tag{7}$$

where n indicates the number of observations, O indicates the observations, and P indicates predictions. The model was calibrated by tuning the basic movement rate $T_{\max}$ from the Eq. (5) to minimize the RMSE value. Simulation performance of a spatial-explicit dynamic model for the same fishery was also compared (Li et al., 2020).

2.4 *Model application and post-hoc statistics*

The validated framework was applied to conduct long-term projections (50 years) starting from 2011 for the three management scenarios indicated in Table 2. The projection simulation intended to identify two things for the small yellow croaker fishery: (1) the long-term management effects under these scenarios, and (2) the impacts of uncertainties associated with implementation and recruitment. Both deterministic and stochastic simulations were conducted in this regard and analyzed with post-hoc statistical analysis. The deterministic simulation was uncertainty-free and conducted with only one iteration. The stochastic simulation incorporated both implementation and recruitment uncertainties and their influences were accounted for with 200 iterations. To understand the long-term management performance of these scenarios in a deterministic perspective, the accumulative catch for the entire simulation period and the final stock biomass were examined. A similar analysis was also conducted for the tradeoff between total catch and biomass to highlight the performance variations caused by the existence of one or both un-

Table 2. Simulated management scenarios and their details

Scenarios	Details
Status quo	This scenario is developed to represent an unmanaged fishery (not with catch control, specifically). This scenario is based on the average fishing mortality level of the seven recent historical years. During this period, fishing mortality consistently exceeded F_{MSY}, indicating severe overfishing. The mean fishing mortality (0.72) of this period was used as the target fishing morality to calculate catch limits in the future years (Table S1)
F_{MSY}	This scenario is developed to represent a well-managed fishery sustained at the maximum sustainable yield (MSY). The value of F_{MSY} (0.25) was identified by running the projection model under a gradient of fishing mortality rates (Fig. S4)
$2F_{MSY}$	This scenario is developed as an intermediate compromise between the unmanaged fishery (status quo) and the well-managed fishery. Target fishing mortality is determined as two-fold of the F_{MSY} (0.5)

certainties. Assuming that uncertainty could also result in stock collapse measured with biomass, a risk analysis was further conducted to investigate the probability and time of collapse, whose threshold was arbitrarily defined as 80% of the initial stock biomass. Risks were calculated in two steps. First the stock collapsing would be identified for each year of each iteration as the biomass dropped below the threshold. Then the probability of collapse was estimated for each year by dividing the number of collapsed iterations by total amounts of iterations.

3 Results

3.1 *Model validation*

The presented projection framework based on the two-patch operating model was compared to the spatial-explicit population model for its performance in reproducing the historical stock development indicated by survey indices (Fig. 2). The simulated trend in biomass and final age structure were examined. The actual biomass variations observed in the simulation period were shaped by the synthetic effects from varying fishing mortality and fluctuating recruitment strength, which were accurately considered in the hindcasting. Results showed that the presented projection framework was able to depict the historical trends in biomass from 2011 to 2017 after calibration. The tuned value for T_{max} was 0.98, returning an RMSE of 67.85, while the RMSE for the spatial-explicit model was 83.99. Compared to the spatial-explicit population model, the two-patch operating model failed to completely match the final biomass (approximately 20% lower than the observation). Despite this, the presented projection framework outperformed the spatial-explicit population model in terms of reproducing the final age structure (RMSE values for the two-patch projection model and the spatial-explicit model were 7.4×10^{-2} and 0.19, respectively). These results indicated that the current model assumptions and calibrated parameterization were solid.

3.2 *Deterministic projection*

Deterministic simulations were conducted for 50 years without uncertainty for three management scenarios. Performance of the three management scenarios was measured with both accumulative catch over the simulated period as well as final biomass (Fig. 3). The status quo scenario developed rapidly towards a complete stock collapse and ended up with a negligible final biomass and the lowest accumulative catch. The $2F_{MSY}$ scenario performed slightly better than the status quo scenario, resulting in both higher final biomass and accumulative catch. However, the equilibrium biomass under the $2F_{MSY}$ strategy was still lower than the initial biomass, indicating the higher accumulative catch was achieved at the cost of stock biomass. The F_{MSY} scenario generated the highest long-term biomass and accumulative catch in comparison. Under a lower fishing mortality, the stock biomass expanded 250% compared to the initial stock biomass and resulted in the highest accumulative catch as much as 170% of that from the $2F_{MSY}$ scenario.

3.3 *Stochastic projection*

3.3.1 *Performance*

Stochastic simulations were conducted for 50 years incorporating both implementation and recruitment uncertainty for three

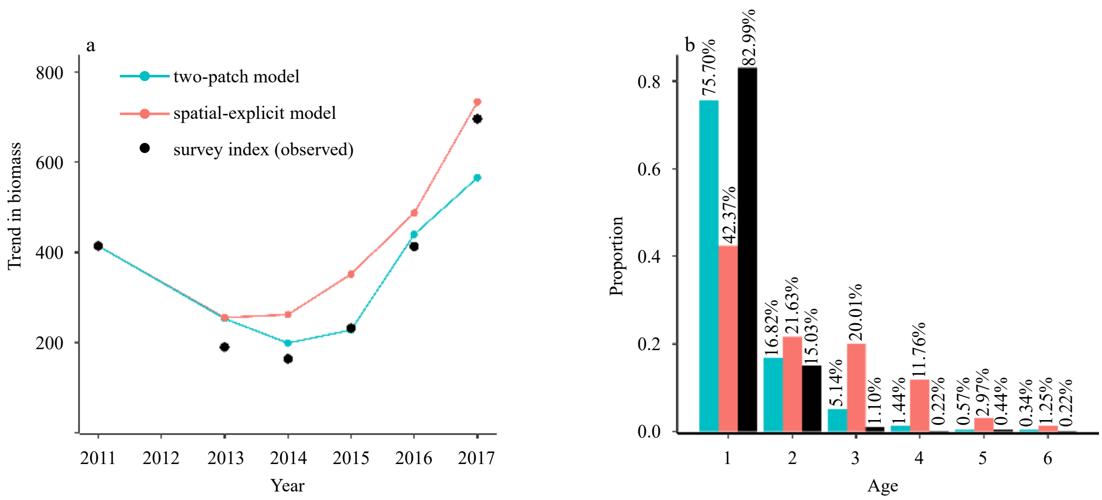

Fig. 2. Validation of the hindcast simulations. Performance of projection based on the two-patch operating model and spatial-explicit population model are compared with the observed survey indices for trend in biomass (a) and age structure (b) of the last simulated year. The biomass in a is unitless as the index is compared to the hindcasting result for their trends.

management scenarios. Performance of the three management scenarios was also measured with accumulative catch over the simulated period as well as biomass for the final year (Fig. 4). In

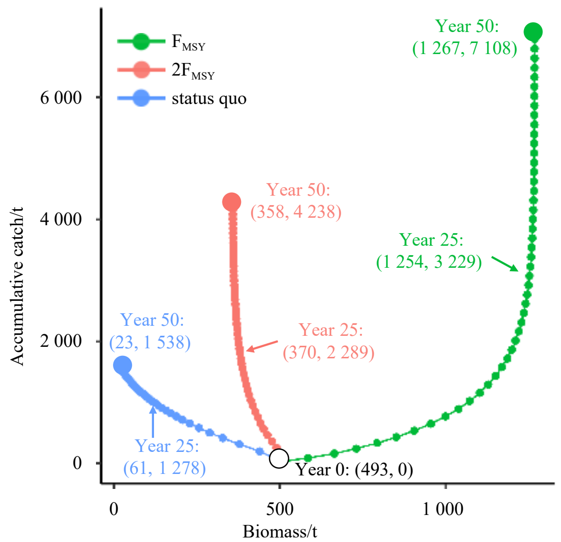

Fig. 3. Performance of deterministic projection for the three management scenarios. Accumulative catch by each year is plotted against the biomass at that year with dots, with the 25th and 50th year highlighted for their coordinates.

general, the incorporation of uncertainty brought substantial performance variations for all three scenarios. The degrees of variation were visualized with eclipses. Similar to the results from deterministic projection, the F_{MSY} scenario performed the best while the status quo scenario performed the worst (Fig. S6). When recruitment uncertainty was considered, wide dispersions of performance coordinates were observed for all scenarios, indicating highly indefinite stock status in the long-term. Implementation uncertainty brought a much smaller degree of dispersion in comparison. Such disparity demonstrated that recruitment uncertainty was more influential than implementation uncertainty when they were at the same level. The eclipses under the recruitment and implementation uncertainty roughly centered around the deterministic status. When implementation and recruitment uncertainties were incorporated simultaneously, the scales of dispersions even expanded. Additionally, the size magnitude of eclipse also decreased with increasing fishing intensities from F_{MSY} to status quo.

3.3.2 *Risk analysis*

Risk analysis was conducted for both stochastic and deterministic simulations based on the biomass of each year. Trajectories for risk of collapsing are presented for the simulated period (Fig. 5). Risk for deterministic simulations was essentially binary (0 and 1) as there was only one iteration. In general, the existence of uncertainty did not influence the F_{MSY} and status quo scenario, while it only impacted the risk performance for the

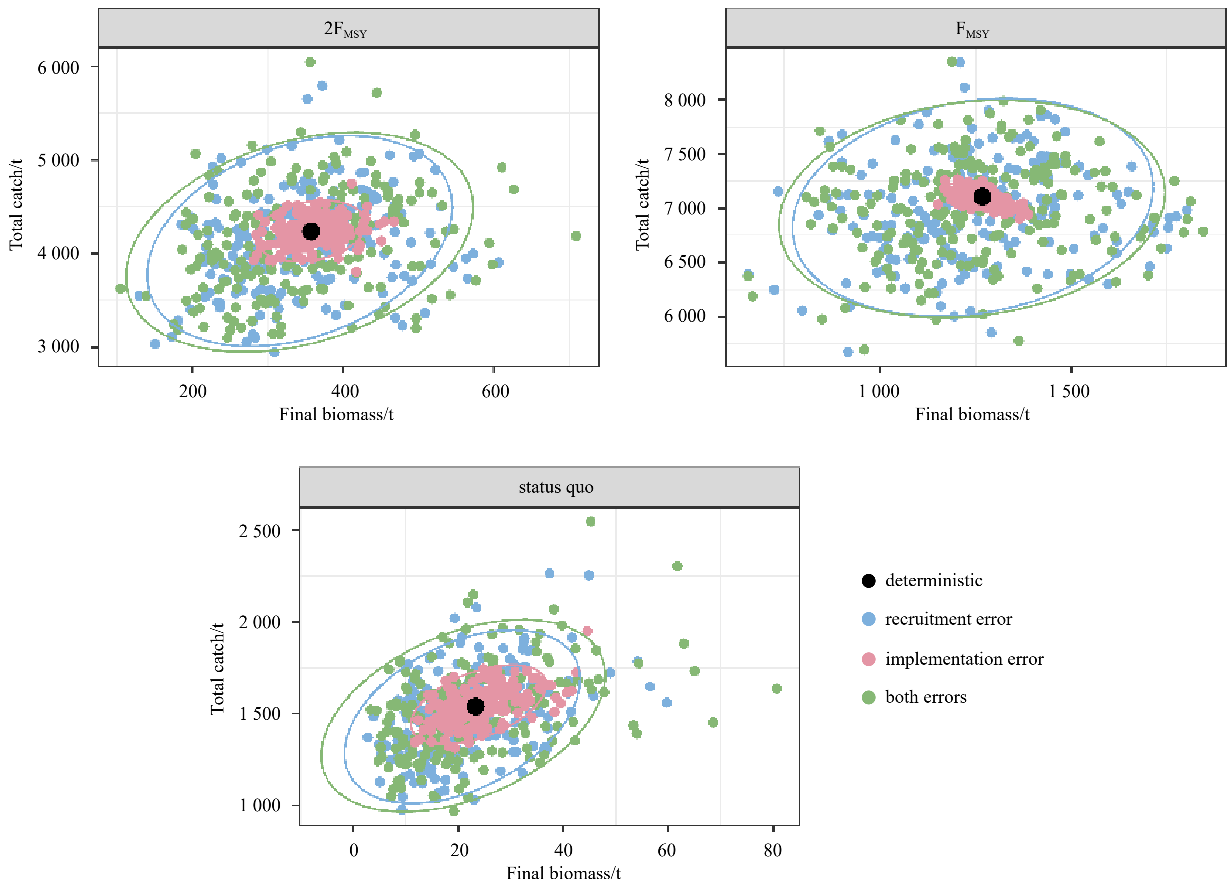

Fig. 4. Performance of stochastic projection for the three management scenarios. Accumulative catch over the period is plotted against final biomass. Results from 200 iterations for the 50th year were presented with dots and eclipse. The panel scales are not unified (the unified figure can be found in Fig. S6).

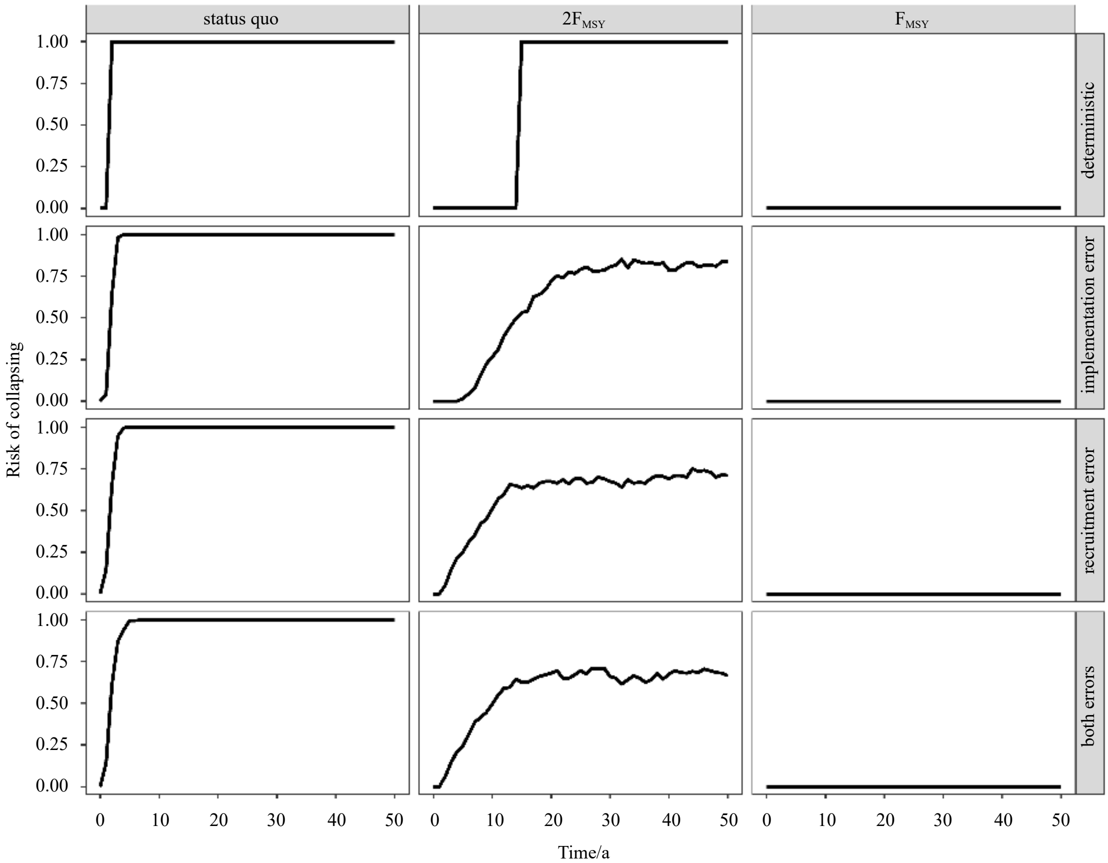

Fig. 5. Risk of collapsing for the three management scenarios from deterministic and stochastic simulations.

$2F_{MSY}$ scenario. Specifically, when managed under the F_{MSY} scenario, the stock showed no possibility of collapsing even in the face of uncertainty, indicating that management failure could be effectively avoided under an optimal exploitation rate. On the contrary, the status quo fishing exploitation rate was so high that the stock collapsed within five years regardless of uncertainty. When the exploration rate was at $2F_{MSY}$, the stock crashed after 10 years when no uncertainty was considered. The incorporation of implementation uncertainty reduced the final risk to approximately 80% and smoothed the sharp curve thanks to more iterations. Uncertainty in recruitment was able to further reduce the risk of collapsing below 70% in long-term. Collectively, uncertainties in recruitment and implementation decreased the risk to below 70%.

4 Discussion

A projection model was introduced in this study and applied to the small yellow croaker fishery in the Haizhou Bay, China, as a case study. This model was able to account for the management measures that are practically used in China's fisheries management with intermediate complexity, which was rarely achieved by earlier modeling efforts. The primary specification of this projection model was the two-patch operating model based on monthly time step to reflect the management effects from the summer closure and marine protected areas. Catch limits determined with target fishing mortality were considered as control measures in the projection model, representing a potential approach to utilize scientific knowledges. Two sources of uncertainty were additionally investigated for their influences. The proposed projection model could realistically capture the population dynamics and its interaction with fishing according to the hindcasting validation. Stochastic projections were conducted for three configured exploitation scenarios based on status quo and MSY, indicating the projection model could be used to evaluate potential candidate management strategies for their effectiveness and risks. Implementation of the framework is critical for providing comprehensive understanding of management effects and valuable in supporting the future of sustainable fisheries in China.

The two-patch operating model was compared to a spatial-explicit model developed for the same fisheries with an emphasis is on evaluating marine protected areas in the Haizhou Bay for their hindcasting performances (Li et al., 2020). It was found that, notwithstanding the relative simpler spatial structure, the presented two-patch operating model outperformed the spatial-explicit model in capturing inter-annual stock size variations and final age structure (Fig. 2). This advantage is highly valuable in advising fisheries management since it can reflect sudden changes in a dynamical population system under multiple stressors (Shan et al., 2017; Sguotti et al., 2019). In this regard, the two-patch model demonstrates a better balance between model complexity and performance. However, the spatial-explicit model is still widely acknowledged for its effectiveness in supporting marine protected area design by incorporating high-resolution spatial data (Costello et al., 2010; Li et al., 2020), indicating the development of projection models should be based on well-defined study objective. Otoliths analysis on the population structure indicates that the Haizhou Bay small yellow croaker belongs to one spawning group (Zhang et al., 2014), which justifies the use of one stock recruitment relationship for two patches based on localized recruitment. The metapopulation simulated with the two-patch model may not impact the results as the size of closed patch is relatively small (4.34% of the entire population). Nevertheless, it should be noted that assuming a metapopulation with two comparable subpopulations can strongly alter the management effects as demonstrated by related study (Sun et al., 2020).

The three projection scenarios contemplated in projections are entirely simulated as potential exploitation schemes in the future. The status quo scenario is regarded as the base scenario representing the current exploitation intensity, the target fishing mortality of which is reevaluated with the presented model. Although the historical fishing mortality was set as a pseudo target to be controlled throughout the projection, it is still noteworthy that current management strategies in China do not limit fishing mortality (or derivative catch) (Shen and Heino, 2014). The historical fishing mortality (0.72) using in the status quo scenario is much higher than F_{MSY} (0.25) and resulted in a long-term stock size below the current level as expected (Fig. 3). These results indicate that the current depletion in fisheries is attributable to the lack of control over the direct fishing intensity, which is unable to be achieved with the current management measures. In the long-term, sustainable fisheries are difficult to achieve by operating under the current "business as usual" practices. In fact, relevant studies have pointed out the risks and limitations of uniform fisheries management measures. For example, the effects of extensive input controls can be unpredictable due to unanticipated dynamics in catchability and fishing behaviors (Anderson et al., 2019). Spatial and temporal closure measures are believed to have limited contributions to sustainable fisheries as they can only redistribute effort imposed to stocks, not reduce it (Stefansson and Rosenberg, 2005; Hoos et al., 2019). Mesh size limits are an effective measure in terms of preserving newly recruited juveniles and untargeted species (Dunn et al., 2011); nevertheless, its effects have been impaired by low level of compliance and inadequate enforcement (Shen and Heino, 2014). The F_{MSY} scenario is designed to simulate a well-managed fishery following a scientifically determined harvest intensity. In this scenario, the stock is successfully rebuilt within two decades and continued to be productive (Fig. 3), suggesting that implementing appropriate management strategies based on science will promote sustainable fisheries management in China as already exhibited in other regions (Hilborn et al., 2020). The $2F_{MSY}$ scenario was originally developed as a compromise between the F_{MSY} and status quo scenarios and expected a slightly improved management effect compared to the earlier practice. Surprisingly, the current stock status is not improved in this scenario. This result strengthens the conclusions drawn from the status quo scenario that, if the high exploitation intensity continues as "business as usual", it will be difficult to effectively achieve sustainability for China's fisheries.

Stochastic projections demonstrate that uncertainty in both recruitment and implementation can cause performance variations for all three scenarios (Fig. 4). However, the uncertainty in recruitment is much more influential than that in implementation by causing larger variations in long-term stock status (Figs 4 and 5). It has been pointed out that reduced recruitment strength can adversely affect the stock status, resulting in unexpected stock collapse and weaker resilience to potential variabilities in fishing and environments (Kuparinen et al., 2014; Sun et al., 2020). The projection results reaffirm that such uncertainty should be considered in fisheries stock assessment. This consideration is essentially quite urgent given the recent emergence of research reporting that the combination of climate change and intensive fishing has taken a toll on China's fisheries (Liang et al., 2018; Ma et al., 2019). Implementation uncertainty has been pointed out as a major issue in many fisheries (Rice and Richards, 1996; Sethi et al., 2005; Shen and Heino, 2014; Sun et al., 2020). The projection results show that implementation uncertainty is much less influential to management effects compared to the recruitment uncertainty in the context of China. This disparity is particularly obvious when exploration rates are maintained at F_{MSY}, suggesting that fishing at optimal exploitation rates can effectively mitigate the effects from inadequate implementation of control limits.

By performing projection with a fishery in China and accounting for realistic management measures as well as potential uncertainties, it can be concluded that the current fishing intensity in China is not effectively restricted without specific control targets in fishing mortality or catch limits. Consequently, depleted fisheries cannot be rebuilt towards sustainable levels, particularly in the face of uncertainty. Implementing control targets based on scientific evidences (following F_{MSY}) can greatly contribute to the long-term sustainability. The work also highlights that applying projections can provide a comprehensive understanding of consequences of fishing and guide future management practice. Yet, the proposed projection framework still needs modifications to more realistically delineate the situation in China. First of all, the data observation process needs to be more compatible with local survey designs, especially when many surveys are the only available data sources without stock assessment. The bias accompanying the observation process may also be a huge source of uncertainty, which needs to be investigated. Furthermore, considering the influences of mixed fishing can offer more practical insights for China's fisheries management. Relevant research has pointed out the increased complexity in management when considering multi-species effects and mixed-fisheries dynamics particularly in the case of China (Zhang et al., 2016). Last but not the least, modeling uncertainty by postulating its plausible forms is a purely "empirical approach" and is appropriate for simulations based on insufficient data and background information. However, this simplified uncertainty modeling approach neglects the response of fisheries stock to variations in ecosystem and supports less realistic simulations in comparison to the "mechanistic approach", especially under the overall context of climate change (Punt et al., 2014; Ma et al., 2019). Future efforts should be devoted to addressing these issues with comprehensive management strategy evolution by collaborating with local management practitioners, employing advanced ecosystem modeling, and incorporating environmental dynamics.

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Supplementary information:

Maximum sustainable yield (MSY) is the maximum long-term catch at equilibrium that can be achieved by fishing at a certainty intensity. F_{MSY} represents the fishing intensity (in the form of fishing mortality rates) corresponding to the MSY (Fig. S4). To calculate the value of F_{MSY}, the developed projection model is used to project the fishery under a gradient of fishing mortality from 0.01 to 0.6 with the interval of 0.01 until the stock size reaches equilibrium. We then compare the annual catch level at equilibrium and identify the peak value (MSY) and the corresponding fishing mortality rate (F_{MSY} at 0.25). This is a purely model-based approach, the result of which is close to the estimation from length-based methods (0.27 by Sun et al. 2018).

Fig. S1. Distribution of existing marine closured area in the study region (Li et al., 2019).

Fig. S2. Catch allocation pattern used in this study. The black dots indicate the catch pattern observed from the local fishery monitoring program. The red bars indicate the adjusted catch allocation pattern fit to a Gaussian function, which is used in this study for simulation.

Fig. S3. Modifications made to the temporal and spatial closured measures in historical years. These modifications are considered in the hindcasting.

Fig. S4. Determination of FMSY with the projection model.

Fig. S5. Stock recruitment relationship fitted from Liu et al. (2015) (blue line) and the observed recruit in the Haizhou Bay (red dots).

Fig. S6. Accumulative catch and final biomass for three management scenarios under the influence of uncertainty (unified scale).

Table S1 Information on the actual historical stock status. Estimations are obtained from Li et al. (2020).

The supplementary information is available online at https://doi.org/10.1007/ s13131-021-1793-3 and www.aosocean.com. The supplementary information is published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.