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A quantitative and qualitative approach to assess climate-driven influences on the population dynamics of two demersal key species in the southern Caspian Sea

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This thesis is dedicated to the memory of my grandfather Azizollah Mari-Oryad (1940-2014).

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Summary

Climatic/environmental conditions are extrinsic driving forces which play a significant role in shaping marine ecosystem structures. Identifying, characterizing and evaluating complex behavior of ecosystem components in response to external physical drivers – particularly those related to ongoing climatic/environmental changes – is considered to be fundamental towards fostering an Ecosystem-based Approach to Management (EAM) to sustainably exploit living resources. This PhD thesis has taken a twofold quantitative-qualitative approach to clarify the potential linkages between the dynamics of commercially important demersal (bentho-pelagic) fish stocks (Caspian kutum and golden grey mullet) and external ecosystem forces (atmospheric climate patterns)/environmental variables in the southern Caspian Sea. The climate-/environment-driven impacts were explored using the following global and local indices as proxies for climatic/environmental conditions, fluctuations and variability over the study area: the North Atlantic Oscillation (NAO), the Southern Oscillation Index (SOI), index of the Siberian High Intensity (SHI), the East Atlantic-West Russia pattern index (EA-WR), Sea Surface Temperature (SST) and upper-layer Chlorophyll-a concentration (Chl-a).

In *SECTION I (Quantitative approach)*, the potential gradual impacts of climate/environment on the long-term dynamics of species were evaluated quantitatively for years 1991-2011. The results of this section showed that the examined climatic/environmental forces (i.e. NAO, SOI, EA-WR, SHI, SST and Chl-a) are likely to gradually influence the dynamics of the two bentho-pelagic stocks under consideration either (a) at recruitment and/or adult life-stages, (b) directly or/and indirectly via intermediate physical-ecological processes and (c) immediately and/or within lag periods (time-delay) of 1 to 5 years. However, inclusion of the identified influential climatic/environmental variables into the basic population dynamics models (i.e. recruitment models) for both species did not improve the explanatory power of these models statistically. Interestingly, further results demonstrated that simplified lag-endogenous recruitment models had the best statistical performance in case of both species, i.e. serially self-influencing models. However, the seemingly self-influencing mechanism is due to the following reasoning: Such simplified lag-endogenous models may partly represent the continued

environmental condition changes resulting from consistent external drivers or specific climatic regimes which might have significantly influenced the recruitment processes in succeeding years.

In *SECTION II (Qualitative approach)*, the occurrence of ecological climate/environment-driven shifts were studied in the Southern Caspian Sea using shiftogram method on the available ecological and hydro-climatic variables. While the shiftogram method is of quantitative nature, the occurrence of rare events such as shifts is a qualitative feature. The explorative findings from the serial shift analyses revealed that the integrated synchronous climate-/environment-driven shifts might have played a substantial role in shaping regional ecological dynamics, not only at species but also at community and ecosystem levels over the last two decades. The cascading and serial order of multiple shift events in hydroclimatic-ecologic conditions of the southern Caspian Sea suggested a synchronous linkage between external forces and dynamics of ecosystem components/structures in the following order: global-scale climate forces → local environmental processes → biological components dynamics.

In summary, with regard to the two commercially most important bentho-pelagic fish stocks in the southern Caspian Sea, this study for the first time achieved general postulations about the so far neglected extrinsic ecosystem forces (global and regional physical processes) and their potential role in shaping the population dynamics of these two stocks. These findings may help to foster a regional Ecosystem-based Approach to Management (EAM) as an integral part of bentho-pelagic fisheries management plans. Moreover, the integrated quantitative and qualitative assessment of the climatic/environmental impacts in the present study contributed basic knowledge on potential global and regional physical processes influencing the unique Caspian environment.

Chapter 1: Introduction

1-1 General overview

Due to long-term exploitation, many marine systems providing fundamental services for human beings (e.g. regulating earth's climate system, fisheries production, entertainment,…), are under pressure of various simultaneous stressors like pollution, overexploitation, climate change, etc… (Selim *et al*., 2014). Marine commercial fisheries as one of the major ecosystem services are considered to provide a significant nutritive source of protein, fatty acids, vitamins and minerals to mankind (Johnson and Welch, 2009; Barange *et al*., 2011). In many countries, particularly the so-called developing nations, fishing is extremely important in sustaining and supporting socio-economic structures (Johnson and Welch, 2009; Keyl and Wolff, 2007). Growing demand for fish as a result of the continuous increase of the world's population and changing human food preferences, lead to additional concerns about sustainability of marine ecosystems and fisheries production (Barange *et al*., 2011; Barange *et al*., 2014).

During the last century, fisheries scientists attempted to identify the mechanisms that regulate the dynamics of exploited fish populations and to predict sustainable yields (Keyl and Wolff, 2007). The major aim of fisheries management is to achieve a sustainable long-term exploitation level to ensure economic profitability. Nowadays it includes governmental, predefined and proper instructions and tools which are working through supervision and a control system (Fernandes, 2010). Attempting to reach a balanced and sustainable fisheries management may lead to an increase in the adaptability of fishing dependent communities (Daw *et al*., 2009).

A rather recent and progressive paradigm of ecosystem-based management is a globally plausible perspective towards a sustainable exploitation of marine natural resources (Browman *et al*., 2004). Ecosystem-based management considers all relations, interactions and processes in an ecosystem, rather than single components separately (Sissenwine and Murawski, 2004; Fernandes, 2010). According to Fogarty (2013), this approach is "an integrated framework for delivering a sustainable key ecosystem service". Perceiving how ecosystem components and interactions are impacted by anthropogenic activities (e.g. fishing) as well as considering the surrounding environment is required for a reasonable ecosystem-based management (Deyle *et al*., 2013). The principle is that - apart from the influences of exploitation on fish populations - the main mechanisms, which control fish population dynamics are alterations in ecosystem forces, such as "climate–ocean impacts and trophic level interactions" (King and Mcfarlane, 2006). Global fisheries processes and activities are inevitably under climate variability regimes (Johnson and Welch, 2009) and the fisheries productivity, fish population dispersal and variability, intensively rely on the environment status (Mackenzie *et al*., 2007) and climate dynamics (Lehodey *et al*., 2006). Climate forces are exogenous, superintendent and latent drivers which induce profound large-scale alterations in marine ecosystems via impacting their environmental state.

Environmental variability is a critical and significant component for marine ecosystem production and recovery capacity (Sissenwine and Murawski, 2004). Evaluating the environmental impacts is one of the elements of the ecosystem-based approach, which is of increasing importance in the upcoming marine management scenarios (Jennings *et al*., 2004). Alterations in hydrographic and weather-related elements influence fish life history and can affect population dynamics of fish species (Mackenzie *et al*., 2007). Environmental conditions can affect various biological and fishing processes which could consequently lead to different managing plans. Therefore it is essential to understand how fish stocks are affected by environmental conditions (Maunder and Deriso, 2010). In order to improve and modify fisheries management towards an ecosystem framework which is "largely controlled by climate dynamics", integrated and cooperative research and investigations are needed (Lehodey *et al*., 2006), as during the past century, different disciplines such as oceanography, marine ecology, population dynamics and biology have been combined in fisheries science (Maunder and Deriso, 2010).

Debates and discourses about climate change and sustainability of marine resources are rising (Rice and Garcia, 2011) and there are plenty of proofs which indicate the effects of contemporary climate change on various ecosystems (Lehodey *et al*., 2006). Climate change is impacting many natural populations such as fish and therefore marine and estuarine fisheries (Roessig and Woodley, 2004; Wilsey *et al*., 2013). For management purposes, perception of nature, extent and spatial distribution of present and upcoming climate change effects is necessary (Wilsey *et al*., 2013). During the last decades, the marine environment has experienced extensive alterations due to changing climate conditions which represents a close connection between marine processes and climate (Niiranen *et al*., 2013). In the next decades climate change is likely to have considerable expectable and unpredictable influences on marine ecosystems, however not all of the impacts are adverse but undoubtedly will intensify the uncertainty in the context of ecological properties and interactions (Grafton, 2010). Thereupon, climate change will influence the food security in fisheries dependent societies (Daw *et al*., 2009) and the results of climate change for these communities, rely on the degree of exposure, sensitivity of ecosystem and commercial species and adaptability of fisheries (Grafton, 2010). A consecutive, comprehensive and holistic perspective of ongoing global climate change impacts on marine ecosystems is well-illustrated by Sumaila *et al*., (2011) (Fig.1-1).

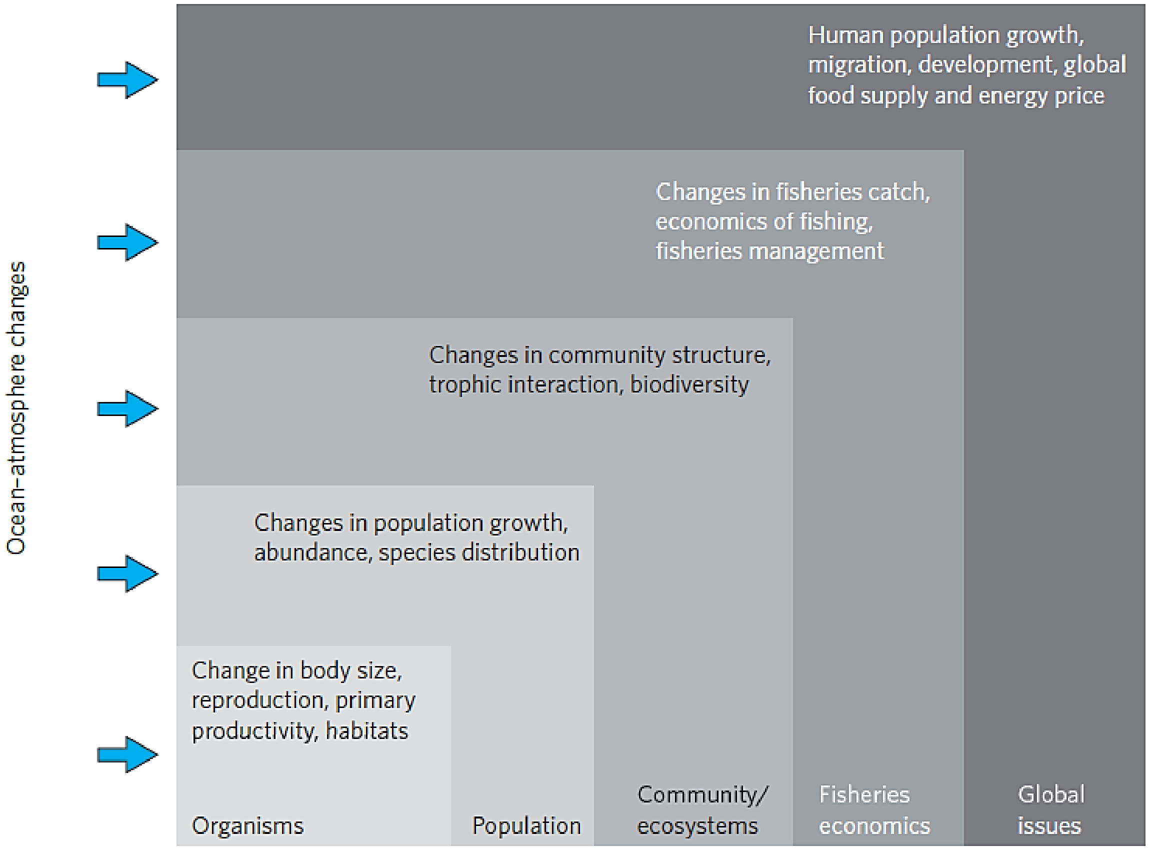


Figure 1-1. Multi-scale influences of ocean-atmosphere changes (from Sumaila *et al*., 2011).Reprinted by permission from Macmillan Publishers Ltd: [NATURE CLIMATE CHANGE] (Sumaila *et al*., 2011), copyright (2011). http://www.nature.com/nclimate/journal/v1/n9/full/nclimate1301.html

1-2 Climate forcing, marine environment and fisheries

Investigating and quantifying climate-dependent ecological responses (spatio-temporally) could be considered as a unique series of natural experiments which is crucial for improving our knowledge of assessing past and present and projecting future climate variability and change effects in marine environments (Pershing, 2001; Stige *et al.,* 2010).

Climate is an extrinsic driving force which plays a significant role in shaping marine ecosystem structures. This back-stage running factor is a rather veiled and impalpable phenomenon. However, climate condition, variability and change are general concepts which are defined interdependently in the context of ‘average weather’ or atmospheric state. According to Drinkwater (2010),”*climate variability is a temporal variation around this average state*” while “*climate change refers to a change in the state of the climate that can be identified (e.g., by using statistical tests) by changes in the mean and/or the variability of its properties, and that persists for an extended period, typically decades or longer*” (IPCC, 2014).

Most of climate forcing variability and climate-induced changes in marine environments and ecosystems are consequences of two major well-known issues: a global warming trend and cyclic climate-ocean patterns (Keyl and Wolff, 2007). In general, the rise of the mean global temperature is largely and directly attributed to post-industrial anthropogenic accumulation of greenhouse-gases emissions as during the last three decades the temperature rise was recorded about ~0.2°C in each ten years (Brierley and Kingsford, 2009; Hoegh-Guldberg and Bruno, 2010). However, natural cyclic climatic patterns and variability are occurring within climate-ocean systems (at different temporal scales from seasonal to decadal) that are recognized and recorded in several large-scale climate variability and quantitative proxies such as North Atlantic Oscillation (NAO), El Niño-Southern Oscillation (ENSO) or Pacific Decadal Oscillation (PDO), etc… (Keyl and Wolff, 2007; Brierley and Kingsford, 2009; Hoegh-Guldberg and Bruno, 2010).

Generally these proxies are considered as investigative and diagnostic means (known as large-scale climate indices) for representing and explaining particular aspects of climate state and variability (by incorporating and merging certain climatological features and weather components and packaging them into a single quantitative index). However, climate forcing processes influence biotic components, structures and functions of marine ecosystems through local physical parameters (e.g. temperature, winds, currents, precipitation, etc…) (Philippart *et al*., 2011), studying climate-associated impacts on ecosystem dynamics by means of these large-scale measures offers several technical advantages (Forchhammer and Post 2004, Drinkwater *et al*., 2010; Gröger and Fogarty, 2011). For instance, compared to individual ambient parameters, by applying large-scale indices in ecological studies some statistical problems (e.g. multi-collinearity, redundancy, error inflation ...) can be eluded.

All trophic components and levels of marine food webs, from primary and secondary producers (phytoplankton and zooplankton) to upper level consumers (e.g. fish, predators …), are affected by climate conditions (Hays *et al*., 2005; Richardson, 2008). Strong direct and indirect impacts of changes in local oceanographic conditions on the individual marine organisms level (overall biological performance) would be reflected in population and community levels (Doney *et al*., 2012).

According to Ottersen *et al*., (2010) general and major ecological responses of marine organisms and populations to climate processes are divided into four categories namely, *direct*, *indirect* and *integrated* responses and *translations*. *Direct* response involves direct ecological response (e.g. physiological and behavioral reactions) to a climate signal whereas *indirect* climate-induced responses occur after one or several intermediate transitional ecological steps, processes and interactions. *Integrated* responses imply the incidence of responses across or after extreme climate events while *translation* concept is applied in a case of spatial movement of organisms due to the physical changes in marine environments. Also the responses in ecosystem organization level (i.e. population and community) can be immediate or occur after a time lag (i.e. delayed response due to the transitioning time of climate signal, from global scale to the organism level).

When looking for complex climate-driven impacts in marine resources, two major modalities (trajectories) can be recognized. On the one hand, marine population dynamics may be affected by gradual trends, continuous cycles and temporal variability of climate forcing factors. On the other hand, sudden and high amplitude climatic perturbations may induce dramatic alterations in marine ecological regimes. Generally, the first type of impacts could be investigated by quantitative correlational analysis of climate-biological datasets (Brander, 2007), whereas the intricate reactions of ecosystem components due to abrupt climate alterations (which is known as climate-induced "regime shifts") are qualitatively studied by comparing successive ecological states. Regime shift is being accounted as a global issue in aquatic ecosystems context with widely-documented and still growing evidences in several marine systems (Hare and Manuta, 2000; Scheffer *et al*., 2001; Scheffer and Carpenter, 2003; Möllmann *et al*., 2009; Gröger *et al*., 2011; Gröger *et al*., 2014; Möllmann and Diekmann, 2012; Levin and Möllmann, 2015; Möllmann *et al*., 2015). By combining various sets of aspects, Lees *et al*., (2006) suggested a comprehensive, multi-criterial and "standard" definition for marine ecosystem regime shifts involving the occurrence of sudden, high-amplitude and low-frequency changes over a large geographical area that are perceptible in several features of the ecological components (biotic and abiotic). Climate-induced regime shifts have profound implications for sustainability of marine resources and fisheries production (Lees *et al*., 2006; Gröger *et al*., 2011; Levin and Möllmann, 2015; Möllmann *et al*., 2015).

Alterations (of trend and amplitude) in local hydrographic condition of marine environment caused by large-scale climate forces, influence fish during the whole life span; however it is well documented that fish in critical early life-stage responds more sensitively to ambient physical perturbations which could result in crucial and explicit consequences in recruitment processes and ultimately in fisheries production (Noakes *et al.*, 1987; Fogarty, 1993; Needle, 2001). Climate impacts on early life-stages of fish can be considered through an ecological cascade proposed by Gröger *et al.*, (2014). Accordingly, climate is considered as the external leading factor provoking alterations in abiotic features of ambient environment. Furthermore, these alterations could be transmitted to subsequent levels including, biotic environment, egg, larvae and finally the recruitment. Hierarchal climate impacts (direct and indirect) are summarized graphically in Fig. 1-2.

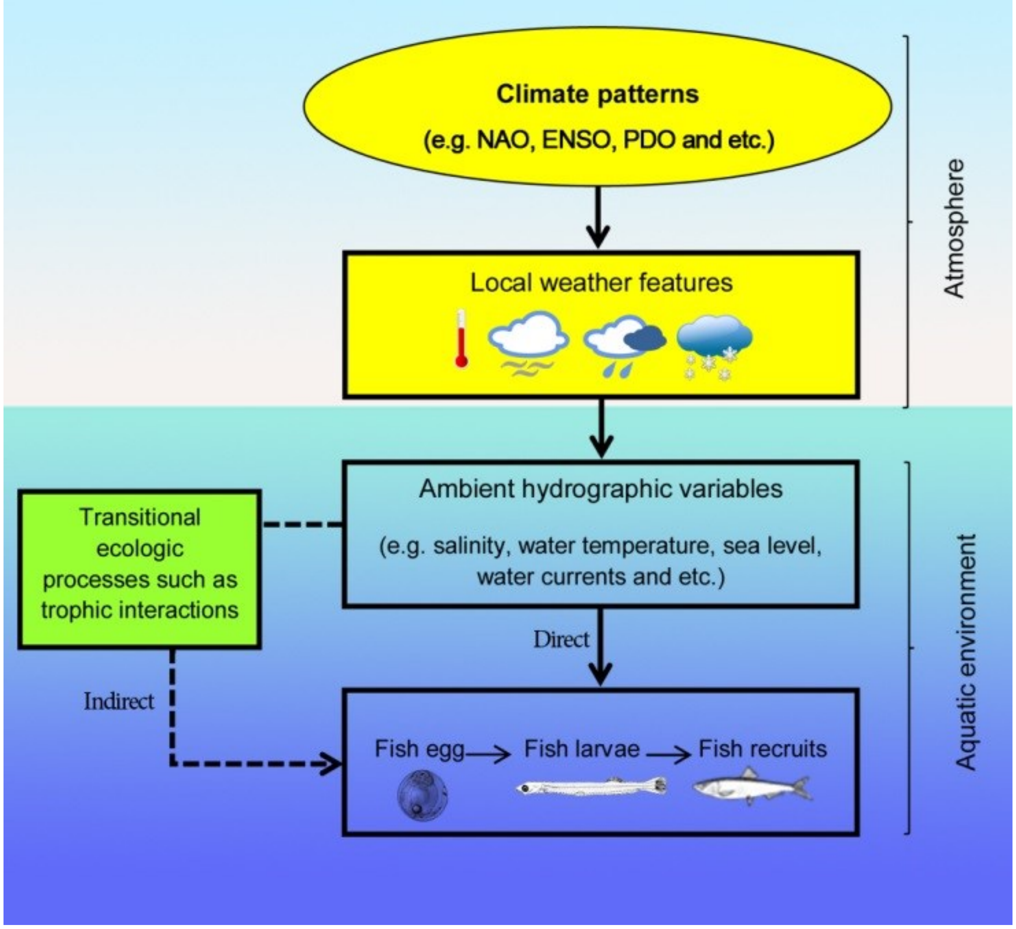


Figure 1-2. Cascadal direct and indirect climate impacts on fish. Partly based on Forchhammer and Post (2004) and Gröger *et al.*, (2014).

Recruitment is the most prevalent demographic function which is believed to be impacted by environmental alterations (as the exogenous sources of variability) (Maunder and Deriso, 2010). It should be kept in mind that as a result of the 1992 UNCED conference in Rio one of the essences of the Brundtland report is that in case of renewable resources the risk of failure for sustainability will increase dramatically if the exploitation rate exceeds their regeneration rate (Gröger, personal communication). Hence, translated into fish stock dynamics the recruitment rate forms the foundation for sustainability in fisheries. Apart from exploring the role of parental stock size in population regulatory processes of exploited fish, providing insights into different aspects of climate-recruitment dynamics have direct and substantial implications in sustainable fisheries management and resilient ecosystem-oriented strategies (Beamish *et al*., 2004; Browman *et al*., 2004; Sissenwine and Murawski, 2004; Gröger and Fogarty, 2011; Rice and Garcia, 2011; Santos *et al*., 2011). Ignoring the evaluation of climate-imposed impacts in the stock assessment of commercial species may lead to poor management practices, ergo unsustainable fisheries production.

1-3 The Caspian Sea, ecological state and commercial fisheries

The Caspian Sea (Fig.1-3) as the largest enclosed water body (with no outlets) of the earth with a total surface area of about 380000 Km^2 is located between Asia and Europe (geographically situated between latitudes 47° 13´ and 36° 34´ North and longitudes 46° 38´ and 54° 44´ East with coastlines shared by five littoral countries including Iran, Azerbaijan, Kazakhstan, Russia and Turkmenistan). This unique water reservoir extends 1200 km from the north to the south and 250-450 km in the east-west direction (Elguindi and Giorgi, 2006). Its average and maximal depths are 184 m and 1025 m, respectively; the water level is 27 m below the world ocean (CEP, 2002) and the Volga River is the main entering runoff (Elguindi and Giorgi, 2006). The Caspian Sea is generally divided into three parts (considerably differing in physico-geographical features) namely, the northern, middle and southern part. The northern part is shallow (average depth 5 m) and covering 29% of surface area while the middle and the southern part have an average depth of 190 and 330 m, respectively. The surface area is about 36 and 35%, respectively (Stolberg *et al.,* 2006, Fendereski *et al*., 2014). Salinity shows a north-south gradient from 0.1 ppt in the northern part to a maximum of 13 ppt in the southern part. Water temperature is changing in the northern part from below zero in winter to 25-26 °C in summer and varying between 7-10 °C in winter to 25-29 °C in summer in the southern part (Ibrayev *et al*., 2010).

Figure 1-3. The location of the Caspian Sea and the neighboring countries, from: http://www. en.wikipedia.org/wiki/Caspian_Sea.

During recent decades the unique ecosystem and biodiversity of the Caspian Sea has been under enormous pressure of numerous anthropogenic stressors and is encountering a multitude of ecological challenges such as industrial and biological contamination (de Mora, 2004; Nezlin, 2005; Stolberg *et al.,* 2006; Askarova *et al*., 2014), sea level fluctuation (Arpe *et al*., 2000; Renssen *et al*., 2007; Ibrayev *et al*., 2010), fisheries overexploitation, management failure and collapse of commercial fish stocks (Daskalov and Mamedov, 2007; Fazli *et al*, 2007; Ustarbekova, 2014), illegal fishing and poaching (Daskalov and Mamedov, 2007; Abdolmaleki and Psuty, 2007; Roohi *et al*., 2010), invasion of *Mnemiopsis leidyi* (Kideys and Moghim, 2003; Kideys *et al*., 2005; Finenko *et al*., 2006; Roohi *et al*., 2010), eutrophication (Leonov and Stygar, 2001; Nasrollahzadeh *et al*., 2008), loss of biodiversity (Karpinsky *et al*., 2005; Valipour and Khanipour, 2006), environmental mismanagement (Barale, 2008; Fenderski *et al*., 2014) and etc. On top of the aforementioned pressures the Caspian Sea environment and bio-resources have been - and will be - inevitably exposed to on-going global climatic changes (like other marine ecosystems); nevertheless, climate is still a largely-ignored issue in marine resources management in this region.

Among 115 fish species and sub-species inhabiting this ecosystem, demersal Chondrichthyes sturgeons, and demersal (bentho-pelagic) bony fish including kutum, mullets, breams, carps, barbus, salmons, as well as pelagic kilka species have been historically important in commercial fisheries of the Caspian Sea (Valipour and Khanipour, 2006).

Exploitation of bony fish (started since 1927) in Iranian waters of the Caspian Sea has always played a prominent role in fisheries economy of the region (Bandpei *et al*., 2010; Valipour and Khanipour, 2006; Fazli *et al*., 2012). Considering the present status of fisheries production, the target species of Caspian kutum (*Rutilus frissi kutum* (Kamensky, 1901)) and the golden grey mullet, (*Liza aurata* (Risso, 1810)) constitute the major commercial fisheries catches in Iranian coastal waters of the Caspian Sea (Valipour and Khanipour, 2006; Fazli *et al*., 2008b; Ghaninejad *et al*., 2010; Fazli *et al*., 2012).

1-3-1 The Caspian kutum

The Caspian kutum (*Rutilus frisii kutum* (Kamensky, 1901), Fig. 1-4), is a medium size endemic migratory (anadromous) fish with a life span of 9-10 years in the southern Caspian Sea; due to the nutritional value and palatable taste for consumers, as well as its profitability for fishermen, kutum is considered as the most important bony fish of the Caspian sea (Valipour and Khanipour, 2006), covering more than 70% of the annual Iranian costal catches (Yousefian and Mosavi, 2008). Male and female fish reach to the maturity stage at between 2-3 and 3-4 years, respectively (Bandpei *et al*., 2010). Although adult kutum is omnivorous, feeding in the early life stages mainly depends on (phyto-/zoo-) plankton and insect larvae (Valipour and Khanipour, 2006). Overfishing, water pollution, environmental alterations and loss of spawning habitat historically caused diminishing of kutum stock (Ralonde and Walzac, 1971; Razavi sayad, 1972; Coad, 1980; Borujeni *et al*., 2015). In order to sustain the population and improve fisheries management, the national stock enhancement program (fingerling release) is being performed annually (started from 1981) by Iranian Fisheries Organization (IFO) (Fazli *et al*., 2012).

The total catch of this species showed high fluctuations during the last two decades in the coastal waters of Iran. In the early 1990s (1991-1992), the recorded catch was 10900 metric tons (mt) while it declined to 6580 mt in the end of this decade (1999-2000); the recorded value was 17200 mt in 2007-2008 but dropped again to 11570 mt in 2010-2011 (Fazli *et al*., 2012).

Figure 1-4. The Caspian Kutum (*Rutilus frisii kutum* (Kamensky, 1901)), from Valipour and Khanipour, (2006).

1-3-2 The golden grey mullet

The golden grey mullet (*Liza aurata* (Risso, 1810), Fig. 1-5) is a euryhaline and eurythermic species (Fazli *et al*., 2008a) found in Mediterranean Sea and Atlantic Ocean (Lebreton *et al*., 2011; Cardona, 2006). Before 1930, mullet was not native in the Caspian Sea. From 1930-1934, 3 million individuals of three different species of mullet from the Black Sea including *L. aurata* were introduced into the Caspian Sea with the aim of increasing fish productivity (Ghaninejad *et al*., 2010). During spring, mullets live in the northern parts of the Caspian Sea while in autumn they are found in the southern parts (Fazli *et al*., 2008b). Male and female fish reach the maturity stage at age 3 and 4, respectively. *L. aurata* in the Caspian Sea spawns from August until November (Fazli *et al*., 2008b; Ghaninejad *et al*., 2010). The spawning habitats are 400-600 m away from the coasts. Although adult mullet is detritivorous, feeding in early life stages primarily depends on plankton (Ghadirnezhad, 1996).

Figure 1-5. The golden grey mullet (*Liza aurata* (Risso, 1810)), from: http://www.seafishinghowto.com/marine-species/fish/golden-grey-mullet-liza-aurata.html

After kutum, *L. aurata* is the second most dominant fish in commercial catch composition of bony fish in the southern Caspian Sea coastal zones (Zorriezahra *et al*., 2014). Also with regards to the increasing market demands, it is considered as one of the most valuable economic resources for local fishermen (Zorriezahra *et al*., 2014). Likewise kutum during the last two decades, golden grey mullet population was also fronting various fluctuations. In the early 1990s (1991-1992) the recorded total catch of this species was about 3200 mt, increased in the early 2000s (2002-2003) and reached to about 6100 mt. The lowest level of catch was observed in 1994-1995 (~ 1200mt) while the recorded value for the late 2000s (2009-2010) was about 3200 mt (Fazli, 2012).

With regards to the legal restrictions for commercial catch of sturgeon species (due to the risk of extinction) during the last two decades (Khodorevskaya and Krasikov, 1999; Mathews *et al*., 2006; Pourkazemi, 2006; Ruban and Khodorevskaya, 2011) as well as the recent collapse of kilka stocks in the Caspian Sea (Daskalov and Mamedov, 2007; Fazli *et al*, 2007; Ustarbekova, 2014), both kutum and mullet are currently considered as the main target species for the entire fisheries in the southern coasts. They are commercially mostly important for the local communities depending on them. Despite their prominent role in sustainability of regional fisheries, the potential effects of climate/environmental variability on their population regulation is still obscure and historically being ignored in conventional stock dynamics studies and management strategies.

1-4 Objectives and hypotheses

This study aimed to clarify the potential linkages between the dynamics of the two bentho-pelagic fish species kutum and golden grey mullet and external ecosystem forces (atmospheric climate patterns)/environmental variables in the southern Caspian Sea. It has been attempted to identify, recognize and statistically quantify the role of climate/environment in regulating these two stocks as important ecological components of the Caspian Sea during last two decades. In order to achieve general postulations about the stocks fluctuations, it is reasonable to investigate different aspects of climate/environment-induced alterations in fish populations and potential underlying mechanisms. As mentioned before, climate and environment impacts on fish stocks maybe direct or indirect, immediate or delayed and gradual or abrupt. To explore the presumed climate-induced impacts on the two key species, a two-fold quantitative-qualitative approach has been designed.

SECTION I: Quantitative investigation and procedures - Firstly, the potential impacts of climate/environment on species dynamics are explored quantitatively. In this context, considering the intertwined crucial role of recruitment process in fish population dynamics along with high sensitivity of early life-stages to environmental alterations is essential. Turning to this issue, long-term dynamics of species in relation to external atmospheric climate and environmental fluctuations was studied. For this purpose and to quantify the extent of population variability relative to climate-environment alterations, an integrated stock-recruitment modelling approach was chosen. This approach combines conventional stock-recruitment models with potential temporal associations between population proxies and global climate proxies/environmental variables (correlational analyses). This framework helps to understand the directness, chronology and extent of climate-induced impacts in marine bio-resources dynamics. The outputs of this approach offer a valuable tool for a better prediction of fish population dynamics and may play a vital role for achieving sustainable fisheries production (e.g. in the context of ecosystem-based management).

SECTION II: Qualitative investigation and procedures - Due to the importance of ecological shifts in fisheries sustainability, the second part was focused on qualitatively exploring the existence of climate-driven shifts in the bentho-pelagic stocks. For this purpose, a statistical shift (detecting/localizing) algorithm was applied for each single component of populations and climate/environmental proxies. Afterwards the potential detected shifts (in biological and physical proxies) were compared for temporal synchronicity. To have a broader and more comprehensive perception of potential climate-induced shifts in the southern Caspian Sea, this procedure was also performed for higher orders of ecological organizations (including bentho-pelagic community and ecosystem levels).

In summary, the fundamental biological assumption of this study was: *There is a significant association between large-scale climate forces/local hydrographic variability and juvenile and/or parental stock fluctuations/population dynamics of two key bentho-pelagic species in the southern Caspian Sea.*

Considering the goals of this thesis and the biological assumption, two principal sets of statistical hypotheses were formulated and examined as below:

a. H_0: *Climate/environment has no impacts on population dynamics and recruitment process of the target case studies.*

   H_1: *Climate/environment has substantial impacts on population dynamics and recruitment process of the target case studies.*

b. H_0: *No obvious shifts in the bentho-pelagic subsystem proxies (including species, community and ecosystem levels) are in compliance with climate/environmental factors shifts.*

   H_1: *Synchronous climate/environmental shifts induced significant explicit shifts in the bentho-pelagic subsystem proxies.*

Chapter 2: Material and Methodology

2-1 Data description

The datasets used in this study can be divided into three categories, namely regional fisheries-derived datasets (i.e. from stock assessments), large-scale climatic indices and local satellite-based environmental time series. Their properties will be described in the subsequent sections; their essentials are finally summarized in Table 2-1.

2-1-1 Regional fisheries-derived (stock assessment) data

Multi-aspect regional data-provision constraints and improprieties in less studied areas such as the southern Caspian Sea always impose many limitations in long-term ecological dynamics research (particularly in climate-driven ecological dynamics studies). Hence, for the purpose of this study, only the available long-term, regular and reliable fisheries-based data series relevant to two major commercial bentho-pelagic species being the Caspian Kutum (*Rutilus frissi kutum* (Kamensky, 1901)) and the golden grey mullet (*Liza aurata* (Risso, 1810)) were utilized.

For both species, the relevant data series (see section 2-2) including spawning (parental) stock biomass (SSB) and the recruit (R) numbers (complete series over a period of 1991-2011) were obtained from the final report of the Iranian Fisheries Research Organization (IFRO) on the stock assessment of bony fishes in Iranian waters of the Caspian Sea (Fazli, 2012). The common annual stock assessment procedure for both species is based on the biomass cohort analysis (Zhang and Sullivan, 1988). The required fisheries data for this procedure is collected by IFRO staffs (of the three affiliated divisions Caspian Sea Ecology, Inland Water Stocks, and Inland Water Aquaculture Research) by sampling from the commercial catches in Iranian waters of the Caspian Sea (Fig. 2-1).

Figure 2-1. Map of commercial catch region of bony fish in Iranian waters of the Caspian Sea located in three provinces of Golestan, Mazandaran and Guilan (from Bandpei *et al.,* 2010).

The required population indices (i.e. R and SSB estimates) were derived from the outputs of the biomass cohort analysis (Zhang and Sullivan, 1988). Recruitment numbers were estimated by dividing the biomass of the youngest fish observed in the catch composition (in both species age 2) by the average individual weight of this age (calculated from von Bertalanffy length-weight equation for each year; based on the IFRO reports). SSB estimates (metric tons) were extracted from the biomass through multiplying the biomass by the maturity index (based on the IFRO reports; Fazli, personal communication) for each age. This procedure is illustrated in Fig. 2-2.

In the case of kutum, due to the existence of regular annual stock enhancement program (releasing ~ 1 g fingerlings to sustain this valuable species production), the released fingerling numbers was also taken into account in subsequent analyses as being described in detail in section 2-2-1-1. The data series were obtained from Abdolhay *et al.,* (2011) and Fazli *et al.,* (2012).

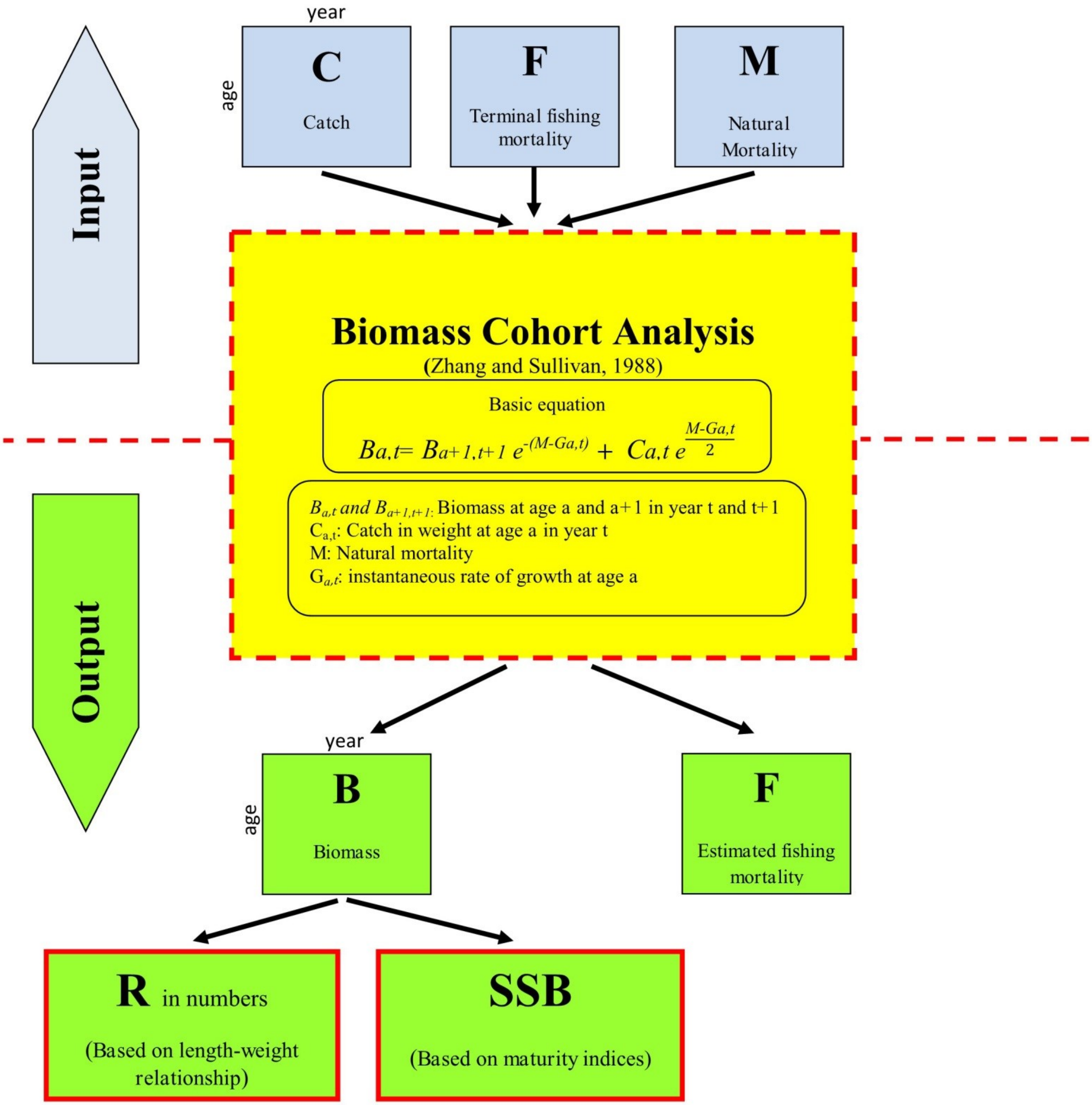


Figure 2-2. General overview of the biomass cohort analysis (Zhang and Sullivan, 1988) - as the standard stock assessment procedure in the southern Caspian Sea- and extracting required populations indices data series (the graphical design is partly based on (Gröger, personal communication)).

2-1-2 Large-scale climatic indices

Large-scale climate indices are integrated quantitative packages comprised of certain weather-related components which are considered as proxies reflecting particular aspects of climate state and variability on a global scale. Considering the characteristics of climate indicators (see Introduction, section 1-2), using these proxies may clarify not only the climate-species relationships and dynamics but also may provide a more comprehensive perspective of the global change in the Caspian Sea. Forasmuch as the Caspian Sea is located in a unique geographic region (i.e. locked bilaterally between two continents of Europe and Asia which could be potentially exposed to and impacted by complex interactions between different regional weather fronts and several global atmospheric circulation systems) and also referring to the previous studies (i.e. the impacts of climate variability patterns on the physical and biological features of the Caspian Sea: e.g. Barnston and Livezey, 1987; Rodionov, 1994; Arpe *et al.,* 2000; Panagiotopoulos *et al.,* 2002; Nezlin, 2005; Kosarev, 2005), the following global climate indices (quantified proxies) were selected and examined as potential representatives of climatic fluctuations and variability (i.e. capture at least a fraction of variability) over the study area.

2-1-2-1 North Atlantic Oscillation (NAO)

The North Atlantic Oscillation (NAO) is one of the oldest known and important global atmospheric variability patterns (with inter-seasonal to inter-decadal fluctuations) which exhibits a wide range of impacts on ecological systems dynamics and processes (Hurrell *et al.,* 2003). The NAO strongly influences the atmospheric circulations and weather conditions, especially during the winter in the northern hemisphere (Hurrell and Dickson, 2004). Similar to other broad-scale climatic oscillations, it is widely accepted that the NAO influences life history of several species in different ecosystems and ecological niches (Blenckner and Hillebrand, 2002).

This large-scale climate variability index is generally (and quantitatively) described by the relevant differences of standardized sea level atmospheric pressure between a high pressure center near Azores and low pressure center near Iceland (Wanner *et al.,* 2001). It is thought that the strength of the NAO, particularly during the wintertime regulates the cold season climate condition in the northern hemisphere (Hurrell *et al.,* 2003). In climatological and ecological studies, various types of NAO indices have been used based on different temporal frames (e.g.

monthly, winter or annual data series), calculation methods and statistical approaches (e.g. station-based or Principle Component Analysis (PCA)). In this study, the monthly-updated measures of the NAO index were downloaded from NCAR/UCAR (U.S. National Center for Atmospheric Research/University Corporation for Atmospheric Research) website (*https://www.climatedataguide.ucar.edu/climate-data/hurrell-north-atlantic-oscillation-nao-index-pc-based*) for further analysis. This data series has been calculated based on a PCA approach which can better represent spatial patterns of NAO variability. Annual (12 months average) and winter (average of December thru March period) NAO indices were utilized as first broad-scale climate proxy to investigate the potential impacts of climate variability on the biological data series.

2-1-2-2 Southern Oscillation (SO)

The Southern Oscillation (SO) is one of the main inter-annual climate (atmospheric pressure) variations with influences all over the world. This climatic phenomenon is quantified based on the normalized broad-scale sea level pressure fluctuations between Tahiti Island (Pacific Ocean) and Darwin (northern Australia) which is generally known as the Southern Oscillation index (SOI). The SOI measures represent the formation and the strength of the El-Niño and La-Niña phases. The El-Niño is concurrent with the SOI (-) period (uncommon lower air pressure in Tahiti and higher atmospheric pressure in Darwin and warm oceanic surface temperature), while La-Niña is associated to the SOI (+) period (concomitant with abnormal cold oceanic surface temperature) (Rasmusson and Wallace, 1983; Philander *et al.*, 1989; Allan *et al.,* 1996).

The annual and winter (from December to February, according to Arpe *et al.,* (2000) on the impacts of ENSO on the hydro-physical properties of the Caspian Sea) averages of SOI were estimated on the basis of the monthly-updated data series (for the period 1951-2011) downloaded from the CPC/NCEP/NOAA (Climate Prediction Center / National Centers for Environmental Prediction / U.S. National Oceanic and Atmospheric Administration) website (*http://www.cpc.ncep.noaa.gov/data/indices/soi*) and used in this study.

2-1-2-3 Siberian High (SH)

In the northern hemisphere, the Siberian High (SH) is considered as one of the main obvious and active air pressure centers and atmospheric-circulation systems during the cold (i.e.

winter) season (Jeong *et al.,* 2011). According to Panagiotopoulos *et al.,* (2005), the quantitative index of the Siberian High Intensity (SHI) is defined as winter (December to February) mean sea level pressure between 40°–65°N and 80°–120°E.

The SHI values were calculated by Panagiotopoulos *et al.,* (2005) based on the climatology of Trenberth and Paolino (1980). This index was obtained from Maria Shahgedanova (personal communication, by Ismael Núñez-Riboni,) for the period of 1900-2001 and was used only as a basis for comparison. To compute the index to 2011, the sea level pressure data from the NCEP/NCAR (U.S. National Centers for Environmental Prediction /the National Center for Atmospheric Research) reanalysis from the NOAA Earth System Research Laboratory website (*http://www.esrl.noaa.gov/psd/data/gridded/data.ncep.reanalysis.derived.surface.html*) was used. Because the NCEP/NCAR reanalysis dataset did not completely match the climatology originally used by Panagiotopoulos *et al.,* (2005), first the SHI was recalculated from 1900-2009 using the climatology of Trenberth and Paolino (*http://jisao.washington.edu/datasets/slp_ncar/*); then the SHI calculated with NCEP/NCAR data was shifted with an offset of 0.6 as to match for the years 1996-2009 the index calculated with the climatology of Trenberth and Paolino (analysis made by Ismael Núñez-Riboni).

2-1-2-4 East Atlantic-West Russian (EA-WR) pattern

The East Atlantic-West Russia (EA-WR) pattern is one of the prominent atmospheric teleconnection patterns affecting the climatic state and weather condition (particularly in wintertime) of the Eurasian region and consists of two major pressure/height anomaly cores (with the spatial centers on the Caspian Sea and western regions of Europe) (Krichak and Alpert, 2005; Lim, 2014).

The annual average of EA-WR pattern index was estimated based on the downloaded monthly data series (derived from standardized 500-hPa height anomalies by the rotated PCA method) from the CPC/NCEP/NOAA website (*http://www.cpc.ncep.noaa.gov/data/teledoc/eawruss.shtml*) and was applied in this study.

2-1-3 Local satellite-based environmental data

Aside from the global-scale climatic indices, I was also interested in investigating the potential impacts of local-scale hydrographic variables (as another source of external variability) on the species dynamics. Regarding the in-appropriate length of the environmental data series and obvious interruptions, irregularities and uncertainties in the available local field-collected data, satellite-derived data series were considered to be a more reliable source for indicating the regional environmental conditions in the southern Caspian Sea. Hence, the dual remotely-sensed (satellite-derived) variables (i.e. the Sea Surface Temperature (SST) and the upper-layer Chlorophyll-a concentration (Chl-a)) were selected as potential local hydrographic indicators in subsequent analyses. SST is one of the most crucial and straightforward-in-touch ambient properties for all aquatic organisms; the upper-layer chlorophyll-a concentration (as a proxy of phytoplankton abundance) can reflect the potential basal-trophic productivity in marine ecological webs which could be assumed to be sequentially transitioned through the ecological chain influencing higher-trophic level organisms – such as fish. It was hypothesized that these environmental variables may also affect the species dynamics in different pathways and modes (i.e. direct or indirect, immediate or delayed and gradual or abrupt; see Introduction, section 1-2).

2-1-3-1 Sea Surface Temperature (SST)

In the present study, the weekly averaged NOAA Earth System Research Laboratory's sea surface temperature data (derived from the optimum interpolation method with an image resolution of $1^{\circ}\times1^{\circ}$ in the geospatial scale) was downloaded from the NOAA website (*http://www.esrl.noaa.gov/psd/data/gridded/data.noaa.oisst.v2.highres.html*) and applied. The time series of monthly and yearly averages of the local (i.e. covering southern part of the Caspian Sea below the geographical latitude of 40° N) SSTs were estimated (from 1982 to 2011) to be used in subsequent statistical analyses (readied by Ismael Núñez-Riboni, personal communication).

2-1-3-2 Upper-layer Chlorophyll-a concentration (Chl-a)

Upper-layer Chlorophyll-a concentrations data, as a qualitative indicator of phytoplankton biomass (basal marine trophic productivity potential), was derived from the global satellite products of ACRI-ST GlobColour service supported by EU FP7 MyOcean and SA GlobColour

Projects (downloaded from *http:// hermes.acri.fr*). Annual averages of the surface chlorophyll-a concentrations for the Southern Caspian Sea (spatially-enclosed to 50° to 52°E and 38° to 40°N) were extracted and estimated from the available images (for a period of 168 months, from the beginning of 1998 until the end of 2011) (prepared by Boris Cisewski, personal communication).

Table 2-1. Summary of the applied data series in this study.

Name	***Period covered***	***Origin***
Regional fisheries-derived data		
The Caspian kutum stock assessment data; fingerling release numbers	1991-2011	IFRO reports; Abdolhay *et al.,* 2011; Fazli *et al.,* 2012
The golden grey mullet stock assessment data	1991-2011	IFRO reports
Large-scale climatic indices		
North Atlantic Oscillation (NAO)	1899-2011	NCAR/UCAR
Southern Oscillation (SO)	1951-2011	CPC/NCEP/NOAA
Siberian High (SH)	1900-2011	Panagiotopoulos *et al.,* (2005); NCEP/NCAR/ NOAA Earth System Research Laboratory; Ismael Núñez-Riboni, personal communication
East Atlantic-West Russian (EA-WR)	1950-2011	CPC/NCEP/NOAA
Local satellite-based environmental data		
Sea Surface Temperature (SST)	1982-2011	NOAA Earth System Research Laboratory; Ismael Núñez-Riboni, personal communication
Upper-layer Chlorophyll-a concentration (Chl-a)	1998-2011	ACRI-ST GlobColour service supported by EU FP7 MyOcean and SA GlobColour Projects; Boris Cisewski, personal communication

2-2 Methodology and Statistical analysis procedures

Based on the paradigm of ecosystem-based management, evaluating ecosystem forces (e.g. extrinsic climatic forces and environmental drivers) may play a crucial role in upcoming commercial fisheries management in the Southern Caspian Sea. To have a closer look at complex climate/environment-imposed impacts on the valuable stocks of bentho-pelagic species and to acquire more profound insights about different aspects of climate-linked ecological dynamics in the region, an explorative bipartite statistical approach has been designed (Fig. 2-3). *SECTION I* is focusing on a quantitative clarification of the potential impacts of climate/environment on the population dynamics of the two target species. *SECTION II* is mainly centered on the qualitative investigation of the occurrence of ecological climate-driven shifts in the Southern Caspian Sea.

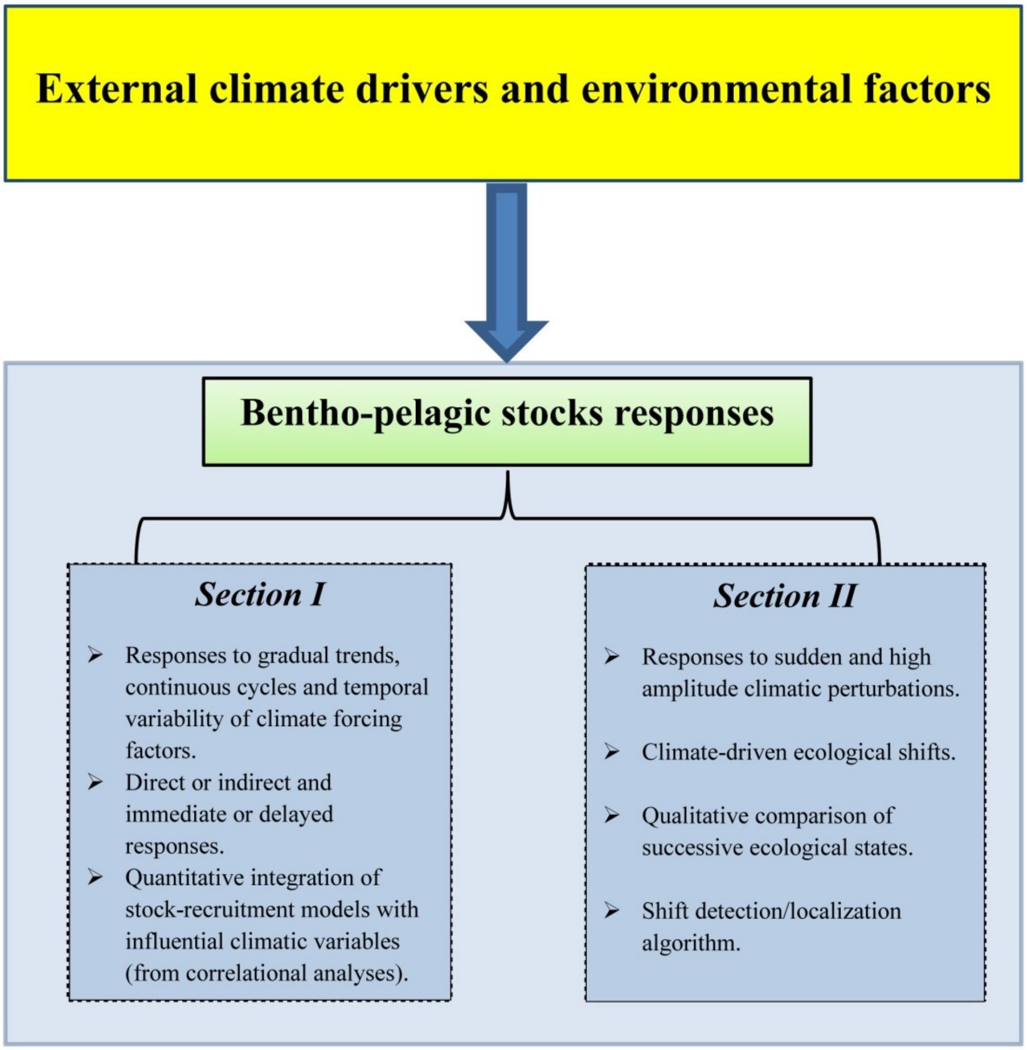


Figure 2-3. General overview of the explorative approach in this study.

2-2-1 *METHODOLOGY SECTION I:* Quantitative investigation and procedures

Considering the scopes of this study in the quantitative section, the best way to investigate (test) the first set of hypotheses and to explore the recruitment variability (either due to the parental stock size and/or climate and environmental effects) of bentho-pelagic species in the Southern Caspian Sea was to conduct a series of statistical modeling steps and comparisons. In this context, besides the role of parental stock size in population regeneration processes, the potential role of external climatic drivers on recruitment variability of the species was considered. For this purpose the following statistical framework consisting of four-steps has been developed (Fig. 2-4):

1- *Begin with setting up a reference model which may explain the relationship between the recruitment and the parental stock size* (a classical stock-recruitment model as a baseline for starting the study considers that the annual generated recruitment numbers may be dependent on the size of parental stock (SSB)). In this step the hypothesis related to the role of SSB in recruitment variability of species was tested (i.e. H_0: no parental stock size effect; H_1: significant parental stock size effect).

2- *Exploring, identifying and selecting the potential climatic and environmental covariates which may influence the recruits.* Since the potential climatic impacts on the recruits may be transmitted indirectly (at any rate) by the parental stocks, investigating the climate-SSB dynamics (apart from the climate-recruits dynamics) is essential and helps to preclude misapprehending the climatic/environmental signals (Gröger *et al.,* 2014). Apart from this, climate-imposed impacts may also appear immediately or after a given time lag (i.e. delayed response due to the cascading and transitioning time of climate signal, from global scale to the species level). Hence, exploring the potential lagged responses of the population components (i.e. both recruits and parental stocks) to climatic factors is necessary (Gröger *et al.,* 2014). For this purpose, based on the functional features and successful application of the cross correlation analysis in similar previous studies (Gröger and Rumohr, 2006; Gröger *et al.,* 2007; Gröger *et al.,* 2009; Gröger and Fogarty, 2011; Gröger *et al.,* 2014), this procedure has been also applied in this context (cross correlation between populations components and extrinsic climate/environment variables).

3- *Extending the reference model by including the candidate exogenous variable(s) (climate/environment) in the basic model, identification of model structure and estimating* *model parameters*. To evaluate the combined effects of climatic/environmental variables on the species dynamics, a generalized linear modeling procedure (i.e. step 1) was developed by incorporating the information obtained from the cross correlation analysis (i.e. step 2).

4- *Comparing different model setups and performances; performing model and residual diagnostics, respectively.* Standard model selection procedures such as checking the statistical assumptions in the context of general linear models and comparing different performance indices to select the best model were performed in this step to choose the ultimate statistically-fitted model (i.e. meet all the statistical conditions).

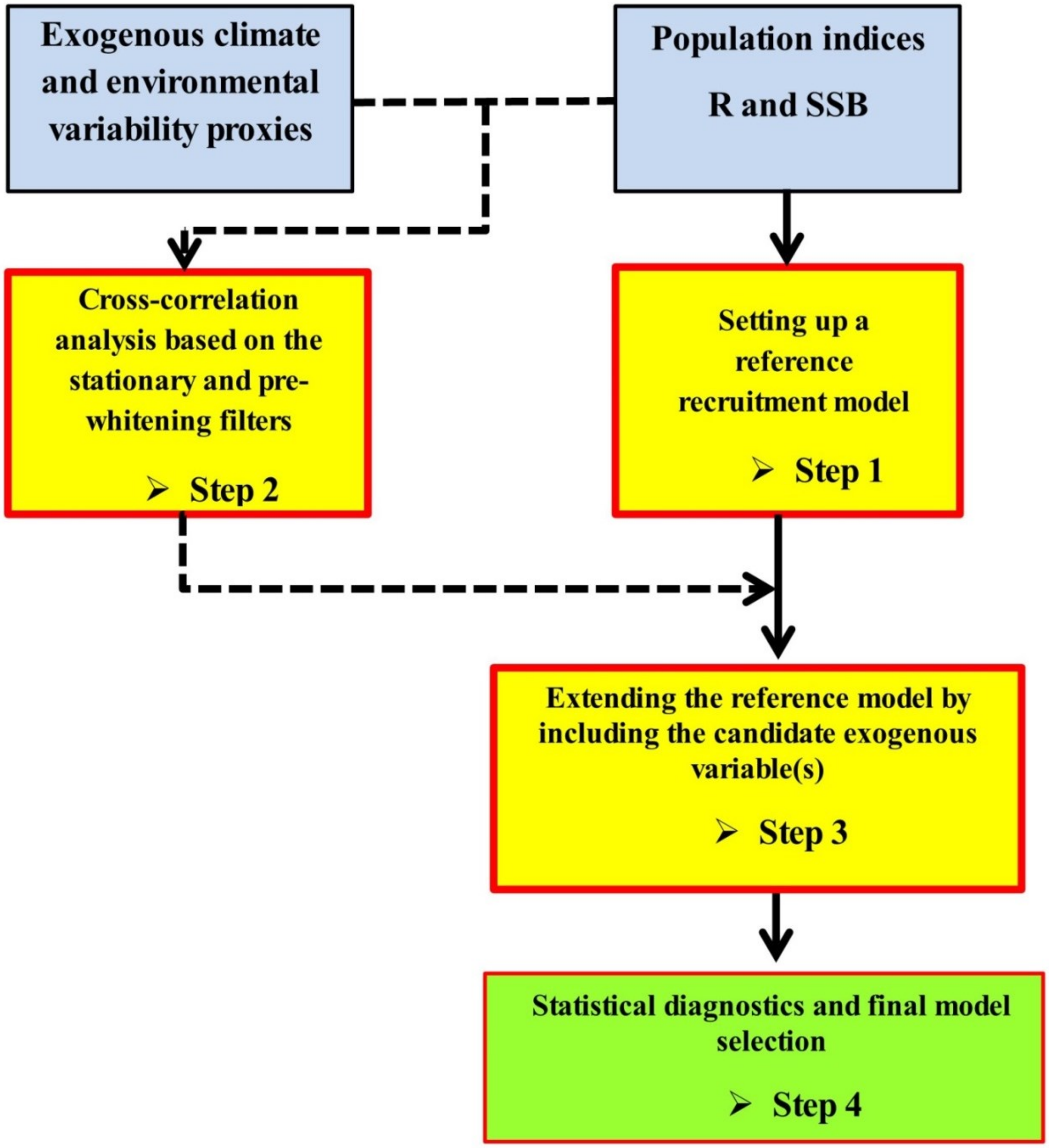


Figure 2-4. General structure of the integrated statistical framework in SECTION I.

2-2-1-1 Recruitment dynamics modeling

As the regeneration process is decisive in population regulation, evaluating and modeling recruitment dynamics has been historically considered as one of the focal goals in commercial fish exploitation management (Fogarty, 1993; Needle, 2001). To functionally represent the relationship between recruitment variability and the parental stock size a Cushing-form stock-recruitment model (Cushing, 1971; Quinn and Deriso, 1999; Gröger *et al.,* 2011) has been used to provide a general reference (basic) model for the Caspian kutum and the golden grey mullet.

In an attempt to explain more of the recruitment variability, the basic Cushing model can be extended through the inclusion of exogenous variable(s) reflecting a “multi-factor” influence on the recruits (Gröger and Fogarty, 2011)); incidentally it can be linearized easily by taking natural-logarithms on both sides of the recruitment equation. Hence, in the present study potential climatic/environmental covariates may be added as linear combinations in a generalized linear regression setting.

To explain more of the recruitment variability of kutum and golden grey mullet, lag-endogenous effects were studied in addition to the role of SSB and climatic/environmental factors, reflecting a potential self-dynamics of recruitment (i.e. the impact of the recruitment process on itself). The reason is that lag-endogenous effects represent unobserved hidden effects of other unknown external factors. As part of this, the assumption of a potential influence of last year’s recruitment (one year lagged recruitment numbers or R_{t-1}) on each year’s recruitment (R_t) has been tested (i.e. H_0: no internal self-dynamic effect; H_1: internal self-dynamic effect) by adding R_{t-1} as linear term to the linearized Cushing-model. As this specific extension of the model reflects both the internal dynamics and the lagged structure of recruits, it may be entitled as *lag-endogenous climate-extended recruitment model* (Gröger, personal communication).

The equations of all model variations, i.e. those of the simple Cushing baseline-model, the baseline-model extended by climate/environment (linear and non-linear versions), as well as the linearized lag-endogenous climate-extended model are presented in the Table 2-2.

Table 2-2. Statistical presentation of different recruitment dynamics modeling setups. *R_t is the recruit numbers in year t. SSB_{t-k} is the spawning stock biomass which produced the recruits of year t and k is the recruitment age (in both cases k=2 as the recruitment age is 2). Serial Ex(s) stand for any potential exogenous source of variability (e.g. climate forces and environmental variables) and h is the relevant effective time lag for each respective Ex, which is determined in cross correlation analysis. α, δ, γ and θ are model parameters and ε_t is the error term.*

** R_{t-1} reflects the endogenous variability of recruits in this setup*

.**Model type**	**Equation**
Basic Cushing model	$R_t =\propto SSB^{\delta}_{t-k}$ (Eq. 2-1)
Extended Cushing model (e.g. by exogenous climatic factors)	$R_t = \alpha SSB^{\delta}_{t-k} e^{\gamma_1 Ex_{1\,t-h_1} + \cdots + \gamma_n Ex_{n\,t-h_n}}$ (Eq. 2-2)
Linearized climate-extended model	$Ln\,(R_t) = Ln(\alpha) + \delta Ln\,(SSB_{t-k}) + \gamma_1 Ex_{1\,t-h_1} + \cdots + \gamma_n Ex_{n\,t-h_n} + \varepsilon_t$ (Eq. 2-3)
* Lag-endogenous climate-extended model	$Ln\,(R_t) = Ln(\alpha) + \delta Ln\,(SSB_{t-k}) + \gamma_1 Ex_{1\,t-h_1} + \cdots + \gamma_n Ex_{n\,t-h_n} + \theta Ln\,(R_{t-1}) + \varepsilon_t$ (Eq. 2-4)

In case of kutum, as part of an annual stock enhancement program ~ 1 g fingerlings are released by the Iranian Fisheries Organization (IFO) on a regular basis to sustain the production of this valuable species in the Southern Caspian Sea (Abdolhay *et al.,* 2011; Fazli *et al.,* 2012). Hence, apart from the role of the spawning stock, an artificial "spawning" effect potentially affecting the recruitment variability has been explored as an extra factor. Thus, beside R=f (SSB) the relationship between the number of released fingerlings and that of the recruits has been considered in addition.

The potential impact of the fingerling release (FR) on the recruitment variability of kutum was tested under the null hypothesis of no FR-effect. For this purpose, first, the following simple linearized Cushing-analogous model (Eq. 2-5) was fitted:

$$Ln\,(R_t) = Ln(\alpha) + \beta Ln\,(FR_{t-k}) + \varepsilon_t \qquad \text{(Eq. 2-5)}$$

Then the combined effects of FR and SSB on recruitment dynamics were evaluated by the following extension of the precedent model (Eq. 2-6).

$$Ln\,(R_t) = Ln(\alpha) + \delta Ln\,(SSB_{t-k}) + \beta Ln\,(FR_{t-k}) + \varepsilon_t \qquad \text{(Eq. 2-6)}$$

FR_{t-k} is the number of released fingerlings which potentially produced the recruits of year t and k is recruitment age. β is model parameter; other terms were defined in Table 2-2.

To take into account the lack of well-investigated survey data on the post-release performance of fingerlings and the potential impacts of SSB-FR interactions on the recruitment variability of the Caspian kutum, it was hypothesized that applying a single comprehensive index reflecting the total reproductive capacity of the species (i.e. by unifying and capturing characteristics of both natural and artificial reproduction potential) may explain more of the recruitment variability. Therefore, it was attempted to develop a unique *Potential Reproductive Capacity (PRC)* index to test the considered hypothesis (H_0: no PRC effect, H_1: PRC effect).

In order to develop the PRC index, the following three-step procedure was performed based on applying the Principal Component Analysis (PCA) technique:

i. Regarding the different nature and measurement units (and scale) of both data series, prior to performing a PCA the values of SSB and FR were standardized in accordance with Eq. 2-6 by first taking their natural logarithms:

$$Variable_{Standard} = \frac{Variable - \mu}{\sigma} \qquad \text{(Eq. 2-6)}$$

where (μ) and (σ) are values of the mean and the standard deviation of each variable (this procedure removes the scale and unit attributes from the data and centers the data-points around zero).

ii. Then running a PCA, integrated the standardized data series and computed a set of principal components (PCs) where the first one (PC1) is taken here as PRC index as it explains most of the variability in the data (i.e. this index was used instead of SSB to develop the reference recruitment model).

In Brief, PCA is a widely-used multivariate statistical procedure to reveal and extract the dominant patterns of variability and reduce the dimensionality of datasets by integrating and transforming (linear orthogonal transformation type) those to a set of new values called Principal Components (PCs). This is performed in a way that the PC scores represent the majority of variation in the data (Jolliffe, 2002; Abdi and Williams, 2010) where PC1 captures most of the variability in the data, PC2 second most, PC3 third most and so on. For detailed information about the mathematical theory behind PCA technique see Jolliffe, (2002).

In the light of this, the model setup for Caspian kutum is as follow:

$$Ln\,(R_t) = Ln(\alpha) + \tau\, PRC_{t-k} \qquad \text{(Eq. 2-7)}$$

While PRC_{t-k} is the potential reproductive capacity which produced the recruits of year *t*, *k* is the recruitment age and τ is model parameter; other terms were defined in Table 2-2.

Then, the best recruitment model among the models containing SSB, FR, and PRC either solely or in combination on the explanatory side was selected as the base-line model through comparing their model performances (see section 2-2-1-3) to be extended by potential climate/environment variables and endogenous recruitment variable as described in Table 2-2.

2-2-1-2 Identifying influential climate/environmental factors (cross-correlation analysis)

One of the most common approaches to provide a general perspective of inherently-complex climatic-ecologic processes and to explore the time-varying and continuous climate/environmental-driven responses of ecosystem components, is revealing and evaluating the nature and the strength of potential causal relationships between two or more relevant climatic-ecologic proxies (by using quantifiable correlational analysis of available time series). Generalization and integration of temporal climate-dependent responses (i.e. immediate vs. delayed responses resulting from the atmospheric-ecologic transitioning time of climate signals, see Introduction, section 1-2) in the context of the Granger causality paradigm (Granger, 1969) provides us a good starting point to explore the potential fingerprint of climate in ecosystem components. This can be achieved statistically by using the time series cross-correlation technique which is one of the most efficient and widely-applied tools in climate-ecological dynamics studies (Olden and Neff, 2001).

Cross-correlation is a specific extension of simple correlation analysis which is helpful to evaluate the existence, the strength, and the time delay of potential linear relationships between two time series (i.e. working through back/forth-directional time-step shifting of one series against another one and estimating a set of relevant correlation coefficients). In this study - to make the cross-correlation technique compatible with the Granger causality concept - only one exclusive direction is selected for shifting the data series; this implies that the time series representing the external driving forces (i.e. climate/environmental proxies) were assumed to be the leading predictor variables (or independent/influential/input factors) being forth-shifted over the time series representing the population indices (i.e. R and SSB as the dependent output/response variables). In other words, only the external force(s) and/or their past values may potentially (and partially) influence the ecological components and help to predict the future variability of the population proxies.

Strength and time delay (lag) of the potential temporal-causal relationships were assessed by applying a “Cross-Correlation Function (CCF)” and testing the significance of sequential cross-correlation coefficients (under the null hypothesis of not differing from zero) within a time window making up to 25% of the total time-span. For this purpose the computed coefficients were plotted (in needle-form) sequentially against their corresponding time lags and their significances were tested statistically by using the upper and lower confidence-bounds (i.e. reciprocal asymptotic limits representing the plus and minus twice the associated standard error ($1/\sqrt{N}$ is usually accounted as the standard error) or simply $\pm 2/\sqrt{N}$, where N is the sample size). $2/\sqrt{N}$ roughly denotes to 97.5% confidence bounds and spikes exceeding the double-sided bounds indicate significant time-lags of the influential factor (Gröger and Rumohr, 2006). This procedure could be called as *lag structure identification of influential factors*.

Given the potential importance of still totally-undiscovered impacts of climate on bentho-pelagic species of the southern Caspian Sea, it was supposed that exploring any sign of climate forces (even non-significant) in their populations features may provide a better understanding of their climate-associated dynamics. This may improve the future regional fisheries management, particularly in ecosystem-oriented strategies. Therefore, not only the conventional confidence-limits, but also an additional set of bounds (i.e. ± 1/√N) was designed and inserted in the cross-correlations plots to serve as a rough statistical indicator (or at least a threshold) to evaluate the non-significant but relatively-strong signals from the external factor(s). The spikes exceeding these bounds were deemed (with caution) as the *"peaking (potentially-influential)"* climate/environmental signals.

For detailed information about the basic statistical procedures behind the cross-correlation technique see Yaffee and McGee, (2000).

Ignoring the temporal nature of the data (ordered sequentially in time) and the intrinsic attributes of time series (e.g. trends, periodicity, internal correlations, etc…) may result in bias and spurious signal detection in the cross-correlation procedure (especially in causal relationships). To reduce the risk of misdiagnosing potential signals, prior to the cross-correlation, two necessary conditions need to be evaluated and fulfilled in the data series: being *stationarity* and *"whiteness"* (i.e. dual pre-requisites and the relevant data treatment/pre-processing helps to minimize the bias through eliminating obvious time-dependent features from the data series) (Gröger and Fogarty, 2011).

i. Stationary condition and treatment

A stationarity concept implies that the statistical indices of distribution must be stable along the given data series (i.e. mean and variance must be consistent over the time and not include apparent temporally-oriented behavior) (Legendre and Legendre, 2012). The treatment providing stationarity includes removing the obvious temporal trends from the time series and stabilizing the variance. In this study, first the presence of significant linear temporal trends in given time series was tested simply, by plotting the trend-line of data series combined with a univariate linear regression analysis (slope test) with time as the predicting (independent) variable. If an obvious trend component exists, it must be removed (filtered) from the time series by using one of the de-trending procedures (e.g. differencing, using residuals from linear regression, curve fittings in case of non-linearity, etc…) to achieve the required stationarity (mean and variance) condition prior to the cross-correlation analysis. Given the advantages of conventional differencing (i.e. transforming the raw data to sequential change measures by successive subtraction) method (e.g. easily performed, extracts the trend, stabilizes the variance and etc...), herein, if necessary, the stationarity condition was attained in this way. Finally the filtered data series were tested by slope tests (under the null hypothesis of the presence of a trend and in-stationary mean) and Levene tests (under the null hypothesis of variance homoscedasticity, see section 2-2-1-3) to confirm fulfilling the stationarity conditions. It should be noted that the variance stationarity condition for the population indices was already (and inevitably) achieved by taking natural logarithms (i.e. Ln (R) and Ln (SSB)) in the recruitment dynamics (linearized) modeling procedure (see section 2-2-1-1).

ii. Pre-whitening procedure

Intrinsic-serial correlation (dynamic autocorrelation) is one of the most common characteristics (behavior) of chronologically-ordered data series. Dynamic autocorrelation implies that the temporally-recorded values of a given variable (e.g. X_t) can be dependent on (or potentially a mathematical function of) their own time-lag (s) (X_{t-1},..., X_{t-k}). Ignoring the potential dynamic autocorrelations (and usually their complicating effects) in causal-temporal relationships could be another source of error and statistical bias in cross-correlation analysis which may result in false signal detection. For instance, if both intended time series (i.e. input and output) to be cross-correlated express a similar auto-correlating behavior, then the resulting signals from the cross-correlation procedure may be spurious and deceptive; in other words the detected time-delayed casual correspondence (between input and output variables) could be potentially driven by a disguised (but still un-clarified) force with the analogous dynamical pattern (autocorrelation behavior). One potential solution to deal with this issue could be a separate analysis and identification of autocorrelation patterns present in a given leading/input time series (e.g. stationary climatic /environmental proxies) and then filtering the recognized patterns of input variable not only from itself but also from a given output/response variable data series (e.g. stationary population proxies). This procedure which is known as “pre-whitening” involved the following sub-steps in the present study (Gröger, personal communication):

Sub-step 1: Distinguish the potential systematic autocorrelation patterns in all input variable data series (the filtered data series from the stationary procedure) by applying a particular type of self-dynamic regression model known as general Auto-Regressive (AR) model. As the temporally-recorded values of the input variables (climate/environmental proxies; Table 2-1) were historically-available for several decades (except Chl-a), this step was performed based on the entire length of the time series. It may help to represent the intrinsic structural dynamics of the input time series more accurately. *Sub-step 2*: Filtering and removing the autocorrelation structures from both, input and output variables, by the same model based on the recognized patterns of each single input variable, derived in sub-step 1. The autocorrelation extraction procedure is conceptually based on a time series modeling approach and was achieved here by applying a so-called generalized ARIMA (Auto-Regressive Integrated Moving Average) method.

The generated data series from the dual-filters treatment (i.e. stationarity treatment and pre-whitening), were then used as input and output datasets in the cross-correlation analysis. The cross-correlation analysis was performed with time-lags up to 25% of the overlapping time-span between input and output variables. It should be noted that in case of Chl-a, due to the shortness of the time series (1998-2011), cross-correlation analysis was performed without pre-whitening.

Finally, selection of the candidate variables influential on recruitment (among all the tested climate/environmental factors in cross correlation analysis) to be incorporated in the further model extension step, was based on the following conceptual criteria (A, B and C). Taking those into account would help to avoid the potential statistical problems such as co-linearity, redundant variables and variance inflation.

A) Since the parent stock is already a component of the baseline stock-recruitment model, the observed signals (especially on SSB) must be checked for potential parental-mediated impacts of climate/environment on recruits. If both recruits and parental stock are affected by a given (same) climatic factor but in a different chronological order in a way that SSB is impacted earlier than recruits, it may represent an indirect via-SSB-mediation process of climatic impact to recruits. In other words, the later-observed climatic impacts on recruits could be potentially (at least partially) transmitted via their earlier-affected parental stock. Hence, to preclude the selection of redundant variables and statistical bias, the potential SSB-transmitted impacts (on recruits) must be ignored and withdrawn in the subsequent recruitment modeling.

B) When the results of cross-correlation in each case represent more than one strong peaking signal, only the strongest correlation would be chosen for the further analysis (to avoid the multi co-linearity issue).

C) Another structural constraint in selecting the proper climatic signal is the potential co-linearity problem arises from the variables with similar functional nature and features (e.g. the annual and winter NAO). To overcome this problem, only the single strongest signal between the analogous indices was considered to be included in the further recruitment modeling step.

2-2-1-3 Model extension, model performance, statistical diagnostics and validation

Extending the reference model (step 1) by incorporating the influential climatic/environmental variables with their relevant lag-structure(s) (step 2) through a generalized modeling approach (step 3), provides an opportunity to evaluate the (potential) combined effects of these external sources of variability on the species dynamics. The multiple (stepwise) regressions modeling structure were chosen for this purpose. Hence, to avoid misapprehension of the final results, the statistical assumptions (validating conditions) relevant to these model structures were considered and checked (i.e. no obvious correspondence between the selected input variables, normally-distributed/homoscedastic/no auto-correlated model residuals). Significance of the models and their relevant parameters were tested by conventional statistical tests (t- or and F-tests at a significance level of $\alpha = 0.05$).

The correspondences between the regressors in a given model may lead to a co-linearity phenomenon (correlated/redundant predictor variables decrease the reliability of a model). To avoid this problem, the potential linear association between the input variables was checked by a pairwise “Pearson product-moment correlation” procedure. Distribution of model residuals was examined by applying Cramer–von–Mises and Anderson-Darling tests along with the visual inspection of quantile–quantile (QQ) plots and sample histograms. Homoscedasticity of the residuals has been evaluated by the Levene test along with the visual diagnostics of scatter plots (residuals versus predictions). As the residuals' distributional and homogeneity assumptions were tested under the null hypothesis of being normal and homoscedastic, the significance level was set to $\alpha = 0.1$ to increase the statistical power ($1-\beta$) of the tests and to decrease the risk of type II error (Gröger *et al.,* 2007). Existence of autocorrelations in residuals was checked by Durbin Watson (DW) and Chi^2-based Ljung/Box tests (in the pre-whitening procedure).

The model selection procedure was based not only on the classical goodness/quality-of-fit measure ($R^2_{performance}$ or coefficient of determination as a qualitative guide), but also Akaike's Information Criterion bias-corrected (AICc) for small sample sizes (Hurvich and Tsai, 1993) and Schwarz/Bayes Criterion (SBC) (Schwarz, 1978) were taken into account. As AICc and SBC consider the degrees of freedom for each model, they could provide a better basis for comparison of the regression models with varying degrees of freedom (models with different number of parameters). The best models were selected based on the smallest AICc and SBC measures.

2-2-2 *METHODOLOGY SECTION II:* Qualitative investigation and procedures

Considering the goals of this study as part of the qualitative section and the importance of ecological shifts with regard to fisheries sustainability, this part focuses mainly on investigating and evaluating the available time series (involving both, the physical and ecological data series) in relation to potential structural breaks or shifts. Subsequent testing of *hypothesis b* (see Introduction, section 1-4) has been performed through comparing any apparent synchronicity between shifts in proxies of the bentho-pelagic populations as compared with those in climatic and environmental proxies in the southern Caspian Sea. This then would reflect potential climate or/and environmentally-induced shift in the ecological data series.

This section deals with implementing and adopting a shift searching algorithm developed by Gröger *et al.,* (2011) that is known as "shiftogram" approach and originated from studying structural breaks in econometric time series models. Compared to other shift detection methods, this approach offers several technical preferences and benefits (e.g. powerful hypothetical context; objective and flexible selection/localization of different break types; accurate and multi-criteria statistical diagnostics testing; dealing with short time series and small samples; facile execution as a software package with robust manifold properties and etc. …); also it has been applied successfully as an explorative "screening device" to characterize the types and locations of potential shifts in several marine studies (in both cases of univariate and complex multivariate set-ups; different levels of ecological organization and time scales) (Gröger *et al.,* 2011; Lindegren *et al.,* 2012; Arula *et al.,* 2014; Gröger *et al.,* 2014).

Briefly, the theory behind this approach is about modeling the structural breaks in time series by inserting external shift variables as additional predictors in a linear regression model for a given response variable (y_t) over time. According to Gröger *et al.,* (2011) and Gröger *et al.,* (2014) a useful specification of this approach is designed by appending a pulse D_t^P (at t_0) as well as a step D_t^S at (t_0+1) intervention variable to a basic time regression model (deterministic time trend model) for each corresponding variable. Therefore, the relevant equation could be formulated as below:

$$y_t = \beta_0 + \beta_1 t + \alpha_1 D_t^P + \alpha_2 D_t^S + \varepsilon_t \qquad \text{Eq. 2-8}$$

where α and β are regression parameters while ε_t is a white noise error term. The dual shift variables (i.e. D_t^P and D_t^S) are defined according to:

$$D_t^S = \begin{cases} 1 \text{ if } t = t_0 \\ 0 \text{ otherwise} \end{cases} \quad \text{“Pulse intervention”}$$

and

$$D_t^P = \begin{cases} 1 \text{ if } t > t_0 \\ 0 \text{ otherwise} \end{cases} \quad \text{“Step intervention”}$$

By means of the pre-defined model (Eq. 2-8), whilst a potential breakpoint t_0 iteratively passes along a given time series in a single step-forward manner (consecutive increment of t_0 by one year per step), pertinent statistical proof criteria (i.e. model-fit-measure and a series of marginal p-values) are recorded during each iteration process. In order to simplify the investigation and interpretation of shift analysis, the original data series and the iterations outputs are then temporally synchronized, summarized and represented graphically in a set of a 10-plots template (entitled as “shiftogram”). Each statistically depicted template comprises the following elements:

- Plot 1: Original time series to be tested.
- Plot 2: AICc as a measure of quality-of-fit.
- Plot 3: p-value regarding the F-test of joint significance of all parameters relevant to the specified structural break model.
- Plot 4: Illustrates the power (1-β) measures as an indication for the chance of incorrect no-warning (type II error); by increasing the power the risk of incorrect no-warning decreases.
- Plot 5: 1st order autocorrelation coefficient of the residuals of the respective structural break model AR (1).
- Plot 6: p-value of the AR (1) relevant to the plot 5 (t-test).
- Plot 7: p-value of the F-test of the pure impulse (a beat).
- Plot 8: p-value of the F-test for detecting a break in slope.
- Plot 9: p-value of the ANOVA F-test of pre- and post-break equivalent levels.
- Plot 10: p-value of the Levene‘s homoscedasticity test of pre- and post-break variances.

Due to their intrinsic statistical properties, the latter two procedures (i.e. ANOVA and

Levene‘s test before and after the potential shift) are capable of reflecting the “small-scale behavior” of a time series based on local data points (Gröger *et al.,* 2011). For this purpose a time series is inspected within a symmetric moving window with a pre-defined size up to 20% of the length of time series (by considering the sample size and potential cyclic element in the time series (Gröger *et al.,* 2011)).

According to Gröger *et al.,* (2014) and Gröger, (personal communication) plots 2, 3 and 4 (i.e. AICc, p-joint and power) must be considered as the major reference indicators for recognizing the locality of the shift (temporal positioning), while all other plots may be informative about the changes in properties of a time series and beneficial for distinguishing the shift type (characterizing).

Here the occurrence of climate-induced shifts was evaluated by the univariate shift analysis through detecting and comparing the synchronicity (positioning) of potential shifts in each single ecological and climatic series. Since an occurrence of climate shifts in the past may also influence the species, the shift inspection process for the climatic time series was initialized from 4 years (20% length of time series) before the beginning of the species population components data series.

Considering the critical (highly changing and deteriorating) ecological state of the Caspian Sea, particularly during the recent decades (see Introduction, section 1-3), it was assumed that investigating the potential (obvious) shift patterns at higher levels of ecological-organizations (by covering the available data) may offer a more profound and historical perspective on climatic-ecologic dynamics and interactions in this unique water body of the world. For this purpose, the PCA technique (for more details see section 2-2-1-1) was adopted to aggregate the data and to develop the bentho-pelagic community (i.e. recruitments and SSBs indices of both species) and the ecosystem subsets (i.e. all the biotic and abiotic data). The relevant first principal components (PC1 scores in each case) were then considered as an input (indicating higher levels of ecological-organizations) for further shift analysis.

All data analysis was performed using the basic statistical procedures of SAS® software version 9.4 of the SAS System for windows. Copyright© 2002-2012 SAS Institute Inc. SAS and all other SAS Institute Inc. product or service names are registered trademarks or trademarks of SAS Institute Inc., Cary, NC, USA and the “shiftogram” module (SAS macro, Prof. Dr. J. Gröger Copyright©, personal communication) was adopted for this study.

Chapter 3: Results

3-1 RESULTS SECTION I

This section includes the results from quantitative analyses of potential impacts of climatic/environmental variability on bentho-pelagic species in the southern Caspian Sea. The results related to each of the species are presented separately. In each case, first the results from exploring and identifying potential influential climatic and environmental covariates (i.e. cross-correlation analysis) are described. In the second part, the relevant results to the recruitment dynamics modeling are provided.

3-1-1 The Caspian kutum

3-1-1-1 Results from cross-correlation analysis

Prior to performing the cross-correlation analysis, the two necessary conditions of *stationarity* and *whiteness* were evaluated and fulfilled (time series pre-processing step) in the data series (see Material and Methods, section 2-2-1-2).

The existence of obvious temporal trends in data series was checked by plotting the trend-line of data series combined with a univariate linear regression analysis (slope test) with time as the predicting (independent) variable. When a significant temporal trend was observed, it was removed (filtered) from the time series by using the first-order differentiation procedure (de-trending) to achieve the required stationarity condition. In case of population quantities the results of the temporal trend test (linear regression) showed no significant trend in both data series of logarithmic-transformed (variance-stationary) recruitment (Ln (R) with a slope = 0.006, p = 0.602, Fig. 3-1 (a)) and spawning stock biomass (Ln (SSB) with a slope = 0.004, p = 0.583, Fig. 3-1 (b)), so there was no need to perform the de-trending process. Therefore, Ln (R) and Ln (SSB) were considered stationary (in mean and variance) and were used in their original form during the further analysis.

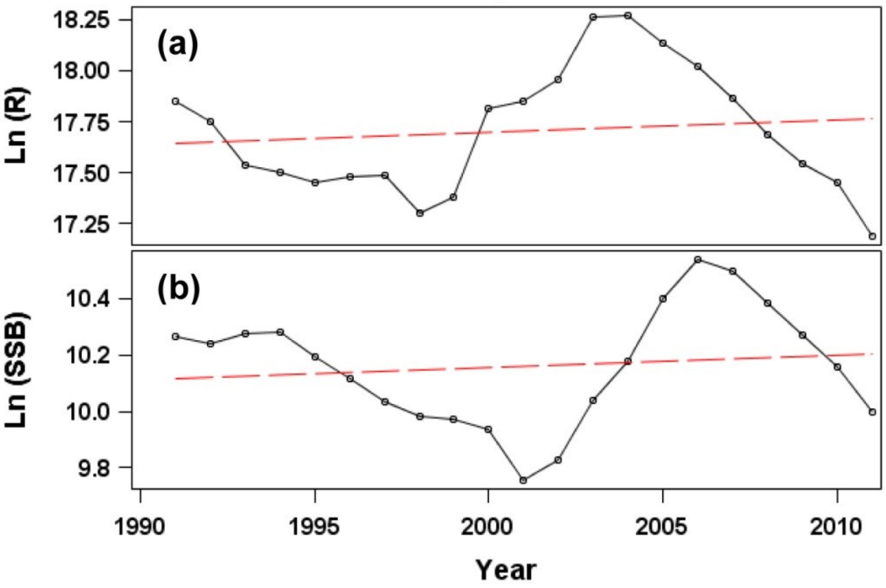
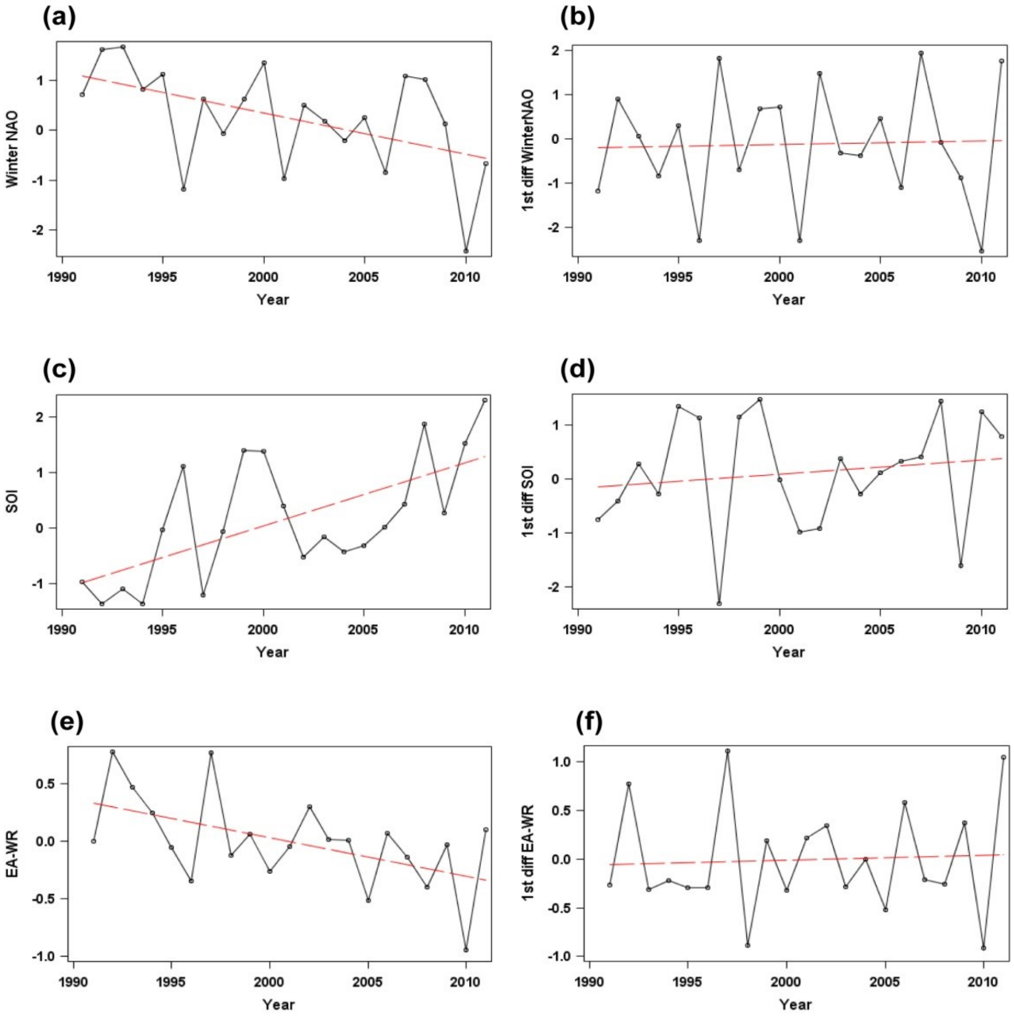


Figure 3-1. Plots (a) and (b) are the originally-stationary data series of Ln (R) and Ln (SSB) of the Caspian kutum with linear trend lines (red broken-line) during 1991-2011, where R is recruitment and SSB is parental stock size.

In contrast to the population indices, the results of the linear regressions (slope test) in case of the climate/environmental time series revealed significant in-stationarity with strong time-trends, especially in the data series of winter NAO (with a slope = -0.082, p = 0.021), annual SOI (with a slope = 0.113, p = 0.001), EA-WR (with a slope = -0.033, p = 0.015) and annual SST (with a slope = 0.044, p = 0.028) (Fig. 3-2 (a), (c), (e) and (g)). The temporal trends were removed from the climate/environmental time series through first-order differencing (as it helps to make the data series stationary in both mean and variance). The differenced time series (now a time series of dynamic changes) showed no significant temporal trends ((Fig. 3-2 (b), (d), (f) and (h)) and exhibited homoscedastic behavior (Levene test, p > 0.1). To be consistent (as well as making the results easier to interpret), the first-order differencing procedure was applied to all climate/environmental time series, converting them into times series of sequential climatic changes which then have been used and investigated in all subsequent analysis steps.



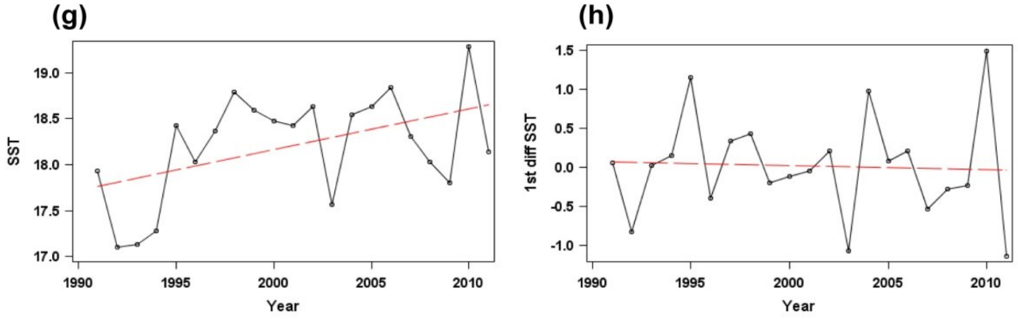


Figure 3-2. Left plots (a), (c), (e) and (g) are the original non-stationary data series and right plots (b), (d), (f) and (h) are the de-trended (first-order differenced) stationary data series of winter NAO, annual SOI, EA-WR and annual SST during 1991-2011, respectively. The linear trend lines are presented by red broken line.

Next, for the purpose of cross-correlation the stationary time series were pre-whitened. To do so, potential systematic auto-correlative signals in all input data series (entire climate/environmental time series) were identified by applying autoregressive (AR) models (Table 3-1) for each input/output variable combination. The autocorrelation structures were then removed by fitting and subtracting exactly the same AR model (separately per each input/output variable combination) to both the stationary input and output variables which resulted in pre-whitened data series.

Table 3-1. Detected order of autocorrelation structures in input (extrinsic climate) variables based on the stationary data series. The autocorrelation structures were removed from both stationary input and output time series (pre-whitening process).

Input variables	The order of systematic autocorrelation structures
Annual NAO	1, 2, 3, 4
Winter NAO	1, 2, 3, 4
Annual SOI	1, 2, 3
Winter SOI	1, 2, 3, 4
SHI	1, 2, 3, 4
EA-WR	1, 2, 3, 4
Annual SST	1

The now stationary and autocorrelation-free data series were then used as input and output datasets during all cross-correlation studies using a lag-window of up to five years (25% of the time-span, 1991-2011). The explorative cross-correlation analysis was performed and repeated between population quantities of the Caspian kutum (i.e. Ln (R) and Ln (SSB), separately) and each of the exogenous climatic/environmental indices in a pairwise manner.

Comparing to other exogenous variables, the Chl-a time series (1998-2011) was not long enough to perform the pre-whitening procedure properly; however, as no obvious temporal trends was observed in annual Chl-a series ($p > 0.05$), the variance stationarity was attained by taking natural logs only. Accordingly, the subsequent cross-correlation analysis was performed by using the Ln (Chl-a) time series without pre-whitening (with time-lags up to four years).

Results of the cross-correlation analysis between broad-scale climate proxies and kutum population quantities showed only several peaking signals (potentially-influential but not significant). The results revealed that NAO (all-year and winter) exerts its greatest impact on recruitment of the Caspian kutum at lag 1 (Fig. 3-3 (a) and (c)). All-year NAO showed a marginal strong influence (with no time lag) on SSB of kutum, however the winter NAO had no impacts on the parental stock (Fig. 3-3 (b) and (d)).

The SOI showed rather strong peaking correlations with R and SSB of kutum. In case of annual SOI, the strongest effects on the recruitment was observed with no time lag and at lag of one year (both with almost similar cross-correlation coefficients ≈ -0.34), while the winter SOI exerted its strongest impacts on the recruits with two years delay (Fig. 3-3 (e) and (g)). In addition, the results of cross-correlation analysis illustrated that all-year and winter SOI had strong influences on parental stock of the Caspian kutum with very similar pattern (both showing the strongest signals at lags 3 and 4, Fig. 3-3 (f) and (h)).

In case of SHI, the greatest impact on the recruitment was observed with two years delay (lag 2 gives the strongest signal), while SSB was not influenced by this climate proxy (Fig. 3-3 (i) and (j)).

Among the climatic proxies, the EA-WR neither affects recruitment nor SSB of kutum (Fig. 3-3 (k) and (l)).

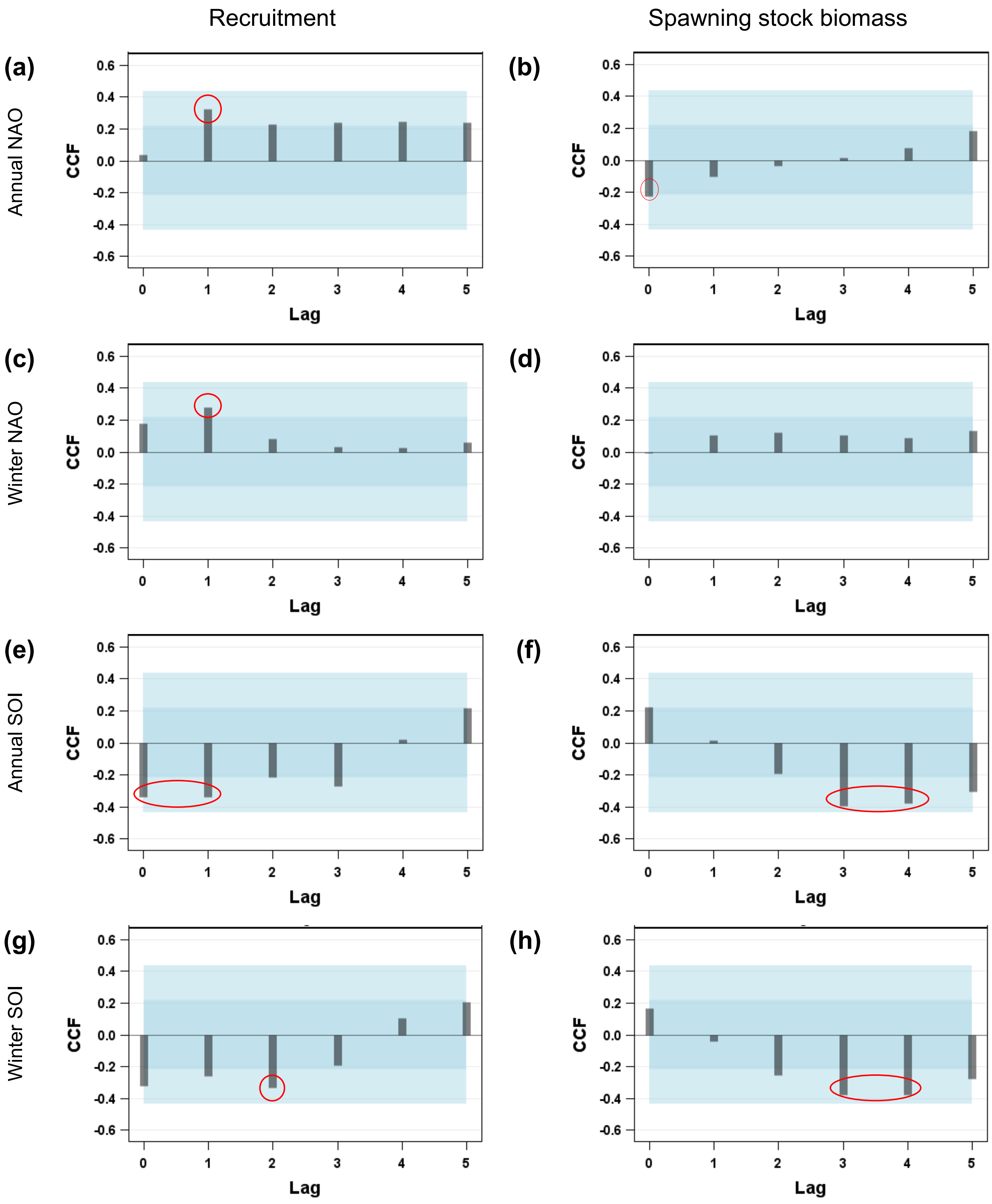


Figure 3-3. Continued.

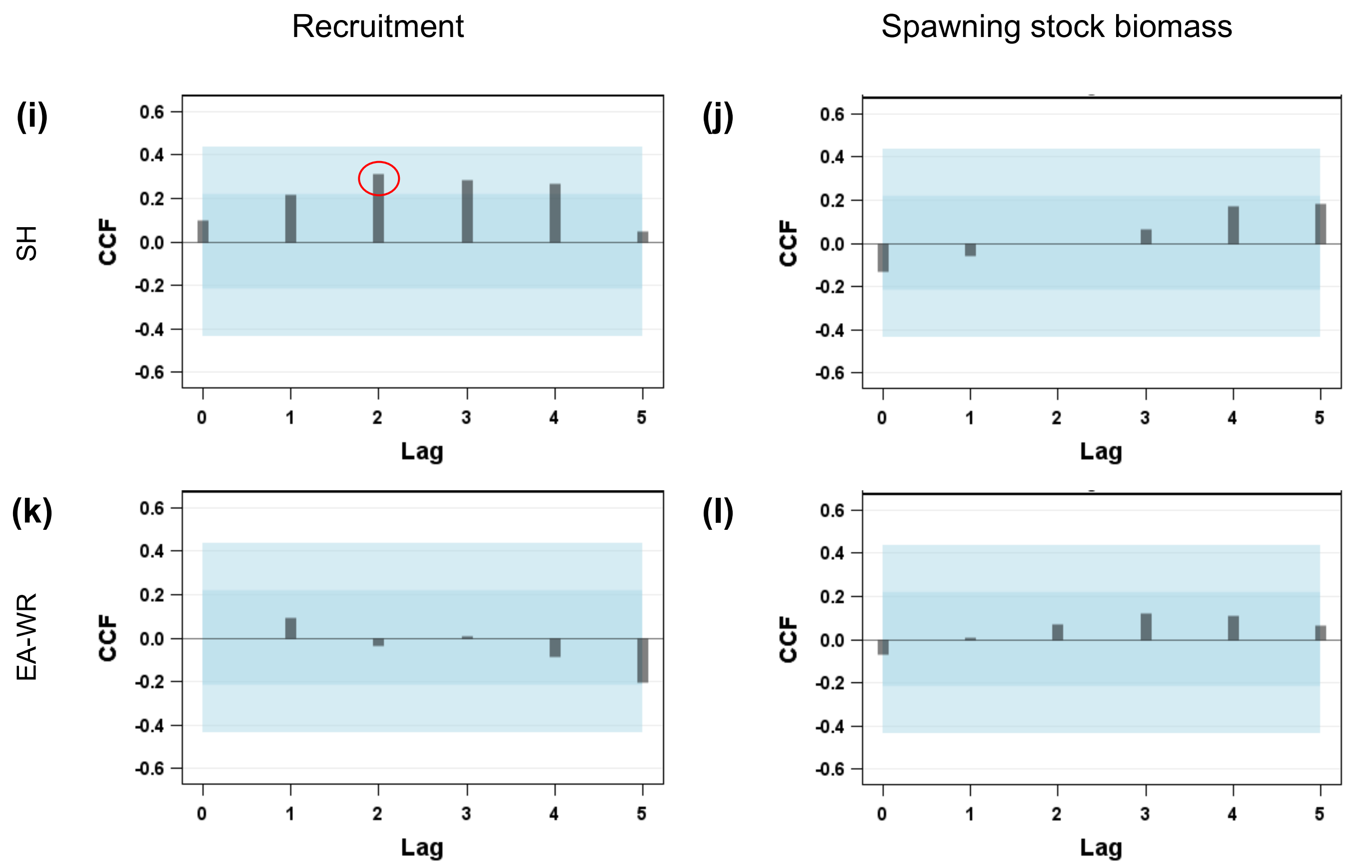


Figure 3-3. Graphical cross-correlation panels (within a lag-window of 5 years) between the stationary and pre-whitened data series of Ln (R) (left column of plots) and Ln (SSB) (right column of plots) of the Caspian kutum and large-scale climate proxies including, the annual NAO ((a) and (b)), winter NAO ((c) and (d)), annual SOI ((e) and (f)), winter SOI ((g) and (h)), SHI ((i) and (j)) and EA-WR ((k) and (l)), respectively. The grey and blue double-bands show upper and lower confidence-bounds at two (i.e. ± 2/√N) and one standard errors (i.e. ± 1/√N) to indicate significant and strong-peaking signals, respectively (see Material and Methods, section 2-2-1-2).

Cross-correlating the population indices with the local satellite-based environmental variables (i.e. SST and Chl-a) also showed only strong peaking signals. The results indicated that the recruitment of kutum could be affected by the yearly SST with a shift of one year. A slightly (marginally) strong impact of annual SST on SSB was observed at lag 5 (Fig. 3-4 (a) and (b)).

While the results showed two strong peaking Chl-a signals at lag 3 and 4 when cross-correlated with the parental stock (Fig. 3-4 (d)), no strong signals was observed on recruitment of the Caspian kutum (Fig. 3-4 (c)).

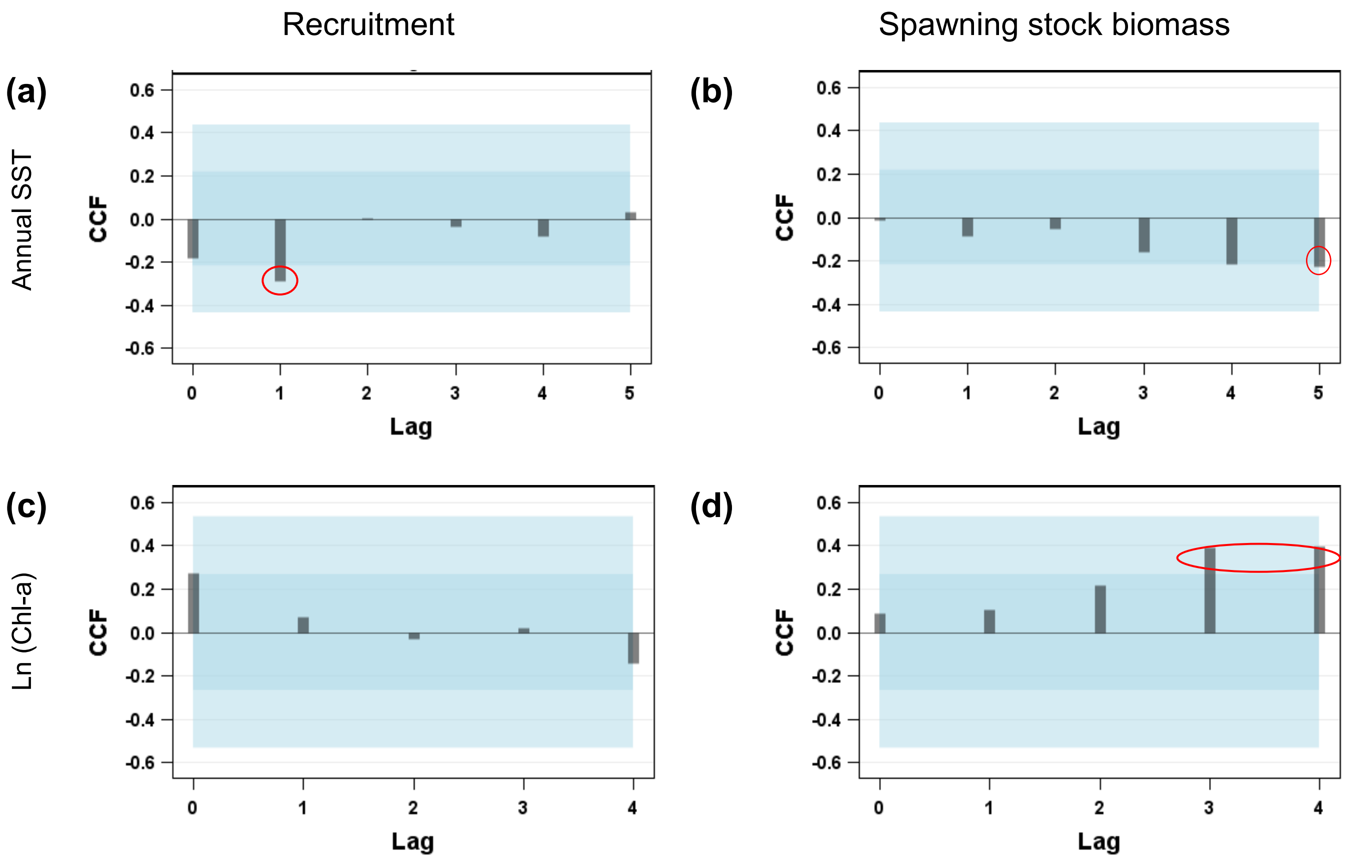


Figure 3-4. Graphical panels of cross-correlation analysis between data series of (left plot) Ln (R) and (right plot) Ln (SSB) of the Caspian kutum and local-environmental variables including, the annual SST ((a) and (b)) and Ln (Chl-a) ((c) and (d)), respectively.

Summarized results of the cross-correlation analysis between population quantities of the Caspian kutum and climatic/environmental variables during 1991-2011 are presented in Table 3-2.

Table 3-2. Summarized results of the cross-correlation analysis between climate/environmental indices and population quantities of the Caspian kutum; only the strongest signals are presented.

Climate/environmental variables	*Signal types and (lags) on R*	*Signal types and (lags) on SSB*
Annual NAO	Strong peaking (1)	Marginally peaking (0)
Winter NAO	Strong peaking (1)	-
Annual SOI	Strong peaking (0, 1)	Strong peaking (3, 4)
Winter SOI	Strong peaking (2)	Strong peaking (3, 4)
SHI	Strong peaking (2)	-
EA-WR	-	-
Annual SST	Strong peaking (1)	Marginally peaking (5)
Annual Chl-a	-	Strong peaking (3, 4)

Based on the results and by taking into account the variable selection criteria including multi-collinearity (see Material and Methods, section 2-2-1-2), only the following variables were selected (at their corresponding lags) as appropriate exogenous candidate variables to extend the basic recruitment model:

- Winter NAO_{t-1}: despite the stronger correlation of the annual NAO with recruitment compared to the winter index, the annual NAO must be withdrawn from the subsequent analysis as it showed a potential via-SSB-mediation impact. Hence the winter NAO at lag 1 (winter NAO_{t-1}) was selected instead of the yearly-averaged index.
- Winter SOI_{t-2}: the annual SOI (at lag 0 and 1) and the winter SOI (at lag 2) showed almost the similar cross-correlation coefficients of ≈ -0.34. However, according to Arpe *et al.,* (2000) the winter index may be a more appropriate proxy for studying the southern oscillation impacts on the hydro-physical properties of the Caspian Sea. Thus, to avoid the co-linearity problem only the winter SOI at lag 2 was chosen for the subsequent analysis.
- SHI at lag 2: the strongest climatic signal on recruitment was observed with a shift of two years.
- Annual SST_{t-1}: the sole strong correlation with recruits was found at lag 1.

3-1-1-2 Results from recruitment dynamics modeling, model selection and statistical diagnostics

To set up the baseline recruitment model for the Caspian kutum, firstly the relationship of recruit numbers with parental stock size (SSB), number of released fingerlings (FR) and potential reproductive capacity (PRC) index was interactively explored (see Material and Methods, section 2-2-1-1). For this purpose (based on Table 2-2 in Material and Methods), the linearized Cushing-form model was fitted to Ln (R) versus Ln $(SSB)_{t-2}$ and Ln $(FR)_{t-2}$ (either in combination or solely) as well as PRC_{t-2}. The summarized results of the reference model search procedure are presented in Table 3-3 (model performance and parameter estimation).

The results revealed that when Ln $(FR)_{t-2}$ is included as a predictor in the recruitment model (i.e. either in combination with SSB in model 1 or solely in model 2b, see Table 3-3), its relevant parameter estimates are not significant ($p > 0.05$). Consequently, these models were not selected as baseline model for the subsequent analysis.

An examination of the relationship between the number of recruits and parental stock size (Model 2a) suggested a significant inverse relationship ($r^2 = 0.34$, $p_{\text{Model}} = 0.009$, Fig. 3-5 (a)). Furthermore, the parameter estimate for Ln $(SSB)_{t-2}$ was significant ($p < 0.05$). The observed inverse relationship may be an indication of a negative density dependent process in the population. In contrast, the linear regression analysis between Ln (R) and PRC_{t-2} (Model 3), showed a significant positive relationship ($r^2 = 0.30$, $p_{\text{Model}} = 0.016$, Fig. 3-5 (b)); also the relevant parameter estimate for PRC_{t-2} was significant ($p < 0.05$). Since the results indicated that the difference between the predictive power of SSB and PRC was quite small (only about 4%), not only model 2a but also model 3 was extended and explored comparatively.

Table 3-3. Summarized results from the explorative baseline recruitment models for the Caspian kutum.

Variables in model	Model performance					Model estimation		
	r^2	r^2_{adj}	SBC	AICc	Pr > F	Variable	Parameter estimate	Pr > |t|
Model 1								
$Ln(SSB)_{t-2}, Ln(FR)_{t-2}$	0.42	0.34	-45.03	-46.49	0.013	intercept	21.09	0.000
						$Ln(SSB)_{t-2}$	-0.88	0.007
						$Ln(FR)_{t-2}$	0.29	0.167
Model 2a								
$Ln(SSB)_{t-2}$	0.34	0.30	-45.86	-47.00	0.009	intercept	26.55	<.0001
						$Ln(SSB)_{t-2}$	-0.87	0.009
Model 2b								
$Ln(FR)_{t-2}$	0.07	0.02	-39.34	-40.48	0.273	intercept	12.38	0.017
						$Ln(FR)_{t-2}$	0.28	0.273
Model 3								
PRC_{t-2}	0.30	0.25	-44.63	-45.76	0.016	intercept	17.73	<.0001
						PRC_{t-2}	0.20	0.016

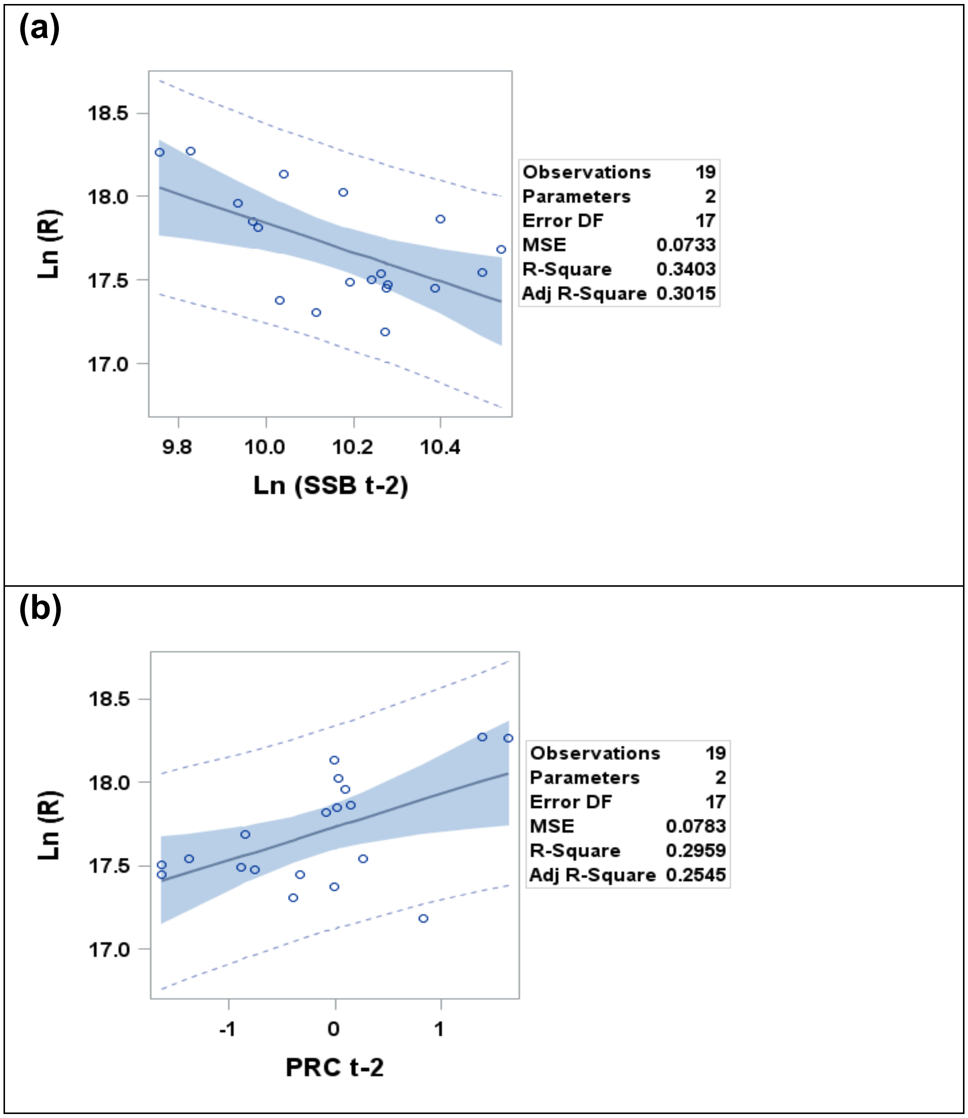


Figure 3-5. Plots of linearly fitted Cushing-form stock-recruitment model to recruitment (Ln (R)) of the Caspian kutum versus (a) parental stock size (i.e. SSB_{t-2}) and (b) the potential reproductive index (i.e. PRC_{t-2}). The blue-shaded area displays upper and lower 95% prediction bounds relevant to these models; the doubled outer broken-lines show the 95% confidence limits of the estimated values.

In a first step of model extension, to avoid the co-linearity problem (correlated/redundant predictor variables), the linear association between all candidate regressors (separately for both reference models) was checked by a pairwise Pearson correlation (Tables A-1 and A-2 in the appendix). In case of the SSB-based model, the results showed a significant pairwise correlation between winter NAO_{t-1} and SST_{t-1} (Table A-1). Therefore, the SSB-based model variations containing simultaneous combinations of winter NAO_{t-1} and SST_{t-1} were ignored. In case of the PRC-based model, apart from the correlation between the winter NAO_{t-1} and SST_{t-1}, also a significant pairwise correlation was observed between the PRC_{t-2} and SST_{t-1} (Table A-2). Hence, the PRC-based model variations containing simultaneous combinations of winter NAO_{t-1} and SST_{t-1} as well as combinations the PRC_{t-2} and SST_{t-1} of were ignored.

In a next step, both baseline recruitment (i.e. SSB- and PRC-based) equations were extended separately by adding linear combinations of the specified (un-correlated) predictor variables on the regressor's side. The predictor variables included the selected candidate climatic/environmental covariates as indicated by the cross-correlation analysis (i.e. winter NAO_{t-1}, winter SOI_{t-2}, SHI_{t-2} as well as SST_{t-1}) plus a recruitment self-dynamics term (i.e. R_{t-1}; see Material and Methods, section 2-2-1-1). This step involved putting all predictors (at the same time) into a multivariate stepwise regression procedure and fitting all possible linear models. The stepwise procedure screens and evaluates all possible predictor combinations and removes statistically insignificant explanatory variables (at $\alpha = 0.05$) from the ultimate model.

Finally, among all parameter permutations (for both SSB-based and PRC-based recruitment equations) the following model structure with the most parsimonious predictor subset was identified as the best model in terms of the information criterion with the lowest measures of $AIC_C = -73.97$ and $SBC = -72.73$:

$$Ln\ (R_t) = 9.45 - 0.59\ Ln\ (SSB_{t-2}) + 0.81\ Ln\ (R_{t-1})\ +\ \varepsilon_t \qquad \text{(Eq. 3-1)}$$

where ε_t is residuals of model.

This model could explain more of the recruitment variability ($r^2 = 0.86$, $r^2_{adj} = 0.85$ and $p_{\text{Model}} < .0001$; Fig. 3-6 (a)). Results of the normality test (Cramer–von–Mises and Anderson-Darling tests, both $p > 0.25$, $\alpha = 0.1$) along with visual inspection of QQ plot and sample histogram (Fig. 3-6 (b) and (c)), confirmed normal distribution of the model residuals. The test on residuals homogeneity (Levene test, $p > 0.1$) and the graphical diagnostics of scatter plots (residuals versus predicted values of Ln (R); Fig. 3-6 (d)) supported the residuals homoscedasticity assumption. Therefore, all statistical assumptions for accepting the model were met.

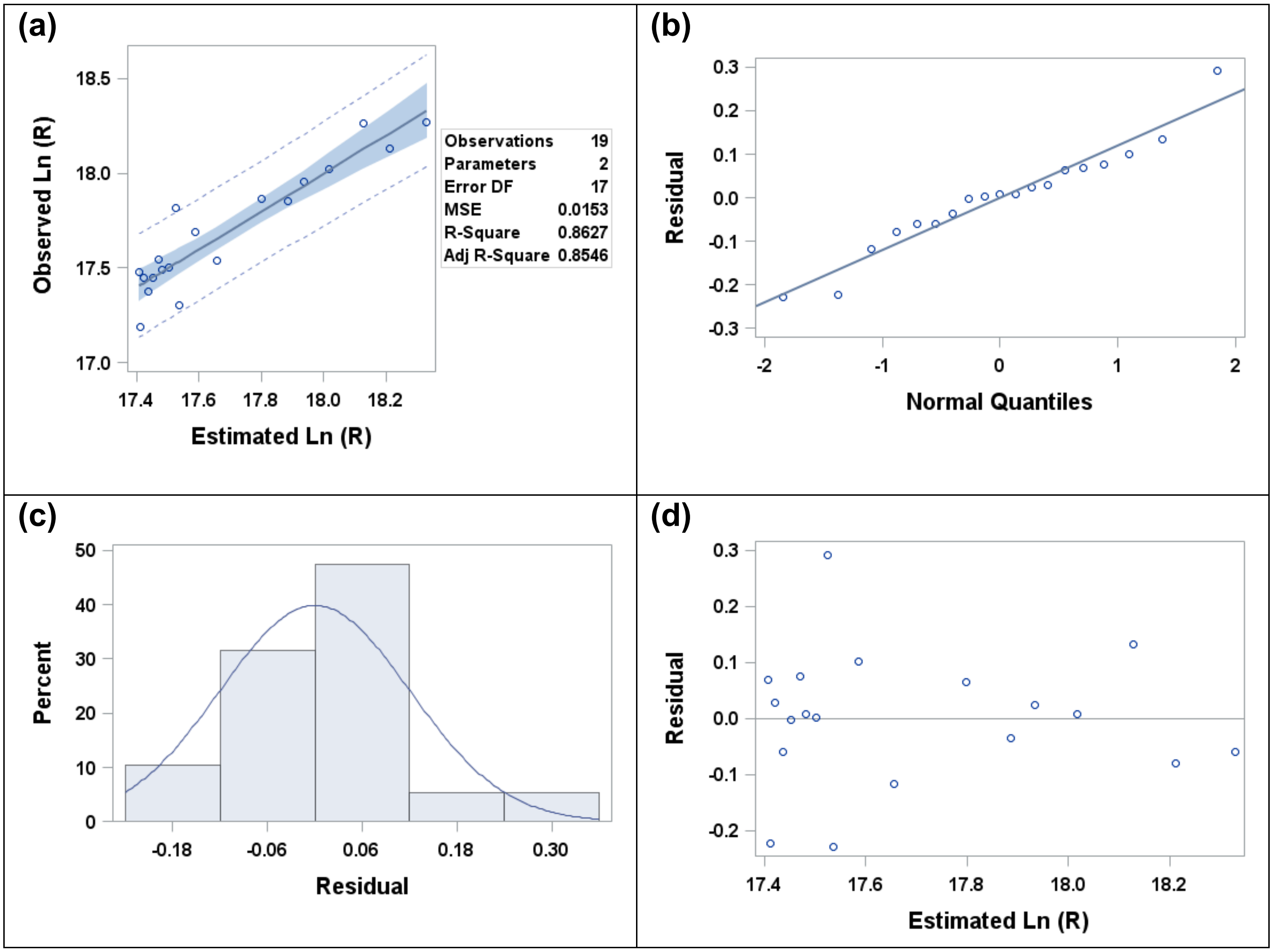


Figure 3-6. The best statistical recruitment model selection plots for the Caspian kutum: (a) plot of observed versus estimated Ln (R) and goodness-of-fit (the blue-shaded area displays upper and lower 95% prediction bounds relevant to these models; the doubled outer broken- lines show the 95% confidence limits of the estimated values); (b) and (c) are the QQ plot and sample histogram of the residuals of the final recruitment model, respectively; (d) shows the scatter plot of model residuals versus predicted values of Ln (R).

As the results showed, the statistically-significant regressors remained in the best model were only the parental stock size and the lag-endogenous term Ln (R_{t-1}). This implies that inclusion of the climatic/environmental covariates could not significantly improve the recruitment model performance for Caspian kutum. They were thus excluded from the final model. As well, none of the extensions to the PRC-based model showed a better statistical performance comparing to the best model (i.e. Eq. 3-1).

3-1-2 The Golden grey mullet

3-1-2-1 Results from cross-correlation analysis

After passing the stationarity filter and the subsequent pre-whitening procedure, the cross-correlation analysis was performed and repeated between log-transformed population quantities of the golden grey mullet (i.e. Ln (R) and Ln (SSB), separately) as input time series and each of the exogenous climatic/environmental indices as output time series in a pairwise manner. The data pre-processing for this step is described briefly in the following part.

Results of the temporal trend test (linear regression) in case of golden grey mullet revealed no significant trends in both population-quantity series of logarithmic-transformed (variance-stationary) recruitment (Ln (R) with a slope = -0.009, p = 0.218, Fig. 3-7 (a)) and parental stock (Ln (SSB) with a slope = 0.012, p = 0.122, Fig. 3-7 (b)), so there was no need to perform the de-trending process. Therefore Ln (R) as well as Ln (SSB) were used in their original form (without transformations) during the further analysis steps (likewise for the Caspian kutum). In case of all climate/environmental time series, the stationarity condition was evaluated and achieved (by first-order differentiation) as already described in section 3-1-1-1.

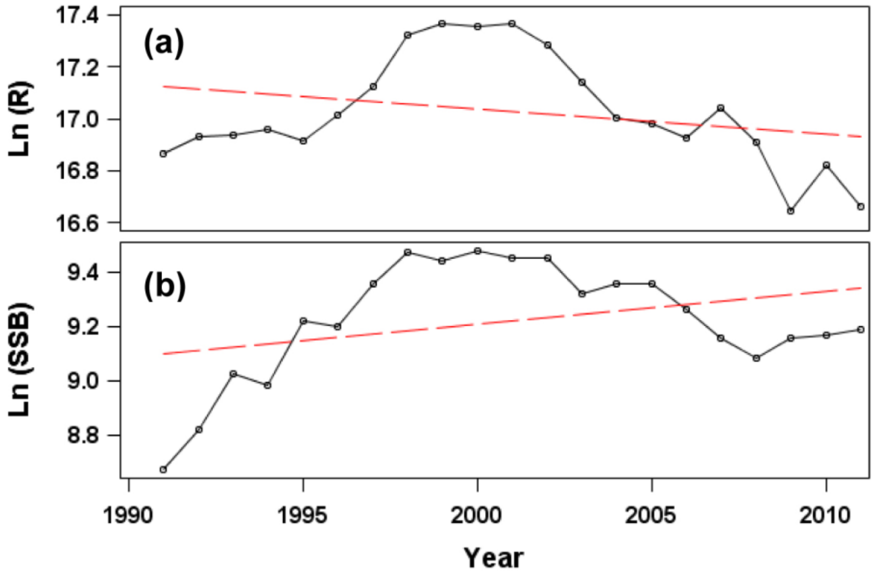


Figure 3-7. Plots (a) and (b) are the originally-stationary data series of Ln (R) and Ln (SSB) of the golden grey mullet with linear trend lines (red broken line) during 1991-2011, where R is recruitment and SSB is parental stock size.

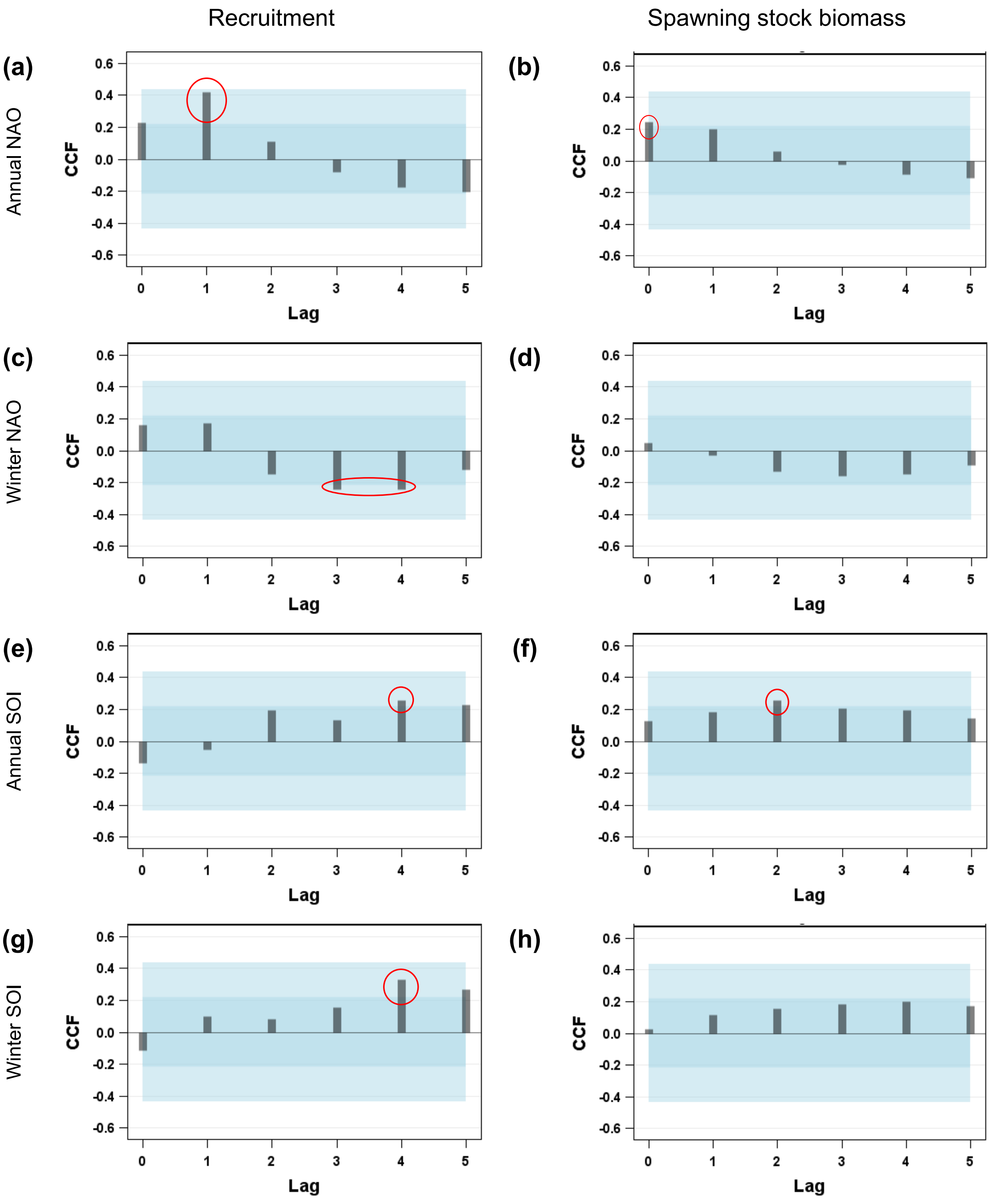
The subsequent pre-whitening treatment (autocorrelation removal) was based on the autocorrelation structures identified in all input variable data series (see Table. 3-1). Then the stationary and autocorrelation-free data series were cross-correlated with time-lags up to five years. Data treatment of Chl-a before for the cross-correlation analysis was entirely similar to that performed for kutum (see section 3-1-1-1).

Results of cross-correlation analysis between NAO and population quantities revealed that the yearly-averaged NAO exerts a very strong impact (a peaking and marginally-significant signal) on recruitment of the golden grey mullet with a time-lag of one year (Fig. 3-8 (a)). Moreover, slightly strong effects of winter NAO on R was observed at lag 3 and 4 (Fig. 3-8 (c)). While the sole impact of the annual NAO on SSB was rather marginal (at no time delay), the winter NAO showed no peaking signals on the SSB (Fig. 3-8 (b) and (d)).

In case of SOI (both the annual and the winter), the strongest peaking signal influencing the recruits was observed with a shift of four years (Fig. 3-8 (e) and (g)). Only the annual SOI (at lag 2) showed a slight peaking impact on the parental stock size of the golden grey mullet (Fig. 3-8 (f) and (h)).

The SHI exhibited a strong cross-correlation with the recruitment of mullet at lag 5 (Fig. 3-8 (i)). Furthermore, slightly strong effects of SHI on SSB were observed at no time delay plus at lag 1 (Fig. 3-8 (j)).

While the EA-WR exerts its greatest effect on the parental stock of golden grey mullet at lag 2, (Fig. 3-8 (l)), no peaking cross-correlations could be found in case of the recruits (Fig. 3-8 (k)).


Recruitment
Spawning stock biomass
(a)
(b)
(c)
(d)
(e)
(f)
(g)
(h)
Annual NAO
Winter NAO
Annual SOI
Winter SOI
CCF
Lag
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
0
1
2
3
4
5

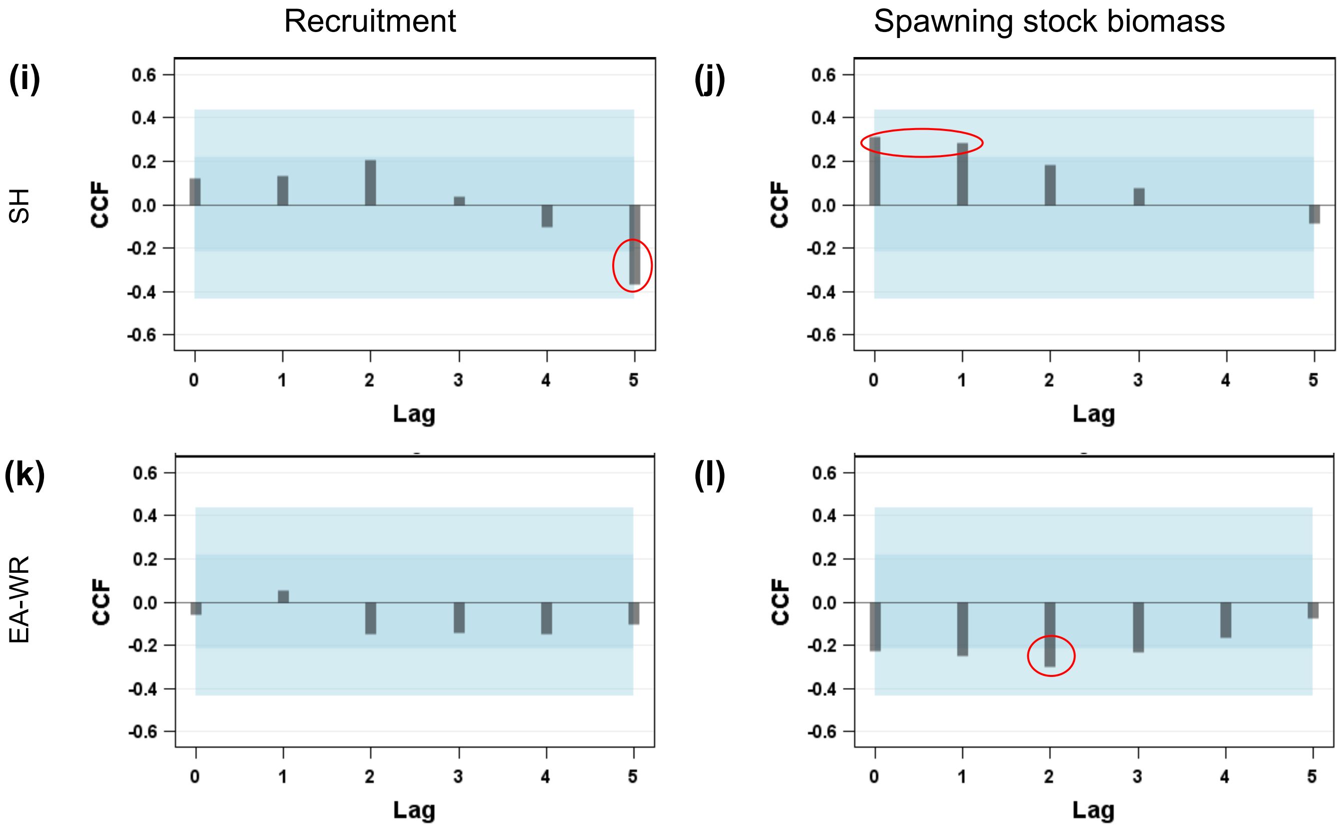


Figure 3-8. Graphical cross-correlation panels (within a lag-window of 5 years) between the stationary and pre-whitened data series of Ln (R) (left column of plots) and Ln (SSB) (right column of plots) of the golden grey mullet and large-scale climate proxies including, the annual NAO ((a) and (b)), winter NAO ((c) and (d)), annual SOI ((e) and (f)), winter SOI ((g) and (h)), SHI ((i) and (j)) and EA-WR ((k) and (l)), respectively. The grey and blue double-bands show upper and lower confidence-bounds at two (i.e. ± 2/√N) and one standard errors (i.e. ± 1/√N) to indicate significant and strong-peaking signals, respectively (see Material and Methods, section 2-2-1-2).

Cross-correlating the population indices of golden grey mullet with the local satellite-based environmental time series (i.e. SST and Chl-a) also showed strong/peaking signals. The strongest impact of the annual SST on R was observed with a shift of three years (Fig. 3-9 (a)). Moreover, the SST showed no strong correlations with the parental stock of golden grey mullet (Fig. 3-9 (b)). Cross-correlating the population quantities of mullet with Chl-a illustrated a similar pattern of correlation for R and SSB. The strongest peaking signal was observed in both cases with a shift of two years (Fig. 3-9 (c) and (d)).

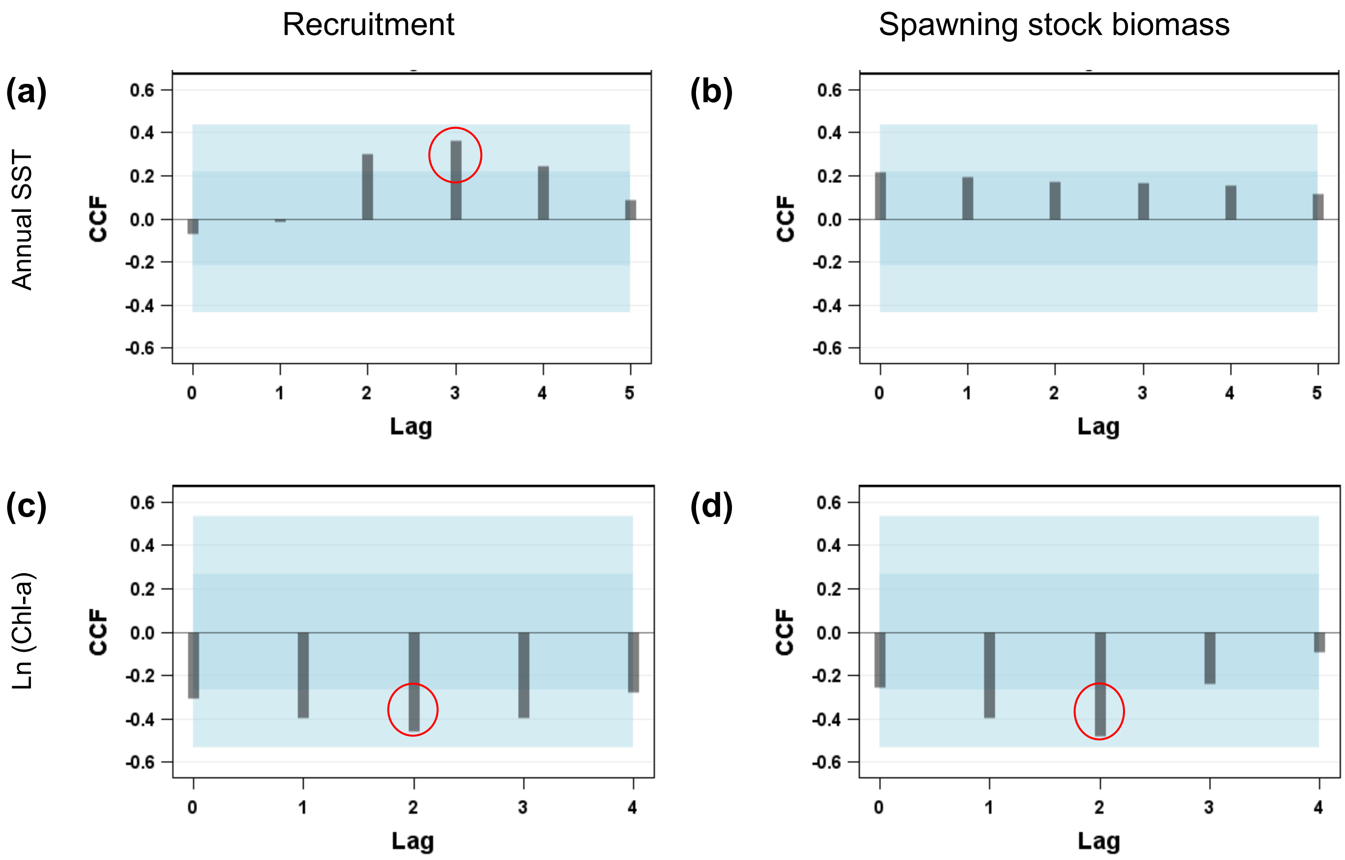


Figure 3-9. Graphical panels of cross-correlation analysis between data series of (left plot) Ln (R) and (right plot) Ln (SSB) of the golden grey mullet and local-environmental variables including, the annual SST ((a) and (b)) and Ln (Chl-a) ((c) and (d)), respectively.

Results of the cross-correlation analysis between the population quantities of golden grey mullet and the climatic/environmental variables are presented in Table 3-4.

Table 3-4. Summarized results of the cross-correlation analysis between climate/environmental indices and population quantities of the golden grey mullet; only the strongest signals are presented.

Climate/environmental variables	*Signal types and (lags) on R*	*Signals type and (lags) on SSB*
Annual NAO	Very strong peaking/marginally-significant (1)	Marginally peaking (0)
Winter NAO	Strong peaking (3, 4)	-
Annual SOI	Strong peaking (4)	Strong peaking (2)
Winter SOI	Strong peaking (4)	-
SHI	Strong peaking (5)	Strong peaking (0, 1)
EA-WR	-	Strong peaking (2)
Annual SST	Strong peaking (3)	-
Annual Chl-a	Strong peaking (2)	Strong peaking (2)

Selection of the candidate variables influential on recruitment (among all the tested climate/environmental factors) being incorporated during subsequent modeling steps, was based on the pre-defined statistical criteria and structural constraints as described for kutum (see Material and Methods, section 2-2-1-2, A, B and C). Therefore, only the following climatic/environmental variables (at their corresponding lags) were selected as exogenous candidate variables to extend the basic recruitment model:

- Annual NAO_{t-1}: the yearly-averaged signal on recruits (at lag1) was much stronger than that of the winter index (at lag 3 and 4). This climatic signal on recruits was on the edge of being significant (very strong peaking signal). Moreover, it was almost twice stronger than the annual NAO signal on SSB (at lag 0). Hence, the slight/marginal correlation between the annual NAO and the parental stock has been ignored as a via-SSB-transmission impact.
- Winter SOI_{t-4}: the winter signal on recruitment (with a shift of four years) was stronger than that of the yearly-SOI. Also, the winter signal did not show any potential SSB-mediating impacts.
- Annual SST_{t-3}: the strongest signal on R was observed at a delay of three years.
- Ln $(Chl\text{-}a)_{t-2}$: the strongest correlation with recruits was found at lag 2. As the strongest signal on SSB was observed at the same time-lag, the potential mediatory effect through the parental stock could be ignored.

As the correlational patterns between SHI and the population indices of the golden grey mullet represented a potential via-SSB-transmission impact, the observed signal was not considered in the further analysis.

3-1-2-2 Results from recruitment dynamics modeling, model selection and statistical diagnostics

In contrast to kutum, the reference recruitment model for the golden grey mullet was set up simply by fitting a linearized Cushing-type model (see Material and Methods, Table 2-2) to Ln (R) versus Ln $(SSB)_{t-2}$. An examination of the relationship between the number of recruits and parental stock size suggested a significant positive relationship ($r^2 = 0.23$, $p_{\text{Model}} = 0.04$, Fig. 3-10 (a)) with estimated AICc and SBC of -58.58 and -57.44, respectively.

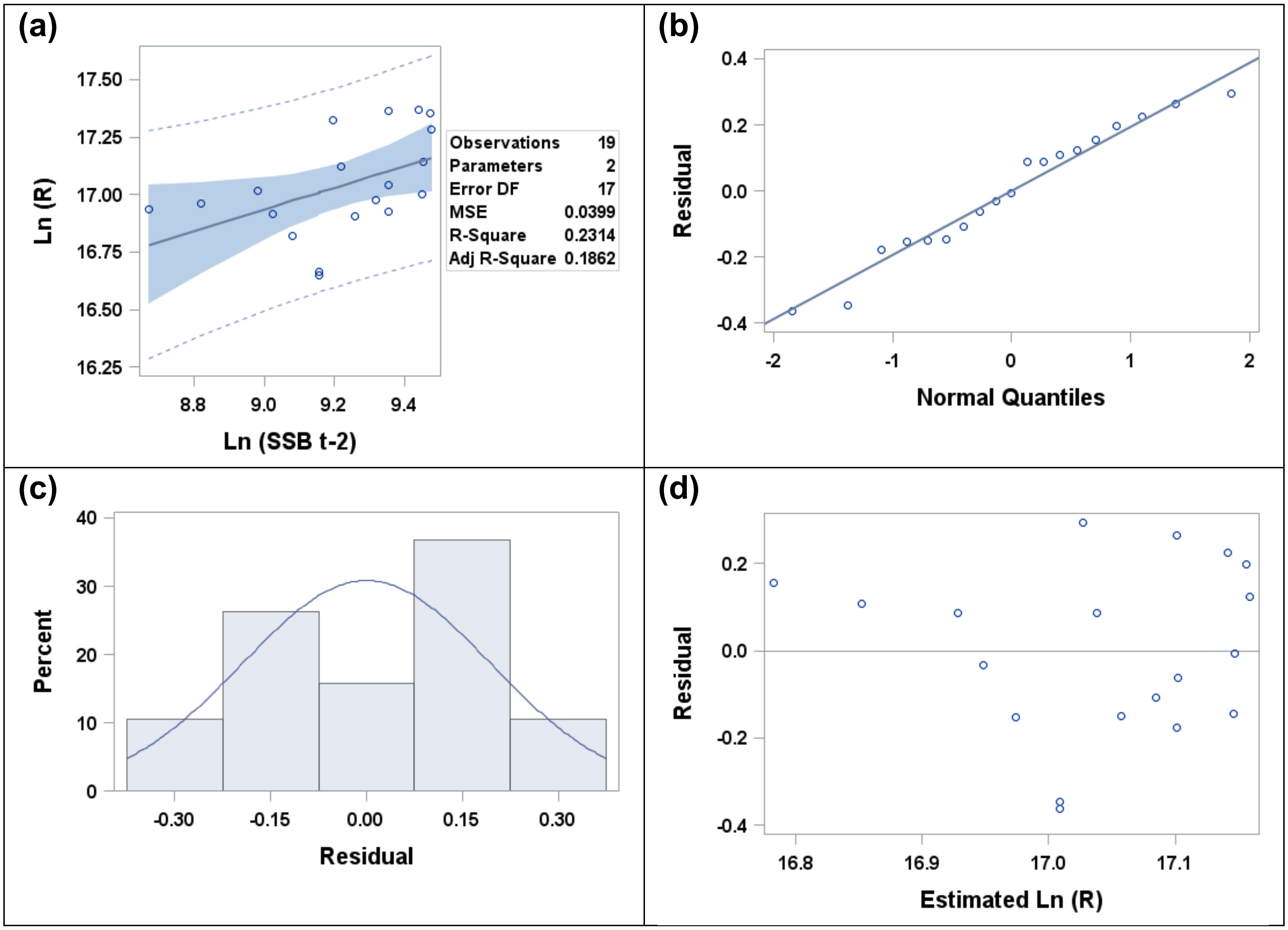


Figure 3-10. Plot (a) shows the linearly fitted Cushing-form stock-recruitment model to recruitment (Ln (R)) of the golden grey mullet versus parental stock size (i.e. SSB_{t-2}); the blue-shaded area displays upper and lower 95% prediction bounds relevant to these models and the doubled outer broken-lines show the 95% confidence limits of the estimated values. Plots (b) and (c) are the QQ plot and sample histogram of the residuals of the reference recruitment model, respectively. Graph (d) illustrates the scatter plots of model residuals versus predicted values of Ln (R).

Results of the normality test (Cramer–von–Mises and Anderson-Darling tests, both $p > 0.25$, $\alpha = 0.1$) along with visual inspection of QQ plot and sample histogram (Fig. 3-10 (b) and (c)), confirmed the normal distribution of the model residuals. The test on residuals homogeneity (Levene test, $p > 0.1$) and the diagnostic graphical inspection of the scatter plots (residuals versus predicted values of Ln (R); Fig. 3-10 (d)) supported the residuals homoscedasticity.

To avoid the co-linearity problem (correlated/redundant predictor variables), the linear association between all regressors was checked by a pairwise Pearson correlation. Table A-3 (appendix) shows a significant pairwise correlation between the SSB_{t-2} and SST_{t-3}. Therefore, the model variations containing simultaneous combinations of SSB_{t-2} and SST_{t-3} were ignored.

In a next step the reference recruitment model was extended by adding linear combinations of non-correlated predictors on the regressor's side. The predictor variables included the candidate climatic/environmental covariates from the cross-correlation analysis (i.e. annual NAO_{t-1}, winter SOI_{t-4}, SST_{t-3} as well as Ln $(Chl\text{-}a)_{t-2}$) and the internal recruitment dynamics term (i.e. R_{t-1}). To obtain the most parsimonious model and predictor combinations, respectively all possible linear combinations were fitted and evaluated through performing a multivariate stepwise regression analysis (at $\alpha = 0.05$; see section 3-1-1-2).

Eventually, among all parameter permutations the following model structure with the most parsimonious predictor subset was identified as the best model in terms of the information criterion with the minimum values of $AIC_C = -81.88$ and $SBC = -80.59$:

$$Ln\ (R_t) = 1.73 + 0.90\ Ln\ (R_{t-1})\ +\ \varepsilon_t \qquad \text{(Eq. 3-2)}$$

where ε_t denotes the model residuals .

This model explained more of the recruitment variation of the golden grey mullet in the southern Caspian Sea ($r^2 = 0.71$, $r^2_{adj} = 0.69$ and $p_{\text{Model}} < .0001$; Fig. 3-11 (a)). Hence, the increase in the coefficient of determination is by about 0.48 which means a tripling of the degree of explanation. Results of the normality test (Cramer–von–Mises and Anderson-Darling tests, both $p > 0.25$, $\alpha = 0.1$) along with visual inspection of QQ plot and sample histogram (Fig. 3-11 (b) and (c)), confirmed the normal distribution of the model residuals. The homogeneity test of the residuals (Levene test, $p > 0.1$) and the diagnostic graphical inspection of the scatter plots (residuals versus predicted values of Ln (R); Fig. 3-11 (d)) validated the residuals' homoscedasticity assumption. Therefore, no model assumption violations were detected and all statistical requirements for accepting the best model were fulfilled.

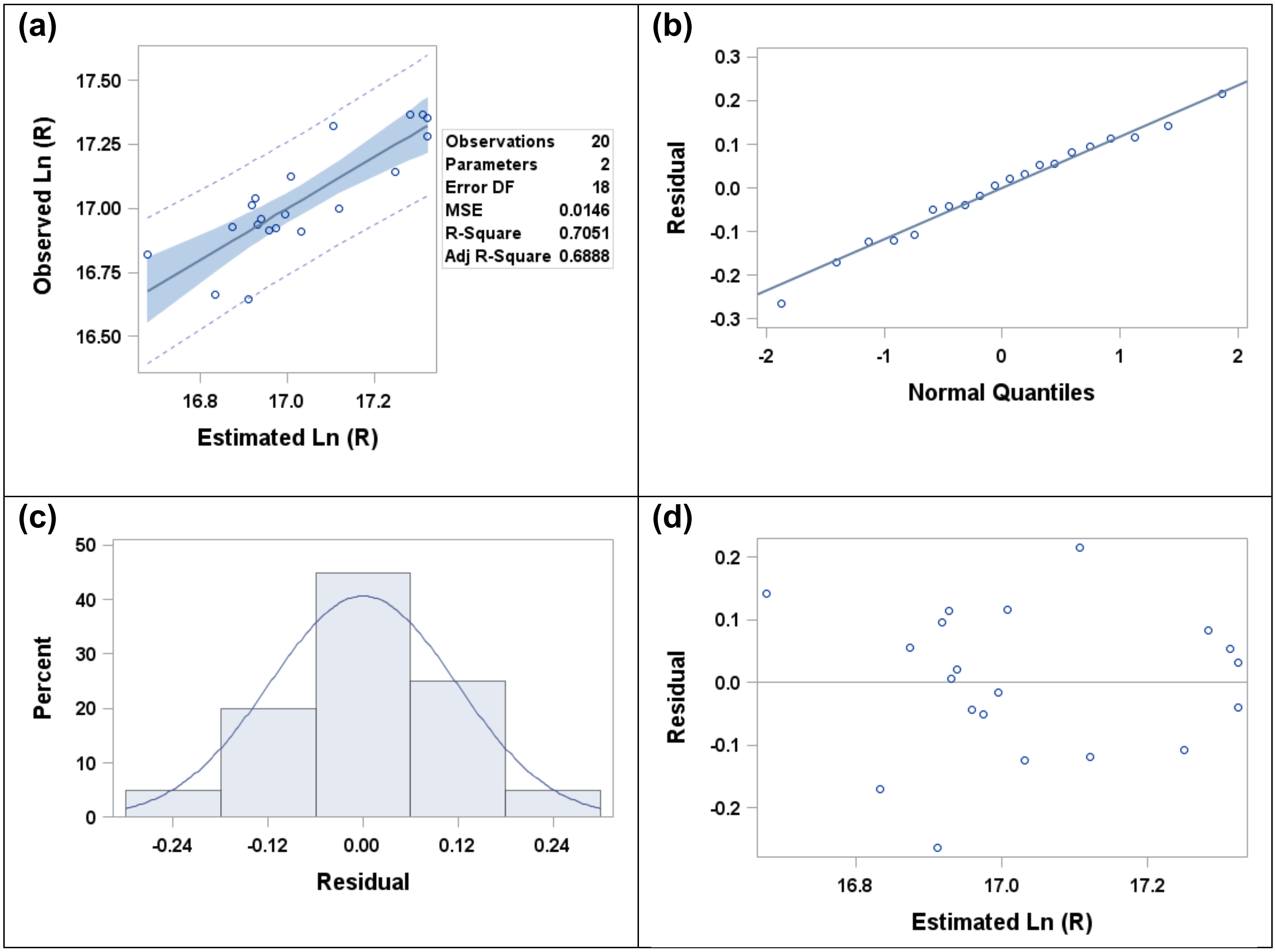


Figure 3-11. The best statistical recruitment model selection plots for the golden grey mullet: (a) plot of observed versus estimated Ln (R) and goodness-of-fit (the blue-shaded area displays upper and lower 95% prediction bounds relevant to these models; the doubled outer broken- lines show the 95% confidence limits of the estimated values); (b) and (c) are the QQ plot and sample histogram of the residuals of the final recruitment model, respectively; (d) shows the scatter plots of model residuals versus predicted values of Ln (R).

As the results showed, the stepwise regression procedure eliminated not only the climatic/environmental variables but also SSB (insignificant regressors) from the final model. Remarkably, the best (and statistically-validated) model to explain the recruitment variation of the golden grey mullet was obtained by solely incorporating information from the recruitment's self-dynamics (lag-endogenous term) by at the same time removing SSB. This implies that the best statistical recruitment model for this species requires neither parental stock size nor other exogenous variables such as climatic/environmental covariates. What appears to be interesting here is that, the observed internal dynamics of recruits had the highest potential power to explain the recruitment variability of this species during the study period. Since this model could not be longer classified as a Cushing-structured model (due to the elimination of SSB), it was entitled *pure lag-endogenous recruitment model*.

3-2 RESULTS SECTION II (Quantitative approach)

This section describes the results from qualitatively studying a prospective shift pattern contained in the available data series. First, the results from the adopted shift screening process for the univariate time series of large-scale climatic/local environmental proxies and species population components are presented. In a next step, the shift inspection results related to the aggregated community and ecosystem subsets (i.e. corresponding PC1 scores; see Material and Methods, section 2-2-2) are described.

3-2-1 Univariate climatic/environmental data series

Figure 3-12 illustrates the corresponding shiftogram profiles of (A-E) climate forcing/environmental variables time series running from 1987 to 2011 and (F) chlorophyll-a time series running from 1998-2011, where the black vertical-dashed lines indicate locations of potential structural breaks (years of shift occurrence). The triple shiftogram panels 2, 3 and 4 (i.e. AICc, p-joint statistics and power) graphically displayed by surrounding rectangles (red-broken lines) were considered as the key-statistical indicators for recognizing the location of the shift (temporal positioning). The results as can be inferred from the shiftograms (Fig. 3-12 (A-F)) are described below:

(A) Shiftogram profile of NAO. From the patterns illustrated in this shift diagram, the center of a major structural break could be identified in year 2010 with a gradual decrease in the level and a sudden increase thereafter: this shock signal is well indicated by the lowest measures of AICc and p-joint and at the same time by the maximum recorded values of power (plots 2, 3 and 4, respectively). P-joint and AICc also indicate that the initial gradual decrease began around 2006. Furthermore, one less strong and rather gradual shift is centered somewhere around (perhaps between) 1989 and 1990. Inspecting the AICc shows that whereas the stronger shift in year 2010 is characterized by an obvious sharp downward impulse-like pattern, the gradual shift centered around 1989 has a rather flat ramp-like pattern. Moreover, while the first gradual shift in 1989 shows a reduction in auto-regression, the more sudden shift in 2010 shows an increase.

(B) Shiftogram profile of SOI. In case of the southern oscillation index a rather strong shift could be observed during the period of the study, being centered around 2007. Beside this, the diagram indicates a prominent (but not significant) shift-like signal around 1999. When inspecting AICc and p-joint the major shift in year 2007 seems to develop from year 2001 on with a gradually decreasing initial transition phase; however, the second signal in the late 1990's seems to develop with a rather bumpy initial transition phase (minor changes in 1994 and 1997).

(C) Shiftogram profile of SHI. Local minima of AICc plus local maxima of power indicate a strong shift during the late 1980's (especially in 1989). Moreover, after 1989 time series shows an obvious gradual upward trend in the AICc and auto-regression. An apparent break in the SHI time series around 2006 is not confirmed by the AICc, p-joint and power panels.

(D) Shiftogram profile of EA-WR. Despite the shiftogram shows repeating bumpy changes along the time series of EA-WR (especially around 1989, 1992, 1997 and 2010), these break-like signals are not confirmed by the AICc, p-joint and power panels.

(E) Shiftogram profile of SST. The shiftogram indicates a shift centered at year 1994, with an asymmetric gradual transition zone with a shorter initial phase when compared with the outgoing phase. The observed shift has a clear level changing pattern. The main changes in time series characteristics represent a long-transitioning period with rather slow slope changes within a considerable width (8 years). This obvious shift is characterized by an initial gradual decrease in AICc and p-joint began around 1991, reached to the deepest point (local minima) in 1994 and followed by a gradual increase until 2000.

(F) Shiftogram profile of Chl-a. During period 1998 to 2011 the chlorophyll shiftogram (Chl-a log-transformed) indicates a rather prominent (but non-significant) break-like signal centered at year 2001. The signal represents a weak indication of an impulse-like (rather flat but not sharp) pattern. This break-like signal is also characterized by an obvious change in auto-regression behavior of the time series. After reaching to the local minima in 2001, the auto-regression initially increased and then reached to a rather plateau-like level by the end of the time series.

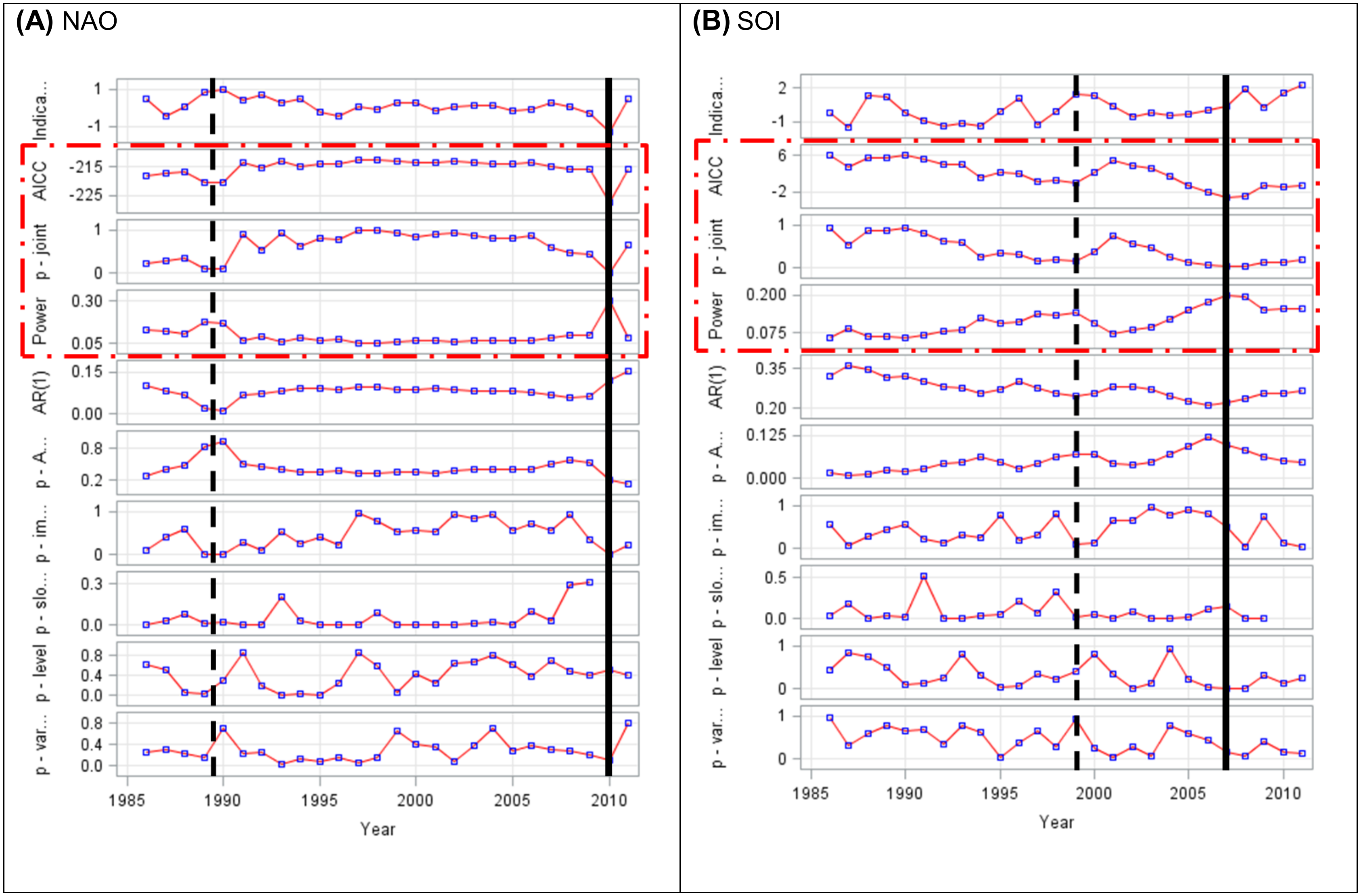
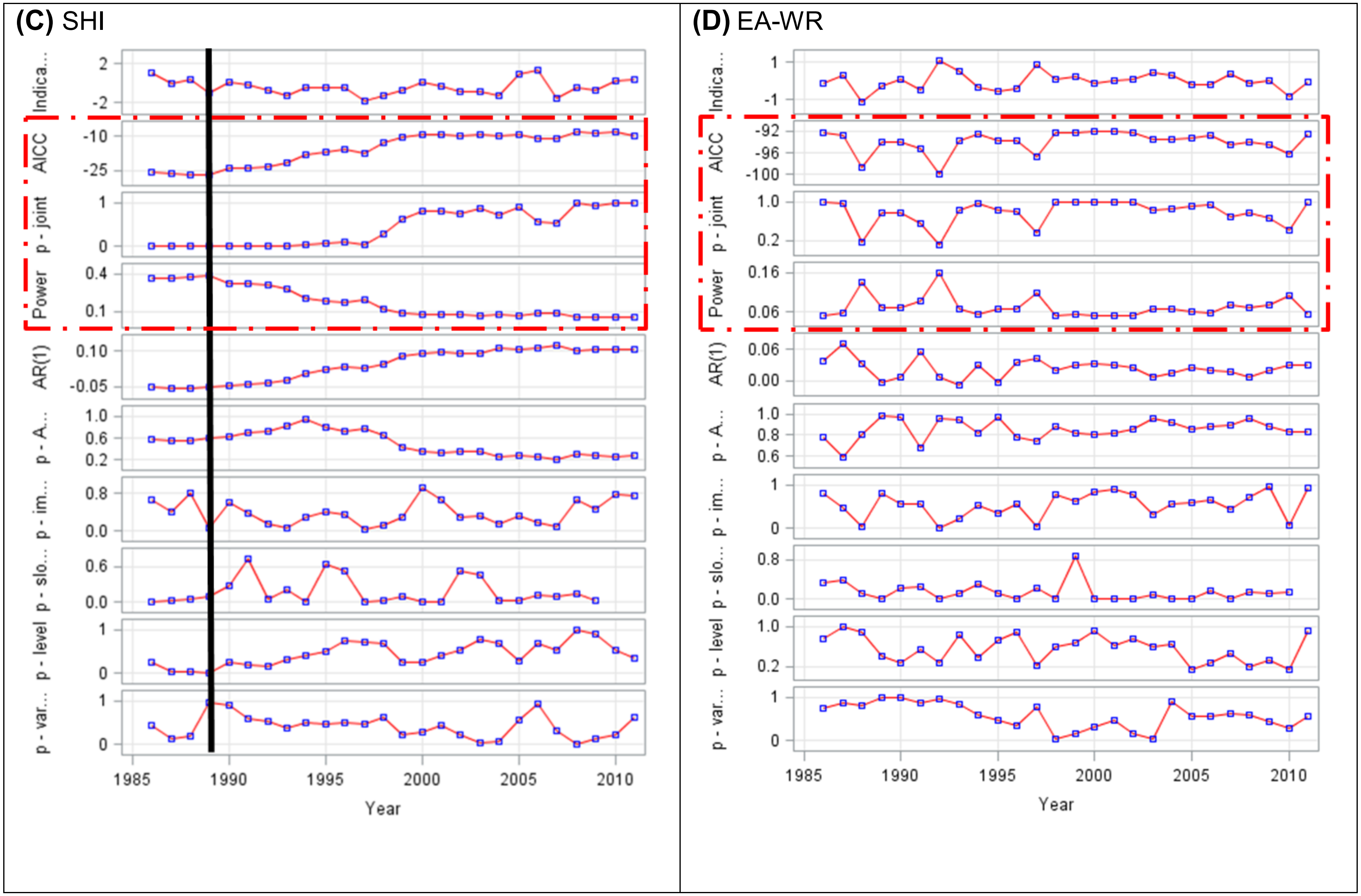


Figure 3-12. Continued.



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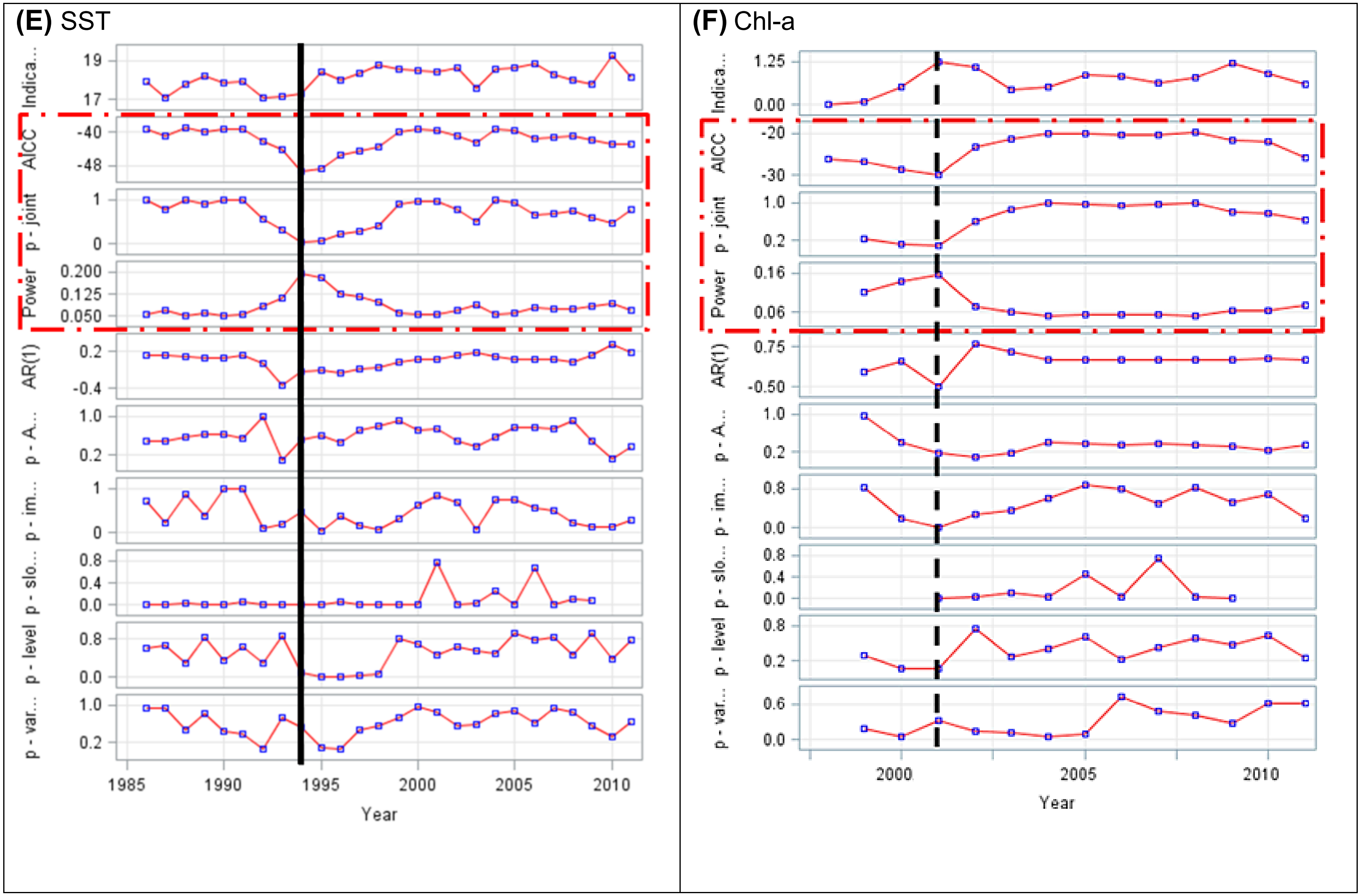

Figure 3-12. Shiftograms of (A) NAO, (B) SOI, (C) SHI, (D) EA-WR, (E) SST and (F) Chl-a. The black vertical-continuous lines indicate location of strong structural breaks (years of shift occurrence); the black vertical-dashed lines indicate location of prominent(less strong and minor) shift-like signals; the open surrounding rectangle with red-broken lines shows the triple key-statistical indicators for recognizing the breaks (i.e. AICc, p-joint statistics and power).

3-2-2 Univariate species population components data series

Figure 3-13 illustrates the corresponding shift screening diagrams for the population components (i.e. recruitment Ln (R) and parental stock size Ln (SSB)) related to Caspian kutum (A and B) and golden grey mullet (C and D). The logarithmic-transformed values of population indices were used as inputs for the shift detection algorithm. The results of the shift analysis (Fig. 3-13 (A-D)) are described below:

(A) Shiftogram profile of the Caspian kutum recruitment. Inspection of the shiftogram suggests a strong break in year 2000. This shift is well characterized by the local maxima of the power along with the lowest measures of AICc and p-joint. The changes in the main statistical break features are rather symmetric and short-lasting (around two years before and after shift center); also inspection of the AICc shows a rather valley-like pattern. Moreover, the auto-regression represents two obvious and separated trends before and after the shift location (downward and upward trends, respectively).

(B) Shiftogram profile of the Caspian kutum SSB. The shiftogram revealed an evident major structural break around 2003-2004. The major characteristics of this shift are rather similar to those of kutum recruits; however, the change in auto-regression before and after the shift location was a little steeper and more sudden.

(C) Shiftogram profile of the golden grey mullet recruitment. The shiftogram suggests a strong shift around 1996-1997 similar to an inflection point. Inspection of AICc shows a rather valley-like pattern initially began about two years before the shift occurrence. The most obvious pattern change in statistical features of the time series is related to the auto-regression behavior: the plateau-like auto-regression pattern appears to be interrupted at years 1996 and 1997 by a reverse valley-type layout.

(D) Shiftogram profile of the golden grey mullet SSB. Based on the corresponding key-statistics, the shiftogram indicates two significant shifts, one in 1995 reflecting the steepest (inflection) point of increase, a second less strong one around 2005-2006 reflecting the steepest (inflection) point of decrease. Inspection of the AICc shows a rather symmetric valley-like pattern for both shifts developments. Furthermore, the entire time series shows a very small auto-regression changing pattern.

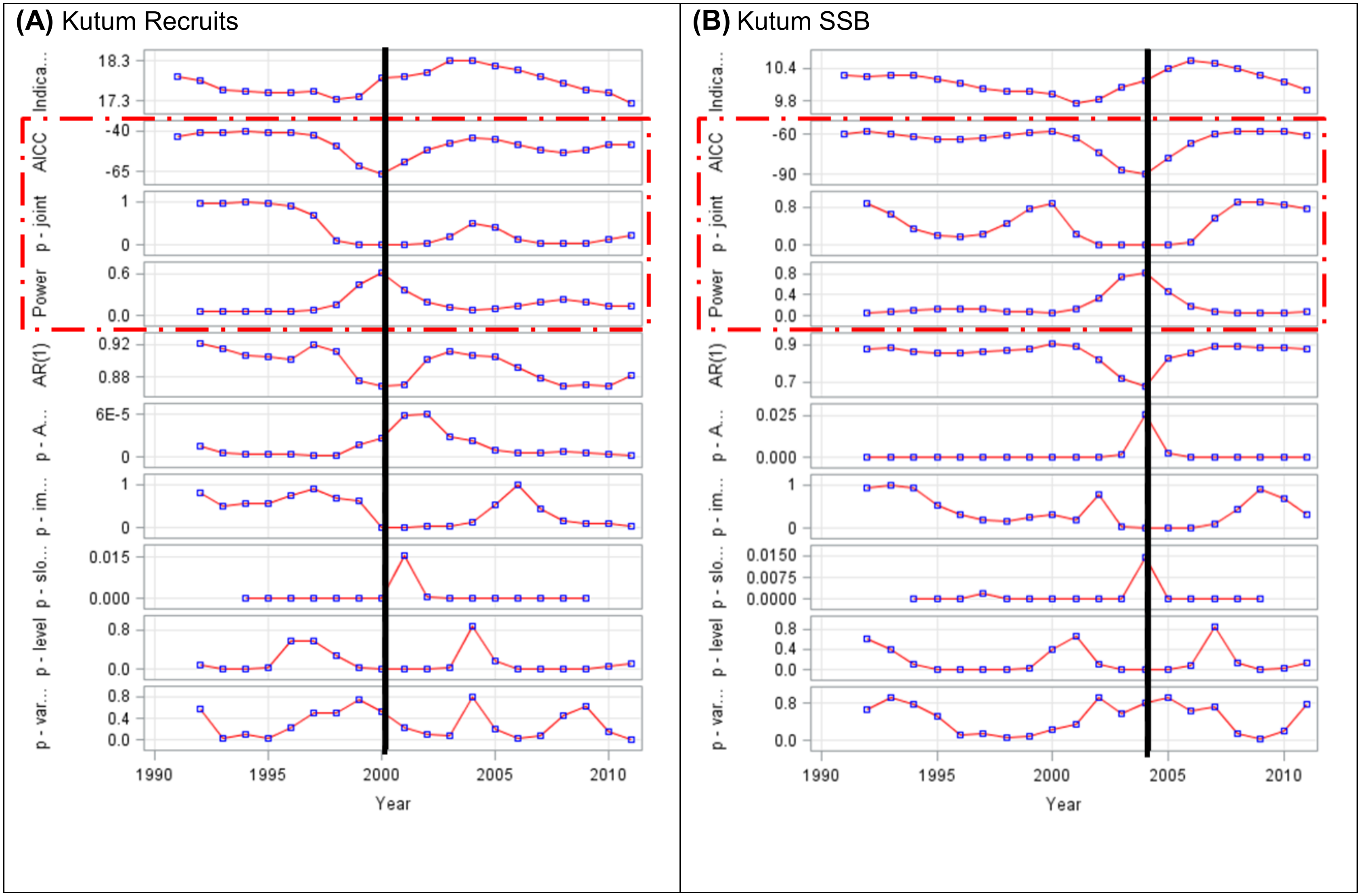

Figure 3-13. Continued.

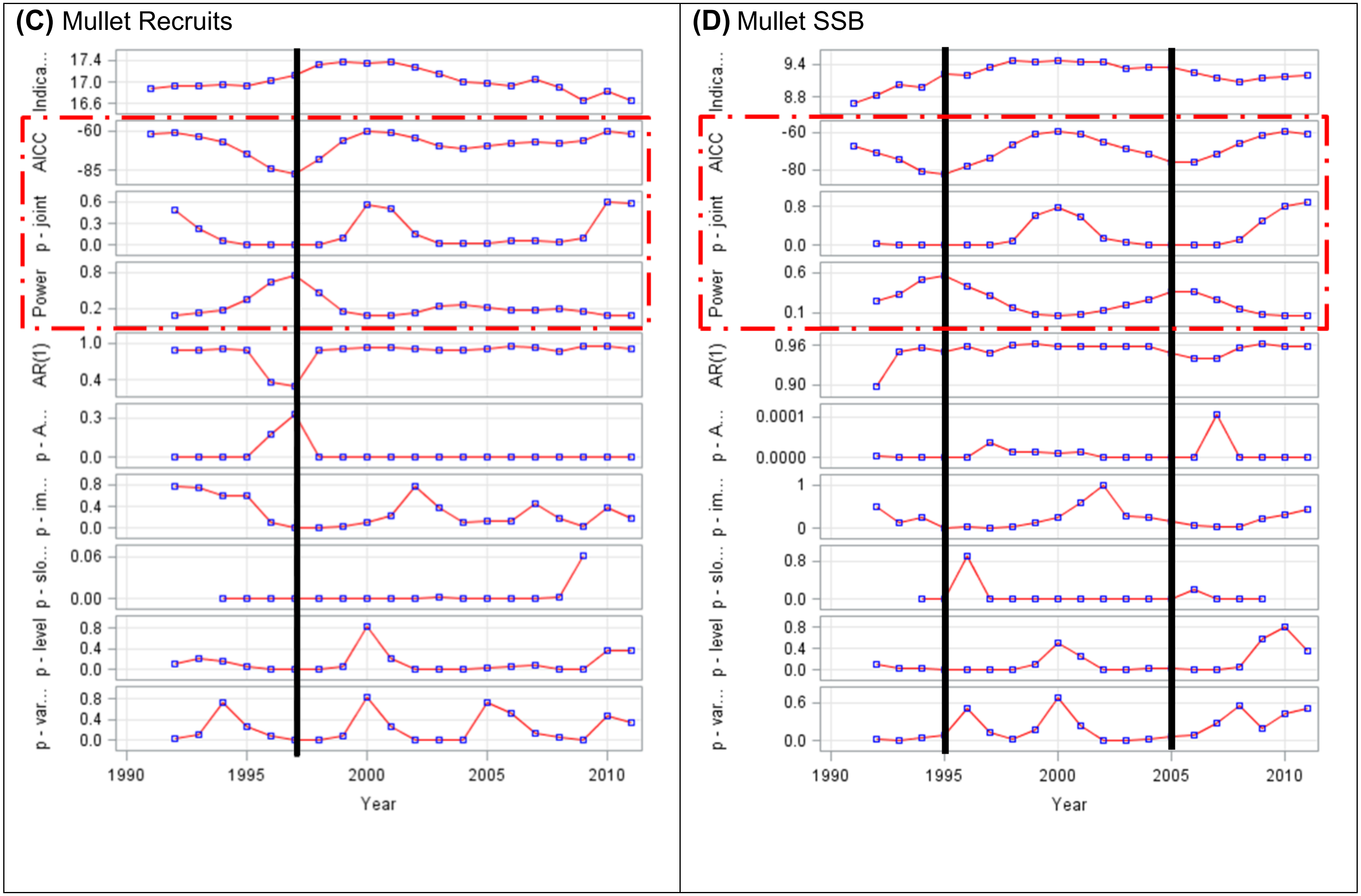

Figure 3-13. Shiftograms of (A and B) recruitment and SSB of the Caspian kutum; shiftograms of (C and D) recruitment and SSB of the golden grey mullet. The black vertical-continuous lines indicate location of strong structural breaks (years of shift occurrence); the open surrounding rectangle with red-broken lines shows the triple key-statistical indicators for recognizing the breaks (i.e. AICc, p-joint statistics and power).

3-2-3 Aggregated community and ecosystem proxies (multivariate indices)

To identify the potential shift patterns on higher levels of ecological organizations in the southern Caspian Sea, first the PCA technique was applied to aggregate the available data series and to develop a bentho-pelagic community as well as an ecosystem index. Then, from the set of PCs only the PC1s were taken as input for the shift detection procedure as these are expected to explain most of the relevant index variation (see Material and Methods; section, 2-2-2). In this context, the bentho-pelagic community index has been formed by the PC1 scores resulting from aggregating both species population components. In case of the ecosystem index all available data series were aggregated by PCA (i.e. fish, climatic and environmental time series) to finally generate the relevant PC1 scores. Given the different length and starting dates of the corresponding data series, the community and ecosystem indices were developed by using the overlapping time span of years 1991 to 2011 (period covering available fisheries-derived time series). Also, it should be noted that the Chl-a time series was not considered in developing the ecosystem index (due to a too short data coverage).

Similarly to using the shiftogram in case of the various univariate data analyses the shift detection algorithm treated the PC1 scores as a single variable. Hence, for the southern Caspian Sea Figure 3-14 displays the corresponding shiftograms for (A) the bentho-pelagic community index and (B) the ecosystem index during the period of this study. The results are explained below.

(A) Shiftogram of the bentho-pelagic community index. The shiftogram based on the PC1 scores representing the community index indicates two pronounced transition zones with almost similar patterns around the mid-1990s and mid-2000s (where not only AICc trajectories but also other key-statistics show a gradual transition) with their centers located in 1996 and 2004 (less strong), respectively. Inspecting the AICc shows that both shifts are well characterized by rather gradual, symmetric and deep valley-like patterns.

(B) Shiftogram profile of the ecosystem proxy. The shiftogram in case of the PC1 scores representing the ecosystem index indicated a rather distinct shift around years 1994-1995 and a less strong (minor and insignificant) one in year 2002. Based on the AICc diagram, the pronounced shift in the mid-1990's has a rather clear and deep valley-like pattern while the minor shift-like signal in 2002 exhibit a shallow valley pattern. There is no obvious difference between auto-regression behaviors of the time series around both shift locations.

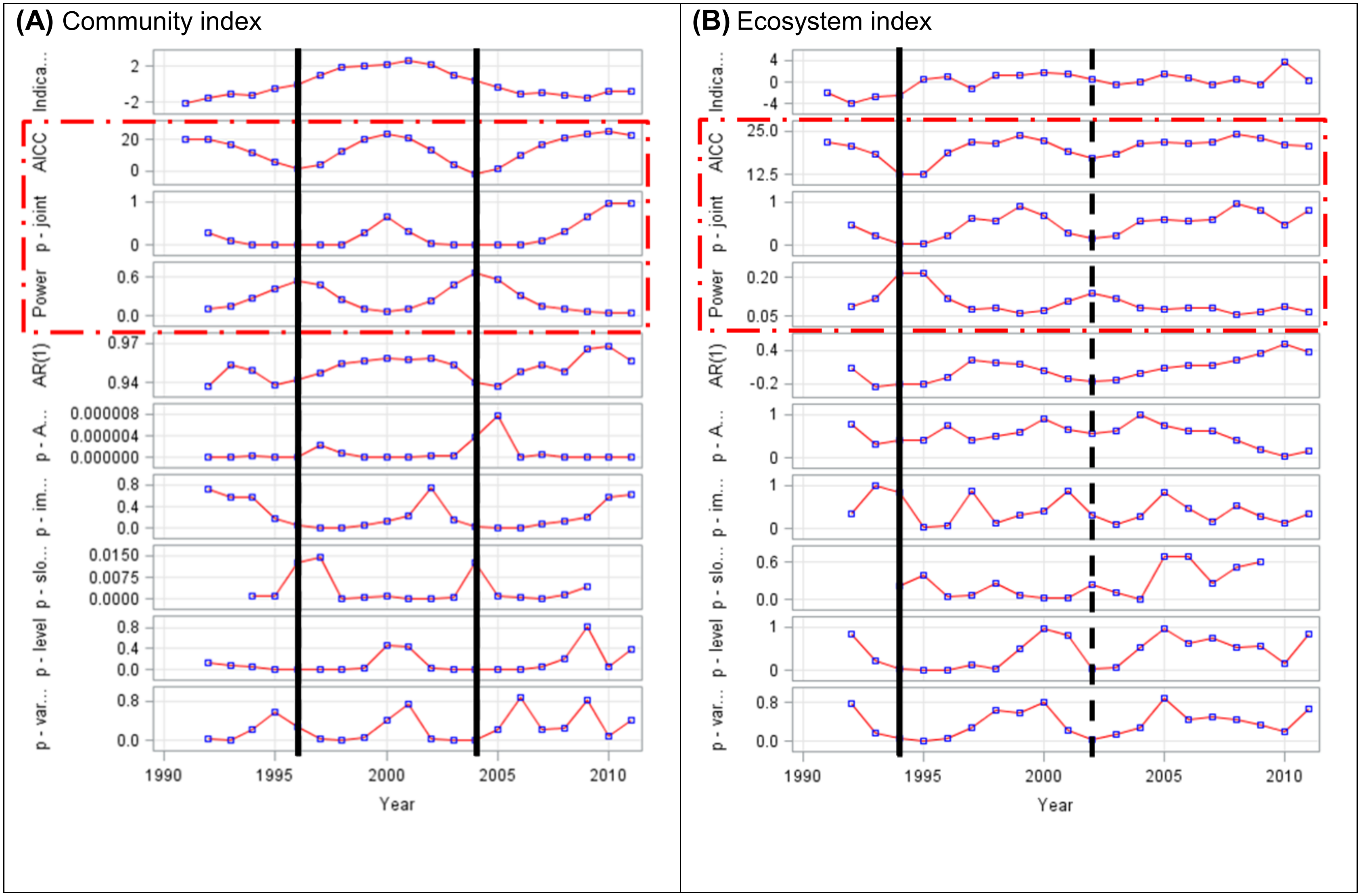

Figure 3-14. Shiftograms of (A) the bentho-pelagic community index time series and (B) the ecosystem proxy data series. The black vertical-continuous lines indicate location of strong structural breaks (years of shift occurrence); the black vertical-dashed lines indicate location of prominent(less strong and minor) shift-like signals; the open surrounding rectangle with red-broken lines shows the triple key-statistical indicators for recognizing the breaks (i.e. AICc, p-joint statistics and power).

Chapter 4: Discussion

The following chapter includes elucidating and interpreting the results of this study from the methodological and ecological perspectives. In this chapter, different aspects of complex climate/environmental variability impacts (see Introduction, sections 1-2 and 1-4) on the dynamics of bentho-pelagic species in the southern Caspian Sea will be clarified and critically discussed. Similar to the preceding chapters, the general structure of this chapter is also based on the approaches applied in this study, namely quantitative and qualitative or *sections I* and *II*, respectively.

4-1 DISCUSSION SECTION I (Quantitative approach)

4-1-1 Identified climate/environmental signals

The identified climatic/environmental signals (from the explorative cross-correlation analysis) reflect the strength of the temporal responses of the Caspian kutum and the golden grey mullet to gradual fluctuations of both, globally and regionally external forces. However, while in all cases the detected signals are obvious in the species responses indicating some stronger climatic influence, they lack statistical significance at a 5% significance level. Nevertheless, prevalence of the strong peaking signals (see Material and Methods, section 2-2-1-2) may aid in illustrating and apprehending the most likely climatic mechanisms involved in the population dynamics of the two bentho-pelagic species. The patterns of correspondence between both stocks components and the large-scale atmospheric processes/local environmental factors reveal quantitatively notable gradual ecosystem-driven signals (with different lag structure/temporal order) potentially impacting the bentho-pelagic species dynamics in the southern Caspian Sea. This part starts with a brief description/characterization of the obtained quantitative signals (separately for the species under consideration) and ends up identifying the potentially influential climatic/environmental mechanisms and a general discussion of the findings from cross-correlation analysis.

4-1-1-1 The Caspian kutum climate-/environmental-population relations

Cross-correlation results suggest that recruitment of Caspian kutum is strongly influenced by the NAO (both the all-year and winter indices) with a time lag of one year, addressing time-delayed NAO dependent effects. Apart from this, the further results indicate only a marginal relationship between parental stock size and the annual NAO (immediate response with no time delay). The observed temporal sequence pattern in the annual NAO signal impacting both R and SSB could be interpreted as an indication of a SSB-mediatory process in the population of Caspian kutum. This means, that the one year later observed annual NAO impact on recruits might be transmitted (at least partially) via the earlier-affected parental stock (with no lag). The Caspian kutum (both R and SSB) seems to be affected rather strongly by the SOI variability over the period considered. The SOI signals appear to act on dynamics of recruits in a manner that the yearly averaged index influences recruitment immediately and with one year lag, while the winter index impacts recruits with two years delay. Moreover, SOI (annual and winter) signals seem to affect the SSB with a similar temporal pattern (at 3 and 4 years lags). The general emerging patterns of SSB responses to SOI variation are expected to be translated (at least partly) from the earlier affected recruits (at lags of 0, 1 and 2 years). The identified (strong two year lagged) signal of SHI on recruits proposes a delayed-type effect while SSB appears not to be influenced by this climatic proxy. Cross-correlation analysis for the EA-WR pattern shows no obvious causal association with the Caspian kutum population quantities (both R and SSB).

Recruitment of the Caspian kutum has a strong correlation with SST at a lag of one year while the only slight response of SSB to the local thermal fluctuation seems to occur with a five year delay. The marginal response of SSB to the ambient SST is rather likely to be translated (at least partially) from the prior SST-impacted recruits. Finally, the cross-correlation (during the overlapping data period 1998-2011) suggests that recruitment of the Caspian kutum is unlikely to be affected by the annual surface chlorophyll-a (Chl-a) concentration. However, interestingly SSB seems to be strongly influenced by Chl-a, with a temporal pattern showing a delay of three and four years.

4-1-1-2 The Golden grey mullet climate-/environmental-population relations

Results of the cross-correlation analysis for the golden grey mullet (see Results, section 3-1-2-1, Table 3-4) suggest that almost all considered climate/environmental variables might be involved in recruitment dynamics and exert their potential impacts within lag periods of 1 to 5 years (except EA-WR, showing no strong signals). However, the detected SSB signals have a maximum lag of two years.

The annual NAO (at lag 1) seems to be the strongest signal on recruits (being on the edge of statistical significance) among all influential climatic/environmental parameters in the present study. This finding also confirms the delayed-type NAO dependent responses of bentho-pelagic stocks observed for the Caspian kutum. The results suggest that the SOI signals strongly affect the recruitment dynamics with a four year time lag. However, it should be noted that the observed annual signal on SSB (at lag 2) might be an indication of the existence of a via-SSB-mediatory process in the stock. The observed correlation patterns between SHI and the population metrics (R-signal at lag 5 and SSB-signal at lags 0 and 1) suggest a sign of via-SSB-transmission impacts potentially acting on the population dynamics of the golden grey mullet. Similar to the Caspian kutum, no obvious causal association (neither immediate nor delayed) was found between EA-WR and mullet recruits, except a two-year delayed signal for SSB. Thermal condition (expressed by SST) is most likely to act exclusively on the recruitment stage and exert its strong effects with a three year time delay. Lastly, the findings in this part suggest a similar time-delay pattern (at lag 2) for the correspondences between both R and SSB of the golden grey mullet and local chlorophyll concentration fluctuations in the southern Caspian Sea. Since Chl-a signals act simultaneously (in terms of temporal delay) on recruitment and adult stages, a via-SSB-transmission mechanism seems to be unlikely.

4-1-1-3 Potential climatic/environmental mechanisms and general pathways

The general temporal pattern of climate-/environmental-population correspondences suggests that - except a small number of immediate signals occurring without time-lags (i.e. NAO-SSB and SOI-R signals in case of kutum; and NAO-SSB and SHI-SSB signals in case of mullet) - all other climatic signals become detectable within lag periods of 1 to 5 years. Although the immediate responses could simply reflect the direct impacts of climate components on the population regulatory processes, the time lagged signals could only be perceived as to affect the population indirectly via intermediate marine physical-ecological processes. Concerning the temporally-delayed responses of the bentho-pelagic stocks to gradual climate-/environmental-induced alterations, the following general pathways (proposed by Post (2004); Fig. 4-1) may be persuasive in explaining the lagged signals: (1) atmospheric processes, (2) food-chain (trophic) interactions, and (3) species life-cycle history.

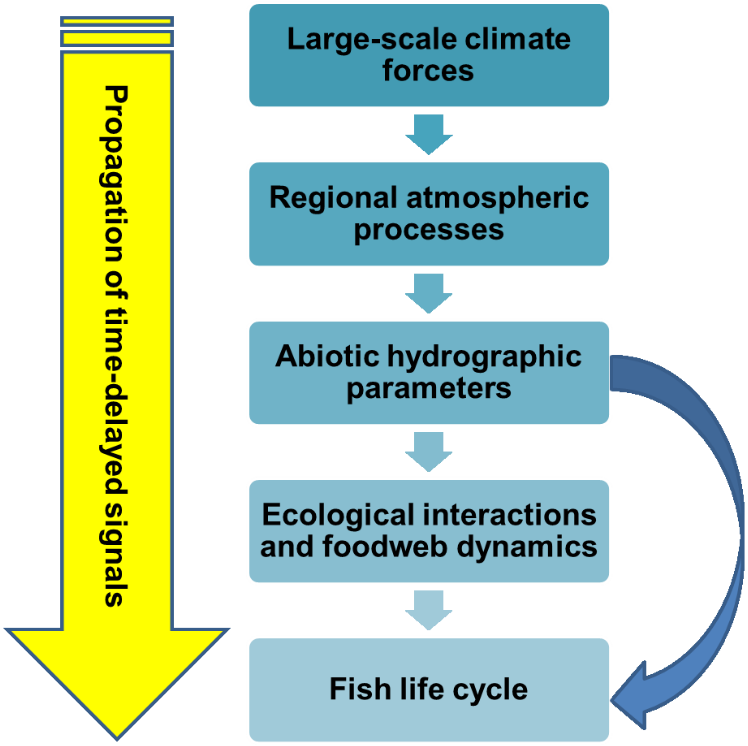

Figure 4-1. Propagation of time-delayed climate-/environmental-driven signals in marine ecosystems (partly based on Post, 2005).

Under (1), Post (2004) suggests that time-delayed climate-population signals may become apparent when the ambient physical factor(s) affecting population regulatory mechanisms is itself dependent on (and governed by) the driving atmospheric forces in the past. In other words, temporal lags may originate from a delayed development of local oceanographic features, such as current patterns and particular attributes of the aquatic environment (e.g. thermal and salinity condition) in response to the broad-scale climatic drivers (Gröger and Fogarty, 2011).

In the study region, dynamics of both northern- and southern-hemispheric large-scale atmospheric circulation forces (especially NAO and SOI) significantly influence the local meteorological system and hence the development of certain hydrological features (Arpe *et al.*, 2000; Panin and Diansky, 2014; Syed *et al.*, 2010; Barnston and Livezey, 1987; Rodionov, 1994; Panagiotopoulos *et al.*, 2002; Nezlin, 2005; Kosarev, 2005). Thermal condition and particularly sea level dynamics (water balance) are major physical oceanographic attributes in the Caspian Sea which are evidently linked to time-delayed atmospheric processes in accordance with NAO and SOI variations (Ginzburg *et al.*, 2005; Lougheed, 2006; Ghanghermeh *et al.*, 2015; Panin *et* *al.*, 2015). Several studies highlighted the direct role of global atmospheric circulation forces in regulation of moisture and heat fluxes (as major weather components) over the Caspian region. In general, sea surface temperature anomalies, precipitation, evaporation, rivers discharge, fresh water input and salinity are among the most important regional (weather-related) acting variables which are temporally (annual and seasonal) linked to the fluctuations of broad-scale climatic proxies such as NAO and ENSO (Arpe and Leroy, 2007; Brönnimann, 2007; Ginzburg *et al.*, 2005; Arpe *et al.*, 2000; McGuire, 2012; Molavi-Arabshahi *et al.*, 2015; Ghanghermeh *et al.*, 2015; Tuzhilkin and Kosarev, 2005). Moreover, climate forces may relatively trigger regional wind-driven currents and general hydrodynamic circulation regime in the Caspian Sea (Gunduz and Özsoy, 2014). The observed lagged signals from the large-scale climatic proxies in this study might (at least partly) be due to the delayed development of local hydrographic factors such as SST, salinity, currents velocity, etc., (resulting from intermediate physical operative mechanisms and interactions). According to the conducted cross-correlation analyses in the present study, the time-lagged SOI signals on recruitment of bentho-pelagic species (particularly golden grey mullet) could be explained partly by time-delayed influences of the southern oscillation atmospheric processes on regional SST variations. In other words, lagged responses of recruitment of bentho-pelagic species to SOI could be related to the lagged relationship between this global-scale proxy and thermal conditions in the Caspian region.

Such time-delayed processes originating from large-scale climate variability were also reported to affect the dynamics of different pelagic fishes (Kilka species) in the southern Caspian Sea (Khosravizadeh, 2015). However, it should be noted that the temporal propagation of climate-related signals for the pelagic Kilka species was different from that of the Caspian kutum and golden grey mullet in terms of (1) statistical significance and (2) time lag structure. On the one hand, climate-associated responses of Kilka species appeared to be significant (at level of 5%) during the period of study while climatic signals for bentho-pelagic species appeared to be quite likely but were statistically insignificant. On the other hand, the maximum detected lag period for climatic signals related to pelagic Kilka species was limited to two years while almost all climatic responses of bentho-pelagic species become detectable within lag periods of 1 to 5 years. The most probable speculation for these distinctions between Kilka (Khosravizadeh, 2015) and bentho-pelagic species (present study) could be associated with their different life-styles. As the entire life cycle of Kilka species is spatially restricted to the pelagic system (highly varying environment), it could be expected that these species are likely to exhibit stronger and more rapid climate-related responses than the bentho-pelagic species. This implies that the successive life-history stages of Kilka species in the pelagic environment are likely to make them more sensitive to direct abiotic climate-driven changes and indirect alterations in pelagic trophodynamic structures and interactions. In this context, life-cycle dependency of bentho-pelagic species to both the pelagic and benthic/demersal system (i.e. a more stable environment) might be considered as the major reason for evolving less strong signals with longer propagation times in the present study.

Under (2), it could be hypothesized that ecological interactions and food-chain dynamics may also be involved in prevalence of time-delayed climate related responses (Post, 2004). For the fish species inhabiting the bentho-pelagic subsystem, this can either concern pelagic or benthic trophic-webs dynamics. Therefore, any environmental change affecting food availability in both trophic structures may lead to indirect and delayed impacts on the bentho-pelagic fish populations. The feeding regime of bentho-pelagic species during the recruitment process (and early life stages) is mainly based on the pelagic planktonic communities. Thus, the environmental processes influencing primary and secondary productivity could play an important role in the development of the observed delayed signals. A recent study by Khosravizadeh (2015) investigated that variability of Chl-a concentration and algal bloom development (as primary production index) in the southern Caspian Sea are significantly linked to the time-delayed climatic effects of physical forces such as NAO, SOI and EA-WR. Furthermore, the populations of zooplankton species in the Caspian region are significantly associated with the time-lagged environmental impacts of NAO (Piontkovski *et al*., 2006). Hence, it is plausible to assume that at least a part of delayed responses of recruits are caused by indirect environmentally-induced changes in pelagic trophic web interactions.

Not only the pelagic food-web but also the benthic trophic interactions might be affected by physical changes. Availability of benthic-dwelling food sources especially during the post-recruitment phases may be crucial for bentho-pelagic species dynamics. Environmental processes may cause an alteration in local ecological-physical regimes impacting zoobenthic food organisms and consequently lead to indirect climate-responses of bentho-pelagic fish community. This can be one possible reason justifying the development of time-delayed reactions of parental stocks observed in this study. This speculation is in line with Gröger and Rumohr, (2006) who demonstrated significant delayed regulatory climatic/environmental processes (especially related to winter NAO and salinity) influencing the dynamics of macrobenthic fauna in the Baltic Sea.

In (3), Post (2004) refers to an alternative mechanism emphasizing on the importance of species life-history traits in development of lagged climatic-population reactions. Climate-/environmental-induced physical changes may influence the sensitive life-history attributes such as those involved in maturity processes, fecundity condition, timing of reproduction, etc. which could be reflected in the dynamics of a population during the following years. This also leads to prevalence of temporally-delayed climate-population signals operating through reproductive processes and mechanisms. The manifested lagged via-SSB-mediated climatic/environmental signals (transmitted to recruits) (see Results, sections 3-1-1-1 and 3-1-2-1) are perhaps associated with the life-history traits of bentho-pelagic species (particularly during the reproductive phase) in the southern Caspian Sea. This hypothesis is also supported by Fazli *et al*., (2008b), Fazli *et al*., (2012) and Fazli *et al.*, (2013) who demonstrated long-term variations in major life-history traits (e.g. fecundity, maturity and condition factor) of the Caspian kutum and golden grey mullet during the last two decades. Time delayed via-SSB-mediated environmental-driven impacts are not only limited to bentho-pelagic subsystem in the southern Caspian Sea. A recent study by Khosravizadeh (2015) also indicated lagged environmental signals (via-SSB, acting through life-history traits and recruitment dynamics) in pelagic Kilka populations of Iranian Caspian waters.

4-1-2 Recruitment dynamics of bentho-pelagic species

Understanding and assessing stock regeneration dynamics (recruitment variability) is fundamental to the ecosystem-oriented approaches for the sustainable exploitation of fisheries resources. Population structure and regulatory processes are influenced by a combination of internal drivers and external forces. In this study, recruitment variation of bentho-pelagic species (Fig. 4-2) in the southern Caspian Sea was analyzed in relation to stock-specific characteristics and multi-factor climate-/environmental-driven impacts. Linearization and extension of the classical Cushing model (by additional explanatory covariates) within a multiple regression setting allowed evaluating combined linear effects of inter-stock driving processes and extrinsic climatic/environmental parameters.

The overall findings from the baseline recruitment modeling step reveal rather weak but totally different (in nature) stock-recruitment relationships in bentho-pelagic species of the southern Caspian Sea, which may suggest important implications for regional fisheries management. In case of Caspian kutum, the annual stock enhancement program makes the recruitment variability pattern more complicated. Thus, analysis of recruitment was done differently for this species (see Material and Methods, section 2-2-1-1). The explorative and comparative examination of different population models involving potential relationships between the number of recruits and parental stock size, the number of released fingerlings and potential reproductive capacity for the Caspian kutum points out unexpected and rather interesting findings. On the one hand, intriguingly the results indicate an inverse dependence of recruitment on parental stock size implying the existence of a density regulatory mechanism in the Caspian kutum population dynamics (effect of SSB on recruitment through density dependency processes). Decoupled from the natural spawning process and thus from the amount of fish in the water, the reproduction mechanism, i.e. the expected functional linkage between SSB and R got disturbed if not lost through the stock enhancement program. However, even in a perfect world the control of SSB on R is only initially and hence partially triggered by the spawning stock through female egg production and the fertilization process, why stock-recruitment relationships appear to be imperfect in general. The reason is, that after releasing the eggs into the environment, external factors take over the control. On the other hand, unexpectedly the results suggest a very weak and insignificant association between the number of released fingerlings and the recruitment rate of the Caspian kutum. These findings are partly in agreement with Fazli *et al.*, (2012) who proposed, that ignoring the density-dependence phenomenon may undermine the positive influence of stock enhancement program on population dynamics of the Caspian kutum. Moreover, Borujeni *et al.*, (2015) while studying the economic profitability of the stock enhancement program, identified indications of density regulatory processes affecting the recruitment variability of the Caspian kutum (during 1989-2007).

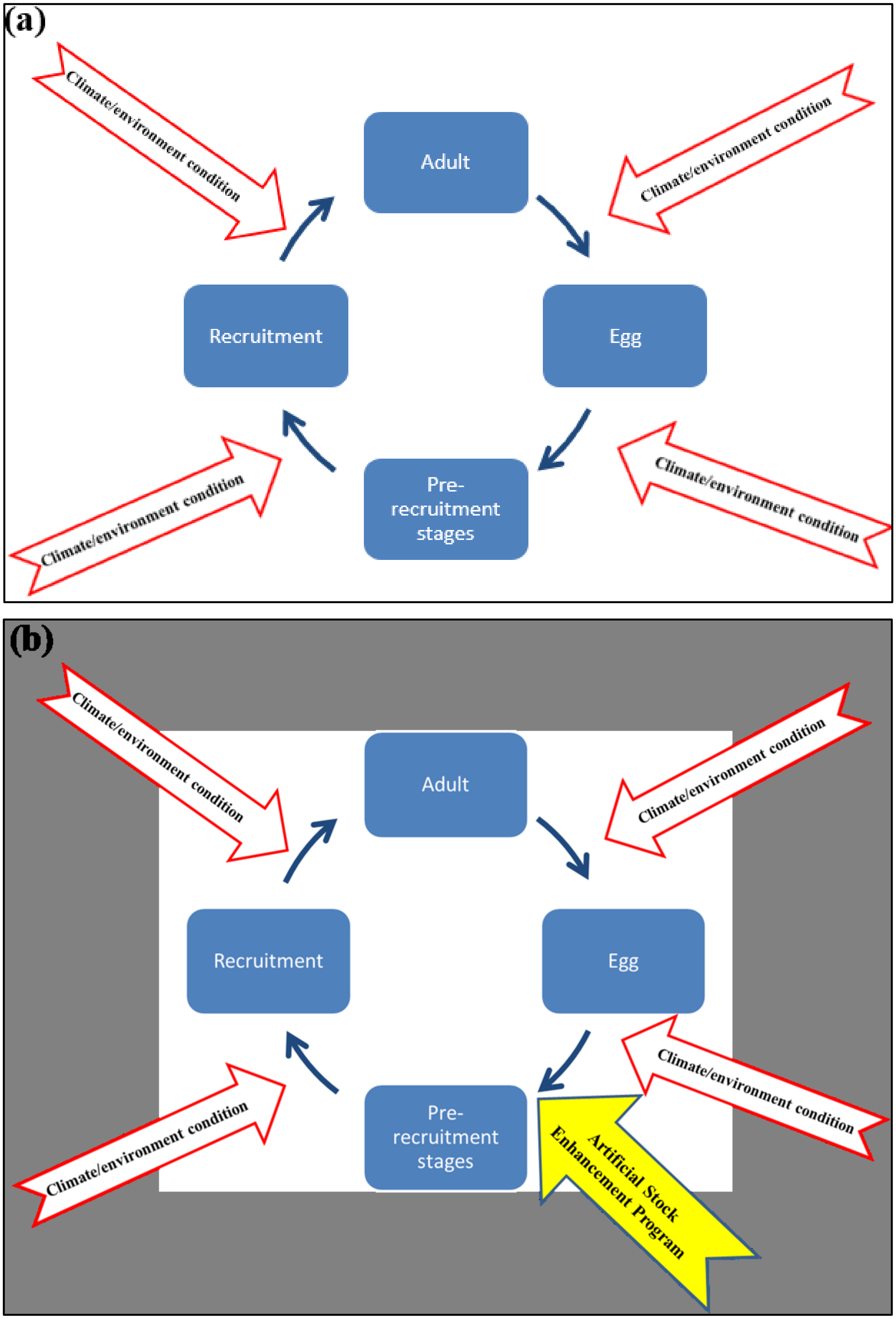

Figure 4-2. Hypothetical recruitment dynamics cycle for (a) Golden grey mullet and (b) Caspian kutum.

From the baseline recruitment models of Caspian kutum, it could be speculated that

(1) either the expected functional relationship between recruitment and SSB may be not only non-linear but completely deteriorated through the artificial stock enhancement program, and thus is not detectable by linear methods.

(2) and/or that the control over recruitment process is perhaps more or less solely through environmental conditions.

In contrast, the results for golden grey mullet from the basic recruitment modeling step suggest positive significant but relatively weak impacts of parental biomass on the recruitment variability. The findings suggest that SSB alone is a rather poor predictor for recruitment dynamics (about only 23% degree of explanation) of the golden grey mullet during the period of this study.

Including the linear combinations of detected climatic/environmental signals in the baseline recruitment models of both bentho-pelagic species does not significantly improve the model performance and statistical predictive ability. Interestingly, in case of both species the results of model extension procedure (through stepwise regression) reveals that recruitment appears to be primarily dependent on internal dynamic processes within the populations rather than the examined climate/environmental parameters. In case of Caspian kutum, the results indicate the statistically-best recruitment model is obtained when the lag-endogenous term Ln (R_{t-1}) is coupled to parental stock size on the regressor's side of the equation. In contrast, for golden grey mullet the best-fitting recruitment model is achieved not only by inclusion of the lag-endogenous term but additionally by elimination of the SSB term (i.e. pure lag-endogenous recruitment model). In other words, the statistically-dominant observed lag-endogenous effect tends to mask SSB-recruitment relationship in golden grey mullet stock. In summary, the results suggest that the internal time link in recruitment process seems to prevailingly explain the recruitment fluctuations of both bentho-pelagic species in the southern Caspian Sea over the period under consideration.

The lag-endogenous model (simplified first-order autoregressive time-series model) assumes that recruitment rate in any year can be projected as a function of last year's recruitment. Statistical dominance of auto-correlation behavior (sequential dependency) in recruitment series partly represented by the internal self-dynamics term (R_{t-1}) seems likely to be triggered by ambient physical driving forces. Generally, consistent (similar) external drivers significantly impacting the recruitment processes in succeeding years are most likely to mask (overlay) the causally-expected SSB-R or climate-R correlations. The self-dynamic (i.e. lag-endogenous) mechanism is of apparent nature: it does only seemingly represent a causal influence of preceding recruitments on succeeding ones. The truth is that this is a pure time link between subsequent recruitments: Such lag-endogenous models may simply express subsumed stable or consistent external effects (environmental/climate conditions) which have significantly influenced the recruitment processes in always the same way in succeeding years. A deterministic value supplemented from recruitment's self-dynamics term to conventional stock-recruitment models may help to improve short-term prediction of recruitment pattern. This could be even more plausible when the fit of stock-recruitment equation is obscure or when no apparent (single or combined) climatic parameters, that might regulate year-to-year variation of recruits (particularly under the condition of short time-series), are found. Moreover, the rather simple structure of the final recruitment models (developed in this study) might potentially help to make them more applicable in practical management actions because they are not relying on a subset of exogenous factors.

4-2 DISCUSSION SECTION II (Qualitative approach)

The worldwide occurrence of complex climate-induced ecological shifts in marine systems (which has been documented substantially) is one of the major challenges in bio-resources management (Möllmann and Diekmann, 2012; Möllmann *et al.*, 2015; Dippner *et al.*, 2012; Lees *et al.*, 2006; deYoung *et al.*, 2004; Jiao, 2009). Identifying potential shift patterns (as well as relevant causalities) in ecosystem components, structures and processes might lead to important implications for ecosystem-centered strategies aiming to achieve a sustainable long-term fisheries governance agenda. Reactions of ecosystem components confronting sudden shifts in external driving forces have a quite different character and conceptual nature (qualitative). Thus, being not assessable via conventional correlational statistics and quantitative causal dependency analysis (i.e. the correspondence could not be expressed on metric scale). Therefore, in complement to quantitative diagnosis of gradual climate-posing impacts, the second part of the present study focused mainly on the regional investigation of potentially-visible shift patterns, dynamics and causalities by applying the qualitative-statistical approach (i.e. "shiftogram") on a range of ecological and hydro-climatic variables in the southern Caspian Sea.

The shiftogram profile analysis highlight evident shift patterns in general hydro-climatic conditions of the Caspian region during the last two decades. The observed structural breaks in global-scale atmospheric forces might potentially act as one of the key-factors triggering the contemporary wide-range alterations in the Caspian ecosystem components, structures and functions. Analyzing data series of broad-scale forces for detecting the development and timing of shock signals demonstrates the following pattern: Apart from discrete shifts of NAO, SOI around late 2010's, all other shifts in atmospheric processes are mainly manifested during a decade from late 1980's until late 1990's. On the other hand, the thermal condition as one of the most crucial local-scale drivers displays a strong (with a long-transitioning period) shift signal during 1991-2000. It seems that the timing of shift development in SST time series is closely linked (and matched) to several shift events in various global atmospheric forces (i.e. NAO, SOI and SHI) particularly those occurred in the late 1980's to late-1990's. Qualitative correspondence of SST with atmospheric processes combined with the concurrent global warming trends on the regional-scale (especially in the southern Caspian Sea (Ginzburg *et al.*, 2005)) may partially reflect the complex climatic condition influences on the ecological dynamics in the Caspian environment.

The general perspective of the findings of the qualitative shift analysis of ecological proxies (i.e. Chl-a, key bentho-pelagic population's metrics, community and ecosystem indices represented by PC1s) suggest a potential causal dependency and chronological compliance with climatic-/environmental-driven shift events in the southern Caspian Sea. Obviously, almost all ecological time series exhibit evidences of major shifts during a period between mid-1990's and mid-2000ies. By comparing the timing of shift events among the investigated variables in this study (summarized in Table 4-1), the potential fingerprint of broad-scale climate forces (particularly those occurred in the late-1980's to late-1990's) is likely to be revealed. Cascading synchronicity (and coincidence) of multiple shift events in the hydroclimate-ecologic conditions of the southern Caspian Sea may demonstrate an empirical linkage between external forces and dynamics of ecosystem components/structures (illustrated graphically in Fig. 4-3). In this context, it could be hypothesized that external atmospheric processes may be partly involved in manifestation of the regional ecological shifts in the following order: global-scale climate forces → local environmental processes → biological components dynamics.

Table 4-1. Temporal profile of the identified shift patterns and break-like changes over a range of ecological and hydro-climatic variables in the southern Caspian Sea.

Temporal profile of the detected shifts	***1980's***	***1990's***	***2000's***	***2010's***
Large-scale climatic indices				
NAO	1989			2010
SOI		1999	2007	
SHI	1989			
Local environmental variables				
SST		1991-1999/2000 (**1994**)		
Chl-a			2001	
Bentho-pelagic species population's metrics				
Caspian Kutum Recruits			2000	
Caspian Kutum SSB			2003-2004	
Golden grey mullet Recruits		1997		
Golden grey mullet SSB		1995	2005-2006	
Community and subsystem indices (PC1s)				
Bentho-pelagic community index		1996	2004	
Ecosystem index		1994-1995	2002	

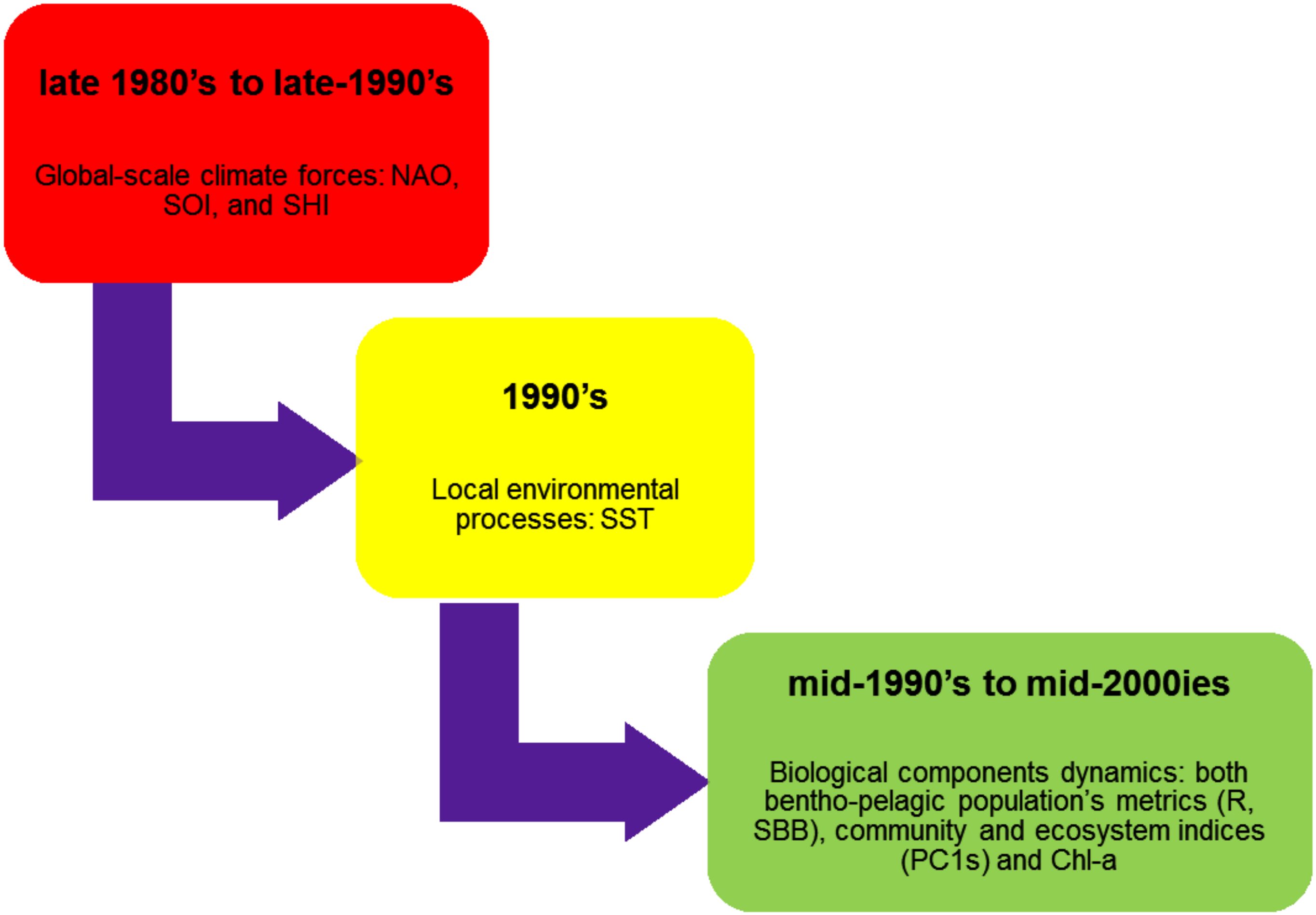

Figure 4-3. Cascading synchronicity (and coincidence) of multiple shift events in the hydroclimate-ecologic conditions of the southern Caspian Sea.

In this study, it was demonstrated that ecological shifts are an integral component of bentho-pelagic subsystem regulatory processes and dynamics. Qualitative correspondence and synchrony of biological responses of bentho-pelagic stocks (expressed by the population metrics/proxies) to hydro-climatic events is one of the supporting evidences that overall Caspian ecosystem structures and functioning might have – at least partially – been impacted by integrated global-scale climate-induced shifts. Furthermore, the concurrent shift signal in primary production (represented in Chl-a data series, covering period 1998-2011) could be assumed as a potential sign of coupled (interlinked) physical-ecological shifts influencing trophic structures/interactions and cascading intermediate food-web processes.

The explorative findings from the qualitative serial shift analyses in this study tend to correspond well with a series of parallel events and recent substantial ecosystem-wide changes in the southern Caspian Sea (i.e. overlap in temporal zone). In this context, a comprehensive review by Roohi *et al.*, (2010) suggested several empirical evidences of significant biotic alterations in the southern Caspian environment (particularly between mid-1990's and mid-2000's) including:

- Major change in primary and secondary trophic production of the ecosystem expressed by significant variations in demographical-phenological traits of local planktonic communities (both phyto- and zooplanktons structures) involving species diversity, abundance, biomass, size composition and seasonal blooming events.
- Appearance, increase in biomass, spatial distribution and outburst of the invasive comb jellyfish (*Mnemiopsis leidyi*) population.
- Structural changes in macrobenthic fauna including biodiversity, biomass, abundance and partial replacement of zoobenthic species.
- Drastic variations in local commercial fisheries especially decrease in catch and collapse of pelagic Kilka species.

Synchronicities of the above-mentioned structural changes in various ecosystem compartments, biodiversity and trophic structures/interactions in the southern Caspian Sea and the identified ecological shift signals (at species-, community- and ecosystem-levels) appear to be (at least in part) driven by physical processes caused by integration of exogenously-forced climatic feedback mechanisms.

4-3 CONCLUSIONS

Identifying, characterizing and evaluating complex behavior of ecosystem components in response to external physical drivers – particularly those related to ongoing climatic/environmental changes – is considered to be crucial towards ecosystem-based approaches in sustainable bio-resources exploitation and management strategies. For the first time, this study attempted to achieve general postulations about the so far neglected extrinsic ecosystem forces and their potential role in shaping dynamics of commercially important bentho-pelagic stocks in the southern Caspian Sea. The study was designated to clarify and integrate multi-dimensional aspects of the interactions between fish stocks, exogenous atmospheric climate forces, and environmental factors (by applying quantitative and qualitative approaches). The presence of different climate-/environmental-related processes and modalities in the Caspian region is reflected well in the findings of this study. The results suggest that climate-induced physical alterations exert their potential impacts on the bentho-pelagic subsystem components in different manners and pathways. The observed ecosystem impacts (potential quantitative and qualitative linkages) in this study could be categorized based on their attributes such as directness, temporal pattern, chronological structure and extent of impacts as well as the type of causal correspondences. In summary, the results (*SECTION I*) demonstrated that the examined climatic/environmental forces (i.e. NAO, SOI, EA-WR, SHI, SST and Chl-a) might have gradually influenced dynamics of the studied bentho-pelagic species either (a) at recruitment and/or adult life-stages, (b) directly or/and indirectly via intermediate physical-ecological processes and (c) immediately and/or within lag periods (time-delay) of 1 to 5 years. However, inclusion of the identified influential climatic/environmental variables to the basic recruitment models (in both case studies) did not improve the statistical explanatory performance of these population models. Further results of recruitment model extension procedure revealed that the single and/or multifactorial (combined) climate-associated impacts (quantitative explanatory power) were dominantly tend to be overlaid by the manifested internal self-dynamics processes in recruitment stage. This issue also seems to confirm the existence of superimposed but unknown mediating processes (e.g. continued physical condition changes resulting from specific climatic regimes) which influence inter-annual variability of recruits.

The role of climatic/environmental factors in regulating population dynamics of the species inhabiting the bentho-pelagic subsystem of the southern Caspian Sea is not limited to gradual impacts. The qualitative correspondences analysis (*SECTION II*) showed that the integrated synchronous climate-/environmental-driven shifts might have played a substantial role in shaping regional ecological dynamics, not only at species level but also at community and ecosystem levels (represented by PC1s).

The integrated quantitative and qualitative assessment of the climatic/environmental impacts in the present study may help to shed some light on the extensive ecological events (and consequently the underlying mechanisms) in the Caspian Sea especially during the last two decades. The findings represented here contribute basic knowledge on potential global and regional physical processes influencing the unique Caspian environment. Subsequently they may help to provide an essential basis to achieve ecosystem-based fisheries management plans in the area. Nevertheless, some questions remaining for upcoming investigations, involving:

1- Tracking a climate change footprint and assessing environmental impacts on multiple trophic levels by using regular long-term data (from the whole Caspian Sea) to get a deeper understanding about the potential impacts of the ongoing physical changes on overall food web dynamics in the ecosystem.

2- Developing and improving knowledge about the main ecological requirements, physical thresholds and habitat preferences of the organisms during different life stages (through laboratory experiments). This would lead to a better understanding of the underlying mechanisms involved in climatic-ecological interactions.

3- Taking into account the potential biological interactions and relationships among the species such as predation and competition in climate-ecological and population dynamics studies.

4- Using global climate models to predict future physical environmental changes on regional scales and their consequences for the biological communities inhabiting the Caspian Sea.

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Appendix

Table A-1. Matrix of Pearson's Correlation between input variables used in extending the SSB-based model for the Caspian kutum during study period (Modified SAS output).

Pearson Correlation Coefficients
Prob > |r| under H0: Rho=0
Number of Observations

	Ln (SSB)$_{t-2}$	WinterNAO$_{t-1}$	WinterSOI$_{t-2}$	SHI$_{t-2}$	SST$_{t-1}$
Ln (SSB)$_{t-2}$	1.00	0.09	-0.14	0.30	-0.16
		(0.723)	(0.560)	(0.211)	(0.516)
	19	19	19	19	19
WinterNAO$_{t-1}$		1.00	-0.15	-0.12	**-0.59**
			(0.521)	(0.601)	**(0.001)**
		21	21	21	21
WinterSOI$_{t-2}$			1.00	0.01	0.26
				(0.959)	(0.252)
			21	21	21
SHI$_{t-2}$				1.00	0.06
					(0.801)
				21	21
SST$_{t-1}$					1.00
					21

Table A-2. Matrix of Pearson's Correlation between input variables used in extending the PRC-based model for the Caspian kutum during study period (Modified SAS output).

Pearson Correlation Coefficients
Prob > |r| under H0: Rho=0
Number of Observations

	PRC$_{t-2}$	WinterNAO$_{t-1}$	WinterSOI$_{t-2}$	SHI$_{t-2}$	SST$_{t-1}$
PRC$_{t-2}$	1.00	-0.43	0.40	-0.08	**0.58**
		(0.068)	(0.092)	(0.754)	**(0.001)**
	19	19	19	19	19
WinterNAO$_{t-1}$		1.00	-0.15	-0.12	**-0.59**
			(0.521)	(0.601)	**(0.001)**
		21	21	21	21
WinterSOI$_{t-2}$			1.00	0.01	0.26
				(0.959)	(0.252)
			21	21	21
SHI$_{t-2}$				1.00	0.06
					(0.801)
				21	21
SST$_{t-1}$					1.00
					21

Table A-3. Matrix of Pearson's Correlation between input variables used in extending the model for the golden grey mullet during study period (Modified SAS output).

Pearson Correlation Coefficients
Prob > |r| under H0: Rho=0
Number of Observations

	Ln $(SSB)_{t-2}$	NAO_{t-1}	$WinterSOI_{t-4}$	SST_{t-3}	Ln $(Chl\text{-}a)_{t-2}$
Ln $(SSB)_{t-2}$	1.00	-0.17	0.10	**0.49**	-0.27
		(0.495)	(0.680)	**(0.035)**	(0.392)
	19	19	19	19	12
NAO_{t-1}		1.00	0.20	0.036	-0.46
			(0.381)	(0.878)	(0.136)
		21	21	21	12
$WinterSOI_{t-4}$			1.00	0.28	0.072
				(0.223)	(0.824)
			21	21	12
SST_{t-3}				1.00	-0.19
					(0.551)
				21	12
Ln $(Chl\text{-}a)_{t-2}$					1.00
					12

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