FISHERIES IN A CHANGING ENVIRONMENT: THE IMPACTS OF THE REDUCTION IN SHATT AL ARAB FLOW ON NEARSHORE FISH STOCKS IN THE NORTHERN PERSIAN GULF

by

Abdulrahman Ben Hasan

B.S., Sultan Qaboos University, 2012

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF

THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF SCIENCE

in

THE FACULTY OF GRADUATE AND POSTDOCTORAL STUDIES

(Resource Management and Environmental Studies)

THE UNIVERSITY OF BRITISH COLUMBIA

(Vancouver)

May 2017

Abstract

When fish catches decline, the standard recommended management solution is to reduce fishing mortality to allow stock recovery to more productive levels. This recommendation is based on the assumption that the most likely cause of the decline in the first place is fishing. Natural regime shifts and human-induced environmental changes are, however, often equally important factors in driving catch declines. In the Northern Persian Gulf, many commercial fish stocks are declining, raising questions about two main causes: overfishing and reduction in the flow of the major river, Shatt Al Arab. In Kuwait, the latter cause is strongly suspected of driving catch declines, especially with the implementation of high length limits and apparently good protection of juvenile nursery areas. Here I assess three case studies of Kuwait fish stocks and investigate the impact of reduced Shatt Al Arab flow on fish recruitment patterns. We found neutral and negative apparent capacity change in the green tiger shrimp stock and the orange-spotted grouper stock, respectively. These results suggest declining productivity in the nursery area of the orange-spotted grouper, but not in that of the tiger shrimp stock. In the case of the yellow-fin seabream assessment, the estimation of the relative recruitment was unreliable, hence the inability to examine the relationship between recruitment and the reduction in the flow rate of Shatt Al Arab. Our results demonstrate that reductions in Shatt Al Arab river flow are likely to impact fish recruitment patterns, causing changes in fish stock sizes. The findings presented here are expected to be a starting point for a more detailed investigation that tries to bring together data on what has been changing over time in the nearshore nursery environments, since most of the commercial fish stocks are inshore/estuarine dependent. Such investigation would be very critical for the fisheries management in deciding, for example, whether a reduction of fishing effort would be beneficial.

Lay Summary

Declining catches are commonly attributed to excessive fishing levels. Therefore, such declines often lead to recommendations of reductions in fishing effort by the fisheries authority. However, it is equally typical that changes in stock sizes are caused by non-fishing related activities including natural, (e.g., El Niño) and anthropogenic, (e.g., dam constructions and river diversions) factors. Here, we assess the status of three fish stocks in the Northern Persian Gulf and investigate the impact of the reduction in the flow of Shatt Al Arab on fish recruitment. Our findings indicate that the spawning stock of the orange-spotted grouper is declining because recruitment has declined due to the dramatic reduction in the flow rate of Shatt Al Arab, while the spawning stock and recruitment of the tiger shrimp have not shown any effects. The relative recruitment pattern of the yellow-fin seabream was inestimable, so the impacts of reduction in Shatt Al Arab flow was not investigated. The findings presented here are expected to have significant implications for the formulation of fisheries regulations in the region.

Preface

This study represents original work by the author and has not been submitted in any form to another university. Where use was made of the work or research samples of others it has been duly acknowledged in the text.

Table of Contents

List of Tables

List of Figures

Acknowledgements

It has truly been a great honor to have Villy Christensen and Carl Walters as my main supervisors. Villy who is known as one of the world's leading ecosystem modelers, was kind enough to accept me as a Master's student. I consider Villy as my mentor and friend that I look up to, especially in my future career at Kuwait University. Villy gave me the choice to decide what I want to be involved in during my Master's program. At this point, I decided that I wanted to focus on fisheries stock assessment. I cannot think of a better way to learn all aspects of fisheries stock assessment than to have the grand master at my side: Carl Walters. Carl has taken over the main supervision at this stage, teaching me a wide range of stock assessment techniques, from basic statistical stock assessment to decision analysis approach in stock assessment. About hundred emails were exchanged between me and Carl, where Carl answered my silly questions, and sometimes explained a complete population dynamics model. Thank you Villy and Carl, for the knowledge, advice and time that you both gave to me.

I would also like to thank my committee supervisory member Rashid Sumaila for his approval to join the committee, even though I have not included much fisheries economics in my work.

I want to show my appreciation to Kuwait University, for funding my studies during the past two years.

Dedication

to

Masoumah and Fatemah

For their prayers, patience and love

Chapter 1: Introduction

Declining catches and population abundances are causes of much concern in modern fisheries management, and the recommended management response is typically to reduce fishing mortality rates so as to allow recovery to more productive stock sizes. This recommendation is based on the assumption that the most likely cause of the decline in the first place is fishing, and it is pragmatic in the sense that it is the only factor that fisheries managers has a chance of impacting. But it is equally typical for fishing interests to argue against fishing restrictions while asserting that decline has been due to other factors like availability (the fish have just moved), increases in predation, or regime changes that will reverse the decline even if no action is taken. Unfortunately for fisheries scientists, we cannot, in fact, claim that fishing does cause most declines and that there is a high probability of good long term results from restrictive regulation (see the debate in Pauly et al., 2013). There are just too many cases where reductions in fishing, even complete closures, have completely failed to result in the desired recovery (Hutchings 2000; Hutchings and Reynolds 2004) and/or recovery has occurred without reduced fishing despite dire warnings from scientists. For example, on the west coast of Canada, complete closures of two of the major herring fisheries and coho and chinook salmon fisheries have been implemented since the mid-1990s. Surprisingly, none of these stocks has shown any sign of rebuilding; closures continue on the assumption that the low stock sizes need protection to allow eventual recovery when it may still be possible to harvest these stocks at fairly high fishing rates (but producing relatively low catches) without endangering them.

Many commercial fish stocks in Northern Persian Gulf (NPG) (Figure 1.1) are declining; the most probable causes are overfishing and human-induced environmental change, (e.g., dam constructions) (Al-Husaini et al. 2014). In Kuwait, landings for most commercial fish stocks have drastically declined over time (CSO, 1979-2015). In addition to the unregulated fishing pressure, dam constructions in Iraq and Turkey are reducing Shatt Al-Arab inflow to alarmingly low levels (Issa et al., 2014). The Shatt Al-Arab river thus plays a key ecological role in the NPG ecosystem. For example, it contributes to the overall primary productivity through delivering essential nutrients, offsets the high salinity arising from high evaporation levels, and triggers biological events such as migration and spawning. Therefore, changes in Shatt Al Arab water flow are very likely to impact inshore/estuarine dependent species by changing the productivity of nursery areas (i.e. causing changes in carrying capacity). Several studies have expected serious impacts on the marine ecosystem of the region upon the completion of dam constructions (UNEP, 2001; Al-Yamani and Khan, 2002).

At this point, there is a high uncertainty in deciding whether recruitment for many species are declining in the NPG because of spawning stock declines (the “overfishing hypothesis”), or instead that spawning stock (which results from recruitment) is declining because recruitment has declined due to other factors (the “environmental factor” hypothesis)? This is an extremely critical question that must be considered by the fisheries management; imposed management measures such as, e.g., marine protected areas can be expected to fail if the “environmental factors” hypothesis is the main cause of fish declines (Hilborn et al., 2004).

While stock assessment involves building mathematical models to provide quantitative answers to predictions required for management, the scientific community in the Persian Gulf have rarely applied stock assessment methods to manage the fisheries. The most likely reasons are a lack of basic fisheries data, (e.g., abundance index time-series data) and insufficient numbers of trained personnel in stock assessment modeling. Therefore, fisheries management measures continue to be based on the life-history of the exploited fish stocks such as size and gear restrictions, and spatial and temporal closures.

The research I present in this thesis is designed to use modern stock assessment approaches to assess the population dynamics in three different case studies in NPG: the tiger shrimp (*Panaeus semisulcatus*), the yellowfin seabream (*Acanthopagrus latus*), and the orange-spotted grouper (*Epinephelus coioides*). Furthermore, I attempt to empirically explore the relationship between fish recruitment and the reductions in Shatt Al Arab flow rate.

In Chapter 2, I analyze the most valuable fishery in Kuwait, the shrimp fishery, using a seasonal statistical catch at age approach (SCA). The SCA model is applied to address the effects of alternative basic assumptions about the relationships between stock size, catch, effort, and recruitment dynamics. I examine the fishing effort dynamics, compare the historical fishing effort with the optimized fishing effort in terms of total revenue, and explore the relationship between Shatt Al Arab flow rate time-series pattern and the estimated relative recruitment. In Chapter 3, I assess the status of the yellow-fin sea bream using the Stock Reduction Analysis (SRA) method and length-composition data. In Chapter 4, I assess a valuable grouper fishery using virtual population analysis and stochastic SRA models, and demonstrate the use of simple calculations from decision analysis to compare difficult management choices.

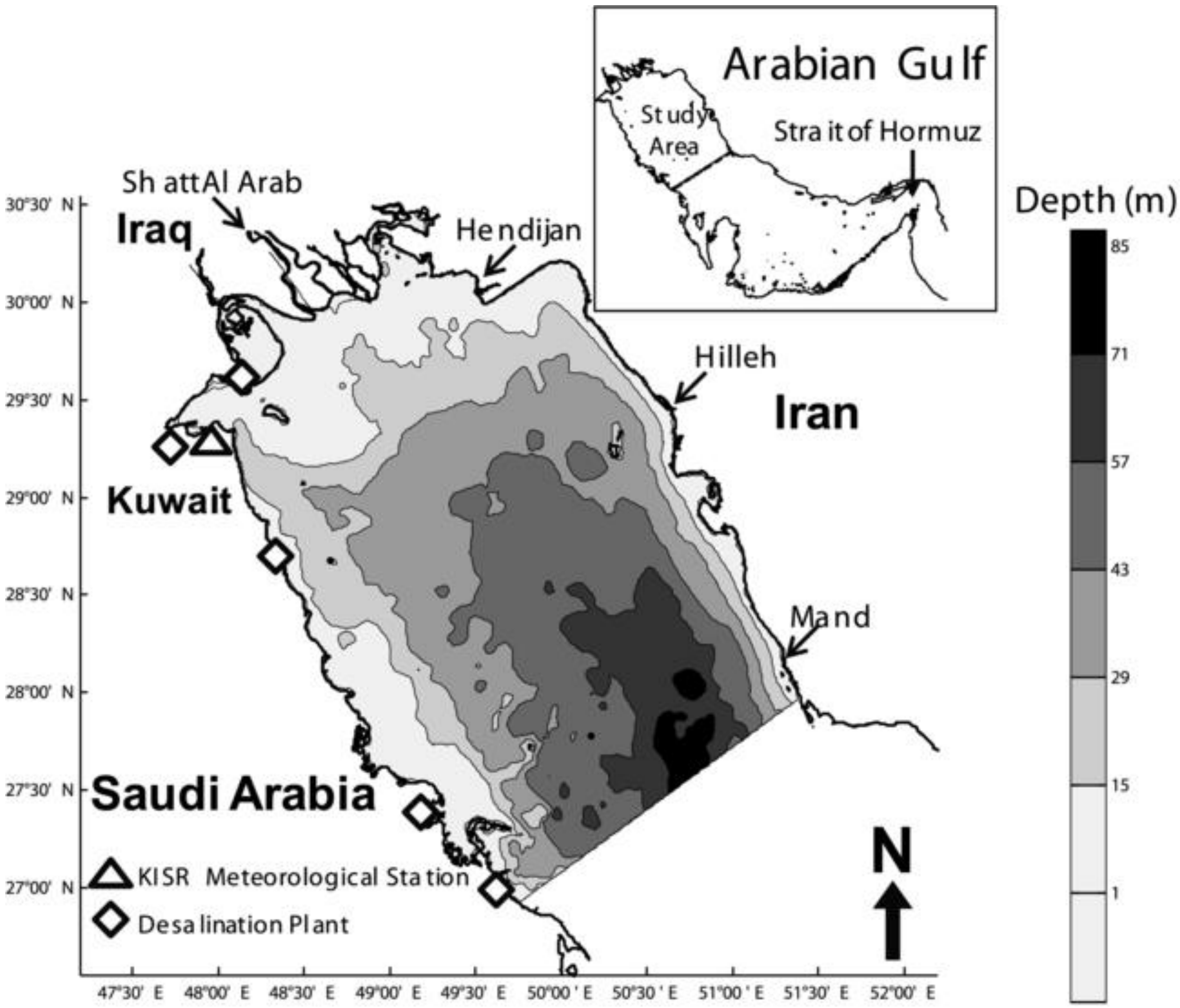


Figure 1.1. The Northern Persian Gulf (source: Alosairi and Pokavanich, 2017).

Chapter 2: Assessment of *Penaeus semisulcatus* in the Northern Persian Gulf

2.1 Introduction

The exploitation of Kuwait shrimp started fifty years ago when several industrial trawlers were transported from the U.S. Gulf of Mexico (Kristjonsson, 1968). Historically, the Kuwait shrimp fishery experienced a rapid growth in effort attracted by high yields, reaching a peak of about 5,000 tons in the late 1980s. Furthermore, the post-Gulf War period showed an overall increasing trend in the fishing effort, but shrimp catches remained stable at about 2,000 tons (Figure 2.1). Currently, the shrimp fishery is considered the most valuable fishery in Kuwait, accounting for 35% of the total landed yearly value (Al-Husaini et al., 2015). The shrimping season starts in August where fishing fleets are only allowed to fish in the international waters. In September, the fishing fleets are permitted to start fishing in Kuwait's territorial waters. The most commercially important and abundant penaeid species in Kuwait is the green tiger prawn (*Penaeus semisulcatus*) with an average contribution of 60% to the overall yearly catches. Therefore, the management of the shrimp fishery is based on the biology of *P. semisulcatus* (Bishop et al., 2001).

Given the commercial importance of the shrimp fishery in Kuwait, several input controls are imposed to buffer against overexploitation including fishing license, seasonal closures (5-6 months) and closed areas (3 miles away from shore and Kuwait Bay). However, factors such as fleet overcapacity, illegal fishing and unfavorable environmental conditions, (e.g., Shatt Al Arab river flow reduction) have contributed to substantial stock biomass declines (Al-Abdulrazzak and Pauly, 2013; Al-Husaini, 2015).

A variety of stock assessment models have been applied to data from Kuwait shrimp fisheries over the years, all with the basic aim of estimating fishery reference points, notably the biomass that would result in the maximum sustainable yields (B_{msy}) and the fishing mortality rate that is needed to obtain the maximum sustainable yield (F_{msy}). For example, the maximum sustainable yield (MSY) was estimated to be in the range of 1,794-1,872 tons attained by a F_{msy} of 6,000-7,000 boat-days (Siddeek et al., 1988). Additionally, a higher MSY (2,460 tons) was estimated by Mathews and Samuel (1989) at F_{msy} of 6,500 boat-days. A more recent analysis conducted by Al-Foudari et al., (2015) using age-structured modelling, estimated that the MSY was 2,011 tons obtainable at F_{msy} of 7,375 boat-days.

This chapter analyses the monthly catch and effort data from the shrimp fishery using a seasonal statistical catch at age (SCA) approach with the basic aim of providing improved estimates of vulnerable biomass, historical fishing mortality rates and patterns of relative recruitment. Furthermore, I determine the status of the shrimp fishery over the years using six management quantities of interest such as B_t/B_{msy} (the ratio of the vulnerable stock biomass relative to the biomass that would produce the maximum sustainable yield) and F_t/F_{msy} (the ratio of the fishing mortality rate relative to the fishing mortality rate that maintains the maximum sustainable yield). A retrospective seasonal analysis is conducted to compare the historical management performance and the optimal management performance with regard to the net revenue. Finally, the relationship between Shatt Al Arab freshwater flow and relative recruitment is broadly investigated using a simple regression analysis.

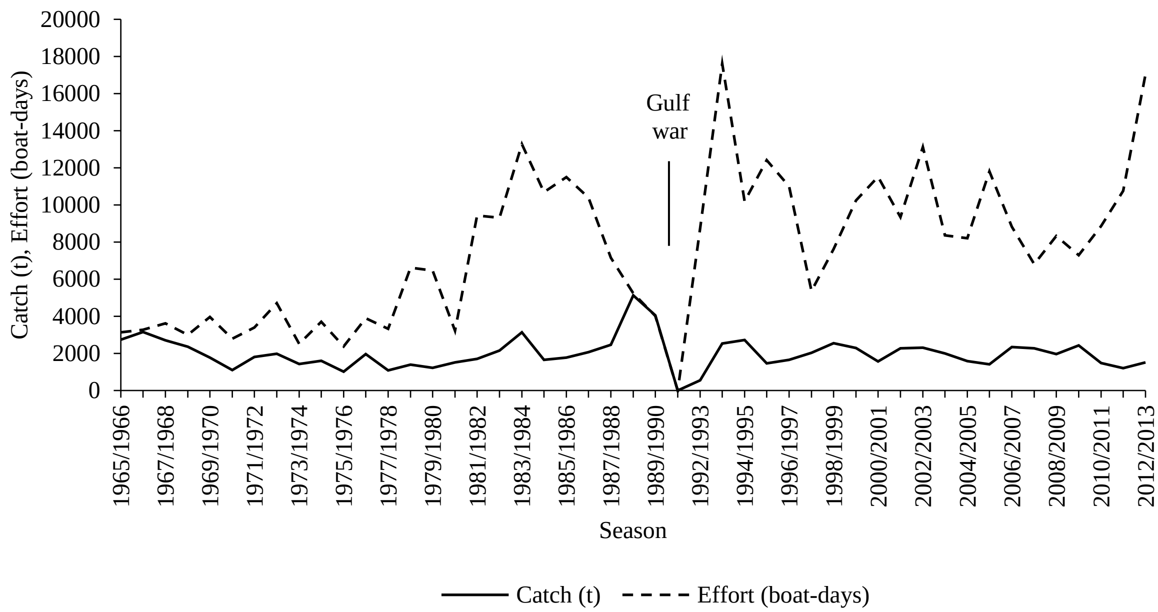


Figure 2.1. Historical catch and effort in the Kuwait shrimp fishery. Catches in tons (t), effort in boat-days (source: Al-Foudari et al., 2015).

2.2 Methods

Data

Time series of catch and effort were collected from both artisanal and commercial shrimp sectors by the Kuwait Institute for Scientific Research (KISR) for the period 1965-2012. Out of these 48 years, the last 21 years (1991-2012) recorded the catch and effort data by month. Hence, monthly effort reconstruction was carried out for the earlier years (1965-1989) using the average proportion of effort by month from the more recent monthly data (total annual effort x proportion by month).

Seasonal statistical catch at age (SCA)

A stock synthesis approach (i.e. SCA model) was applied to reconstruct the exploitable biomass and recruitment of the shrimp stock given initial estimates of the leading parameters: the unfished biomass (B_o) and the relative improvement in juvenile survival rate when the stock is greatly reduced, known as the compensation ratio (CR) (Goodyear 1977, 1980). The B_o and CR values were obtained through numerical search in which CR was constrained between 1.2-30. Relying on auxiliary information, the majority of the parameters used in the model were assumed known (Table 2.1). However, parameters including the catchability coefficients were estimated by minimizing the sum of squared deviations between observed and predicted catches (in weight)

$$(1.1) \quad SS = \sum_t \{\ln\left(C_t / C_t^{prd}\right)^2\} + \sum_m \{\ln(C_m - C_m^{prd})^2\} + \sum_t (x_t - 1)^2$$

Where C_t is the observed annual catch, C_t^{prd} is the predicted annual catch, C_m and C_m^{prd} are the observed and predicted monthly catches, respectively, and x_t refers to the variation in maximum recruitment. Penalty for variation in recruitment from the mean stock-recruitment relationship and more weight on the annual catch data (missing high early catch in 1990 otherwise) were applied in the SS objective function. Inputs such as relative vulnerability at age (v_a), rate of natural mortality (M), growth and survival schedules, relative fecundity at age (f_a), unfished survivorship at age (lx) and relative fraction mature at age are assumed to be fixed over seasons. The mean weight at age (w_a) was accounted as an average over males and females with different length growth. Assumption here is that sex ratio stays near 0.5, as is evident in Al-Foudari et al., (2015). In this case, only the effect of sex is on average weight of prawns at age and in catch. It should be noted that the shrimp female is twice as long as a male (i.e. weighs about eight times as much), therefore, we would expect the biomass of the catch to be dominated by females.

Numbers over age a (in months) and months m during season t were estimated as described by Walters et al., (2005)

$$(1.2) \quad N_{a+1,(t,m+1)} = N_{a,(t,m)} S\left(1 - v_a F_{t,m}\right)$$

Where S is the survival from natural mortality rate ($S = e^{-M}$) and $F_{t,m}$ is the fishing mortality rate on fully vulnerable fish ($v_a = 1$) in month m during season t. It was assumed that $M = 0.17$ month^{-1}, a typical natural mortality rate value associated with tropical and sub-tropical *P. semisulcatus* (Siddeek, 1991; Dichmont et al., 2003). The fishing mortality rate ($F_{t,m}$) in Eq. (2.2) was estimated for each month m in season t

(1.3) $F_{t,m} = E_{t,m} q q_s$

Where $E_{t,m}$ is the monthly observed effort (in boat-days) over the season, q denotes the catchability coefficient (assumed to be fixed over the entire historical seasons) and q_s represents the catchability coefficient at the first month of the shrimping season to account for the higher catchability coefficient at the beginning of the seasonal fisheries. The widely applied Beverton-Holt function was used to predict recruitment rates

(1.4) $N_{1,(t,m+1)} = \frac{\alpha G_{t,m} r_m}{1+\beta G_{t,m}} e^{(x_t-1)}$

Where α denotes the productivity at low stock size, β represents density dependence r_m is the proportion of shrimp reproducing in month m and $G_{t,m}$ is the egg production in month m and season t, $G_t = \sum N_{a,t} f_a$. It should be noted that x_t is assumed to vary around an average of 1 with low x_t representing years of high maximum recruitment and high x_t representing low capacity years. Further, the seasonal reproductive schedule of *P. semisulcatus* was set to peak around December, consistent with Niamaimandi et al., (2008) findings. Both α and β were determined using information on the unfished egg-per-recruit ($\emptyset_{E_o} = \sum lx_a f_a$), unfished biomass-per-recruit ($\emptyset_{B_o} = \sum lx_a w_a v_a$) and unfished recruitment ($R_o = \frac{B_o}{\emptyset_{B_o}}$) (Walters and Martell, 2004)

(1.5) $\alpha = \frac{CR}{\emptyset_{E_o}}$

(1.6) $\beta = \frac{CR-1}{R_o \emptyset_{E_o}}$

The catch ($C_{t,m}$) for each month m in season t can be predicted from the vulnerable biomass ($B_{t,m} = \sum N_{a,(t,m)} w_a v_a$) and fishing effort $E_{t,m}$ using the seasonal catch equation

(1.7) $C_{t,m} = (1 - e^{-F_{t,m}})B_{t,m}$

Table 2.1. Values of the parameters used in the seasonal SCA model based on auxiliary information (source: Al-Foudari et al., 2015)

Parameter	Value
Asymptotic length (L_∞)	15 cm CL, averaged over males and females
Curvature parameter (k)	1.5 year^{-1}
Length-at-vulnerability (L_v)	4 cm CL, averaged over males and females
Length-at-maturity (L_m)	9 cm CL
Natural mortality (M)	0.17 month^{-1}

CL: carapace length

Effort dynamics

The total effort necessary to attain any annual catch was estimated as follows (Walters and Martell, 2004)

(1.8) $E_t = \frac{C}{q \times B_t}$

where E_t is the boat-days necessary to achieve the target catch (C) in season t.

Fishery reference points

The status of the Kuwait shrimp fishery was evaluated by the biomass that would produce the maximum sustainable yield (B_{msy}) and the fishing mortality rate that would maintain the maximum sustainable yield (F_{msy}). The terms "overfishing" and "overfished" are defined as ($F_t/F_{msy} > 1$) and ($B_t/B_{msy} < 1$), respectively. The calculations of maximum sustainable yield (MSY), B_{msy} and F_{msy} were based on the assumption of long-term average recruitment (mean x_t anomaly = 1). A point estimate of MSY was estimated by maximizing the average long-term catch (Eq. (2.7)) for a 10-year projection period (2013-2023). Further, B_{msy} and F_{msy} were summed over the projected averages of fishing mortality and vulnerable biomass ($B_{t,m} = \sum N_{a,(t,m)} w_a v_a$), respectively.

A key determinant to the estimation of management quantities of interest is the CR value. It was observed that there is a lack of contrast in spawning abundances in the data, so that a range of combinations of B_o and CR can equally well explain the data (i.e., stock could equally well be large and unproductive (and have had lower F) or small and productive (and have had higher F)). Finally, several scenarios were conducted to test the sensitivity of some of the estimated parameters (B_o, q) and management quantities (B_{msy} and F_{msy}) to different assumed values of CR.

Retrospective analysis

The current policy conducted by Kuwait fisheries management is based on the protection of the shrimp stock during the spawning period (February-July). Further, the Kuwait shrimp fishery is considered an open-access fishery in the sense that fishing effort is not regulated. The concept of the omniscient manager was implemented to evaluate the current policy (see Martell et al., 2008 for a detailed description of the omniscient manager). A critical point about such an omniscient procedure is that the best fishing pattern during a given season depends on the seasonal reproductive timing of the shrimp. For instance, a common solution for an omniscient manager when there is no cost is to fish very hard in only one month, just after the time of spawning. In most cases, fishing operators would likely refuse to go out longer within each month than the number of days needed to drive the catch per unit effort (CPUE) down to their operating costs (i.e. operating at daily costs greater than daily income). Hence, an important assumption has been made in the retrospective model: if CPUE declines within a month as $CPUE = qBe^{(-qE)}$, fishers should be unwilling to exert more effort than $E = -\frac{1}{q}\ln\left(\frac{V}{qB}\right)$ where cost (V) is estimated by multiplying the cost per CPUE (assumed to be equal to a fixed value of 0.5) to the historical average CPUE. Furthermore, a new parameter ($F_{\max}$), describing the maximum allowable fishing mortality in any month ($F_{\max} = 1$), was used as a constraint so that the fishing effort is more spread out during the season. This way, the omniscient manager "seeks" the most profitable fishing pattern over the season but makes it uneconomical to generate high exploitation rates if cost is high enough.

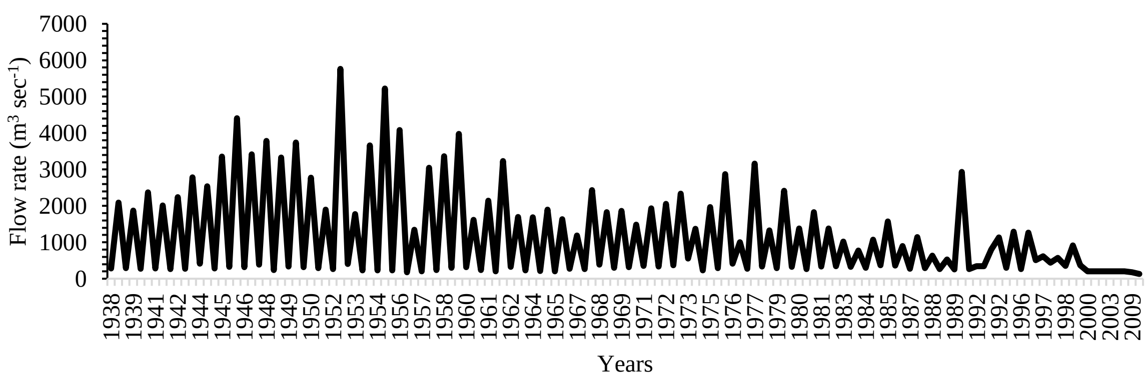
The purpose of the retrospective analysis was to compare between the maximum economic effort needed to drive the CPUE down to cost/effort in a given shrimping season (i.e. omniscient policy) and the current policy in terms of net revenue, conditional on the leading parameters (B_o and CR), recruitment anomalies (x_t) estimated from the historical data set and the seasonal reproductive timing

(1.9) $R = \sum C_t - \sum V_t T_t$

Where R is the net revenue, C_t is catch, V_t denotes cost and T is the effort over season t. The comparison included the post-Gulf War shrimping seasons (1991-2012) because the fleet size and effort were lower over the early part of the historical period. A numerical search is conducted to maximize R by finding the best fishing effort and seasonal opening pattern. Finally, several scenarios were drawn on the effect of different cost per CPUE (referred to “cost/CPUE” hereafter) on the total revenue and total effort.

Regression analysis

We extracted the flow rate time-series data associated with Kut flow-gaging station (Figure 2.2) from the Issa et al., (2014) study. Using the square of Pearson correlation coefficient (r^2), the flow rate time-series data was fitted against the estimated relative recruitment to investigate the relationship between the Shatt Al Arab flow pattern and shrimp production, from the start of the fishery to the end of the flow rate dataset (1965-2010).



2.3 Results

Model fit and fishery reference points

Figure 2.2. Flow rate time-series data recorded at Kut flow-gaging station (source: Issa et al., 2014).

The model mimics the observed catches well (Figure 2.3). A range of CR estimates fitted the observed catch data equally well indicating lack of contrast in the spawning abundances in the data (i.e. large unproductive shrimp stock vs. small productive shrimp stock). Figure 2.4 shows how the estimated parameters q, B_o, and the objective function (SS) varied to obtain the fits over different assumed CR values. The estimated parameters B_o and q showed decreased and increased trends toward higher CR values, respectively. However, q showed less variations whereas B_o was highly sensitive to changes in assumed CR values. Furthermore, Figure 2.4 showed that SS values were stable over different assumed CR values, indicating that model fit is about the same. Both F_t/F_{msy} and B_t/B_{msy} quantities were found to be insensitive to the effects of CR (Figure 2.5 and Figure 2.7). According to the specified reference points, the stock is considered overfished ($B_t < B_{msy}$) during the last three years (2009-2012) and experience high overfishing ($F_t > F_{msy}$) in the last two years of data (2011-2012) (Figure 2.6). The highest overfishing occurred in 2012 with F_{2012}/F_{msy}= 2.0 and the year in which the lowest shrimp biomass observed is 1994 (B_{1994}/B_{msy}=0.5). The shrimp stock appeared to be in its best conditions at the very beginning of the fishery and just before the Gulf War. Management quantities of interest including MSY, B_{msy} and, F_{msy} are presented in Table 2.2.

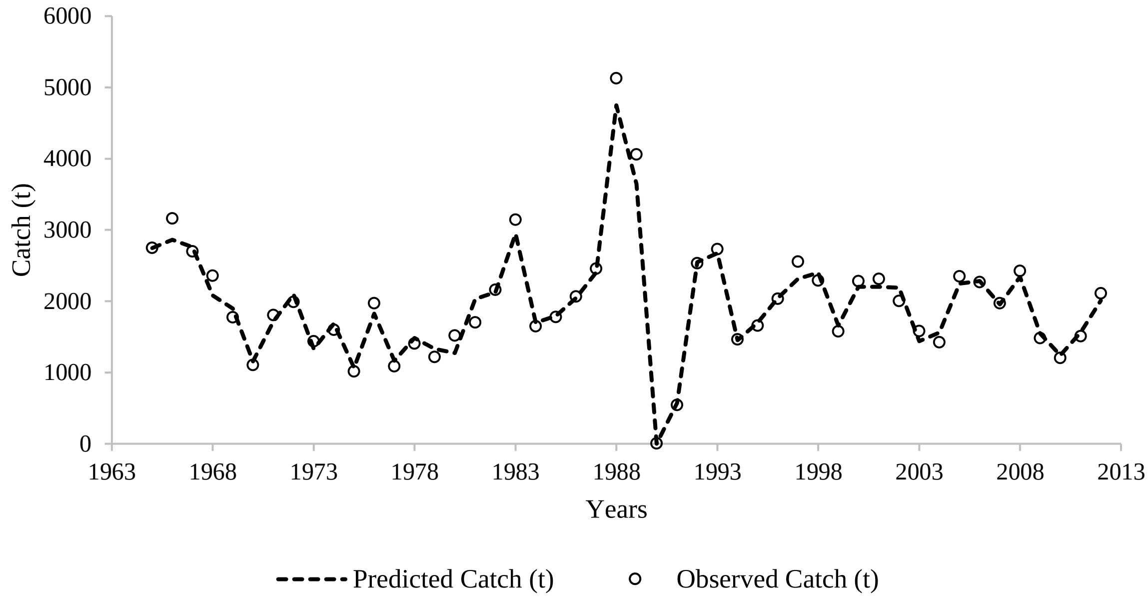


Figure 2.3. Predicted catch fitted to the observed catch time series (1965-2012) in Kuwait shrimp fishery.

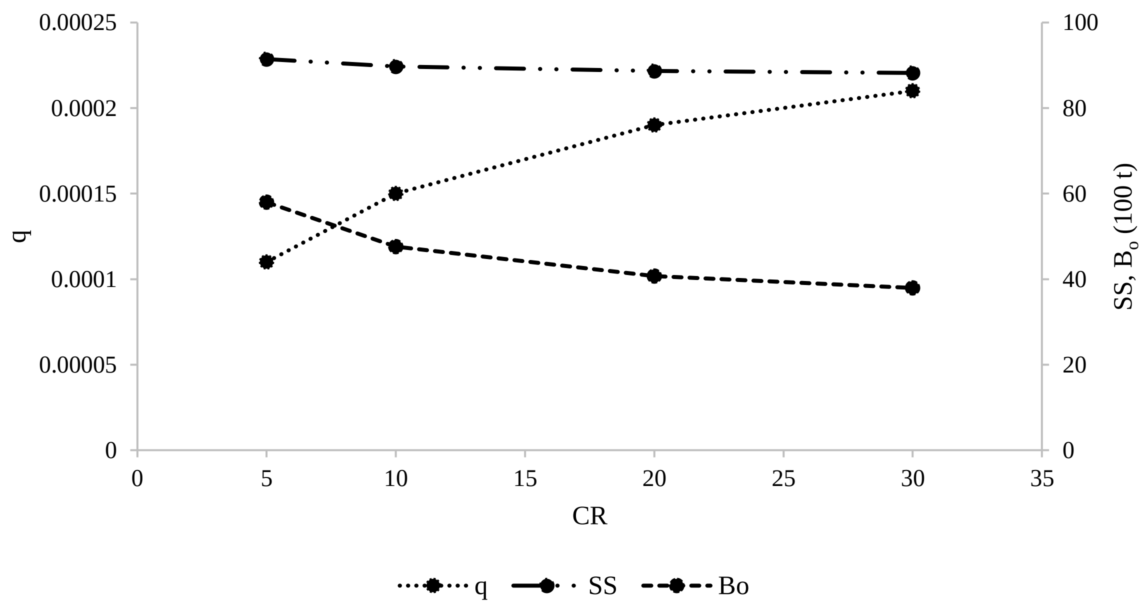


Figure 2.4. The effect of alternative $\boldsymbol{CR}$ assumptions on estimated parameters $\boldsymbol{B_o}$, $\boldsymbol{q}$ and the sum of squared deviations (SS) of observed from predicted catches.

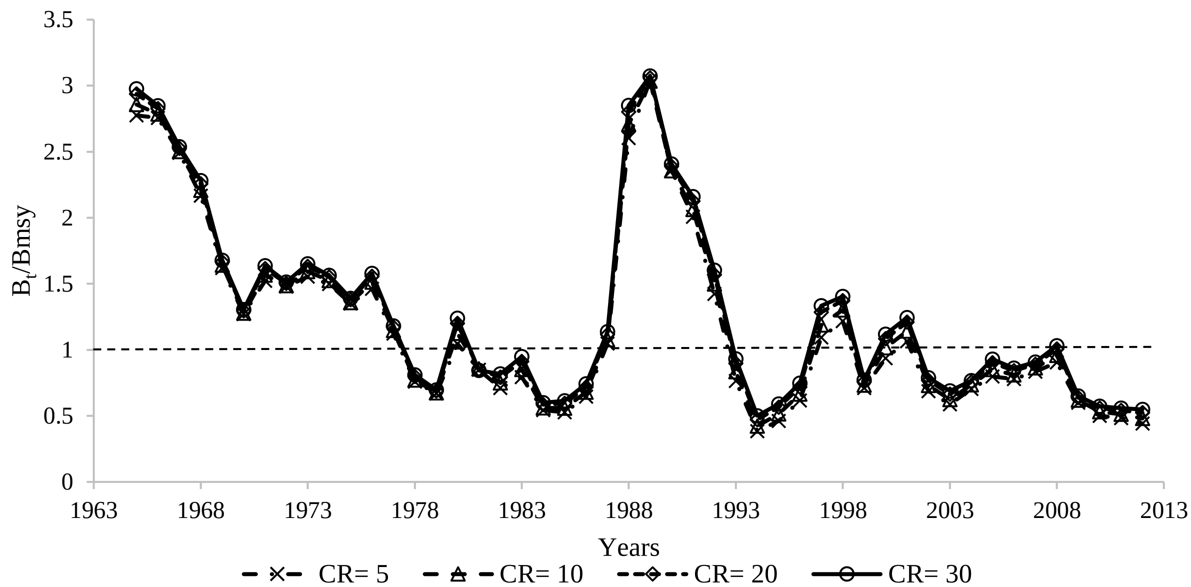


Figure 2.5. The effect of alternative $\boldsymbol{CR}$ assumptions on the estimated trend in B_t/B_{msy}. The grey dashed line indicates the reference point ($B_t = B_{msy}$). Points below the dashed grey line represents overfished years ($B_t < B_{msy}$).

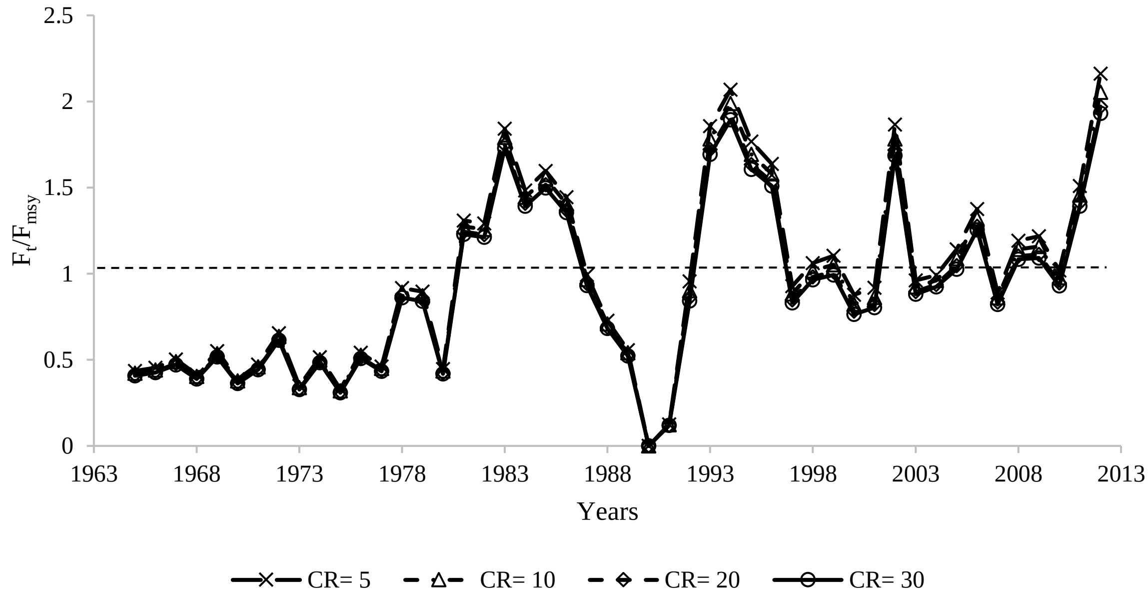


Figure 2.7. The effect of alternative $\boldsymbol{CR}$ assumptions on the estimated trend in F_t/F_{msy}. The grey dashed line indicates the reference point ($F_t = F_{msy}$). Points above the dashed grey line represents overfishing years ($F_t > F_{msy}$).

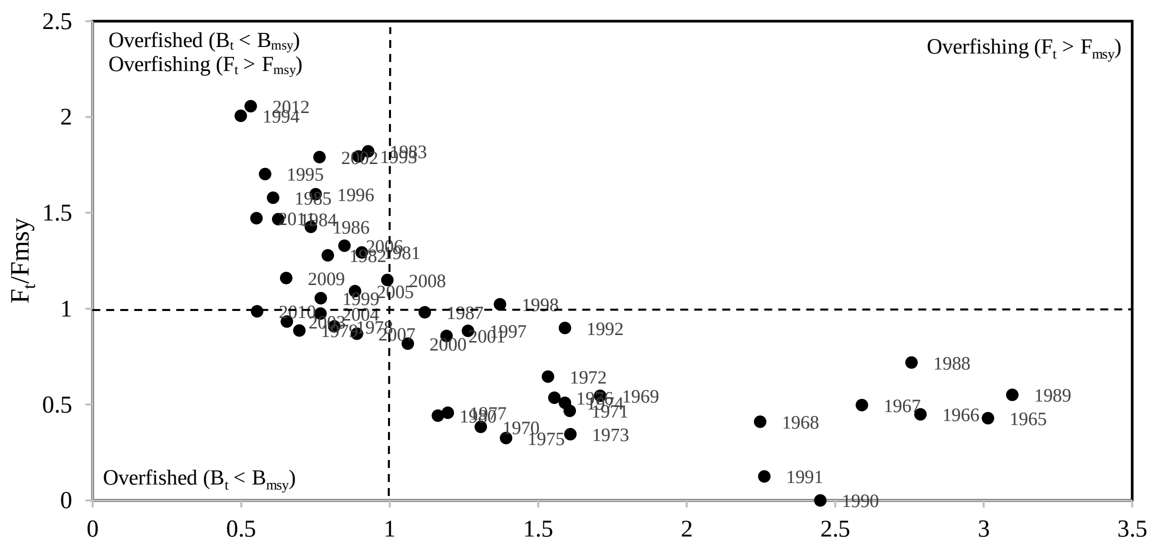


Figure 2.6. Kobe plot with the vulnerable biomass in season *t* (B_t) relative to B_{msy} (x-axis) vs. fishing mortality rate in season *t* (F_t) relative to F_{msy} (y-axis) for Kuwait shrimp fishery. Numbers represent years. The dashed grey lines indicate reference points.

Table 2.2. Estimates of management quantities for Kuwait shrimp stock.

Management quantity	Estimated value
B_{msy} (t)	1365.44
F_{msy} (yr^{-1})	1.59
MSY (t)	2088.52

Effort dynamics

Figure 2.8 shows the seasonal effort pattern for Kuwait shrimp fishery, in relation to biomass changes. Interestingly, the fishers are trying to achieve some overall seasonal catch, and work harder (i.e., expend more effort) in low biomass years so as to still try and reach that target catch.

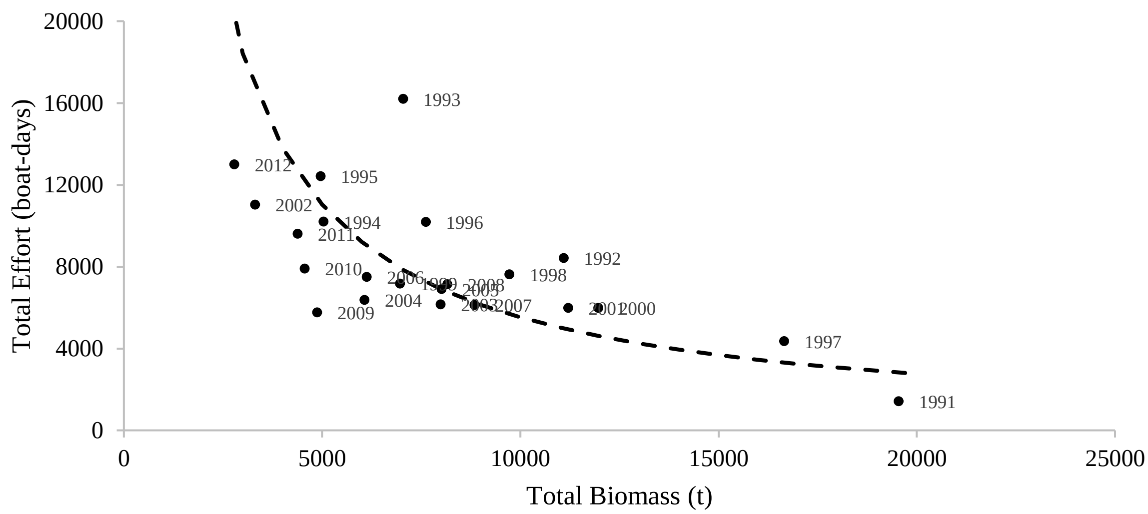


Figure 2.8. Effort dynamics in Kuwait shrimp fishery. Dots and numbers indicate the observed total effort and years, respectively. The dashed line denotes the predicted total effort to achieve the target catch in each season.

Retrospective analysis

Table 2.3 shows the results of the retrospective analysis where the net gain values are the result of the comparison with the current policy. Assuming the cost/CPUE = 0.5 (base-case scenario), the omniscient manager "sees" potential for about 4% increase in revenue compared to the current policy, from opening the fishery over months October-December, after peak reproduction in months January-March. Furthermore, increasing cost/CPUE beyond the base-case scenario, (e.g., 0.75-1.25), resulted in a lower total effort and a shorter shrimping season. On the contrary, setting the cost/CPUE lower than the base-case scenario, (e.g., 0.25), showed greater total revenue obtained at a shorter shrimping season with higher effort per month, approaching the MSY policy as cost/CPUE approaches zero.

Table 2.3. Comparison between the optimized policy under several cost/CPUE values and the current policy for the post-Gulf War period (1991-2012)

Criteria	Current policy	Optimized policy				
		Cost/CPUE				
		0.25	0.50	0.75	1.00	1.25
Total catch (t)	42,155	45,695	43,942	41,542	39,217	36,428
Net gain (%)	-	+ 8	+ 4	-1	-7	-14
Season length (months)	6 (Aug-Jan)	3 (Nov-Jan)	3 (Oct-Dec)	2 (Oct-Nov)	2 (Oct-Nov)	2 (Oct-Nov)
Average effort (boat-day)	716	504	421	354	307	265

Regression analysis

Figure 2.9 suggests that there is a very weak correlation ($r^2 = 0.03$) between the freshwater flow rate of and estimated relative recruitment for the period 1965-2010, indicating weak effects of changing estuarine conditions (increasing salinity over time) on shrimp recruitment. However, it was notable that the highest estimated relative recruitment in the stock history occurred on an unusually high flow year (Figure 2.10).

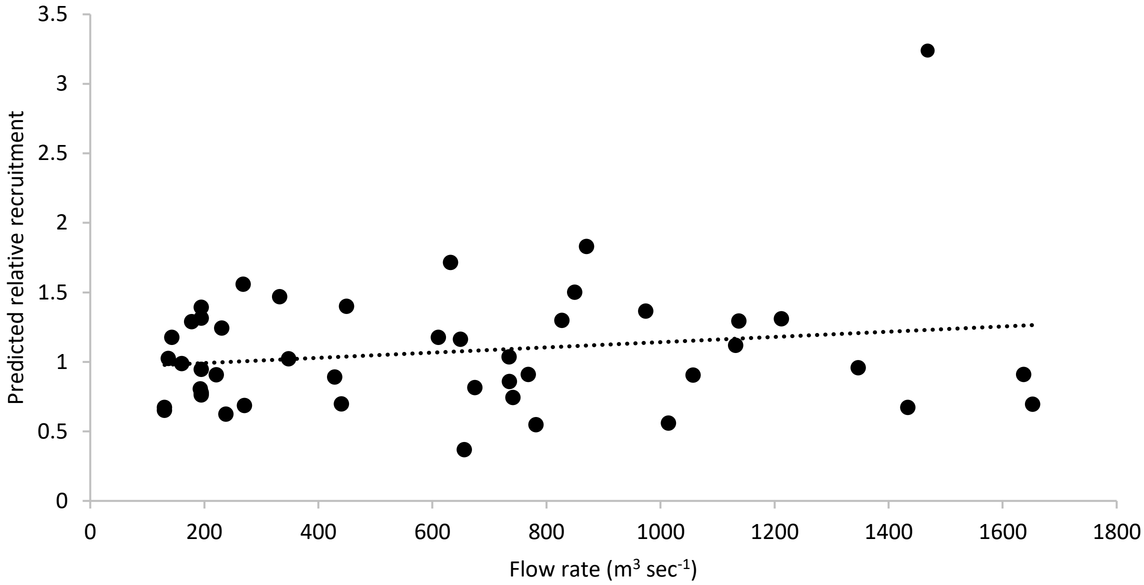


Figure 2.9. The relationship between the flow rate recorded for the period 1965-2010 at Kut flow-gaging station and predicted relative recruitment for *P. semisulcatus* in Kuwait waters.

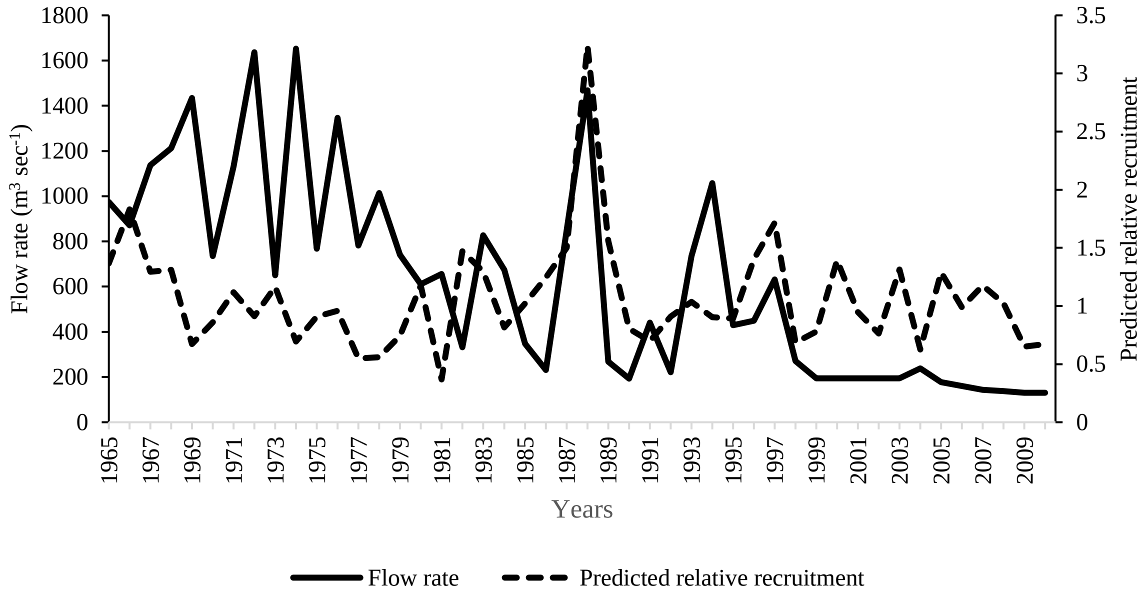


Figure 2.10. Time-series pattern of the flow rate recorded for the period 1965-2010 at Kut flow-gaging station and predicted relative recruitment for *P. semisulcatus* in Kuwait waters.

2.4 Discussion

The seasonal SCA, a simple monthly accounting model, was used to explain the seasonal details of catch and effort in Kuwait shrimp fishery while accounting for rapid growth and high mortality rates of the penaeid shrimp. This model allowed for addressing the effects of key basic assumptions about the relationships between stock size, catch, effort, and recruitment dynamics. However, there are potential pitfalls associated with the use of the SCA approach. First, the applied model requires often unknowable assumptions about the vulnerability-at-age of each fishing fleet. Consequently, these assumptions introduce large biases in results when they are incorrect. For instance, Walters et al. (2005) drew attention a white sturgeon case, where assigning high vulnerability-at-age values for the older fish in a stock reduction analysis model, might result in the underestimation of the historical exploitation rate of the fishery. Ultimately, such assumption impacts the estimate of relative stock size (i.e., how large the stock is relative to its unfished state). Second, seasonal SCA requires an informative contrast in catch biomass time series and corresponding responses in abundance indices. In our analysis, the problem of lack of contrast led to confounding between CR and B_o estimates. The sensitivity analysis conducted showed that B_o was sensitive to the effects of assumed CR values while q showed marginal variations (Figure 2.4). On the other hand, the reference point estimates B_{msy} and F_{msy} were insensitive to the assumed values of CR (i.e. it is a robust finding that there has been a historical overfishing).

Defining management reference points have always been a controversial subject (Hilborn,2007; Branch et al., 2011). For instance, while this study defines the term “overfished” to be $B_t < 1\ B_{msy}$, the United Nations for Food and Agriculture Organization (FAO) defines the same term as $B_t < 0.8\ B_{msy}$. Moreover, the legal definition of the term “overfished” is also different; the United States and Australia declare a stock to be overfished if $B_t < 0.5\ B_{msy}$ (Hilborn, 2010; Hilborn and Stokes, 2010). Based on the management reference points used in this study, the shrimp stock showed rapid recovery in the late 1980s. Additionally, Figure 2.6 shows that Kuwait shrimp stock is currently considered overfished and experience high overfishing. The recent precarious situation of Kuwait shrimp stock is believed to be attributed to both overfishing as well as non-fishing activities (Al-Abdulrazzak and Pauly, 2013; Al-Husaini et al., 2015).

Typically, a high effort is observed initially in seasonal fisheries, declining later in the season as an increasing proportion of the fishers cannot achieve CPUE high enough to keep them fishing. For example, major seasonal fisheries such as the Gulf of Mexico shrimp fishery and the North Territory Gulf of Carpentaria mud crab fishery followed the same effort dynamics (Walters and Grubert, 2011; Walters, 2016). Interestingly, for most years, there is no such pattern in the Kuwait seasonal effort data. Figure 2.8 showed a “satisficing” rather than profit-maximizing behavior which apparently is not very common (Walters and Martell, 2004). Several reasons could describe such effort dynamics: a) operating costs are relatively cheap allowing the fishers to continue operating even at low CPUE, due to cheap labour and fuel and b) because of the fact that only local people are allowed to be boat owners, who very often demand fixed total payment from the fishers (expats), forcing them to keep fishing.

It has long been known from fisheries economics modeling that the fishing effort and annual fishing mortality that maximize net economic value are lower than the efforts that maximize total catch (MSY), so fishing to maximize profit leads to larger stock sizes and lower fishing mortality goals. Nonetheless, some studies (see Christensen, 2010) have argued based on other economic considerations, (e.g., employment, the processing value and fish use) that the overall economic optimum may still be close to MSY. The retrospective model used in this study behaves like the standard economic models, predicting lower total effort and fishing mortality than would result in MSY (Table 2.3). Moreover, the model calculated the maximum effort each month that operators should be willing to exert. Compared to the current fishing season, the optimal fishing seasons are shorter and with lower fishing effort, but higher overall profitability (Table 2.3). It is recommended that the trade-off between fishing effort, the length of season and profitability should be discussed and evaluated by the license holders because it is their future that is at risk.

While overfishing is adversely impacting fish stocks in Kuwait, several studies noted that environmental issues such as reduced Shatt Al Arab river flow discharge and Mesopotamian marshland drainage are equally detrimental (Al-Yamani et al., 2007; Al-Husaini et al., 2014; Alosairi and Pokavanich, 2017). The regression analysis carried out in this study indicated a lack of relationship between the flow rate of Shatt Al Arab river and the production of the shrimp stock (Figure 2.9). Similarly, studies correlating rainfall with catches of banana prawns in the Gulf of

Papua, Australia found a lack of relationship between the two variables (Vance et al., 1985; Staples et al., 1995). Nevertheless, this finding need not be considered conclusive in the Northern Persian Gulf marine system for several reasons. First, the time-series pattern of the flow rate and estimated relative recruitment showed a remarkable agreement in years 1987-1989, consistent with the highest landings in the history of Kuwait shrimp fishery (Figure 2.1 and Figure 2.10). Al-Husaini et al., (2014) ascribed such high landings to several reasons including suitable environmental conditions, vessel buy-backs and strict enforcement of fisheries regulations. Secondly, several studies have shown strong associations between freshwater flow, recruitment, and migration of fish and shellfish. For instance, a study conducted in Florida Bay concluded that there is a strong positive correlation between pink shrimp yields and the freshwater flowing into the Everglades National Park estuaries (Browder, 1985). Additionally, Loneragan and Bunn (1999) explored the impact of the seasonal and total annual flow of Logan River on the yields of adjacent fish and shellfish fisheries in southeast Queensland, Australia. Attributed to the high primary production triggered by Logan river runoff, improved survivorship and growth of shrimp at larval stage resulted in high shrimp yields. Thirdly, the impact of the reduced Shatt Al Arab flow could be masked by predator-prey interaction: reduced predation mortality by both environmental changes and overfishing has served to mask declines in shrimp nursery area. For the aforementioned reasons, we recommend that the fisheries management authority be critically aware about the environmental changes experienced in the Northern Persian Gulf and to initiate monitoring programs for inshore/estuarine dependent species.

Chapter 3: Assessment of *Acanthopagrus latus* stock in the Northern Persian Gulf

3.1 Introduction

The yellow-fin seabream (*Acanthopagrus latus*) is a common species of the Sparidae family that occur in the Northern Persian Gulf (NPG) (Valinassab et al., 2006; Raeisi et al., 2010). Similar to many Sparids, *A. latus* is a protandrous hermaphrodite where individuals undergo sex-change behavior (Buxton and Garrat, 1990). The reproductive biology such as the reproductive strategy, spawning seasons and age-at-maturity of *A. latus* has been examined extensively in NPG. For instance, Abou-Seedo et al., (2003) found that *A. latus* undergoes four different reproductive styles which are gonochorism, functional males, transitional individuals, and ultimately functional females. Furthermore, the spawning season of *A. latus* has been found to occur during January-April. *A. latus* mature relatively fast: at 20 months or in size range of 20.3-23.7 cm for all sex classes (Abou-Seedo et al., 2003; Lee and Al-Baz, 1990).

In Kuwait, *A. latus* is considered among the commercially valuable fish species. Thus, almost every fishery including shrimp trawlers as a by-catch, trap fishery, gillnet fishery and hook and line target *A. latus* stock. Whereas landings for the most commercial species are in decline, (e.g., *Pampus argenteus*, *Tenualosa ilisha*, *Epinephelus coioides*, *Lutjanus malabaricus*) (Al-Husaini et al., 2015), *A. latus* landings showed a steady increase from 1978-2012, followed by significant declines during 2013-2015 (Figure 3.1) (CSO, 1978-2015).

Few stock assessments have been applied to evaluate the stock of *A. latus* in NPG. For instance, Lee and Al-Baz (1990) applied a basic per-recruit model to assess the status of *A. latus* stock using catches from the trap fishery. Their results suggested that *A. latus* stock is underexploited by the trap fishery. In contrast, Morgan (1985) showed that any increase in fishing mortality would result in a suboptimal yield-per-recruit of *A. latus* stock. While the major advantage of using a per-recruit model is that only life-history information is required, (e.g., growth rate, mortality, and age-at-first-capture), there are several serious limitations. First, the assumption of steady-state neglects the impacts of fishing on the numbers of different age groups and life-history parameters. Second, failure to account for recruitment and spawning stock size which prevents the setting of sustainable exploitation levels (King, 2013).

None of the previous assessments attempted to model the full time-series of *A. latus* catch data, as is here done using the stock reduction analysis (SRA) approach introduced by Kimura et al., (1984) and revisited by Walters et al., (2006). In this chapter, I attempt to assess the current stock status of *A. latus* relative to its unfished biomass using SRA. Additionally, I demonstrate the use of predicted length frequency moments (i.e. annual mean length and variance) to improve the fitting of SRA model to relative abundance data (Fournier and Doonan, 1987).

The basic idea of SRA is to run a population assessment model starting at unfished conditions, remove the observed catch history from the fish population while accounting for recruitment and natural mortality (Kimura and Tagart, 1982; Kimura et al., 1985). The fundamental question to be answered by the SRA approach is "How large did the population have to be to have sustained the observed catches and have resulted in the current relative stock size?". The SRA approach rests on two fundamental propositions: a) having the complete catch history of a fishery to estimate the unfished biomass of the stock and b) the ability to account for the age-structure effects of a fishery as it proceeded over the years (Walters et al., 2006).

A major way to improve assessments for data-limited fisheries is to use information from length distribution to place bounds on recent exploitation rates. Several assessment fitting exercises are based on prediction of length frequencies, assuming near equilibrium length distribution each year, and using Beverton-Holt equation for equilibrium mean length to estimate annual total and fishing mortalities (O'Farrell and Botsford, 2004; Hordyk et al., 2015; Prince et al., 2015). The mean length can be a useful indicator of the population size and status because it is sensitive to both recruitment variation and exploitation rate, generally decreasing when exploitation rate is high. For instance, Ault et al., 2004 used the mean length to estimate the fishing mortality and the stock status of the hogfish in the Florida Keys. Here, I emphasize the importance of taking into consideration the effects of recruitment variation, stock-recruitment relationship, and selectivity in the calculation of the annual mean length. To address these effects, I predict the annual length distribution from the age-structured stock reduction model, and apply Fournier and Doonan (1987) approach to calculate the annual mean and variance of length.

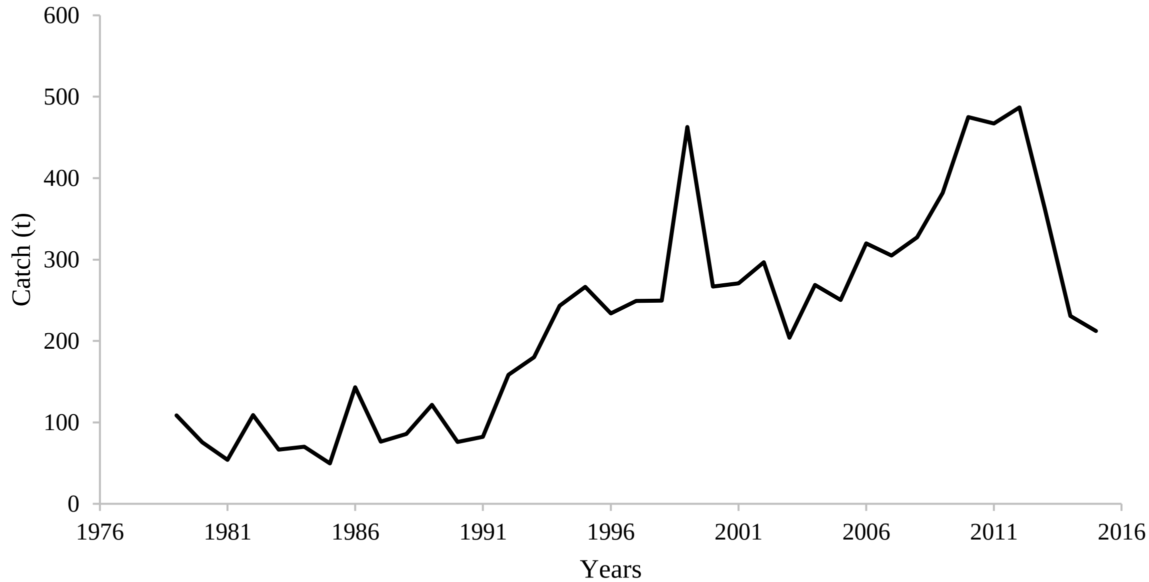


Figure 3.1. Historical total catch of *A. latus* in Kuwait waters (source: Kuwait's Central Statistical Office, 1978-2015).

3.2 Methods

Data

I used three different data sets in the SRA model to assess *A. latus* stock. First, catch data (in tons) during 1978-2015 were obtained from Kuwait's Central Statistical Office (CSO). Second, Kuwait Institute for Scientific Research (KISR) has provided length frequency data (total sample size (n) = 2,749 fish) that have been collected using different fishing gears, (e.g., traps, gillnets, and trawl), over the periods 1980-1985, 1989-1990, 1992-1994, 1997-2000 and 2002-2004. Third, trawl bycatch rates (CPUE in ton/boat-days) collected from the shrimp fishery were used to construct a relative abundance index for the period 1997-2012 (Al-Foudari et al., 2015). I generated catch for earlier years (1965-1977) using the average CPUE for later years (1979-1986), multiplied by the shrimp fishery effort for each of the early years.

Stock reduction analysis (SRA)

I applied the stock reduction analysis (SRA) approach described in Walters et al., (2006) to reconstruct the exploitable biomass and recruitment of *A. latus* stock given initial estimates of the following leading parameters (see Walters and Martell, 2004): the unfished biomass (B_o) and the relative improvement in juvenile survival rate when the stock is greatly reduced, known as the compensation ratio (CR). I estimated B_o and CR values through numerical search in which CR value was constrained between 2-30, consistent with meta-analyses of historical stock-recruitment data sets (e.g., Goodwin et al., (2006)). Inputs such as relative vulnerability-at-age (v_a) which assumed equal for all fishing gears, rate of natural mortality (M), growth and survival schedules, relative fecundity-at-age (f_a), unfished survivorship-at-age (lx) and relative fraction mature-at-age were assumed to be fixed over years. The von Bertalanffy growth curve (von Bertalanffy, 1938) was fitted to estimate the growth parameters and fit the mean length-at-age for the construction of the growth schedule (Table **3.1**). Since I assumed vulnerability to depend on the length in the analysis of length data (section 2.3), I calculated the v_a in this model by integrating the length-vulnerability function over the length-at-age distribution for each age to get the correct mean vulnerability, rather than calculating vulnerability-at-age only from mean length-at-age (i.e., ignoring the distribution of lengths for each age).

Table 3.1. Inputs quantities used in the SRA model to construct life-history schedules for *A. latus* in Kuwait waters

Parameter	Value	Source

Asymptotic length (L_∞)	38 cm	KISR
von Bertalanffy metabolic rate (k)	0.35 year^{-1}	KISR
Length-at-maturity (L_m)	24 cm	Lee and Al-Baz, 1989
Natural mortality (M)*	0.32 year^{-1}	This study

* Using Hoenig$_{nls}$ equation from Then et al., (2015)

I used the following equation to predict numbers over age a and year *t* (Walters et al., (2006))

(3.1) $N_{a+1,t+1} = N_{a,t}S\left(1 - v_{a,t}U_t\right)$

where S is the survival from natural mortality rate ($S = e^{-M}$); and U_t is the exploitation rate in year *t*. In SRA model, U_t is varied so as to force the model to exactly predict the observed catches C_t given model predicted vulnerable biomass B_t (Walters et al., 2006)

(3.2) $U_t = \frac{C_t}{B_t}$

where C_t is the catch in year *t* and B_t denotes the biomass in year *t*. For predicting recruitment the SRA model assumes a Beverton-Holt relationship of the form

(3.3) $N_{1,(t)} = \frac{\alpha G_t}{1+\beta G_t} e^{(x_t - 1)}$

where α denotes productivity at low stock size; β represents density dependence; and G_t is the egg production in year *t* $G_t = \sum N_{a,t} f_a$ and x_t denotes stochastic variation in maximum recruitment. It should be noted that x_t is assumed to vary around an average of 1 with low x_t representing years of high maximum recruitment and high x_t representing low capacity years. Both α and β were determined using information on the unfished egg-per-recruit ($\emptyset_{E_o} = \sum lx_a f_a$), unfished biomass-per-recruit ($\emptyset_{B_o} = \sum lx_a w_a v_a$) and unfished recruitment ($R_o = \frac{B_o}{\emptyset_{B_o}}$) (Walters and Martell, 2004)

(3.4) $\alpha = \frac{CR}{\emptyset_{E_O}}$

(3.5) $\beta = \frac{CR-1}{R_O \emptyset_{E_O}}$

The CPUE observations are assumed to be proportional to vulnerable biomass, (i.e., $CPUE = qB_t e^{v_t}$), where q is the catchability coefficient and v_t is a normal observation error. To estimate q conditional on B_t, I used the Walters and Ludwig method of *Z* statistics. The *Z* statistic in year *t* for each CPUE observation was calculated as $Z_t = ln(\frac{CPUE}{B_t})$. The mean of *Z* statistic is a conditional (on the biomass prediction) maximum likelihood estimate of $ln(q)$. A fitting criterion was constructed to compare the observed CPUEs to predicted CPUEs based on the weighted sum of squared deviations of the *Z* values from $ln(q)$

(3.6) $SSCPUE = \frac{\ln\sum \ (Z_t - \ln q)^2}{\sigma^2_{CPUE}}$

Representation of uncertainty

I conducted sensitivity analyses to represent uncertainty in U_t estimates by comparing a baseline estimate of initial biomass (B_o= 2,000 t), calculated from default model parameters mentioned above, vs an assumed large initial biomass (B_o= 5,000 t). Here, I forced B_o to be high, so as to force U_t to be much lower and observe the model fitting. Finally, three scenarios were applied to view the effects of assumed weights (σ^2_{CPUE},σ^2_d,$\sigma^2_{\overline{V}}$ and weight for x, σ^2_x) on the annual vulnerable biomass and U_t estimates (Table 3.2).

Table 3.2. The assumed weight values ($\boldsymbol{\sigma^2_{CPUE}}$,$\boldsymbol{\sigma^2_d}$,$\boldsymbol{\sigma^2_{\overline{V}}}$ and $\boldsymbol{\sigma^2_x}$) in each scenario. Higher variance indicates less weight

Weights	Scenario 1	Scenario 2	Scenario 3

σ_d^2	100	10	1
$\sigma_{\overline{V}}^2$	1000	100	10
σ_{CPUE}^2	100	10	1
σ_x^2	1	0.1	0.01

Length frequency analysis

I predicted the length frequency distribution of *A. latus* by conducting the following series of procedures:

a) Divide length classes on a 1-cm interval from 7-45 cm, following the recommendation by Neumann et al., (2012);

b) Estimate the mean length at age (L_a) using the von Bertalanffy equation (von Bertalanffy, 1938);

c) Set up the matrix $P(L|a)$, (i.e., proportions at length L given age a) (Hilborn and Walters, 1992)

(3.7) $P(L|a) = \emptyset\left(\frac{L_{j+1}^u - L_a}{\sigma_{L_a}}\right) - \emptyset\left(\frac{L_j^u - L_a}{\sigma_{L_a}}\right)$

where $\emptyset$ denotes the standard cumulative distribution; L_j^u the upper bound of length class j; and σ_{L_a} is the standard deviation of mean length-at-age;

d) Given that the mean vulnerability-at-length is assumed to follow a logistic function $v = 1/(1 + e^{(-(L_j - L_v)}/sdl)$ (where L_j is length in class j, L_v length-at-50% vulnerability to capture and sdl is a measure of how spread the vulnerability is over age), the total proportions of each length class was summed over all ages and multiplied by the mean vulnerability-at-length to calculate the predicted vulnerable numbers at length over years.

Finally, I formed a weighted total sum of squared deviations between observed and predicted length counts (rather than proportions, so as to weight big samples more)

(3.8) $SSD = \frac{\sum(L_{tj}^{obs} - L_{tj})^2}{\sigma_d^2}$

where L_{tj}^{obs} is the observed length in year t and length class j; L_{ij} denotes the predicted length in year t and length class j; and σ_d^2 is the weight in the objective function of the length distribution.

After predicting the length distributions, I carried out calculations to predict annual mean ($\overline{L}$) and variance ($\overline{V}$) of lengths (i.e., length distribution moments: 1st moment is the mean, and 2nd moment is the variance as described by Fournier and Doonan (1987))

(3.9) $\overline{L} = \sum\sum L_j P_t$

where L_j is the length at class j and P_t is the standardized proportion of predicted vulnerable numbers at length over year *t*.

(3.10) $\overline{V} = \sum\sum(L_j - \overline{L})^2 P_t$

Then, I formed two objective functions: (i) weighted sum of squares includes observed and predicted mean lengths (Eq. (3.11))

(3.11) $SS\overline{L} = \frac{\sum(\overline{L}_t^{obs} - \overline{L}_t)^2}{\sum \sigma_{\overline{L},t}^2}$

where $\overline{L}_t^{obs}$ is the observed mean length in year t and $\sigma_{\overline{L},t}^2$ is the variance of $\overline{L}$ divided by the sample number in *t* year, and (ii) sum of squares term for observed and predicted variance of length (Eq. (3.12))

(3.12) $SS\overline{V} = \frac{\sum(\overline{V}_t^{obs} - \overline{V})^2}{\sum \sigma_{\overline{V},t}^2}$

where $\overline{V}_t^{obs}$ denotes the observed variance of length in year t; and $\sigma_{\overline{V},t}^2$ is the weight for the variance of length calculated over the year t.

It should be noted that the inverse variance data weight in Eq. (3.11) for each annual mean length is the variance of the mean length (i.e., the sample variance among length measurements divided by the number of measurements included in the sample mean estimate). The variance of lengths in the length frequency sample is the variance among length measurements.

To include the length frequency information along with CPUE information in the SRA fitting, I formed a total objective function

(3.13) $SS_{total} = SSCPUE + SSD + SS\overline{L} + SS\overline{V}$

I used an optimization procedure to fit the observed and predicted data, (i.e., CPUE data, length frequency data and annual mean and variance of length), by finding U_t values that minimize the objective function SS_{total}. The parameters that allowed to vary during the fitting procedure are shown in Table 3.3.

Table 3.3. Summary of the varied parameters and their constraint values during the fitting procedure of the SRA model

Parameter	Constraint	Description
CR	2-30	Relative improvement in juvenile survival rate when the stock is reduced
B_o	none	Initial biomass
sdl	none	Measure of variation of the vulnerability over age
cvl*	>= 0.08	Coefficient of variation multiplied by mean length-at-age

		to estimate sdl for each age
x_t	none	Relative variation in maximum recruitment, one x for each year

*Assumed constant for all mean length-at-age (for more details, see Taylor et al., 2005)

3.3 Results

Representation of uncertainty

Length distribution, mean length and CPUE data were best fitted when B_o ranged between 2,000-2,600 t, under all scenarios (Figure 3.2 (a) and (b)). Furthermore, the assessment indicates that *A. latus* stock is experiencing high exploitation rates in recent years, causing unsustainable declines in the vulnerable biomass. Also, the observed CPUE trend shows some hint of decline in the last couple of years, similar to the predictions from the SRA calculation of declining biomass of *A. latus* in the face of the rapid recent catch increases (Figure 3.1 and Figure 3.2 (b)). When B_o is assumed to be large, the resulted predictions fit the data equally well with comparable SS_{total}

values (small B_o = 230 and large B_o = 260); the findings that vulnerable biomass is large and current vulnerable biomass is small are very uncertain) (Figure 3.3 (a) and (b)).

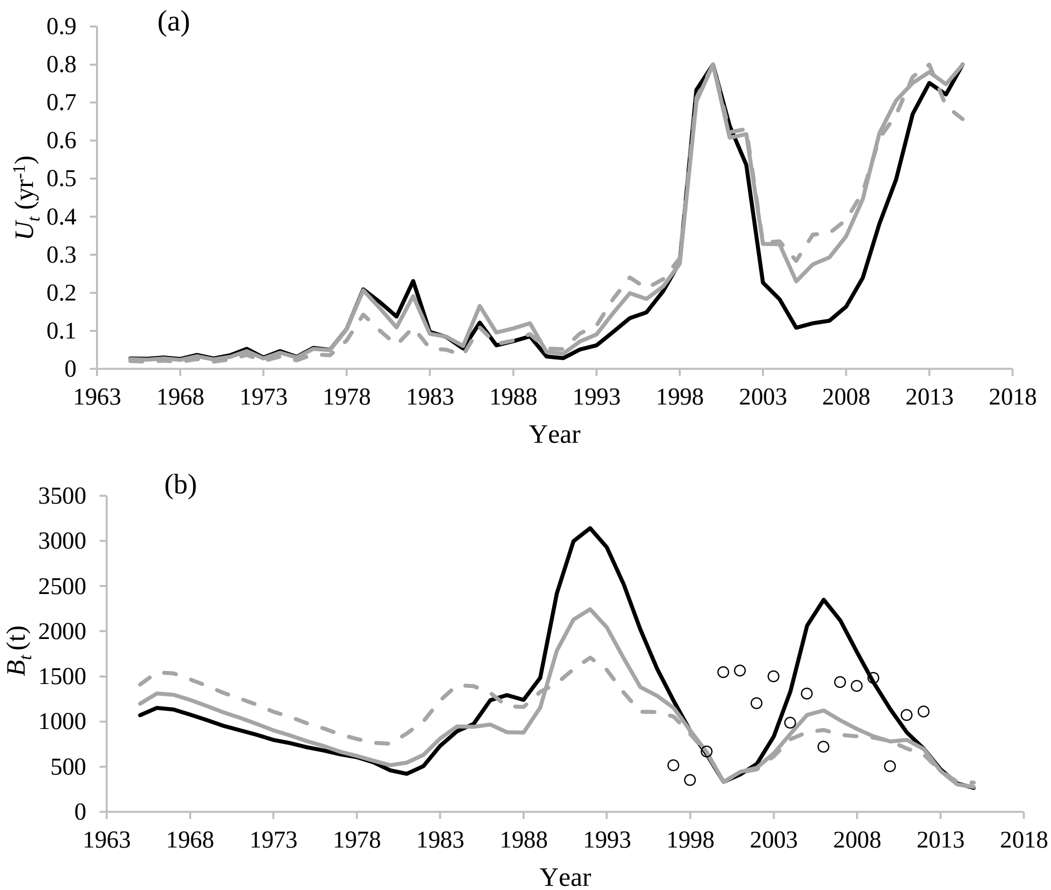


Figure 3.2. (a) Alternative reconstructions of $\boldsymbol{U_t}$ for *A. latus* in Kuwait waters from 1965-2015, corresponding to scenario 1 (solid black line), scenario 2 (solid grey line), scenario 3 (dashed grey line). (b) Alternative reconstructions of $\boldsymbol{B_t}$ for *A. latus* in Kuwait waters from 1965-2015, corresponding to scenario 1 (solid black line), scenario 2 (solid grey line), scenario 3 (dashed grey line). Unfilled dots represent observed bycatch CPUE from the shrimp trawl fishery recorded over the years 1997-2012.

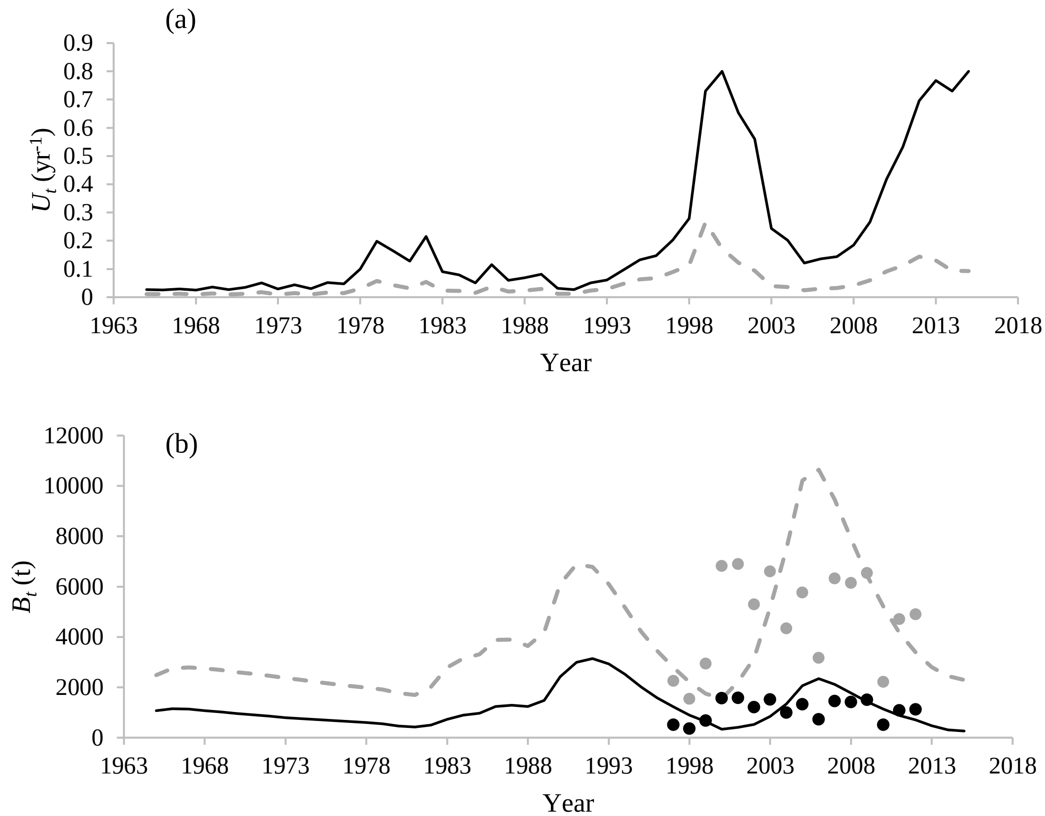


Figure 3.3. (a) Alternative reconstructions of $\boldsymbol{U_t}$ for *A. latus* in Kuwait waters from 1965-2015, in relation to small $\boldsymbol{B_o}$ (solid black line) vs large $\boldsymbol{B_o}$ (dashed line). (b) Alternative reconstructions of $\boldsymbol{B_t}$ for *A. latus* in Kuwait waters from 1965-2015, in relation to small $\boldsymbol{B_o}$ (solid black line) vs large $\boldsymbol{B_o}$ (dashed line). Black (small $\boldsymbol{B_o}$ scenario) and grey (large $\boldsymbol{B_o}$) dots represent the same observed bycatch CPUE from the shrimp trawl fishery for the years 1997-2012, fitted to each scenario.

Length frequency analysis

The length frequency distributions are not well predicted for years with very low sample sizes (Figure 3.4). Moreover, the annual length frequency samples contain many small fish in some of the years, presumably caught as bycatch by shrimp trawlers. The observed and predicted mean length trends shows sharp declines in several years (1983, 1989 and 2000) (Figure 3.5 (a)). The predicted mean length calculation indicates a decrease in mean length in recent years compared with the first 15 years from the beginning of the fishery (1965-1980). While the observed mean length is easily predicted, the observed variances are consistently lower than the predicted variance for most years (Figure 3.5 (b)). In Figure 3.6, I have calculated and fitted the equilibrium relationships between exploitation rate U_t, mean and variance of lengths. The variance of length shows a severe discrepancy between the observed and predicted variance of lengths, with the sample data showing much less variance in measured lengths than should have occurred given the growth, vulnerability, and mortality rate parameters (Figure 3.6 (b)).

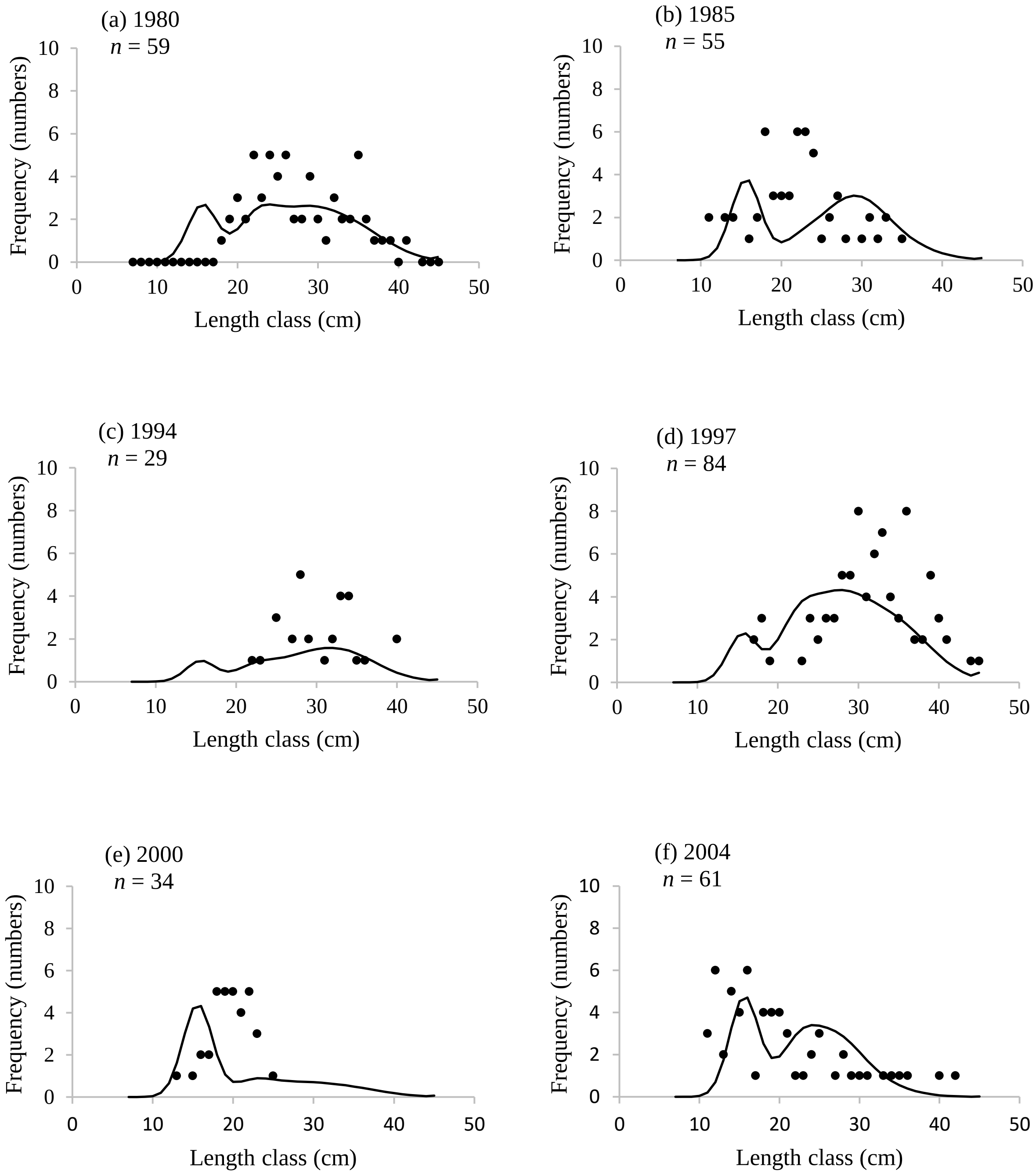


Figure 3.4. Observed (black dots) and predicted (solid line) length frequency distributions of *A. latus* in Kuwait waters for selected years (1980, 1985, 1994, 1997, 2000, 2004) and their sample sizes (*n*).

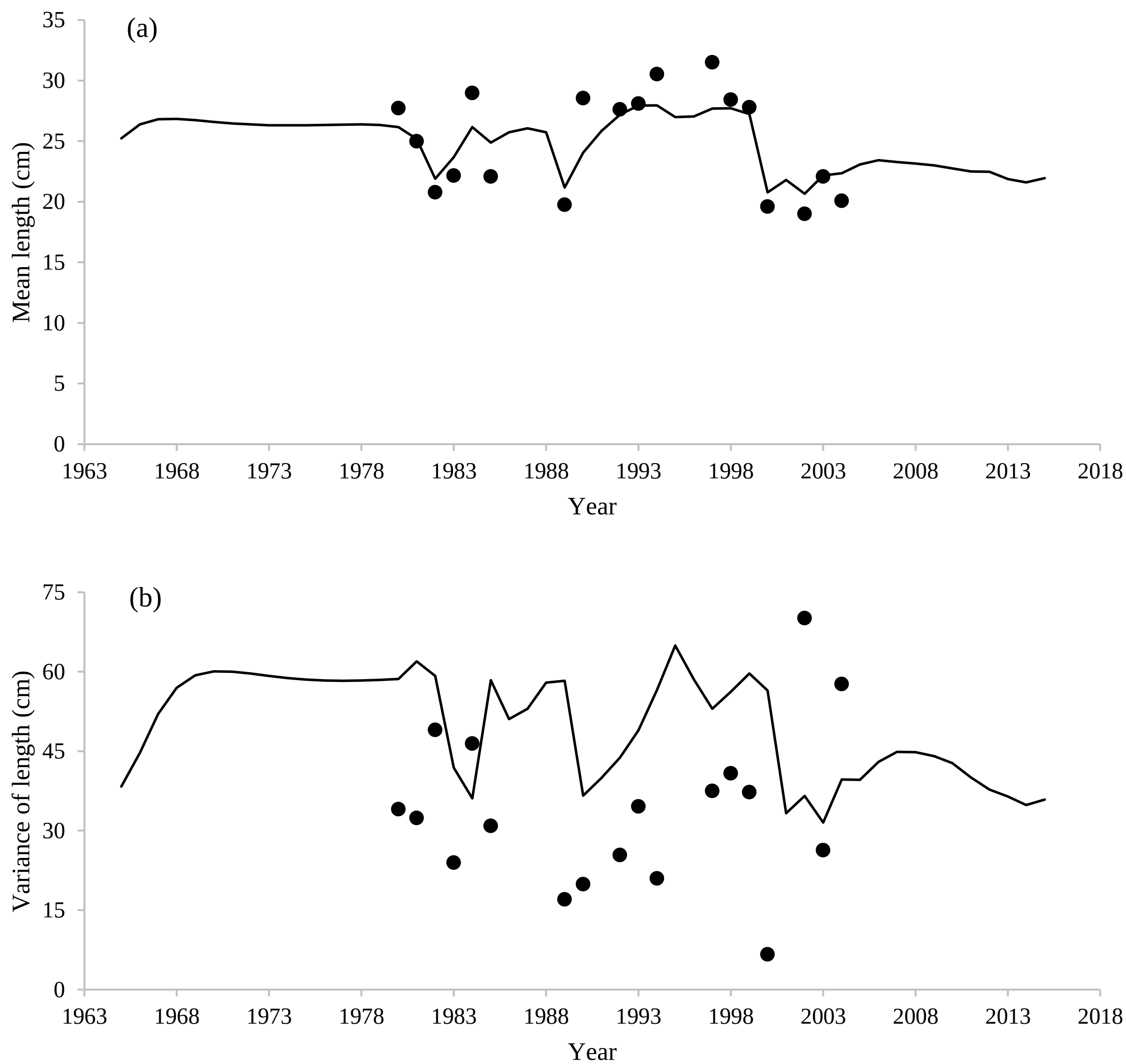


Figure 3.5. (a) Changes in observed (black dots) and predicted (solid line) mean length for *A. latus* in Kuwait waters over time. (b) Changes in observed (black dots) and predicted (solid line) variance of length over time.

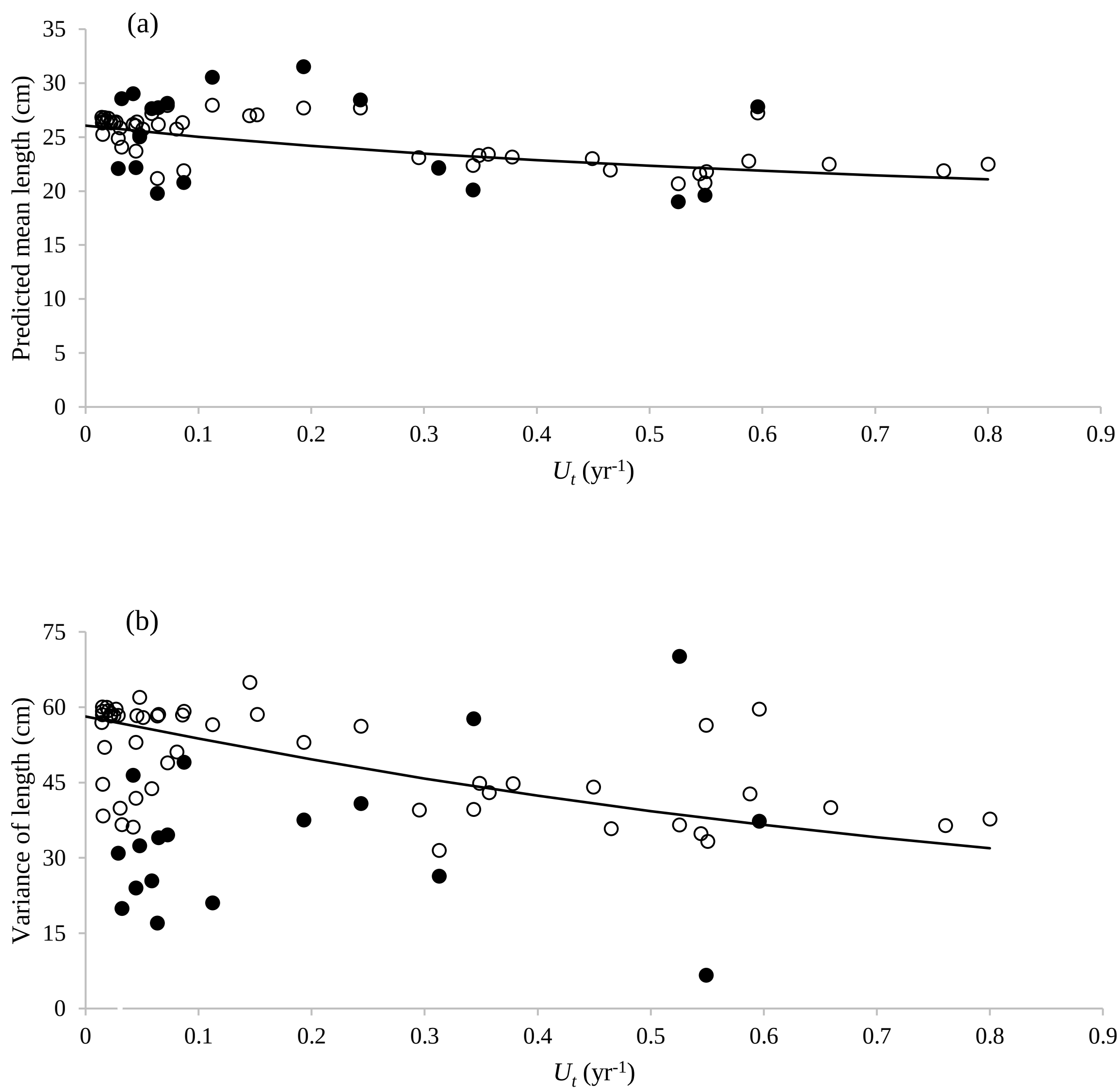


Figure 3.6. (a) predicted equilibrium mean length (solid line) fitted to predicted mean length (unfilled dots) and observed mean length (black dots) over $\boldsymbol{U_t}$ for *A. latus* in Kuwait waters. (b) predicted equilibrium variance of length (solid line) fitted to predicted (unfilled dots) and observed variance of length (black dots) over $\boldsymbol{U_t}$ for *A. latus* in Kuwait waters.

3.4 Discussion

The results presented above show that the observed and predicted mean lengths could vary substantially over time, depending on the stock-recruitment relationship and variabilities in annual recruitment and exploitation rates (Figure 3.5 (a) and Figure 3.6 (a)). Ault et al., (2005) estimated the fishing mortalities from the mean length (Lbar) and compared those estimates with other stock assessment models and data sources for several reef fish in the Florida Keys. The study concluded that Lbar is a robust indicator of total mortalities with almost no bias. However, Ault et al., (2005) study used restrictive assumptions including knife-edge selection, exclusion of stock-recruitment relationship, and stochastic recruitment variation in which all applied on long-lived fish species, (e.g., groupers, grunts, and wrasses), for which Lbar tends to be stable. This, in turn, have led to very optimistic results about fishing effects on Lbar than would be obtained with realistic assumptions. Our analysis shows that equilibrium calculation in estimating mean length can be misleading since it ignores effects of recruitment variation on the annual mean length.

The predicted variance of length was consistently less than the observed one (Figure 3.5 (b) and Figure 3.6 (b)). This might be a sign that the length frequency sampling was badly biased, either due to measuring fish caught by one gear type, (e.g., trawl bycatch), that has dome-shaped selectivity, or having the sampling people just select more “typical” sized fish each year. The length frequency samples used in this study was collected using several fishing gear types including traps, gillnets, and trawling. On the other hand, it is generally very difficult to obtain a representative length frequency samples. Imagine the case where one takes a bucket of fish or a pile of them on a market table; the physics causes the little fish to end up on the bottom and the biggest fish on top. Hence, it is recommended that all fish collected are measured where possible, or physically line up the fish and take every 3rd or 5th fish in the line (or whatever spacing is needed to get desired sample size). This approach is equivalent to sampling the fish at random even if the fish are lined up by size (C. Walters, personal communication, February 19, 2017).

I viewed the effects of different assumed weights on the baseline results and tested the sensitivity of the model to small, (i.e., baseline), vs large B_o (Figure 3.2 and Figure 3.3, respectively). The SRA model outputs were slightly sensitive to the effects of assumed weights on the reconstructions of U_t and vulnerable biomass. However, both U_t and vulnerable biomass estimates showed high sensitivity to the choice of B_o (i.e., both small and large B_o fitted the length and CPUE data equally well). This is a typical problem resulting in assessments with inadequate temporal contrast in the exploitation rates and the relative abundance index (Hilborn and Walters, 1992). This inadequate contrast in the relative abundance index has also impaired the estimation of the relative variation in maximum recruitment x_t over time, hence whether or not has *A. latus* recruitment trend been impacted by the reduction in the flow rate of Shatt Al Arab.

It is worth noting that information from the annual mean length was not consistent with large B_o scenario (low U_t); the recent downward trend in the predicted mean length indicates that *A. latus* stock is more likely experiencing high U_t (Figure 3.3 (a)). Therefore, a scenario with small B_o and high recent U_t appears more plausible. It must be pointed out that in the case where the fishery selection function, (i.e., size-vulnerability curve), is dome-shaped, due to larger fish either moving out of the coastal fishing area or becoming less vulnerable for other reasons, (e.g., escaping trawl nets), the mean and variance of the length distribution fail to contain any information about changes in mortality rate or recruitment, even if the sampling program has been fully representative (i.e., the whole approach of fitting to the length data should be avoided for any assessment). Some sparids like *Pagrus auratus* in northern New Zealand undergo a seasonal onshore-offshore movement pattern to spawn (Willis et al., 2003). However, little is known about the life-history and movement patterns of *A. latus* in Kuwait. A convenient method to broadly determine the sensitivity of the species to dome-shaped selectivity is by examining the ratio of natural mortality to growth rate (M/k). Hordyk et al. (2015) argued that species with a high ratio of M/k, (e.g., M/k > 0.8), are less sensitive to the dome-shaped fishery selection function, since only few individuals survive to reach L_∞. The assessed species in this study has M/k = 1, but because dome-shaped selectivity is not easily distinguished, results obtained from length data must be interpreted cautiously.

The current precarious situation of *A. latus* stock could be attributed to the absence of any fisheries management measures, except for minimum size limit. Using length restrictions have two main effects on fisheries: a) protecting recruitment (i.e. allowing fish to spawn before harvest), and maximizing yield per recruit which typically is highest when fishing starts at sizes not much below L_∞ (Myers and Mertz, 1998). However, when there is high discard or illegal mortality of smaller fish, yield is maximized at lower fishing rate, regardless of what the yield-per-recruit analyses suggest (Coggins et al., 2007). This is essentially evident by the high number of discards of juvenile fish associated with Kuwait shrimp fishery (Ye et al., 1999; Chen et al., 2013).

Chapter 4: Assessment of *Epinephelus coioides* in the Northern Persian Gulf

4.1 Introduction

The orange-spotted grouper (*Epeinephelus coioides*) is a large species of the Serranidae family that occupies a wide geographical area including the Persian Gulf, the Red Sea, Australia, Palau and Fiji (Randall et al. 1997). *E. coioides* is considered a demersal species, found in the muddy seafloor at a depth not exceeding 100 meters (Liesky and Myers, 1994). Among all other grouper species caught in Kuwait, *E. coioides* is the most sought after species by all parts of the fishery sector including the recreational fishery, artisanal fishery and commercial fishery. Despite the commercial importance, very few assessments have been carried out in the region to evaluate the stock status of *E. coioides*. In the southern Persian Gulf, Grandcourt et al., (2005) assessed the level of fishing mortality using basic per-recruit analysis. The study concluded that *E. coioides* is experiencing growth and recruitment overfishing. In Kuwait, the average catch per unit effort for the trap fishery have declined by 89%, i.e. from 4.8 kg/trap pull during 1982-1987 to 0.49 kg/trap pull during 2003-2005 (Al-Husaini et al., 2015). Furthermore, the fisheries statistics for *E. coioides* show a steady decline in catches after 1999, while the most recent catches (2011-2015) show a stable trend with an average catch of 157 tons/year (
Figure 4.1).

Declining abundance and catch is typically associated with declining recruitment, rather than reduced growth or increasing natural mortality rate of older fish. But there is a serious logical problem when we try to interpret stock-recruitment data: if we see recruitment declining as spawning stock size declines, should we assume that recruitment is declining because of the spawning stock decline (the “overfishing hypothesis”), or instead that spawning stock (which results from recruitment) is declining because recruitment has declined due to other factors (the "environmental factor" hypothesis)? There have been various recent attempts to tease apart this fundamental confounding of effects by using various statistical modeling approaches, (e.g., Vert-Pre et al., 2013; Szuwalaski et al., 2014; Britten et al., 2016). However, none of these can resolve the basic logical problem during periods of progressive decline; all depend on having long enough time series to provide informative reversals in recruitment rates.

To make matters worse, there are two ways that stock-recruitment relationships can change over time. First, the slope (or steepness) of the stock-recruitment relationship can change due to changes in density-independent mortality factors so as to imply a change in the optimum fishing mortality rate. Second, the carrying capacity or maximum recruitment can change due to changes in density-dependent effects, (e.g., juvenile nursery area size), which implies changes in sustainable catch, but not in optimum fishing mortality rate (Walters and Parma 1996).

At any point in time during a period of correlated decline in recruitment and spawning stock size, fisheries managers are confronted with the basic decision analysis or adaptive management problem shown in Table 1. If we think of "continued fishing" as the default or baseline policy option, then "reduced fishing" can be viewed as an experimental policy option with some promise for improving future yields (i.e. an untested opportunity for improvement as defined in Walters 1986). Undertaking the experiment will result in an immediate loss in value to fishing interests, with the possibility of a long-term gain that more than makes up for the loss. Failing to conduct the experiment (continuing to fish) may result in collapse, or simply in lower future yields (or an environmentally driven recovery). Walters and Martell (2004) note that such decision situations commonly result in "inaction as rational choice", i.e. in managers waiting to make difficult fishery reduction decisions in hopes that recovery will occur anyway. When constructing decision tables, it is tempting for scientists to display their knowledge of uncertainties by adding many columns (admitting lots of alternative hypotheses) and by adding many rows to represent various experimental policy choices and/or optimum policy options for each of the hypotheses. Such articulation of the decision problem is not actually necessary for exposing basic uncertainties and for deciding whether or not to adopt an experimental approach; it can lull decision makers into thinking that the mechanics of the decision analysis have provided them with a fully optimum choice, rather than simply an indication of the best direction for policy change. A variety of alternative hypotheses about the details of variation (alternative parameter values for dynamic models) can be represented just by averaging over such variation for each broader hypothesis column. There are in fact only two critical rows that should be included in all decision tables for adaptive management: one for “no deliberate action” (business as usual, continue historical policy), and one “experimental” involving changes deliberately aimed at encouraging learning.

Another temptation in decision analysis has been to populate the decision table with a utility measure calculated from some complicated multi-attribute utility function that weights a variety of performance measures, (e.g. mean catch, variance of catches, and probability of very low stock size). Use of such utility functions has become common in structured decision making, (see, e.g., McGowan et al. 2015). A basic problem with using such weighted utility measures in fisheries decision making is that there is typically wide divergence in the weights recommended by different stakeholders. For instance, conservation interests call for high weights on measures related to the risk of severe stock decline and fishing interests call for high weights on economic performance measures (net present value, or simply total long term catch) that reflect greater willingness to accept the risk of stock decline. There is no accepted way to combine these divergent utility functions into a single best one for public policy. One attractive option is to stick with simple economic performance measures that all stakeholders can agree are important to fisheries management. Then, deal with the risk of undesirable situations (bad system states like extinction) by introducing threshold decreases in utility if/when undesirable states (for all stakeholders) are predicted, (e.g., Martin et al. 2009).

This chapter assesses *E. coioides* stock in Kuwait waters using VPA and SRA approaches and demonstrates the use of simple calculations from decision analysis to compare difficult management choices like those shown in Table 4.1.

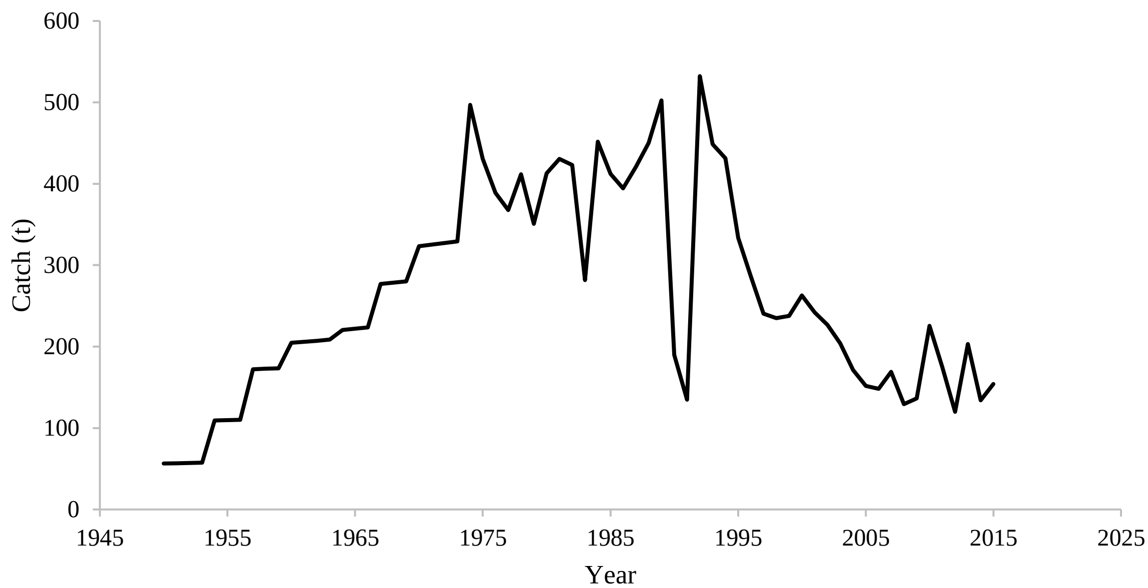


Figure 4.1. Historical total catch of *E. coioides* in Kuwait waters (sources: Al-Abdulrazzak and Pauly, 2013 and Kuwait's Central Statistical Office to obtain the most recent catch data (2011-2015)).

Table 4.1. Basic decision table that fisheries managers face during periods of stock and recruitment decline.

		State of Nature (correct model)	
		Overfishing (weak compensation)	Environmental factor (SR curve changing)
Policy option	Continue fishing	Stock collapse will continue, yields decline toward zero	Collapse will continue, yields continue at lower levels
	Reduce fishing	Stock will recover, higher long term yields	Stock will not recover, yields will not continue at lower levels

4.2 Methodology

Decision analysis for comparing experimental policy options

A general and easily understood approach to the comparison of adaptive policy options was suggested by Walters and Green (1997). This approach simply involves the construction of decision tables like Table 4.1, with broad policy options as rows and broad hypotheses about the ecological response to the policies as columns, then doing time simulations of each policy-hypothesis combination so as to populate the table with some quantitative performance measure representing utility or value aggregated over time. Given such an aggregated utility measure, and measures of prior probability or credibility for each hypothesis, it is simple to identify the policy that maximizes expected utility over possible outcomes (hypotheses), and to calculate the expected value of perfect information (EVPI) for knowing, which of the hypotheses is correct.

The critical assumption in such calculations is of course that one of the hypotheses is correct, i.e. that nature does not behave according to some "none of the above" dynamics. To represent adaptive learning over time for policies involving experimental manipulations, Walters and Green recommended treating the learning process as a two-stage one, by dividing the time simulations into experimental and long term management periods with the duration of the experimental period determined by simulation gaming methods (Walters, 1995).

Estimation of vulnerable biomass using virtual population analysis (VPA) and stochastic stock reduction analysis (SRA)

VPA

There are enough growth and age composition data for *E. coioides* (ages 0-22 years for 1981-1999 and 2007-2008, with interpolation of composition for the VPA for the missing years 2000-2006) and by-catch CPUE from the shrimp fishery (for the period 1999-2008) to permit constructing and tuning of VPA using Walters and Punt (1994) method

(4.1) $N_{a,t} = C_{at} + N_{a+1,t+1}/s$

Where $N_{a,t}$ is the backward simulated total numbers at age a in the second to last year t younger than the oldest age, C_{at} is the total numbers of fish caught at age a in the second to last year t younger than the oldest age, s is natural survival rate $s = \exp(-M)$ (von Bertalanffy parameters k =0.2 year-1, L_{∞}=100 cm) suggest a natural mortality rate (M) near 0.2 year-1) and is time-invariant. To initialize the terminal numbers N_{aT}, the following equation was used (Walters and Punt, 1994)

(4.2) $N_{aT} = C_{a,t}/(v_{a,t}u_T)$

where N_{aT} is the numbers at age a in the terminal year T, v_a denotes the vulnerabilities at age a and year t (assuming fully recruited fish (12-22 unit) in T have vulnerability of 1 and pre-recruit v_a in last year given by average of v_a in previous 10 years), and u_T is the terminal exploitation rate. The oldest age in each year was calculated by the catch of oldest age divided by u_T of fully recruited fish. The u_T estimation started with a trial value and then "tuned" by minimizing the objective function (SS) between the predicted annual vulnerable biomass B_t and the observed CPUE (Walters and Punt, 1994)

(4.3) $Z_t = ln(\frac{CPUE}{B_t})$

where the mean of Z_t is a conditional on maximum likelihood estimate of $ln(q)$. The objective function calculated as

(4.5) $SS = ln\sum(Z_t - lnq)^2$

Stochastic SRA

The stochastic *SRA* model (Walters et al., 2006) was applied using the stochasticSRA software to estimate biomass and recruitment trends associated with the catch decline by fitting to the by-catch CPUE data. The stochasticSRA software uses an MCMC algorithm to start with the trajectory that has the highest likelihood given the data. Then, it chooses random steps in all leading parameters (unfished biomass and compensation ratio) and recruitments, and calculates the likelihood for another trajectory. If the new trajectory is accepted (i.e. has a higher likelihood than the one before), it becomes the new point. The MCMC algorithm in the stochastic SRA software runs many times sampling the parameters space at a rate proportional to the likelihood of the data, creating the posterior distribution of the parameters. It assumes a Beverton-Holt relationship of the form

(4.6) $R = \alpha E/(1 + \beta E)$

where R is age 1 recruits, E is relative egg production (sum of numbers at age times relative fecundity at age), α is maximum egg-recruit survival, and β represents recruitment carrying capacity (higher β implies lower capacity). The α parameter is a critical determinant of the exploitation rate for maximum sustainable yield, U_{msy}. For assumed α (U_{msy}), we can calculate apparent changes in β by inverting the calculation, i.e. $\beta = (\alpha S/R - 1)/S$ for a set of "empirical" stock-recruitment observations.

4.3 Results

The VPA back-calculation indicates a very steep decline in B_t over time since 1981 (Figure 4.2). Furthermore, there was a downward stock-recruitment relationship over the years, indicating unusual sensitivity toward fishing (Figure 4.3).

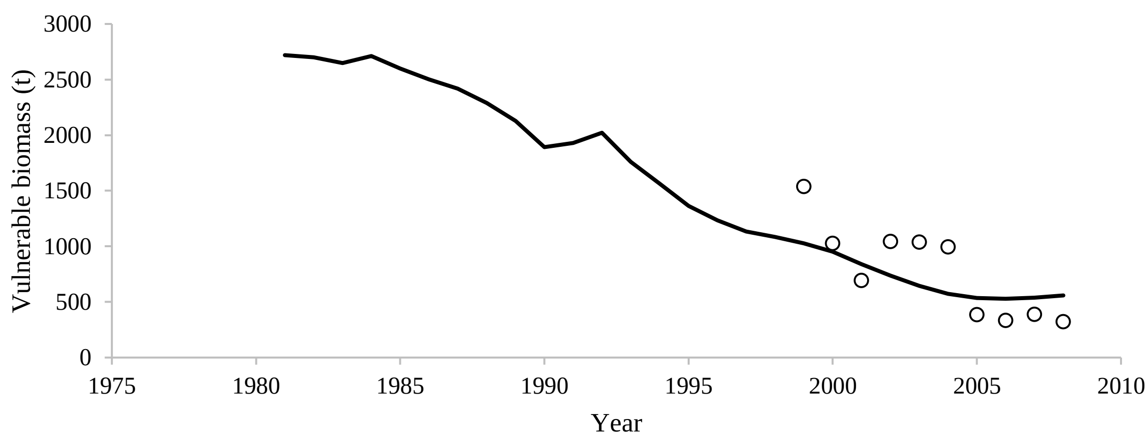


Figure 4.2. Reconstructed vulnerable biomass (solid line) for *E. coioides* in Kuwait waters using tuned VPA for the period 1981-2008. The unfilled dots represent CPUE.

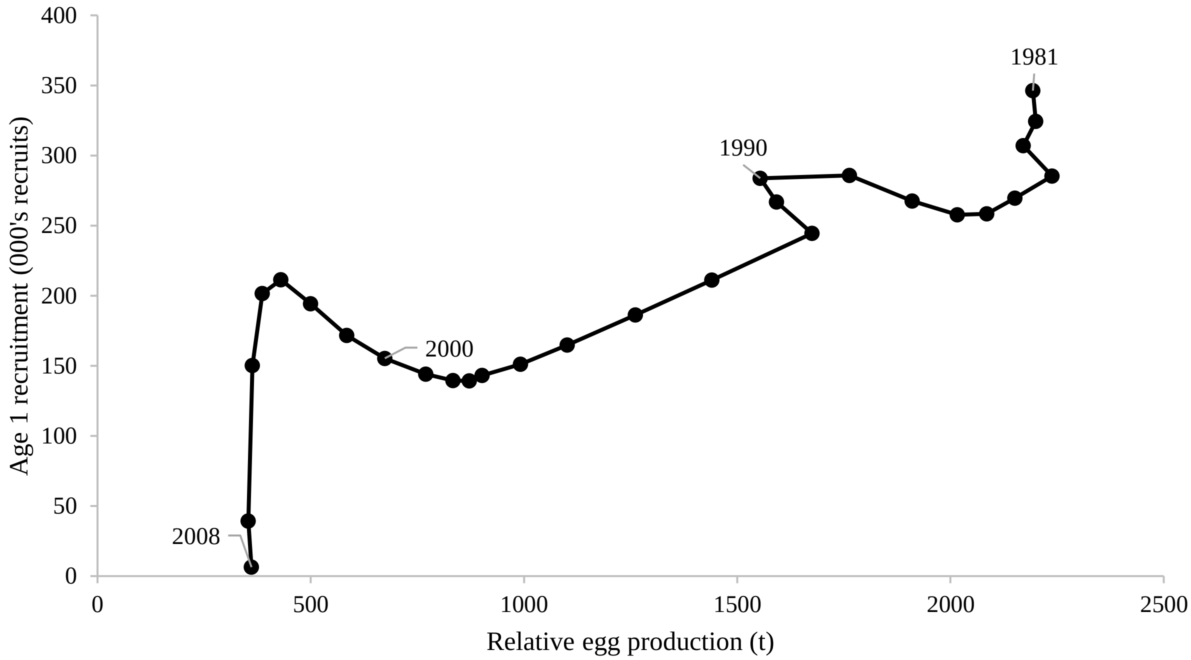


Figure 4.3. Stock-recruitment relationship estimated from the VPA model for *E. coioides* in Kuwait waters. Numbers in the graph reflect years.

When α is set to values implying exploitation level at maximum sustainable yield (U_{msy}) near M or typical steepness values for stock-recruitment relationships in many fish stocks (steepness h=0.6 or higher), the SRA trend that leads to current U=0.2 is much less steep than indicated by the VPA (Figure 4.4, overfishing case), and calculated historical exploitation rate trends (Figure 4.5) would have to have been much lower than indicated by the tuned VPA. The SRA model indicated a U_{msy} value in the range 0.06-0.1 and recruitment steepness $h<0.3$ (or Goodyear compensation ratio 2.0-3.0).

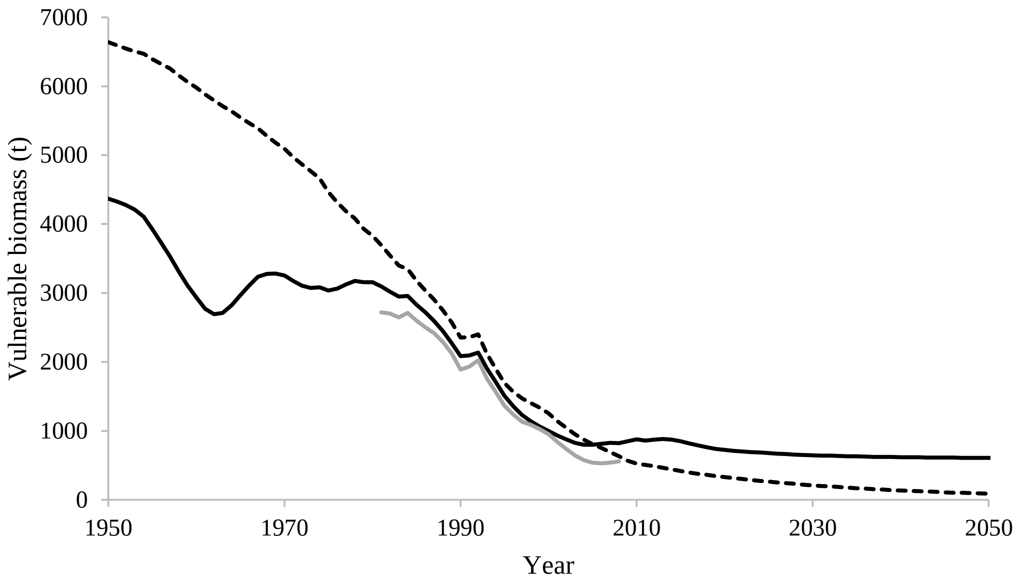


Figure 4.4. Vulnerable biomass reconstructions using tuned VPA model (gray solid line) and the stochasticSRA application for the *E. coioides* in Kuwait waters. Forward projections from stochastic SRA age-structured model under continued high exploitation rates (U=0.2). Overfishing model (dashed line) results based on assuming stationary SR relationship with very low steepness (h=0.33), while capacity change model (black solid line) assumes higher steepness (h=0.7) but decreasing recruitment carrying capacity over time, starting in the early 1970s and stabilizing after 2010.

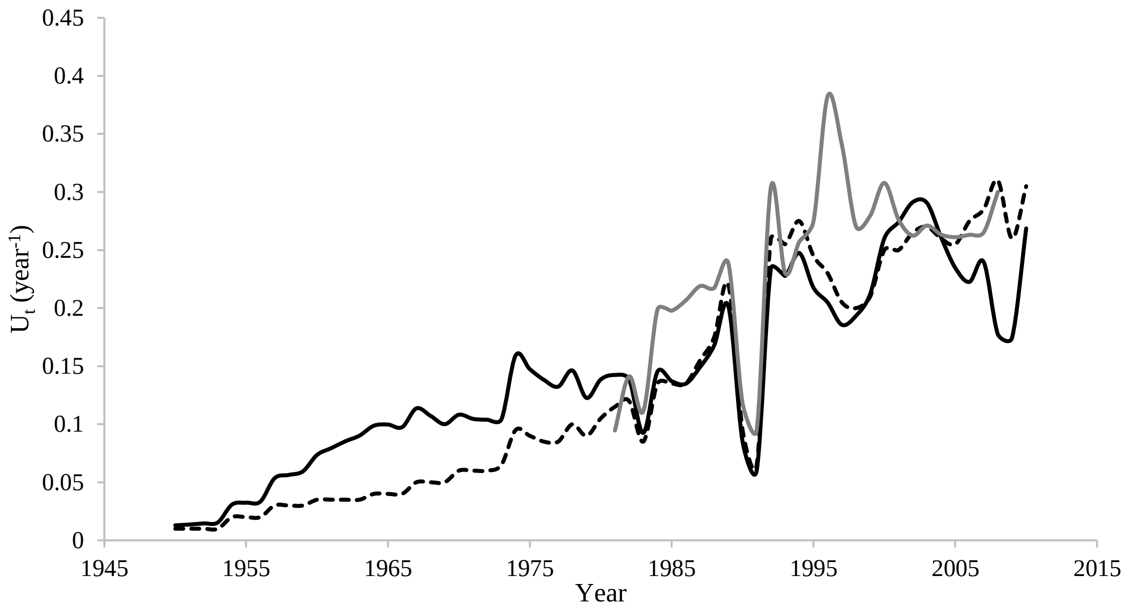


Figure 4.5. Alternative hypotheses about historical trends in exploitation rates of *E. coioides* in Kuwait waters. The gray solid line represents the VPA estimates of U. Estimates from SRA for two recruitment hypotheses: weak recruitment compensation (overfishing model, shown in dashed line) and strong recruitment compensation (capacity change model, shown in black solid line).

So, the VPA and SRA methods both indicate that if recruitment did (and will in future) follow a stationary stock-recruitment relationship, that relationship must be much less steep than we would expect from any meta-analyses of historical stock-recruitment data sets, (e.g., Goodwin, et al., (2006)). We cannot reject the hypothesis out of hand that steepness is low and $U_{msy}<0.1$ implying that fishing mortality should be reduced by at least 50%. Still, such unusual sensitivity of recruitment to spawning stock size certainly deserves further scrutiny and recognition that the recruitment decline may have been due to factors other than the impact of fishing on spawning abundance.

Using the stochasticSRA software while assuming U_{msy} near 0.2 and random recruitment variation with high temporal autocorrelation (r=0.8), a declining trend in recruitment anomalies was observed. This declining trend indicates that the stock-recruitment β increased by a factor of 2.5-3.0 over the period from about 1970 to the mid-1990s, i.e. implying that the maximum annual recruitment α/β declined by around 60-70% over that period. The declining recruitment anomaly trend (increasing β trend) suggested by the SRA software is disturbingly similar to trends in flows of the Tigris and Euphrates Rivers reviewed in Issa et al., (2014) associated with the extensive development of dams and diversions (Figure 4.6). The FishBase biology summary for *E. coioides* says: "inhabit turbid coastal reefs (Lieske and Myers, 1994) and are often found in brackish water (Randall et al., 1997) over mud and rubble (Kailola et al., 1993). Solitary. Juveniles are common in shallow waters of estuaries over sand, mud and gravel and among mangroves (Kailola et al., 1993)." Given these observations, it is not at all unlikely that decreases in water inflows to Kuwait waters of the Northern Persian Gulf have indeed led to reduced nursery area and recruitment capacity for the stock.

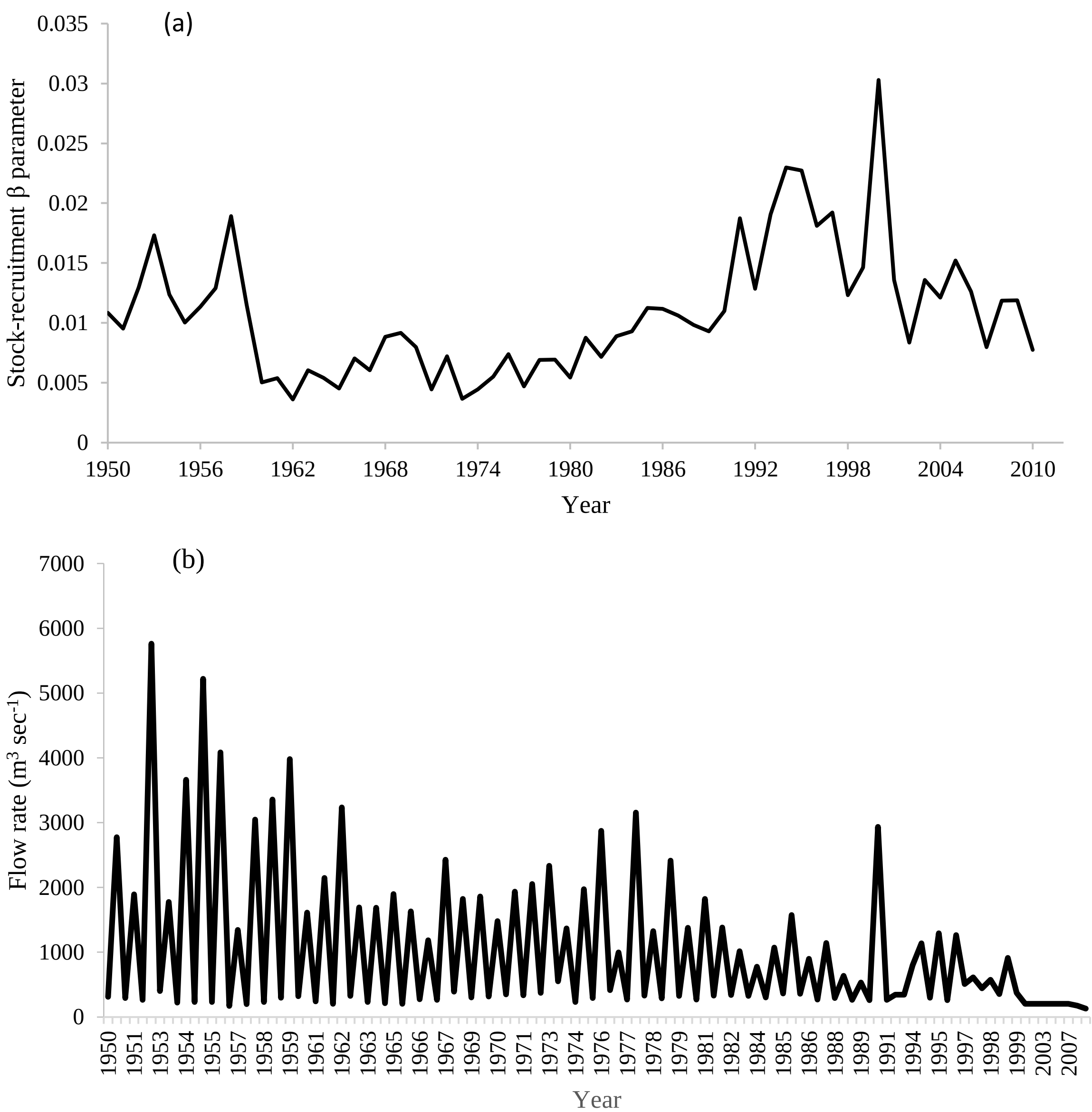


Figure 4.6. (a) Apparent trends in the stock-recruitment density-dependence parameter β for *E. coioides* in Kuwait waters, and (b) trends in water flows for Kut flow-gauging station from Issa et al., (2014).

At this point, the assessment methods have led to exactly the decision making situation shown in Table 1: there are two very distinct hypotheses about *E. coioides* recruitment, which imply very different predicted future catches from the stock (Figure 4.7). The first hypothesis is that the stock always or at least recently has weak recruitment compensation, implying continuing decline unless exploitation rate is radically reduced, and only very slow recovery if it is reduced. Alternatively, the second hypothesis is that the stock has relatively strong compensation (h>0.6, U_{msy}=0.2 or higher), but now has a much lower recruitment carrying capacity that is unlikely to increase if capacity is related to river flows into the Northern Persian Gulf. Hence, catches will remain low, and will be even lower if exploitation rate is reduced.

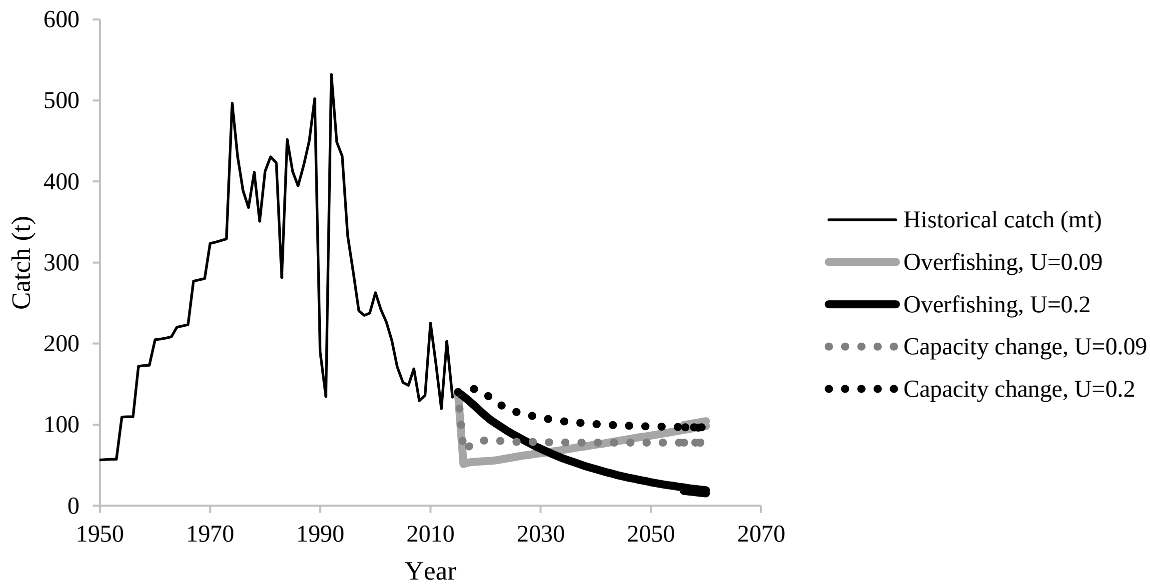


Figure 4.7. Historical catches of *E. coioides* in Kuwait waters and predicted catch trends under alternative hypotheses (overfishing versus capacity change) and U policies. Predictions obtained with an age-structured model assuming Beverton-Holt recruitment and no future change in growth, natural mortality, and vulnerability patterns.

If we populate the decision table with predicted total catch over the next 50 years from Figure 4.7, or the discounted sum of those catches, as simple utility or performance measures, the result is to conclude that expected value (averaged over the two hypotheses) would be maximized by continuing to fish at U=0.2 (i.e. not to reduce fishing (

Table **4.2** and Table 4.3) if there is no future learning about which hypothesis is correct. Absent discounting, we would have to place a prior probability of at least 0.64 on the overfishing hypothesis before we would assign a higher expected value to the effort reduction option. With discounting, we would have to be 95% sure of the overfishing hypothesis before we would assign higher expected value to the effort reduction option. In short, the simple decision analysis makes a very clear prediction given no future learning about which hypothesis is correct: the effort reduction "experiment" would not be a wise policy choice given anything close to even odds on the hypothesis that decline has been due to habitat/environmental change rather than overfishing.

Table 4.2. The same decision structure as Table 4.1, populated with 50-year predicted future catches (t) from Figure 4.7 as the basic utility measure for each element of the decision table. Total catches (t) projected with an age-structured model with stationary stock-recruitment curves after 2015.

		State of Nature (correct model)		
		Overfishing (weak compensation)	Environmental factor (SR curve changing)	Expected Value assuming equal probabilities
Policy option	Continue fishing (U=0.20)	2,160	5,865	4,012
	Reduce fishing (U=0.09)	2,891	4,573	3,733

EVPI = 0.5 x 2891+0.5 x 5865 – 4012 = 366

Table 4.3. The same decision structure as

Table 4.2, populated with sums of predicted future catches (t) discounted at 3% per year as the utility measure.

		State of Nature (correct model)		
		Overfishing (weak compensation)	Environmental factor (SR curve changing)	Expected Value assuming equal probabilities
Policy option	Continue fishing (U=0.20)	1,511	3,204	2,357
	Reduce fishing (U=0.09)	1,556	2,374	1,966

EVPI = 0.5 x 1556 +0.5 x 3204 – 2357 = 22

The basic results in

Table **4.2** is reversed (Table 4.4) if it is assumed (perhaps optimistically) that the correct hypothesis will be detected after 10 years (i.e. there will be rapid learning whether or not fishing is reduced and exploitation rate will be reduced or increased to the best value under each hypothesis). The policy with highest expected value becomes the effort reduction policy, essentially because the loss associated with initially adopting this policy when it is not correct is much lower (predicted value of initially reducing effort when it actually should remain high is closer to the value of maintaining higher effort for all years). For longer learning times, the values in Table 4.4 shift toward those in

Table **4.2**, such that there is a learning time (near 25 years) for which it switches to be best not to conduct the effort reduction experiment. It should be noted that the recommendation from Table 4.4 is not robust to discounting; including a 3% discounting rate as in Table 4.3 results in the prediction that effort should not be reduced. In other words, the discounted long term catch gains due to avoiding the wrong policy after 10 years do not make up for the losses incurred over the first 10 years by reducing effort.

Table 4.4. The same decision structure as

Table 4.2, but with 50-year predicted catches calculated under the assumption that correct hypothesis is detected after 10 years (reduce fishing if overfishing hypothesis is correct, increase it if environmental change hypothesis is correct).

		State of Nature (correct model)		
		Overfishing (weak compensation)	Environmental factor (SR curve changing)	Expected Value assuming equal probabilities
Policy option	Continue fishing (U=0.20)	2,359	5,865	4,111
	Reduce fishing (U=0.09)	2,891	5,848	4,370

For the *E. coioides* case, it would be unwise to assume rapid discrimination among recruitment hypotheses, even if it is possible to measure relative recruitment rate over time as a sensitive, immediate indicator of response. Following experimental effort reduction, both hypotheses predict a modest short-term recruitment increase due to recovery in spawning stock biomass per recruit, but then the overfishing hypothesis predicts only very slow rebuilding in recruitment rate (Figure 4.8). Even if the fishery were closed completely, doubling of recruitment rate under the overfishing hypothesis would likely take at least 20 years, and that doubling might be difficult to detect given likely random variation in recruitment rates and observations.

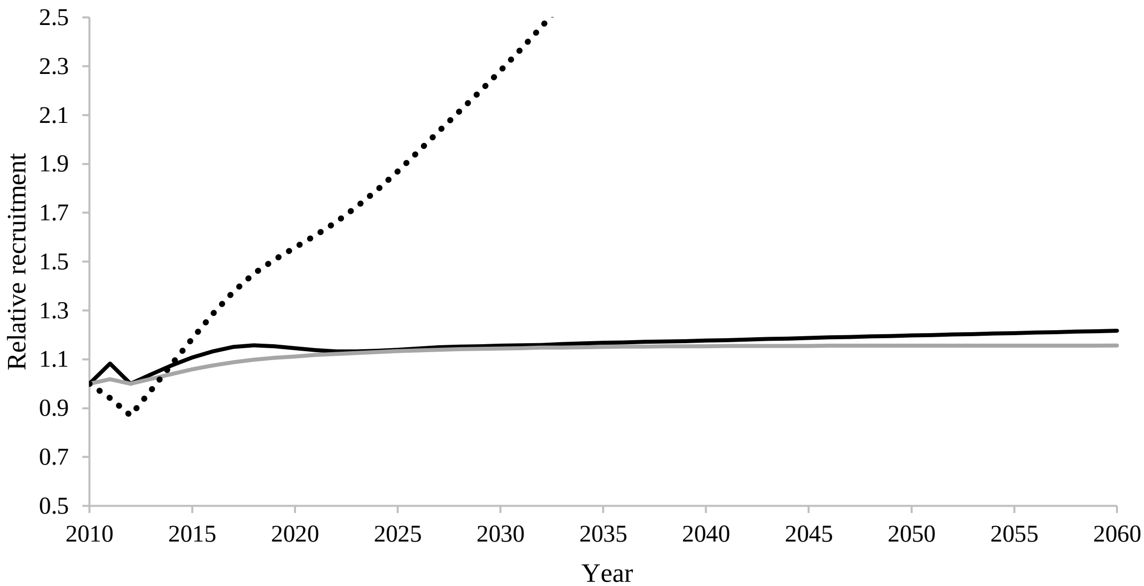


Figure 4.8. Predicted future patterns in relative recruitment rate of *E. coioides* in Kuwait waters, following a halving or complete closure of fishing. The solid black line represents overfishing hypothesis, the solid gray line represents capacity change hypothesis and the dotted line indicates a complete closure of the fishery under the overfishing hypothesis.

Another factor that could favor an effort reduction experiment in this example would be to use the sum of log catches as the utility measure. This is to capture the assumption that fishers show diminishing marginal utility for higher catches (i.e. are highly averse to having very low catches), as assumed in recent catch optimization analyses by Hawkshaw and Walters (2015). When the sum of log catches replaces the sum of catches in

Table **4.2**, the result is indeed to predict that an effort reduction would be the best policy even if there is no future learning (Table 4.5).

Table 4.5. The same decision structure as

Table 4.2, populated with sums of logarithms of future catches as the utility measure, to reflect importance to fishers of avoiding low catches but diminishing the marginal utility of high catches.

		State of Nature (correct model)		
		Overfishing (weak compensation)	Environmental factor (SR curve changing)	Expected Value assuming equal probabilities
Policy option	Continue fishing (U=0.20)	177.0	241.9	209.4
	Reduce fishing (U=0.09)	205.3	228.9	217.1

EVPI = 0.5 x 205.3 +0.5 x 241.9 – 217.1 = 6.46

The expected value of perfect information (EVPI) is relatively low for this example (

Table **4.2** and Table 4.3), especially if the value of future catches is discounted in the calculation of utility. This is a common outcome in decision analyses for adaptive management, i.e. there is little value of knowing which hypothesis is correct when the main benefits of the knowledge would occur far in the future. Note in Figure 4.7 that predicted catches following effort reduction under the overfishing hypothesis are not even predicted to build back up (due to stock rebuilding) to the current (2015) level for almost 50 years, and would not even exceed the catches under continued depletion until about 30 years from now.

4.4 Discussion

The basic approach taken in the *E. coioides* example was to first try to find a single best stock assessment based on available data, but then to identify a second and very different hypothesis (declining recruitment capacity) when recruitment parameter estimates under the assumption of a stationary stock-recruitment relationship indicated suspiciously weak recruitment compensation. This is likely to be a common or perhaps universal finding when assessments are made for stocks with declining catches but no evidence that the declines are just due to declines in exploitation rates. Also, when scientists deliberately attempt to identify alternative hypotheses that are consistent with historical data but imply widely divergent predictions about future responses to harvest management.

Construction of very simple 2 x 2 decision tables was very helpful in identifying basic sensitivities in the decision analysis to alternative assumptions about how to measure long term management performance (effect of discounting, log utility measures) and about how long it might take to detect whether an incorrect policy choice was implemented initially. As indicated in Tables 4.2-4.5, there is no single robust policy choice that maximizes expected utility over the alternative hypotheses that were identified. In the *E. coioides* case, reductions in the effort (exploitation rate) would only be worthwhile (and probably in most cases where there is good evidence of declining recruitment capacity) if there is a strong aversion to low catches and/or the expectation of rapid learning in the future. As is typical in adaptive management decision analyses, discounting future benefits results in not valuing the benefits that might accrue even from rapid learning.

Imagine presenting commercial fishing interests with a decision analysis result like Table 4.4. The explanation for the result would need to go something like this: “We believe there is a good chance that the stock has been overfished despite evidence that its decline might also have been due to other factors. If you are willing to accept a 50% reduction in catches over the next 10 years, there is a good enough chance of gains over the following 40 years (due to what we will learn about stock recovery) to more than make up for your losses.” Why in the world would any fisher agree with this argument, even if he trusted the scientist’s assessment that 10 years would be long enough to find the right model? He is being asked to give up perhaps half of his career catches, for a prediction of higher catches that would mostly accrue to others. Fishers have supported experimental reduction in harvests in a few cases involving Pacific salmon, (e.g., Rivers Inlet, Walters et al., 1993), but in those cases, there was a good reason to expect compensating gains within 4-6 years. In short, scientists should, in general, expect fishing interests to favor the use of performance measures involving at least modest discount rates, (e.g., Table 4.3) and not to trust predictions about how good scientists will be at gathering and interpreting data about whether recovery is occurring.

Given results from simple 2x2 decision tables to indicate whether experimental policy options are worth considering, a reasonable next step is to develop more elaborate m x n tables with m rows representing various intermediate exploitation rate policies (that might be more acceptable to stakeholders) and a richer set of alternative hypotheses. Policy options involving intermediate exploitation rates might also include options for how long each initial rate is to be maintained before moving to a stable long-term rate, with alternative durations resulting in different odds of choosing the correct long term rate at the end of the experimental period. Alternative hypotheses might include a variety of possible patterns of future recruitment carrying capacity change derived for example from alternative models for future climate change. A key point about the development of more complex decision analyses is that the simple initial 2x2 analysis can be used to bound the range of alternatives worth spending more time to develop.

There is much interest in development and comparison of assessment and harvest control methods for data-limited fisheries (Carruthers et al., 2014; Sagarese et al., 2015). Therefore, it is worth asking just what information is necessary to develop credible alternative hypotheses about the role of recruitment changes in causing declining catches when age-structured models like SRA are used to explicitly account for changes in recruitment.

We suggest that there are five basic information requirements. Given a catch time series as the first requirement, the second obvious requirement is a growth curve, to provide both size-at-age information and estimates of natural mortality rate, M. A third requirement is an estimate of the current stock size or exploitation rate, (which implies stock size as catch/rate); without this, we have no way of saying whether the historical catches came from a very large stock that has not been touched by fishing or a much smaller one that has suffered strong historical fishing impacts. This third requirement cannot be replaced by having historical effort data showing growing potential impact over time since just knowing that impact has grown does not mean that impact has ever been large. However, the third requirement can be met by methods such as recent age-composition data. For example, by constructing a swept area abundance estimate using fishing gear characteristics and effort, or by fitting an equilibrium model to length distribution data (Hordyk et al., (2015)). The Hordyk et al., (2015) size composition fitting method also provides an estimate of the age-selectivity pattern, which is the fourth requirement. The fifth requirement is to have at least a few observations, spread as widely as possible over time, of either (a) age composition of catches to help place bounds on probable changes in total mortality rate, or (b) changes in relative abundance of harvestable fish that can be used to "tune" or fit an age-structured SRA model.

In cases where policy screening using decision tables does indicate that an experimental fishing reduction would be a good gamble, a critical task for scientists is to recommend the most valuable data to collect during the experimental period, so as to detect recruitment responses (or lack of them) as quickly as possible. Typically, in stock assessment, our priority recommendations are the initiation of abundance surveys and routine collection of size-age composition data from the catch, for fitting age-structured models. Unfortunately, these are probably not the best recommendations; short-term changes in composition data can be highly misleading particularly for species that exhibit ontogenetic habitat shifts such that fisheries may shift targeting practices so as to cause changes in the age-vulnerability schedule. For instance, such shifts appear likely in the most recent (2007-8) age composition data for the *E. coioides* case, with increasing proportions of smaller fish in the catch that could be due either to recruitment increases or deliberate targeting of areas where these fish are concentrated. The most valuable data would, in fact, be to have direct fishery-independent survey indices specifically of recruit abundance (fish just entering the fishery but old enough for most density-dependent mortality to have occurred), to provide response information well before age-structured assessment models can reliably do so. Such surveys need to broadly cover the spatial distribution of recruiting fish, so as to provide information on changes in nursery area use.

Instead of just recommending expensive fishery-independent recruitment surveys, assessment scientists could be much more imaginative about seeking ways to gather recruitment index information from existing fisheries that do not specifically target the recruits. For example, most nursery areas are near shore, and very commonly there are intensive fisheries, (e.g., shrimp trawling) in such areas. Sampling recruit bycatch rates in such fisheries need not be expensive at all, with carefully designed observer sampling programs, and recent advances in geo-statistical methods (Thorsen et al., 2015) offer much promise for better analysis of such spatial data. Absent nursery area fisheries, there may also be relatively inexpensive incentive programs for commercial fishers to collect recruit density samples while traveling to and from fishing areas, or even to organize their sampling programs; after all, it is they who will be the main beneficiaries if adaptive learning rates can be accelerated.

Chapter 5: Conclusion

In this thesis, I assessed three fish stocks using modern stock assessment methods, and investigated the impacts of the reduction in Shatt Al Arab discharges on fish recruitment patterns in the Northern Persian Gulf (NPG). As a whole, the thesis provides a general guideline to the fisheries managements in the NPG: to take into account the impacts associated with reductions in Shatt Al Arab flow on inshore fish stocks. Considering such impacts, fisheries management could avoid implementing regulations that are ineffective in the face of the environmental changes. Chapter 2 assesses the most valuable fishery in Kuwait: the shrimp fishery. Chapter 3 evaluates the status of the seabream (*Acathopagrus latus*) stock using a stock reduction analysis approach with the aid of length-composition data. The analyses presented in chapter 4 focus on evaluating the status of the orange-spotted grouper stock (*Epinephelus coioides*) using virtual population analysis and stochastic stock reduction analysis approaches, and demonstrates the use of simple calculations from decision analysis to compare difficult management choices.

To our surprise, the benchmark findings in Chapter 2 indicate that the shrimp stock has not shown apparent capacity change: the nursery area of the shrimp has not been notably influenced by the Shatt Al Arab flow reduction. Although catches of the shrimp fishery have been stable for the last 40 years, our analysis showed that the stock is experiencing excessive fishing mortality. Furthermore, analysis of the relationship between seasonal effort and shrimp abundance indicated a “satisficing” rather than profit-maximizing behavior, which is not apparently very common in seasonal fisheries. The retrospective analysis of catch and effort suggested a 4% increase in the net revenue under the optimized policy (i.e. maximum economic profit policy), compared to the current policy (i.e. unregulated effort).

Among the results in Chapter 3 is that the recent precarious situation of *A. latus* stock is probably driven by growth overfishing as observed in the length-composition data.

The main argument in Chapter 4 is that giving declining catch patterns, supposedly precautionary decisions to reduce fishing should be treated as experimental management options. These management options should be considered with a high probability of not resulting in the desired recovery to more productive stock sizes. The assessments conducted on *E. coiodes* data indicated unusually weak recruitment compensation or progressive decline in recruitment carrying capacity, possibly caused by decreases in estuarine rearing habitat associated with declining flows of Shatt Al Arab. The case study used in Chapter 4 concluded that experimental effort reduction is often not the best policy from a decision analysis perspective, at least when there are substantial reasons to expect recruitment changes unrelated to stock size.

The analyses presented in this thesis emphasize the importance of collecting data on what has been changing over time, particularly nearshore nursery environments as influenced by declines in Shatt Al-Arab flows. A combination of fisheries and oceanographic data help in developing ecosystem models that could discriminate between the impacts of overfishing and environmental changes on the fish stocks.

References

Abou-Seedo, F. S., S. Dadzie, and K. A. Al-Kanaan. 2003. “Sexuality, Sex Change and Maturation Patterns in the Yellowfin Seabream, *Acanthopagrus Latus* (Teleostei: Sparidae) (Houttuyn, 1782).” Journal of Applied Ichthyology 19 (2). Blackwell Verlag GmbH: 65–73.

Al-Abdulrazzak, D., and D. Pauly. 2013. “From Dhows to Trawlers: A Recent History of Fisheries in the Gulf Countries, 1950 to 2010.” Fisheries Centre Research Reports 21 (2).

Al-Foudari, H., J.M. Bishop, W. Chen, A. H. Alsaffar, T. Al-Said, A. Al-Baz, and A. Ben Hasan. 2015. “A Comprehensive Management Strategy for The Long-Term Sustainability Of Kuwait's Shrimp Stocks, Final Report (FM047C)”. Kuwait Institute for Scientific Research.

Al-Husaini, M., J. M. Bishop, and H. M. Al-Foudari. 2015. “A Review of the Status and Development of Kuwait’s Fisheries.” Marine Pollution Bulletin. Elsevier. http://www.sciencedirect.com/science/article/pii/S0025326X15004737.

Alosairi, Y., and T. Pokavanich. 2017. “Seasonal Circulation Assessments of the Northern Arabian/Persian Gulf.” Marine Pollution Bulletin, January. Elsevier. doi:10.1016/j.marpolbul.2016.12.065.

Al-Yamani, F. Y., and N. Y. Khan. 2002. “Changes in Riverine Input and Loss of Wetlands.” The Gulf Ecosystem Health and Sustainability. Backhuys, 235–51.

Al-Yamani, F. Y., J. M. Bishop, K. Al-Rifaie, and W. Ismail. 2007. “The Effects of the River Diversion, Mesopotamian Marsh Drainage and Restoration, and River Damming on the

Marine Environment of the Northwestern Arabian Gulf.” Aquatic Ecosystem Health & Management 10 (3): 277–89.

Ault, Jerald S., Steven G. Smith, and James A. Bohnsack. 2005. “Evaluation of Average Length as an Estimator of Exploitation Status for the Florida Coral-Reef Fish Community.” ICES Journal of Marine Science: Journal Du Conseil 62 (3). Oxford University Press: 417–23.

Beddington, J., and Kirkwood, G. 2005. The estimation of potential yield and stock status using life–history parameters. Philosophical Transactions of the Royal Society B: Biological Sciences 360:163-170. doi: 10.1098/rstb.2004.1582

Bertalanffy, v. 1938. “A Quantitative Theory of Organic Growth (Inquiries on Growth Laws. II).” Human Biology 10 (2). Wayne State University Press: 181–213.

Bishop, J. M., Y. Ye, A. H. Alsaffar, N. Fetta, E. Abdulqader, Q. Lui, and E. H. Al-Ibrahim. 2001. “Shrimp Stock Assessment in the Western Arabian Gulf by Countries of the Gulf Cooperation Council, Final Report (MB021C).” Annual Research Report. Kuwait Institute for Scientific Research, no. 6291.

Branch, Trevor A., Olaf P. Jensen, Daniel Ricard, Yimin Ye, and Ray Hilborn. 2011. “Contrasting Global Trends in Marine Fishery Status Obtained from Catches and from Stock Assessments.” Conservation Biology: The Journal of the Society for Conservation Biology 25 (4): 777–86.

Britten, G.L., Dowd, M., and Worm, B. 2016 Changing recruitment capacity in global fish stocks. PNAS 113:134-139. doi/10.1073/pnas.1504709112

Browder, Joan A. 1985. "Relationship between Pink Shrimp Production on the Tortugas Grounds and Water Flow Patterns in the Florida Everglades." Bulletin of Marine Science 37 (3). ingentaconnect.com: 839–56.

Buxton, Colin D., and Patrick A. Garratt. 1990. "Alternative Reproductive Styles in Seabrearns (Pisces: Sparidae)." In Alternative Life-History Styles of Fishes, edited by Michael N. Bruton, 113–24. Developments in Environmental Biology of Fishes 10. Springer Netherlands.

Carruthers, T. R., Punt, A. E., Walters, C. J., MacCall, A., McAllister, M. K., Dick, E. J., and Cope, J. 2014. Evaluating methods for setting catch limits in data-limited fisheries. Fisheries Research 153:48-68. doi: 10.1016/j.fishres.2013.12.014

Chen, Weizhong, Sulaiman Almatar, Adel Alsaffar, and Abdul Rehman Yousef. 2012. "Retained and Discarded Bycatch from Kuwait's Shrimp Fishery." Brazilian Journal of Aquatic Sciences and Technology 1 (1): 86–100.

Coggins, G., Catalano, M., Allen, M., Pine, W., and Walters, C. 2007. "Effects of Cryptic Mortality and the Hidden Costs of Using Length Limits in Fishery Management." Fish and Fisheries 8 (3). Blackwell Publishing Ltd: 196–210.

CSO, 1995–2004. Fisheries Statistics, 1995–2004. Central Statistical Office, Ministry of Planning, State of Kuwait.

CSO, 2011–2015. Fisheries Statistics, 1995–2004. Central Statistical Office, Ministry of Planning, State of Kuwait.

Dichmont, C. M., A. E. Punt, A. Deng, Q. Dell, and W. Venables. 2003. “Application of a Weekly Delay-Difference Model to Commercial Catch and Effort Data for Tiger Prawns in Australia’s Northern Prawn Fishery” 65 (1): 335–50.

Dick, E., and MacCall, A. D. 2011. Depletion-Based Stock Reduction Analysis: A catch-based method for determining sustainable yields for data-poor fish stocks. Fisheries Research 110:331-341. doi: 10.1016/j.fishres.2011.05.007

Fournier, David A., and Ian J. Doonan. 1987. “A Length-Based Stock Assessment Method Utilizing a Generalized Delay-Difference Model.” Canadian Journal of Fisheries and Aquatic Sciences. Journal Canadien Des Sciences Halieutiques et Aquatiques 44 (2): 422–37.

Froese, R. and Pauly D. “*Epinephelus Coioides* Summary Page.” 2017. FishBase. Accessed April 5. http://www.fishbase.org/summary/Epinephelus-coioides.html.

Goodwin, N.B., Grant, A., Perry, A.L., Dulvy N.K., and Reynolds, J.D. 2006. Life history correlates of density-dependent recruitment in marine fishes. Can. J. Fish. Aquat. Sci. 63: 494–509.

Grandcourt, E. M., T. Z. Al Abdessalaam, F. Francis, and A. T. Al Shamsi. 2005/8. “Population Biology and Assessment of the Orange-Spotted Grouper, *Epinephelus Coioides* (Hamilton, 1822), in the Southern Arabian Gulf.” Fisheries Research 74 (1–3): 55–68.

Hawkshaw, M., and Walters, C.J. 2015. Harvest control rules for mixed-stock fisheries coping with autocorrelated recruitment variation, conservation of weak stocks, and economic well-being. Can. J. Fish. Aquat. Sci. 72:759-766.

Hilborn, R., and C. J. Walters. 1992. “Quantitative Fisheries Stock Assessment: Choice, Dynamics and Uncertainty.” Chapman and Hall, New York 570: 0–4.

Hilborn, R. 2010. “Pretty Good Yield and Exploited Fishes.” Marine Policy 34 (1): 193–96.

Hilborn, R., and Kevin Stokes. 2010. “Defining Overfished Stocks: Have We Lost the Plot?” Fisheries 35 (3): 113–20.

Hilborn, R., Kevin Stokes, Jean-Jacques Maguire, Tony Smith, Louis W. Botsford, Marc Mangel, José Orensanz, et al. 2004. “When Can Marine Reserves Improve Fisheries Management?” Ocean & Coastal Management 47 (3–4): 197–205.

Hilborn, R. 2007. “Moving to Sustainability by Learning from Successful Fisheries.” Ambio 36 (4): 296–303.

Hordyk, Adrian, Kotaro Ono, Sarah Valencia, Neil Loneragan, and Jeremy Prince. 2015. “A Novel Length-Based Empirical Estimation Method of Spawning Potential Ratio (SPR), and Tests of Its Performance, for Small-Scale, Data-Poor Fisheries.” ICES Journal of Marine Science: Journal Du Conseil 72 (1). Oxford University Press: 217–31.

Hutchings, J. A. 2000. “Collapse and Recovery of Marine Fishes.” Nature 406 (6798): 882–85.

Hutchings, Jeffrey A., and John D. Reynolds. 2004. “Marine Fish Population Collapses: Consequences for Recovery and Extinction Risk.” Bioscience 54 (4): 297–309.

Issa, E., N. A. Al-Ansari, Govand Sherwany, and Sven Knutsson. 2014. “Expected Future of Water Resources within Tigris-Euphrates Rivers Basin, Iraq.” Journal of Water Resource and Protection 2014. Scientific Research Publishing. http://file.scirp.org/Html/2-9402125_45022.htm.

Iwatsuki, Y. 2013. "Review of the Acanthopagrus Latus Complex (Perciformes: Sparidae) with Descriptions of Three New Species from the Indo-West Pacific Ocean." Journal of Fish Biology 83 (1): 64–95.

Kimura, Daniel K., and Jack V. Tagart. 1982. "Stock Reduction Analysis, Another Solution to the Catch Equations." Canadian Journal of Fisheries and Aquatic Sciences. Journal Canadien Des Sciences Halieutiques et Aquatiques 39 (11): 1467–72.

Kimura, Daniel K., James W. Balsiger, and Daniel H. Ito. 1984. "Generalized Stock Reduction Analysis." Canadian Journal of Fisheries and Aquatic Sciences. Journal Canadien Des Sciences Halieutiques et Aquatiques 41 (9): 1325–33.

King, Michael. 2013. Fisheries Biology, Assessment and Management. John Wiley & Sons.

Kristjonsson, Hilmar. 1967. Techniques of Finding and Catching Shrimp in Commercial Fishing. Food and Agriculture Organization of the United Nations.

Lee, J. U., and A. F. Al-Baz. 1989. "Assessment of Fish Stocks Exploited by Fish Traps in the Arabian Gulf Area." Asian Fisheries Science 2 (2). researchgate.net: 213–31.

Lieske, Ewald, and Robert Myers. 1994. Coral Reef Fishes: Caribbean, Indian Ocean and Pacific Ocean Including the Red Sea. HarperCollins.

Loneragan, Neil R. 1999. “River Flows and Estuarine Ecosystems: Implications for Coastal Fisheries from a Review and a Case Study of the Logan River, Southeast Queensland.” Australian Journal of Ecology 24 (4). Blackwell Science Pty: 431–40.

Martell, Steven J. D., Carl J. Walters, and Ray Hilborn. 2008. “Retrospective Analysis of Harvest Management Performance for Bristol Bay and Fraser River Sockeye Salmon (Oncorhynchus Nerka).” Canadian Journal of Fisheries and Aquatic Sciences. Journal Canadien Des Sciences Halieutiques et Aquatiques 65 (3): 409–24.

Martin, M., Runge, M.C., Nichols, J.D., Lubow, B.C., and Kendall, W.L. 2009. Structured decision making as a conceptual framework to identify conservation thresholds for conservation and management. Ecological Applications 19:1079-1090.

Mathews, C. P., and M. Samuel. 1989. “The Relation between by-Catch, Shrimp Catches and Shrimp Landings in Kuwait.” Kuwait Bulletin of Marine Science 10: 135–46.

McGowan, C.P., Lyons, J.E., and Smith, D.R. 2015. Developing objectives with multiple stakeholders: adaptive management of horseshoe crabs and red knots in the Delaware Bay. Environmental Management 55:972-982. DOI 10.1007/s00267-014-0422-8.

Morgan, G. R. 1985. “Assessment of Sheim (*Acanthopagrus latus*) in Kuwait Waters.” In Proceedings of the 1984 Shrimp and Fin Fisheries Management Workshop, Kuwait Institute for Scientific Research, Report No. KISR1856, Kuwait, 66–115.

Myers, R. A., and G. Mertz. 1998. “The Limits of Exploitation: A Precautionary Approach.” Ecological Applications: A Publication of the Ecological Society of America 8 (sp1). Ecological Society of America: S165–69.

Neumann, Robert M., Christopher S. Guy, David W. Willis, A. V. Zale, and D. L. Parrish. 2012. “Length, Weight, and Associated Indices.” Fisheries Techniques, 3rd Edition. American Fisheries Society, Bethesda, Maryland 637: 676.

O’Farrell, Michael R., and Louis W. Botsford. 2005. “Estimation of Change in Lifetime Egg Production from Length Frequency Data.” Canadian Journal of Fisheries and Aquatic Sciences. Journal Canadien Des Sciences Halieutiques et Aquatiques 62 (7): 1626–39.

Pauly, Daniel, Ray Hilborn, and Trevor A. Branch. 2013. “Fisheries: Does Catch Reflect Abundance?” Nature 494 (7437): 303–6.

Prince, J., A. Hordyk, S. R. Valencia, N. Loneragan, and K. Sainsbury. 2015. “Revisiting the Concept of Beverton -Holt Life-History Invariants with the Aim of Informing Data-Poor Fisheries Assessment.” ICES Journal of Marine Science: Journal Du Conseil 72 (1): 194–203.

Raeisi, H., S. Y. Paighambari, R. Davoodi, M. Bibak, S. A. Hoseini, and M. J. Shabni. 2010. “Length-Weights Relationships and Relative Weights of Some Demersal Fish Species from the Persian Gulf, Iran.” African Journal of Agricultural Research 7 (5). Academic Journals: 741–46.

Randall, John E., Gerald R. Allen, and Roger C. Steene. 1997. Fishes of the Great Barrier Reef and Coral Sea. University of Hawaii Press.

Sagarese, S.R., Walter, J.F., Isely, J.J., Bryan, M.D., and Cummings, N. 2015. A comparison of data-rich versus data-limited methods in estimating overfishing limits. SEDAR46-DW-01. SEDAR, North Charleston, SC. 28 pp.

Siddeek, M, A. R. Abdul Ghaffar, and M. Ei-Musa. 1988. “Shrimp Fisheries Management Project Phase IV, Final Report.” Kuwait Institute for Scientific Research, Kuwait, KISR 2570: 65.

Siddeek, M. S. M. 1991. “Estimation of Natural Mortality of Kuwait’s Grooved Tiger Prawn Penaeus Semisulcatus (de Haan) Using Tag-Recapture and Commercial Fisheries Data.” Fisheries Research 11 (2). Elsevier: 109–25.

Smith, A.D.M. and Walters, C.J. 1981. Adaptive management of stock-recruitment systems. Can. J. Fish. Aquat. Sci. 38: 690-703.

Staples, D. J., D. J. Vance, and N. R. Loneragan. 1995. “Penaeid Prawn Recruitment Variability: Effect of the Environment.” In Proceedings of the Workshop on Stock-Recruitment Relationships (SRRs) in Australian Crustacean Fisheries, 41–50. publications.csiro.au.

Szuwalski, C.S., Vert-Pre, K., Punt, A.E., Branch, T.A., and Hilborn, R. 2014. Examining common assumptions about recruitment: a meta-analysis of recruitment dynamics for worldwide marine fisheries. Fish and Fisheries, 16:633-648. DOI: 10.1111/faf.12083

Taylor, N., Walters, C., and Martell, S. 2005. “A New Likelihood for Simultaneously Estimating von Bertalanffy Growth Parameters, Gear Selectivity, and Natural and Fishing Mortality.” Canadian Journal of Fisheries and Aquatic Sciences. Journal Canadien Des Sciences Halieutiques et Aquatiques 62 (1). NRC Research Press: 215–23.

Then, A., Hoenig, J., Hall, N., and Hewitt, D. 2015. “Evaluating the Predictive Performance of Empirical Estimators of Natural Mortality Rate Using Information on over 200 Fish

Species.” ICES Journal of Marine Science: Journal Du Conseil 72 (1). Oxford University Press: 82–92.

Thorson, J. T., Shelton, A. O., Ward, E. J., and Skaug, H. J. 2015. Geostatistical delta-generalized linear mixed models improve precision for estimated abundance indices for West Coast groundfishes. ICES Journal of Marine Science, doi: 10.1093/icesjms/fsu243.

UNEP, (Partow, H), 2001. The Mesopotamian marshlands: Demise of an ecosystem. Division of Early Warning and Assessment, United Nations Environment Program, Nairobi, Kenya.

Valinassab, T., R. Daryanabard, R. Dehghani, and G. J. Pierce. 2006. “Abundance of Demersal Fish Resources in the Persian Gulf and Oman Sea.” Journal of the Marine Biological Association of the United Kingdom. Marine Biological Association of the United Kingdom 86 (06). Cambridge Univ Press: 1455–62.

Vance, D. J., D. J. Staples, and J. D. Kerr. 1985. “Factors Affecting Year-to-Year Variation in the Catch of Banana Prawns (*Penaeus Merguiensis*) in the Gulf of Carpentaria, Australia.” ICES Journal of Marine Science: Journal Du Conseil 42 (1). Oxford University Press: 83–97.

Vert-pre K.A., Amoroso R.O., Jensen O.P., Hilborn R. 2013. Frequency and intensity of productivity regime shifts in marine fish stocks. Proc Natl Acad Sci USA 110(5):1779–1784. doi/10.1073/pnas.1504709112

Walters, C.J., Hilborn, R. 1976. Adaptive control of fishing systems. J. Fish. Res. Bd. Canada, 33:145-159.

Walters, C.J. 1981. Optimum escapements in the face of alternative recruitment hypotheses. Can. J. Fish. Aq. Sci., 38(6):678-689.

Walters, C.J. 1986. Adaptive management of renewable resources. Blackburn Press, Caldwell New Jersey.

Walters, C.J., R. Goruk, D. Radford. 1993. Rivers Inlet Sockeye salmon; an experiment in adaptive management. North Am. J. Fish. Mgmt. 13:253-262.

Walters, C.J., and A. Punt. 1994. Placing odds on sustainable catch using virtual population analysis and survey data. Can. J. Fish. Aquat. Sci. 51:946-958.

Walters, C.J. 1995. Use of gaming procedures in adaptive policy design. Can. J. Fish. Aquat. Sci. 51:2705-2714.

Walters, C.J., A. Parma. 1996. Fixed exploitation policies for dealing with effects of large-scale climate change. Can. J. Fish. Aquat. Sci. 53:148-158.

Walters, C.J. and R. Green. 1997. Valuing large scale management experiments for natural resources. J. Wildl. Mgmt. 61:987-1006.

Walters, C.J., and Martell, S.J. 2004. Fisheries ecology and management. Princeton University Press, Princeton, New Jersey.

Walters, Carl J., Steven J. D. Martell, and Josh Korman. 2006. "A Stochastic Approach to Stock Reduction Analysis." Canadian Journal of Fisheries and Aquatic Sciences. Journal Canadien Des Sciences Halieutiques et Aquatiques 63 (1): 212–23.

Walters, Carl J. and M. Grubert. 2011. “Dynamics of numbers, carapace width, and sex ratios in the Northern Territory mud crab stock.” Commonwealth Scientific and Industrial Research Organisation (CSIRO).

Walters, Carl J. 2016. “A reassessment of recruitment overfishing risk for the Northern Territory mud crab fishery.” Commonwealth Scientific and Industrial Research Organization (CSIRO).

Willis, Trevor J., Russell B. Millar, and Russ C. Babcock. 2003. “Protection of Exploited Fish in Temperate Regions: High Density and Biomass of Snapper Pagrus Auratus (Sparidae) in Northern New Zealand Marine Reserves.” The Journal of Applied Ecology 40 (2). Blackwell Science Ltd: 214–27.

Ye, Yimin, A. H. Alsaffar, and H. M. A. Mohammed. 2000. “Bycatch and Discards of the Kuwait Shrimp Fishery.” Fisheries Research 45 (1): 9–19.