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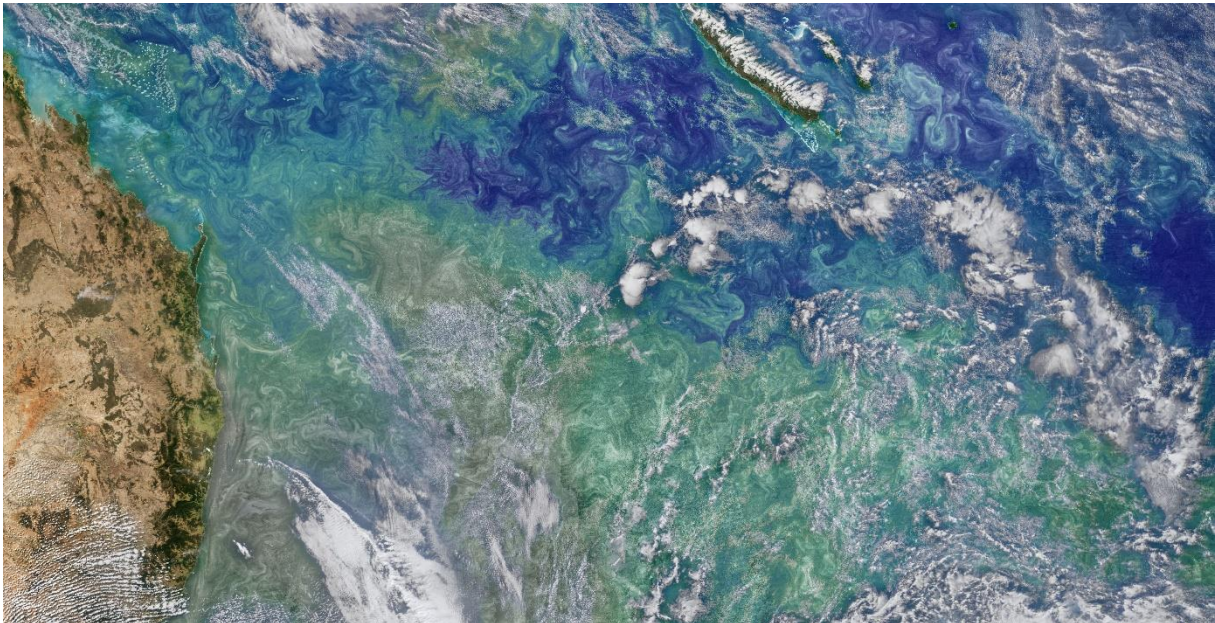


**THE UNIVERSITY
OF QUEENSLAND**
AUSTRALIA

Final Report

Modelling environmental changes and effects on wild-caught species in Queensland

Environmental drivers



**J. A. Filar, A. J. Courtney, L. J. Gibson, R. Jemison, S. Leahy, Y. Lei, M. Mendiolar, J. Mitchell,
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List of abbreviations

AIMS	Australian Institute of Marine Science
B	Biological
BBLT	Bottom Boundary Layer Temperature
BOM	Bureau of Meteorology
BRAN	Bluelink ReANalysis
CARM	Centre for Applications in Natural Resource Mathematics at The University of Queensland
CFISH	Commercial Fisheries Information System
Chl-a	Chlorophyll a Concentrations
CL	Carapace length of Spanner Crab
CPUE	Catch Per Unit Effort
DAF	Queensland Department of Agriculture and Fisheries
densSPR	Snapper Pre-recruit Nominal Density
DPI	Department of Primary Industries and Regional Development
E	Environmental
EAC	East Australian Current
EHMP	Ecosystem Health Monitoring Program Queensland
ENSO	El Niño-Southern Oscillation
FIS	Fishery Independent Survey
FON	Fraser Offshore North
FOS+SCO	Fraser Offshore South & Sunshine Coast Offshore
FRDC	Fisheries Research and Development Corporation, Australian Government
GA	Geoscience Australia
GBRMPA	Great Barrier Reef Marine Park Authority
GLM	Generalised Linear Model
GSLA	Gridded Sea Level Anomaly
H	Harvest/ Economic
IMOS	Integrated Marine Observing System
IOD	Indian Ocean Dipole
ITQs	Individual Transferable Quotas
JAMSTEC	Japan Agency for Marine-Earth Science and Technology
MB	Moreton Bay
MHW	Marine Heatwaves
MLR	Multiple Linear Regression
MLS	Minimum Legal-size
MSE	Management Strategy Evaluation
NSW	New South Wales
NM	Nautical Mile
NOAA	National Oceanic and Atmospheric Administration
OFAM3	Ocean Forecasting Australia Model version 3
PDO	Pacific Decadal Oscillation
QFB	Queensland Fish Board
QLD	Queensland
QLDRAC	Queensland Research Advisory Committee
RAPT	Rapid Adaptive Projections Tool
RO	Rockhampton Offshore
SCPUE	Standardised Catch Per Unit Effort
SEQ	South Eastern Queensland

SOI	Southern Oscillation Index
SP	Surplus Production Models
SPRR	Spawning Stock-Recruitment Relationships
SST	Sea Surface Temperature
TACC	Total Allowable Commercial Catch
TL	Total Length
u	East-West current
UQ	The University of Queensland
v	North-South current
w	Vertical current

Executive Summary

We report on the findings of a collaborative research project that was designed to identify and measure the effects of environmental drivers on the abundance and population dynamics of key Queensland fishery species. The project was co-funded by the Commonwealth Government's Fisheries Research and Development Corporation (FRDC) and carried out by a multi-disciplinary team of scientists from the University of Queensland (UQ), the Queensland Department of Agriculture and Fisheries (DAF) and the Australian Institute of Marine Science (AIMS). The research team applied modern statistical, data science and modelling techniques in combination with biological insights into the life cycles of the three target species.

Background

With increasing evidence that environmental conditions in the marine environment are changing rapidly, it is becoming ever more important to understand how these changes may impact on the population dynamics and abundance of important fish stocks. Understanding the influence of environmental conditions can provide greater certainty that the risk of overfishing (under adverse environmental conditions) or under harvesting (under favourable conditions) are accounted for by resource managers.

This project aimed to identify the environmental factors which may be influencing the recruitment, catchability or productivity of Snapper, Pearl Perch, and Spanner Crab stocks in Queensland. Results from this work will support sustainable management of Queensland's fisheries by directly informing the assessment and management of these key species within Queensland waters.

Aims/objectives

The project had three key objectives: (1) To find indices of association between the abundance of target species and key environmental drivers; (2) To use these indices to enhance the existing stock assessment models for each species; (3) To enable forecasting of environmentally driven fluctuations in target species' abundance, including enhancing Management Strategy Evaluations (MSEs), with the help of a Rapid Adaptive Projections Tool (RAPT).

Methodology

Target species – Spanner Crabs, Snapper and Pearl Perch – were selected by Fisheries Queensland (FQ) based on their categorisation as 'depleting' or 'depleted' in the national Status of Australian Fish Stocks Reporting (SAFS, 2018). Spatial and temporal statistical analyses were carried out on a range of environmental variables to investigate whether relationships existed with fishery dependent and independent datasets. A wide range of statistical techniques was utilised to test for associations between environmental indicators and measures of abundance. The techniques used included, but were not limited to: exploratory data analyses, correlation analyses, time series analyses, Bayesian Gaussian mixtures to search for clusters, lasso, ridge and trigonometric regression.

A novel modelling strategy was proposed to determine the most effective way to incorporate these environmental indices into stock assessment via: (a) surplus production models, and (b) generalised linear models for CPUE standardisation. These outputs were then incorporated into a user-friendly rapid adaptive projections tool (RAPT) to facilitate ease of engagement with end users.

Results/key findings

Across the three target species, Chlorophyll a concentration (Chl-a) and sea level anomaly (GSLA product) were found to have strong associations with either abundance or catchability of the three target species. These associations occurred at spatio-temporal scales relevant to each species' biology.

Snapper specific findings

Several environmental variables were found to have strong associations with either the abundance or catchability of Snapper. These included GSLA, sea surface temperature (SST), Chl-a, river discharge (truFlo), tidal range (TideR), Southern Oscillation Index (SOI) and others.

(1) There is evidence of a negative linear association between the fishery independent survey (FIS) pre-recruit density in November and December and SST in the preceding June and July (i.e. adult spawning period) in offshore areas where the majority of Snapper spawning stock is thought to be present.

(2) A threshold temperature sensitivity range of 19.8 °C to 21.8°C was identified for offshore Snapper during the known spawning season. A higher frequency and larger magnitude of temperatures above these thresholds in June were found to be negatively associated with subsequent Snapper FIS pre-recruitment, with a correlation value at or below -0.8.

(3) There is evidence of positive linear relationships between FIS pre-recruit density and Chl-a in the preceding June-October period in offshore areas and in the preceding September-October period within Moreton Bay. This is potentially related to high levels of primary productivity improving Snapper larval survival and/or growth rates in the plankton.

(4) A linear combination of SST in June and Chl-a in September was found to account for 75% of the variability in the FIS density of Snapper pre-recruits.

(5) There is evidence that FIS density of Snapper pre-recruits is an indicator of subsequent commercial line standardised CPUE in Queensland. The strongest correlation is between the density of Snapper pre-recruits and commercial catch rates four years later. Four-year-olds are typically one of the most abundant age classes in the Queensland Snapper line fishery.

Spanner Crab specific findings

Extensive analyses of Spanner Crab associations with environmental variables revealed a complex pattern of both positive and negative correlations occurring in the six different regions and on different time scales. The environmental variables that were found to have significant associations include (but are not limited to): GSLA, SST, Chl-a, SOI, components of ocean current velocity and marine heatwaves (MHW). There are indications that some of the differences in these associations are based on the large latitudinal gradient across the Spanner Crab management regions as well as on the cross-shelf depth gradient of the surveyed locations within each management region.

(1) Catch rate of legal-size crabs (i.e. carapace length (CL) of at least 100 mm) in Region 4, which produces the largest commercial catch of Spanner Crabs in Queensland, appeared to be insensitive to fluctuations in the following important environmental variables: Chl-a, GSLA (i.e. eddies and upwelling), SST, and MHW. Catch rate of legal-size crabs in Region 4 is positively correlated with bottom current speed during the month of capture (i.e. current speed appears to affect catchability).

(2) Chl-a is significantly associated with the catch rate of legal-size crabs in four of the five Queensland regions. Significant positive correlations in Regions 2, 3, 5 and 6 are present at multiple monthly lag times. Regions 2 and 3 are particularly strongly associated at the majority of time lags in the year preceding the catch. Chl-a is a proxy for primary productivity at the ocean surface, which is expected

to be beneficial to higher trophic levels in the plankton, such as larval Spanner Crabs. Given that Spanner Crabs captured in the fishery are likely at least 4 years old, the mechanism by which Chl-a influences catch rates the following year is unclear.

(3) GSLA is negatively associated with the FIS catch rate of legal-size crabs in three of the five Queensland regions. Significant negative correlations were found for Regions 2, 3 and 6, at multiple monthly lag times. The negative correlation with Spanner Crab FIS catch rates indicates that downwelling may be deleterious, while upwelling may be beneficial, to subsequent Spanner Crab catch rates.

(4) The direction of significant associations in Region 7 is generally opposite to those in Regions 2, 3 and 6. This applies to the correlations of the FIS catch rate of legal-size crabs with GSLA, Chl-a and SST. While the biological mechanism for this is unclear, it is conceivable that in this southernmost region the long-term warming trend could be beneficial rather than detrimental. Alternatively, these associations may be an artefact of large reductions in commercial fishing effort in this region in recent years improving local catch rates, coincidentally during the same period that GSLA and SST have been increasing and Chl-a has been decreasing.

Pearl Perch specific findings

There were no fishery independent surveys for Pearl Perch to permit similarly detailed analyses to those conducted on Snapper and Spanner Crab. However, CFISH data for the Queensland and NSW commercial Pearl Perch line fisheries revealed similar types of strong associations with Chl-a and GSLA.

(1) In Queensland, GSLA had a significant negative association with the standardised annual CPUE, lagged by 0 to 6 years. GSLA is an indicator of upwelling, downwelling, and eddy events. A negative association with SCPUE indicates that downwelling and warm-core eddies are deleterious to Pearl Perch catches, while upwelling and cold-core eddies have positive associations with Pearl Perch catches. Upwelling and cold-core eddies typically trigger primary productivity blooms.

(2) There were statistically significant positive correlations between Pearl Perch standardised annual CPUE and Chl-a, lagged by 0, 1 and 2 years. The current year (lag 0) yielded the strongest association, suggesting a positive effect of Chl-a on Pearl Perch catchability. This may be related to more active feeding by Pearl Perch during periods of higher productivity, such that they may be more likely to take bait and be captured.

Implications for relevant stakeholders

The identified association between Chl-a and GSLA and abundance indicators should be of particular interest to fisheries managers, as these factors were found to correlate negatively with stock productivity. Therefore, continued shifts in environmental conditions may have consequences for rebuilding stocks. In particular, this project identified long-term, persistent increases in GSLA and concurrent decreases in Chl-a, in line with the literature on climate change impacts on coastal oceanographic processes. As a result, our preliminary investigations incorporating these environmental variables into simple surplus production stock assessment models result, under some scenarios, in substantially increased times to stock recovery.

The outputs of this project inform fishery managers, industry stakeholders and the public about the possible associations and impacts of environmental variables on these fishery stocks, and considerations for future stock modelling and management strategies. More specifically:

1. The results from this project indicate that environmental variables can be used to inform future harvest strategy development through setting of reference points which reflect changes in

productivity and should be considered for incorporation into performance measures that are used to set harvest limits via harvest strategies. Further work is required to determine the preferred method for forecasting the effects of environmental variables on biomass into the future.

2. Fishery stakeholders need to be cognisant of possible, near term, adverse scenarios if the observed increasing trends in sea level anomalies and SST and decreasing trends in Chl-a continue.
3. Short-term surplus product model forecasts indicate that historical levels of harvest of these three species are unlikely to be achievable in the future. When environmental variables are incorporated in these models they suggest that, under some TACC scenarios, the re-building timeframes (to sustainable levels) are extended in each of the stocks.

Recommendations

1. Continue annual fishery independent abundance surveys of Snapper and Spanner Crabs to validate stock status and to optimise management procedures. Consider developing fishery independent monitoring of Pearl Perch recruitment using methods similar to those used to monitor Snapper recruitment. As the time series for the FIS abundance indices are relatively short, confidence in the study's main findings should improve with additional annual survey data.
2. Consider key environmental variables (GSLA, Chl-a, and SST) and their forecasts when developing harvest strategies.
3. Ideally, undertake targeted investigations which distinguish the effects of fishing from environmental effects, for example whether environmental associations are detectable in areas not subject to recent fishing pressure (protected or unfished area).
4. Investigate underlying causes of the relative resilience of Spanner Crab catch rates in Region 4 to environmental fluctuations, possibly with greater focus on oceanographic processes specific to that region.
5. Continue monitoring those identified, unexplained, associations between catch rates (both FIS and commercial) and key environmental drivers that may be indicators of enhanced, or stable, future harvests. For instance, in Regions 7 and 4 of the Spanner Crab fishery.
6. Regularly update the biomass ratio trajectories of Kobe plots in surplus production models as a simple, diagnostic tool of progress towards goals of MSEs.
7. Further explore the incorporation of environmental effects into the CPUE standardisation procedure for each species. The current procedure incorporates a categorical "year" factor, which likely absorbs much of the interannual variability potentially stemming from environmental conditions. Explicit and iterative replacement of the "year" factor, as well as seasonality parameters, with different environmental variables could identify and quantify the environmental conditions affecting catch rates. "Logbook grid" is a spatial explanatory term in the CPUE standardisation procedure in many Queensland fished species, which is also likely correlated with environmental influence. Hence, if environmental influences are incorporated in the standardisation GLM, inclusion of potentially redundant temporal (e.g. year) and spatial (e.g. grid) factors requires further consideration.
8. Empirically quantify fishing power for use in the CPUE standardisation procedures for Snapper and Pearl Perch.

Keywords

Snapper, *Chrysophrys auratus*, Spanner Crab, *Ranina ranina*, Pearl Perch, *Glaucosoma scapulare*, environmental drivers, stock assessment models, statistical analyses, correlation, regression, Bayesian models, age-structured models, surplus models, Southern Oscillation Index, marine heatwaves, ocean currents.

1 Introduction and Background

The sustainable management of Australia's fish stocks relies heavily on quantitative assessments of stocks of harvested species. These depend on databased, detailed, scientific stock assessment models, most of which do not currently account for the effect of fluctuating environmental factors (e.g. SST, primary productivity, surface currents) on marine systems. Deeper understanding of the influence of environmental factors on fish stocks will support adaptive management approaches, which can actively adjust harvest regulations in response to environmental conditions. This is increasingly important as climate change drives changes in environmental conditions leading to a complex range of phenomena which may influence the movement patterns, distribution and life history of fishery species in different ways.

The scientific challenge lies in quantifying the correct, evidence based, responses to fluctuations in environmental conditions that will benefit both the fishing stakeholders and the sustainability of the harvested species. We begin to address this challenge by identifying and quantifying the relationship between major environmental drivers and key parameters of fishery population dynamics for three species for which this information is lacking. We then incorporate these relationships into surplus production stock assessment models for each species. Currently, most stock assessment models do not explicitly include impacts of fluctuating environmental factors on key population biology parameters (e.g. recruitment, natural mortality) despite the fact that such impacts are known to occur.

The project has been developed to maximise its value to the sustainable management of Queensland fisheries. In particular, the project's three focal species - Spanner Crab, Snapper and Pearl Perch - have been adopted on request by Fisheries Queensland. These species are at high risk of depletion, may be at risk of range shifts as a result of environmental change, and are of significance to fishery stakeholders. Recent assessments of Pearl Perch and Snapper have found that populations of both species are between 10-40% of virgin biomass, which is well below the 60% unfished biomass by 2027 target of the Sustainable Fisheries Strategy. Furthermore, in 2018 Fisheries Queensland decreased the commercial Spanner Crab fishery quota by 50% to reduce pressure on the stock after a decade of decline in indicators of abundance. These declines in the three target species are likely driven by a combination of high fishing pressure, changes in fleet dynamics and environmental changes.

This project takes advantage of recent advances in remote sensing and modelling of the marine environment to enrich our understanding of environmental influences on the populations of targeted species. Improvements to stock assessment models for these species should result in better predictions for management of the stocks. These predictions can also be incorporated into Management Strategy Evaluations (MSEs) which are a scenario-testing approach that are used to determine an adequate management response (e.g. Total Allowable Commercial Catch (TACC) increase/reduction, duration of fishing season) to changes in population status indicators. Development of the Rapid Adaptive Projections Tool (RAPT) dashboard allows stakeholders to take ownership of the accumulated scientific knowledge and data embedded in the improved stock assessment models and to better visualise their projections.

The project addresses the FRDC National RD&E priorities (#1) well managed sustainable fisheries and (#3) maximising benefits from fisheries. The overall objectives of the project are also supported by the Great Barrier Reef Marine Park Authority (GBRMPA).

1.1 Background Information on Target Species

1.1.1 Snapper, *Chrysophrys auratus* – biology and management

Snapper, *Chrysophrys auratus* (formerly *Pagrus auratus*) are distributed throughout the central Indo-Pacific. In Australia, it inhabits coastal waters around southern Australia, from Mackay in Queensland to Exmouth, Western Australia. It is a long-lived, slow-growing fish targeted in commercial, recreational and charter fisheries. Currently, the Queensland portion of the east Australian stock is classified as depleted (below 20% of virgin biomass levels) (Wortmann *et al.* 2018). In this sub-section we briefly outline the main aspects of Snapper biology and ecology that are relevant to the current project.

Life cycle & habitat

Snapper spawn in offshore areas during winter (May to October), synchronised with the lunar cycle (Wortmann *et al.* 2018). The exact timing and duration of spawning is further influenced by water temperature (Scott and Pankhurst 1992; Francis 1993; Lenanton *et al.* 2009). For example, cooler water temperatures in NSW leads to later spawning (Hamer *et al.* 2011; Scott and Pankhurst 1992). Larvae are present in the plankton for 4-31 days, where they feed on phytoplankton and smaller zooplankton. Ocean currents can transport Snapper larvae large distances, generally in a southerly direction due to the flow of the East Australian Current (Sumpton *et al.* 2008). After this time, juveniles settle into sheltered inshore bay nursery areas, such as Moreton Bay, where they feed mainly on small crustaceans, worms and other invertebrates (Usmar 2012).

Adults are found in coastal marine waters to a depth of 200 m and feed mainly on small fish, cephalopods and hard-shelled invertebrates. In Queensland, Snapper typically reach maturity at 26-32 cm (1.7-3 years old). However, this varies with latitude, with subtropical Snapper exhibiting faster growth rates than those in temperate waters (Wortmann *et al.* 2018). The maximum life span of this species is thought to be greater than 30 years, however fish this age are very rare in Queensland, where 90% of fish caught are less than 10 years old.

Spatial extent

Snapper are distributed widely across western, southern and eastern Australia. Within Australian waters, there are 12 genetically or biologically separate Snapper populations (Fowler *et al.* 2018). The east coast population extends from Mackay (21°S) to Eden on the Southern NSW border (38°S) (Morgan *et al.* 2019). Southward larval transport is thought to be the key mechanism responsible for mixing of this stock (Stewart *et al.* 2020) but larval dispersion models indicate ~5% of larvae spawned in northern NSW are transported to QLD (FRDC 2018-074 preliminary results). Results from a large-scale tagging study indicate that adult Snapper generally move over relatively small areas (<20 km), with limited movement of adults out of Moreton Bay (Sumpton *et al.* 2003b).

Queensland Snapper fishery management

Due to the popularity of Snapper as a target species for commercial, charter and recreational fisheries (with approximately 75% of the catch coming from the recreational and charter sectors), there has been extensive fishing pressure on this species for decades. This consistent high fishing pressure has contributed to declining biomass over time. Recent assessments of Snapper abundance within Queensland waters estimate the biomass at <20% of virgin levels (Wortmann *et al.* 2018). To reduce the impact of fishing mortality on the stock, increasingly stringent management measures have been introduced over the past 20 years. Management measures that apply to all fishing sectors in Queensland include a minimum legal-size (MLS) of 35 cm and a state-wide seasonal spawning closure

from 15 July to 15 August (introduced in 2019). In addition, recreational and charter fishers are limited to an in-possession limit of 4 fish per person (with one fish >70cm) and commercial fishers are limited to a 42 t TACC.

Available fisheries data

Both fisheries-dependent and fisheries-independent datasets are available for this species. Commercial daily catch data are available from mandatory logbooks from 1988, with catch recorded at 30 nautical mile (NM) grid cells (6 NM where possible). Comprehensive charter fishing data on both retained and released fish are available for the Gold Coast region from 1993 to 2010; and charter logbook data for the wider sector are available from 1993 to the present. Recreational catch data have been collected through boat ramp and phone-based survey approaches since 1995, with state-wide surveys taking place every 2-5 years. These surveys collect information on the number of fish caught and their length. The state-wide creel surveys are designed to collect information on the recreational fishing population and their fishing activities, rather than information on the abundance of target stocks. As a result, this data does not provide an index of abundance, limiting its use in assessing trends in Snapper abundance. Age and length frequency data are available across all fishing sectors since 2007, although this was discontinued for the charter fishery after 2011.

Commercial fishing logbook data are used to develop standardised catch rates for Snapper. The catch rate standardisations use the statistical application of linear mixed models using restricted maximum likelihood as outlined by Wortmann *et al.* (2018) and include latitude (defined by one degree latitude bands), lunar phases, wind speed and direction, year, month, and fishing power to account for variation in gear technologies (the impact of GPS, colour sounders, electric fishing reels and four-stroke engines) on fishing.

Juvenile Snapper are caught in a fishery independent beam trawl survey (FIS), conducted annually since 2007, excluding 2016. The FIS catches juvenile, young-of-year Snapper from 3 to 13 cm total length. The FIS is conducted in November and December in five locations: Moreton Bay, offshore of Moreton Island, offshore of Stradbroke Island, Hervey Bay, and offshore of Fraser Island at Double Island Point (Bessell-Browne *et al.* 2020). The consistent methodology and sampling design of this survey ensures that it provides a robust index of catch-per-unit-effort for this species, which can be used as an index of abundance.

Potential environmental influences

The influence of environmental variables on Snapper abundance and catchability has been studied throughout Australian and New Zealand waters. Temperature has been shown to influence spawning patterns (Lenanton *et al.* 2009), with an optimal spawning temperature range of 19-21°C for this species (Wakefield *et al.* 2015). The larval phase of Snapper is also sensitive to temperature, with optimal growth and development occurring between 18-22°C and 100% mortality occurring above 27°C (Mihelakakis and Yoshimatsu, 1998; Fielder *et al.* 2005). In New Zealand, the abundance of one year old Snapper was significantly influenced by temperature in April-June of the preceding year and accounted for 94% of the variation in one year old Snapper abundance (Francis 1993). However, a linear relationship between temperature and Snapper abundance was not recorded during research in southern Australia (Fowler and Jennings 2003). Overall, warming ocean temperatures are projected to have negative impacts on spawning and larval growth of Snapper in Queensland waters, with the optimal 19-21°C temperature window becoming shorter and potentially ceasing to occur altogether by mid-century (Hamer *et al.* 2011).

Southward transport of Snapper larvae by the East Australian Current (EAC) is thought to be a key process driving mixing of the Australian East Coast Snapper population, with larvae being transported

from Queensland into New South Wales (Sumpton *et al.* 2008). Therefore, any future changes in the EAC are likely to influence this dispersal pattern. Indeed, the EAC has strengthened by 20% and now penetrates 350 km further south (Ridgway 2007), which may have already influenced Snapper larval dispersal.

In a New Zealand study, Sim-Smith *et al.* (2013a) found that temperature, tidal range and onshore winds explained up to 38% of the variability in the abundance of newly settled juvenile Snapper. Specifically, larval recruitment success was found to be higher in conditions of large tides and stronger onshore winds (Sim-Smith *et al.* 2013b).

Moreton Bay is a key settlement area for Snapper in Queensland; therefore riverine inputs could be expected to have important influences on juvenile Snapper abundance. Specifically, higher rainfall can lead to increased outflows into Moreton Bay, leading to increased productivity as nutrients enter the bay from rivers.

Based on the range of variables that have been found to influence Snapper abundance in Australian and New Zealand waters previously, as well as those theorised to have impacts due to the specific conditions that occur within Queensland waters, our search for environmental influences included, but was not limited to, the examination of:

- SST range, mean, minimum/maximum, 10th and 90th percentiles,
- The occurrence, strength and duration of MHWs
- Bottom temperature range, mean, minimum/maximum
- Chl-a, range, mean, minimum/maximum
- EAC strength
- Onshore wind strength, duration, timing
- Tidal range

1.1.2 Pearl Perch, *Glaucosoma scapulare* – biology and management

Pearl Perch (*Glaucosoma scapulare*) are found in offshore waters along the east coast of Australia. They are a prized eating fish frequently targeted by both commercial and recreational fishers using line fishing techniques. The harvest of Pearl Perch is managed separately by Queensland and NSW. Pearl Perch were a secondary target species in the Queensland rocky reef fishery; however, declining Snapper catch rates in the late 1990s resulted in fishers targeting Pearl Perch instead (Sumpton *et al.* 2013). In 2015 Pearl Perch were classified as “depleted” in the Status of Australian Fish Stocks. This listing was based on a spawning stock biomass estimate below the 20% threshold for an overfished stock (Sumpton *et al.* 2017). There remain significant gaps in knowledge concerning the life cycle and reproductive biology of this species. The list of main project-pertinent issues discussed below is based primarily on Stewart *et al.* (2013), Sumpton *et al.* (2013) and Sumpton *et al.* (2017).

Life cycle & habitat

Until recently, the reproductive biology of Pearl Perch was unknown (Stewart *et al.* 2013). Prior to 2010, spawning animals had not been recorded from the traditional fishing grounds in southern Queensland and northern New South Wales. This led researchers to hypothesise that the species undertook a northward spawning migration like tailor (*Pomatomus saltatrix*) and sea mullet (*Mugil cephalus*), and the resulting larvae were dispersed southward by the EAC. Since 2010, spawning animals have been sampled in commercial catches from the Swains Reef area (22°S) and in deeper (>180 m) water offshore from the Sunshine Coast and Fraser Island. Current research suggests that

individuals may make cross-shelf migrations into deeper waters to aggregate for spawning; however, this remains unsupported at this time.

The larval period of Pearl Perch is thought to be approximately 45 days, based on the congeneric *G. hebraicum* (Pironet and Neira 1998). Previous research indicates juveniles are present over sandy substrates, where they are caught by prawn trawl vessels targeting eastern king prawns (*Melicertus plebejus*) (Montgomery *et al.* 2007) and by fishers targeting sand crabs (*Portunus armatus*) using pots in southern Queensland (Sumpton *et al.* 2003a). As adults, Pearl Perch form schools around submerged reefs, pinnacles, and rocky seabeds at depths of up to 250 m. They are also known to aggregate over shipwrecks, gravel substrates and adjacent areas, particularly those where gorgonian sea whips occur. In contrast to Snapper, the Pearl Perch life cycle occurs exclusively in offshore (>20 m deep) areas.

Pearl Perch mature at ~26 cm TL (L_{50}) (Sumpton *et al.* 2013). Age-at-maturity is unknown at present; however, this metric is being quantified as part of current research (FRDC 2018-074). Pearl Perch grow to at least 75 cm TL and >25 years old. Queensland fish exhibit faster growth rates than those from New South Wales (Stewart *et al.* 2013). Fishery dependent sampling indicates Pearl Perch were fully recruited to the fishery at five years at the MLS of 35 cm TL, although this is likely to change slightly given the MLS has recently increased to 38 cm TL.

Spatial extent

Pearl Perch are endemic to the east coast of Australia between Mackay (21°S) and Newcastle (33°S). Traditionally, Pearl Perch were targeted in Queensland offshore from the Sunshine Coast, Brisbane and the Gold Coast. However, as the populations in these areas declined, fishers moved to areas well offshore and to the northern extent of the species' range (Sumpton *et al.* 2013). The introduction of modern marine electronics, particularly GPS, have facilitated this shift.

As a result of their limited range and the southerly movement of the EAC, Pearl Perch should be considered a single biological stock (Stewart *et al.* 2013). However, recent research has shown that the timing of spawning differs throughout the species' range: spawning appears to occur September to December in the Swains Reef area and March to May in Southern Queensland. Current research (FRDC project 2018-074) is collecting genetic information from fish across the species' distribution to determine if a sub-population may be present in the northern part of the species' distribution.

Queensland Pearl Perch fishery management

Prior to 1993, catch restrictions were absent. In 1993, an MLS of 30 cm TL, and a bag limit of ten were introduced. In response to declining catch rates, the MLS was increased to 35 cm and the bag limit was reduced to five in 2003. In 2011, a six-week closure was introduced for Snapper, Pearl Perch and teraglin between 16 February to 31 March to reduce fishing mortality; this closure was not repeated. In 2019, the MLS was further increased to 38 cm and the in-possession limit further reduced to four. In response to the requirement imposed by Fisheries Queensland to reduce catch by 30%, a one-month closure was introduced between 15 July and 15 August. This closure is likely to be ongoing. In line with the broader management changes, a 15 t TACC was implemented for Pearl Perch in 2019.

On easily accessible fishing grounds, fish size is skewed toward the MLS. Larger fish occur in areas where fishing effort is relatively low. Several large aggregations have been located, and are characterised by a high proportion of large, older individuals. Such aggregations are likely to be subject to increasing fishing pressure in future due to the introduction of automated fishing equipment, such as electric reels and increasingly powerful (2 kW) sounders.

Available fisheries data

The Queensland Fish Board (QFB), which was responsible for marketing fisheries product, collected catch information from 1936 until 1981, but these data are unreliable for Pearl Perch. Commercial daily catch data are available from mandatory logbooks from 1988 at 30 nautical mile (NM) grid cells (6 NM since about 2005). However, prior to 2003 Pearl Perch were reported by commercial fishers on an *ad hoc* basis. Logbook data have been used to develop standardised catch rates using the same approach outlined for Snapper (see Wortmann *et al.* 2018, for details). Charter fishing logbook data are collected and include Pearl Perch that are retained or released. Recreational catch data are available from both state-wide creel recreational fishing surveys and boat ramp surveys. Age and length frequency data are available across all fishing sectors from 2007 onwards. Unlike Snapper, Pearl Perch are not subject to fishery independent monitoring.

Potential environmental influences

According to Sumpton *et al.* (2017) Pearl Perch differ from other rocky reef species (such as Snapper) for which the spatial and temporal extent of spawning are relatively well known. There is increasing certainty around Pearl Perch spawning and reproductive biology: spawning is occurring at the northern end of the species' range and in deeper offshore waters off the Sunshine Coast. Therefore, EAC dynamics and eddies are likely to influence the dispersal of Pearl Perch larvae southwards into southern Queensland and New South Wales. In addition, lunar phase may influence the timing of spawning. Increasing water temperatures on traditional fishing grounds may see Pearl Perch move southwards and eastwards to deeper water to cope with increasing water temperature. However, this potential temperature effect may be masked by the shift in fishing effort towards the north due to depletion of stocks in southern fishing grounds (FRDC 2018-074 preliminary results).

1.1.3 Spanner Crab, *Ranina ranina* – biology and management

Spanner Crab (*Ranina ranina*) is a widely distributed species across the Indo-Pacific. On the east coast of Australia, Spanner Crabs inhabit waters along the continental shelf (0-200 m). Currently, the status of Spanner Crab on the east coast of Queensland is listed as 'depleting' under the Status of Australia Fish Stocks, after over a decade of decline in population status indicators (Fowler *et al.* 2018, and State of Queensland 2019). In this sub-section we briefly outline the main aspects of Spanner Crab biology and ecology that are relevant to the current project.

Life cycle & habitat

Spanner Crab spawning can occur from October to January, and peaks in November and December (Skinner and Hill 1987; Minagawa *et al.* 1993). Females carry the fertilised egg mass (giving them a "berried" appearance) for 24 to 43 days, after which the eggs are released and hatch in the plankton (Minagawa *et al.* 1993). Larval Spanner Crabs, called zoea, spend 5 to 9 weeks in the plankton (Minagawa 1990). Their dispersal at this stage is strongly dependent on oceanic and tidal currents. Spanner Crab zoea metamorphosise and settle to the sea floor as megalopa between early February and mid-April, where they prey on small interstitial and demersal invertebrates (Vicente *et al.* 1986). As they grow into their adult form, their diet shifts to scavenging and preying on larger invertebrates such as polychaetes and other crustaceans (Vicente *et al.* 1986). Adult Spanner Crabs prefer sandy substrates, with minimal vertical structure and minimal silt content (Brown 1994). They can be found in shallow intertidal waters through to at least 100 m deep, with the majority of catch coming from the 30-80 m depth range (Dichmont and Brown 2010). Adult Spanner Crabs spend most of their time buried in the seafloor to avoid predation (Skinner and Hill 1987). This is especially true during their moulting period in February/March, during which time catchability is distinctly reduced (Skinner and Hill 1987). Spanner Crabs can attain a maximum carapace length of approximately 150 mm for males and 110 mm

for females (Kirkwood *et al.* 2005), which is estimated to occur around 15 years of age. However, the relationship between age and carapace length in this species is unclear due to lack of a reliable structure for ageing and low survival of Spanner Crabs in tagging studies (Brown *et al.* 1999, 2008).

Spatial extent

Spanner Crabs are widely distributed across the Indo-Pacific, with fisheries in Hawaii, southern Japan, Taiwan, the Philippines, Indonesia, Thailand, the Seychelles, and Australia. In Australia, Spanner Crabs inhabit waters along the continental shelf of the east coast of Australia, from Yeppoon in Queensland (23°S) to the northern coast of New South Wales (29°S) and are also present off the coast of Western Australia. The Queensland/NSW population of Spanner Crab is assumed to form a single biological stock (Brown *et al.* 1999). The commercial Spanner Crab fishery area has shifted away from some traditional grounds (e.g. Hervey Bay) after large reductions in catch and catch rate.

Queensland Spanner Crab fishery management

Spanner Crabs in Queensland are captured by entanglement in baited, bottom-set dillies, which are size-selective, minimising the catch of sublegal individuals. In the Queensland Spanner Crab fishery both males and females can be taken, but visibly gravid (egg-bearing females) must be released. Spanner Crabs have low post-release survival, related to limb damage during entanglement and subsequent release (Kennelly *et al.* 1990; Kirkwood and Brown 1998).

The catch of Spanner Crab in Queensland is managed through a TACC that is reviewed every two years, based on the performance of fishery indicators and in accordance with the Spanner Crab fishery harvest strategy (State of Queensland 2020). An annual spawning closure is in place from 1 November to 15 December. The minimum legal size has been 100 mm since the 1980s (Dichmont and Brown 2010); due to differences in the growth rate of males and females, this results in predominantly males in the catch. Legal-size is estimated to be attained at 4.5 years old for males and 6.5 years old for females (Kirkwood *et al.* 2005), although there is uncertainty around the age-at-length for Spanner Crabs.

Available fisheries data

A fishery independent survey (FIS) has been conducted for Spanner Crab annually since 2000. The FIS uses standardised gear to sample Spanner Crabs > 50 mm carapace length, and records sex and size composition. The FIS takes place in May each year in a range of locations in each of the Spanner Crab management regions in Queensland and New South Wales (Figure 8). Catch rate measures of abundance are generated from 25 sampled areas (6 × 6 NM grids) across the Queensland fishery. Fifteen individual ground lines (the sampling units), each consisting of 10 nets, are set in each area. The net soak times, with the number of Spanner Crabs caught and their sex and size (rostral carapace length) are recorded. The consistent methodology and sampling design of this survey ensures that it provides a robust index of catch-per-unit-effort for this species.

Commercial catch data are available from fisher logbooks in both Queensland and NSW since 1988, with catch recorded at 30 NM grid cells (6 NM where possible) daily in Queensland, and monthly in NSW until 2009, after which catch is recorded daily. Commercial catch rates are then standardised to account for a range of potential influencing variables. The current catch rate standardisation considers fishing years, regions and months, as well as the main effects of fishing effort of individual vessels, the number of net lifts (which is a function of the number of ground lines used, nets per ground line and lifts per ground line), the spatial resolution of catches based on 30 × 30 NM grids, fishing power and the lunar cycle. The charter and recreational take of this species are negligible in Queensland, representing less than 1% of the total harvest in recent years (State of Queensland 2020).

Potential environmental influences

The influence of environmental variables on catchability of Spanner Crabs has been extensively studied, with strong indications that catch rates are affected by a number of environmental conditions, including current velocity, bottom temperature, El Niño Southern Oscillation (ENSO) cycles, and swell (Spencer *et al.* 2017, 2018, 2019).

Catch rates have been shown to improve with increasing bottom current speed, potentially as a result of the odour from the baited dillies being carried to a larger area (Spencer *et al.* 2017, 2019). Cooler Bottom Boundary Layer Temperatures (BBLT) improve catch rates, even after controlling for seasonality and depth effects (Spencer *et al.* 2018). Catch rates are higher in El Niño years, potentially as a result of lower wind speeds in those years (Brown *et al.* 2008). Higher catch rates are associated with wind-driven seasonal upwelling during the austral spring (northerlies). Catch rates decline when winds change to favour downwelling (south-easterlies), which warm the BBLT (Spencer *et al.* 2018). These upwelling effects can be identified by subsequent Chl-a blooms resulting from upwelling, or from the 7-day mean alongshore wind stress that triggers up- or downwelling (Spencer *et al.* 2018). Similarly, mesoscale warm-core eddies that pull warm shelf waters to the seabed have also been hypothesised to decrease local catch rates of Spanner Crab (Spencer *et al.* 2017). Wave height also affects catch rates, with low catch rates during and immediately following periods of heavy swell (Brown *et al.* 2008, Thomas *et al.* 2013). This is potentially a result of changes in turbidity and oscillation of the seabed caused by heavy swell (Spencer *et al.* 2017).

The literature on direct effects of environmental variables on Spanner Crab abundance is less extensive. Salinity has been demonstrated to have a direct effect on the survival of Spanner Crabs during metamorphosis, with 27-34 ppt salinity ideal for metamorphosis. Salinities < 20 ppt and > 40 ppt were lethal to zoea (Minagawa 1992). An optimal temperature range of 25-29°C has been identified for larvae in aquaculture environments (Minagawa 1990). Previous work has identified promising correlations between ENSO cycles and Spanner Crab CPUE that may be a result of ENSO-induced changes in local salinity (Brown *et al.* 2008).

Based on the range of variables that have been found to influence Spanner Crabs directly or indirectly, our search for environmental influences spanned, but was not limited to:

- SST range, mean, minimum/maximum, 10th and 90th percentiles
- Bottom temperature range, mean, minimum/maximum, 10th and 90th percentiles
- The occurrence, strength and duration of MHW
- Chl-a range, mean, minimum/maximum
- Salinity
- EAC strength
- Onshore wind strength, duration, timing
- Eddy type, duration, and frequency

1.2 Data Acquisition and Development of Environmental Indices

The data acquisition process has collected data on a wide range of environmental variables from established databases from sources such as AIMS, BOM, BRAN, EHMP, GA, IMOS, JAMSTEC, NOAA and Waverider buoys. Variables included but were not limited to sea temperatures (at surface and various depths), salinity, turbidity, components of current velocities, river discharge volume, Chl-a, tidal measurements, SOI, IOD and many others.

An extended compilation of possible indices directed the search for significant environmental drivers. The team biologists supplied a list of 56 possible quantitative indices based on their knowledge of the lifecycles of the three species under investigation as well as a wide range of relevant scientific studies (see Table 1). This ensures that the statistical and data science analyses are more targeted and remain relevant to the project's objectives. Analyses of a large portion of these are reported in this document. In Section 8.1 we recommend further examination of the remaining indices.

Table 1: Potential quantitative environmental indices hypothesised to be associated with study species biology.

Index	Short name	Unit	Data source spatial resolution	Environmental index resolution and extent	Data source
Measured river discharge at the furthest downstream gauge for each catchment, total discharge per month, and per wet season (Dec-Mar)	truFlo	ML/month	per major river in SEQ	Nerang River, Albert River, Logan River, Brisbane River, Mary River, Burnett River, Fitzroy River	https://water-monitoring.information.qld.gov.au/
Modelled river discharge, for each catchment, total discharge per month, and per wet season (Dec-Mar)	modFlo	ML/month	per major river in SEQ	Fitzroy, Mary, Burnett, Calliope, Boyne, Caboolture, Logan, Pine, Brisbane Rivers	http://dapds00.nci.org.au/thredds/dodsC/fx3/gbr4_2.0_rivers/gbr4_rivers_simple_2019-11.nc.html
Measured monthly river discharge anomalies (subtract monthly values from long-term average)	truFloa	ML/month	per major river (or multi-river area) in SEQ		https://water-monitoring.information.qld.gov.au/
Median monthly temperature at a particular depth slice (7.5m, 17.5m, 22.7m, 34.2m, 48.5m, 75.2m, 105m). Only estimate temperature value at a depth slice for a CFISH grid if >50% of the CFISH grid has valid data at that depth	BBLTmed	°C	11km grid (0.1° x 0.1°)	per CFISH grid cell and per Bay of interest	BRAN https://research.csiro.au/blueink/outputs/data-access AIMS https://ereefs.aims.gov.au/ereefs-aims
Minimum monthly temperature at a particular depth slice (7.5m, 17.5m, 22.7m, 34.2m, 48.5m, 75.2m, 105m)	BBLTmin	°C	11km grid (0.1° x 0.1°)	per CFISH grid cell and per Bay of interest	BRAN https://research.csiro.au/blueink/outputs/data-access AIMS https://ereefs.aims.gov.au/ereefs-aims
Maximum monthly temperature at a particular depth slice (7.5m, 17.5m, 22.7m, 34.2m, 48.5m, 75.2m, 105m)	BBLTmax	°C	11km grid (0.1° x 0.1°)	per CFISH grid cell and per Bay of interest	BRAN https://research.csiro.au/blueink/outputs/data-access AIMS https://ereefs.aims.gov.au/ereefs-aims
Bottom temperature anomaly, i.e., deviation from long-term monthly mean, at particular depth slice (7.5m, 17.5m, 22.7m, 34.2m, 48.5m, 75.2m, 105m)	BBLTa	°C	11km grid (0.1° x 0.1°)	per CFISH grid cell and per Bay of interest	BRAN https://research.csiro.au/blueink/outputs/data-access AIMS https://ereefs.aims.gov.au/ereefs-aims
Sea surface temperature 6 day mean	SST6d	°C	0.01° x 0.01° (approx. 11x11km)	for each CFISH grid cell and for 1° x 1° areas along the coast	https://portal.aodn.org.au/search?uuid=023ae12a-8c0c-4abc-997a-7884f9fec9cd
SST monthly mean	SSTmean	°C	0.01° x 0.01° (approx. 11x11km)	for each CFISH grid cell and for 1° x 1° areas along the coast	https://portal.aodn.org.au/search?uuid=023ae12a-8c0c-4abc-997a-7884f9fec9cd
SST monthly median	SSTmed	°C	0.01° x 0.01° (approx. 11x11km)	for each CFISH grid cell and for 1° x 1° areas along the coast	https://portal.aodn.org.au/search?uuid=023ae12a-8c0c-4abc-997a-7884f9fec9cd
SST monthly minimum	SSTmin	°C	0.01° x 0.01° (approx. 11x11km)	for each CFISH grid cell and for 1° x 1° areas along the coast	https://portal.aodn.org.au/search?uuid=023ae12a-8c0c-4abc-997a-7884f9fec9cd
SST monthly maximum	SSTmax	°C	0.01° x 0.01° (approx. 11x11km)	for each CFISH grid cell and for 1° x 1° areas along the coast	https://portal.aodn.org.au/search?uuid=023ae12a-8c0c-4abc-997a-7884f9fec9cd
SST winter minimum (May-Oct)	SSTwmin	°C	0.01° x 0.01° (approx. 11x11km)	for each CFISH grid cell and for 1° x 1° areas along the coast	https://portal.aodn.org.au/search?uuid=023ae12a-8c0c-4abc-997a-7884f9fec9cd
SST winter maximum (May-Oct)	SSTwmax	°C	0.01° x 0.01° (approx. 11x11km)	for each CFISH grid cell and for 1° x 1° areas along the coast	https://portal.aodn.org.au/search?uuid=023ae12a-8c0c-4abc-997a-7884f9fec9cd
SST monthly anomaly, i.e. deviation from long-term monthly mean, night time 1993-2011	SSTa	°C	0.01° x 0.01° (approx. 11x11km)	for each CFISH grid cell and for 1° x 1° areas along the coast	http://www.bom.gov.au/marinenwaterquality/ ; or https://portal.aodn.org.au/search?uuid=d9618fb2-1a71-4afd-b1c8-56a6871b224a

Marine Heatwaves - number of MHW days in preceding summer (1st Dec - 31 March) MHW definition as per Hobday <i>et al.</i> (2016)	MHWd	days	0.01° x 0.01° (approx. 11x11km)	Moreton Bay; and each CFISH grid cell	https://portal.aodn.org.au/search?uuiid=023ae12a-8c0c-4abc-997a-7884f9fec9cd
Marine heatwave intensity (highest maximum anomaly above long-term mean temperature)	MHWint	°C	0.01° x 0.01° (approx. 11x11km)	Moreton Bay; and each CFISH grid cell	https://portal.aodn.org.au/search?uuiid=023ae12a-8c0c-4abc-997a-7884f9fec9cd
Number of winter days (between May and Oct) with mean SST below 22°C – derived for each CFISH grid and for 1° x 1° areas	SSTwd	days	0.01° x 0.01° (approx. 11x11km)	Moreton Bay; and each CFISH grid cell	https://portal.aodn.org.au/search?uuiid=023ae12a-8c0c-4abc-997a-7884f9fec9cd
Degree heating days - number of days (out of 120) where positive SST anomalies were observed over summer (1st Dec - 31st March)	DHD	days	0.01° x 0.01° (approx. 11x11km)	Moreton Bay; and each CFISH grid cell	http://www.bom.gov.au/marinewaterquality/
Tidal range during Snapper settlement season (1 June to 31 Sept)	TideR	m		Moreton Bay (tide at Brisbane Bar)	https://www.data.qld.gov.au/dataset/brisbane-bar-tide-gauge-archived-interval-recordings
Duration of onshore winds during Snapper settlement season (1 June to 31 Sept), i.e. count of days with wind direction between 45 and 135 degrees	WindDirOn	days	12km grids	Moreton Bay	http://www.bom.gov.au/research/projects/reanalysis/
Mean speed of onshore winds (u component of wind, negative values) during Snapper settlement season (1 June to 31 Sept)	WindUmean	m/s	12km grids	Moreton Bay	http://www.bom.gov.au/research/projects/reanalysis/
Median speed of onshore winds (u component of wind, negative values) during Snapper settlement season (1 June to 31 Sept)	WindUmed	m/s	12km grids	Moreton Bay	http://www.bom.gov.au/research/projects/reanalysis/
Duration of upwelling conditions from Spencer <i>et al.</i> (2018)	UpDur	weeks	approx. 20x20km	for each CFISH grid cell and for 1deg lat * 1deg long areas along the coast	IMOS Ocean Current - Gridded Sea Level Anomaly https://portal.aodn.org.au/search?uuiid=3162c844-d45c-491c-b326-6ae37e4079f9
Intensity of upwelling conditions from Spencer <i>et al.</i> (2018)	UpInt	index	approx. 20x20km	for each CFISH grid cell and for 1deg lat * 1deg long areas along the coast	IMOS Ocean Current - Gridded Sea Level Anomaly https://portal.aodn.org.au/search?uuiid=3162c844-d45c-491c-b326-6ae37e4079f9
Mean strength of u component of surface current (E-W) during the month of the survey or catch	CurU	m/s	0.01° x 0.01° (approx. 11x11km)	for each CFISH grid cell and for each Spanner Crab management region	IMOS Ocean Current - Gridded Sea Level Anomaly https://portal.aodn.org.au/search?uuiid=3162c844-d45c-491c-b326-6ae37e4079f9
Mean strength of v component of surface current (N-S) during the month of the survey or catch	CurV	m/s	0.2° x 0.2°	for each CFISH grid cell and for each Spanner Crab management region	IMOS Ocean Current - Gridded Sea Level Anomaly https://portal.aodn.org.au/search?uuiid=3162c844-d45c-491c-b326-6ae37e4079f9
Cold-core (cyclonic, negative sea surface height anomaly) eddy frequency (number of cold-core eddies occurring in SEQ in half of year (1 Oct to 30 Mar, 1 Apr to 30 Sept))	EddyCCf	number	0.2° x 0.2°	all of SEQ from Fraser island to border, up to 1.5° longitude offshore	IMOS Ocean Current - Gridded Sea Level Anomaly https://portal.aodn.org.au/search?uuiid=3162c844-d45c-491c-b326-6ae37e4079f9
Cold-core eddy duration (total number of days per season (time frame specified above) with identified cold-core eddies)	EddyCCd	days	approx. 20x20km	all of SEQ from Fraser island to border, up to 1.5° longitude offshore	IMOS Ocean Current - Gridded Sea Level Anomaly https://portal.aodn.org.au/search?uuiid=3162c844-d45c-491c-b326-6ae37e4079f9
Warm-core (anti-cyclonic, positive sea surface height anomaly) eddy frequency (number of warm-core eddies occurring in SEQ in half of year (1 Oct to 30 Mar, 1 Apr to 30 Sept))	EddyWCf	number	approx. 20x20km	all of SEQ from Fraser island to border, up to 1.5° longitude offshore	IMOS Ocean Current - Gridded Sea Level Anomaly https://portal.aodn.org.au/search?uuiid=3162c844-d45c-491c-b326-6ae37e4079f9
Warm-core eddy duration (total number of days per season (time frame specified above) with identified warm-core eddies)	EddyWCd	days	approx. 20x20km	all of SEQ from Fraser island to border, up to 1.5° longitude offshore	IMOS Ocean Current - Gridded Sea Level Anomaly https://portal.aodn.org.au/search?uuiid=3162c844-d45c-491c-b326-6ae37e4079f9
Monthly average distance of EAC from coast at north tip Fraser island, north tip north stradbroke island, QLD/NSW border, Byron Bay, and any other key locations	EACdistF, EACdistS, EACdistQ, EACdistB	km	0.2° x 0.2°	Distance-from-point, calculated using OceanCurrent data as per Bolin <i>et al.</i> (2020)	IMOS Ocean Current - Gridded Sea Level Anomaly https://portal.aodn.org.au/search?uuiid=3162c844-d45c-491c-b326-6ae37e4079f9
Speed of EAC at 27.5°S, 154°E	EACsp	m/s	0.2° x 0.2°	Point-based	IMOS Ocean Current - Gridded Sea Level Anomaly https://portal.aodn.org.au/search?uuiid=3162c844-d45c-491c-b326-6ae37e4079f9
Swell (wave height)	SwH	m	Bouy locations	Closest available waverider buoy to each CFISH grid cell	Waverider buoys (AODN) https://portal.aodn.org.au/search?uuiid=2807f3aa-4db0-4924-b64b-354ae8c10b58
Southern Oscillation Index – atmospheric pressure difference between Darwin and Tahiti. Annual mean, and quarterly means (JanFebMar, AprMayJun, etc)	SOI	N/a	N/a	Whole study region	http://www.bom.gov.au/climate/current/soihtm1.shtml
Pacific Decadal Oscillation (annual mean and quarterly means)	PDO	N/a	N/a	All Qld	https://www.ncdc.noaa.gov/teleconnections/pdo/
Indian Ocean Dipole (annual mean and quarterly means)	IOD	N/a	N/a	All Qld	https://www.esrl.noaa.gov/psd/gcos_wgsp/Timeseries/Data/dmi.long.data
Mean bottom depth of CFISH grid	DepthMean	m	0.5° x 0.5°	per CFISH grid cell	https://ecat.ga.gov.au/geonetwork/srv/eng/catalog.search#/metadata/115066
Median bottom depth of CFISH grid	DepthMed	m	0.5° x 0.5°	per CFISH grid cell	https://ecat.ga.gov.au/geonetwork/srv/eng/catalog.search#/metadata/115066

Max bottom depth of CFISH grid	DepthMax	m	0.5° x 0.5°	per CFISH grid cell	https://ecat.ga.gov.au/geonetwork/srv/eng/catalog_search#/metadata/115066
Salinity	salMean	unitless psu	0.1° x 0.1°	per CFISH grid cell	https://dap.nci.org.au/thredds/remoteCatalogService?catalog=http://dapds00.nci.org.au/thredds/catalog/gb6/BRAN/BRAN_2016/catalog.xml
Gridded sea level anomaly	GSLA	m	0.2° x 0.2°	per CFISH grid cell	https://portal.aodn.org.au/search?uuid=3162c844-d45c-491c-b326-6ae37e4079f9 or https://thredds.aodn.org.au/thredds/catalog/IMOS/OceanCurrent/GSLA/DM01/catalog.html
Monthly mean chlorophyll a concentration	ChlMean	mg/m ³	1 km ²	per CFISH grid cell	https://catalogue-imos.aodn.org.au/geonetwork/srv/eng/metadata.show?uuid=f73daf07-eb81-4995-a72a-ca903834509f
Monthly median chlorophyll a concentration	ChlMed	mg/m ³	1 km ²	per CFISH grid cell	https://catalogue-imos.aodn.org.au/geonetwork/srv/eng/metadata.show?uuid=f73daf07-eb81-4995-a72a-ca903834509f
Monthly average chlorophyll a anomalies	Chlanom	mg/m ³	1 km ²	per CFISH grid cell	https://catalogue-imos.aodn.org.au/geonetwork/srv/eng/metadata.show?uuid=f73daf07-eb81-4995-a72a-ca903834509f
Monthly mean chlorophyll concentration (from the GBR4 model)	ChlMod	mg/m ³	approx. 4x4km	per CFISH grid cell and per Bay of interest	AIMS https://ereefs.aims.gov.au/ereefs-aims
Monthly mean chlorophyll concentration anomaly	ChlModa	mg/m ³	approx. 4x4km	per CFISH grid cell and per Bay of interest	AIMS https://ereefs.aims.gov.au/ereefs-aims
Lunar phase	Lun	%	N/a	whole study region	https://CRAN.R-project.org/package=suncalc
Monthly average seagrass biomass	SGN	gN/m ²	approx. 4x4km	per Bay of interest	AIMS https://ereefs.aims.gov.au/ereefs-aims
Monthly average seagrass biomass anomalies	SGNa	gN/m ²	approx. 4x4km	per Bay of interest	AIMS https://ereefs.aims.gov.au/ereefs-aims
Monthly average EpiPAR_sg (light intensity above seagrass)	EpiPAR	mol photon/ m ² d ¹	approx. 4x4km	per CFISH grid cell and per Bay of interest	AIMS https://ereefs.aims.gov.au/ereefs-aims
Monthly average EpiPAR_sg anomalies	EpiPARa	mol photon/ m ² d ¹	approx. 4x4km	per CFISH grid cell and per Bay of interest	AIMS https://ereefs.aims.gov.au/ereefs-aims
Monthly average TSS (Total Suspended Sediment, calculated by adding the suspended sediments in the water column: Fine sediment, Mud, Mud carbonate, Dust, Sand mineral and Sand carbonate)	TSS	kg/ m ³	approx. 4x4km	per CFISH grid cell and per Bay of interest	AIMS https://ereefs.aims.gov.au/ereefs-aims
Monthly average TSS anomaly	TSSa	kg/ m ³	approx. 4x4km	per CFISH grid cell and per Bay of interest	AIMS https://ereefs.aims.gov.au/ereefs-aims
Monthly average Kd_490 (measure of water clarity)	Kd490	m ⁻¹	approx. 4x4km	per CFISH grid cell and per Bay of interest	AIMS https://ereefs.aims.gov.au/ereefs-aims
Monthly average Kd_490 anomaly	Kd490a	m ⁻¹	approx. 4x4km	per CFISH grid cell and per Bay of interest	AIMS https://ereefs.aims.gov.au/ereefs-aims

2 Objectives

The project has three key objectives:

- (1) Find indices of association between measures of abundance and key environmental drivers;
- (2) Use these indices to enhance the existing stock assessment model for each species;
- (3) Enable forecasting of environmentally driven fluctuations in targeted species' abundance, including enhancing Management Strategy Evaluations (MSEs), with the help of a Rapid Adaptive Projections Tool (RAPT).

3 Materials and Methods

Our approach recognises that abundance of fish populations has three main drivers: (B) biological, (H) harvest/economic, and (E) environmental. Existing stock assessment models and accompanying management strategies depend crucially on the interface between B and H. To date, E has received little attention in Queensland or elsewhere, with some notable exceptions such as saucer scallop (O'Neill *et al.* 2020). The scientific challenge lies in quantifying the correct, evidence based, responses to fluctuations in the environmental factors that will benefit both the fishing industry and the sustainability of the harvested species. We will address this by examining how to incorporate environmental factors into the emerging new generation of rapid (Bayesian surplus production) stock assessment models.

It is already clear from Table 1 that data considered in this project come from very diverse sources and hence will, of necessity, be of highly varied quality and spatiotemporal resolutions. This issue will be further compounded by inclusion of fisheries data that will be introduced in this section. The latter will also be of widely varied quality as they include data from scientific fishery independent surveys (FIS), self-reported logbook data and questionnaire data that statewide surveys of recreational catch generate. Thus, the accuracy and reliability of various variables used in this study can also be expected to vary widely, ranging from direct accurate gauge measurements of river flows, through algorithmic estimates of Chl-a from satellite images, to sampling estimates of recreational catch. Furthermore, in some cases, time series of certain key variables contain as few as 11 points. Collectively, such data are not well suited for hypothesis testing.

Consequently, much of the data analyses carried out in this project were in the spirit of an exploratory, rather than a confirmatory, study. Thus, a range of specific statistical techniques was used for identifying associations among variables that the data reveal rather than hypotheses testing tasks. Many of the statistical techniques used such as regression analysis or generalised linear models are, nowadays, quite standard (see, for instance, Timm 2002).

Since correlational analysis is used extensively we, briefly, mention that it is a group of techniques designed to measure the strength (or lack) of associations among variables of interest with the help of statistics designed for that purpose such as Pearson correlation, Spearman correlation or Kendall tau. Of these, Pearson correlation is the most widely used statistic to capture the degree of linear association between two continuous variables. It is usually called simply correlation coefficient, or correlation, and takes values between -1 and 1. A correlation close to 0 signifies lack of linear association between the variables while a correlation close to 1 signifies strong positive association implying that as one variable increases the other one tends to also increase. Similarly, a correlation

close to -1 signifies strong negative association implying that as one variable increases the other one tends to decrease. When considering more than two variables at once, we usually analyse their correlation matrix. The latter is a symmetric matrix whose off-diagonal elements are the pairwise correlation coefficients.

A threshold p-value of 0.05 was used to determine statistical significance for all correlations and regressions. A range of threshold adjustment tools are available to account for applying multiple statistical tests to the same dataset (e.g. Bonferroni correction). We chose to stay with the standard threshold of 0.05, despite the extremely large number of correlations explored in the project, for two main reasons. First, in this project we pursue exploratory rather than confirmatory analyses, and as such prefer to over-detect rather than under-detect relationships with statistical significance, which are then identified for further inspection. Second, we apply a filter of “biological meaningfulness” to all statistically significant correlations. This involves our team’s domain-expert fisheries scientists and oceanographers hypothesising potential biological mechanisms for each statistically significant correlation. In the absence of a clear biological mechanism for a correlation, we identify the correlation as a potential statistical or data artefact. The bulk of statistically significant correlations are presented in the Results section, but the Discussion section is focused on correlations with clear biological merit.

In addition to the routine statistical tools, such as the above, we use some more advanced techniques as well as some non-standard indices developed for the purpose of this specific study. These are described, in more detail, later in this section.

3.1 Fisheries and Fishery Independent Survey Data

In this section we briefly describe the fisheries and fishery independent survey data for the three species: Snapper, Spanner Crab and Pearl Perch. We also describe the spatial extent of these fisheries in Queensland and NSW waters.

3.1.1 Snapper

For Snapper, harvest and catch rates were obtained from several data sources: Queensland commercial logbooks, NSW commercial logbook systems as well as historical records. Only one fishery independent data source was available for this analysis, FIS pre-recruit survey at Moreton Bay. The data collection consists of sampling young Snapper (<150 mm in fork length) at Moreton Bay during November – December from 2007-2019.

3.1.1.1 Queensland Snapper fishery

The analyses in this report covered both the regions of Fraser Coast, Sunshine Coast and Moreton where most of the commercial catch comes from and Moreton Bay where FIS data were collected. Figure 1 shows a map of Australian east coast waters and spatial stratifications for Snapper.

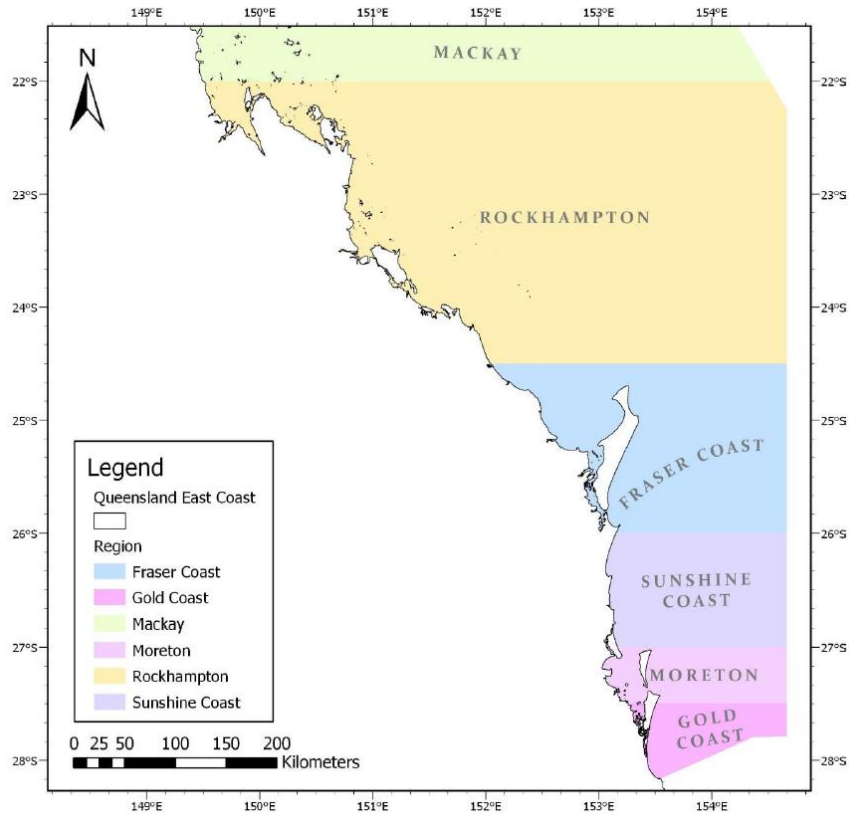


Figure 1: Map of Queensland waters and spatial stratifications for Snapper and Pearl Perch (Wortmann 2020).

Figure 2 shows the annual harvest of the Queensland Snapper fishery from 1940 to 2019. The Snapper fishery is composed of three sectors: charter, commercial line, and recreational catch. In particular, the contribution of recreational harvest to the total harvest is substantial. The estimated recreational harvest is based on estimates of the combined Queensland and NSW recreational harvest reported in Wortmann *et al.* (2018) and the recreational survey data of Queensland and NSW in years 2000 and 2013 from the 2020 rock reef finfish report (see Wortmann 2020).

To extract estimates of Queensland’s recreational catch from these combined estimates, we use data from years 2000 and 2013 which are the only two overlapping years when recreational catch surveys were conducted in both states. These surveys reported the 2000 recreational catch of 227 t in Qld and 188 t in NSW for total of 415 t, and the 2013 recreational catch of 82 t in Qld and 148 t in NSW for total of 230 t.

To estimate recreational catch in Queensland, we assumed that it constitutes $0.55=227/415$ of the combined catch every year prior and including year 2000, and $0.36=82/230$ of the combined catch every year from 2013 on. For the period 2001 to 2012, we used ratios from linear interpolation between 0.55 and 0.36. This resulted in the Queensland breakdown of harvest from various sectors displayed in Figure 2.

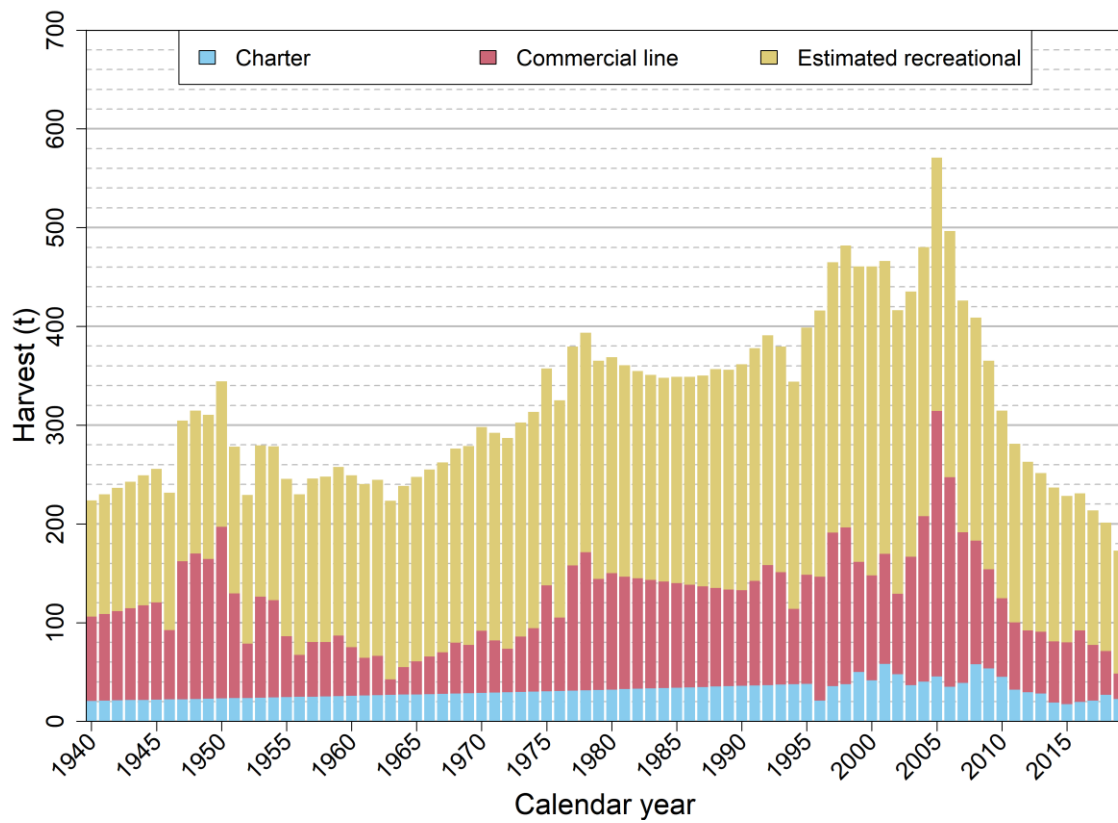


Figure 2: Estimated annual Snapper harvest from Queensland (1940-2019) across three fishery sectors.

Figure 3 displays the standardised annual catch rates of Snapper, with fishing power (FP), from Queensland commercial line fishing (Wortmann 2020). Overall, there was a decrease in catch rates from 1989-2019, with a peak occurring in 2005.

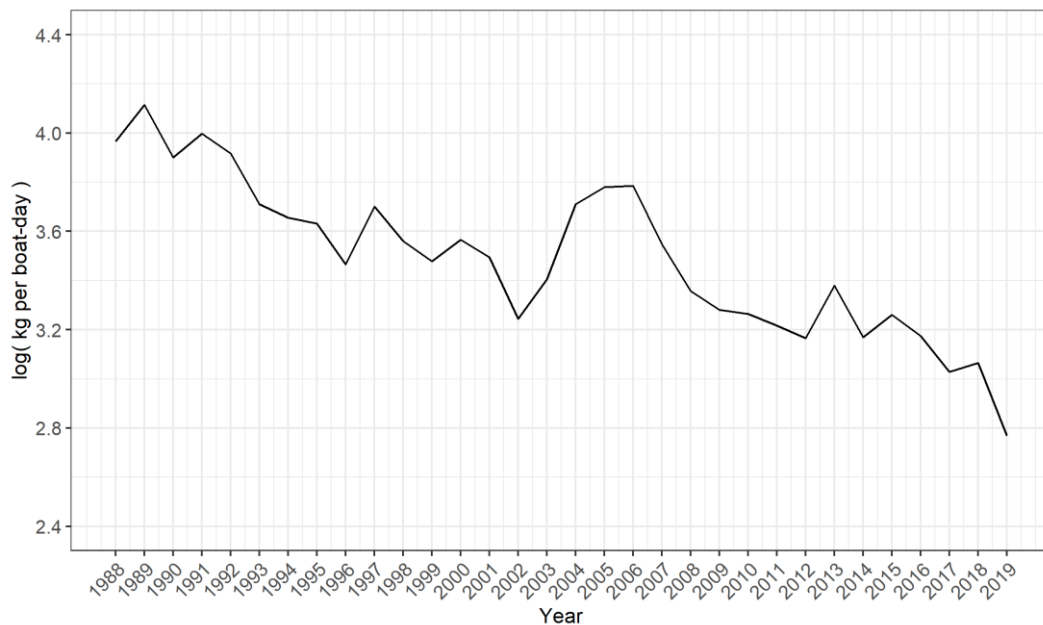


Figure 3: Time series of annual log transformed standardised catch rates for Snapper (1988-2019) for the Queensland commercial line fishery. Note that fishing power was accounted for in the standardisation.

The map in Figure 4 shows the fishery independent survey strata. Only pre-recruits caught at Moreton Bay (during November and December) with fork length of 150 mm and under were included in this analysis.

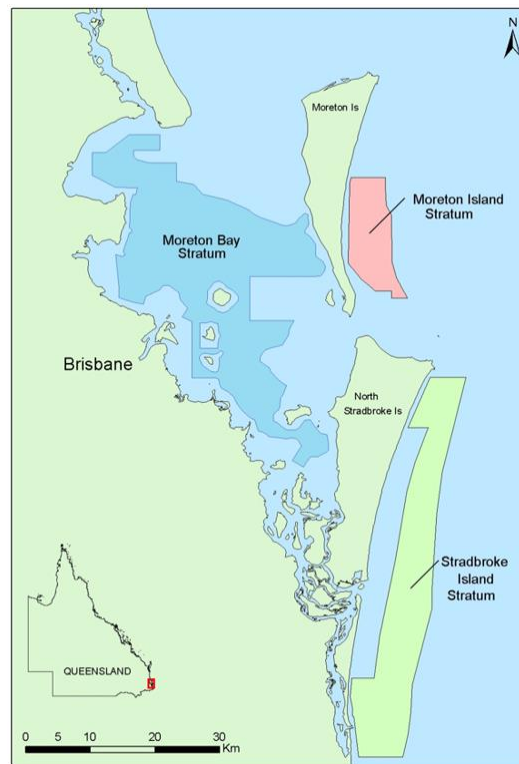


Figure 4: Map of survey strata for the annual fishery independent beam trawl survey for Snapper pre-recruits (Bessell-Browne et al. 2020).

The average number of pre-recruit Snapper sampled in each survey from Moreton Bay area varied between 2007 and 2019. From 2010-2011 we can see an increase in abundance, reaching the peak in 2011, followed by a marked decline up to 2015 when it reached the lowest number of pre-recruits per hectare sampled (Figure 5).

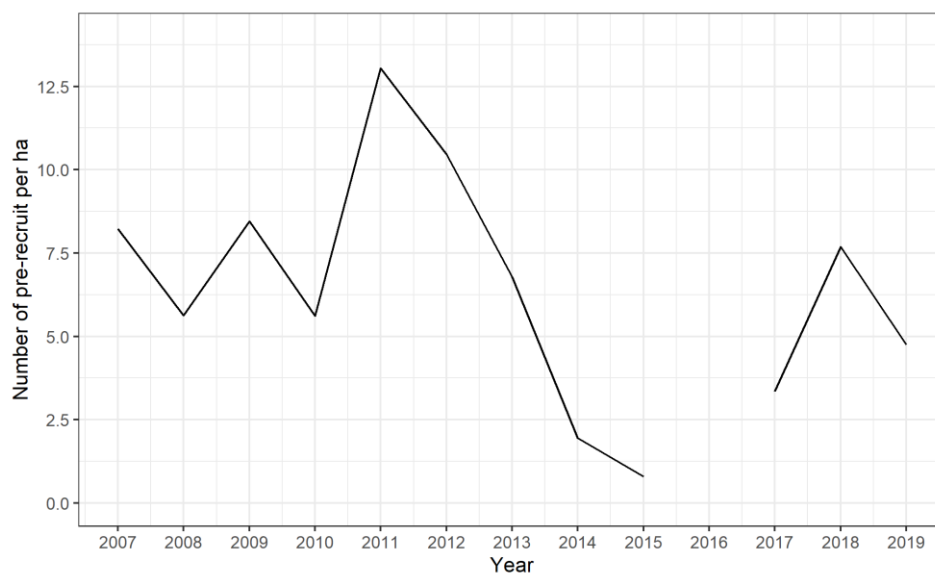


Figure 5: Annual relative abundance of Snapper pre-recruits (2007-2019) in Moreton Bay area.

3.1.1.2 New South Wales Snapper fishery

In Figure 6 we display the NSW Snapper harvest for the line and trap fisheries combined in 2009-2019. The data used come from the most recent NSW commercial fishing catch and effort reporting (fishonline logbook) where catch is recorded daily. Prior to this period, spatial reporting of the commercial catch data was 60 x 60 nm grids, with a temporal reporting of monthly catch and effort.

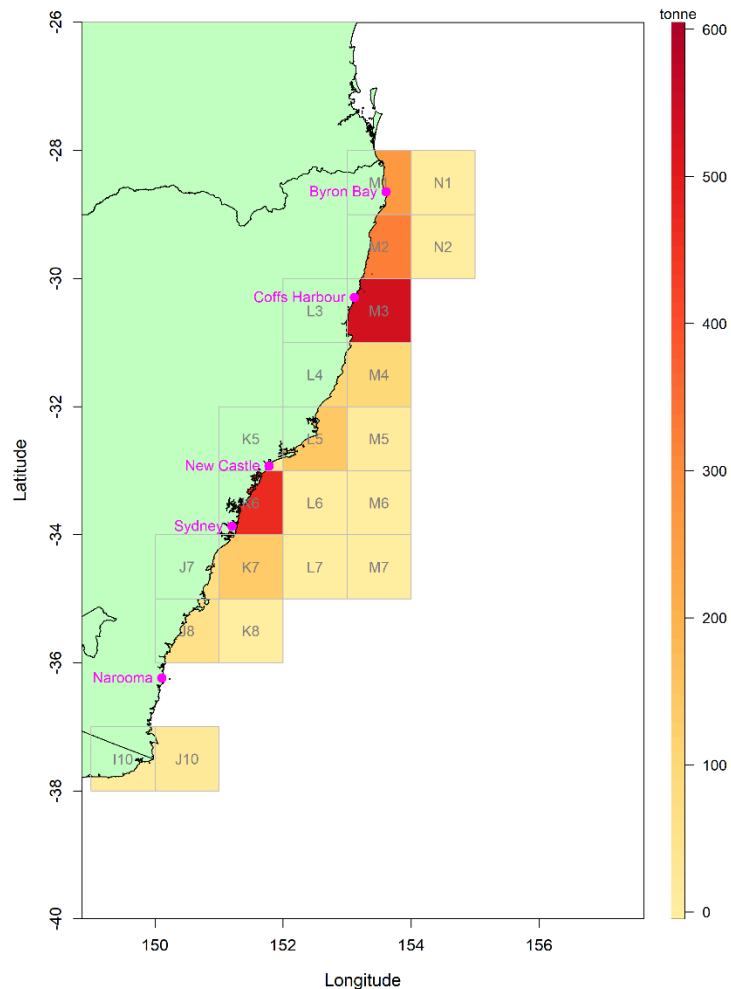


Figure 6: NSW Snapper line and trap fisheries colour coded by amount harvested (2009-2019). Grid codes at 1 degree scale.

Top panel of Figure 7 displays the standardised catch rate for the NSW commercial line for years 1997-2018. The NSW catch rate standardisation for line fishing method started from 1997 because fishing method was not recorded before that year (Wortmann *et al.* 2018). As can be seen, catch rates remained without much variation from 1997-2010 and then decreased from 2011-2016 (Wortmann 2020). The bottom panel of Figure 7 presents the standardised catch rate of the commercial trap fishery scaled with respect to the mean catch rate of 2009-2019 (DPI NSW personal communication 2021).

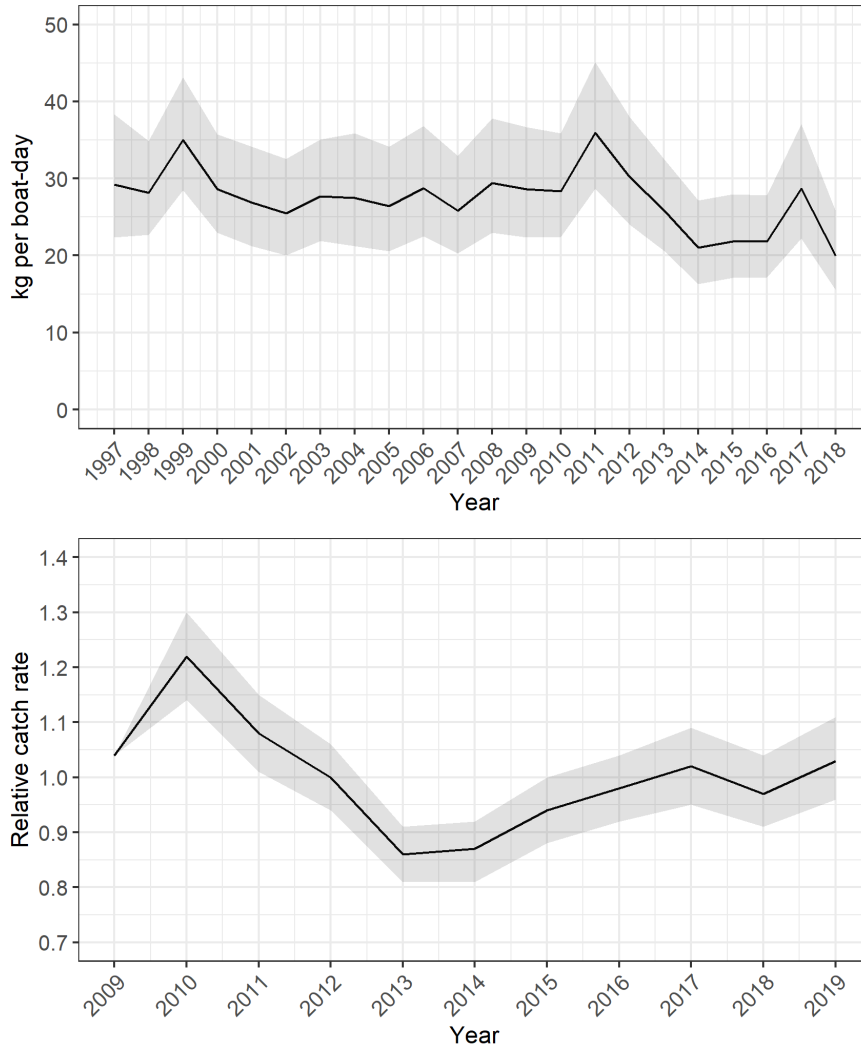


Figure 7: Annual standardised CPUE of Snapper for NSW commercial line (top) and trap (bottom) fisheries. Note that fishing power was accounted for in the standardisation of the line fishery. Grey shaded area covers 95% confidence intervals.

3.1.2 Spanner Crab: Queensland

Figure 8 illustrates the Spanner Crab in the Queensland and NSW waters between about 23°S and 29.5°S. The fishery was divided into six regions: Regions 2-6 in Queensland waters within Managed Area A from where most of Queensland catch comes (Campbell *et al.* 2016; State of Queensland 2020), and Region 7 in New South Wales waters. The map also represents the sites (i.e., 6'x 6' subgrids) of the annual Spanner Crab fishery independent survey. Since 2000, the fishery independent survey was usually conducted in May each year (see Department of Primary Industries and Fisheries 2005 and McGilvray *et al.* 2006, for detail).

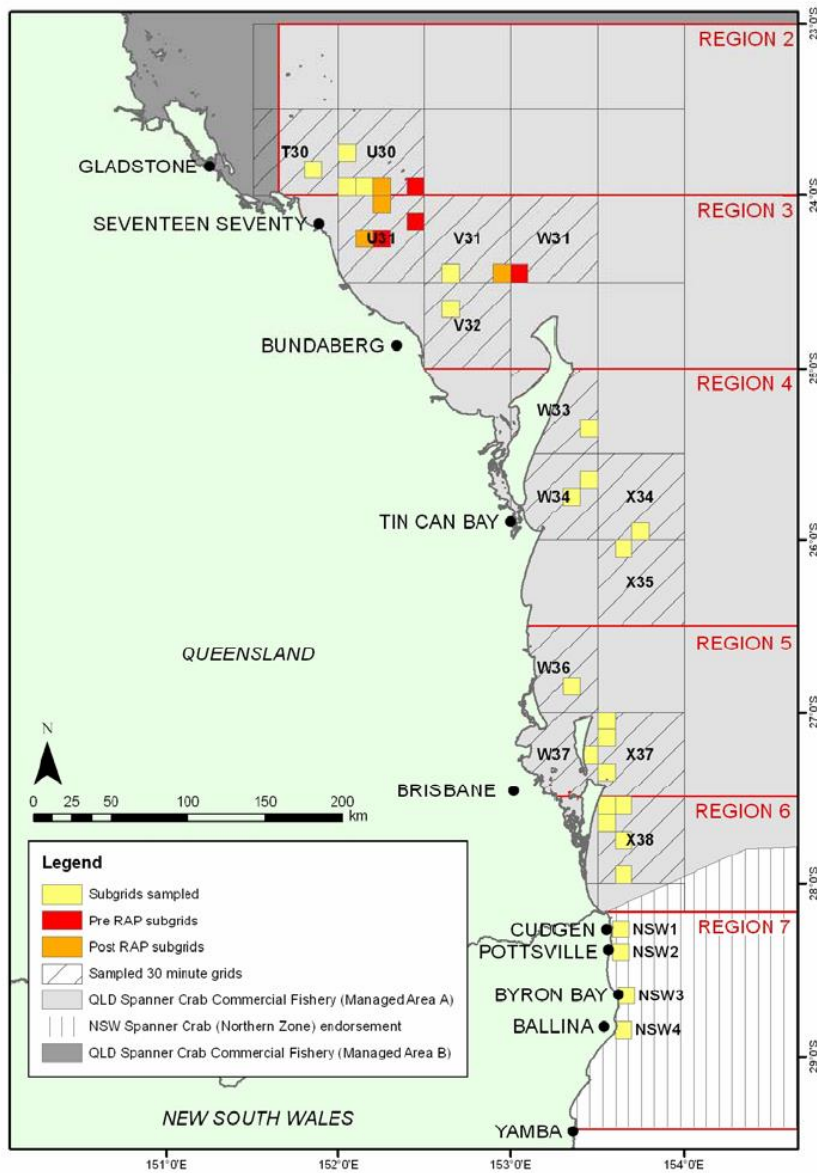


Figure 8: Six-minute subgrids (yellow squares) in the Spanner Crab survey in Queensland (Region 2 to 6) and New South Wales (Region 7). This figure is reproduced from Brown et al. (2008) with permission.

Figure 9 depicts Queensland’s commercial harvest from 1988 to 2019 based on the Queensland CFISH logbook records. The commercial harvest peaked at about 3,454 t in 1994, but started decreasing since 1998. In that period, the most apparent feature is that the harvest of Region 3 is declining. Region 4 became the productive area where most of Queensland catch is taking place.

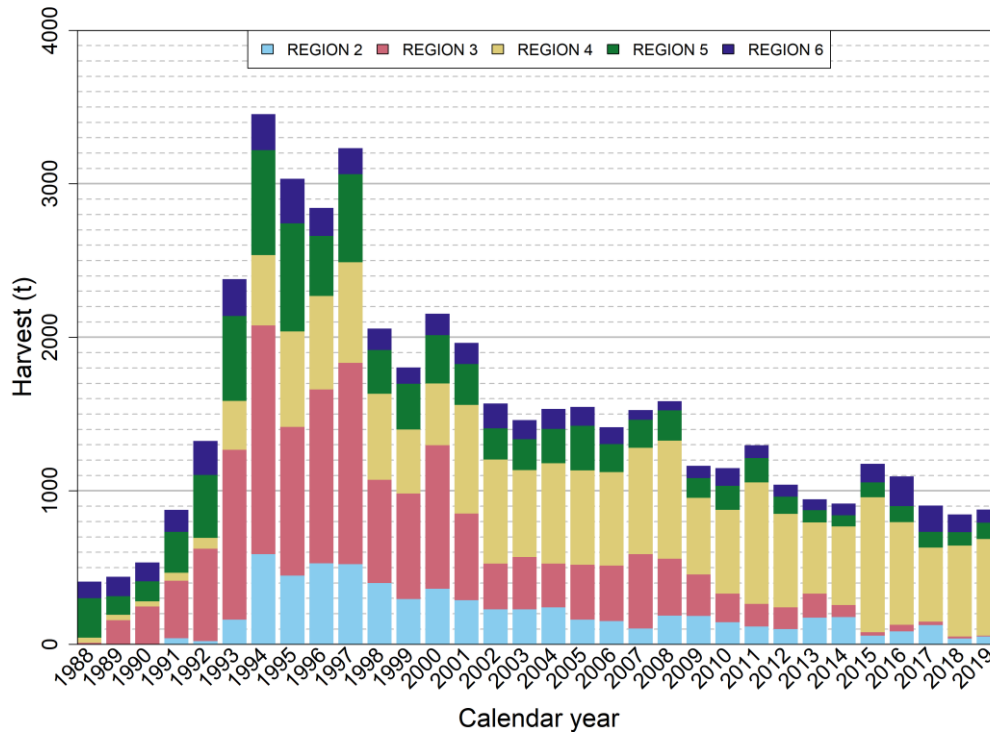


Figure 9: Queensland's commercial harvest of Spanner Crab for 1988-2019, colour coded by region.

Figure 10 displays the time series of standardised catch rates (SCPUE) for the whole of Queensland (left panel) and Regions 2-6 (right panel). These SCPUEs were generated using a generalised linear model fitted to CFISH data from 2000 to 2019 (see Section 3.5.2 and Campbell *et al.* 2016, for detail). The left panel shows that the SCPUE of the whole fishery decreases from 2008 to a low level in 2017 and then gradually recovers. However, the 2019 level is still low. The right panel indicates that SCPUEs of Regions 2-4 are generally higher than those of Regions 5-6. However, SCPUEs of Regions 2-3 decrease in 2007-2018, and SCPUE of Region 4 declines in 2010-2017. Moreover, Region 4 recovers faster than Regions 2 and 3, since 2017.



Figure 10: Spanner Crab SPCUE based on CFISH commercial logbook data for the whole of Queensland (left) and individual regions (right) for the period 2000-2019.

We relied on Spanner Crab FIS data collected around May, from 2000 to 2019, in the environmental correlation analyses. In Queensland there were approximately 75 sampling sites per region, but there were no surveys in 2004 and 2012. In NSW, Region 7, there were 60 sampling sites from 2005 to 2018.

Nominal CPUE from this FIS was estimated for the period 2000 to 2019, inclusive. The estimates were calculated – in each year and each region of interest - using the formula

$$CPUE = \frac{\text{number of catch}}{\text{soak time} \times \text{number of dillies}} \times 50 \text{ minutes} \times 10 \text{ dillies},$$

where soak time \times number of dillies represent fishing effort, and 50 minutes and 10 dillies are standard soak time and number of dillies used in the survey. Thus, the above is expressed in the units of number of crabs per ground-line. With the equation, the two $CPUE$ s of two spatial extents were calculated:

- (a) $CPUE_{reg}$: $CPUE$ by region for the six regions, labelled Region 2-Region 7,
- (b) $CPUE_{sub}$: $CPUE$ by each of the 34 six-minute subgrids.

The $CPUE$ time series in the six FIS regions are displayed in Figure 11. Note that sublegal cohort is defined as crabs less than 100mm carapace length (CL). Several important trends are clearly visible in Figure 11. These include (but are not limited to): near zero levels in Region 3 during 2017-2018; steep declines in both Regions 2 and 3 from 2013; relative stability of Regions 5-6 and generally increasing trend in Region 7 since 2012.

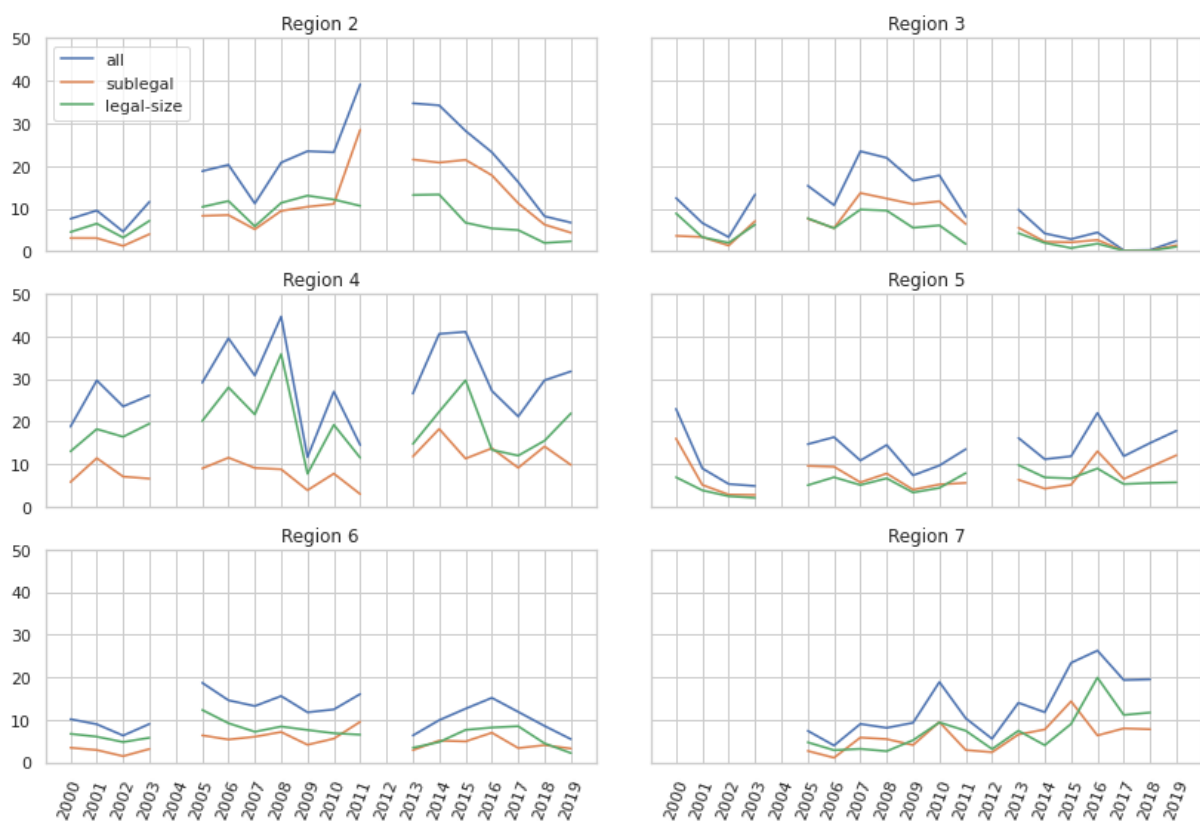


Figure 11: Time series of $CPUE_{reg}$ in May each year in the six regions of the sublegal crabs (<100mm in brown), the legal-size crabs (≥ 100 mm in green) and the whole (in blue) from the FIS data, in the units of number of crabs per ground-line.

In the case of $CPUE_{sub}$ there are several six-minute subgrids in each of the six regions. Hence it is convenient to represent these data with their box-plot distributions as in Figure 12 to Figure 14.

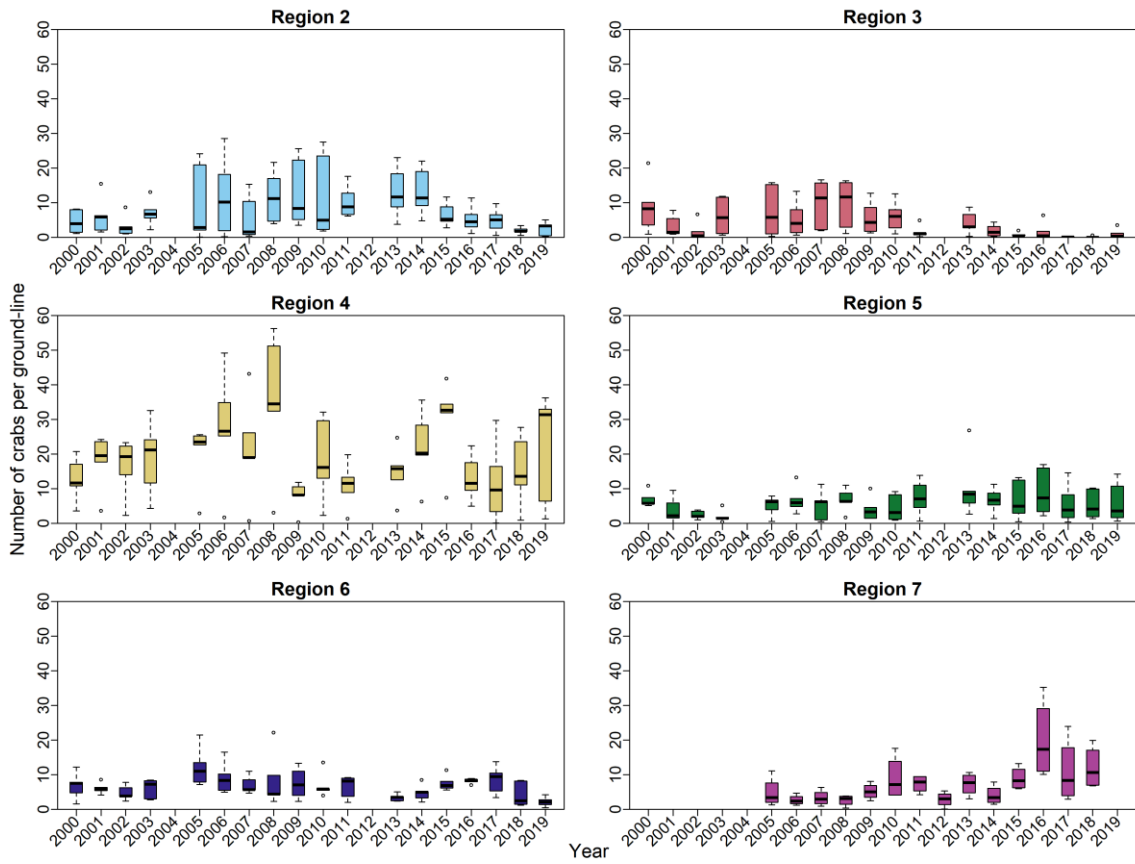


Figure 12: Boxplots of $CPUE_{sub}$ of legal-size crabs at 6'x6' resolution across all regions.

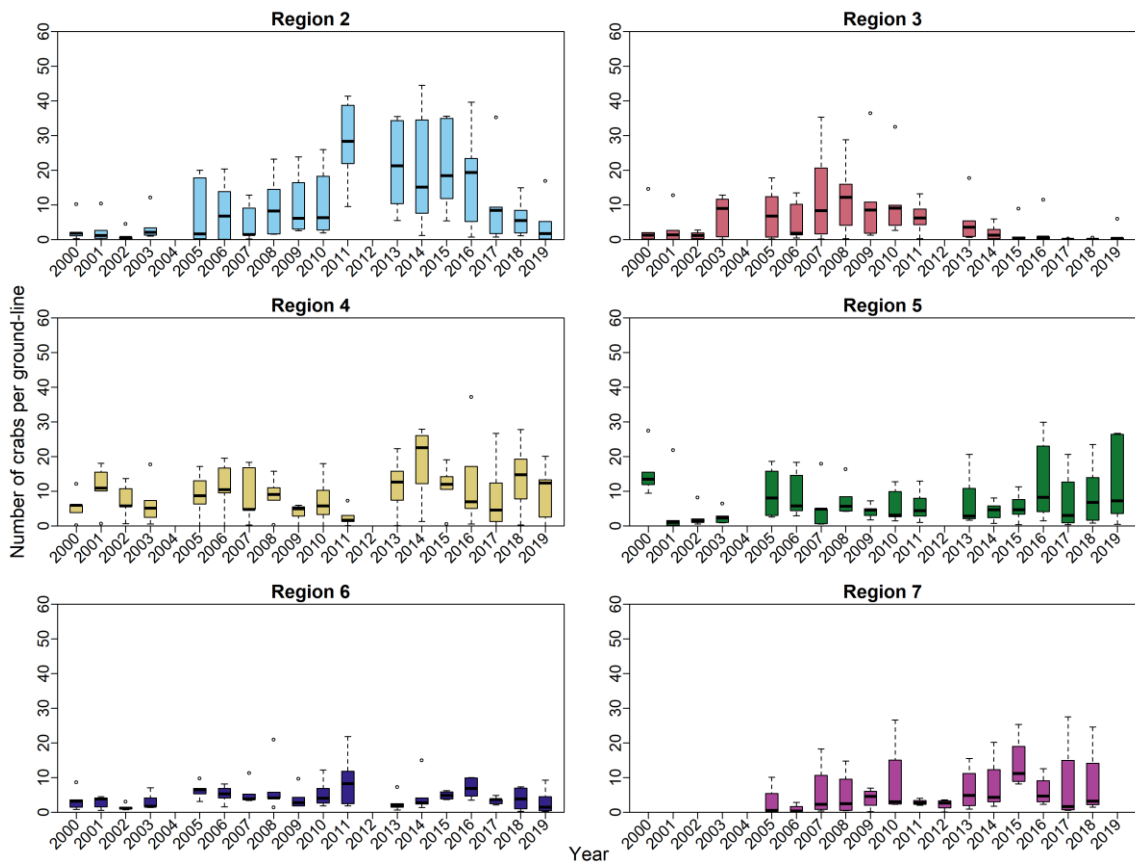


Figure 13: Boxplots of $CPUE_{sub}$ of sublegal crabs at 6'x6' resolution across all regions.

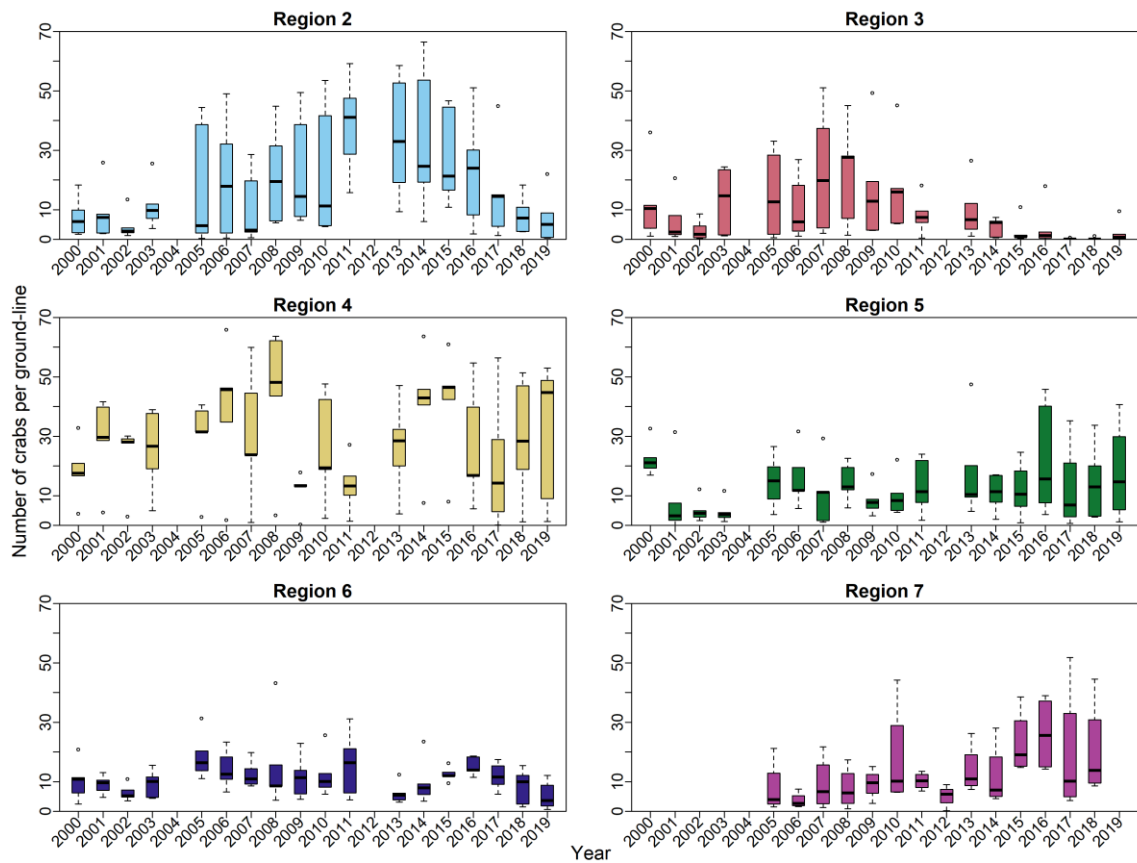


Figure 14: Boxplots of CPUE_{sub} of all crabs at 6'x6' resolution across all regions.

3.1.3 Pearl Perch

For Pearl Perch, harvest and catch rates were obtained from several data sources: Queensland commercial logbooks, NSW commercial logbook systems as well as historical records.

3.1.3.1 Queensland Pearl Perch fishery

Queensland commercial Pearl Perch fishery shares the same spatial extent as that of Snapper (Figure 1). Figure 15 displays the annual harvest of the Queensland Pearl Perch fishery from 1988 to 2019 according to commercial (line), charter and recreational sectors. The estimated recreational harvest was acquired using RFish catch estimates of 1999 and 2002 and QLD statewide recreational survey estimates of 2000, 2010 and 2013 (Higgs 2001, Higgs *et al.* 2007, Webley *et al.* 2015). The estimation was performed in two steps. First, we used the method of Lovett *et al.* (2020) to level the RFish catch estimates of 1999 and 2002. Then, we estimate the Queensland recreational catch by interpolating and extrapolating the updated RFish catch estimates and the statewide recreational survey estimates. We note that the 2005 recreational estimate was not considered due to methodological differences (see caption of Figure 15 in Wortmann 2020). The Pearl Perch commercial harvest peaked in 2005 and has declined since that time (Figure 15).

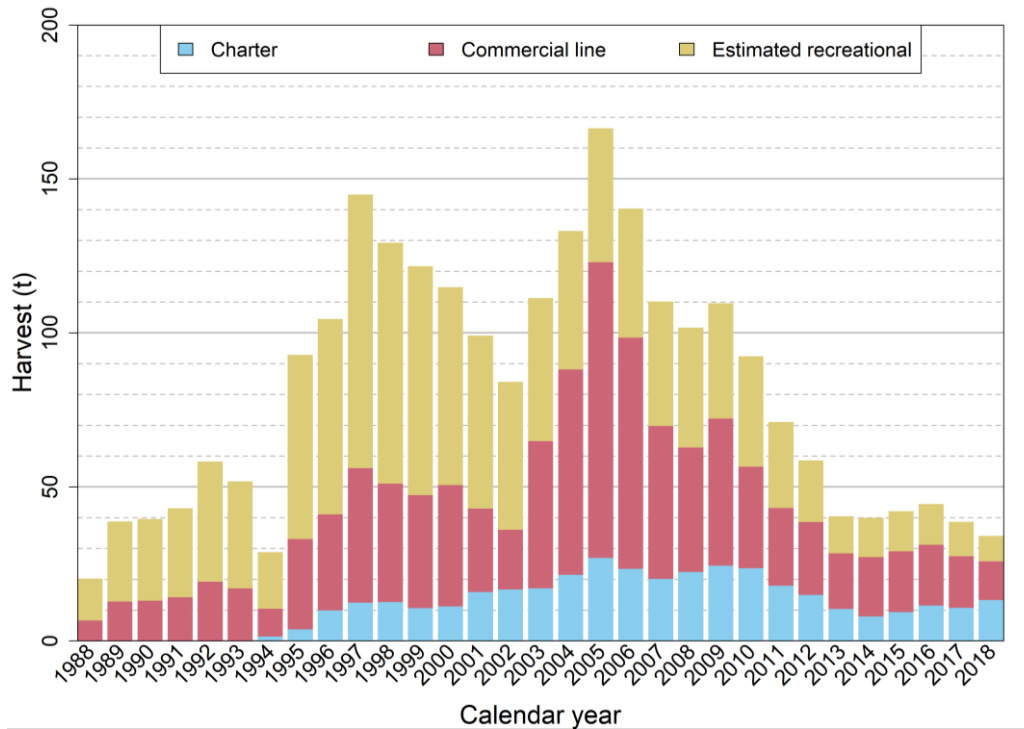


Figure 15: Queensland's Pearl Perch harvest colour coded by fishery sectors over the period 1988-2018.

Figure 16 shows the standardised CPUE of Pearl Perch for Queensland commercial line fishing. Details of standardisation can be found in Wortmann (2020). From 1988 to 2002, the standardised catch rate remained stable followed by an increasing up to 2005. After that period, there is a general declining trend in catch rates.

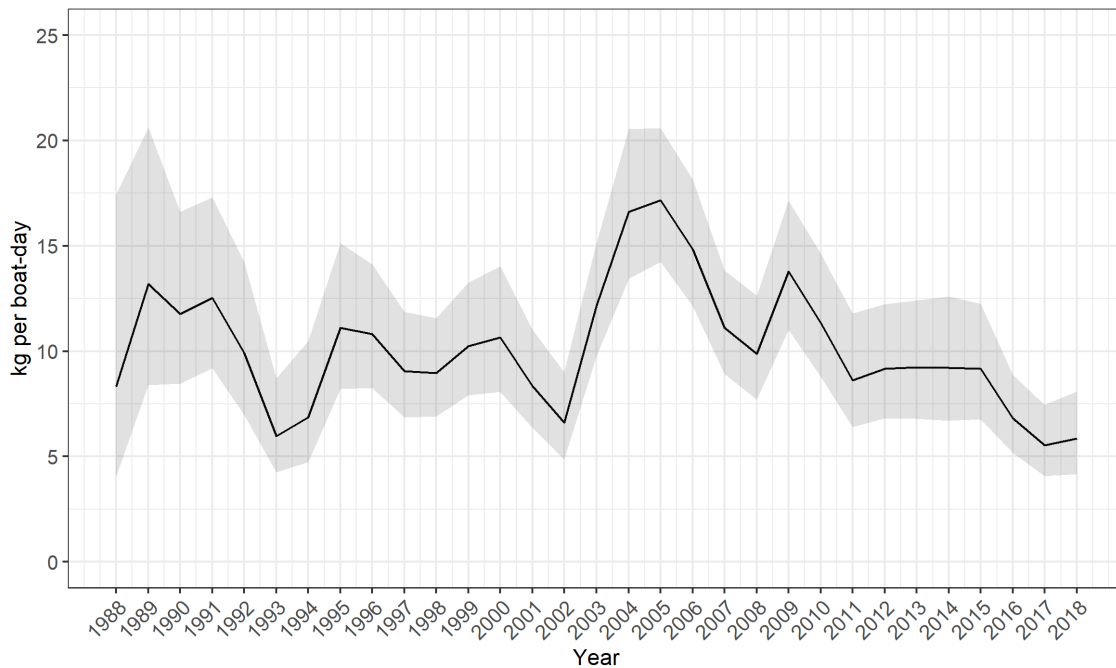


Figure 16: Time series of standardised Pearl Perch catch rates (1988-2018) for Queensland commercial line fishery. Fishing power was included in the standardisation. Gray shaded area covers 95% confidence intervals.

3.1.3.2 New South Wales Pearl Perch fishery

In Figure 17 we can see the spatial extent of NSW Pearl Perch line fishery and the spatial distribution of the harvest between 2009 and 2019. The data used come from the most recent NSW commercial fishing catch and effort reporting (fishonline logbook) where catch is recorded daily. Prior to this period, spatial reporting of the commercial catch data was 60 x 60 nm grids, with a temporal reporting of monthly catch and effort. Historically, majority of the commercial fishery in NSW records had been taken by line fishing methods.

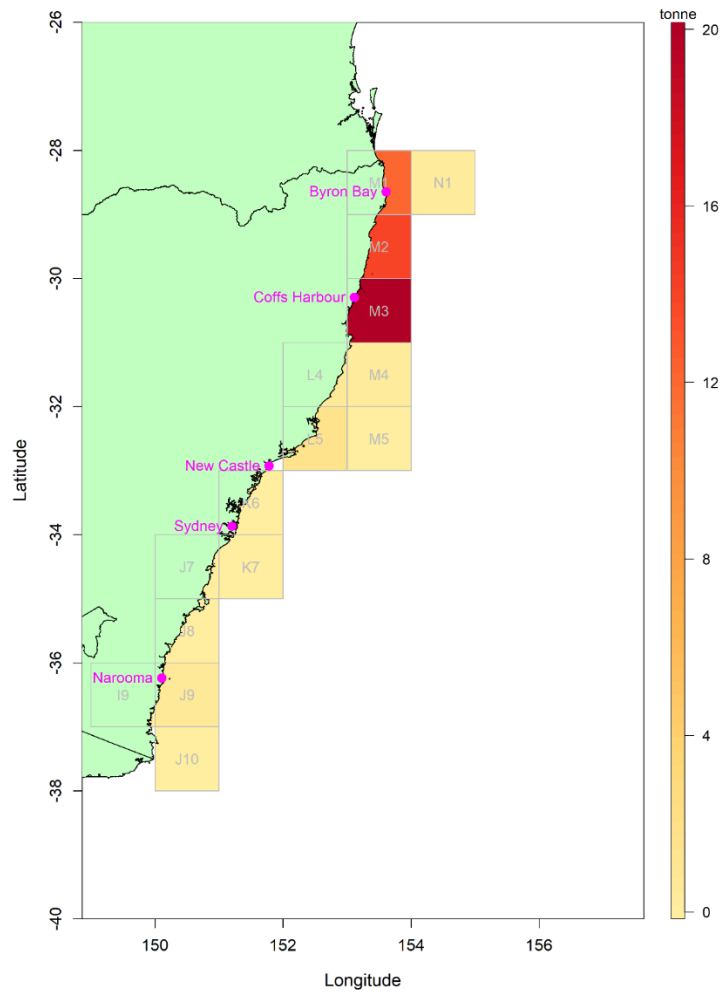


Figure 17: NSW Pearl Perch line fishery colour coded by amount mean harvested (2009-2019). Grid codes at 1 degree scale.

The corresponding standardised catch rate is presented in Figure 18. Overall, there was an increasing trend in Pearl Perch commercial standardised catch rate until 2006. After that there was a general gradual declining trend.

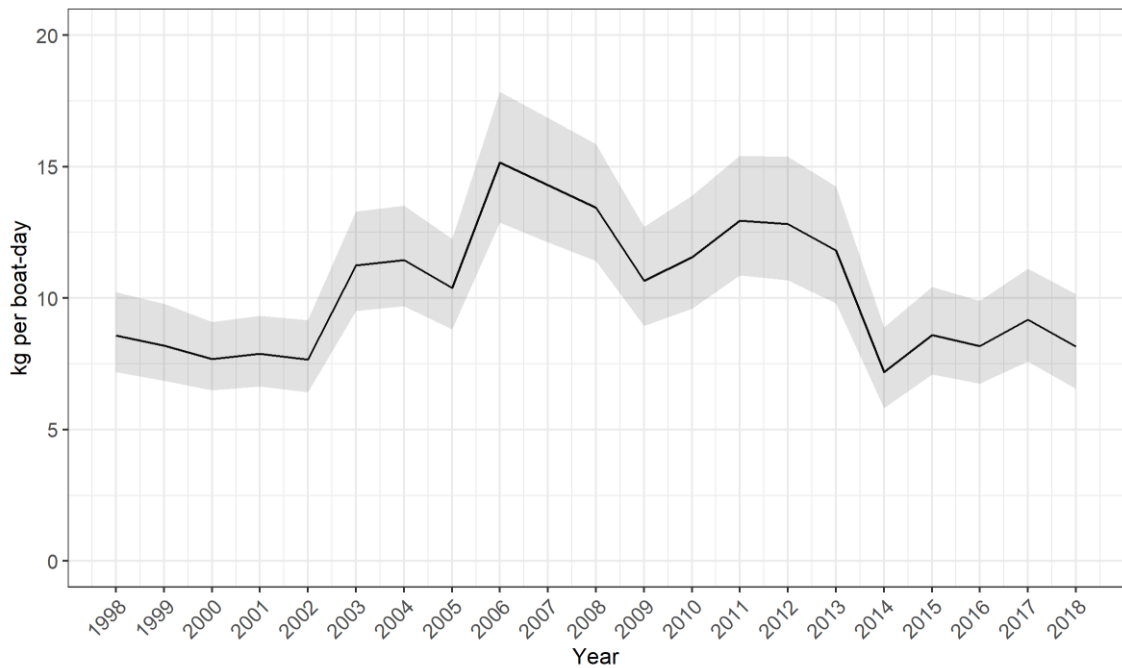


Figure 18: Time series of annual standardised catch rates for Pearl Perch (1998-2018) for New South Wales commercial line fishery. Fishing power was included in the standardisation (Wortmann 2020). Gray shaded area covers 95% confidence intervals.

3.2 Environmental Variables

In Section 1.2 we described the process of data acquisition of the environmental variables analysed in this project (see Table 1). In this section we outline the spatial extent of where most of these variables were calculated. The latter vary from species to species and are influenced by the location of commercial fisheries as well as of FIS sites.

3.2.1 Spatial extent of environmental variables

3.2.1.1 Snapper

Figure 19 shows the areas in the Queensland Snapper fishery where time series of environmental variables were calculated for correlational analyses with Snapper catch rates. The left panel shows areas relevant to the FIS data, while the right panel is relevant to CFISH data.

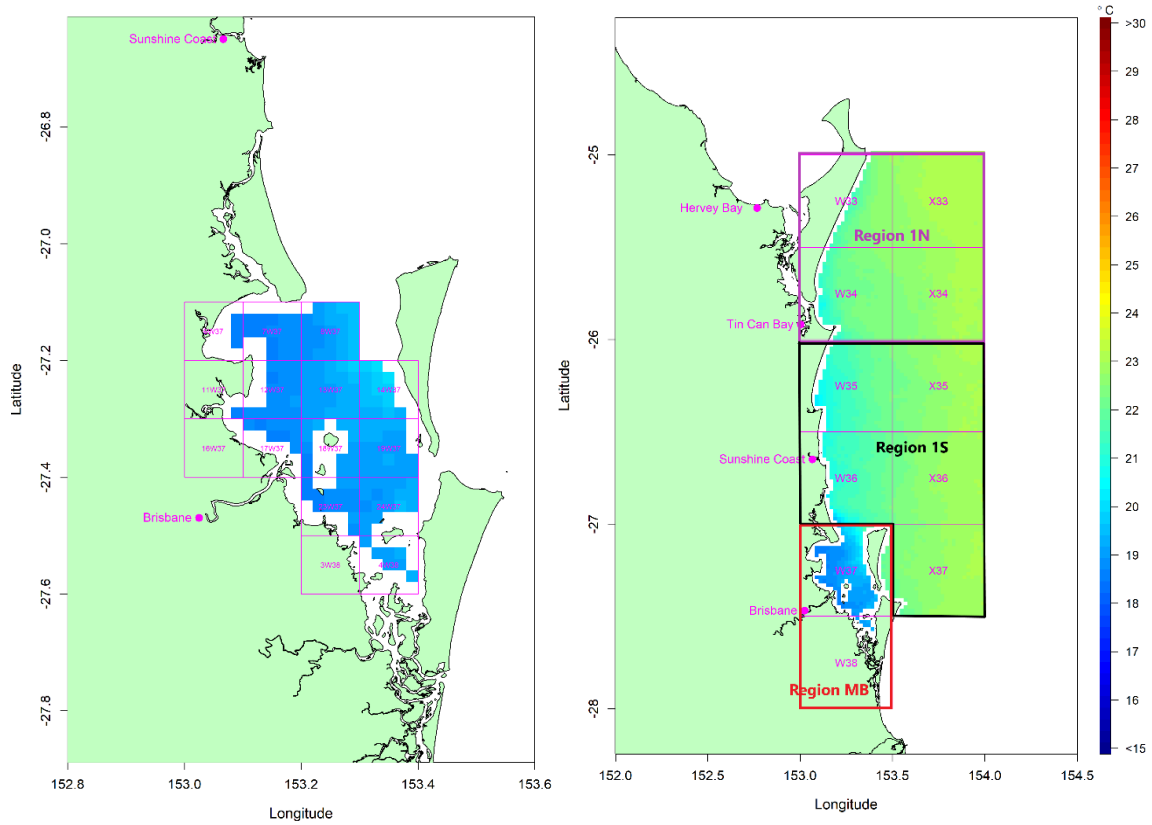


Figure 19: Moreton Bay Snapper pre-recruit area (left) adult Snapper areas (right). The combined offshore adult regions 1N and 1S constitute Region 1W. The coloured grids illustrate an example of average monthly SST.

The maps in Figure 20 indicate the areas in the NSW Snapper fishery where time series of environmental variables were calculated for correlational analyses with Snapper catch rates. The left panel shows areas relevant to the commercial line fishery, while the right panel is relevant to the trap fishery.

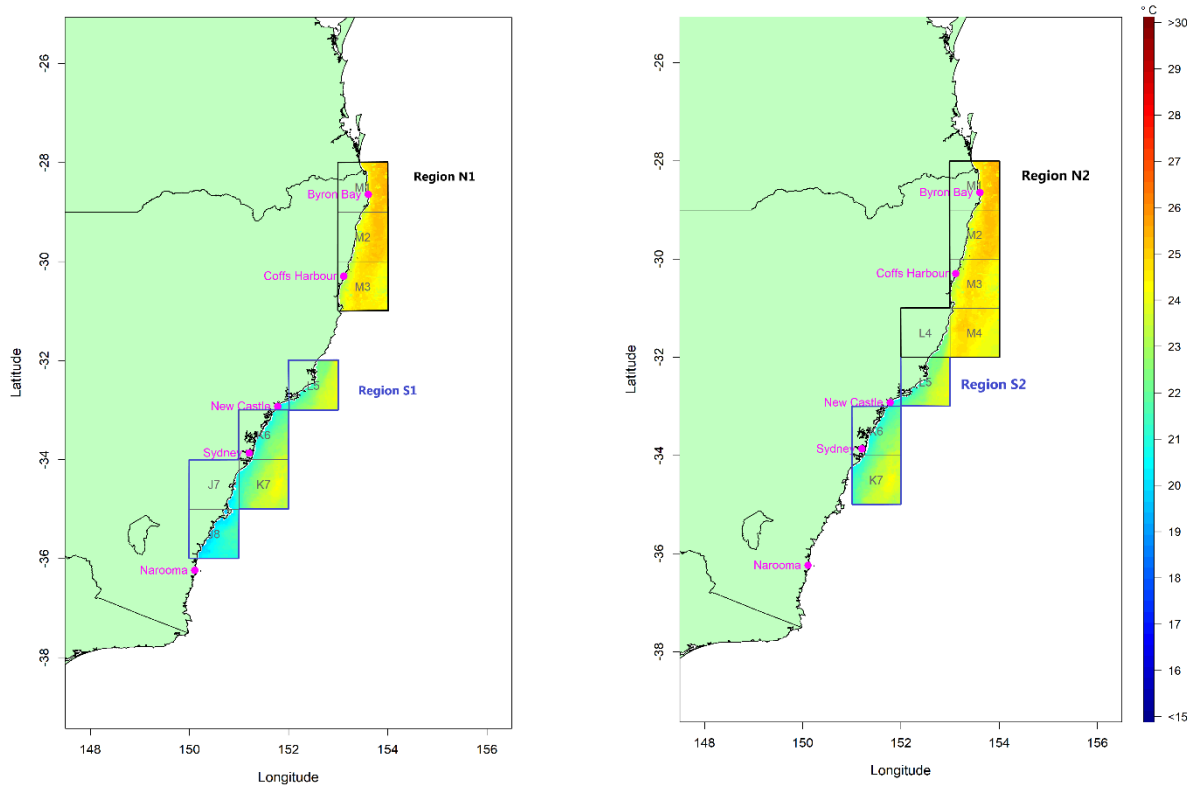


Figure 20: NSW regions of Snapper commercial line fishery (left) and trap fishery (right). Regions from which data were analysed consisted of N1 and S1 marked in the left panel and N2 and S2 marked in the right panel. For Pearl Perch analysis only Region N1 was considered. The coloured grids illustrate an example of average SST in February 2009.

3.2.1.2 Spanner Crab

The map below shows the spatial extent of Regions 2 to 6 used to extract features of environmental variables. Then, the extracted features are summarised as time series for correlating with the FIS CPUE.

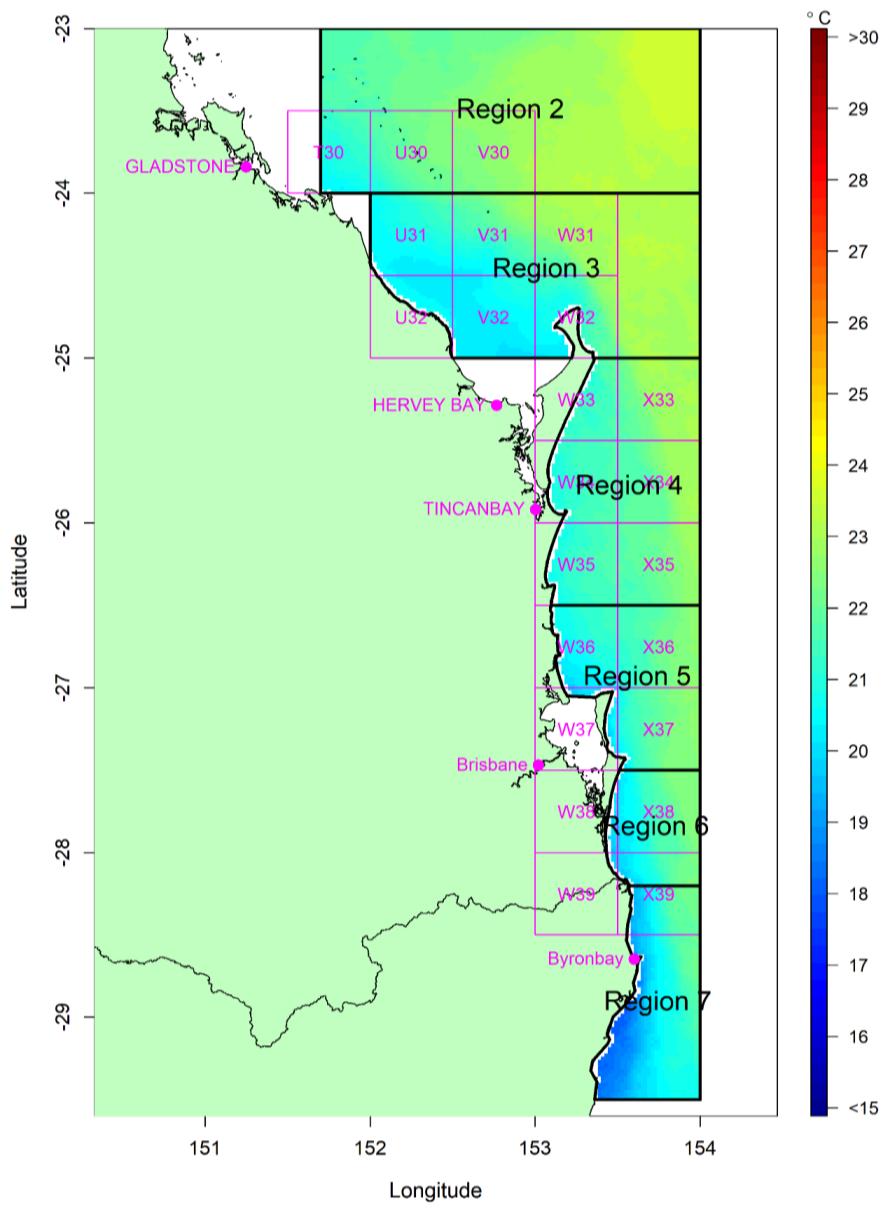


Figure 21: Spatial extent for environmental variables to correlate with Spanner Crab FIS CPUE.

3.2.1.3 Pearl Perch

Figure 22 indicates the areas in the Queensland Pearl Perch line fishery where time series of environmental variables were calculated for correlational analyses with Pearl Perch catch rates. For NSW Pearl Perch commercial line fishery, the area considered coincides with Region N1 indicated in the map of Figure 20.

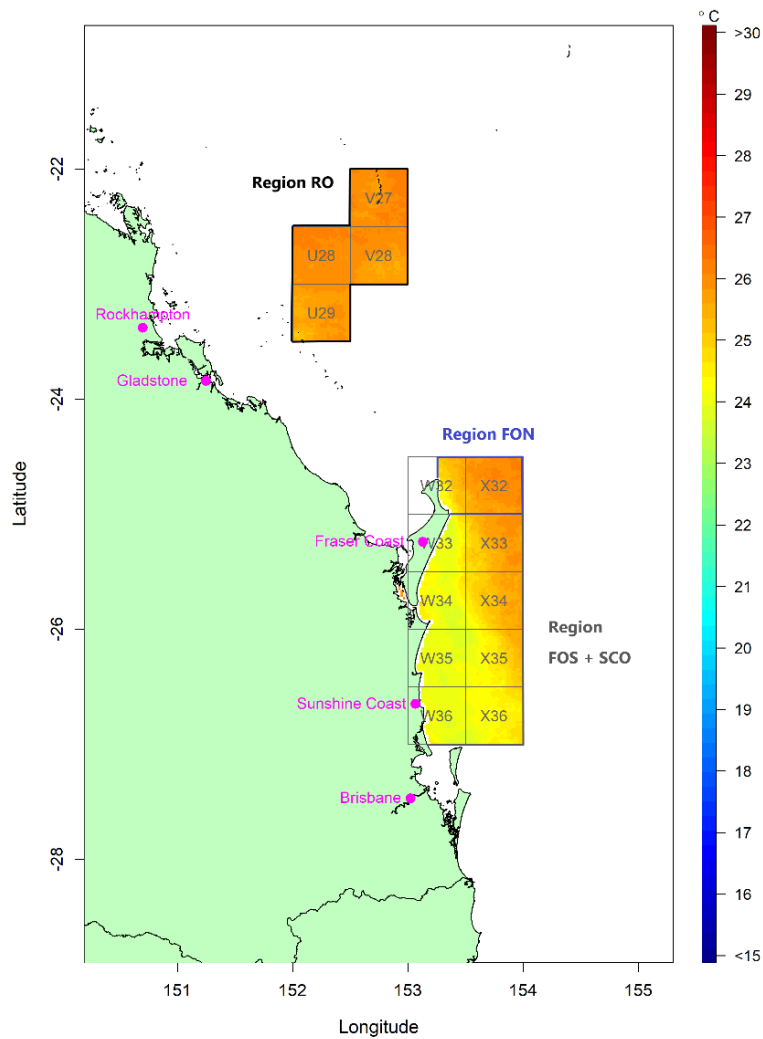


Figure 22: Spatial 30' x 30' grids highlighted for each region covered in the analysis of Pearl Perch commercial line fishery in Queensland.

3.3 Indices Capturing Historic Profile of Environmental Variables

This sub-section is dedicated to developing a generic family of mathematical indices that can be extracted from a “signal” of recorded observations of a relevant random variable which can be almost any environmental variable that is relevant to this project. The formulation of this family of indices is a contribution that requires detailed mathematical notation to be precise.

A time series of values of an environmental variable can be represented as $X_t = X_1, X_2, \dots, X_M$, where t represents time (e.g. in months, days or years) and M is the maximum time-lag to be considered in the analysis. From this history of past observations, we can often extract a series of environmental *episodes*, where each episode represents conditions during an interval of time such as a season or the duration of a La Niña or El Niño event. These intervals might be periodic and fixed in duration (e.g. a season or year) or they may have a variable duration defined by the interval between values of X_t crossing a threshold (e.g. the value of the Southern Oscillation Index is used to define El Niño and La Niña episodes and the temperature is used to define heatwave episodes). The impact of each episode on the fishery of interest will depend on its *intensity*, I , and its *weight*, w , relative to the weight of other

episodes. The parameter M will be called a *cumulative memory* (or just *memory*, for short) which we may also count in terms of a ratio M/m (e.g. a memory of $M=48$ months, or four years, with $m=12$). The impact of some environmental variables on a species of interest may depend on the frequency, the duration, and the intensity of certain episodes. These are to be construed broadly as they can be tailored to capture potentially important phenomena of interest such as intermittent MHW, or seasonally recurring winter cooler periods. Whatever their definition, the essential requirement of the episodes is that there is some number $K \leq M$ of them and that the entire remembered history of the signal $\mathbf{X} = \{X_1, X_2, \dots, X_M\}$ can be sub-partitioned into these K mutually exclusive episodes $E_k = \{X_{s_k}, X_{s_k+1}, \dots, X_{s_k+n_k-1}\}$, $k = 1, \dots, K$, where n_k denotes the length of the k^{th} episode and s_k is its starting time location. Namely,

$$\cup_{k=1}^K [E_k] \subseteq \mathbf{X}. \quad (1)$$

Note that, for the sake of simplicity of notation, in the above we assumed that each episode E_k consists of n_k consecutive observations of the signal. However, episodes consisting of non-consecutive observations can also be considered analogously. With respect to the above sub-partition, we can next define a family of associated indices extracted from the signal of the environmental variable X . This family is of the form

$$X(\mathbf{I}, \mathbf{w}) = \sum_{k=1}^K w(E_k)I(E_k), \quad (2)$$

where $w(E_k)$ and $I(E_k)$ denote importance weights and intensity measures associated with episodes E_k . Defining episodes E_k is crucial for constructing the index $X(\mathbf{I}, \mathbf{w})$. Two important types concern the cases of (a) persistent threshold crossing, and (b) periodic seasonality. They are differentiated by the way the sub-partitions are defined.

(a) Persistent threshold-crossing indices.

Let δ be a threshold of interest and let the k^{th} episode of interest, of duration n_k , be defined by either

$$E_k = E_k(\delta^u) = \{X_{k_j} \mid X_{k_j} > \delta, j = 1, \dots, n_k\} \quad (3)$$

or

$$E_k = E_k(\delta^d) = \{X_{k_j} \mid X_{k_j} < \delta, j = 1, \dots, n_k\}. \quad (4)$$

For instance, in the case where X is the Southern Oscillation Index (SOI), $\delta=-8$ may be used to identify episodes $E_k = E_k(\delta^d)$ of length $n_k > 5$ (consecutive) months sometimes used to identify El Niño episodes.

(b) Periodic seasonality

In this case each episode E_k is of equal length $n_k = n$ and they occur with periodic regularity.

$$E_k = \{X_{k_1}, X_{k_2}, \dots, X_{k_n}\}, \quad k = 1, \dots, K, \quad (5)$$

where the number K of these episodes is limited by spacings between them and the total memory M under consideration. For instance, in the case of Snapper consider a memory of, say, $M=48$ months counting backwards from December of the current year. If the episodes capture the May-October spawning aggregations, there would be exactly $K=4$ such episodes consisting of $E_1 = \{X_3, X_4, \dots, X_8\}$, $E_2 = \{X_{15}, X_{16}, \dots, X_{20}\}$, $E_3 = \{X_{27}, X_{28}, \dots, X_{32}\}$, $E_4 = \{X_{39}, X_{40}, \dots, X_{44}\}$.

To complete the construction of the $X(\mathbf{I}, \mathbf{w})$ indices we must supply the intensity $I(E_k)$ functions and the $w(n_k, M)$ weights associated with episodes E_k of the sub-partition (1). There are clearly many possible choices for these functions. We list only those that we used in subsequent analyses.

(c) Intensity functions $I(E_k)$

An intensity function $I(E_k) = I(X_{k_1}, X_{k_2}, \dots, X_{k_{n_k}})$ must map observed values in the episode onto a number capturing the intensity or strength of that episode. We considered several natural candidates for such functions including, the mean of the observations $\{X_{k_1}, X_{k_2}, \dots, X_{k_{n_k}}\}$, their median, geometric mean, signal-to-noise ratio and the logarithm of their sum (ensuring that each is well defined). The two candidates that, to date, yielded promising results were

$$I(E_k) = \bar{I}(E_k) := \frac{1}{n_k} \sum_{j=1}^{n_k} X_{k_j}, \quad (6)$$

and

$$I(E_k) = I^l(E_k) := \ln \left\{ \sum_{j=1}^{n_k} X_{k_j} \right\}. \quad (7)$$

(d) Weights of episodes E_k

The final ingredient in the construction of the $X(\mathbf{I}, \mathbf{w})$ index, is the determination of the relative importance weight of the k^{th} episode E_k , for each k . We propose the following form of these weights

$$w(E_k) = w_1(n_k, M)w_2(s_k, M), \quad (8)$$

where $w_1(n_k, M)$ is intended to capture the relative importance of the persistence of the k^{th} episode E_k of length n_k , and $w_2(s_k, M)$ is to capture the importance of the starting position s_k of the same episode in the M -step history. Of course, in absence of deeper understanding of the persistence and memory aspects, the modeller has the option of setting $w_1(n_k, M) = w_2(s_k, M) = 1$, for every k . We used the following functional form of the first of these weights

$$w_1(n_k, M) = \exp \left\{ a \left(\frac{n_k}{M} - 1 \right) \right\}, \quad (9)$$

where $a > 0$ was selected based on experimentation. Note that short episodes are discounted more strongly by the above formula.

The default second weight values of $w_2(s_k, M) = 1$ were used in some of our settings. However, we also experimented with more sensitive weights of the form

$$v(s_k, M) = d \left(\frac{s_k}{M} \right)^c \left(1 - \frac{s_k}{M} \right)^{1-c}, \quad (10)$$

or alternatively

$$w_2(s_k, M) = \exp \left\{ -b(1 - v(s_k, M)) \right\}. \quad (11)$$

In the above, s_k denotes the starting time (e.g. month) of the episode E_k and c lies between 0 and 1. For instance, from Figure 23 we see that when $c=0$ (red line), episodes starting late in the remembered history (s_k close to M) obtain $v(s_k, M)$ values that are smaller than episodes starting early in that history (s_k close to 1), and conversely when $c=1$ (purple line). A value of c strictly between 0 and 1 can

be selected to ensure that episodes starting at a prescribed time in the middle of the remembered history obtain the highest $v(s_k, M)$ value. The scaling parameter $d > 0$ is chosen to ensure that the highest possible $v(s_k, M)$ is 1. Then, when (10) is substituted into (11), with $b > 0$, this ensures that the importance weights $w_2(s_k, M)$ also range between 0 and 1 and attain a maximum when $v(s_k, M) = 1$. However, the parameter b can be used as a dampening (or accelerating) factor of the rate of decay away from the maximum. For instance, from the right panel of Figure 23 we see that $b=0.3$ dampens the rate of decay of these weights to always remain above 0.7, while $b=1.5$ permits them to drop to below 0.3. It is envisaged that, in future research, parameters c and b could be calibrated to reflect the natural mortality or longevity of the species under investigation.

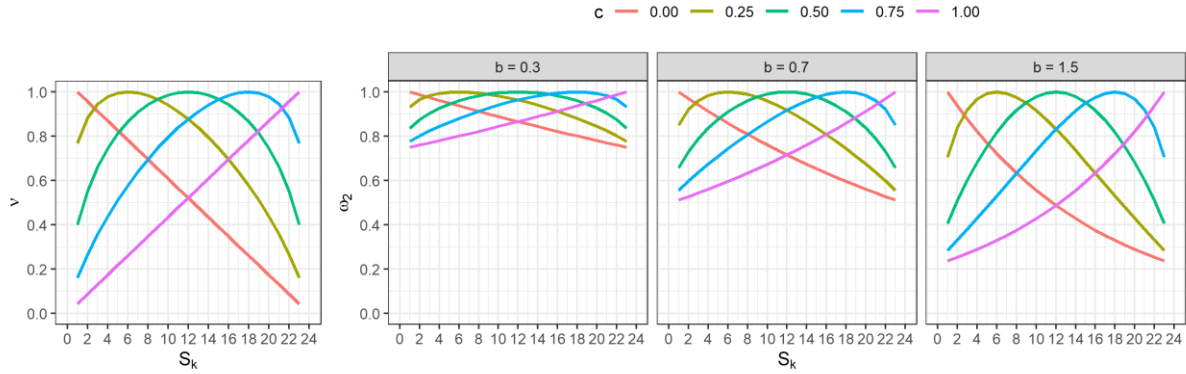


Figure 23: Examples of the shape of the $v(s_k, M)$ (left panel) and $w_2(s_k, M)$ (right panel) functions when $M=24$ and parameters c and b take the indicated values.

It should also be clear that, in some application, we may want to “zero-out” effects of the environmental signal in certain periods of interest and that is easily achieved by setting $w_2(s_k, M)=0$, during these periods. Similarly, we are able to assign other prescribed values (between 0 and 1) to these weights, in selected periods, on the basis of exogenous factors such as whether these correspond to spawning or juvenile periods in the life-cycle of the species.

Remark: Note that most standard statistical indices can be easily recovered within the above $X(\mathbf{I}, \mathbf{w})$ family. For instance, if we wanted the mean of observations X_1, X_2, \dots, X_{12} , all we need to do is define $E_k = X_k$ for each k , the memory $M=12$, the intensity function to be $I(E_k) = \frac{X_k}{12}$ and all the weights to be identically 1. Similarly, other indices such as medians, moving averages, or coefficient of variation can be naturally constructed in the above form.

(e) The up/down δ -rectified means

This is just a special case of δ threshold crossing indices introduced in (a) when $K=1$, the importance weights are set to $w_1(n_1, M) = w_2(1, M) = 1$, and the following variant of the intensity function is used

$$I(E_1) = \bar{I}_M(E_1) := \frac{1}{M} \sum_{j=1}^{n_1} X_{1j}. \quad (12)$$

Note that we also experimented with the direct form (12) where is M replaced by n_1 , but found that in the cases where the episode E_1 is short (small n_1), the corresponding index $X(\mathbf{I}, \mathbf{1})$ seemed to inflate the importance of the episode. When $E_1 = E_1(\delta^u) = \{X_{1j} \mid X_{1j} > \delta, j = 1, \dots, n_1\}$, this index now simply coincides with

$$X^u(\delta) := \frac{1}{M} \sum_{j=1}^{n_1} X_{1,j}. \quad (13)$$

The above can be seen as the strength of δ -exceeding signal relative to the length of the memory period of interest and we shall refer to it as an *up δ -rectified mean*.

Of course, $X^d(\delta)$ for the strength of the signal falling below the threshold $X^d(\delta)$ is defined the same way but with respect the episode $E_1 = E_1(\delta^d) = \{X_{1,j} \mid X_{1,j} < \delta, j = 1, \dots, n_1\}$. For example, when the signal is the SST observed daily in, say, June in a given location and $\delta=21^\circ\text{C}$ is the threshold, then the down 21° -rectified mean is given by

$$X^d(21) := \frac{1}{30} \sum_{j=1}^{n_1} X_{1,j}, \quad (14)$$

where n_1 is the number of days in June when the recorded temperature was below 21°C . Such δ -rectified means are helpful in identifying important thresholds when they correlated with species abundance indices such as density of Snapper pre-recruits.

We illustrate the techniques (a), (c), (d) and (e) with the monthly SOI signal considered with a memory of $M=24$ months and threshold up (3) and down (4) episodes corresponding to two different δ values: 0, and 8, respectively. The intensity function (6) was used with all $w_2(s_k, M)$ weights set to 1 and $w_1(1, M)$ calculated according to equation (9) with the parameter $a=2$. Figure 24 displays the resulting up/down indices so constructed, with the red curves corresponding to those using $\delta=0$ threshold and the green curves corresponding to the $\delta=8$ threshold. It can be seen that these curves capture several key up/down characteristics of the SOI signal, with the green curves emphasizing fluctuations somewhat more than the red curves.

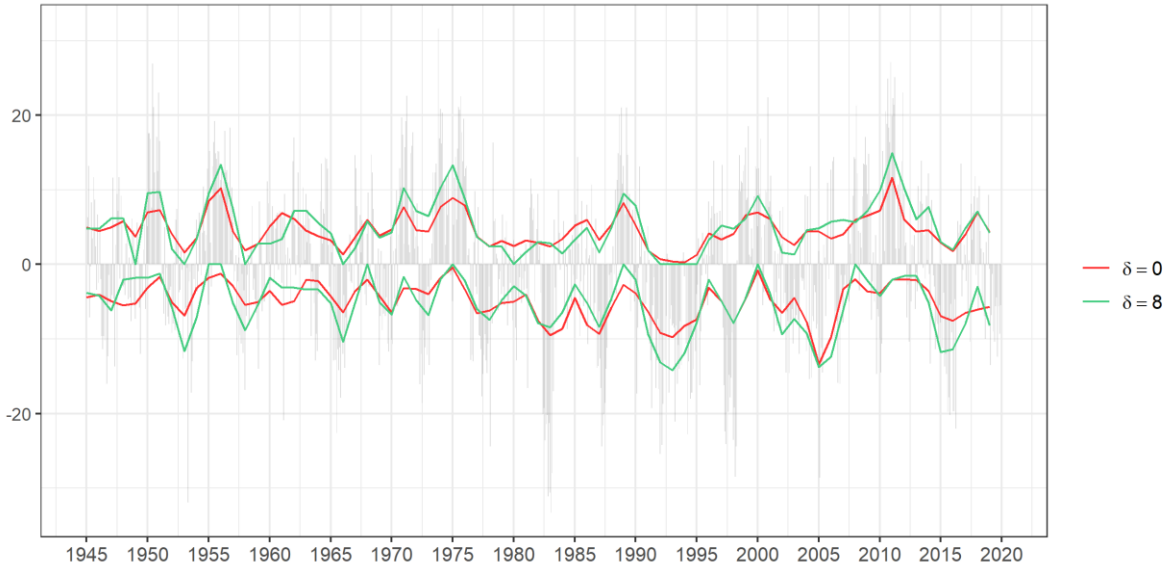


Figure 24: Four $X(I,w)$ indices extracted from the monthly SOI signal and memory $M=24$ months. Red for threshold $\delta=0$ and green for threshold $\delta=8$. The two curves above the 0 level correspond to the up episodes and those below correspond to the down episodes, with respect to the two thresholds.

3.4 Marine Heatwaves

Marine heatwaves (MHW) are anomalous sea temperature events that can be caused by configurations of atmospheric and oceanographic processes. They are not restricted to Australian waters and are expected to become both more frequent and intense in response to climate change. Adverse impacts of MHW on western rock lobster and other species were identified by Caputi *et al.* (2014). Consequently, we also investigated the potential impact of the MHW phenomenon as a potentially important environmental driver in this study. We note also that it is a phenomenon the impact of which may well depend on the issues of memory, persistence, intermittence and thresholds discussed in the preceding section.

We relied on a hierarchical definition of MHW episodes (Hobday *et al.* 2016) comprising the following key ingredients: (i) Anomalously warm temperatures with respect to a baseline average temperature over a period of 30 years, and a high percentile threshold of 90%; (ii) Prolonged events persisting for at least five days; (iii) Discrete events appearing with sufficient separation between successive events. Following the convention in Hobday *et al.* (2016) one MHW event could have one of the following forms:

- at least 5 hot days, or
- at least 5 hot days, followed by no more than 2 normal days, followed by at least 5 hot days, or
- at least 5 hot days followed by no more than 2 normal days, followed by at least 1 but fewer than 5 hot days, or
- at least 1 but fewer than 5 hot days, followed by no more than 2 normal days, followed by at least 5 hot days.

Here “normal” temperature refers to any temperature below the 90th percentile and “hot” refers to any temperature at or above that percentile. It should also be clear that two successive MHW events must be separated by more than two days of normal temperatures.

The MHW events characterised above permit us to form episodes E_k and MHW indices of the $X(\mathbf{I}, \mathbf{w})$ type considered in Section 3.3. The intensity function that calculates the strength $I(E_k)$ of the k th event, its weight $w(E_k)$ and the length M of the memory, must be set. Hobday *et al.* (2016) provide a wide selection of possible intensity functions and we have selected the one that is called the “mean temperature anomaly during the MHW”. This corresponds to area between the black and blue curves in Figure 25 during the MHW episode E_k , divided by the duration of that episode.

In our application baseline temperature from IMOS database was used with (6 day average night time, “ghrsst_L3S_6d_ngt”) resolution over a period of approximately 28 years (01/04/1992 to 31/12/2019), only slightly below the above mentioned 30 years. The 6 day average night time dataset was used in order to avoid any daytime temperature artefacts (e.g. sun glint), and 6 day averaging fills gaps that are otherwise present in the daily time series as a result of cloud cover blocking satellite view of the ocean surface. To make the concept clearer Figure 25 illustrates a typical MHW event occurring in April 2016, shaded in red, in the Snapper offshore area of Brisbane and Sunshine Coast (see Figure 19).

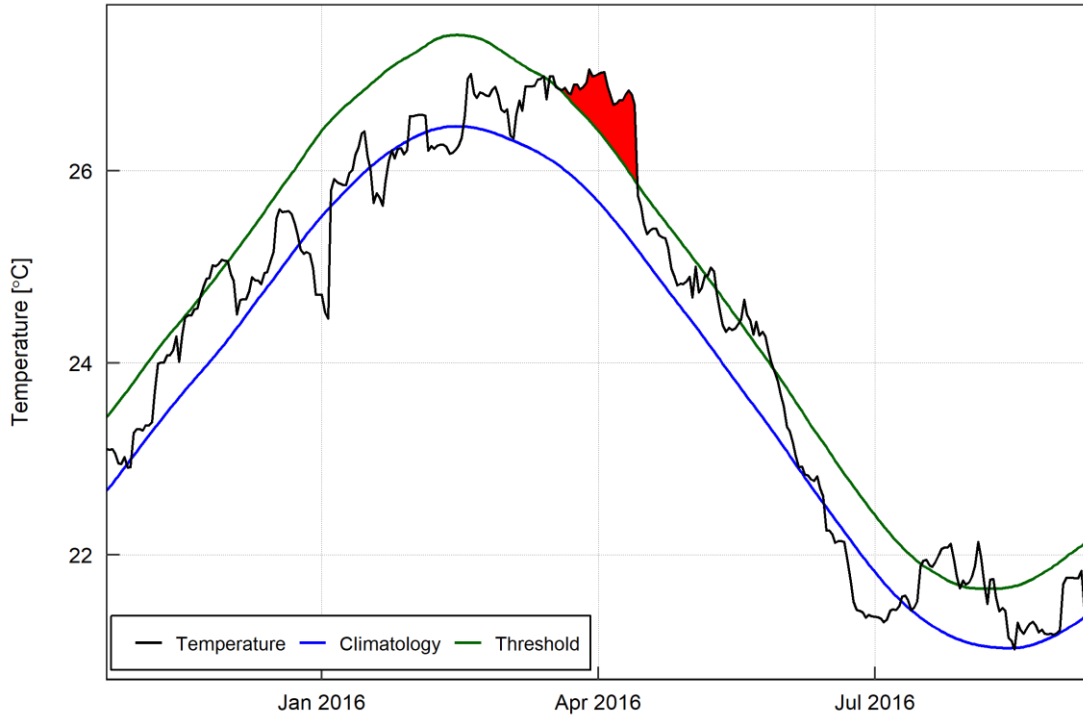


Figure 25: A typical MHW event, shaded in red, in April 2016 in the Snapper offshore area of Brisbane and Sunshine Coast. The blue curve indicates the baseline long-term mean daily temperature, the green curve is its 90th percentile upper bound and the black curve represents the daily averages.

3.5 A Strategy for Incorporating Environmental Factors

For the sake of illustration of the methodology, assume that one or more environmental variables have been identified that significantly impact the species under investigation and that these variables are captured in an environmental index z_t , constructed so that it produces negative values if it is detrimental for the species and positive values if it is associated with increased abundance. We explored two distinct, yet related, approaches for incorporating such an index into stock assessment models based on: I. Surplus production models, and II. CPUE standardisation models. Below, we use a green font to indicate possible modifications to models' equations.

I. Surplus production models

Consider a surplus production model of the generic form:

$$B_t = B_{t-1} + SP(B_{t-1}) - C_{t-1}, \quad (15)$$

where B_t denotes biomass in year t , $SP(B_{t-1})$ denotes the natural surplus during the previous year and C_{t-1} denotes the biomass harvested. Now, there are two natural ways by which environmental index z_t can be incorporated into the model:

- a. Environmental index influences the biomass proportionally; that is

$$B_t = (B_{t-1} + SP(B_{t-1}) - C_{t-1})e^{\beta z_{t-1}}.$$

- b. Environmental index influences the surplus production proportionally; that is

$$B_t = B_{t-1} + SP(B_{t-1})e^{\beta z_{t-1}} - C_{t-1}.$$

II. CPUE standardisation models

We also consider incorporating environmental indices in CPUE standardization. One step in the standardization process is building a model that relates the CPUE to a set of observed variables, using models like GLM or GAM. The generic form of the latter is:

$$SCPUE = H(x_1, x_2, \dots, x_k), \quad (16)$$

where the variables x_1, x_2, \dots, x_k denote known (or expected) systematic factors affecting catchability such as year, season, type of gear, lunar phase etc. Recognising that some of our environmental indices may also affect catchability we shall also examine modified SCPUE models of the form

$$SCPUE = H(x_1, x_2, \dots, x_k, z), \quad (17)$$

where the inclusion of the environmental index z in the above is also allowing for the possibility of including it with appropriate time lags.

We note that approach II. can be adopted in conjunction with approach I. because it is certainly possible that some environmental indices may impact catchability while some others may impact reproductive potential/abundance.

3.5.1 Including environmental factors in a surplus production JABBA model

Next, we consider in a little more detail of approach I. The advantage of such models is that with only a few parameters and minimal data requirements they enable us to estimate maximum sustainable yield (MSY) and accompanying reference points for fisheries management. We have selected the modelling platform and framework of Winker *et al.* (2018) that is known under the acronym JABBA (Just Another Bayesian Biomass Assessment). While JABBA can accommodate several forms of surplus biomass functions $SP(B_t)$, their detailed analysis centres around a rather flexible Pella and Tomlinson (1969) model with the mathematical form

$$SP(B_t) = \frac{r}{m-1} B_t \left(1 - \left(\frac{B_t}{K} \right)^{m-1} \right), \quad (18)$$

where r is the intrinsic rate of population increase at time t , K is the carrying capacity and m is a shape parameter. These parameters are assumed to be larger than zero. If we denote the biomass corresponding to the maximum sustainable yield by B_{MSY} , then it can be easily shown that for m not equal to 1

$$B_{MSY} = K \left(\frac{1}{m} \right)^{\frac{1}{m-1}}, \text{ or equivalently, } \frac{B_{MSY}}{K} = \left(\frac{1}{m} \right)^{\frac{1}{m-1}} \quad (19)$$

Because of certain biologically undesirable properties when $m \leq 1$, we will assume $m > 1$. It is also well known that fishing mortality corresponding to the maximum sustainable yield, denoted by F_{MSY} , is given by the simple formula

$$F_{MSY} = \frac{r}{m-1} \left(1 - \frac{1}{m} \right). \quad (20)$$

With B_{MSY} and F_{MSY} used as reference points and prior distributions selected, MCMC (Markov chain, Monte Carlo) technique is exploited to calibrate the model's parameters to best fit historical catch data recovered from time series of CPUE records.

The trajectory of the system can be conveniently visualised in a so-called Kobe phase plot which uses the biomass ratio B/B_{MSY} and the fishing mortality ratio F/F_{MSY} as performance criteria on the horizontal and vertical axis, respectively (see Figure 26). The lines of the biomass ratio and fishing mortality ratio equal to one split the plotted area into four rectangles. The area of $B/B_{MSY} < 1$ and $F/F_{MSY} > 1$, indicating low biomass and high fishing mortality, is the least desirable high risk state (coloured red, depleted) for the system's trajectory to reside in. On the other hand, the area of $B/B_{MSY} > 1$ and $F/F_{MSY} < 1$, indicating high biomass and low fishing mortality, is the most desirable and sustainable state (green, sustainable). The states of $B/B_{MSY} < 1$ and $F/F_{MSY} < 1$ (yellow, recovering), and of $B/B_{MSY} > 1$ and $F/F_{MSY} > 1$ (brown, depleting) are ones where exactly one of the criteria represented by these ratios is taking undesirable values.

The advantage of the Kobe plot visualisation is that as the trajectory of the fishery evolves (e.g. yearly) it can be represented as a sequence of points residing, at different times, in one of these four different regions. This enables managers to assess whether the trajectory is either in, or moving towards, the most sustainable green rectangle.

In the illustration depicted in Figure 26 below, for Queensland's Spanner Crab fishery, it was assumed that $B_{MSY} \approx 0.5K$ and that the starting biomass in year 1988 was approximately 80% of the virgin biomass level. Under this scenario, the trajectory begins in 1988 deep in the sustainable (green) state, before entering the depleting state in 1994, then re-enters the sustainable state in 2002 where it remains until 2012, and finally ends up in the recovering state from 2013 to 2019. Naturally, uncertainties accumulate as the trajectory evolves. In the JABBA visualisation the roughly oval grey shaded shapes correspond to the 50%, 80% and 95% confidence regions for the location of the final 2019 point of the trajectory. In the case of the Spanner Crab setup scenario illustrated here we note that while these states are wide, a large portion of them overlaps either the depleted (red) or the recovering (yellow) states.

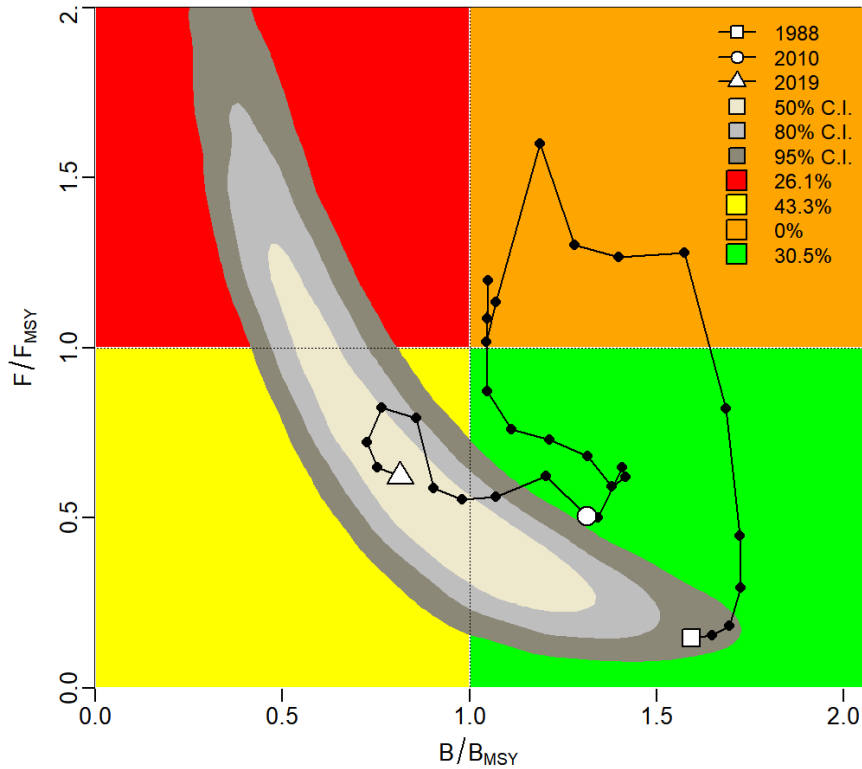


Figure 26: Kobe plot for the Queensland's Spanner Crab fishery over 1988-2019.

From the perspective of this project, the most important question is whether the inclusion of environmental variables into the surplus production model in the manner discussed in Section 3.4, significantly impacts either the trajectory or the uncertainty regions in the above Kobe plots. If it turns out that such impacts are negligible, or small, that suggests that – at the coarse surplus production level – stock assessment omitting environmental variables from the model does not materially alter the models' outputs.

Remark: We recall that in Section 3.4 we proposed two options for including environmental drivers: (a) Environmental variable influences the biomass proportionally, and (b) Environmental index influences the surplus production proportionally, namely, $B_t = B_{t-1} + SP(B_{t-1})e^{\beta z_{t-1}} - C_{t-1}$, where z_t denotes the environmental variable. Preliminary exploration of these two options indicated that only (b) yielded meaningful results. Hence the results reported later in this report pertain to that option.

3.5.2 Including environmental variables in CPUE standardisation

Catch rate or catch per unit effort (CPUE) standardisation becomes essential in the process of fisheries stock assessment because comparing with nominal CPUE (i.e., reported catch divided by reported fishing effort), standardised CPUE is independent of factors other than fish abundance and is less biased as an abundance index used in stock models (Maunder 2004).

A catch rate standardisation model is adapted to model catch (C) with fishing effort offset in the model or CPUE data. Here, we represent the modelling of C in the generic form

$$E(C|\mathbf{x}) = H(x_1, x_2, \dots, x_k), \quad (21)$$

where the vector \mathbf{x} consists of variables x_1, x_2, \dots, x_k denoting observed factors affecting catchability such as year, season, type of gear, lunar phase etc. The expression $E(C|\mathbf{x})$ denotes expected catch given the vector \mathbf{x} .

In this project, we studied whether environmental factors need to be taken into account in the CPUE standardization process. To do so, we calculate the SCPUEs for Spanner Crab and Snapper using models with and without environmental factors, then compare the models and SCPUEs to check whether including the environmental factors results in any difference.

Hence, we explored the possibility of appending one or more environmental variables z to the vector \mathbf{x} of systematic factors influencing catchability. Effectively, this changes (21) above to

$$E(C|\mathbf{x}, z) = H(x_1, x_2, \dots, x_k, z). \quad (22)$$

Spanner Crabs

For Queensland's Spanner Crab fishery, the baseline GLM model was analogous to that used by DAF and reported in Campbell *et al.* (2016). We assumed that catch C conditional on a vector of predictors \mathbf{x} is quasi-Poisson distributed with the variance proportional to the expected catch.

$$E(C|\mathbf{x}) = \exp \{ \beta_0 + \beta_l l + \beta_g g + \beta_{l_{adv}} l_{adv} + \beta_b b + \beta_y y + \beta_r r + fp + \beta_{ge} \cdot (g \times e) + \beta_{yr} \cdot (y \times r) + \beta_{rs} \cdot (r \times s) + \beta_{rcs} \cdot (r \times cs) + \beta_{rs_6} \cdot (r \times s_6) + \beta_{rcs_6} \cdot (r \times cs_6) + \beta_{rs_4} \cdot (r \times s_4) + \beta_{rcs_4} \cdot (r \times cs_4) \}, \quad (23)$$

where the variables of the model are specified in Table 2. The coefficients with double subscripts correspond to interaction terms between pairs of variables, which are denoted with \times symbol. The \cdot notation stands for the inner product of two vectors. For instance, with y taking on 18 possible values and r corresponding to 5 regions, the interaction $y \times r$ denotes a 90 dimensional vector with zeros except for unity in the entry corresponding to year y and region r , and the coefficient vector β_{yr} has length 90. Thus, this is a heavily parameterised model designed to ensure that any trends are able to reflect changes in abundance.

Table 2: Description of variables used in model (23).

Variable	Type	Definition
lunar (l)	continuous	lunar phase represented as the calculated luminance measure, which follows a sinusoidal pattern.
lunaradv (l_{adv})	continuous	the same lunar data replicated and advanced seven days.
gfpid (g)	binary	Indicating whether the boat has a general fisheries permit (GFP).
potsliftlog (e)	continuous	logarithm of the number of pots lifted.
boat (b)	categorical	the boat id (213 levels).
year (y)	categorical	year (18 levels).
region (r)	categorical	region (5 levels).
c12 (s)	continuous	seasonality, calculated as $\cos(2\pi d/D)$, where d and D are the number of days lapsed in the year and the total number of days in the year.
c6 (s_6)	continuous	$\cos(4\pi d/D)$.
c4 (s_4)	continuous	$\cos(6\pi d/D)$.
cs12 (cs)	continuous	$\sin(2\pi d/D)$.
cs6 (cs_6)	continuous	$\sin(4\pi d/D)$.
cs4 (cs_4)	continuous	$\sin(6\pi d/D)$.
logfp (fp)	continuous	logarithm of fishing power (coefficient set to 1).

Equation above is the more detailed form of the generic equation (21). After inclusion of an environmental variable z , the corresponding analogue of (22) becomes

$$\begin{aligned}
E(C|x, z) = & \exp \{ \beta_0 + \beta_l l + \beta_g g + \beta_{l_{adv}} l_{adv} + \beta_b b + \beta_y y + \beta_r r + fp + \beta_{ge} \cdot (g \times e) \\
& + \beta_{yr} \cdot (y \times r) + \beta_{rs} \cdot (r \times s) + \beta_{rcs} \cdot (r \times cs) + \beta_{rs_6} \cdot (r \times s_6) \\
& + \beta_{rcs_6} \cdot (r \times cs_6) + \beta_{rs_4} \cdot (r \times s_4) + \beta_{rcs_4} \cdot (r \times cs_4) + \beta_z z \},
\end{aligned} \tag{24}$$

where z can be a variable such as SST, GSLA, Chl-a, etc.

Snapper

In the case of Snapper, the CPUE standardisation procedure is more complicated since commercial logbook data contain a moderately high proportion of records (approximately 24%) where zero catch is recorded. Now, a GLM approach is used to model the probability of obtaining a non-zero catch that is combined with an LMM (Linear Mixed Model) approach to estimate the expected logarithm of such positive catch. The resulting benchmark model is the same as the one reported in Wortmann *et al.* (2018, Table 5.12). We do not elaborate the details because the findings are even less significant than those reported above for Spanner Crabs. These details can be found in working files stored on AARNET cloudstor (see Section 9.1).

3.6 Modelling Time Series of Environmental Variables

In the preceding section we discussed methodologies for incorporating a time dependent environmental index z_t into surplus production models. However, once that is done, there is a need to construct future scenarios of such an index to enhance Management Strategy Evaluations (MSEs). There is a large body of quantitative techniques that can be used to construct such future scenarios of an index based on time series of historical data for that same index. In this project, for the most part, we exploited rather routine curve fitting and extrapolation methods that do not require further elaboration. In this section, we very briefly outline our use of one somewhat more advanced technique known as polynomial-trigonometric regression (Eubank and Speckman 1990). This technique is appropriate when that time series of the variable of interest is strongly periodic, as is the case with SST that features importantly in this study.

For the purpose of this outline, let z_t denote SST in month t , in a given region of interest. As will be seen later this variable exhibits a very strong annual cycle and is generally expected to have slight time trend induced by global climate change. Hence, it is reasonable to attempt to fit the following mathematical model to this variable

$$z_t = c_1 + c_2 t + c_3 \sin\left(\frac{2\pi}{12} t\right) + c_4 \cos\left(\frac{2\pi}{12} t\right) + R_t, \tag{25}$$

where the linear terms are designed to model the mean trend (via coefficients c_1 and c_2), the trigonometric terms are to capture the annual cycle (via c_3 and c_4) and R_t denotes the residual. Auto-correlations in R_t are modelled by an autoregressive (AR) model of the form

$$R_t = c_5 R_{t-1} + \epsilon_t, \tag{26}$$

where c_5 is the AR coefficient and ϵ_t is a white noise error term. The model coefficients are estimated using maximum likelihood estimation (Hyndman and Khandakar 2008; Trapletti and Hornik 2020). Once these coefficients have been estimated, equations (25)-(26) lead to the following recursive relationship that can be used to estimate z_{t+m} , at m months in the future

$$z_{t+m} = c_1 + c_2(t + m) + c_3 \sin\left(\frac{2\pi(t + m)}{12}\right) + c_4 \cos\left(\frac{2\pi(t + m)}{12}\right) + c_5^{m+1}R_{t-1} + \sum_{i=0}^m c_5^i \epsilon_{t+m-i}. \quad (27)$$

In the above, depending on the application, the error term ϵ_t would either be replaced by its estimated expected value of 0, or simulated by random sampling from the appropriate distribution (typically, $N(0, \sigma^2)$). Of course, σ^2 can be estimated from the time series of the errors generated by (26). Figure 27 illustrates the fit of monthly average SST data from the offshore Region 1N (indicated in the right panel of (Figure 19) and the output generated by the above trigonometric regression technique.

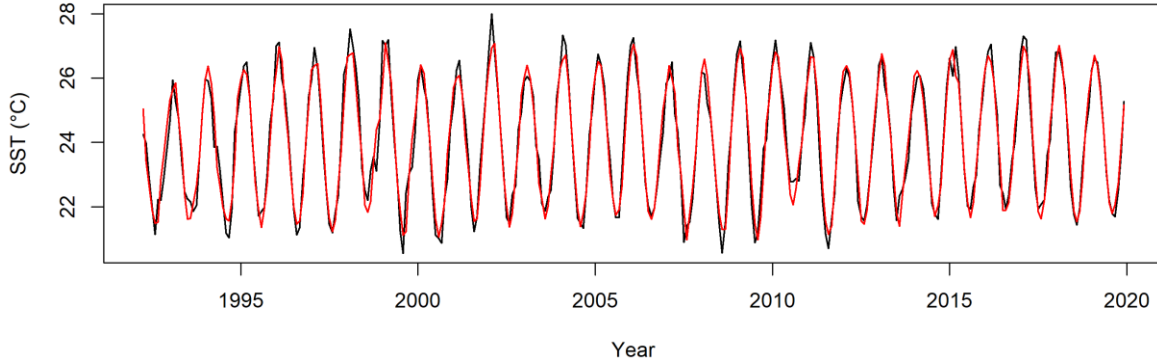


Figure 27: Monthly average SST in Snapper offshore area 1N (black curve), and trigonometric regression generated model (red curve).

We note that the model in equation (25) is said to be of *polynomial order 1* and of *trigonometric order 1*. This is because the terms $c_1 + c_2t$ formed an order 1 polynomial in t and there was only one pair of trigonometric terms with only one frequency. Clearly, these orders could be changed but, naturally, higher orders necessitate estimation of more parameters. Polynomial order 0 corresponds to the case of absence of long-term trend. The highest trigonometric order used in this study is 2 (see Section 4.4.2).

4 Results

4.1 Snapper: Correlation Analyses for Key Environmental Variables

Environmental indices were analysed in Moreton Bay where juvenile Snapper abundance data are available from the annual FIS and the CFISH grid cells from which the majority of the commercial catch is reported (Figure 19). Note that the four northern grid cells in the right panel of Figure 19 constitute Region 1N, the five southern cells form Region 1S and the nine cells combined makeup Region 1W. Consistency between nominal and standardised density response variables was confirmed in the sense that qualitatively similar results are obtained using either one of these variables. A detailed comparison can be found in working files stored on AARNET cloudstor (see Section 9.1).

Several environmental variables were found to have strong associations with either the abundance or catchability of Snapper. These included GSLA, SST, Chl-a, truFlo, TideR, SOI and others.

1. There is evidence of a negative linear association between pre-recruit density in the November-December FIS and SST in preceding June and July (i.e. adult spawning period) in offshore areas where the majority of Snapper spawning stock is thought to be present (see Figure 1).

2. A threshold temperature sensitivity range of 19.8°C to 21.8°C was identified for offshore Snapper spawning. Higher frequency and larger magnitude of temperatures above these thresholds in June are negatively associated with subsequent Snapper pre-recruitment, with a correlation value equal to or smaller than -0.8.

3. There is evidence of positive linear relationships between pre-recruit density in the November-December FIS and Chl-a in the preceding June-October period in offshore areas and in the preceding September-October period within Moreton Bay. This is potentially related to high levels of primary productivity improving Snapper larval survival and/or growth rates in the plankton.

4. A linear combination of two environmental variables (SST in June and Chl-a in September) was found to account for 75% of the variability in the nominal density of Snapper pre-recruits in the November-December FIS.

5. There is evidence that the density of Snapper pre-recruits in the annual FIS in Moreton Bay is an indicator of subsequent annual commercial line CPUE in Queensland. The strongest correlation is between the density of Snapper pre-recruits and commercial catch rates four years later. Four-year-olds are typically one of the most abundant age classes in the Queensland Snapper line fishery.

In the remainder of this sub-section, we summarise a representative sample of various analyses supporting these findings. Further details of these analyses are documented in the project’s repository of files stored on AARNET cloudstor (see Section 9.1).

4.1.1 Snapper pre-recruits overview and summary of strength of associations

In the association analysis, the response variables used were nominal FIS density (densSPR), standardised density and their logarithmic transformations. However, as the results were largely very consistent, we illustrate only with nominal density. Table 3 highlights several important correlations and their corresponding R² statistic showing the proportion of variability in densSPR explained by each of these environmental variables. All but one of these associations are statistically significant at the <0.05 level. These are colour coded in green.

Table 3: Correlation coefficients between nominal density of Snapper pre-recruit and selected environmental variables at Moreton Bay. Months refer to the most recent year. River discharge (truFlo) and tidal range (TideR) refer to Brisbane river and Brisbane bar.

Lag (month)	Environmental index	Correlation with densSPR	R ²
-Jun	Mean SST	-0.71	0.51
-Sep	log (median Chl-a)	0.62	0.39
-Jun	log (mean truFlo)	0.54	0.30
-Sep	Mean TideR	-0.63	0.40
-Nov	Mean GSLA	-0.74	0.55

The possibility of combining these environmental variables into more complex and powerful indices will be explored further. However, the temptation to do so will be tempered by the recognition of both the dangers of model overfitting and collinearity among the environmental variables that Figure 28 shows. Some candidate pairs of variables are not strongly correlated and are pursued in further analyses in Section 4.1.4.

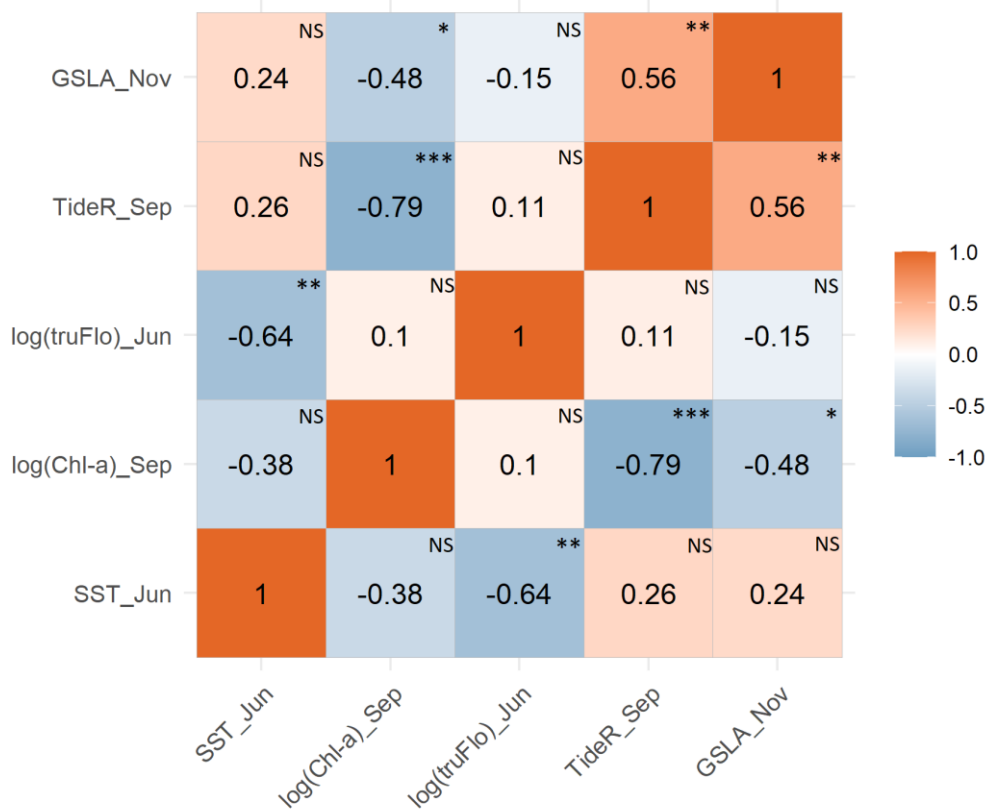


Figure 28: Correlation values between key environmental variables. Colour intensity (light to dark) is proportional to the correlation coefficients (0 to 1 for the positive coefficient and 0 to -1 for negative coefficient). An asterisk * denotes the significance of the correlation between 0.05 and 0.10, double ** corresponds to level between 0.01 and 0.05, triple *** corresponds to level below 0.01, and NS stands for non-significant.

In Table 4, we summarise the pattern of positive and negative associations between the nominal Snapper pre-recruits and several key environmental variables including those highlighted earlier in Table 3, at a range of different monthly lags in the year preceding the sampled observations.

We also considered the proposition that, indirectly, environmental variables in the adult Snapper areas 1N, 1S and 1W (closest to the pre-recruit Moreton Bay (MB)) may also influence pre-recruit density. As can be seen from Table 4, this is the case for SST lagged 6 months to the most recent June and is indicated by the green column of negative correlations for all four areas of interest. Adjacent months' columns (July and May) also contain some associations significant at the same level.

Similarly, the logarithmically transformed Chl-a variable in the most recent July and June (and adult regions 1N, 1S, 1W) had moderate¹ positive correlations with FIS densSPR in November-December, even though only the one in Region 1N was statistically significant at the 95% level. The same variable lagged only two months to the most recent October also had a significant positive association in regions 1S and 1W, with correlations in regions MB and 1N still noteworthy but not quite reaching the 95% level cut-off.

¹ Sufficiently high absolute values of the correlation coefficient are possible indicators of the presence of a linear relationship between covariates. While there is no universally accepted threshold, a simple rule-of-thumb of the correlation being greater than $1/\sqrt{n}$ is sometimes used (e.g. Krehbiel 2004).

Table 4: Summary table of the linear regression analyses performed to explore the effect of environmental indices on FIS density of pre-recruit Snappers in Moreton Bay in November-December, 2007-2019. Values in green indicate correlations statistically significant at the 95% level.

Month	Dec	Nov	Oct	Sep	Aug	Jul	Jun	May	Apr	Mar	Feb	Jan
Lag	0	1	2	3	4	5	6	7	8	9	10	11
Sea Surface Temperature												
Mean SST												
Region												
MB	-.50	-.11	-.51	.11	-.06	-.48	-.71	-.04	-.08	-.20	.22	-.55
1N	-.42	-.28	-.23	-.24	-.48	-.58	-.71	-.59	-.49	-.19	.31	-.07
1S	-.53	-.30	-.63	-.31	-.48	-.79	-.73	-.44	-.40	-.26	.01	-.32
1W (1N+1S)	-.51	-.37	-.31	-.21	-.39	-.58	-.75	-.33	-.35	-.12	.31	-.12
Chlorophyll a												
Log (Median Chl-a)												
Region												
MB	.18	.28	.55	.62	.25	.34	.19	.01	.14	.44	.34	.21
1N	.35	.35	.54	.39	.43	.58	.37	.19	.12	.04	.15	.17
1S	.33	.31	.63	.44	.32	.50	.51	.22	.11	-.06	.13	.40
1W (1N+1S)	.32	.34	.62	.43	.37	.53	.43	.19	.12	-.03	.13	.35
Gridded Sea Level Anomaly												
Mean GSLA												
Region												
MB	-.13	-.74	-.63	.02	-.45	-.58	-.34	-.48	-.52	-.13	-.35	-.31
1N	.20	-.42	-.07	-.58	-.30	-.13	-.32	-.41	.00	-.19	.01	.27
1S	-.48	-.55	-.55	-.39	-.64	-.66	-.70	-.45	-.41	-.43	-.42	-.36
1W (1N+1S)	-.10	-.63	-.49	-.31	-.46	-.72	-.51	-.29	-.40	-.31	-.26	-.03
River Discharge												
Log (Mean truFlo)												
Station												
Caboolture River (142001A)	.16	-.23	-.16	-.02	.15	.36	.38	.16	.16	.17	.31	.53
Brisbane River (143001C)	.07	.23	-.14	-.14	.24	.43	.54	-.23	.23	.46	.50	.61
Logan River (145014A)	.08	.06	.20	.24	.19	.11	.18	-.07	-.30	-.19	.33	.46
Tidal Range												
Mean TideR												
Tide gauge												
Brisbane Bar	-.17	-.61	.06	-.63	-.35	-.10	-.26	.23	.17	.17	.07	.47
Mooloolaba Bar	-.09	-.56	.12	-.66	-.39	.06	-.15	.32	.40	.35	.04	.52
Southport Bar	.20	-.39	.07	-.56	-.35	-.05	-.25	.17	.08	-.06	-.14	.17
Southern Oscillation Index												
Mean SOI												
	.44	.37	.34	.41	.31	.36	.26	.20	.40	.69	.43	.46

The GSLA variable in the most recent periods from November to October and August to June had several significant negative associations with the FIS densSPR in November-December, in at least one of the four areas considered. Notably, in Region 1S, the observed correlations for August, July and June were -0.64, -0.66 and -0.7, respectively. The Moreton Bay GSLA correlations for November and October were -0.74 and -0.63.

As far as the logarithmically transformed river discharge variable truFlo was concerned, it was tested for association with densSPR for Caboolture, Brisbane and Logan rivers. Of these, the only statistically significant positive association was detected for the Brisbane river's discharge in January (lag 11). However, there were also two other moderate positive correlations that missed the 95% significance level cut-off. This also applied to the Caboolture river's discharge in previous January.

The mean TideR variable observations were taken from three gauges: Brisbane Bar, Mooloolaba Bar and Southport Bar. For the Brisbane Bar, significant negative associations with the FIS densSPR in November–December were observed for most recent November (lag1) and September (lag3) TideR. For the Mooloolaba Bar the only association meeting the 95% significance level was again observed in September (lag3). There were other moderate negative correlations that did not meet the 0.05 p-value cut-off. The effects of the SOI signal will be discussed in more detail later in this report (Section 4.1.7).

4.1.2 Snapper pre-recruits and sea surface temperature

A strong and highly significant correlation ($r = -0.71$, $p = 0.015$)² was identified between FIS pre-recruit Snapper nominal density in November–December and SST in Moreton Bay in the preceding June (see Table 3). Replacing the mean SST with a suitable δ -rectified mean SST variable in the preceding June yielded several even stronger correlations³. The strongest correlation ($r = -0.84$, $p < 0.001$) was attained using a threshold of $\delta = 18.2^\circ\text{C}$, resulting in a change in R^2 from 0.51 to 0.70. That is, an 18.2° -rectified mean SST in the preceding June explains 19% more of the variability in densSPR than the standard mean SST approach.

Moreover, June SST may be impacting the spawning adult populations in the nearby Fraser, Sunshine Coast and Brisbane offshore areas (Region 1W in Figure 19). Hence, the above δ -rectified mean SST analysis was repeated using water temperatures from these areas and is illustrated in Figure 29. An even stronger negative correlation of $r = -0.86$ was identified but with a higher threshold of 21.0°C . This accounts for nearly 74% of the variability in the FIS pre-recruit nominal density.

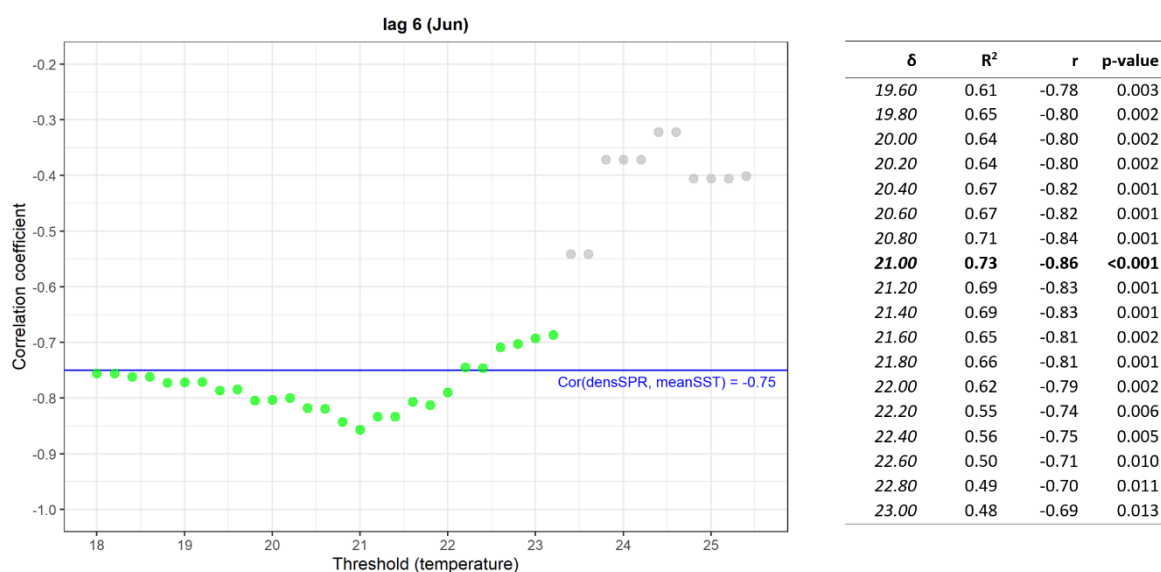


Figure 29: Correlations (r) between FIS pre-recruit nominal density and δ -rectified mean SST in preceding June in the offshore Region 1W, for a range of δ values. Green dots indicate correlations significant at the 95% level.

In fact, if we search for the temperature range for which the correlation between δ -rectified mean SST and the nominal density of pre-recruits falls at, or below, the -0.8 level, this occurs between 19.8°C and 21.8°C . This can be seen from the right panel of Figure 29. The choice of the cut-off level may be driven by the degree of improvement in R^2 over the correlation with regular mean. In this instance, R^2

² Here, r denotes the (Pearson) correlation coefficient and p denotes the associated “p-value”, indicating how low is the probability that the corresponding, or stronger, value of r could have occurred purely at random.

³ Recall that in calculating the 18.2° -rectified mean SST variable in the preceding June, we zero-out all daily temperatures at or below 18.2°C and use equation (12) to average observations above that level.

improved from approximately 0.56 to 0.64, an increase of roughly 14%. These findings suggest that the 21°-rectified mean SST in preceding June in the nearby offshore areas (1W) may be a relevant environmental driver of the density of Snapper pre-recruits in the Moreton Bay area. Figure 30 shows that this single variable accounts for 73% of variability in the density.

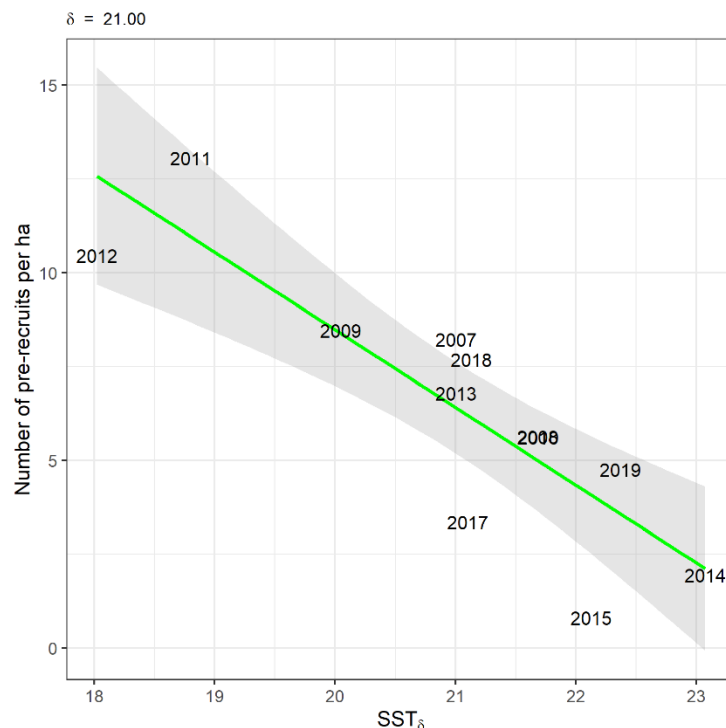


Figure 30: Scattergram of FIS pre-recruit nominal density in November-December and 21°-rectified mean SST in preceding June in offshore Region 1W, $r = -0.86$, $R^2 = 0.73$ and p -value much smaller than 0.05.

4.1.3 Snapper pre-recruits and chlorophyll a

Strong associations with highlighted environmental variables were preserved even when the response variable was logarithmically transformed but, sometimes, with somewhat different values. In Figure 31, we illustrate one such relationship between the logarithmically transformed nominal density of FIS pre-recruits in November-December and logarithmically transformed median values of Chl-a in the previous September corresponding to a lag of 3 months (with respect to December). The observed correlation between these variables was 0.62 and had p -value of 0.03 and $R^2 = 0.39$.

The three panels of Figure 31 demonstrate presence of a strong, positive association. In particular, panel A shows that all but two of the years covered by the data fall within the uncertainty bands of a straight line fit. The 2018 observation only just misses out while the 2015 observation corresponds to an exceptionally low catch rate that may be an outlier. Panels B and C illustrate the roughly similar trends between the logarithmically transformed density of Snapper and similarly transformed Chl-a median in the previous September. Time series of Chl-a (median values) were calculated from IMOS in September over the period 2007-2019 for Moreton Bay (30 nm by 30 nm grids). Note that Chl-a values above 15 mg/m³ were excluded as potentially erroneous due to the way in which remote sensing platforms measure Chl-a (Davies *et al.* 2018).

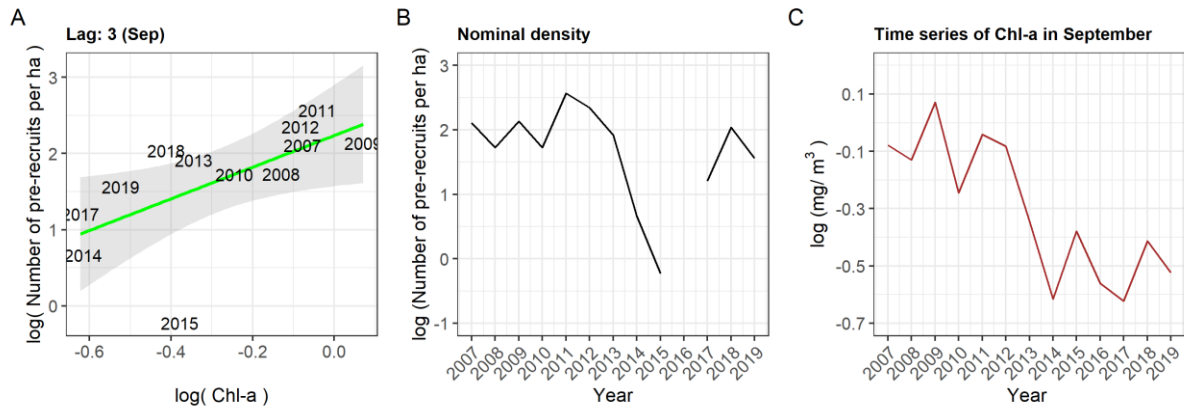


Figure 31: A) Scatterplot between density of Snapper pre-recruits in November-December and three month lagged September median Chl-a (log-log); B). Nominal density of Snapper pre-recruits in log scale and C) Chl-a (median values) in log scale at Moreton Bay region, $r = 0.62$, $R^2=0.39$ and p -value = 0.030.

To ensure that the inclusion of the outlier year 2015 does not artificially increase the linear association exhibited in Figure 31, we repeated the analysis with that data point excluded. The results indicate that this only increases the strength of the association.

4.1.4 Combinations of key environmental variables

As indicated earlier, the feasibility of combining these environmental variables into more complex and powerful indices needs to be explored. In particular, we would like to know whether significantly more of the variability in the FIS nominal density of Snapper pre-recruits variable densSPR can be explained by meaningful linear combinations of the environmental drivers summarised in Table 4. While there are many statistical techniques that could be employed for this purpose, we are constrained by data limitations (only 12 annual FIS data points) and multicollinearity already noted in Figure 28. In view of this, we focused on parsimonious multiple linear regression (MLR) techniques that would retain no more than two explanatory variables. Stepwise regression was used to identify promising pairs of explanatory variables. The addition or subtraction from the set of explanatory variables was based on Akaike information criterion (AIC). As the order of the variables matters, we run the stepwise in all directions and compare AIC values. Effectively, for each such pair MLR creates a combined index of the two variables with coefficients estimated by the technique.

The scattergrams in Figures 11-13 illustrate the performance of such combined indices. Each of these displays the corresponding scatterplot of observed vs fitted, with the regression line for the nominal FIS density of pre-recruits.

The best fit pair identified by MLR is shown in Figure 32. The fitted values correspond to the model with the log mean Brisbane river discharge in June and mean Brisbane tidal range in September. Note that the correlation is 0.89, which is considerably higher than the correlation if we separately considered only the river discharge in June ($r=0.54$), or only the tidal range in September ($r=-0.63$).

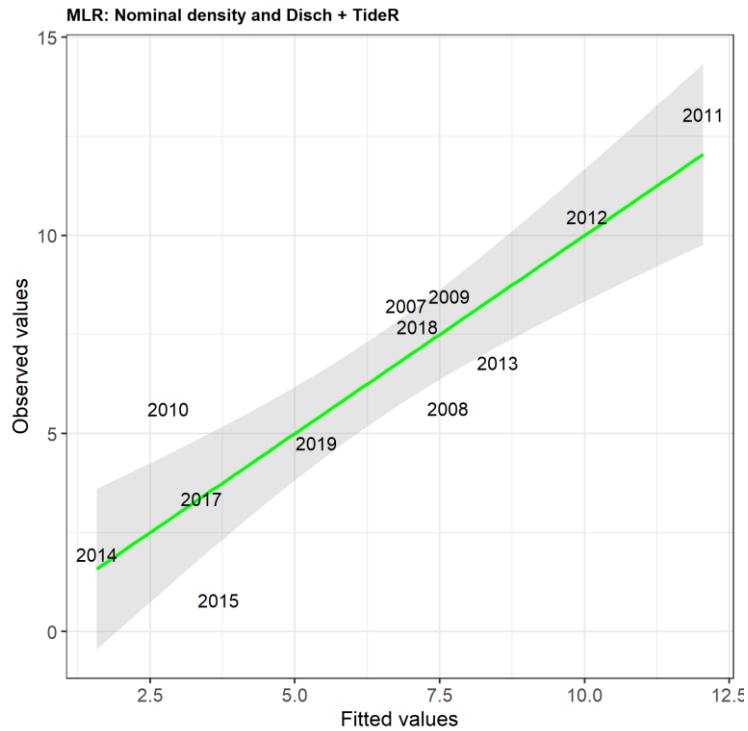


Figure 32: Scatterplot of FIS densSPR in November-December vs best MLR combination of Brisbane river discharge in June and Brisbane Bar tidal range in September, $r = 0.89$, $R^2=0.80$ and $p\text{-value} = 0.002$.

Despite the statistically excellent diagnostics of this pair of environmental variables, it was recognised that they are not well suited for incorporation into future trend scenarios because they are both tied to a specific location and have a lot of variability as well as limited biological meaning. Consequently, two other pairs of combined environmental variables were considered which have clearer potential biological mechanisms and provide statistical fits close to the above river discharge and tidal range pair.

From Figure 33, we see that the best combination of SST in June and Chl-a in September has a correlation of 0.87 with density and explains approximately 75% of the variability in the latter. This is a higher correlation than we would have obtained using SST in June (-0.71) or of Chl-a in September (0.62), separately.

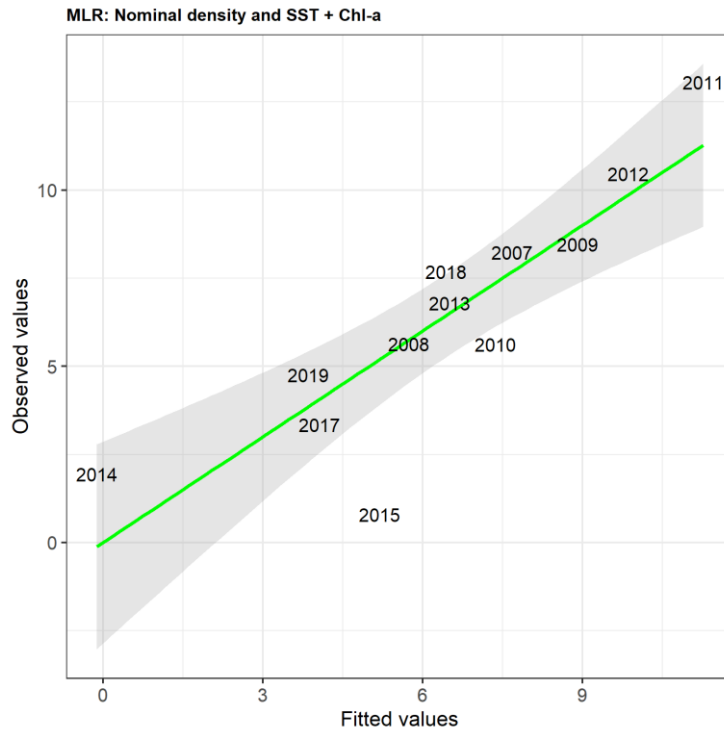


Figure 33: Scatterplot of FIS densSPR in November-December vs best MLR combination of SST in June and Chl-a in September, at Moreton Bay region, $r = 0.87$, $R^2=0.75$ and $p\text{-value} = 0.002$.

To ensure that the inclusion of the outlier year 2015 does not artificially increase the linear association exhibited in Figure 33, we repeated the analysis with that data point excluded. The results indicate that this only increases the strength of the association.

4.1.5 Snapper pre-recruits and large scale climatological/oceanographic indices

We also compared relative associations of two large-scale climatological/oceanographic indices with Snapper pre-recruit density. The two indices were SOI (Southern Oscillation Index) and PDO (Pacific Decadal Oscillation). Table 5 summarises correlations obtained to explore the effect of annual and seasonal means of SOI and PDO indices on FIS density of pre-recruit Snapper in Moreton Bay in November-December, 2007-2019. The analyses were conducted considering nominal as well as the standardised density as the response variable. When considered across the four seasons Summer and Autumn return the biggest positive correlations with SOI.

Table 5: Correlation of FIS nominal and standardised pre-recruit density with annual and seasonal large-scale climatological indices, 2007-2019. Values in green indicate correlations statistically significant at the 95% level.

Period	Nominal density		Standardised density	
	SOI	PDO	SOI	PDO
annual	0.57	-0.83	0.54	-0.72
summer	0.61	-0.84	0.50	-0.78
autumn	0.63	-0.84	0.57	-0.59
winter	0.36	-0.67	0.27	-0.59
spring	0.40	-0.77	0.40	-0.67

The consistently strong negative correlations with PDO are noted as worthy of further investigation. These are not pursued further as we are not aware of studies linking this index to the biology of any of the three species that are targets of this project and because the long-term nature of PDO and its effects on the environment and biology of marine species are poorly understood.

4.1.6 Association between Snapper pre-recruits and adults

Since Snapper pre-recruits FIS data are only from Moreton Bay area it is not a priori clear whether they are indicative of any trends in the adult Snapper population. Here we demonstrate that density of Snapper pre-recruits in the annual fishery independent survey in Moreton Bay is a reasonable indicator of commercial line CPUE in Queensland, four years later. In Table 6, we display the correlations between the log transformed SCPUE of commercial line catch, and log of densSPR from k years earlier, where $k = 0, 1, \dots, 6$. For instance, when $k = 2$, values of SCPUE in 2009, 2010, ..., 2019, correspond to values of densSPR in 2007, 2008, ..., 2017, since our FIS data series begins in 2007. Hence, as the delay index k increases by one, the length of the series used in the calculation decreases by one.

Table 6: Correlations between commercial log-transformed SPCUE and log-transformed FIS densSPR delayed by k years. Values in green indicate correlations statistically significant at the 95% level.

k	Correlation with densSPR	R ²
0	0.16	0.03
1	-0.02	0.00
2	0.60	0.36
3	0.50	0.25
4	0.78	0.61
5	0.34	0.12
6	-0.35	0.12

The strongest correlation of 0.78 observed in Table 6 is between the FIS density of Snapper pre-recruits and commercial catch rates four years later. Four-year-olds are typically one of the most abundant age classes in the Queensland Snapper line fishery. Figure 34 displays the scattergram corresponding to this association.

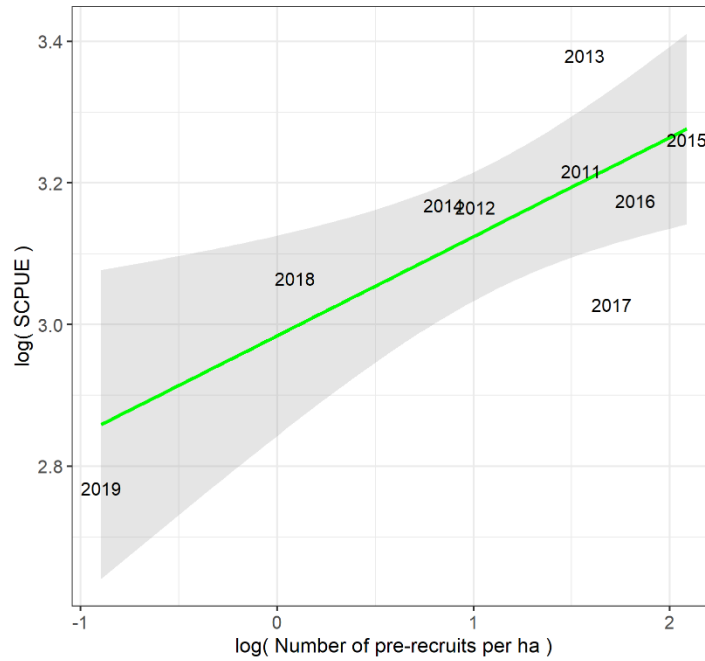


Figure 34: Scattergram of commercial log-transformed SCPUE delayed by 4 years vs log-transformed FIS densSPR. Yearly labels are for SCPUE, $r = 0.78$, $R^2=0.61$ and $p\text{-value} = 0.013$.

4.1.7 Commercial Snapper CPUE and long-term SOI associations

We also investigated associations between commercial standardised Snapper CPUE in Queensland and the SOI signal indices constructed using the methodology of Section 3.3 (a), (c), (d).

From the monthly SOI signal, we extracted indices $S^{\delta+}$ and $S^{\delta-}$ corresponding to the positive and the negative episodes of the signal for the values of $\delta=0$ and $\delta=8$ defined by equations (3) and (4) from Section 3.3. Note that thresholds of 8 and -8 are used to characterise La Niña and El Niño episodes, respectively. Mathematically, the threshold $\delta=0$ is more fundamental by merely separating the positive and negative components of the SOI signal.

The intensity of these episodes was calculated in accordance with either equation (6) or (7) and persistence weights by (9) with parameter $\alpha=2$. The location importance weights were all set to 1. We also considered a range of memory parameters $M = 1, 2 \dots 6$ corresponding to one to six years. Thus, for each of these six values of M we constructed time series of indices $S^{\delta+}$ and $S^{\delta-}$ over the years 1988 to 2019, separately for $\delta=0$, $\delta=8$ and under intensity functions (6) or (7). Finally, correlations between annual logarithmically transformed SCPUE and $S^{\delta+}$ and $S^{\delta-}$ were calculated.

The columns of A) in Table 7 give key statistics when intensity function (7) was used. It is clear that the association begins weakly and strengthens as the length of memory increases. We note the sustained increases in the absolute values of the consistently negative correlations. When the memory is increased to six years, the p-value drops to 0.014 and that $S^{\delta-}$ accounts for 19% of the variability in $\log(\text{SCPUE})$.

The columns of B) in Table 7 give the corresponding statistics when the intensity used to calculate $S^{\delta-}$ was changed from equation (7) to (6). Despite this change, the pattern is generally similar, but the strength of correlations is lower, and their p-values do not decrease monotonically with the length of the memory. However, the maximum memory of six years still corresponds to the strongest correlation of -0.39 and the lowest p-value of 0.027.

The results presented in Table 7 are somewhat counterintuitive because they suggest that sustained histories of stronger negative values of the SOI signal (i.e. El Niño events) are associated with better catch rates of Snapper. El Niño events are often associated with warmer SSTs; because SST has been demonstrated previously (Table 3) to have a negative association with Snapper abundance, this outcome suggests that different, non-SST aspects of El Niño episodes may be impacting Snapper measures of abundance (e.g. lower rainfall or wind speeds). Similar results are also observed in NSW commercial line Snapper and Pearl Perch fisheries (see Section 4.8, Tables 20 and 24) also in Regions 3 and 6 of the Spanner Crab fishery (see Section 4.2.6, Figure 52).

Table 7: Correlations of $\log(\text{SCPUE})$ versus $S^{\delta-}$ for $\delta=0$, commercial line catch, 1988-2019. A) intensity using equation (7), B) intensity using equation (6).

A) $\log(\text{SCPUE})$ vs $S^{\delta-}$				B) $\log(\text{SCPUE})$ vs $S^{\delta-}$			
Memory	r	R^2	p-value	Memory	r	R^2	p-value
1	-0.03	0.00	0.866	1	-0.18	0.03	0.328
2	-0.27	0.07	0.141	2	-0.27	0.07	0.139
3	-0.33	0.11	0.062	3	-0.30	0.09	0.098
4	-0.38	0.14	0.033	4	-0.33	0.11	0.069
5	-0.40	0.16	0.025	5	-0.31	0.10	0.084
6	-0.43	0.19	0.014	6	-0.39	0.15	0.027

4.1.8 Marine heatwaves

We now return to the consideration of the impact of MHW episodes on Snapper commercial line SCPUE with the help of the methodology introduced in Section 3.3. We considered the period from 01/04/1992 to 31/12/2019 (approximately 28 years) and corresponding SST data from IMOS to calculate the frequency and duration of MHW episodes in Snapper regions 1N, 1S and 1W. These results are summarised in Table 8.

Table 8: Number of MHW events and their average and maximum duration for Snapper regions 1N, 1S and 1W.

Region	# of events	Average duration (days)	Max duration (days)
1N	70	12.2	50
1S	64	12.8	59
1W	67	12.5	67

Over the period 2007-2019, we analysed correlations between logarithmically transformed standardised CPUE and the $X(\mathbf{I}, \mathbf{w})$ type MHW indices (see equation (2)) taking into consideration cumulative memories of 1 up to 8 years. The weight of $w(E_k) = w_1(n_k, M)w_2(s_k, M)$ of the k^{th} episode was calculated using equation (9) with $a=2$ for $w_1(n_k, M)$, and $w_2(s_k, M) = v(s_k, M)$ as in equation (10) with $c = 0$ and $d = 1$. We carried out the analyses for offshore regions 1N, 1S and 1W. Table 9 below summarises the results obtained.

Table 9: Correlations between log transformed Snapper SCPUE and MHW indices for a range of values of the cumulative memory parameter. Values in green indicate correlations statistically significant at the 95% level.

Memory	1N	1S	1W
1	-0.45	-0.27	-0.27
2	-0.49	-0.59	-0.53
3	-0.43	-0.48	-0.47
4	-0.54	-0.56	-0.52
5	-0.45	-0.51	-0.47
6	-0.34	-0.41	-0.33
7	-0.20	-0.31	-0.20
8	0.08	-0.08	0.09

We note the presence of strong, negative associations for short memory of two years. In the case of Region 1S, Figure 35 illustrates these findings in a little more detail. The left panel of that figure shows that in the case of log transformed Snapper standardised CPUE there was a significant negative association with MHW indices for memories of 2 and 4 years. This can be seen from the fact that the blue curve and its green (95%) confidence bands lie below the horizontal axis for $M=2$ and 4. Furthermore, the scattergram in the right panel of that same figure shows that when $M=2$, the MHW index accounts for approximately 35% of the variability of the log transformed catch rate. We note that this result is clearly impacted by the low catch rates of 2017-2019.

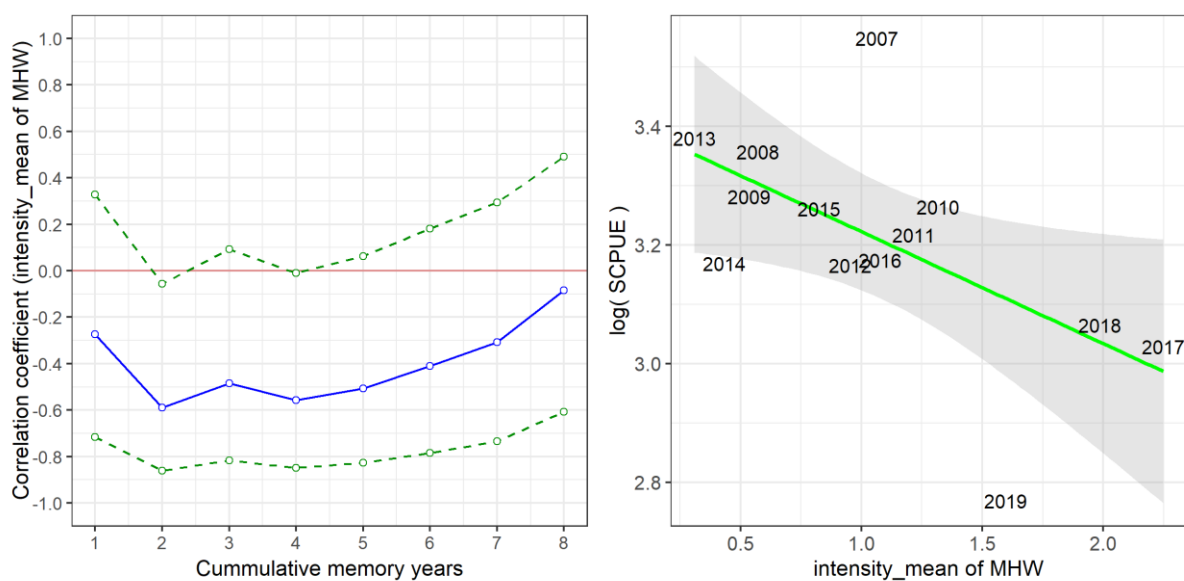


Figure 35: Left panel: correlations of log transformed SCPUE with MHW index (blue curve) and their 95% confidence bands in green, at Snapper Region 1S. Right panel: scattergram for the correlation corresponding to the cumulative memory of 2 years in Region 1S, $r = -0.59$, $R^2 = 0.35$ and p -value = 0.034.

4.2 Spanner Crab: Correlation Analyses for Key Environmental Variables

Because juvenile and adult Spanner Crabs are bottom dwelling, several environmental variables with available values-at-depth were considered at six depth levels: top (sea surface), 22m, 34m, 48m, 75m and bottom. This recognises that in some areas the bottom occurs at depths lower than some of the preceding levels and that data for some of the deeper levels would be more sparse. Similarly, because Spanner Crabs are estimated to recruit to the fishery at approximately 4.5 years old (male) and 6.5

years old (female), a history of up to 48 months (i.e. four years) was considered when considering possible lags of environmental variables.

A wide range of statistical analyses was carried out for a range of environmental variables including (but not limited to): water temperature at depth, GSLA, Chl-a, SST, current velocity, MHW, salinity, SOI and PDO. The results of these analyses are fully documented in working files stored on AARNET cloudstor (see Section 9.1).

For the sake of completeness, a series of preliminary consistency analyses was performed to guard against potential bias due to a choice of datasets, or of one of the widely used variable transformations. The general findings in that category were that there was:

- A high degree of consistency between analyses carried with BRAN 2016 and IMOS data (1996-2016);
- A high degree of consistency between analyses carried with raw environmental variables and their anomaly counterparts (e.g. for SST and its anomaly with respect to long-term average);
- A high degree of consistency between analyses carried out with raw catch rate variables and their logarithmic transforms.

In this report, we highlight a representative sample of those results that either indicate a presence of an association, or the absence of such an association in the cases where there may have been reasons to expect a contrary finding (such as previous studies). Extensive analyses of Spanner Crab associations with environmental variables revealed a complex pattern of both positive and negative correlations manifesting themselves differently in the six regions and on different time scales. The environmental variables that were found to have significant associations include (but are not limited to): GSLA, Chl-a, SST, SOI, current velocity and MHW. There are indications that some of the differences in these associations are based on the large latitudinal gradient across the Spanner Crab management regions and the cross-shelf depth gradient of the surveyed location in each management region.

The four main Spanner Crab findings that emerged from the analyses were:

1. Catch rate of legal-size crabs in Region 4 (the region with the largest commercial catch) appears to be insensitive to fluctuations in the following important environmental variables: Chl-a, sea level anomalies (i.e. eddies and upwelling), SST, and MHW. Catch rate of legal-size crabs in Region 4 is positively correlated with bottom current speed during the month of capture (i.e. related to catchability).

2. Chl-a is significantly associated with the catch rate of legal-size crabs in four of the five Queensland regions. Significant positive correlations in Regions 2, 3, 5 and 6 are present at multiple monthly lag times. Regions 2 and 3 are particularly strongly associated with the majority of time lags in the year preceding the catch. Chl-a is a proxy for primary productivity at the ocean surface, which is expected to be beneficial to higher trophic levels in the plankton, such as larval Spanner Crabs. Given that Spanner Crabs captured in the fishery are likely greater than 4 years old, the mechanism by which Chl-a influence catch rates the following year is unclear.

3. GSLA is negatively associated with the catch rate of legal-size crabs in three of the five Queensland regions. Significant negative correlations were found for Regions 2, 3 and 6, at multiple monthly lag times. GSLA is indicative of eddies, upwelling, and downwelling events. The negative correlation with Spanner Crab catch rates indicates that upwelling is beneficial to subsequent Spanner Crab catch rates. Upwelling typically triggers primary productivity blooms.

4. In Region 7, the direction of statistically significant associations between the catch rate of legal-size crabs and GSLA, Chl-a and SST is generally opposite to the corresponding associations in Regions 2, 3 and 6. Furthermore, it is the only region exhibiting a significant positive association with MHW. This finding requires further study of its underlying causes. It is conceivable that in this southernmost region the long-term warming trend could be beneficial rather than detrimental. Alternatively, these associations may be an artefact of large reductions in commercial fishing effort in this region in recent years improving local catch rates, coincidentally during the same period that GSLA and SST has been increasing and Chl-a has been decreasing.

Next, we present a representative sample of results supporting the above, as well as several other findings. The presentation is organised around the analyses carried out for each environmental variable. Greater emphasis was placed on findings for legal-size Spanner Crab than for sublegal crabs because it was assumed that catch data for legal-size crabs were more reliable since the dillies used in the surveys were specifically designed to catch legal-size animals.

4.2.1 Chlorophyll a

The analyses of the Chl-a reveal multiple significant, but complex, associations. Our main findings are:

- For both legal-size and sublegal crabs there are strong positive associations between catch rate and Chl-a in Regions 2, 3 and 6 at multiple monthly lag times.
- Catch rate of legal-size crabs in Region 4 is largely insensitive to fluctuations in Chl-a.
- For the sublegal crabs in Region 5, and to a lesser degree Region 4, there are several significant negative associations. This also applies to Region 7 for legal-size crabs.

The time series plots of logarithmically transformed Chl-a across the Spanner Crab Regions 2-7 are provided in Figure 36. The large spikes in 2019 in Regions 6 and 7 are interpreted as outliers and are monitored in subsequent analyses.

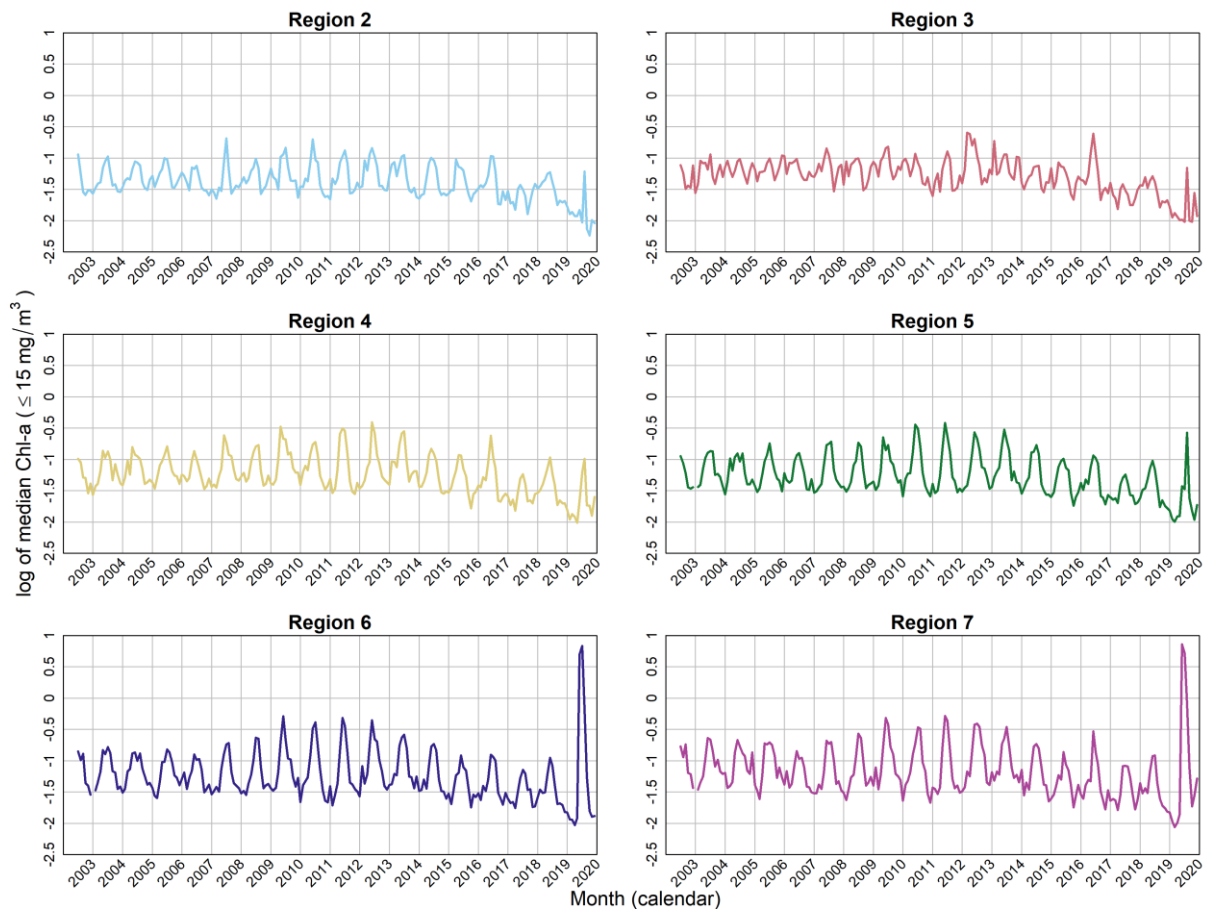


Figure 36: Time series of Chl-a across Regions 2-7 from 2003 to 2019. MODIS GSM Chl-a data from IMOS accessed in March 2020 (also see Table 1).

We considered the effect of monthly time lags for Chl-a over the previous four years. Figure 37 displays the plots of the corresponding correlations (blue curves) in Region 3 (top panel) and Region 4 (bottom panel) accompanied by their 95% confidence interval bands.

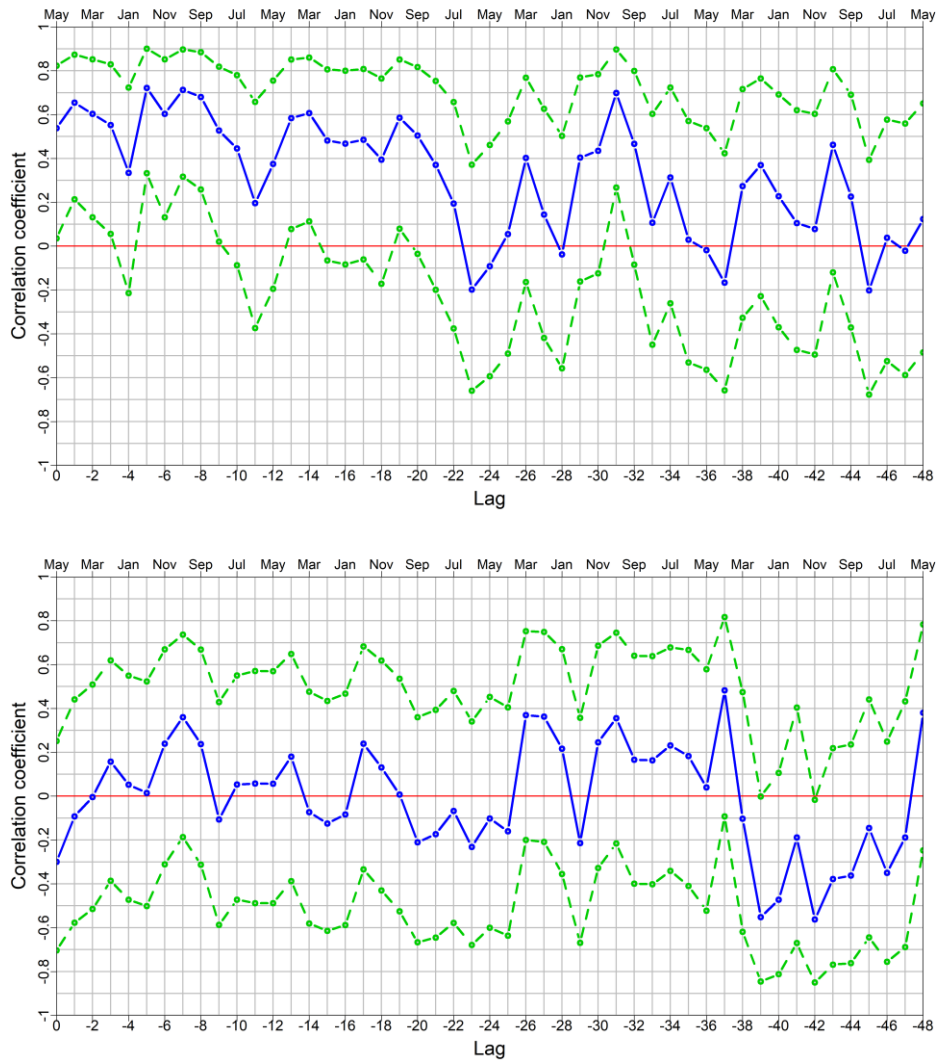


Figure 37: *Chl-a* correlation coefficient plots with 95% (green) confidence intervals for regional FIS legal-size CPUE in Region 3 (top) and Region 4 (bottom). The horizontal axis corresponds to the monthly time lag of *Chl-a* and the vertical axis corresponds to the correlation between the log transformed regional FIS CPUE and the log transformed monthly median *Chl-a*.

The catch rate in Region 3 is much more sensitive to *Chl-a* than in Region 4. Furthermore, Region 3 exhibits several significant associations with *Chl-a* with rather short time lags, May to February and December to August of the preceding year. In Region 4 there are no strong associations for short time lags.

Such analyses were repeated for Regions 2-7 with both legal-size and sublegal crabs and are recorded in Figure 38. As before, the green colour denotes correlations significant at the 95% level. The grey coloured numbers indicate associations that are not significant at that level.

The patterns of positive and negative correlations in Figure 38 exhibit several interesting features. For instance, predominance of positive correlations were expected as *Chl-a* is generally seen as an indicator of higher local primary productivity. Indeed, for legal-size crabs, this is generally what columns corresponding to Regions 2, 3 and 6 reflect. Similarly, for Regions 2 and 3 there is a cluster of statistically significant positive correlations in the six rows of the left hand panel, corresponding to lags of 0 to 5 months (May to December) of the preceding year.

Besides this, lags corresponding to the winter and spring months (June to November) cover a large proportion of significant correlations in Regions 2 and 3. In fact, for legal-size crabs in these two regions, the Chl-a correlations in the month of October in the previous three years (lags 7, 19 and 31) correspond to positive associations significant at the 95% level. At a lag of 43 months (i.e. October of the fourth year) there are moderate associations in three out of the six regions, with the one in Region 6 being significant at the 95% level.

For legal-size crabs, Regions 4 and 5 exhibit very few significant correlations with Chl-a. In particular, in Region 4 there is no statistically significant correlation for 0-38 lags reaching back more than three years. For Region 5 there are only two significant correlations in the 48 lagged months. On the other hand, Region 7 stands apart by having three statistically significant negative correlations in the first 30 lagged months. This is just one of several instances where Region 7 correlations differ markedly from those in Regions 2 and 3.

For sublegal crabs, the Chl-a associations in Regions 2, 3 and 6 are roughly consistent with those of legal-size crabs. With just two exceptions, associations in Region 4 are statistically non-significant for the first 35 lagged months. In Region 7, there is just one statistically significant correlation in the entire 49 lags. However, the dominance of negative associations in Region 5 stands out and requires deeper investigation since nine of these are significant at the 95% level.

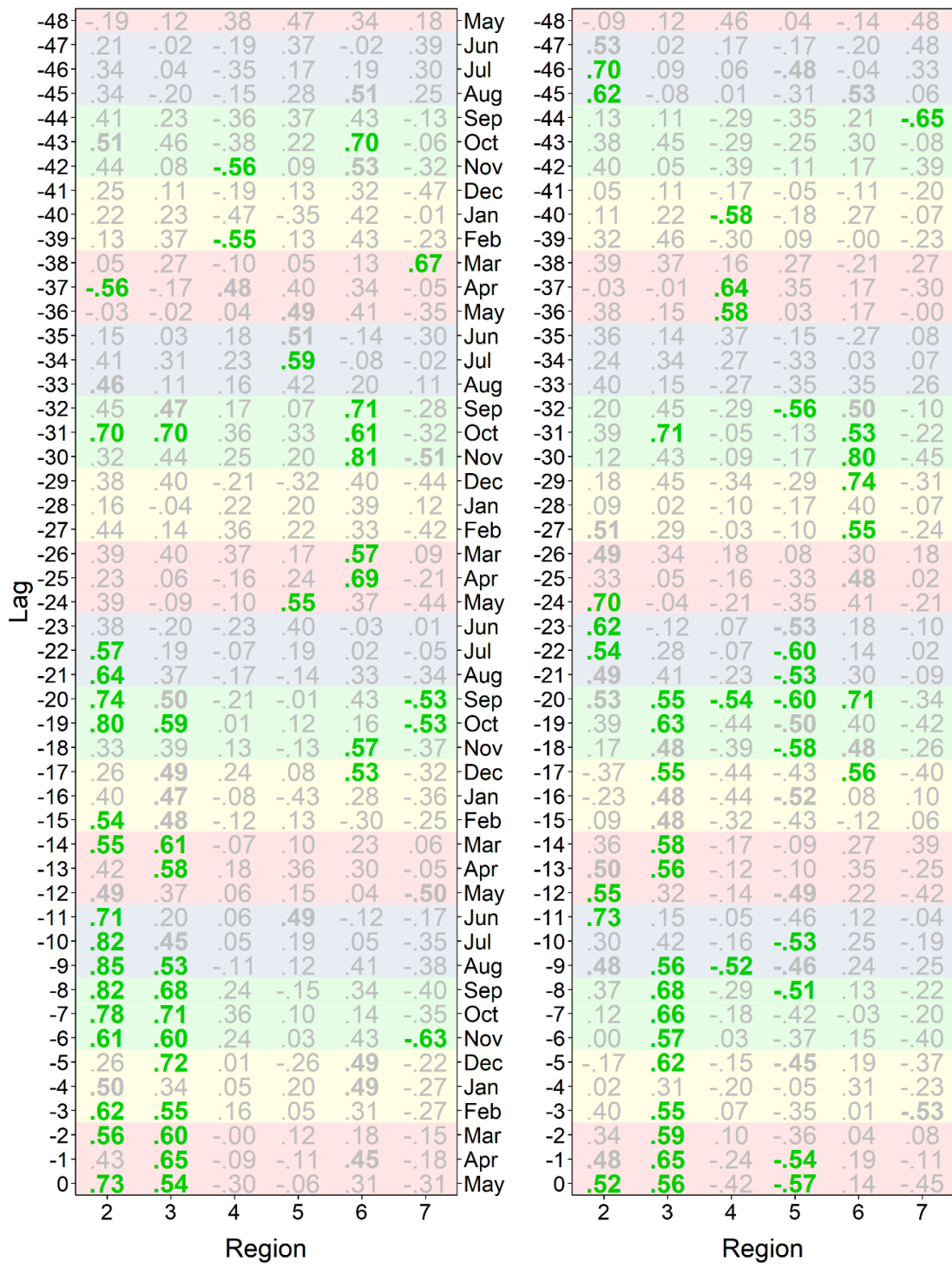


Figure 38: Correlation coefficients between log transformed regional FIS CPUE and the log transformed median Chl-a at various time lags. Left panel applies to legal-size Spanner Crab and right panel to sublegal Spanner Crab. Colour green indicates that the 95% confidence interval does not cover zero.

4.2.2 Sea Level Anomaly

The time series of GSLA reflects differences among the Spanner Crab Regions 2-7, as displayed in Figure 39. It is worth noting that Regions 2-3 exhibit a similar upward trend which becomes quite pronounced

from 2009. The post 2009 trend is also noticeable, but marginally less pronounced, in Regions 4-5 and becomes even smaller in Regions 6-7. The size of the oscillations between positive and negative values increase from northern to southern regions.

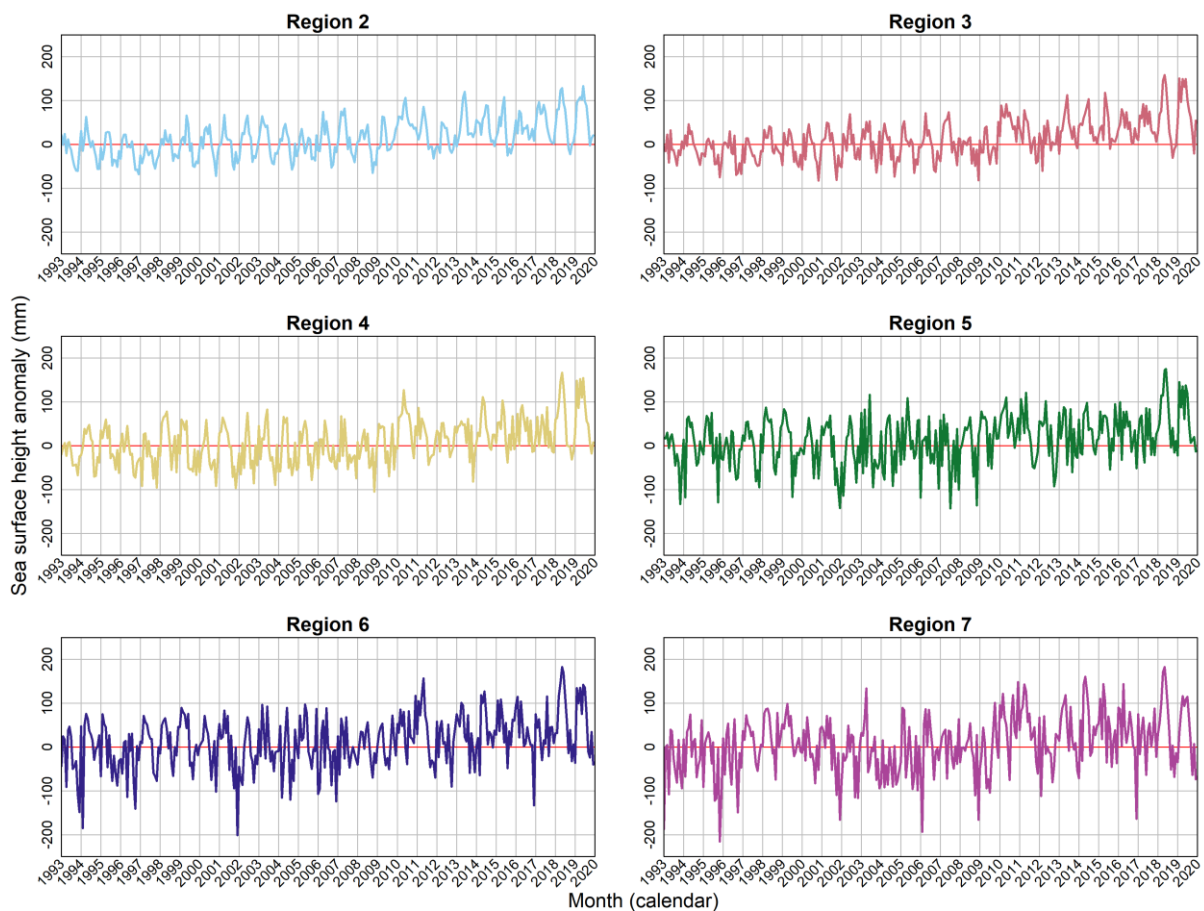


Figure 39. Time series of GSLA across Regions 2-7 from 1993 to 2019. MODIS DM01 GSLA data from IMOS (also see Table 1).

Similar to Chl-a, the GSLA correlation analyses were performed between log transformed FIS CPUE with the results summarised in Figure 40. Once again, the patterns of positive and negative correlations in Figure 40 exhibit several interesting features. Negative correlations were expected because negative GSLA indicates upwelling, which typically results in locally higher primary productivity, which may enrich the local food chain, eventually benefitting bottom-dwelling Spanner Crabs. Indeed, for legal-size crabs, this is generally what columns corresponding to Regions 2, 3 and (to a lesser extent) also Region 6 reflect (Figure 40).

As with Chl-a, the catch rate of legal-size crabs in Region 4 seems to be largely unaffected by fluctuations in GSLA. With just two exceptions, correlations in Region 4 are statistically non-significant for the first four years of lagged months. However, for sublegal crabs, statistically significant positive associations dominate for lags of 21 months and greater, with just one significantly negative exception.

In Regions 5 and 7 there are several significant positive correlations for both legal-size and sublegal crabs, likely because differences in local benthic coastal topography affect the activity and consequences of coastal processes such as eddies and upwelling. In addition, we note that overall increasing trend in GSLA is weaker in these regions than in Regions 2-3. For legal-size crabs in Regions 2 and 3 lags corresponding to the most recent four months, May to preceding February, contain a high

proportion of statistically significant correlations. In Region 3, the winter and spring months June to November also contain many significant correlations.

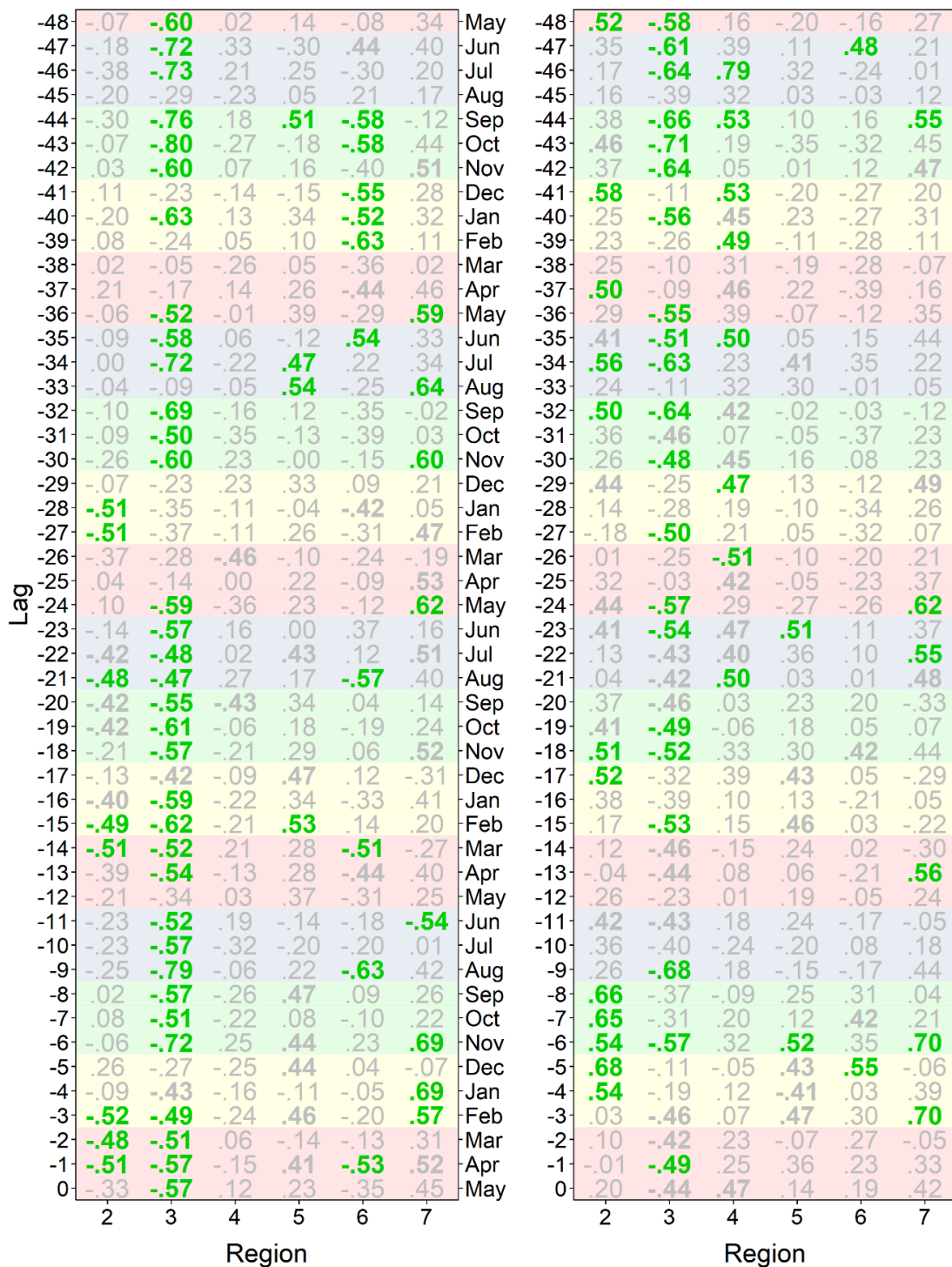


Figure 40: Correlation coefficients between log transformed regional FIS CPUE and the lagged monthly mean GSLA. Left panel applies to legal-size Spanner Crab and right panel to sublegal Spanner Crab. Colour green indicates that the 95% confidence interval does not cover zero.

4.2.3 Temperature

Water temperature was already shown to correlate with Snapper in important ways. Consequently, it was also investigated in some detail for Spanner Crabs. Furthermore, since SST is correlated with temperatures at greater depths in most cases the associations of crab CPUEs with SST were examined in the first instance.

The time series plots of mean SST across the Spanner Crab Regions 2-7 are provided in Figure 41 for 1992-2019. As expected, the strong annual cycle is clearly observable in all regions. The very slight upward trend (of the order of 0.13° per decade) is harder to detect but noticeable, especially in Regions 2-4, by focussing on the minima of mean SST in each year. This trend will be quantified later using the trigonometric regression technique discussed in Section 3.6.

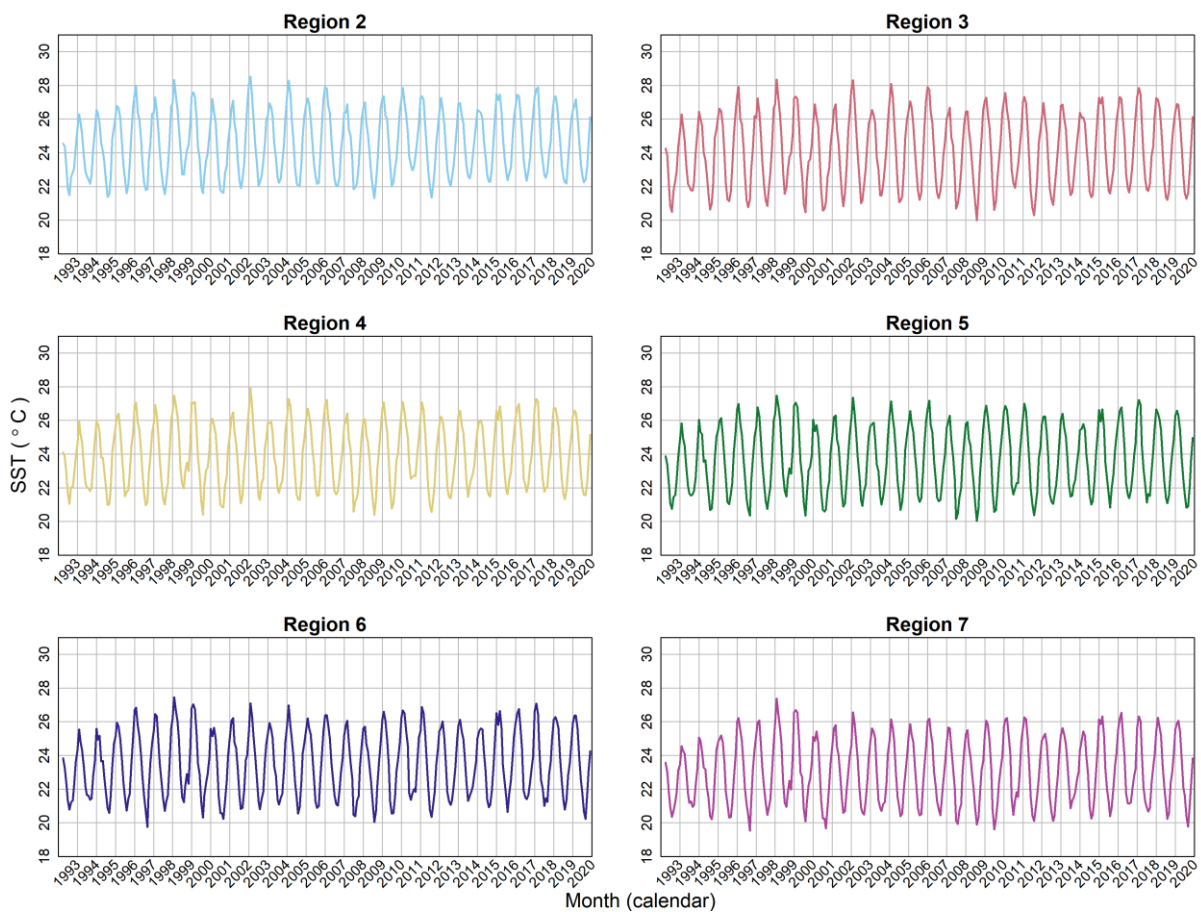


Figure 41: Time series of SST across Regions 2-7 from 1992 to 2019. SRS ghrsst L3S 6d nighttime SST from IMOS (also see Table 1).

Several meaningful findings were obtained when we considered Spanner Crabs in two distinct groups: legal-size and sublegal. Once again, the results exhibit strong regional differences. We will illustrate them with the simple mean SST variable lagged by up to 48 months. However, we note that analogous analyses were carried with a range of SST related variables such as minimum, maximum, 10th percentile, 90th percentile of the corresponding lagged SST variables. The results of these additional analyses are recorded in the project's file repository but are not reported here as their outcomes are broadly consistent with those obtained with the mean SST.

Figure 42 and Figure 43 display the corresponding correlations (blue curves) in Region 3 (top panel) and Region 4 (bottom panel). For both legal-size and sublegal crabs in Region 3 there are significant

negative associations between logarithmically transformed CPUE and mean SST at three monthly time lags. However, in the case of Region 4 there are no significant associations at that level for legal-size crabs. With one exception, at lag 0, the same holds for sublegal crabs in that region.

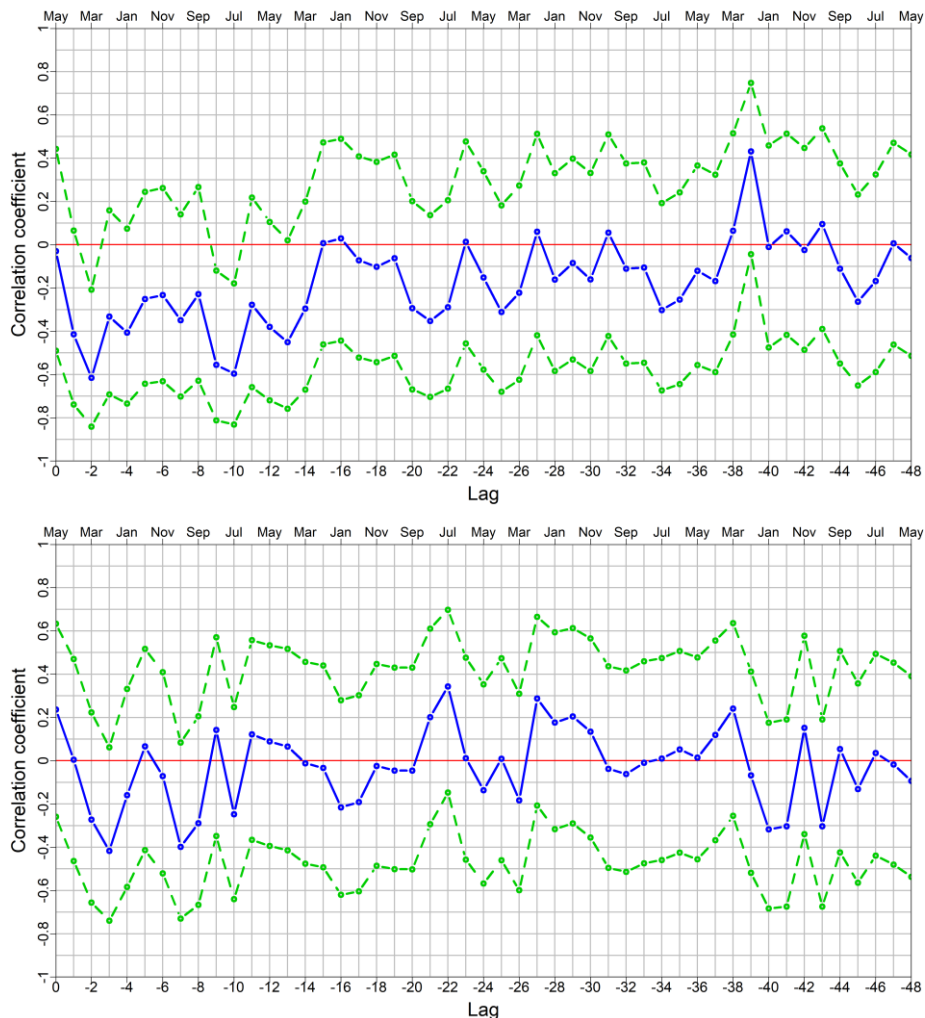


Figure 42: SST correlation coefficient plots with 95% (green) confidence intervals for regional FIS legal-size CPUE in Region 3 (top) and Region 4 (bottom). The horizontal axis corresponds to the monthly time lag of SST and the vertical axis corresponds to the correlation between the log transformed regional FIS CPUE and the monthly mean SST.

In the case of legal-size Spanner Crabs in Region 3 the strongest negative correlations of -0.62 occur in the preceding March (lag 2) as well as in the preceding winter months of August (lag 9) and July (lag 10) with correlations of -0.56 and -0.60, respectively. In the case of sublegal crabs (Figure 43) in Region 3 the strongest negative associations occur in the preceding March (lag 2), July (lag 10), and April (lag 25) with the corresponding correlations of -0.53, -0.48 and -0.49, respectively. The consistent significance of most recent March and July months is noted.

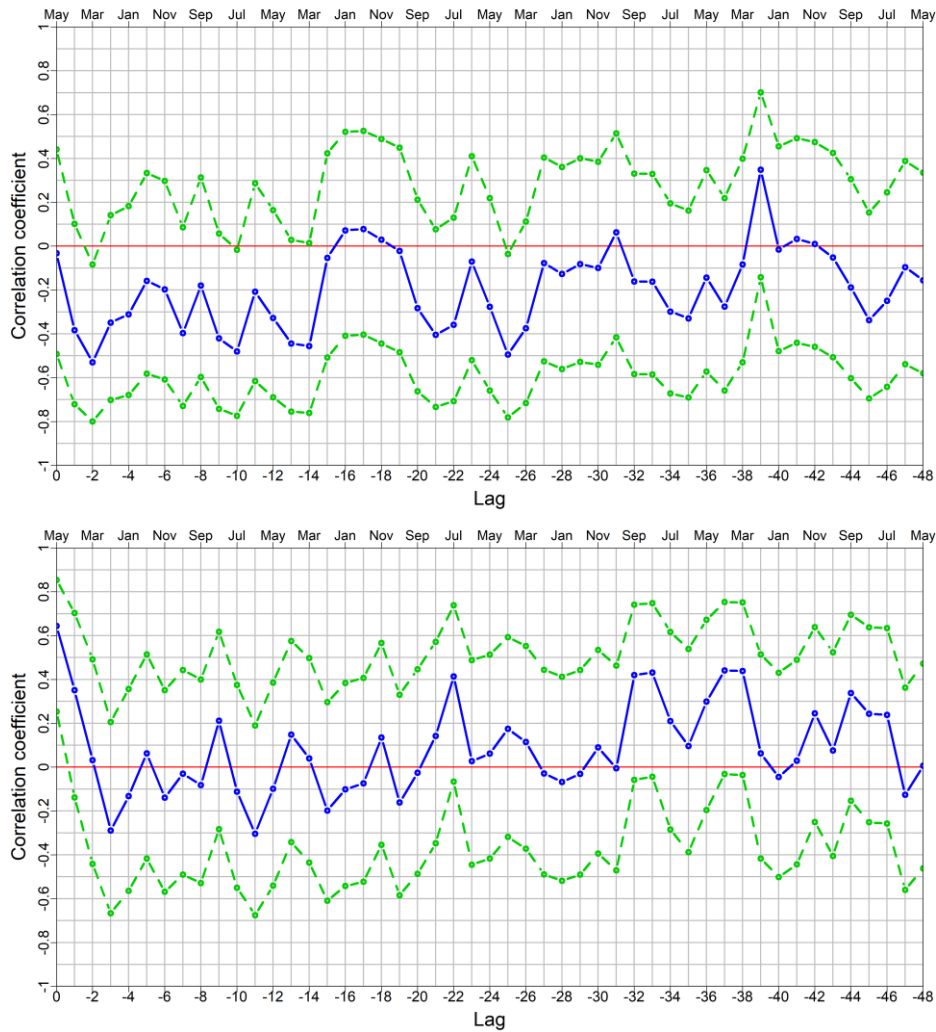


Figure 43: SST correlation coefficient plots with 95% (green) confidence intervals for regional FIS sublegal CPUE in Region 3 (top) and Region 4 (bottom). The horizontal axis corresponds to the monthly time lag of SST and the vertical axis corresponds to the correlation between the log transformed regional FIS CPUE and the monthly mean SST.

The summary of the associations with lagged mean SST variable, across all six regions, is displayed in Figure 44. Once again, for legal-size crabs, we note the presence of a few strong negative correlations in Regions 2, 3 and also Region 6 (but at much longer time lags). In Region 7 most moderate correlations are positive and three (at lags of 3, 4 and 6 months) are significant at the 95% level.

As with Chl-a and GSLA, the catch rate of legal-size crabs in Region 4 seems to be largely unaffected by fluctuations in mean SST. With just one exception, correlations in Region 4 are statistically non-significant for up to 48 months. If we discount the high (0.64) correlation for lag 0 (being the month of catch), then there is strong consistency in the relative insensitivity of Region 4 to mean SST fluctuations for both legal-size and sublegal crabs.

For sublegal crabs in other regions we see rough consistency with legal-size correlations in Regions 3, 5 and 6. For sublegal crabs, Region 7 has no associations significant at the 95% level. In the case of Region 2 some statistically significant positive associations arise in the winter months of the preceding year and there are no significant negative correlations left in the first column of the right panel in Figure 44.

Thus, similarly to the case of associations with GSLA, there is an inconsistency between the direction of significant associations for legal-size and sublegal crabs in Region 2. That direction switches from the expected negative for legal-size to the counterintuitive positive for the sublegal crabs.

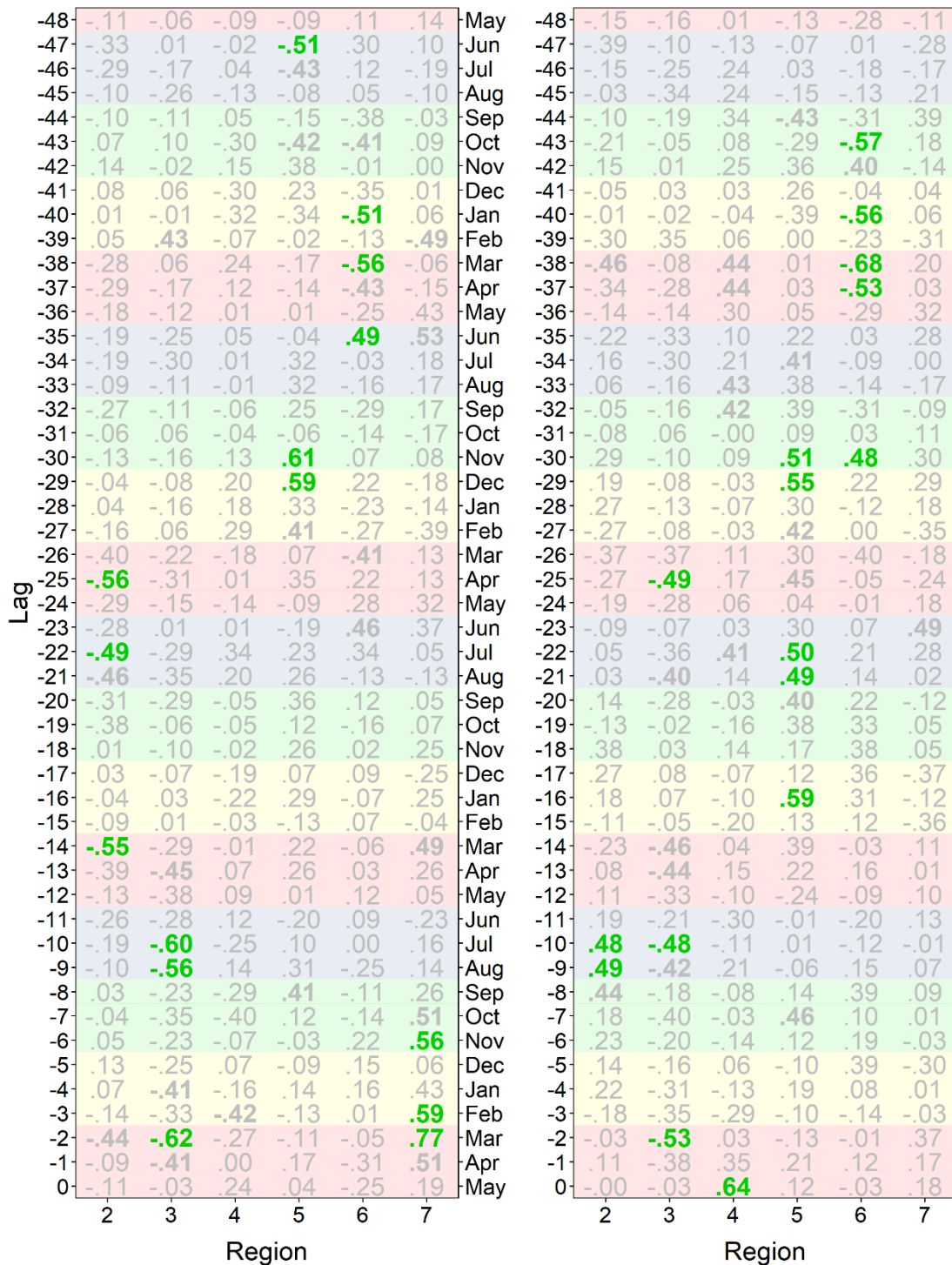


Figure 44: Correlation coefficients between log transformed regional FIS CPUE and the lagged mean SST. Left panel applies to legal-size Spanner Crab and right panel to sublegal Spanner Crab. Colour green indicates that the 95% confidence interval does not cover zero.

Since Spanner Crabs are bottom dwelling, it is also worthwhile to compare correlations between FIS CPUE and temperatures at the bottom with the analogous correlations at the surface. The comparisons

expose a complex pattern of associations with CPUE in certain regions and certain times of the year. Importantly, the direction of these associations is not uniform. Below, we illustrate some of these patterns for the pooled Spanner Crab size classes in a given region.

Figure 45 shows the correlations between log transformed FIS CPUE and temperature lagged by months, at the bottom level for Regions 2-7. The solid dots indicate correlations that are statistically significant at the 95% level. Despite this, we also note that a great majority of the plotted points correspond to correlations smaller than 0.3 in absolute value and as such do not account for much of the variability in the response variable.

However, the yellow curve corresponding to Region 4 is notable because of the periodicity of the statistically significant lags corresponding to November-February months (lags 6-3, 18-15, 30-27 and 42-39). Most of the corresponding correlations are below -0.4 and, as such, account for at least 16% of the log transformed FIS CPUE variable. Furthermore, the November-February period overlaps Spanner Crabs' spawning season.

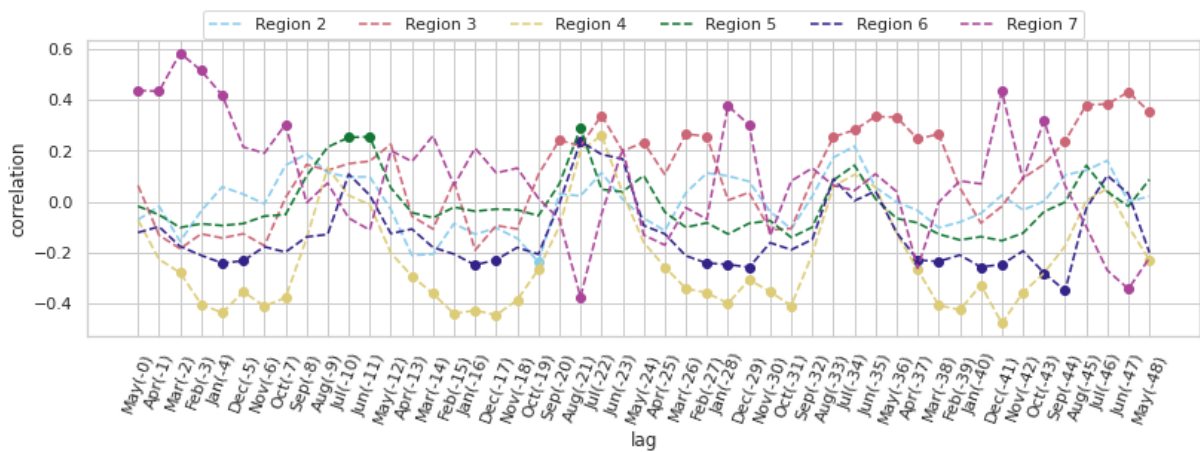


Figure 45: Correlations of log transformed FIS legal-size CPUE and temperature at the bottom of all the 6'x6' fishing sites, lagged by k months, $k=0,1,\dots,48$. The solid dots indicate correlations that are statistically significant at the 95% level.

To underscore this point in Figure 46, we plotted scattergrams of FIS log CPUE (legal-size) and bottom temperature at January lags of 4, 16, 28 and 40, in Region 4. The relationship between FIS log CPUE (legal-size) and bottom temperature in January appears to be consistent and negative at a number of time lags. However, further inspection of these correlations indicated that they are primarily driven by spatial patterns among the FIS sites, in particular consistent warm temperatures and low catch rates at site 14W34 (see also <https://cloudstor.aarnet.edu.au/plus/s/8Hb3kHOAhcWJCSZ>).

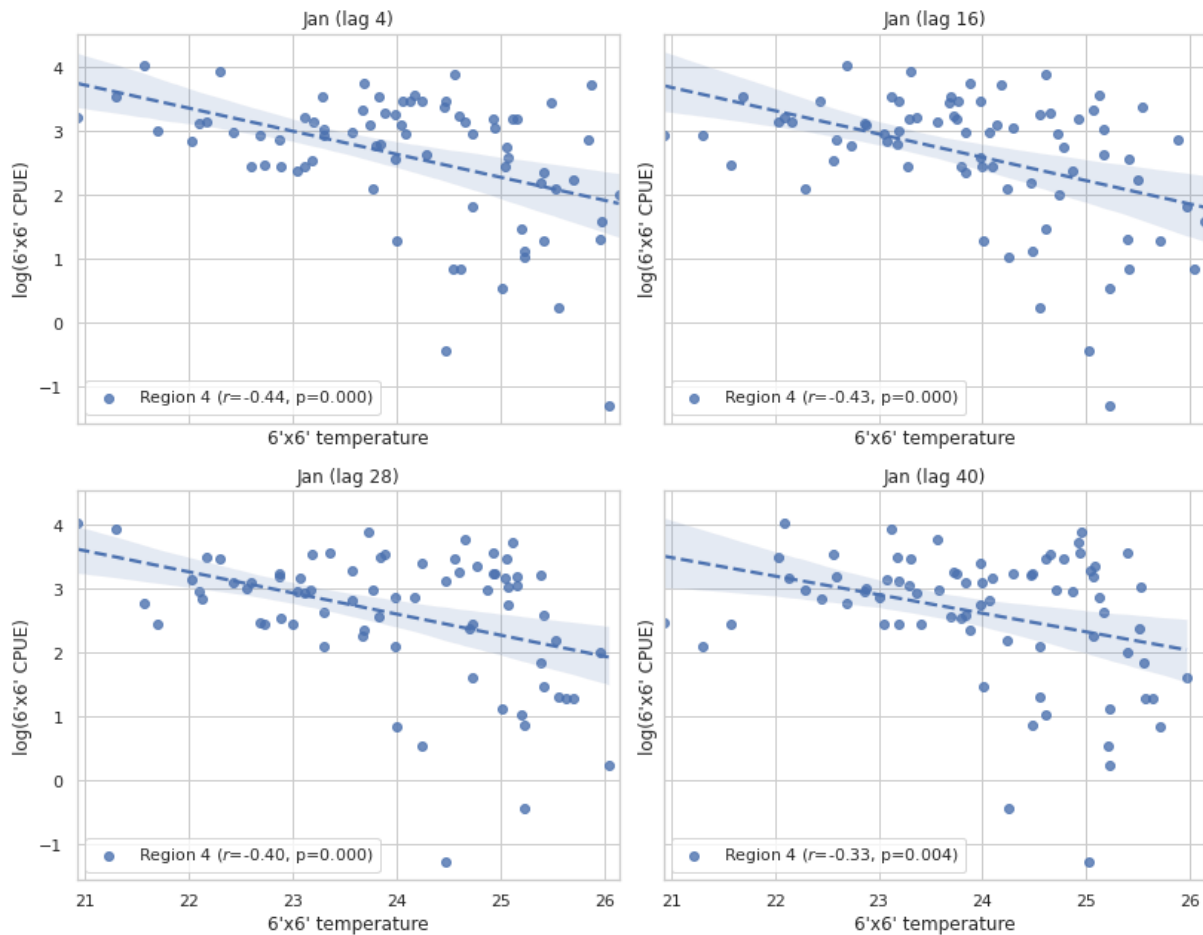


Figure 46: Scattergrams of log transformed FIS legal-size CPUE and bottom temperature at January lags of 4, 16, 28 and 40, calculated over all 6'x6' fishing sites in Region 4.

4.2.4 Ocean current

We also investigated the speed of the ocean current derived from the current velocity components supplied in the BRAN 2016 dataset for possible association with Spanner Crab CPUE_{sub} (see Section 3.1.2). These components were denoted by u (East-West), v (North-South) and w (vertical) and were measured in metres per second and supplied at various depth levels⁴. The speed was calculated as the usual Euclidean norm of the (u, v, w) vector. However, the vertical w component was not always available at greater depths and even when available its absolute values were negligible compared to the u and v components. Thus, for the sake of consistency of calculations, the speed calculation used only the u and v components. Furthermore, the bottom speed at each location was actually calculated using deepest available u and v values at that location.

We focussed especially on current speed at the bottom level and searched for associations over 48 monthly lag times. For log transformed CPUE_{sub} and the cohort of legal-size crabs, it was shown that:

- Regions 2, 3 and 5 stood out by having essentially no significant correlations with the current speed at the bottom.
- Catch rate of legal-size crabs in Region 4 has moderately strong positive correlations with the ocean current speed at the bottom. This is most pertinent at lag 0 (month of the catch) but is

⁴ By convention, $u > 0$ corresponds to East, $v > 0$ corresponds to North and $w > 0$ corresponds to up.

periodically and consistently moderately strong at many time lags, including September to October for up to four years in the past. The latter period overlaps the Spanner Crabs' spawning season of October to January.

- Region 7 also had several statistically significant positive correlations with the current speed at the bottom at various time lags. However, these were viewed as less important than those in Region 4 because they lacked periodicity and all but one were less than 0.4.
- Region 6 stood out by having several strong negative correlations with the current speed at the bottom which also lacked periodicity.

Most of the findings can be seen from the plots displayed in Figure 47. In particular, note the narrow range (roughly between -0.25 and 0.25) of the blue, red and green curves corresponding to Regions 2, 3 and 5 which indicates little association in these regions. The findings concerning Regions 6 and 7 are reflected in the violet and purple curves, respectively. The consistently high positive correlations observed in Region 4 raise the question of whether they are a manifestation of another phenomenon influencing CPUE_{sub}.

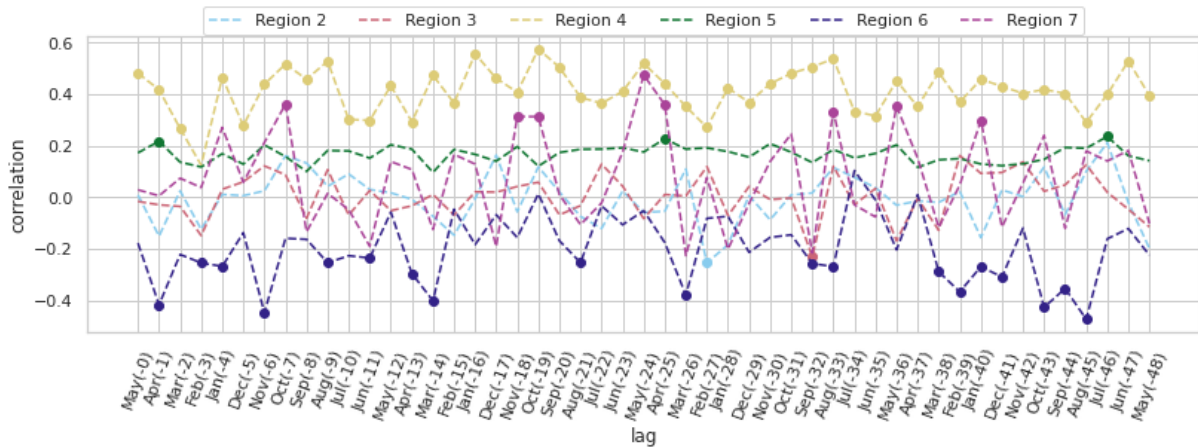


Figure 47: Correlations between log transformed FIS legal-size CPUE and current speed at the bottom of 6'x6' fishing sites, lagged by k months, $k=0,1,\dots,48$; across all regions. Solid dots denote correlations with p -value < 0.05 .

In Figure 48 we highlight the regularity of significant positive correlations with bottom speed in October in Region 4. The four panels correspond to lags of 7, 19, 31 and 43 months preceding the catch. We note that the corresponding correlation coefficients are displayed in the figure. Thus, the bottom current speed variable accounts for a surprising amount of the variability in the response variable $\log(\text{CPUE}_{\text{sub}})$, as measured by the R^2 coefficients (27%, 33%, 23% and 18%, respectively). Interestingly, perhaps, the association with current speed in October of 19 months prior to is stronger than that with speed in the most recent October at lag 7. However, closer inspection of these correlations indicated that they are entirely driven by spatial patterns among the FIS sites, in particular low current speeds and low catch rates at site 14W34 (see <https://cloudstor.aarnet.edu.au/plus/s/8Hb3kHOAhcWJCSZ>).

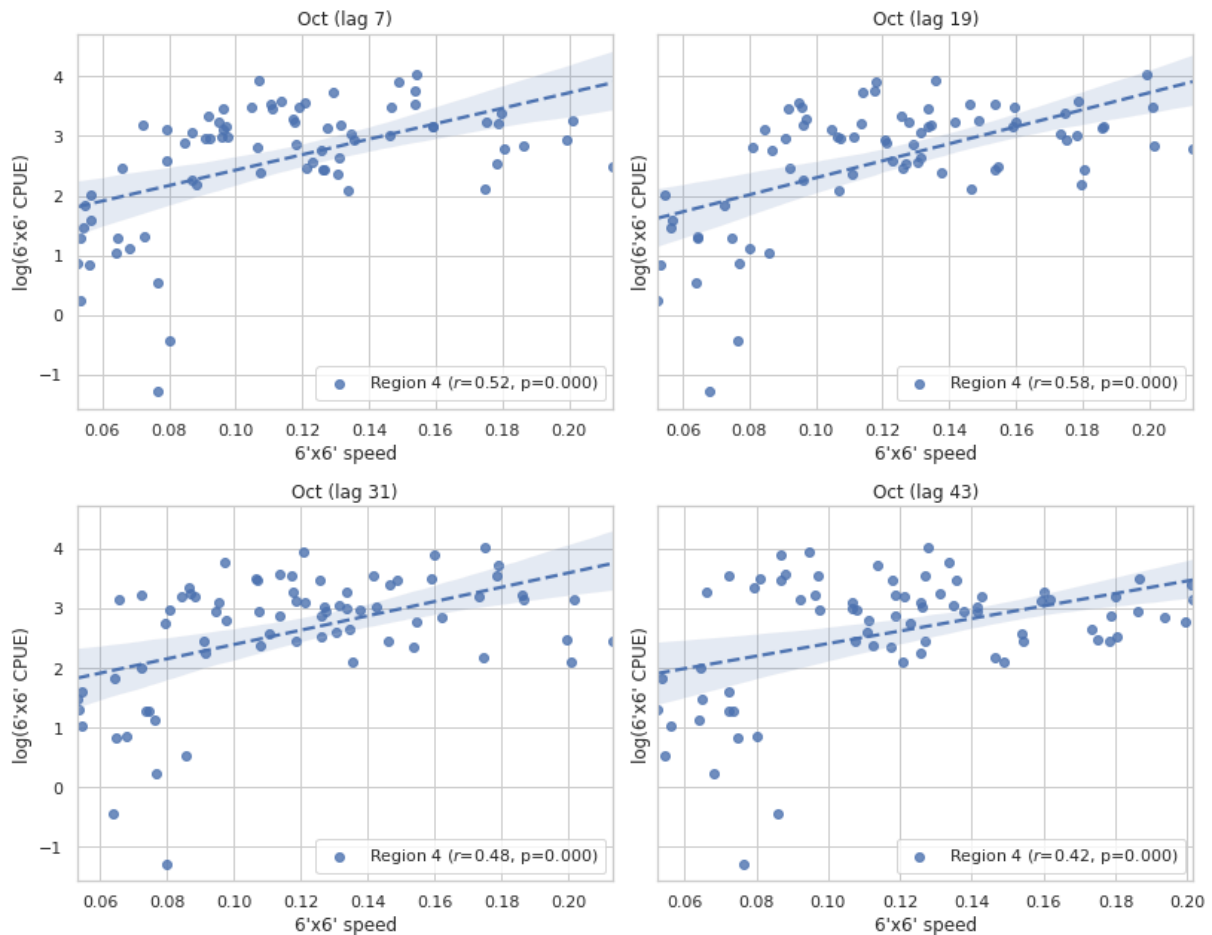


Figure 48: Scattergrams of log transformed FIS legal-size CPUE against current speed at the bottom of 6'x6' fishing sites in four Octobers preceding the catch, Region 4.

Naturally, from the perspective of catchability, the association between $CPUE_{sub}$ and the bottom current speed in the month of the catch (lag 0) is of greatest importance. The leftmost points of the curves in Figure 47 show that, with the important exception of Region 4, these associations are minor as the corresponding correlations are smaller than 0.2 in absolute value.

In Region 4, the lag 0 correlation of 0.46 is not only statistically significant with p-value much smaller than 0.05 but also accounts for approximately 21% of the variability in the log transformed $CPUE_{sub}$ response variable. Closer examination of the corresponding scattergram in Figure 49 reveals an interesting pattern consisting of two consecutive segments exhibiting linear growth. However, the first of these – up to the speed of approximately 0.08 m/sec – has a much higher slope than the segment with current speeds greater than 0.08 m/sec.

Remark: The following limitations affect the analysis: the speed we calculated is the monthly average of model predicted value at a “nearest” location that can be some distance away from the fishing sites (up to 11km in some instances). Thus, our current speed may not accurately reflect the actual speed at the fishing sites during the fishing period.

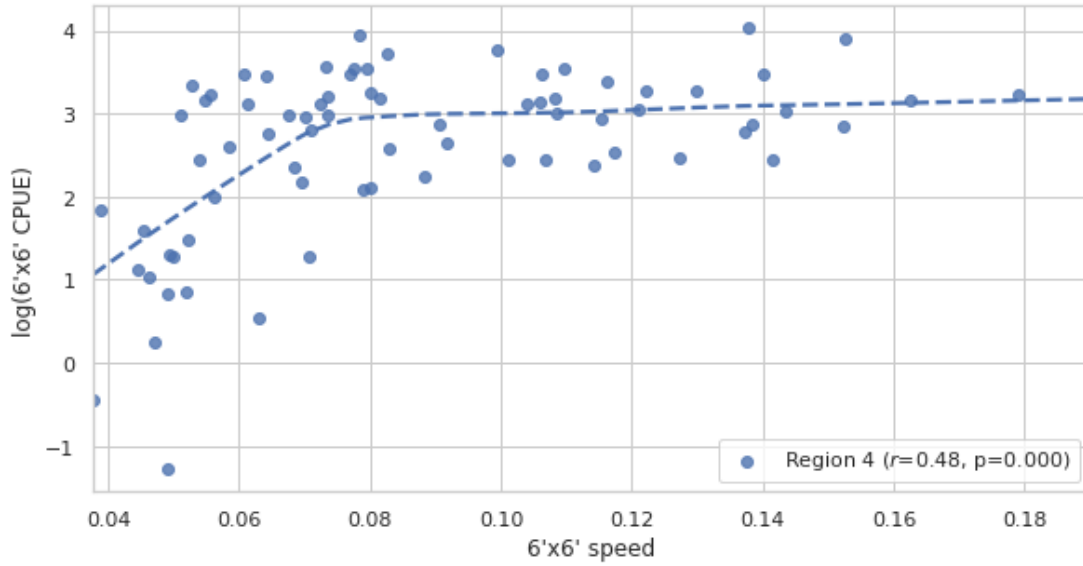


Figure 49: Scattergrams of log transformed FIS legal-size CPUE against current speed at the bottom of 6'x6' fishing sites in the month of the catch (lag 0), Region 4.

We note that the fitted dashed curve displayed in Figure 49 was derived using the so-called LOWESS local regression of the response variable on the explanatory variable (current speed) that was developed by Cleveland (1979).

4.2.5 Marine Heatwaves

We now return to the consideration of the impact of MHW episodes on Spanner Crabs with the help of the methodology introduced in Section 3.3. As with Snapper, we considered the period from 1992-04-01 to 2019-12-31 (approximately 28 years) and corresponding SST data from IMOS to calculate the frequency and duration of MHW episodes in Spanner Crab regions 2-7. These results are summarised in Table 10 and show a slightly increasing frequency as we move southward.

Table 10: Number of MHW events and their average and maximum duration for Spanner Crab Regions 2-7.

Region	# of events	Average duration (days)	Max duration (days)
2	56	14.3	70
3	66	11.9	64
4	64	13.0	71
5	67	11.8	44
6	69	11.9	47
7	69	11.4	64

Over the period 2000-2019, we analysed correlations between logarithmically transformed Spanner Crab FIS CPUE and the $X(I, \mathbf{w})$ type MHW indices (see equation (2)) taking into consideration cumulative memory of 1 up to 7 years. The weight of $w(E_k) = w_1(n_k, M)w_2(s_k, M)$ of the k^{th} episode was calculated using equation (9) with $a=2$ for $w_1(n_k, M)$, and $w_2(s_k, M) = v(s_k, M)$ as in equation (10) with $c=0$ and $d=1$. Analyses were undertaken separately for legal-size and sublegal crabs in Regions 2-7. While majority of these correlations were not statistically significant, there were two important exceptions.

The results of one such exception are displayed in Figure 50. The left panel of that figure shows that in the case of sublegal crabs in Region 3 there was a significant negative association with MHW indices

for cumulative memory ranging from 2 to 5 years. This can be seen from the fact that the blue curve and its green (95%) confidence bands lie below the horizontal axis for $M=2, \dots, 5$. Furthermore, the scattergram in the right panel shows that when $M=2$, correlation $r=-0.52$ and so the MHW index accounts for approximately 27% of the variability of the log transformed FIS CPUE.

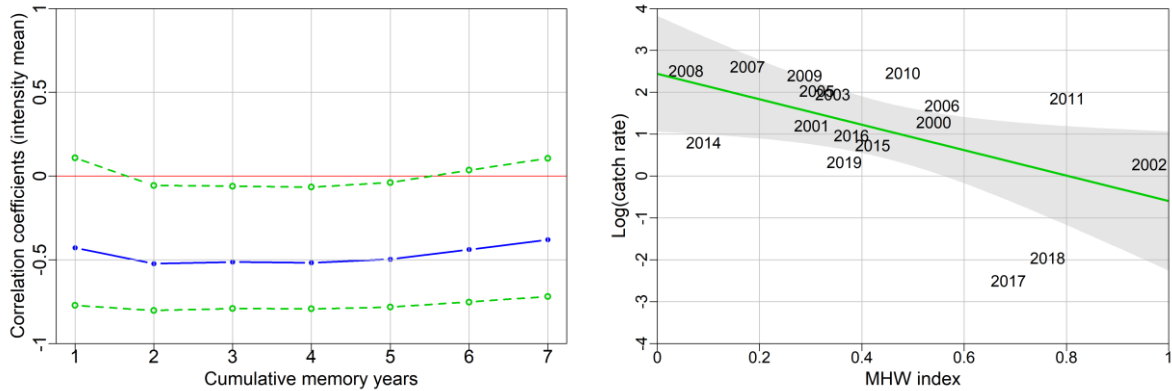


Figure 50: Region 3 sublegal crab. Left panel: correlation coefficients between log transformed FIS sublegal CPUE and MHW index (blue curve) and their 95% confidence intervals in green. Right panel: The scatter plot when the cumulative memory is equal to two years.

The results of the second exception are displayed in Figure 51. The left panel of that figure shows that in the case of legal crabs in Region 7 there was a significant, sustained, positive association with MHW indices for cumulative memory ranging from 1 to 7 years. This can be seen from the fact that the blue curve and its green (95%) confidence bands lie above the horizontal axis for $M=1, \dots, 7$. Furthermore, the scattergram in the right panel shows that when $M=2$, correlation $r=0.71$ and so the MHW index accounts for approximately 50% of the variability of the log transformed FIS CPUE. This may be related to the fact that Region 7 is close to the southern limit of the species so warming trends could initially be beneficial to Spanner Crabs in Region 7. Alternatively, these associations may be an artefact of large reductions in commercial fishing effort in this region in recent years improving local catch rates, coincidentally during the same period that GSLA and SST has been increasing and Chl-a has been decreasing. In future it might be worth investigating whether the biological mechanism by which MHW phenomena appear to benefit Spanner Crab in this region.

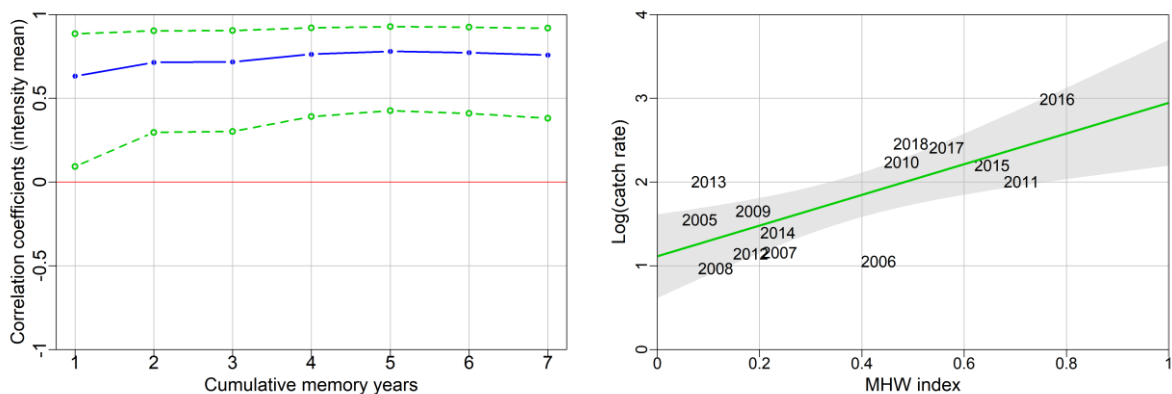


Figure 51: Region 7 legal-size crab. Left panel: correlation coefficients between log transformed FIS legal-size CPUE and MHW index (blue curve) and their 95% confidence intervals in green. Right panel: The scatter plot when the cumulative memory is equal to two years.

4.2.6 Large scale climatological/oceanographic indices

We also compared associations for two large-scale climatological/oceanographic indices with Spanner Crab FIS CPUE. The two indices were SOI and PDO.

Table 11 summarises correlations obtained to explore the effect of annual and seasonal means of SOI and PDO indices on FIS CPUE of all Spanner Crabs (legal-size and sublegal) for the period 2000-2020. The SOI and PDO variables corresponded to mean annual, Spring (Sep-Nov), Summer (Dec-Feb), Autumn (Mar-May) and Winter (Jun-Aug) in the 12 month period that ends with the May survey.

Region 3 is the only one where statistically significant positive correlations are recorded, with the most significant one corresponding to the preceding Spring (Sep-Nov). FIS CPUE in all other regions seems largely insensitive to these mean SOI fluctuations.

Table 11: Correlations of FIS CPUE with SOI and PDO, respectively, for legal-size and sublegal crabs combined; across Regions 2-7. Values in green indicate correlations statistically significant at the 95% level.

Index	Period	Region 2	Region 3	Region 4	Region 5	Region 6	Region 7
Mean SOI	annual	0.28	0.44	-0.31	0.17	0.27	-0.21
	summer	0.21	0.30	-0.18	-0.10	0.15	-0.45
	autumn	0.33	0.17	-0.26	0.27	0.09	-0.29
	winter	0.30	0.46	-0.30	0.17	0.25	0.13
	spring	0.07	0.49	-0.28	0.22	0.36	-0.03
Mean PDO	annual	-0.08	-0.50	0.35	-0.02	-0.10	0.58
	summer	-0.19	-0.49	0.43	-0.10	-0.09	0.61
	autumn	0.12	-0.38	0.28	0.25	0.15	0.64
	winter	-0.17	-0.34	0.28	0.01	-0.03	0.39
	spring	-0.05	-0.53	0.24	-0.22	-0.39	0.44

The consistently strong negative correlations with PDO in Region 3 and even stronger positive correlations in Region 7 require further investigation. However, mean values of SOI in the 12 months preceding the May FIS may miss the importance of the ENSO signals for two main reasons: cancellations of positive and negative values and insufficiently long memory of past episodes. Consequently, as was the case with Snapper, we also investigated associations between FIS CPUE and the SOI signal indices constructed using the methodology of Section 3.3 (a), (c), (d).

In particular, from the monthly SOI signal we extracted indices $S^{\delta+}$ and $S^{\delta-}$ corresponding to the positive and the negative episodes of the signal for the values of $\delta=0, 3$ and 8 defined by equations (3) and (4) from Section 3.3. The value $\delta=8$ was selected to match the standard definition of ENSO events (Bureau of Meteorology 2012). The value $\delta=3$ was selected after numerical experimentation with several thresholds lying between 0 and 8.

For all three thresholds, the intensity of episodes was calculated in accordance with equation (6) and persistence weights by (9) with parameter $a=2$. The location importance weights were all set to 1. We also considered a range of memory parameters $M = 1, \dots, 8$ corresponding to the cumulative memory of one to eight years. Thus, for each of these eight values of M we constructed time series of indices $S^{\delta+}$ and $S^{\delta-}$ over the years 2000 to 2020, separately for $\delta=0, 3$ and 8 and using the intensity function (6). Finally, correlations between FIS CPUE and $S^{\delta+}$ and $S^{\delta-}$ were calculated. Figure 52 shows a summary of the results for the combined size classes.

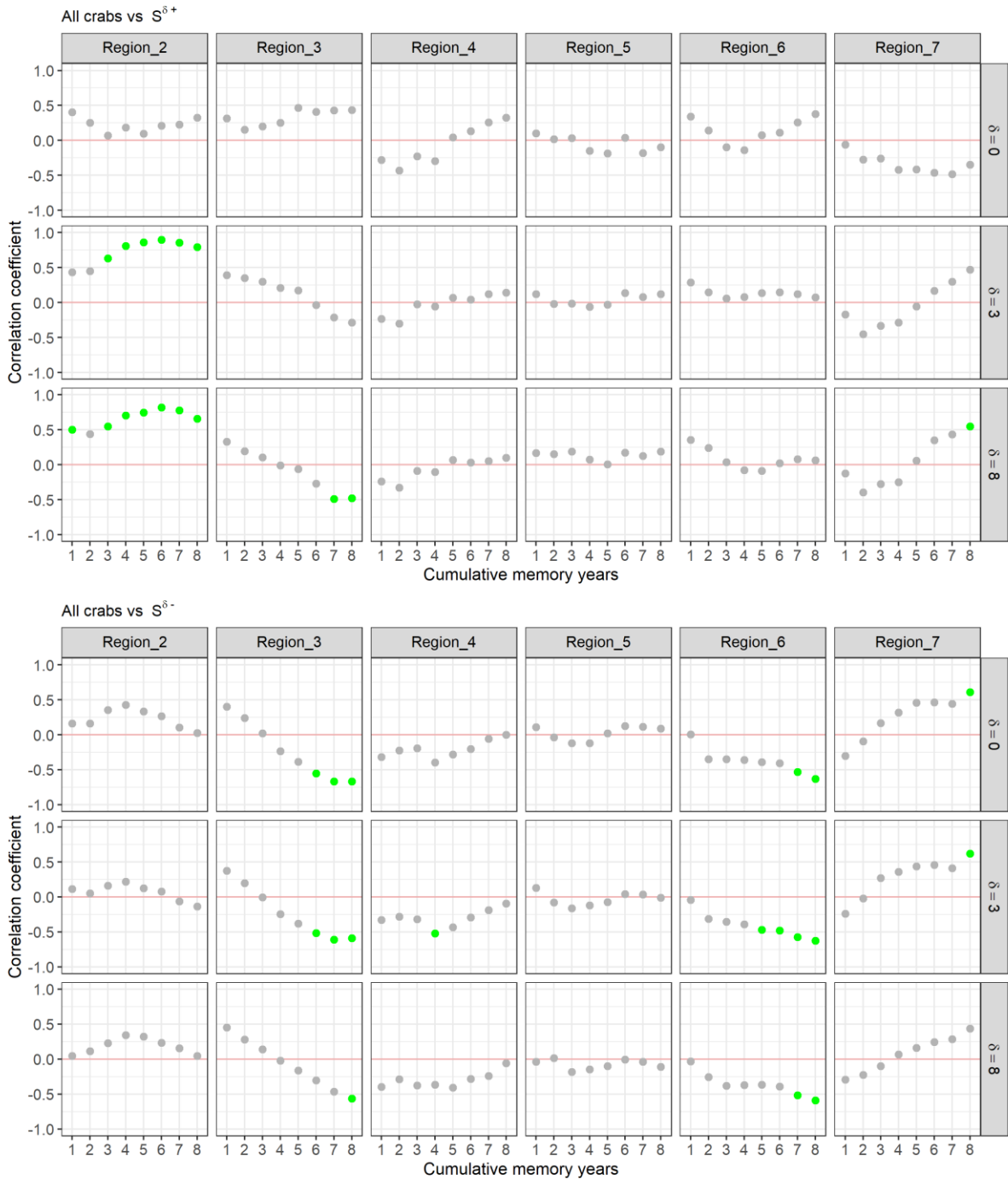


Figure 52: Correlations of FIS all crab CPUE with $S^{\delta+}$ (top panel) and with $S^{\delta-}$ (bottom panel) for $\delta=0, 3$ and 8 for $M=1, \dots, 8$. Values in green indicate correlations statistically significant at the 95% level.

The top panel of Figure 52 shows a lack of significant linear associations between CPUE and $S^{\delta+}$ in nearly all cases in Regions 4, 5 and 6. Furthermore, the strongest associations manifest themselves for the threshold of $\delta=3$ and $\delta=8$. In particular, in Region 2 these associations become significant at 95% level for all cumulative memories greater than $M=2$. We note that positive sign of these significant correlations is biologically expected as $S^{\delta+}$ corresponds to the La Niña signal. Significant correlations also occur in Region 7 but only for the cumulative memory of $M=8$. However, in Region 3 we observe the counterintuitive significant negative correlations for $M=7$ and 8 and $\delta=8$.

The results presented in the bottom panel of Figure 52 suggest that sustained histories of stronger negative values of the SOI signal in Regions 3 and 6 are associated with better catch rates of Spanner Crab. This calls for further investigation. However, we note that related associations have been reported in Brown *et al.* (2008) who state that “The negative correlations between the SOI and effort, while not significant at the 95% level, indicate a tendency toward more effort in El Niño years than in La Niña, with wind strength tending to be the most strongly related variable.”

Some of the linear associations represented by the green dots in Figure 52 are quite strong. For instance, the correlation from the top panel when $M=3$ and $\delta=3$, in Region 2, corresponds to the scattergram in Figure 53. We see that it has the value of 0.85 correlation accounting for roughly 73% of the variability in FIS CPUE. We recall that Region 2 is the most northerly of the six regions, and as such may be more strongly influenced by the La Niña signal (e.g. see Redondo-Rodriguez *et al.* 2011, Bureau of Meteorology 2012), which may partly explain this association.

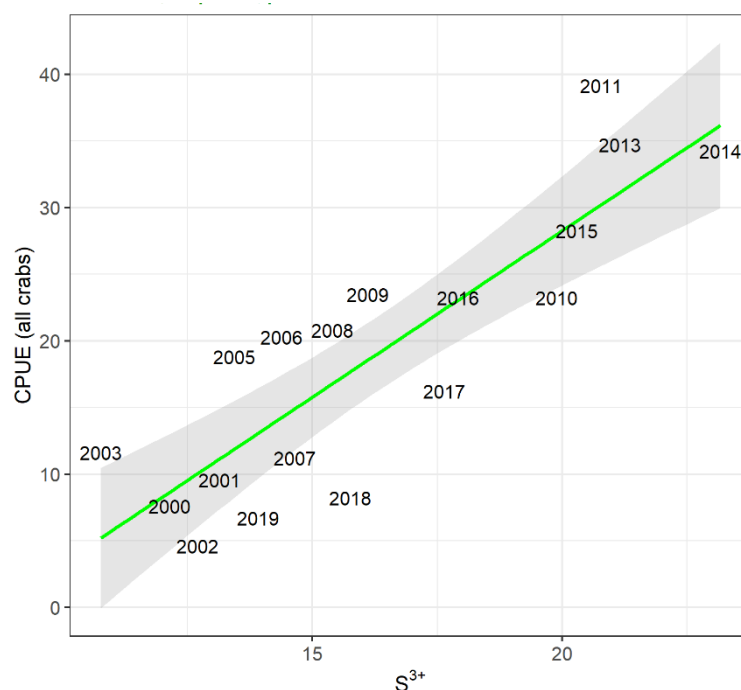


Figure 53: Scattergram between FIS all crab CPUE and S^{3+} for Region 2, with $M=7$, $r=0.85$, $R^2=0.73$ and p -value < 0.001 .

4.2.7 Spanner Crabs and environmental associations over 2009-2019

Several analyses already reported associations with three key environmental variables: GSLA, Chl-a and SST. However, a closer inspection of time series plots of these variables in Sections 4.2.1-4.2.3 suggests that underlying trendlines for GSLA and Chl-a may have accelerated over, roughly, 2009-2019 of FIS observations (e.g. see Figure 39). Furthermore, during that decade significant catch rate changes were recorded not only in standardised CPUE from CFISH but also in FIS nominal CPUE in several regions (see Figure 9 to Figure 14).

Consequently, in this section, the analyses focus on the above period which spans the most recent ten years of FIS observations (since none were taken in 2012 for Regions 2-6 and in 2019 for Region 7). We acknowledge the limitations caused by the reduced number of observations but also note that this time span includes the period of steep declines in FIS CPUE in Regions 2 and 3 that have raised serious

concerns among fishery managers. In particular, it is important to examine further the differences – over that decade – between previously productive Region 3 and the currently productive Region 4.

Results summarised in Figure 54 qualitatively reaffirm the main Spanner Crab findings 1-3, typically generating more statistically significant associations in Regions 2 and 3. They also highlight the presence of several significant negative correlations with SST in Regions 2 and 3 as well as a few in Regions 5 and 6.

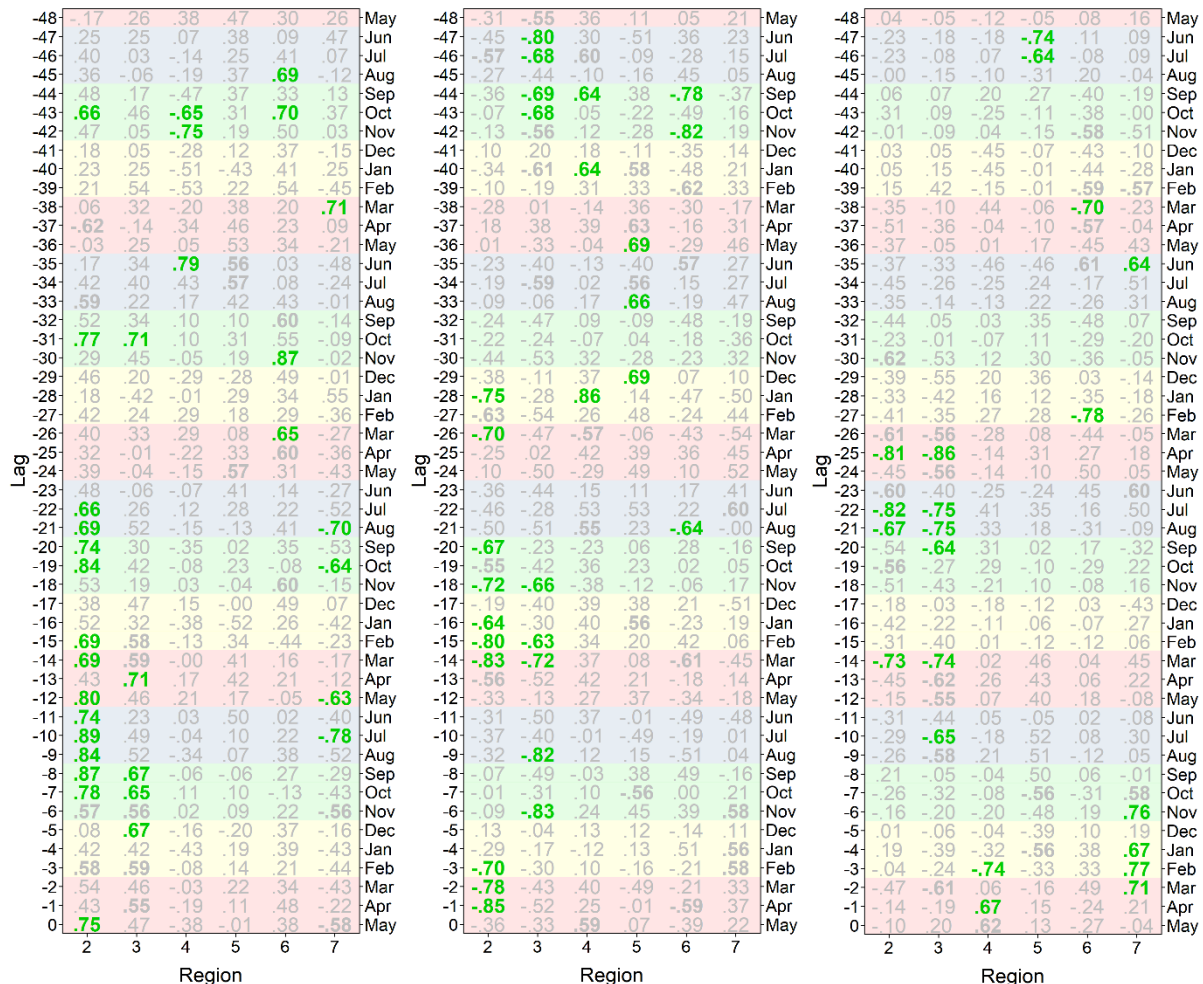


Figure 54: Correlation coefficients between log transformed regional FIS legal-size CPUE and three key environmental variables for Regions 2-7 in 2009-2019. From left to right: log transformed Chl-a, GSLA and SST lagged by 0, ..., 48 months.

To illustrate the preceding finding more clearly in Figure 55 we present the correlations between log transformed legal-size crab FIS CPUE in Region 3 with the lagged mean SST variable (top panel) and compare them with the corresponding correlations in Region 4 (bottom panel).

We note from the top panel of that figure that six significant negative correlations occur at multiple time lags including July (lag 10), March (lag 14), three month long period September-July (lag 20-22) and April (lag 25). Their values range from -0.64 to -0.86. Furthermore, in the top panel, all but one of 25 correlations exceeding 0.3 in absolute value are negative.

On the other hand, for Region 4 (bottom panel) there were only two correlations that were statistically significant. The first in April (lag 1) was positive while the second (in February (lag 3)) was negative.

Overall, there were 38 correlations (out of 49) smaller than 0.3 in absolute value, corroborating one of the main findings concerning the relative resilience of Region 4.

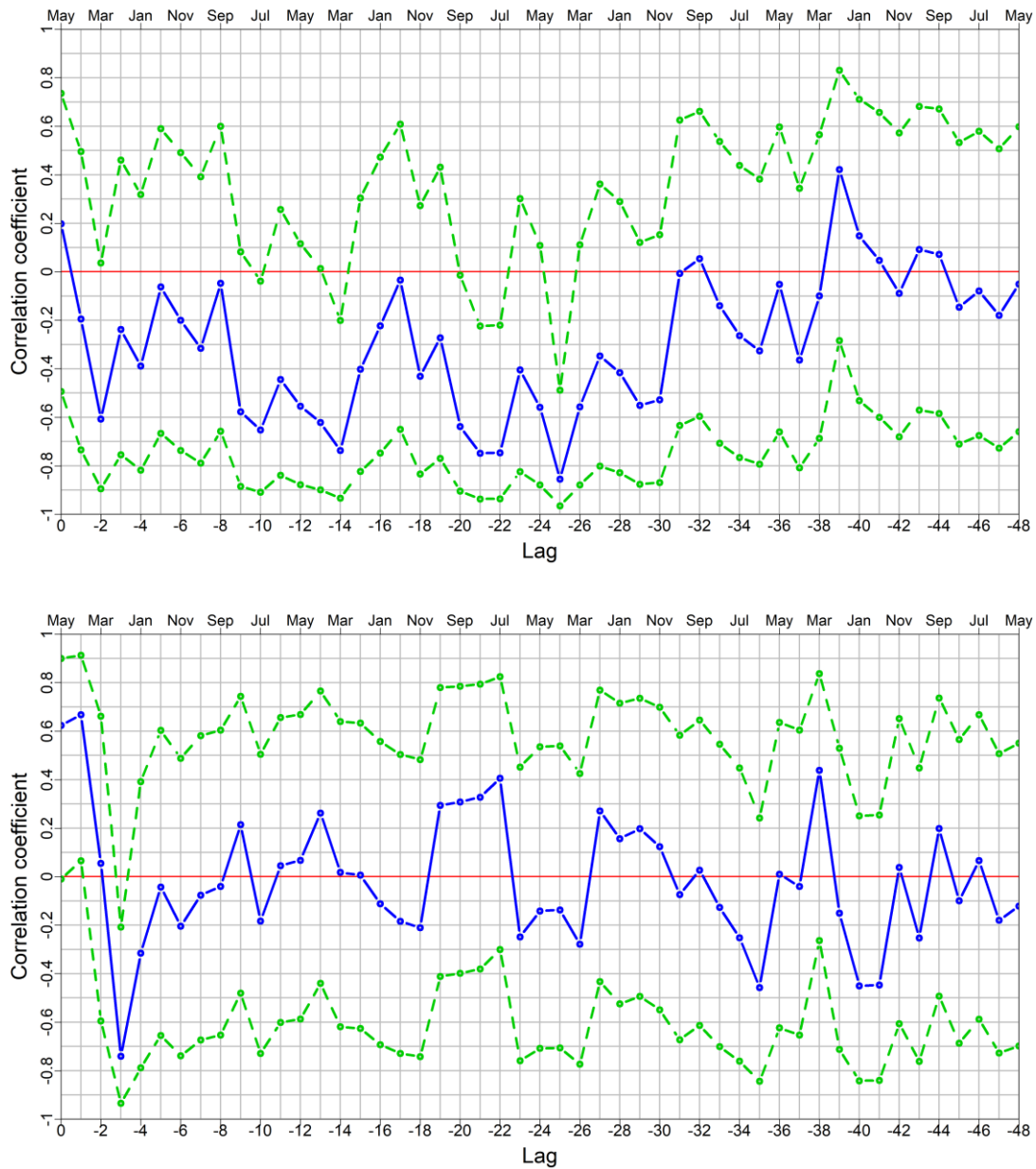


Figure 55: Correlation coefficient with 95% (green) confidence intervals between log transformed regional FIS legal-size CPUE and mean SST in Region 3 (top) and Region 4 (bottom). The horizontal axis corresponds to the monthly time lag and the vertical axis corresponds to the correlation between the log transformed CPUE and mean SST lagged by the respective number of months.

Analogous distinction between strong associations in Region 3, and a relative insensitivity in Region 4 also manifest themselves with respect to Chl-a and GSLA environmental drivers. In Figure 56 we illustrate this phenomenon only with the correlations of the mean GSLA and the log transformed FIS legal-size crab CPUE.

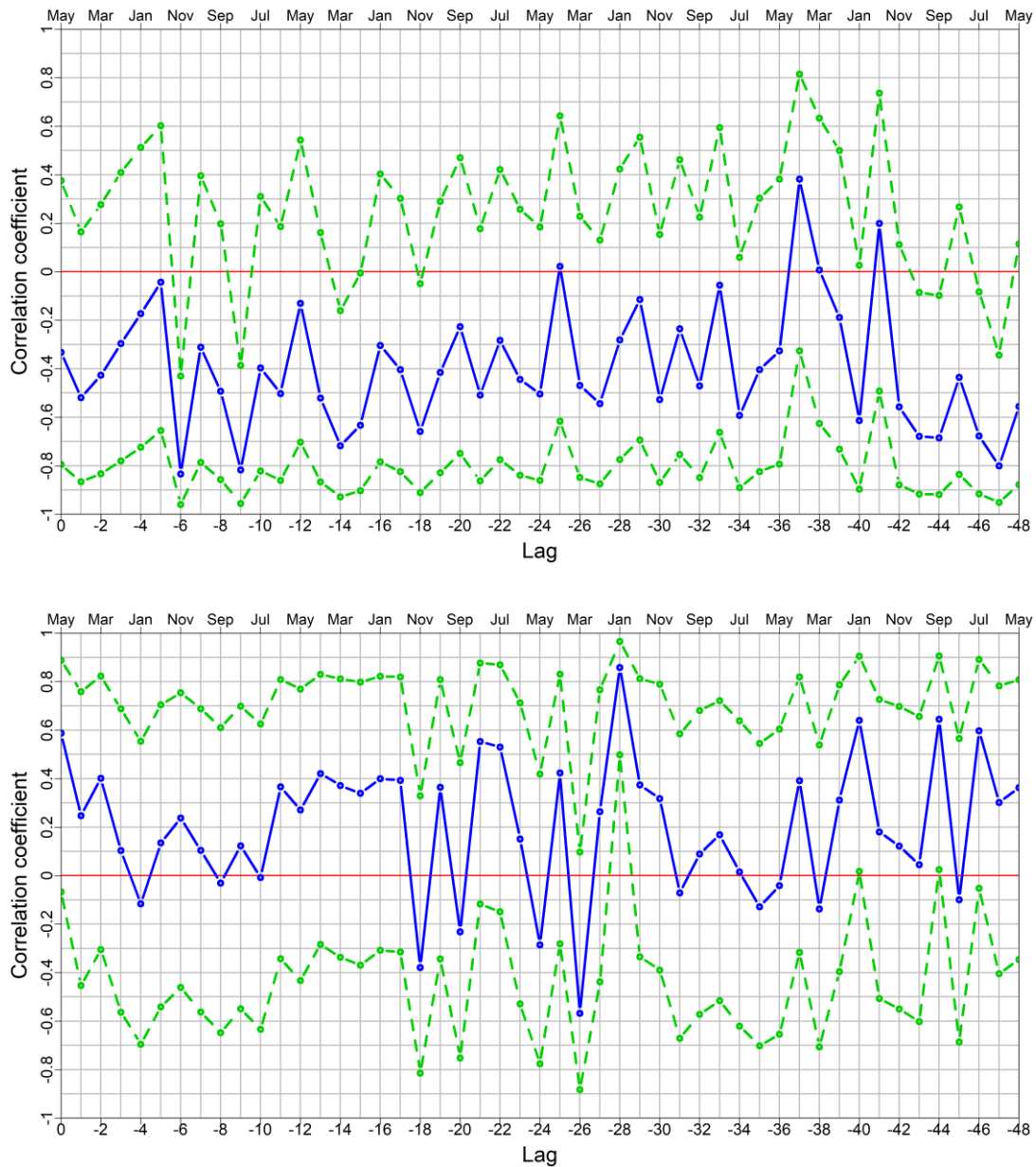


Figure 56: Correlation coefficient with 95% (green) confidence intervals between log transformed FIS legal-size CPUE in Region 2 (top) and Region 4 (bottom). The horizontal axis corresponds to the monthly time lag and the vertical axis corresponds to the correlation between the log transformed CPUE and the mean GSLA lagged by the respective number of months.

The top panel of that figure shows that moderate negative correlations occur at many lags. Indeed, nine of these are statistically significant at the 95% level and range from -0.63 to -0.83. In contrast, in Region 4 (bottom panel), there are only three statistically significant positive correlations occurring at rather large lags of 28, 40 and 44 months. There were only 12 negative correlations and all but two of these were smaller than 0.3 in absolute value.

A natural, but challenging, question arises from the above and some of the earlier analyses presented in Sections 4.2.1-4.2.6: *What underlies the qualitatively different levels of associations observed in Region 4 as compared to Region 3?*

We believe that tackling this important question would require a deeper study of oceanographic, climate or biological processes that is beyond the scope of this project. However, we offer some preliminary evidence hinting that, in Region 4, such processes may be mitigating the potentially adverse impacts of trends in the three key environmental drivers that we analysed in most detail.

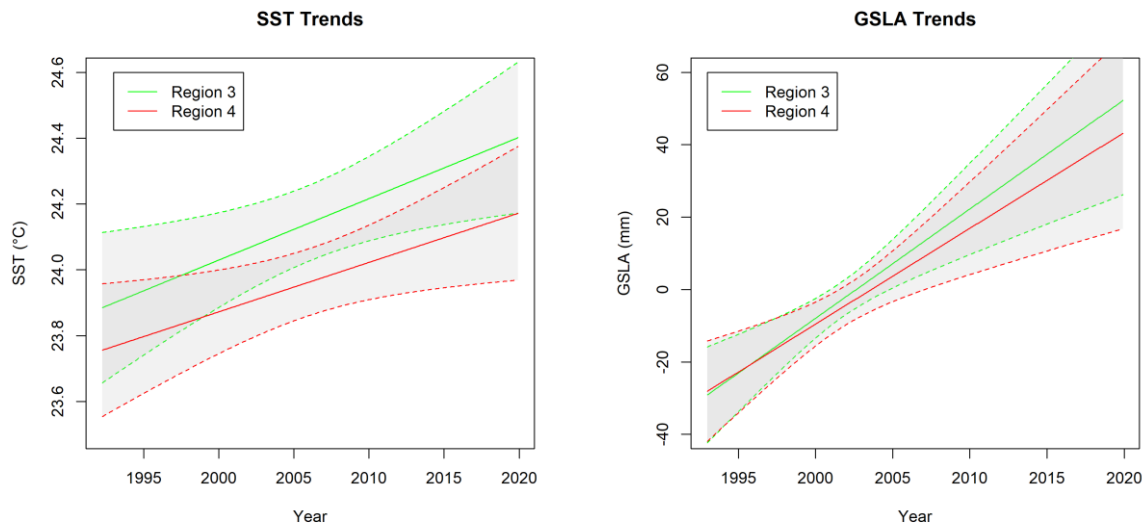


Figure 57: Comparison of mean trend lines of SST (left) and GSLA (right) in Regions 3 and 4 for the period 1992-2019.

In Figure 57, we present mean trend lines of SST and GSLA variables for the period 1992-2019 in Region 3 (solid green line) and Region 4 (solid red line), with their 95% uncertainty bands (in dashed green and red curves, respectively). The small positive slopes of all four of these trend lines are in rough agreement with climate change modelling (e.g. see White *et al.* 2014 and Benveniste *et al.* 2020).

Naturally, because of its geographic location the SST red trend line of Region 4 begins at a lower temperature than the SST green line of Region 3. More importantly, however, the slope of the green line is greater (by approximately 24%) than that of the red line; thus, the disparity between these trend lines increases over time. Interestingly, the GSLA red trend line of Region 4 begins at a very marginally higher level than the GSLA green line of Region 3. However, once again the slope of the green line is greater (by approximately 14%) than that of the red line; thus, the green line overtakes the redline in the late 1990s and the disparity between Regions 3 and 4 grows from that time on.

In Figure 58, we present mean trendlines of median log transformed Chl-a variable for the period 2002-2019 in Region 3 (solid green line) and Region 4 (solid red line), with their 95% uncertainty bands (in dashed green and red curves, respectively). Both trendlines have negative slopes. In 2002, the log(Chl-a) of Region 4 begins at essentially the same level as that of Region 3. However, the log(Chl-a) slope of Region 3 is more negative (by approximately 21%) than that of Region 4. Thus, the decline in Chl-a is more rapid in Region 3 compared to that in Region 4.

The above results show that, for all three key environmental drivers (Chl-a, GSLA and SST) over the past 17 years, the trend lines in Region 3 were steeper than those in Region 4. Potentially, that disparity became sufficiently great in the past decade that – in combination with fishing pressure – there was a

cumulative effect that contributed to falling abundance in Region 3 as compared to Region 4. If so, a similar cumulative effect may have also occurred in Region 2.

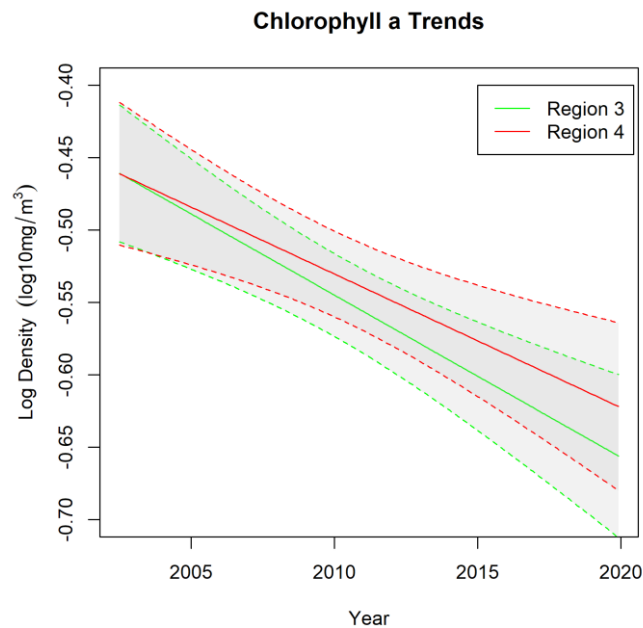


Figure 58: Comparison of mean trend lines of median log transformed Chl-a variable in Regions 3 and 4 over 2002-2019.

4.3 Pearl Perch: Correlation Analyses for Key Environmental Variables

In our analysis of Pearl Perch catch rates from Queensland line fishery, we only consider catch rate time series from 2005 onwards. This decision was made on the basis that changes to the logbook (Line Fishery) may have impacted on the quality of the data reported prior to 2004 (Sumpton *et al.* 2017). Analysis of early logbook data suggested that Pearl Perch's harvest could have been under-reported or in many cases not recorded at a specific species level category.

Regions covered included Rockhampton Offshore (RO), Fraser Offshore North (FON) and Fraser Offshore South and Sunshine Coast Offshore (FOS+SCO) as this is where most of the commercial catch data come from (see Figure 22). Standardised CPUE was used as a measure of abundance (see Figure 16).

The results resembled some of those reported in Section 4.1 for the Snapper fishery. However, the amount of commercial logbook data for Pearl Perch is relatively low and fishery independent survey data are non-existent. As such, only annual rather than monthly time series could be considered. Below we highlight three main findings:

- GSLA had a significant negative association with the standardised CPUE, across 0-6 yearly time lags and all three regions considered.
- Chl-a in both current and previous year, had a very strong positive association with the standardised CPUE, across all three regions considered.
- Long-term associations with the negative SOI signal were found to be significant.

Many of these results are summarised in Table 12-14.

Table 12: Summary table of associations between environmental indices and standardised CPUE (log transformed) of Pearl Perch for Queensland commercial line fishery. Values in green indicate correlations statistically significant at the 95% level.

		Lag (years)										
		0	1	2	3	4	5	6	7	8	9	10
Sea Surface Temperature												
Mean SST	Region											
	RO	-.15	-.38	-.33	.05	.28	-.02	-.12	.12	-.10	-.13	.06
	FON	-.22	-.51	-.53	-.15	.25	-.08	-.27	.03	-.05	.01	.14
	FOS + SCO	-.11	-.34	-.43	-.05	.31	.00	-.18	.07	.03	.06	.20
Chlorophyll a												
Log (Median Chl-a)	Region											
	RO	.71	.60	.19								
	FON	.70	.69	.61								
	FOS + SCO	.73	.60	.52								
Gridded Sea Level Anomaly												
Mean GSLA	Region											
	RO	-.66	-.73	-.55	-.61	-.73	-.53	-.53	-.67	-.76	-.67	-.40
	FON	-.70	-.82	-.69	-.65	-.54	-.54	-.62	-.44	-.30	-.17	-.30
	FOS + SCO	-.65	-.76	-.75	-.72	-.56	-.55	-.64	-.51	-.45	-.35	-.01
Southern Oscillation Index												
Mean SOI		-.09	.06	.19	-.08	-.26	-.21	-.16	-.39	-.51	-.13	-.03
Pacific Decadal Oscillation												
Mean PDO		-.19	-.39	-.30	-.10	.12	.40	.31	.30	.47	.57	.39

Table 13: Summary table of associations between environmental indices in the year of the catch and standardised CPUE of Pearl Perch for Queensland commercial line fishery (2005-2018). The effect of environmental indices was analysed in summer (Dec-Feb), autumn (Mar-May), winter (Jun-Aug), spring (Sep-Nov) and spawning seasons according to each region (Sep-Nov in Region RO and Mar-May in the other regions). In the case of Chl-a we considered the effect of the log transformed median, for the remaining variables the effect of the mean of the log transformed standardised CPUE. Correlations indicated in green are statistically significant at the 95% level.

	SST			Chl-a			GSLA			SOI	PDO
	RO	FON	FOS+ SCO	RO	FON	FOS+ SCO	RO	FON	FOS+ SCO		
Season											
summer	0.15	-0.14	-0.01	0.69	0.57	0.61	-0.64	-0.56	-0.51	-0.02	-0.19
autumn	-0.22	-0.27	-0.17	0.48	0.51	0.56	-0.59	-0.44	-0.44	-0.10	-0.21
winter	-0.14	-0.10	0.01	0.51	0.60	0.45	-0.49	-0.60	-0.71	-0.09	-0.02
spring	-0.14	-0.11	-0.18	0.64	0.70	0.68	-0.42	-0.73	-0.40	-0.10	-0.26
Spawning											
Sep-Nov	-0.14			0.64			-0.42			-0.10	-0.26
Mar-May		-0.27	-0.17		0.51	0.56		-0.44	-0.44	-0.10	-0.21

In Figure 59, we display the scattergrams corresponding to strong negative associations between lagged mean GSLA and log transformed standardised CPUE in Region RO, for lags of 0, 1, and 2 years. The association peaks at lag 1 (previous year) where the correlation attains a high negative value of -0.73 where it accounts for 54% of the variability in the response variable. Interestingly, perhaps, that association remains significant at 95% level for mean GSLA lagged by as much as nine years (see Table 12).

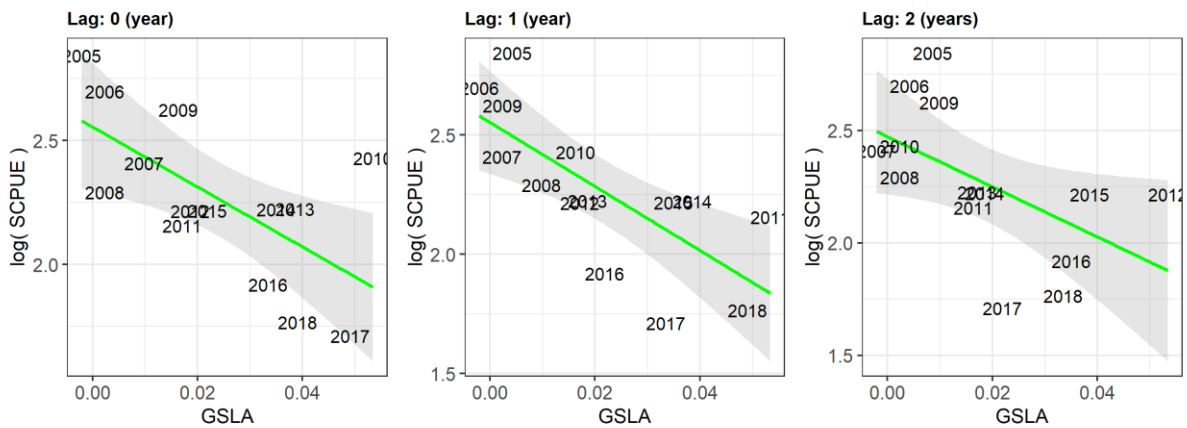


Figure 59: Scattergrams of Pearl Perch log transformed standardised CPUE vs lagged mean GSLA in RO. From left to right panel: Lag 0 (current year), Lag 1 (previous year) and Lag 2 (two years before).

It is worth mentioning the high positive correlation with Chl-a in RO in a potential spawning season of September-November in current year, but not nearly as high in the potential spawning season of March-May for Regions FON and FOS + SCO. These results can be seen from Figure 60.

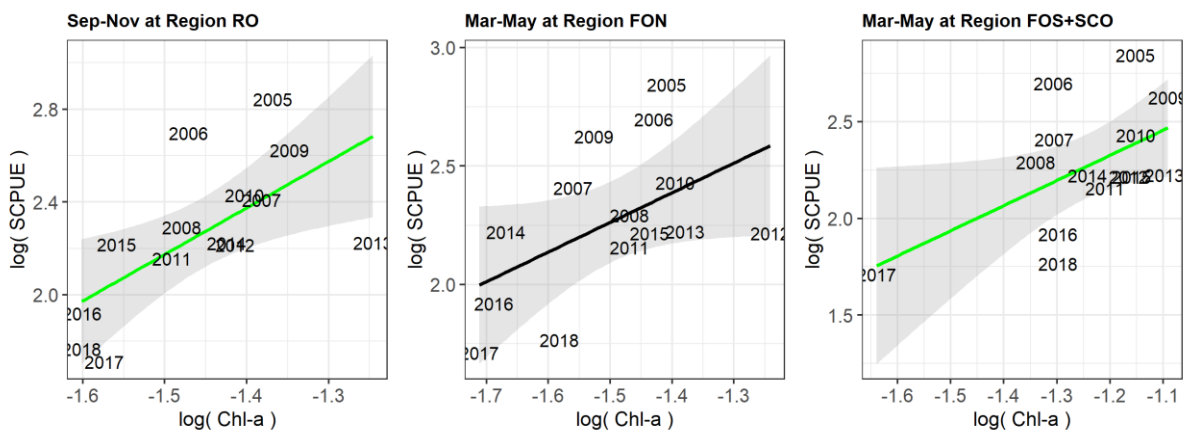


Figure 60: Scattergrams of commercial standardised CPUE vs lagged median Chl-a (log-log) in spawning season according to Regions RO (left), FON (middle) and FOS+SCO (right). Left: $r = 0.64$, $R^2 = 0.41$ and p -value = 0.013; Middle: $r = 0.51$, $R^2 = 0.26$ and p -value = 0.062 and Right: $r = 0.56$, $R^2 = 0.31$ and p -value = 0.039.

Just as in the case of Snapper, we also investigated associations between commercial standardised Pearl Perch CPUE and the SOI signal indices constructed using the methodology of Section 3.3 (a), (c), (d). As before, we extracted the index $S^{\delta-}$ corresponding to the negative episodes of the signal for $\delta=0$ defined by equation (4). The intensity of these episodes was calculated in accordance with equation (6) and persistence weights by equation (9) with parameter $\alpha=2$. The location importance weights were all set to 1. We also considered a range of memory parameters $M=1, \dots, 8$ corresponding to one to eight years. The plot of correlations of these $S^{\delta-}$ indices with the commercial SCPUE, together with their 95% significance bands is displayed in Figure 61.

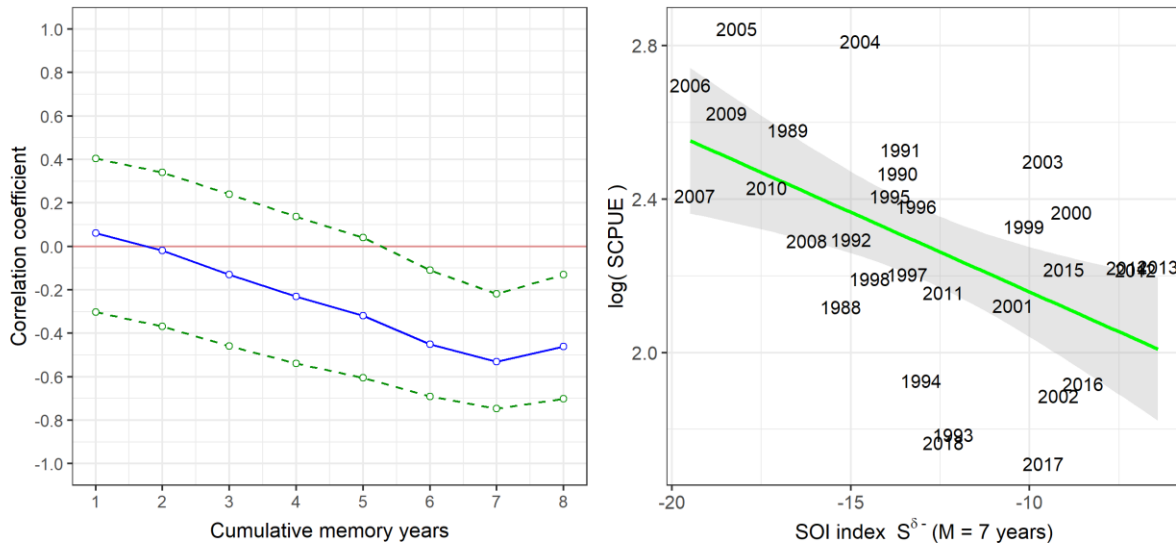


Figure 61: Left panel: correlations of log transformed commercial SCPUE with SOI index $S^{\delta-}$ (for $\delta=0$ and intensity function (6)) and their 95% confidence bands in green, for cumulative memory of 1, ..., 8. Right panel: scattergram for the correlation corresponding to the cumulative memory of 7 years ($M=7$).

It is clear from Figure 61 that the association begins weakly with only one year of memory ($M=1$) and strengthens as the length of memory increases to seven years. The columns of Table 14 give the corresponding key statistics. We note the sustained very strong negative correlations for cumulative memories ranging from six to eight years. Just as in the case of Snapper these results suggest that sustained histories of stronger negative values of the SOI signal are associated with better catch rates of Pearl Perch. However, we have no suggested biological mechanism for such associations.

Table 14: Correlations of commercial SCPUE versus $S^{\delta-}$ for $\delta=0$ and cumulative memory of 1, ..., 8 years plus their R^2 and p -values. Correlation indicated in green are statistically significant at the 95% level.

Memory	Correlation	R^2
1	+0.06	0.00
2	-0.02	0.00
3	-0.13	0.02
4	-0.23	0.05
5	-0.32	0.10
6	-0.45	0.20
7	-0.53	0.28
8	-0.46	0.21

4.4 Estimating Possible Future Trends of Selected Environmental Variables

Many environmental variables that are of interest in this project exhibit varying degrees of periodicity (e.g. annual cycles and multi-year cycles). Consequently, they lend themselves to a range of time series modelling techniques including the trigonometric regression approach briefly described in Section 3.6. These models enable us to estimate future trends of the variables of interest together with accompanying uncertainty bands. In this section, we present the results of such trend estimation for three key variables that already featured prominently in the preceding sections.

4.4.1 Possible future trends in sea surface temperature

We illustrate the analysis with monthly time series of SST based on IMOS data. The series was constructed for the Snapper Region 1W indicated earlier in Figure 19. Daily data were aggregated across months and $0.02^\circ \times 0.02^\circ$ grids were aggregated across the whole 1W region. The available data spanned the period 1992-2019. The five parameter trigonometric regression model of equation (22) was fitted with the help of the maximum likelihood estimation method and extrapolated forward to December 2029.

In Figure 62 we display the fitted model (red curve) and its extrapolation, together with IMOS data points (in black) and the expected value trendline (green line). The shaded area around the trendline constitutes the 95% uncertainty band around the mean. The shaded area around the red curve constitutes the corresponding uncertainty band around the fitted model. It should be clear that the model provides an extremely good fit. Importantly, the slope of the trendline represents a small, but significant, warming trend of approximately 0.15°C per decade, with the standard deviation of 0.06°C . This is roughly consistent, but slightly greater, than NOAA's warming trend of 0.13°C per decade at a nearby location (-26°S , 154°E). Naturally, NOAA's standard deviation of 0.01°C is much smaller as it is based on a much longer time series, going back to 1920.

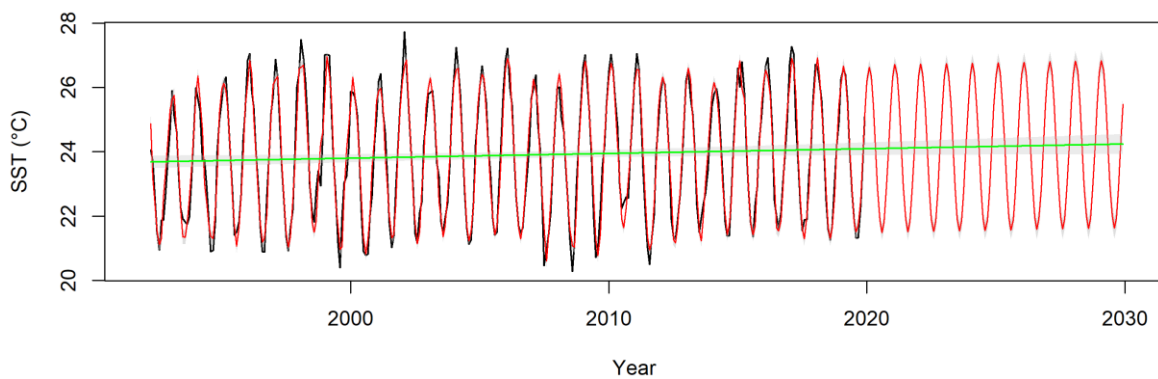


Figure 62: Trigonometric regression fit (red line) of SST time series (black line) for Snapper Region 1W. The shaded area around the trendline constitutes the 95% uncertainty band around the mean. The shaded area around the red curve constitutes the corresponding uncertainty band around the fitted model.

4.4.2 Possible future trends in gridded sea level anomaly

The time series for the GSLA variable was constructed for the aggregated Spanner Crab Regions 2 and 3, indicated earlier in Figure 8. The available data spanned the period 1993 – 2020 (see Table 1). This time the trigonometric regression model was of polynomial order 1 and trigonometric order 1, in the terminology introduced in Section 3.6.

In Figure 63, we display the fitted model, its extrapolation and the expected value trendline. We note that, due to much greater volatility of this time series, the model does not capture the extreme fluctuations in the data. However, the fit can still reasonably predict the expected value. Importantly, the slope of the trendline represents a strong increasing trend of approximately 2.9 cm per decade, with the standard error of 0.7 cm . The shaded region in the figure includes uncertainty in the linear trend.

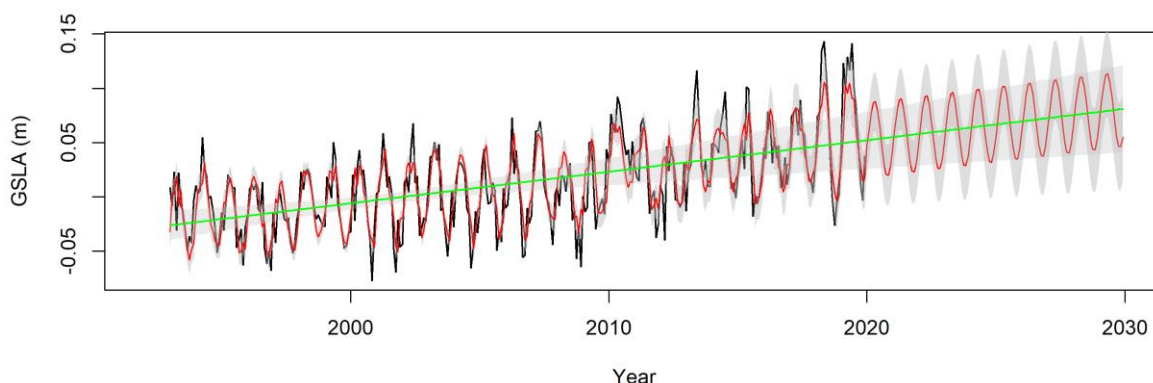


Figure 63: Trigonometric regression fit (red line) of GSLA time series (black line) for Spanner Crab Regions 2-3 for a model with polynomial order 1 and trigonometric order 1. The shaded areas represent the 95% uncertainty bands around the mean and the fitted model, respectively.

4.4.3 Possible future trends in chlorophyll a

The time series for the log transformed Chl-a variable was constructed for the same Snapper Region 1W indicated earlier in Figure 19. Daily data were aggregated across months and $0.02^\circ \times 0.02^\circ$ grids were aggregated across the whole 1W region. The available data spanned the period 2002 – 2020 (see Table 1).

Unlike the SST time series, the Chl-a time series in Figure 64 indicates the presence of second periodic oscillation, in addition to the strong annual cycle. This can also be confirmed by examining the periodogram of that series which is reported in the working files. Consequently, the model equation (25) for the SST now needs to be extended by adding two additional trigonometric terms to capture the secondary oscillation. The resulting seven parameter trigonometric regression model was fitted via maximum likelihood estimation method and extrapolated forward to December 2029. Thus, it became a trigonometric regression model with the polynomial order 1 and trigonometric order 2, in the terminology introduced in Section 3.6.

In Figure 64, we display the fitted model (red curve) and its extrapolation, together with data points (in black) and the expected value trendline (green line). The shaded area including the trendline constitutes the 95% uncertainty band around the mean. Except for some small discrepancies in 2019, the fitted model provides a generally good fit. Importantly, the slope of the trendline represents small, but significant, declining trend of approximately -0.1 per decade on the log scale, with a standard error of 0.02. This implies a reduction of Chl-a concentration by approximately 21% in a decade (see remark concerning Chl-a IMOS data in Section 3.2).

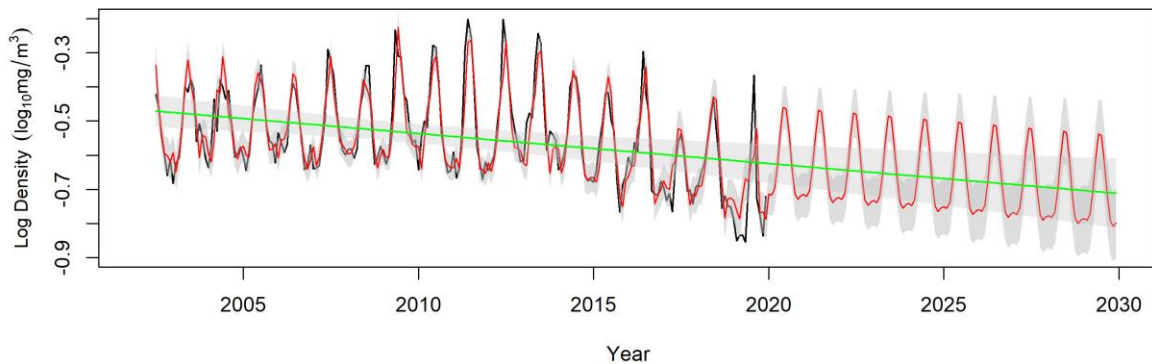


Figure 64: Trigonometric regression fit of Chl-a time series for Snapper Region 1W for a model with polynomial order 1 and trigonometric order 2. The shaded areas represent the 95% uncertainty bands around the mean and the fitted model, respectively.

We note, however, that if we forced the model to be of polynomial order 0 the declining trend would vanish and the extrapolation would result in a perfectly flat trendline depicted in Figure 65. The latter model would not capture the decreasing trend in Chl-a and would not provide adequate explanatory power.

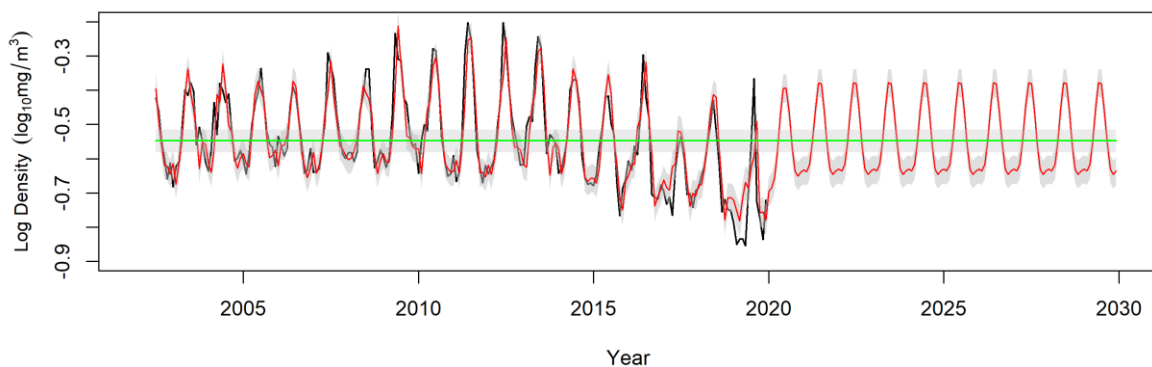


Figure 65: Trigonometric regression fit of Chl-a time series for Snapper Region 1W for a model with polynomial order 0 and trigonometric order 2. The shaded areas represent the 95% uncertainty bands around the mean and the fitted model, respectively.

4.5 Including Environmental Factors in a Surplus Production Model

In this section we return to the surplus production model introduced in Section 3.5.1 and the task of incorporating environmental drivers into such a model. Below, we describe the development and calibration of such models, separately, for Snapper and Spanner Crabs. Analogous results for Pearl Perch are documented in the project's file repository.

4.5.1 Snapper and the surplus production model for Queensland

An important aspect of the harvest data time series displayed in Figure 2 is that it spans long periods of diverse management regimes and harvest data estimation methods going back to 1940, with the modern logbook reporting commencing only in 1988. In order to address differences in input data uncertainty and potential variability arising from using a combination of reconstructed and logbook

harvest estimates (1940 onwards), or logbook-only harvest estimates (1988 onwards), a decision was made to calibrate the surplus production model with two alternative setup scenarios: M0_y1940 and M0_y1988 which use data starting in 1940 and 1988, respectively.

Table 15 displays the JABBA parameter settings that were selected to run these two versions of the model. The only difference lies in the selection of the prior distribution of the depletion parameter φ . Normally, this requires an estimate of the biomass to virgin biomass ratio for Queensland Snapper in 1988. We relied on the Wortmann *et al.* (2018) stock assessment report which analysed spawning biomass ratios for Snapper from 1880-2016 across 72 possible trajectories (see Figure 3.15 in that report). The distribution of that biomass ratio in 1988 guided our choice of the parameters of the prior distribution of φ .

Table 15: Setup scenario parameters for M0_y1940 and M0_y1988.

Parameter	M0_y1940: original JABBA		M0_y1988: original JABBA	
	mean of prior	std dev of prior	mean of prior	std dev of prior
m - shape	$m = 2 \Rightarrow B_{MSY} = 0.5K$		$m = 2 \Rightarrow B_{MSY} = 0.5K$	
r - intrinsic growth rate	0.5	0.3	0.5	0.3
φ - depletion parameter at initial year	0.85	0.1	0.3	0.1

The Kobe plots of the Snapper fishery trajectories generated by the setup scenarios M0_y1940 and M0_y1988 are displayed in Figure 66. Some of the most striking differences are easily explained as natural consequences of the construction of these setup scenarios. For instance, the fact that the trajectory of the M0_y1940 scenario (on the left) resides in the sustainable state prior to 1993 reflects both the moderate harvests prior to 1997 and the relatively high 0.85 estimate of the mean of the prior distribution of φ , in 1940. By contrast, the fact that the trajectory of the M0_y1988 scenario (on the right) begins at the boundary of the depleted state and remains there reflects both the high harvest rates during 1996-2008 and the relatively low estimate of the mean of the prior distribution of φ , namely 0.30, in 1988. The fact that, post 2010, the trajectory moves down with respect to the vertical axis is a reflection of declining harvests. However, because fishing mortality is still too high that movement is accompanied by a slight undesirable drift to the left along the horizontal axis. Overall, the trajectory of the M0_y1940 is more optimistic with regards to the current status of the Snapper stock than the M0_y1988 setup scenario.

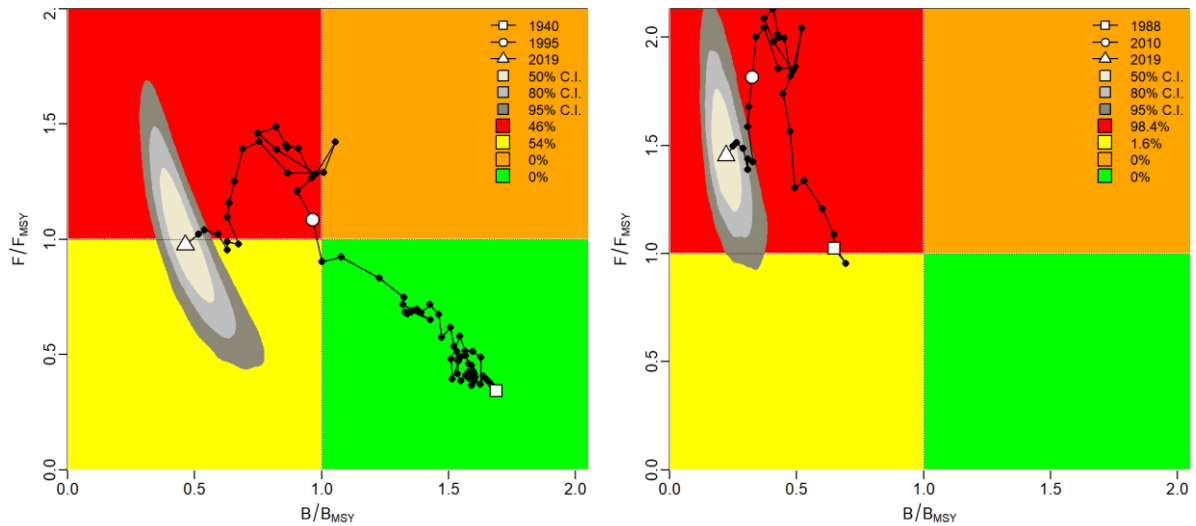


Figure 66: Kobe plot for the Queensland's Snapper fishery under the setup scenarios $M0_y1940$ (left) and $M0_y1988$ (right).

Naturally, we are also interested in comparing forward projections of the fishery's trajectory under a range of total annual harvest scenarios. We considered five scenarios corresponding to TACC of 20, 40, 60, 80 and 100 t, respectively. In Figure 67 we display the JABBA models, projections of the biomass to virgin biomass ratio B/B_0 through to 2029, under these five harvest scenarios. We observe that in $M0_y1940$, even under the highest 100 t scenario (orange curve), the stock is projected to recover to $B_{msy} = 0.5K$ level by 2025, according to the mean trend. However, in $M0_y1988$, also under the 100 t scenario (orange curve), the stock's projection will still not reach $B_{msy} = 0.5K$ level by 2029. As expected, the uncertainty bands in both models, represented by the shaded areas, in Figure 67, grow rather fast.

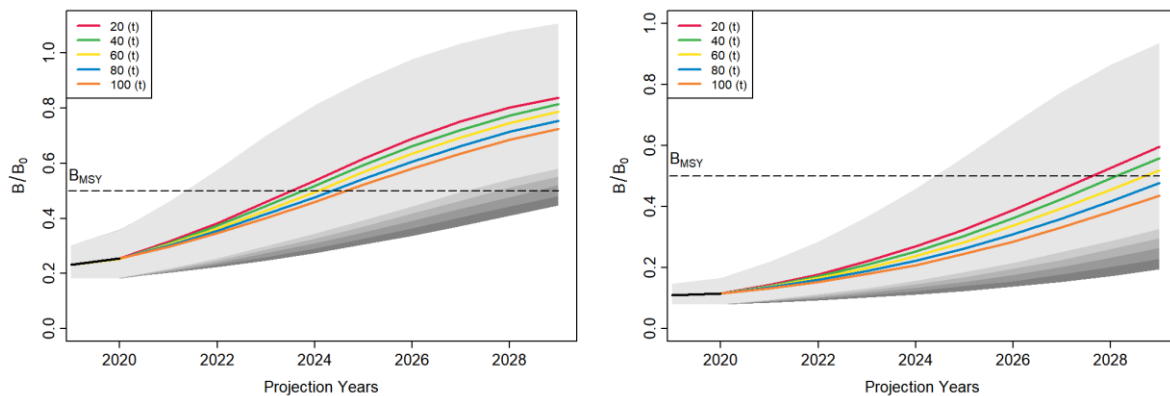


Figure 67: Projections of five harvest scenarios for $M0_y1940$ (left) and $M0_y1988$ (right) models.

It is likely that the more optimistic trends exhibited by $M0_y1940$ are a consequence of the low estimated harvest rates during the period from 1955 to 1975 (Figure 2), which were reconstructed

from archival and historical data sources (Wortmann 2018)⁵. In view of the larger number of data inferences required to develop the historical harvest rate timeseries used in MO_y1940, we regard the MO_y1988 and its projections as more reflective of likely future trends.

Next, we demonstrate the impact of including May SST in the Snapper Region 1W as an additional variable in the JABBA model affecting its surplus production term. In Section 4.4.1, the time series of SST was very well approximated with the help of a trigonometric regression technique (see Figure 62). From that model the fitted values of May SST were extracted plotted in Figure 68 (in blue) while the IMOS time series of that variable is displayed in the same figure (in red). Note that the modelled (blue) curve includes linear mean trendlines in the years preceding available IMOS observations and in the future period 2020-2029.

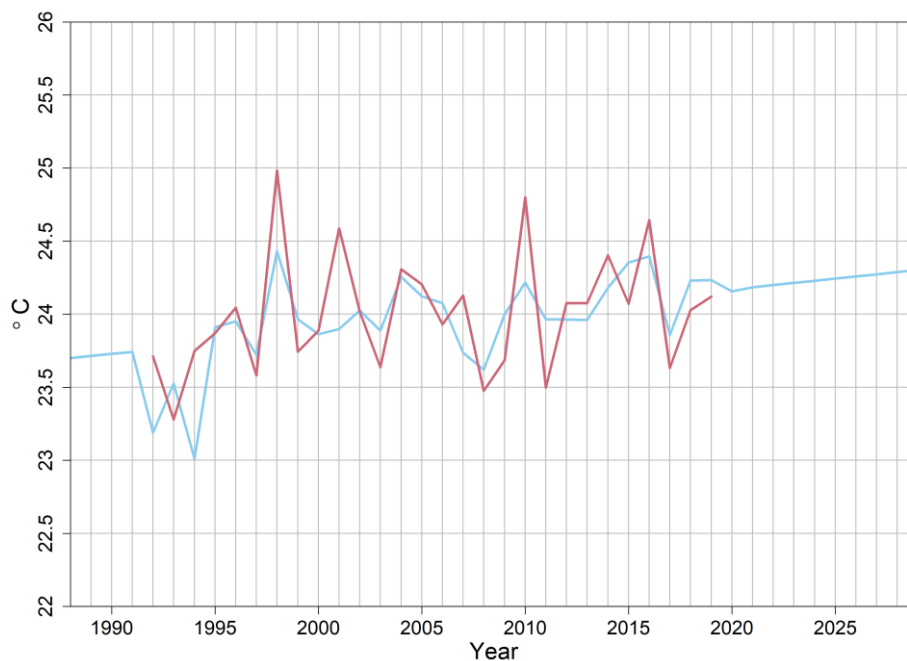


Figure 68: IMOS time series of mean May SST (red) in the Snapper Region 1W and statistically fitted model (blue) and its extrapolations.

We take 23.52° as the reference May SST in Region 1W as it is the 30-year mean of May SST means over the period 1961-1990. Then we define z_t to be the May SST anomaly with respect to this long-term mean of 23.52° and include it as an additional variable in the JABBA model affecting its surplus production term as in $SP(B_t)e^{\beta z_t}$ with the $\beta = \beta_{sst}$ parameter to be estimated.

We note that following the correlation analysis in Section 4.1.1 (for pre-recruits), we had implemented May, June, and July SST, respectively, in the JABBA model using CFISH data. The posterior medians of those three monthly SST effects are negative and consistent with the correlation analysis results. However, the 95% credible intervals show that May SST effect is more significant than the other months. This and the fact that May is the first month of Snapper’s spawning season guided its selection for this analysis (see also Section 1.1.1).

⁵It is not clear that the relatively low harvests during the period 1955-1975 captured the true trend in the Snapper catch, especially as Queensland population doubled from 1 to 2 million persons between 1938 and 1974, according to the Australian Bureau of Statistics (ABS).

The yearly values of the z_t variable from 1988-2019 are thus known. We now extend the previous M0_y1988 setup scenario to create two new setup scenarios both of which use the above May SST anomaly values from 1988-2019 but which differ primarily in the fixed values of the shape parameter with $m=2$ implying $B_{msy} = 0.5K$ and $m=3.4$ implying $B_{msy} = 0.6K$. The specification of these scenarios is given in Table 16.

Table 16: Setup scenario parameters for SST(5)_y1988_0.5K and SST(5)_y1988_0.6K.

Parameter	SST(5)_y1988_0.5K		SST(5)_y1988_0.6K	
m - shape	$m = 2 \Rightarrow B_{MSY} = 0.5K$		$m = 3.4 \Rightarrow B_{MSY} = 0.6K$	
r - intrinsic growth rate	mean of prior = 0.5	std dev of prior = 0.3	mean of prior = 0.5	std dev of prior = 0.3
K - carrying capacity	mean of prior = 6×10^6	CV of prior = 1	mean of prior = 6×10^6	CV of prior = 1
φ - depletion parameter at initial year	mean of prior = 0.3	std dev of prior = 0.1	mean of prior = 0.3	std dev of prior = 0.1

When JABBA is calibrated using these two scenarios, the results yield rather similar trajectories of the B_t/B_0 biomass to virgin biomass ratios but differ substantially in median maximum sustainable yield (MSY). There are also some, less pronounced, differences in the important r and β_{sst} parameters, as illustrated in Figure 69.

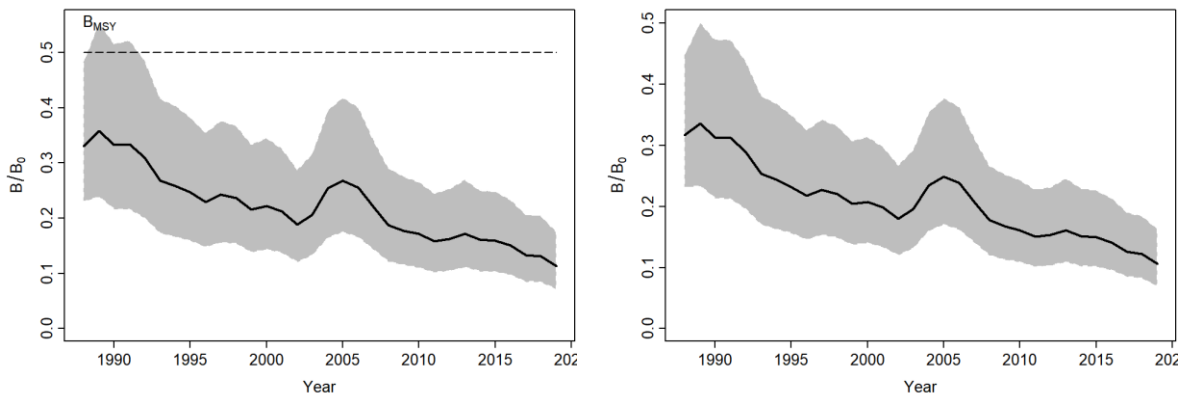


Figure 69: JABBA outputs of scenario SST(5)_y1988_0.5K (left) and SST(5)_y1988_0.6K (right).

Similarly, the Kobe plots of the system's trajectories under these two scenarios are qualitatively very similar. This can be seen from Figure 70 where, perhaps, the only differences that can be easily noticed are in the slightly lower, most recent, B_{2019}/B_{msy} ratio and slightly narrower uncertainty region around the 2019 endpoint. Overall, perhaps, some preference could be given to the SST(5)_y1988_0.5K scenario on the grounds that median MSY of 654t is less unrealistic than the 835t under the SST(5)_y1988_0.6K scenario.

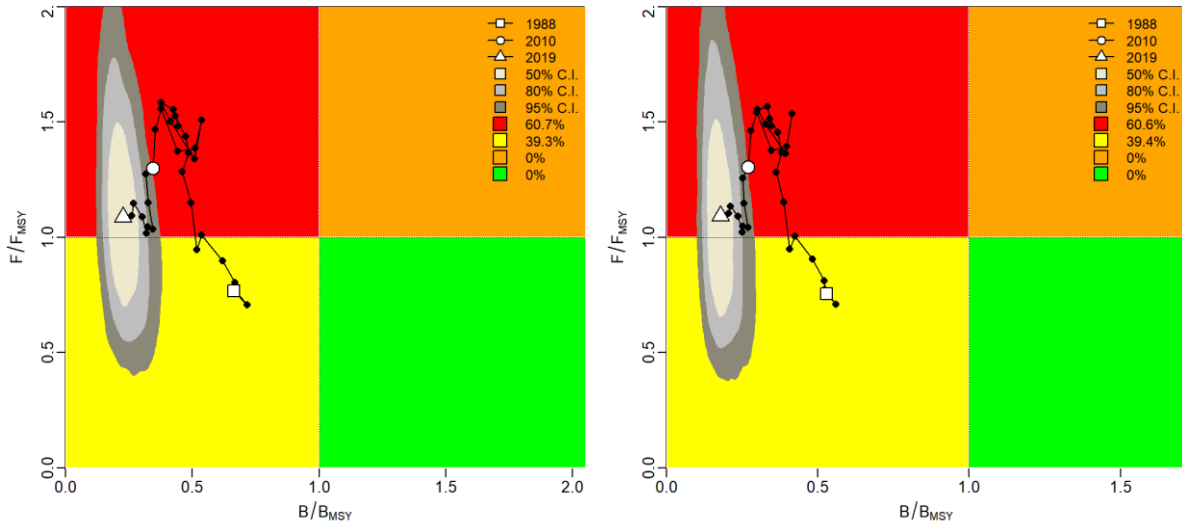


Figure 70: JABBA Kobe plot of scenario SST(5)_y1988_0.5K (left) and SST(5)_y1988_0.6K (right).

However, in this project, the main task is to quantify the possible future impact of an environmental driver such as May SST on the attainment of Queensland’s objectives in Sustainable Fisheries Strategy. To do that we must make some assumptions about future projections of May SST in the 1W Snapper region. We illustrate the analysis with three alternative projections for the period 2020-2029:

- PI. May SST will remain constant at 23.52° (the mean over 1961-1990);
- PII. May SST will remain constant at 24.12° (its value in May 2019);
- PIII. May SST will continue to increase according to the blue trendline indicated in Figure 68.

Arguably, PI could be considered as overly optimistic and PIII as pessimistic in assuming the continued upward trend. We next illustrate that, within the JABBA model framework, these three projections have a large impact on the consequences of the SST(5)_y1988_0.5K and SST(5)_y1988_0.6K scenarios in terms of likely reachability of their respective B_{msy} levels. As before, we considered five harvest scenarios of 20, 40, 60, 80 and 100 t, respectively. The results corresponding to projections PI, PII and PIII are displayed in Figure 71, Figure 72 and Figure 73, respectively.

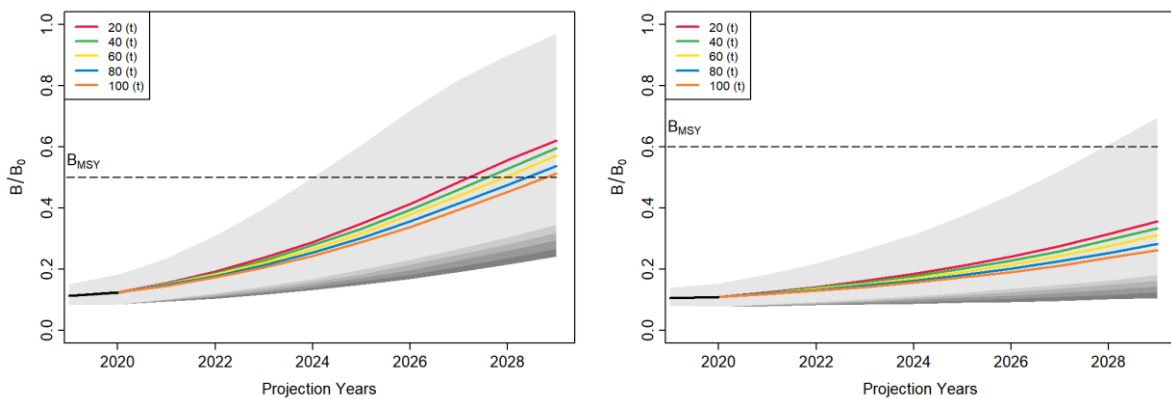


Figure 71: Projection PI; five harvest futures under SST(5)_y1988_0.5K (left) and SST(5)_y1988_0.6K (right).

We note that the projection PI of steady 23.52° mean May temperature and scenario SST(5)_y1988_0.5K are the only configuration under which the Snapper stock recovers to B_{msy} sometime between roughly 2027 and 2029 as the harvest level ranges from 20 t to 100 t. Under the

SST(5)_y1988_0.6K scenario no such recovery takes place even with the low PI temperature projection. In fact, the level of recovery over the next decade is very low from $B_{2019}/B_0 = 0.11$ to somewhere between 0.26 and 0.36 as the harvest level ranges from 20 t to 100 t (see right panel of Figure 71).

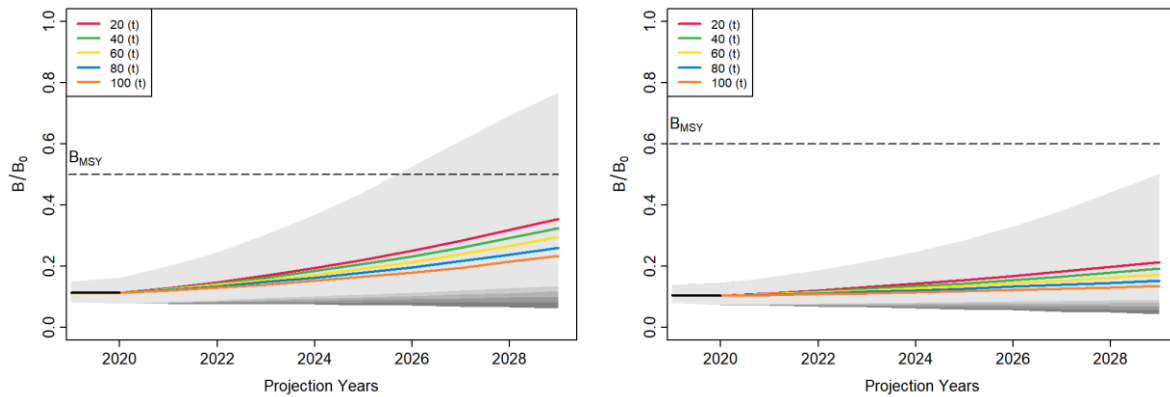


Figure 72: Projection PII; five harvest futures under SST(5)_y1988_0.5K (left) and SST(5)_y1988_0.6K (right).

Surprisingly, perhaps, the projection PII of steady 24.12° mean May SST (Figure 72) makes a significant difference under scenario SST(5)_y1988_0.5K but not in SST(5)_y1988_0.6K. In the former case, the level of recovery over the next decade is very low from $B_{2019}/B_0 = 0.11$ to somewhere between 0.23 and 0.35 as the harvest level ranges from 20 t to 100 t (see left panel of Figure 72). On the other hand, comparison of right panels in Figure 72 and Figure 71 shows only minimal decline as a result of this 0.6° increase in the projected temperature.

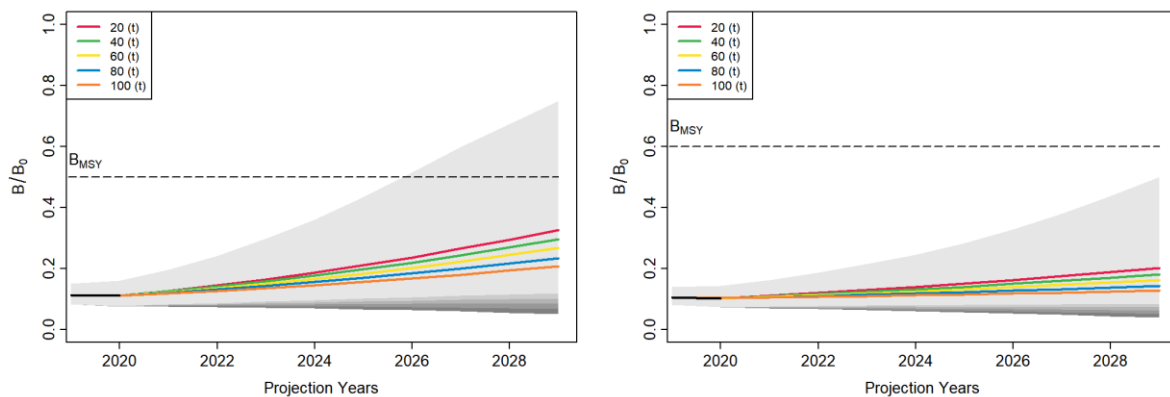


Figure 73: Projection PIII; five harvest futures under SST(5)_y1988_0.5K (left) and SST(5)_y1988_0.6K (right)..

Finally, the projection PIII of linear increase in mean May temperatures creates a further, but only small, decline in stock recovery rates under scenario SST(5)_y1988_0.5K (see left panel of Figure 73). In the case of SST(5)_y1988_0.6K and projection PIII the level of recovery over the next decade is again very slow from $B_{2019}/B_0 = 0.11$ to somewhere between 0.12 and 0.20 as the harvest level ranges from 20 t to 100 t (see right panel of Figure 73).

4.5.2 Spanner Crabs and the surplus production model for Queensland

Next, we extend the preceding methodology for incorporating environmental variables into surplus production models to Queensland’s Spanner Crab fishery, using commercial logbook catch data for the period 1988-2019. The fishery spans previously considered Regions 2-6, the whole area of which will

referred to as managed area A. Because of the previously noted similarities between Regions 2 and 3 with respect to their responses to several environmental variables, they will be combined into a region called the ‘north Spanner Crab fishery’. Similarly, combined Regions 4, 5 and 6 will be called the ‘south Spanner Crab fishery’. The standardised catch rates of commercial logbook database CFISH for the whole management area A and individual regions are displayed in Figure 10 in left and right panels, respectively.

To proceed with creating a JABBA model three benchmark setup scenarios were created, one each for the whole, the north and the south Spanner Crab fisheries. The details of these scenarios are in Table 17. Note that some parameter choices were influenced by those cited in Haddon (2018) for the assessment of Hawaiian Kona Crab fishery (which is the same species, *R. ranina*).

Table 17: Setup scenario parameters for $M0_whole_0.5K$, $M0_north_0.5K$ and $M0_south_0.5K$.

Parameter	$M0_whole_0.5K$		$M0_north_0.5K$		$M0_south_0.5K$	
m - shape	$m = 2 \Rightarrow B_{MSY} = 0.5K$		$m = 2 \Rightarrow B_{MSY} = 0.5K$		$m = 2 \Rightarrow B_{MSY} = 0.5K$	
r - intrinsic growth rate	mean of prior = 0.3	std dev of prior = 0.3	mean of prior = 0.3	std dev of prior = 0.3	mean of prior = 0.3	std dev of prior = 0.3
K - carrying capacity	mean of prior = 2.8×10^7	CV of prior = 1	mean of prior = 1.5×10^7	CV of prior = 1	mean of prior = 1.3×10^7	CV of prior = 1
φ - depletion parameter at initial year	mean of prior = 0.8	std dev of prior = 0.15	mean of prior = 0.8	std dev of prior = 0.15	mean of prior = 0.8	std dev of prior = 0.15

The Kobe plots of the 1988-2019 trajectories resulting from these scenarios are displayed in Figure 74. The drastic decline in SCPUE in the north fishery (Regions 2-3) in the past decade is reflected by the location of the last few points on the trajectory in the top right panel which ends at a very low, left of the centre, point. Surprisingly, perhaps, the last few years of the trajectory of the south fishery (Regions 4-6) also reside in undesirable regions of the Kobe plot (see right panel of Figure 74). This could be driven by SCPUE declines in the productive Region 4 during 2010-2014 and 2015-2017. Furthermore, the region of uncertainty around the final 2019 point is much greater in the south fishery. The trajectory of the whole fishery (left panel) is somewhat less erratic but still ends in an undesirable quadrant of Kobe plot in 2019 and with a large uncertainty region.

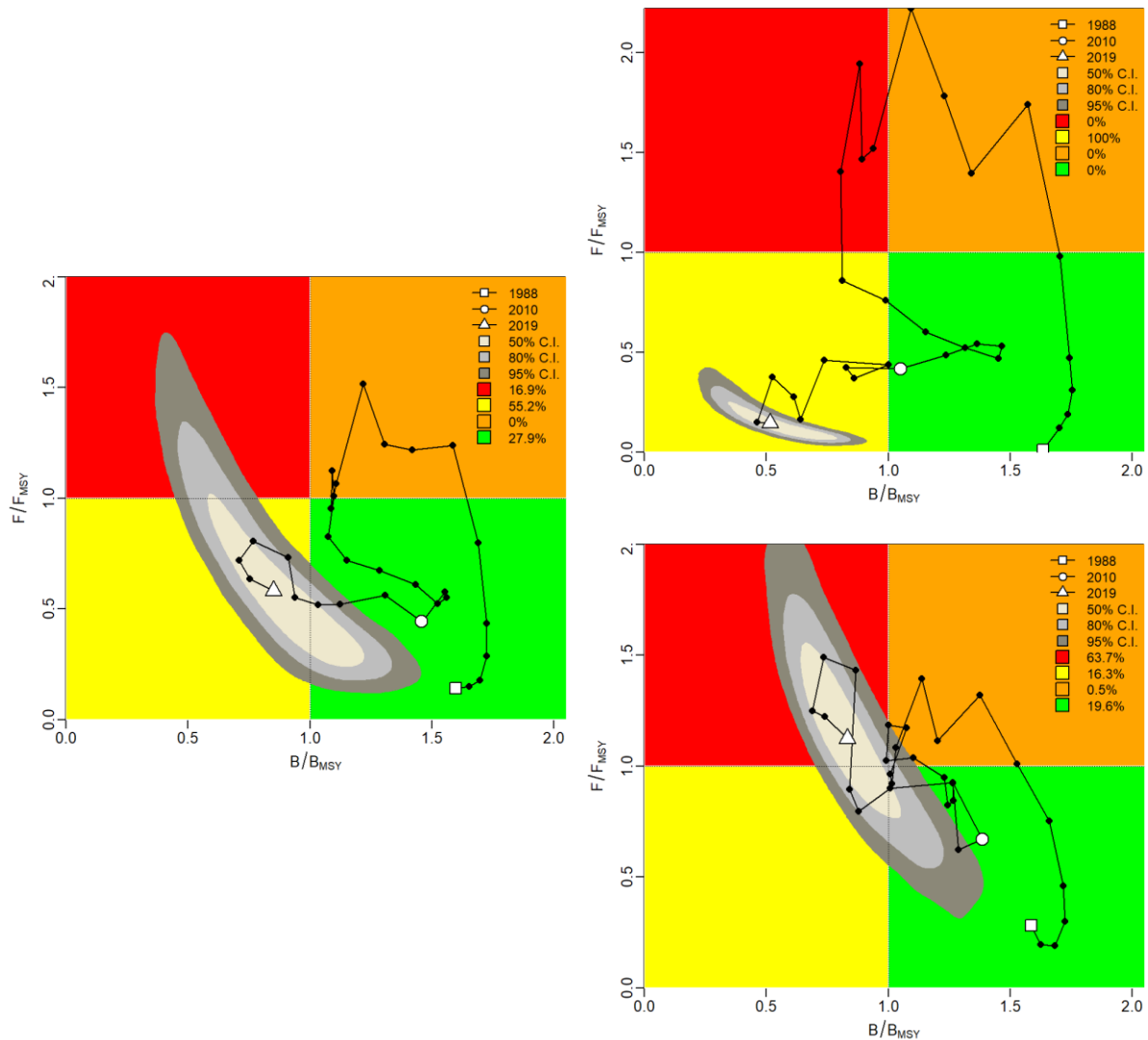


Figure 74: Kobe plots of Spanner Crab scenarios for $M0_whole_0.5K$ (left), $M0_north_0.5K$ (top right) and $M0_south_0.5K$ (bottom right).

As in the case of Snapper, we are also interested in comparing forward projections of the fishery's trajectory under a range of total annual harvest scenarios. We considered four scenarios corresponding to TACC of 600, 800, 1000 and 1200 t, respectively, for the whole management A area fishery. It should be noted that biomass estimates of B and B_0 should be interpreted in terms of total biomass. However, TACCs refer to exploitable biomass. The projections of the biomass to virgin biomass ratios for the whole fishery, under these four harvest scenarios, indicate rapid recovery to the $0.5 B/B_0$ level by 2024, as indicated in the left panel of Figure 75. However, from right panels of the same figure we see that the stock recovery is slower in the north fishery and in the south the 1000 t and 1200 t annual harvest scenarios lead to further decline rather than a recovery. Quick recovery still takes place under the 600 t harvest scenario.

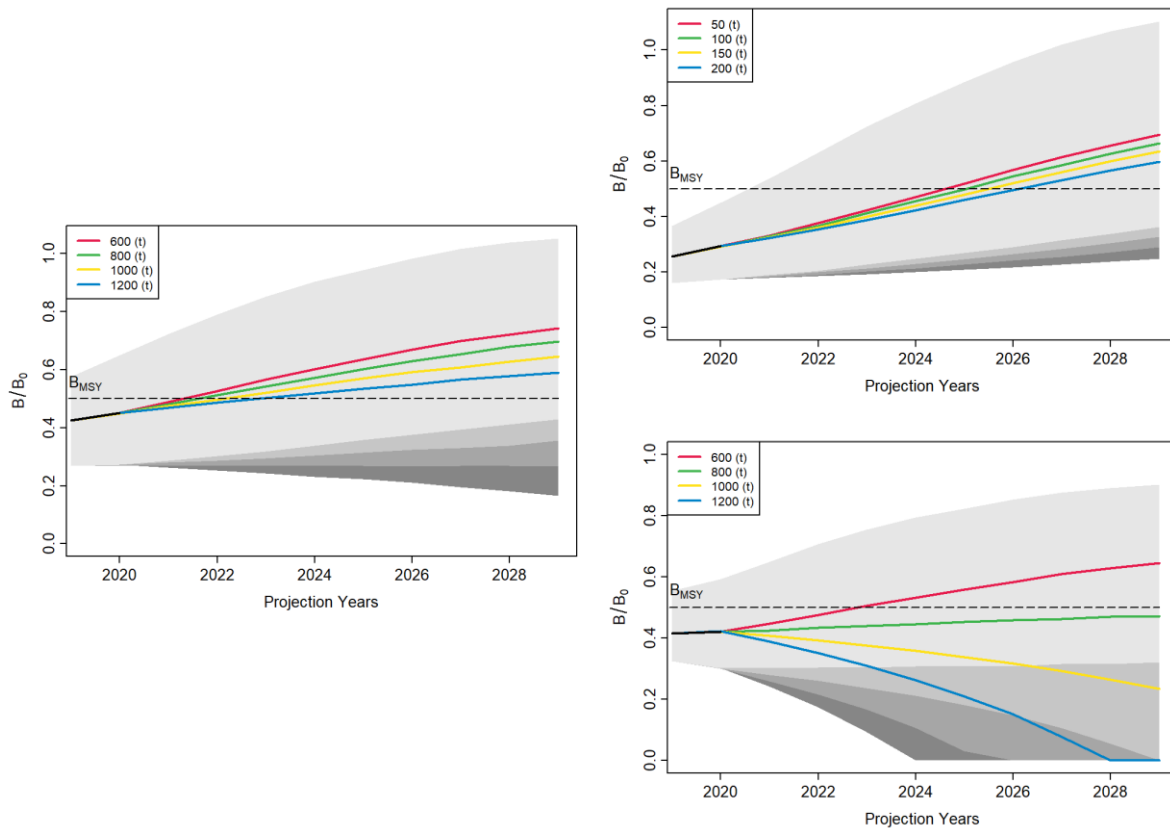


Figure 75: Projections of four Spanner Crab harvest scenarios for $MO_whole_0.5K$ (left), $MO_north_0.5K$ (top right) and $MO_south_0.5K$ (bottom right).

Next, we demonstrate the impact of including GSLA as an additional variable in the JABBA model affecting its surplus production term. In Section 4.4.2 the time series of GSLA in the north fishery was well approximated with the help of a trigonometric regression technique and this was repeated for the south and the whole fisheries. From these statistical models the fitted values of GSLA were extracted and plotted in Figure 76 (in blue) while the IMOS time series of that variable for 1993-2019 were displayed in the same figure (in red). Note that the modelled (blue) curve includes linear mean trendlines in the years preceding available IMOS observations and in the future period 2020-2029.

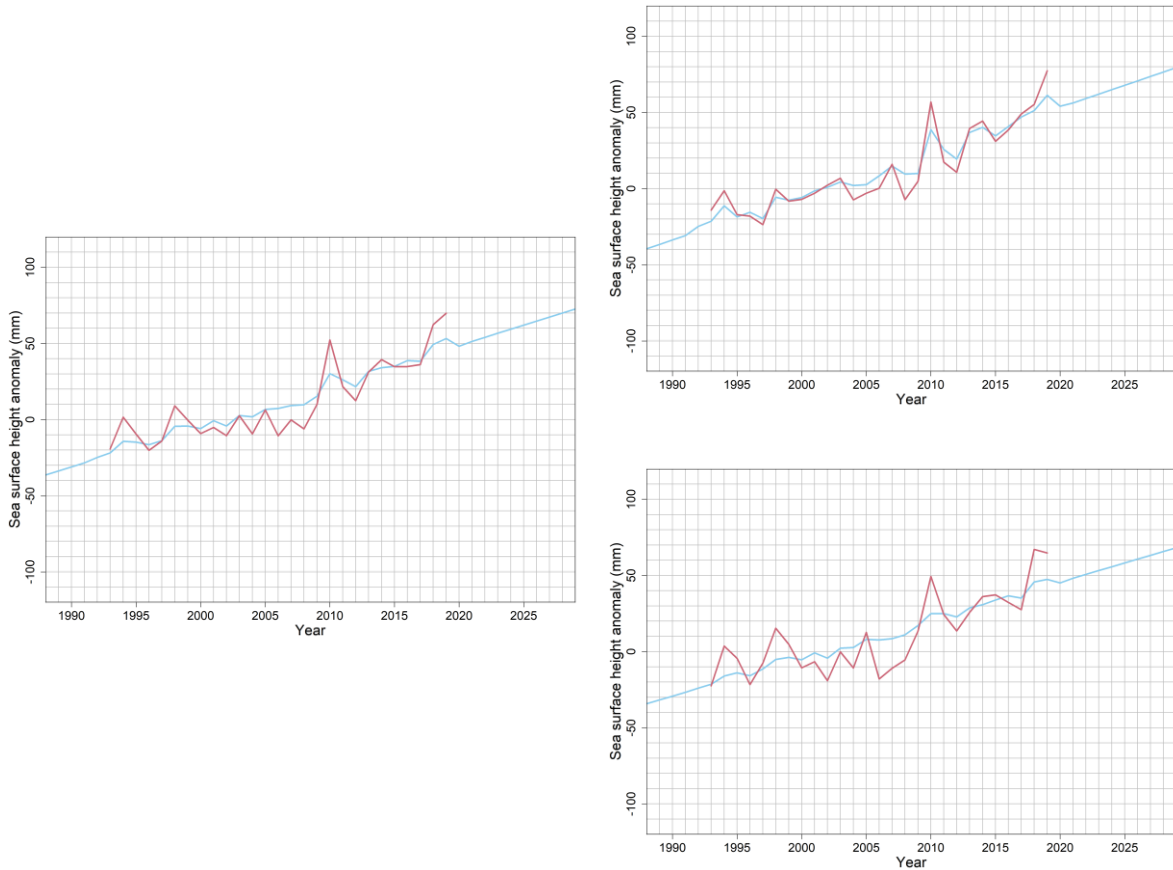


Figure 76: IMOS time series of GSLA (red) in the Spanner Crab whole (left), north (top right) and south (bottom right) fisheries; and statistically fitted models (blue) and their extrapolations.

For the whole management area A we take the reference GSLA to be -0.070m as it is the mean GSLA for the 30-year period 1961-1990. Similarly, for the north and south fisheries we take the corresponding 30-year means as reference GSLAs: -0.076m for north and -0.065m for south.

As in the case of Snapper, we must make some assumptions about future projections of GSLA in three Spanner Crab fisheries under consideration. We carried out the analyses with three alternative projections for the period 2020-2029 applied correspondingly across the whole, the north and the south fisheries

PI. GSLA will remain constant at their respective reference GSLAs;

PII. GSLA will remain constant at their respective 2019 values;

PIII. GSLA will continue to increase according to their respective blue trendlines in Figure 76.

Arguably, PI can be seen as too optimistic and PII as too pessimistic because the observed 2019 GSLA values were the highest from 1993-2019 in each of the three fisheries. Hence, we highlight only the results obtained under the PIII future projection.

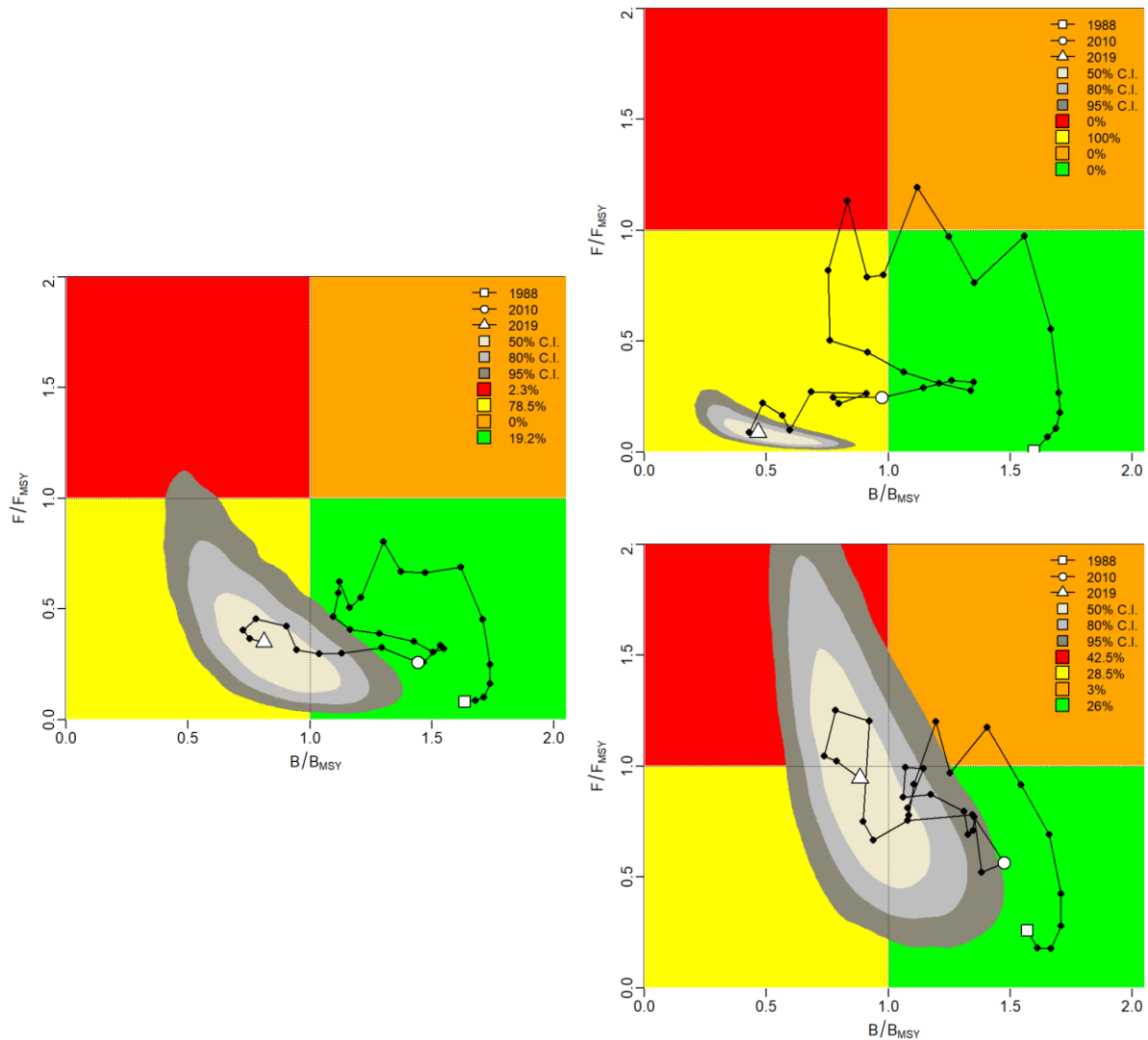


Figure 77: Kobe plots of Spanner Crab scenarios for $M0_whole_0.5K$ (left), $M0_north_0.5K$ (top right) and $M0_south_0.5K$ (bottom right), with GSLA trends included.

The new Kobe plots of the 1988-2019 trajectories resulting from the inclusion of GSLA are displayed in Figure 77 and should be compared with the benchmark case in Figure 74. It is immediately noticeable that the inclusion of GSLA has smoothed the trajectories but that the location of the 2019 endpoints is very similar for the whole and north fisheries. In the case of the south fishery, the 2019 end point has moved down from the depleted red region to the recovering yellow region but that the uncertainty region around the 2019 end point has increased considerably. Even so, over the past decade, trajectories of the whole, north and south fisheries reside in comparable regions of the Kobe plots, irrespective of whether GSLA is included in their respective models.

However, comparison of forward projections of the fisheries' trajectories under corresponding ranges of total annual harvest scenarios yields drastically different results for the whole and the north fisheries. This can be seen by comparing the left and top right panels in Figure 78 to the corresponding panels in Figure 75. As before we considered four scenarios corresponding to TACC of 600, 800, 1000 and 1200 t, respectively, for the whole management A area. Before GSLA was included the biomass to virgin biomass ratios recovered rapidly to the 0.5 level by 2024. However, once GSLA has been incorporated the 0.5 level is still out of reach even by 2029 for the 600 and 800 t harvest levels. For the 1000 and 1200 t harvest levels these biomass ratios decline rather than grow, albeit relatively slowly.

For the north Spanner Crab fishery, before including GSLA, we observed recovery of the biomass ratios to 0.5 by 2007, under all four annual harvest scenarios of 50, 100, 150 and 200 t, respectively. However, after GSLA is included, the top right panel of Figure 78 shows only minimal improvement under the 50 t and 100 t harvests and further declines under the 150 t and 200 t annual harvests. Interestingly, however, the differences in south fishery are very minor as can be seen by comparing the bottom right panels of Figure 78 and Figure 75. This is consistent with the relative resilience to environmental drivers of the most productive Region 4 in the south fishery.

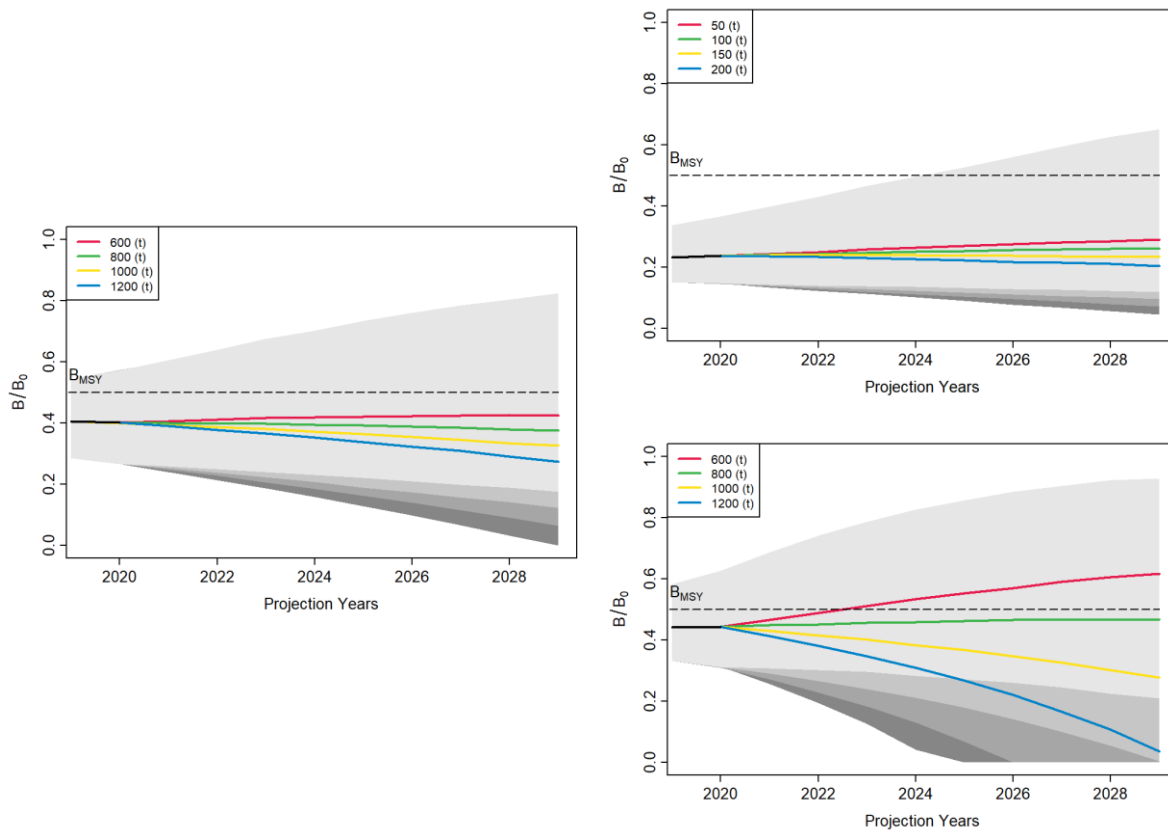


Figure 78: Projections of four Spanner Crab harvest scenarios for $MO_whole_0.5K$ (left), $MO_north_0.5K$ (top right) and $MO_south_0.5K$ (bottom right), with future projection PIII of GSLA included.

4.6 Including Environmental Factors in CPUE Standardisation

Below we summarise very briefly the results of this exploration for Spanner Crab and Snapper CPUEs. For both species, the main findings were:

- Despite some environmental variables being statistically significant in GLM models currently used, they contributed only in a negligible way to their goodness-of-fit.
- The current, heavily parametrised, GLM models likely already account for nearly all the variability in CPUE that could be explained by these environmental factors.

In view of the above, further investigation of appending environmental variables to GLM models for SCPUE is impractical unless there was interest in also re-examining the composition of the currently systematic factors used, in particular the categorical year factor appears to account for a large

proportion of the interannual variation in environmental conditions. Next, we present some evidence to support these findings.

Spanner Crabs

It can be seen from Table 18 that seven key environmental indices are statistically significant when appended to the benchmark GLM model (23), respectively. In particular, we see that SST, SOI and current speed near the bottom are all highly significant. However, that does not mean that their inclusion would appreciably improve the GLM model.

Table 18: Estimates, standard error, t value and p-value of the seven key environmental indices when appended to the benchmark GLM model (23), respectively, for Spanner Crab commercial CPUE standardisation.

Environmental index	Coefficient	Std. Error	t value	p-value
SST	0.169	0.008	20.624	<0.001
Chl-a	-0.004	0.002	- 1.865	0.062
GSLA	0.030	0.003	10.625	<0.001
bottom temperature	0.016	0.005	3.182	0.001
SOI	- 0.012	0.002	- 5.121	<0.001
PDO	0.005	0.004	1.435	0.151
bottom speed	0.045	0.003	15.941	<0.001

In fact, we found that inclusion of environmental indices barely affects the annual standardised CPUE. For instance, Figure 79. We observe that the curves are nearly identical except for some minor differences in years 2007-2010. This lack of appreciable effect is also reflected in some standard diagnostics such as R^2 changing from 0.574 to only 0.576, an improvement of only 0.002. It is entirely possible that variables such as the year, seasonality, and region and their interactions, included in the benchmark model, may have already accounted for nearly all the variability that could be explained by SST.

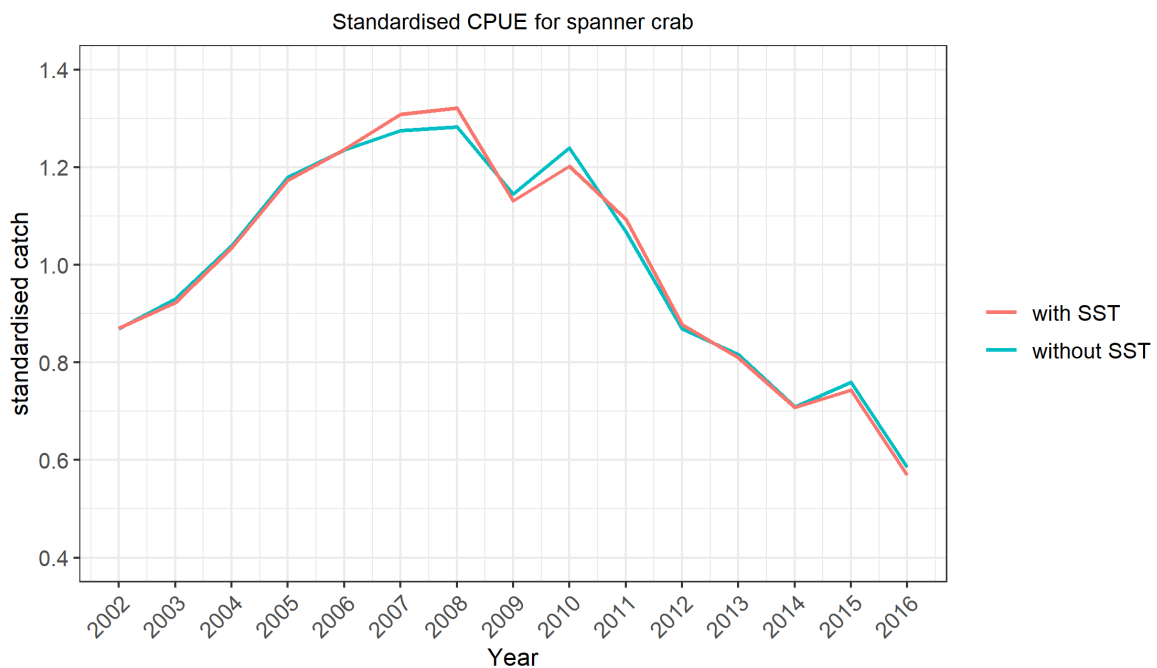


Figure 79: Prediction of commercial standardised CPUE for Spanner Crab with and without SST.

The above lack of appreciable effect is not unique to the SST variable. Analogous findings repeat themselves with Chl-a, GSLA, bottom temperature, bottom current speed, SOI and PDO.

Snapper

From Table 19 we see that SST is the only environmental variable identified as statistically significant when added to the benchmark model.

Table 19: Estimates, standard error, t value and p-value of five environmental indices when appended to the benchmark GLM model, respectively, for Snapper commercial CPUE standardisation.

Environmental index	Coefficient	Std. Error	t value	p-value
SST	0.078	0.016	4.937	<0.001
Chl-a	0.007	0.005	1.402	0.161
SOI	-0.003	0.006	-0.508	1.388
PDO	0.004	0.010	0.451	0.652
GSLA	0.001	0.008	0.092	0.926

As was the case with the comparison of CPUEs plots for Spanner Crabs (see Figure 79), we again find that including SST in the benchmark CPUE model has a negligible effect. In Figure 80, we observe that the model fit is nearly identical except for some very minor differences in years 2010-2011.



Figure 80: Prediction of commercial standardised CPUE for Snapper with and without SST.

4.7 Observed Patterns Needing Further Study

It is clear from results reported so far that in the case of the Spanner Crab fishery the complex pattern of positive and negative associations with environmental variables calls for further investigation of the underlying processes contributing to them across the six regions and on different time scales.

There are indications that some of the differences in these associations are due to the large latitudinal gradient across the regions as well as on the cross-shelf depth gradient of the surveyed locations within each region. Several of the environmental variables we investigated exhibit markedly different features, the causes of which are likely related to the pattern of associations we observed. These variables include, but are not limited to, components of the current velocity, current speed, and water temperatures at different depths.

Furthermore, there is already a body of literature pointing to dynamic oceanographic and climate processes influencing large segments of the Spanner Crab fishery environment. For instance, Brieva *et al.* (2015) studied the effects of East Australian Current (EAC) on the distribution of phytoplankton blooms (as indicated by Chl-a) near the Fraser Island continental shelf and linked them to two distinct quasi-climatological patterns. They found that the area overlaps with a hot-spot in EAC-generated bottom layer stress connected with the “Southeast Fraser Island Upwelling System”. Furthermore, in Ismail *et al.* (2017), the authors identify “The Fraser Gyre”, a characteristic recurring wind-driven cyclonic flow located south of Fraser Island between about 25°S and 27°S. They conjecture that the Fraser Gyre could be “facilitating the offshore transport of fish larvae, sediments, nutrients, river discharges, and other properties across the shelf break and into the southward flowing EAC during the austral autumn and winter”.

While deeper investigation of such physical processes is beyond the scope of this project, in this subsection we highlight a sample of just three patterns which, we believe, may be connected with these processes. We hope that other research teams will be able to shed more light on these patterns, in the future.

In Figure 81, we display time series of regional monthly averages of the (u,v,w)-components of ocean current velocity - in Spanner Crab Regions 3, 4 and 7 – at three depth levels: top, bottom and 23m. It should be understood that, in each site covered, “top” and “bottom” refer to depths as close as practical to the surface and bottom, at that site. Also, u, v and w are the east-west, north-south and up-down components, respectively. The figure exposes a lot of qualitative differences between the regions. For instance, in Region 3 the green u component at the bottom is nearly everywhere positive, indicating predominantly eastward (offshore) flows. On the other hand, in Region 4, the same component is more negative than positive, indicating a balance of westward (inshore) flows and this is accompanied by largely eastward flows closer to the surface. Such phenomena could, perhaps, be indicators of upwelling events. Consistent with that, note also that the green up-down component w at the bottom is largely positive while the orange w component at 23m is largely negative in Region 4. That pattern is, at least partially, reversed in Region 3. The north-south component v (centre panels in Figure 81) indicate predominantly southwards flows in all three regions, with Region 7 having the strongest such flows but exhibiting the greatest variability. The latter may be induced by properties of the East Australian Current.

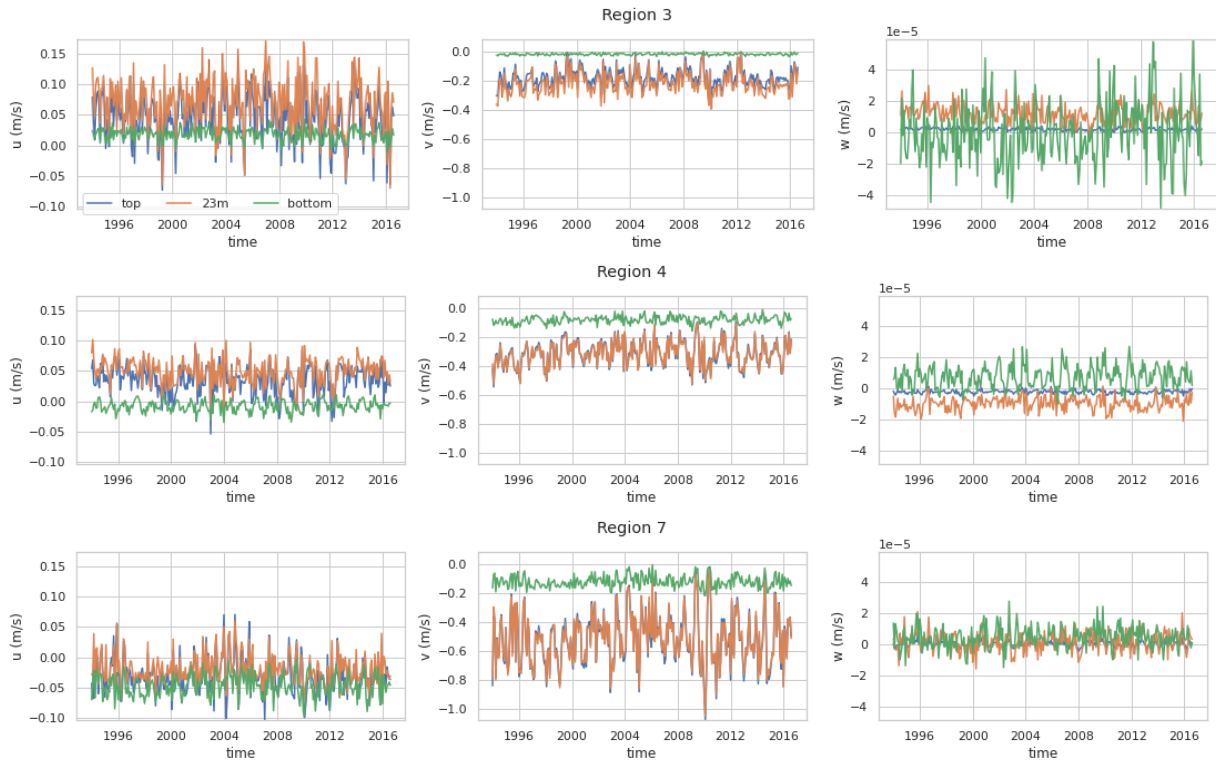


Figure 81: Regional monthly averages of East-west (u), North-south (v) and up-down (w) components of ocean current at three depth levels: top (blue), 23m (orange) and green (near bottom).

In Figure 82, we display analogous plots for the (undirected) current speed variable for the same three regions. We note that – at all three depth levels – both the speed and its variability increase as we move from Region 3, through Region 4 to Region 7. Once again, this may be related to the influence of EAC.

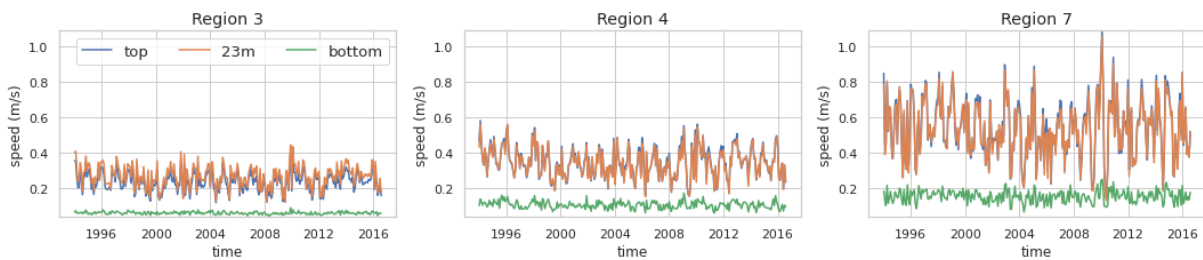


Figure 82: Regional monthly averages of ocean current speed at three depth levels: top (blue), 23m (orange) and green (near bottom).

In Figure 83, we display monthly averages of water temperature - at 6' by 6' resolution - at three depth levels: top (blue), 23m (orange) and green (near bottom), for Spanner Crab Regions 2-7. At that finer resolution, the plots display the temperatures averaged in areas that are close to the sites where the FIS crabs were caught. We first note that in Regions 2 and 3 there is so little difference in these averaged temperatures at the top and 23m depth levels that their plots essentially overlap. Their differentiation becomes clearer in Region 4. The separation from the bottom temperature increases markedly in Regions 5. Interestingly, however, the southernmost Region 7 is, once again, exceptional in exhibiting a pattern that appears closer to that of Region 3 than of the adjacent Region 6. Closeness

to shore of FIS sites in Region 7 may be part of the explanation for this last observation. However, we also note from Figure 8 that FIS sites in Regions 3 and 4 are not as close to shore as those in Region 7.

Additionally, the difference between regions may be influenced by the stratification of the water column, which is related to the depth profile. Shallower water is typically more well mixed and therefore has a weaker gradient between top and bottom temperatures. Deeper waters are more likely to be stratified, with thermoclines developing, across which a rapid drop in temperature occurs. Thermoclines are strongest in summer due to greater solar heating at the top of the water column. However, storms and strong currents can mix the water column and break down the thermocline. Regions 5 and 6 may have greater variation between top and bottom temperature due to their greater depths and the presence of one or more thermoclines, which may be weaker (or absent) in the other regions, causing this disparity seen in Figure 83.

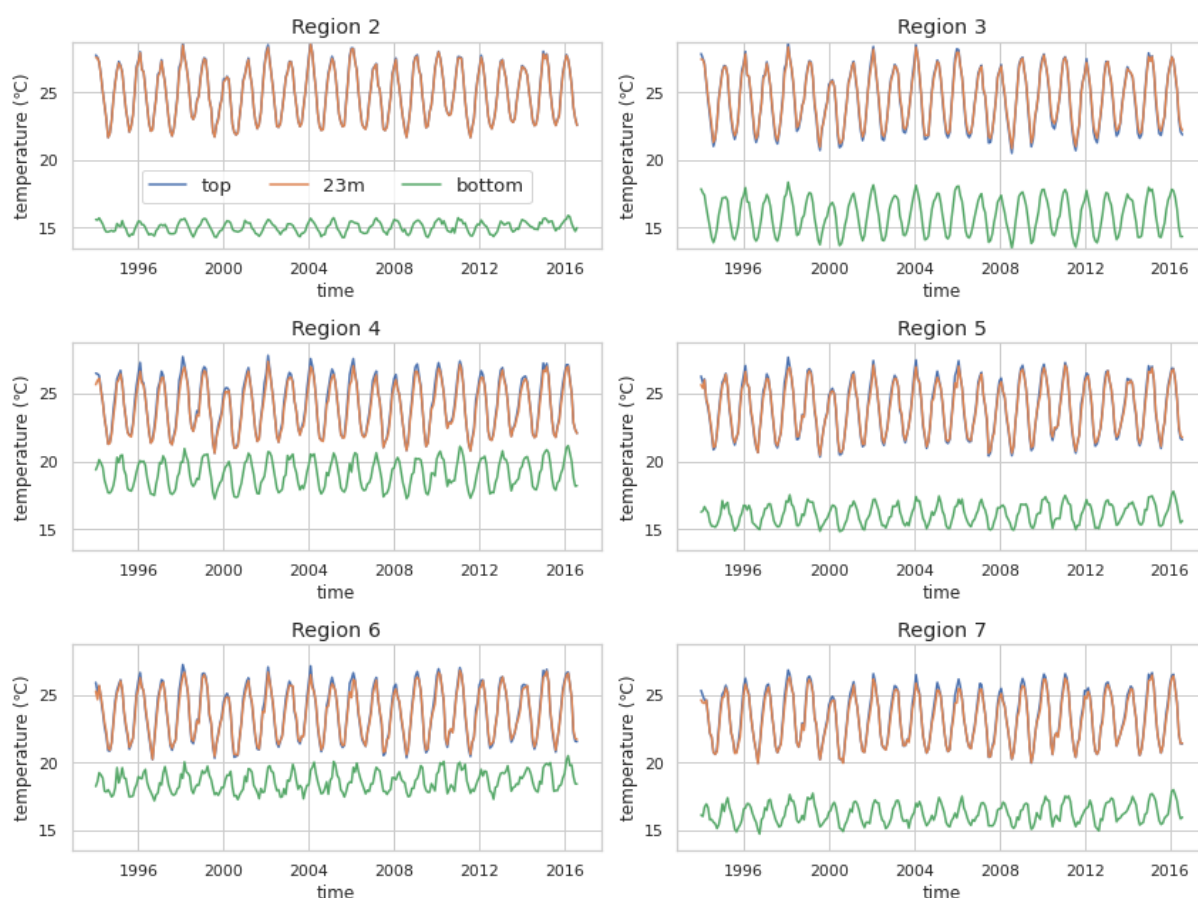


Figure 83: Monthly averages of water temperature at the 6'x6' fishing sites at three depth levels: top (blue), 23m (orange) and green (near bottom), for Spanner Crab Regions 2-7.

4.8 Findings for NSW Snapper and Pearl Perch

As the title of this project suggests, its main mission was the analysis of the impact of environmental changes and effects on Snapper, Pearl Perch and Spanner Crab caught in Queensland. However, its secondary mission was to perform at least a portion of similar analyses on the same species caught in NSW. Indeed, in the case of Spanner Crabs, the NSW Region 7 data from FIS were analysed alongside Queensland data from Regions 2 to 6. For NSW Snapper and Pearl Perch there are no FIS data, but we

were given access to their commercial harvest data for these two species. In this section, we present a summary of analyses performed on data from two main sectors: commercial line, and commercial trap fisheries. These two fisheries account for bulk of commercial harvest of these species. However, fishing effort on Pearl Perch is difficult to quantify for trap fishing, so in the following analyses, only results for Pearl Perch line fishery are presented. Line catch-rate may provide a better index of relative fish abundance (Sumpton *et al.* 2017).

Our analyses were restricted to regions N1 and S1 for the Snapper line fishery, N2 and S2 for the Snapper trap fishery, as indicated in Figure 20. For the Pearl Perch only region N1 was considered. The environmental variables considered were: SST, GSLA, Chl-a, SOI and PDO.

Starting with Snapper we had access to standardised CPUE commercial line data from 1997 to 2018, and commercial trap data from 2009 to 2019, as shown in Figure 7. We note that in 2001 the MLS was increased from 28 cm to 30 cm. In 2008, escape gaps were introduced in commercial fish traps to address discards. Further, recent, reforms introduced in 2018/19 would have no impact on our analyses. Based on discussions with NSW DPI scientists, it was determined that the standardised CPUE data for the period 2009-2019 were the most reliable and hence the associations reported below are based on this time series. For Pearl Perch commercial line fishery, the corresponding SCPUE data are shown in Figure 18.

Results for Snapper commercial line fishery

The summary of short-term seasonal effects of environmental indices on the log transformed SCPUE for the commercial line fishery is given in Table 20. We observe that for the three key variables of SST, GSLA and Chl-a, statistically significant correlations occur in the winter season in the northern region N1. However, only Chl-a yields significant correlation in winter in the more southern region S1. Chl-a is the only one of these three variables that yields significant correlations in spring and also in the spawning season of July to September, in region N1. Similarly, the correlations with the SOI index are statistically significant only in summer. The correlations with PDO index are uniformly consistent and significant but, as before, we cannot offer meaningful interpretation of these associations.

Table 20: Summary of short-term seasonal effects of environmental indices on the log transformed SCPUE for the commercial line Snapper fishery. The effect of environmental indices was analysed in summer (Dec-Feb), autumn (Mar-May), winter (Jun-Aug) and spring (Sep-Nov), as well as in the spawning season (Jul-Sep), in the year of the catch. 2009-2018.

	SST		Chl-a		GSLA		SOI	PDO
	N1	S1	N1	S1	N1	S1		
Season								
summer	0.09	-0.20	0.24	0.19	-0.19	-0.32	0.64	-0.81
autumn	-0.40	-0.26	0.14	-0.06	-0.54	-0.45	0.54	-0.61
winter	-0.67	-0.08	0.65	0.68	-0.62	-0.53	0.39	-0.76
spring	-0.02	-0.48	0.56	0.65	-0.06	0.35	0.61	-0.76
Spawning								
Jul-Sep	-0.30	-0.08	0.59	0.52	-0.49	-0.07	0.53	-0.75

The summary of long-term yearly lagged effects of environmental indices on the log transformed SCPUE for the commercial line fishery is given in Table 21. We observe that of the three key variables of SST, Chl-a and GSLA, only the latter contains 95% statistically significant negative correlations at lags of both 4 and 5 years in regions N1 and S1. Furthermore, a 6 year lag also yields a moderate correlation in the south region S1. While these long-term GSLA associations may be related to abundance, the lag 0 significant positive correlation with SOI may be related to catchability. However, the statistically

significant negative correlation with SOI at year lag of 8 is counterintuitive but also consistent with some of the results concerning the negative SOI signal reported in Section 4.1.5. Once, again the significant correlations with PDO index are recorded for the sake of completeness.

Table 21: Summary of long-term lagged effects of environmental indices on the log transformed SCPUE for the commercial line Snapper fishery, 2009-2018. Values in green indicate correlations statistically significant at the 95% level.

		Lag (years)										
		0	1	2	3	4	5	6	7	8	9	10
Sea Surface Temperature												
Mean SST	Region											
	N1	-.47	.07	-.14	-.46	-.50	-.44	.09	.10	-.39	-.22	.32
	S1	-.38	-.37	-.39	-.48	-.19	-.20	.38	-.02	-.14	-.19	.54
Chlorophyll a												
Log (Median Chl-a)	Region											
	N1	.26	.45	.19	.10	-.17	-.09	-.22				
	S1	.38	.44	.12	.05	-.40	-.29	-.32				
Gridded Sea Level Anomaly												
Mean GSLA	Region											
	N1	-.53	-.16	-.33	-.46	-.68	-.67	-.47	-.19	-.43	-.46	.27
	S1	-.42	-.48	-.25	-.53	-.73	-.73	-.60	-.25	-.31	-.53	-.04
Southern Oscillation Index												
Mean SOI		.69	.55	.17	.20	-.14	-.57	-.38	-.61	-.65	.03	.02
Pacific Decadal Oscillation												
Mean PDO		-.80	-.48	-.21	-.12	-.03	.52	.63	.69	.58	.02	-.15

Results for Snapper commercial trap fishery

Overall, there are very few strong associations when looking at both the short-term seasonal effects (see Table 22) and the long-term lagged effects (see Table 23). In Table 22 we regard the moderately strong correlation of -0.60 and the significant one of -0.61 with SST and Chl-a, respectively, as spurious because of lack corroborating substantial correlations in other seasons and regions. On the other hand, we regard the correlations of 0.59 and 0.61 with SOI as meaningful because of corroborating corresponding correlations with SOI in commercial line fishery (see Table 20).

Table 22: Summary of short-term seasonal effects of environmental indices on the log transformed SCPUE for the commercial trap Snapper fishery. The effect of environmental indices was analysed in summer (Dec-Feb), autumn (Mar-May), winter (Jun-Aug) and spring (Sep-Nov), as well as in the spawning season (Jul-Sep), in the year of the catch. 2009-2019.

	SST		Chl-a		GSLA		SOI	PDO
	N2	S2	N2	S2	N2	S2		
Season								
summer	0.48	0.16	-0.05	-0.61	0.04	0.32	0.25	-0.31
autumn	0.10	-0.06	-0.12	-0.23	0.03	0.12	0.22	-0.26
winter	-0.37	-0.09	0.35	0.25	-0.12	-0.06	0.42	-0.37
spring	-0.02	-0.60	0.29	0.40	0.37	0.38	0.59	-0.55
Spawning								
Jul-Sep	0.00	-0.28	0.42	0.20	0.10	0.11	0.61	-0.45

As far as the long-term lagged effects are concerned it is worth highlighting that there are no correlations that are statistically significant at the 95% level (see Table 23). This suggests that the Snapper commercial trap fishery may be relatively resilient to these environmental drivers.

Table 23: Summary of long-term lagged effects of environmental indices on the log transformed SCPUE for the commercial trap Snapper fishery.

		Lag (years)						
		0	1	2	3	4	5	6
Sea Surface Temperature								
Mean SST	Region							
	N2	.01	.08	-.22	-.35	-.15	.05	.06
	S2	-.28	-.21	-.29	-.09	.28	.22	.12
Chlorophyll a								
Log (Median Chl-a)	Region							
	N2	.06	.06	-.14	-.22	-.37	-.02	.28
	S2	.11	.01	-.25	-.37	-.45	-.15	.45
Gridded Sea Level Anomaly								
Mean GSLA	Region							
	N2	.07	-.16	-.33	-.51	-.50	-.22	-.10
	S2	.18	-.04	-.31	-.52	-.55	-.27	-.12
Southern Oscillation Index								
Mean SOI		.47	.15	-.01	-.33	-.43	-.60	-.42
Pacific Decadal Oscillation								
Mean PDO		-.41	-.03	.12	.28	.35	.60	.45

Results for Pearl Perch commercial line fishery

The summary of short-term seasonal effects of environmental indices on the log transformed SCPUE for the commercial line fishery is given in Table 24. We observe that from the three key environmental variables of SST, GSLA and Chl-a only the latter registers statistically significant correlations occurring in the winter and spring season in the northern Region N1.

Table 24: Summary of short-term seasonal effects of environmental indices on the log transformed SCPUE for the commercial line Pearl Perch fishery. The effect of environmental indices was analysed in summer (Dec-Feb), autumn (Mar-May), winter (Jun-Aug) and spring (Sep-Nov), in the year of the catch. 2009-2018.

	SST	Chl-a	GSLA	SOI	PDO
	N1	N1	N1		
Season					
summer	-0.07	0.54	-0.11	0.51	-0.85
autumn	-0.23	0.52	-0.38	0.53	-0.71
winter	-0.58	0.78	-0.59	0.42	-0.88
spring	-0.03	0.69	-0.14	0.57	-0.88

The summary of long-term lagged effects of environmental indices on the log transformed SCPUE for the commercial line fishery is given in Table 25. There are a number of similarities between corresponding correlations in the previously discussed Snapper line fishery. Like Snapper, the lag of four years yields the strongest correlations with both SST and GSLA of -0.65 and -0.84, respectively. We also note the presence of strong negative associations with SOI at lags of 6-8 years.

Table 25: Summary of long-term lagged effects of environmental indices on the log transformed SCPUE for the commercial line Pearl Perch fishery.

		Lag (years)										
		0	1	2	3	4	5	6	7	8	9	10
Sea Surface Temperature												
Mean SST	Region											
	N1	-.41	-.25	-.05	-.30	-.65	-.42	-.02	-.01	-.29	-.16	.20
Chlorophyll a												
Log (Median Chl-a)	Region											
	N1	.45	.49	.07	.32	-.22	-.33	-.09				
Gridded Sea Level Anomaly												
Mean GSLA	Region											
	N1	-.46	-.34	-.27	-.37	-.84	-.64	-.51	-.42	-.42	-.36	.18
Southern Oscillation Index												
Mean SOI		.64	.55	.58	.13	-.20	-.33	-.66	-.65	-.65	-.22	.01
Pacific Decadal Oscillation												
Mean PDO		-.91	-.65	-.44	-.17	.00	.49	.74	.72	.66	.31	-.01

4.9 Rapid Adaptive Projections Tool (RAPT)

An important benefit of incorporating abiotic environmental variables into stock assessment models is that many of them are accompanied by reliable forward projection/forecasting tools. To effectively communicate the results of this project we have developed a rapid adaptive projection tool (RAPT) within the R-shiny environment (Chang *et al.* 2020). This tool permits running forward scenarios substituting forecasts of environmental variables into the surplus production models discussed in Section 4.5, under alternative harvest management scenarios. The computation of such projections is fast and is built in to RAPT's user friendly online calculator.

Naturally, the uncertainty accompanying of RAPT's projections will grow with the number of time steps into the future. We expect that these reliability periods will vary from species to species. Parameters underlying the stock models should be scheduled for regular updates as successive years' data become available.

RAPT's graphical user interface also provides a "dashboard" of projected of biomass ratios of the selected species for regions of interest. Users are thus able to view convenient displays of both historical trajectories of the system and future projections for the fishery. The dashboard allows stakeholders to easily assimilate the accumulated scientific knowledge and data embedded in the surplus production stock assessment models and to better visualise their projections. This allows users to explore the effects of different environmental conditions and harvest rates on stock recovery.

The RAPT software and instruction files can be found in the project's repository directory on <https://cloudstor.aarnet.edu.au/plus/s/8Hb3kHOAhcWJCSZ>.

5 Discussion

In line with the objectives of this project we have constructed several novel, as well as many standard, environmental indices and shown a wide range of associations between these indices and measures of either abundance or catchability for the three target species. Furthermore, we developed a methodology for incorporating these indices into surplus production stock assessment models. Results obtained were discussed in Sections 4.5.

Broad issues and limitations

Collectively, the methodology, datasets, analyses, and findings gave rise to several important issues that deserve further discussion and reflection, in the context of both what has been previously reported in the literature and the limitations of the present study.

1. All three species studied are depleted or depleting, making it particularly difficult to distinguish potential environmental effects from the effects of fishing.

Specifically, Queensland stocks of all three focal species for this work are listed as either “depleting” or “depleted” (SAFS, 2018), with pronounced declines in CPUE over time apparent in all available datasets. In this context, it is challenging to detect potential historical environmental effects influencing stocks whose abundance trajectories may have been driven by declines in spawning biomass (Wortmann *et al.* 2018; Sumpton *et al.* 2017; Campbell and O’Neill 2016). The prolonged and persistent decline in measures of abundance for these stocks is coincident with the prolonged and persistent shifts in key environmental variables (increases in SST and GSLA, decline in Chl-a) resulting from a changing climate. This has the potential to conflate statistical correlations between environmental variables and measures of species abundance and should be kept in mind when interpreting these correlations. As such, we treat correlations that are persistent across multiple time lags, and that do not occur at time scales relevant to the species’ biology or across all regions, as coincidental rather than causative.

2. Long-term trends and future projection in environmental variables are difficult because many of them are interacting with each other and are affected by climate processes operating on annual (e.g. SOI) and decadal (e.g. PDO) timescales as well as the non-linear effects of climate change.

The simplified environmental forecasting produced for this report was carried out mainly for the purpose of informing realistic scenarios for the surplus production models. Actual long-term trends in SST, Chl-a, and GSLA are likely to be far more complex, resulting from large-scale oceanographic and climate processes interacting with local conditions at annual (e.g. SOI) and decadal (e.g. PDO) time scales, overlaid with non-linear effects of climate change (Steinberg 2007). Short-term extreme events such as MHWs can also have rapid and profound impacts on marine species, which can affect the population for a number of years after (Caputi *et al.* 2019, Benthuyzen *et al.* 2020). That said, a general trend of increasing SSTs, enhanced water column stratification, and declining primary productivity has been observed in marine waters across Australia (Richardson *et al.* 2020), at rates comparable to those presented here.

3. A relatively small number of fishery data points were available.

The limited number of observations related to species abundance should be kept in mind when interpreting the patterns discussed in this paper. Both FIS and commercial SCPUE datasets were provided at annual timesteps, and for a limited number of years, such that all correlations identified in

this report are drawn from fewer than 30 data points each. In particular, correlations with the Snapper pre-recruit dataset are based on just 11 observations. Analyses based on small datasets are known to be particularly vulnerable to overfitting, with extremely high, “optimistic” correlation coefficients frequently resulting from chance alone (Smith *et al.* 2014) and noted in previous research on Snapper pre-recruits (Francis 1993). In this project we guarded against overfitting by focusing on parsimonious models.

4. Recent revision of IMOS chlorophyll a data.

It should be noted that the Chl-a data that we used were the daily MODIS GSM Chl-a data from IMOS downloaded in March 2020⁶. The source data were revised late in August 2020. These revisions show a weaker declining trend that also weakens our findings concerning associations with Chl-a. Since the revised Chl-a data have not yet been subjected to broad scrutiny of the scientific community, we retain the current findings.

5. Spawning stock-recruitment relationship.

We acknowledge the need to study the impact of environmental factors on spawning stock-recruitment relationships (SPRR) along the lines pioneered in Penn and Caputi (1986). However, Queensland’s FIS Snapper data were collected annually during the November to December period as it focused on pre-recruits. As such they do not overlap with the May to October spawning period. It is not clear whether commercial CPUE data from that period could have been used as a proxy, because the latter omit recreational catch that accounts for a very significant proportion of total Snapper harvest in Queensland. Moreover, in the case of Spanner Crab, FIS data do not permit identification of the age of crabs caught which presents another challenge to investigating SPRR.

Main Snapper findings and biological hypotheses

1. Snapper pre-recruit density and its negative correlation with SST in offshore areas in the preceding June & July (see Section 4.1).

The negative correlation between pre-recruit density and SST in the preceding June and July may be associated with an influence of temperature on egg production (i.e., spawning adults), larval survival, or both. The timing and duration of Snapper spawning are known to be influenced by water temperature (Scott and Pankhurst 1992; Francis 1993; Lenanton *et al.* 2009; Wakefield *et al.* 2015), with earlier spawning at low latitudes and later spawning at higher latitudes observed on both the east (Hamer *et al.* 2011; Scott and Pankhurst 1992) and west (Wakefield *et al.* 2015) coasts of Australia. The negative correlation detected between Snapper pre-recruit density in the November/December FIS and SST in offshore areas in the preceding June and July suggests that ideal Snapper spawning temperatures are attained in this region in June and July, as observed in a similar latitude Snapper population on the west coast (Wakefield *et al.* 2015).

In addition, the use of our δ -rectified mean technique allowed us to identify a specific SST sensitivity range of 19.8 °C to 21.8°C, in June. Higher frequency and larger magnitude of temperatures above these thresholds were negatively associated with subsequent Snapper FIS pre-recruitment, with a correlation value ≤ -0.8 (and p-values ≤ 0.002).

Previous research has identified 18°C as the optimum temperature for larval Snapper survival in captivity at Port Stephens, NSW (Fielder *et al.* 2005), while work from New Zealand demonstrated that

⁶<http://thredds.aodn.org.au/thredds/catalog/IMOS/SRS/OC/gridded/aqua/P1D/catalog.html> .

warmer SSTs (within the observed range of 16.0 to 18.5°C) improved Year Class Strength, potentially as a result of greater larval growth rates and survival rates in relatively warmer waters (Francis 1993). The cooler ideal temperatures identified in the earlier Snapper research as compared to the current work may be a result of the different latitudes and stocks studied.

2. Snapper pre-recruit density and its positive correlation with Chl-a in the preceding June-October in offshore areas, and the preceding September-October within Moreton Bay (see Section 4.1).

The positive correlation between Snapper pre-recruit density and Chl-a in the preceding June to October period in offshore areas, and in the preceding September/October period within Moreton Bay, suggests a direct relationship between primary productivity and larval Snapper growth rates or survival. Given that Snapper spawning in this region occurs between May and October, with a peak in the June/July period (Wortmann *et al.* 2018), larval Snapper are likely to be in the plankton in offshore areas, where they would benefit from the trophic consequences of greater primary productivity (Murphy *et al.* 2013, Parsons *et al.* 2013), between June and October, as was identified in the current study. Research from New Zealand indicates that newly-settled Snapper predominantly feed on zooplankton rather than benthic invertebrates (Martin Lohrer *et al.* 2018), which could explain the secondary correlation between pre-recruit density and Chl-a in September/October within Moreton Bay.

3. Snapper pre-recruit density and its negative correlation with tidal range in September (see Section 4.1).

The negative correlation between Snapper pre-recruit density in the November/December FIS and tidal range in the preceding September may be related to Snapper settlement, with reduced water movement associated with neap tides potentially making it easier for larval Snapper to move into Moreton Bay. However, this is the opposite of the association previously identified in New Zealand, where Snapper larval settlement was greater following larger tidal ranges, potentially due to larval taking advantage of “tidal-stream transport” to access suitable settlement habitat (Sim-Smith *et al.* 2013). The larvae of perciform fishes such as Snapper are known to have behaviours and abilities that can influence their dispersal trajectories, particularly in warmer waters (Leis 2007). The difference between our result and that of the previous New Zealand work may be due to differences in the tidal dynamics in these two locations, the metrics used (monthly mean tidal range, this study; daily tidal range, Sim-Smith *et al.* 2013), or to the shape of the settlement bays relative to prevailing currents.

4. Snapper pre-recruit density and its positive correlation with QLD-wide commercial line CPUE four years later (see Section 4.1).

The positive correlation between Snapper pre-recruit density and commercial SCPUE four years later represents a crucial link between the long-term FIS work and subsequent commercial catch rates (see Section 4.1.6). The timing of the lagged relationship is plausible, as four-year-old fish are the most abundant age class in the commercial catch of Snapper in Queensland (Wortmann *et al.* 2018).

Previous work by Francis (1993) indicated that Snapper year class strength is affected by post-settlement processes, such as warmer autumn water temperatures increasing juvenile growth rates and subsequently improving winter survival rates. Further work is required to confirm this hypothesis for Queensland Snapper. As a first step, the current project quantifies the relationship between juvenile and adult abundance and provides a critical step for improving future stock assessments for the species, informing adaptive, active management of this iconic fishery.

5. Negative effect of MHW on Snapper SCPUE two years later (see Section 4.1.8).

The negative relationship between MHW and Snapper SCPUE two years later suggests that MHW may briefly depress SCPUE in the years following MHW events. We hypothesise that this may be a result of MHW events displacing adult Snapper towards deeper, cooler waters that are not typically targeted by fishers, or southwards outside of the bounds of the Queensland fishery. A similar temperature-induced displacement of large juvenile and adult finfish was observed in Western Australia in the two years following the 2011 MHW event (Caputi *et al.* 2014).

6. Possibility of compounding effects

We note that some of the environmental indices explored could potentially have compounding effects on the study species. Hypothetically, an environmental driver could correlate positively with catchability of adults and negatively with recruitment or survival rates of juveniles. That could, potentially, create a cumulative risk for the sustainability of the species. This point is raised because in Table 4 we listed a significant positive correlation of 0.69 between densSPR of Snapper pre-recruits and the mean SOI variable in the most recent March (lag 9). This suggests that low SOI values (i.e., El Niño conditions) in March may result in lower densities of Snapper pre-recruits later that year. If El Niño conditions coincidentally increase catchability of adult Snapper (e.g. due to improved conditions for offshore fishing), this could result in a situation in which the same environmental phenomenon (SOI) would be contributing to simultaneously reducing recruitment and increasing catch rates. The possibility of such “double jeopardies” on the fishery merits further investigation.

Main Pearl Perch findings and biological hypotheses

1. Qld line Pearl Perch SCPUE and its negative correlation with GSLA with lags of 0 and up to 9 years, and positive correlation with Chl-a with lags of 0,1,2 years (no older Chl-a data) (see Section 4.3).

Positive correlations between Pearl Perch SCPUE in Queensland and Chl-a, along with concurrent negative correlations with GSLA, were identified at lags of 0 to 9 years, although Chl-a data were unavailable for lags greater than 2 years. We do not see any credible biological mechanisms for these associations and hypothesise that the consistency of these correlations indicates that they are statistical artefacts of the decadal decline in the Pearl Perch fishery resulting from overfishing, coincident with the decadal increase in GSLA associated with climate-change, and the concurrent decadal decrease in Chl-a (Richardson *et al.* 2020).

Main Spanner Crab findings and biological hypotheses

1. Spanner Crab CPUE in Region 4 was insensitive to many of the environmental variables tested, with some exceptions (see Section 4.2):
 - a. The strong, positive, non-linear correlation between Spanner Crab CPUE in Region 4 and bottom current speed at lag 0 hints at an effect on crab catchability, with a similar relationship previously reported in the literature, and is suggested to be related to stronger currents carrying the odour of bait to a larger area (Spencer *et al.* 2019). However, we are cautious with this interpretation because the correlation was not detected in other regions, as would be expected if the mechanism behind the correlation was due to greater distribution of the odour of bait. Furthermore, the strong correlation between Spanner Crab CPUE in Region 4 and bottom current speed was persistent across a number of temporal lags (Figure 49), hinting at a different, unmeasured covariate influencing the relationship observed in the present study.

- b. The negative correlation detected between bottom temperature and Spanner Crab CPUE in Region 4 was observed during months from November to February every year for up to four years (Figure 45). While this period coincides with Spanner Crab spawning season, and it is unlikely that these correlations are linked to biological processes such as egg production or survival of pre-recruits. This is because legal-size Spanner Crabs are not caught in the fishery until they are four or more years of age (Kirkwood *et al.* 2005), and therefore the occurrence of optimal or sub-optimal bottom temperature one year prior could not be the driver of changes in stock productivity. This is further re-enforced by the absence of relationships in data from other regions.
2. Spanner Crab FIS in Regions 2 and 3 and their many positive correlations with Chl-a and negative associations with GSLA in the months leading up to the catch (see Section 4.2).
 - a. Spanner Crab CPUE in Regions 2 and 3 was frequently negatively correlated with GSLA and positively correlated with Chl-a in the months leading up to the FIS. The location of the FIS subgrids within Regions 2 and 3 (Figure 8) coincides with a known hot-spot for eddy formation and consequent upwelling: the Swains Reefs trigger frequent eddy formation off the EAC, with eddies typically “spinning up” offshore of the Capricorn Bunker reefs (23.4394°S) (Weeks *et al.* 2010) and leading to local Chl-a blooms. It is possible that reduced primary productivity in the preceding months is associated with lower Spanner Crab catch rates, with reduced food availability shifting Spanner Crabs out of traditional foraging areas.
 - b. The catch rate of sublegal sized Spanner Crabs in Region 3 was negatively correlated with GSLA and positively correlated with Chl-a during spawning months four-years prior (i.e., October and November, 42 and 43 month lags). The sublegal index is predominantly made up of four year olds crabs, and therefore it is possible that declines in food availability – driven by increases in GSLA and reductions in Chl-a – may have contributed to lower recruitment success within Region 3. Given that Region 3 historically received high fishing pressure, it is plausible that with already reduced egg production in the area, persistent unfavourable environmental conditions may be adding to stock recruitment pressures.
 - c. Regions 2 and 3 are particularly strongly associated with Chl-a at the majority of time lags in the year preceding the catch. Chl-a is a proxy for primary productivity at the ocean surface, which is expected to be beneficial to higher trophic levels in the plankton, such as larval Spanner Crabs. Given that Spanner Crabs captured in the fishery are likely > 4 years old, the mechanism by which Chl-a influence catch rates the following year is unclear but may relate to food web effects of high levels of primary productivity enhancing productivity of prey species of adult Spanner Crabs.
3. Spanner Crab Region 7’s association patterns are often opposite to other regions (see Section 4.2).
 - a. Spanner Crab management Region 7 was notable for consistently demonstrating contradictory environmental correlations with those detected in other regions. This may be a result of beneficial effects of climate change-induced warming on a species at the southernmost extent of its range, as has been reported in a number of other marine taxa (Poloczanska *et al.* 2016, Wolfe *et al.* 2020, Champion *et al.* 2021). This may be the case here, with positive correlations between catch rates in the Spanner Crab FIS and MHW at a number of different time lags (Figure 51).
 - b. We note that Region 7’s catch rate is somewhat confounded by a shift in fishing activity within NSW waters which results in a multi-year decline in local fishing effort. This effort shift likely contributed to increasing CPUE in Region 7 during the same period that other regions have

recorded declines in CPUE. This apparent increase in Region 7's CPUE is coincident with long-term environmental trends, such as increased SST, GSLA, and MHWs, and declining Chl-a, not necessarily causative. This hypothesis is supported by statistical associations such as a persistent negative relationship between Chl-a and Spanner Crab CPUE in Region 7, which is in opposition to established biological associations between primary productivity and catch rates of other taxa (Blanchard *et al.* 2012; Friedland *et al.* 2012).

4. No convincing correlations between Spanner Crab FIS data and any SST metric in any region (see Section 4.2). However, analyses of the last decade of FIS data (see Section 4.2.7) suggest that possible associations with MHW (see Section 4.2.5) should continue to be monitored.

In general, there were few convincing correlations between Spanner Crab CPUE and different measures of SST or bottom temperature. This is somewhat similar to previous research indicating that the relationship between Spanner Crab catch rates and water temperature is complex, and highly variable by region (Spencer *et al.* 2019).

6 Conclusions

This project aimed to identify the environmental factors which may be influencing the recruitment, catchability or productivity of Snapper, Pearl Perch, and Spanner Crab stocks in Queensland. Results from this work are intended to support sustainable management of Queensland's fisheries by directly informing the assessment and management of these key species within Queensland waters.

The original spirit of this project was to tell "the story that the data tell". The reported analyses, results and discussions indicate a level of complexity that requires further research to more fully resolve the impact of environmental factors on Queensland's fish stocks. This is because, fundamentally, the data of the environmental drivers and their impacts on the target species reflect intricate dynamics of diverse processes and include their associated feedbacks such as multi-scale climate oscillations.

More specifically, we demonstrated that while there is no shortage of strong associations, some of these indicate the presence of complex interactions among biological, oceanographic, and climate processes, as well as fishing harvest activities and changes in fishing effort. Accordingly, the identified associations with environmental drivers may manifest themselves differently in space and time. Moreover, some observed associations may be due to an environmental phenomenon impacting species abundance, catchability, or both.

Across the three target species, two environmental variables, GSLA and Chl-a, were found to have strong associations with either abundance or catchability across the three target species. These associations occurred at spatio-temporal scales relevant to each species' biology. SST also had strong associations with Snapper as well as more nuanced, associations with Spanner Crabs in specific regions.

Importantly, all three of these environment variables, GSLA, SST and Chl-a, were found to have certain consistent long-term trends, with rates of change depending somewhat on the region under consideration. In particular, these trends show that GSLA and SST have been increasing, while Chl-a has been decreasing.

If these trends are sustained, and the direction and strength of the identified associations are maintained, they have the potential to delay the effectiveness of sustainable stock management strategies. In particular, we demonstrated that incorporating these environmental variables into

simple surplus production stock assessment models results in, under some scenarios, delays in stock recovery.

However, we also demonstrated that incorporating environmental variables into existing CPUE standardisation models did not lead to significantly improved performance of these models. The latter are so heavily parametrised that the influence of environmental variables may have already been accounted for by year, month and region-specific interaction terms already included in the standardisation. This is despite some of the environmental variables being classified as statistically significant within the generalised linear models' framework.

In addition, we also identified intriguing long-term associations with several environmental drivers including those consisting of intermittent events such as MHW or El Niño and La Niña episodes. While these could be indicative of potential impacts on the species' abundance, biological mechanisms related to these associations were unclear. Moreover, their frequency and intensity in the future were very hard to model and forecast. They are recorded in this report so that other researchers have an opportunity to investigate them in more depth.

Similarly, in the case of the Spanner Crab fishery, we identified a complex pattern of positive and negative associations with environmental variables that calls for further study of the underlying processes contributing to them across the six regions and on different time scales. Several of these environmental variables exhibit starkly different features the causes of which are likely related to the observed pattern of associations. These variables include, but are not limited to, current speed, individual components of the current velocity, and water temperatures at different depths. They deserve further investigation by oceanographers and marine biologists.

The stock models produced as part of this research were developed primarily for the purposes of observing and testing the influence of environmental factors on the stock productivity, now and into the future. In achieving this outcome some model assumptions, adjustments and simplifications have been introduced to the models presented herein that may result in them differing from those currently being used to inform biomass estimates and harvest levels for each stock. Therefore, while we hope that the important outcomes demonstrated through this work result in the enhancement of future stock assessments to inform management, we stop short of recommending that the biomass projections and TACCs developed herein should be used to support management decisions.

6.1 Snapper Specific Conclusions

Of the three species studied Snapper yielded the most convincing results of the type of associations that might be expected. Furthermore, the availability of FIS data for Snapper pre-recruits made it possible to attribute some of the identified associations as impacting species abundance rather than catchability. Several environmental variables were found to have strong associations with either the abundance or catchability of Snapper. These included GSLA, SST, Chl-a, river discharge volume, tidal range, SOI and others.

There was evidence of strong, negative, linear association between pre-recruit FIS density in November – December and SST in the preceding June and July (i.e., adult spawning period) in offshore areas where the majority of Snapper spawning stock is thought to be present. Furthermore, certain threshold sensitivity SST temperatures (in the range of 19.8°C to 21.8°C) were identified for offshore Snapper spawning. Higher frequency and larger magnitude of temperatures above these thresholds in June are negatively associated with subsequent Snapper pre-recruits, with correlation values at or below -0.8. There was also evidence of positive linear relationships between pre-recruit FIS density in November – December and Chl-a in the preceding June-October period in offshore areas and in the preceding

September-October period within Moreton Bay. This may be related to high levels of primary productivity improving Snapper larval survival and/or growth rates in the plankton.

The density of Snapper pre-recruits in the annual FIS in Moreton Bay was shown to be an indicator of subsequent commercial line CPUE in Queensland. The strongest correlation was between the density of Snapper pre-recruits and commercial catch rates four years later. Four-year-olds are typically one of the most abundant age classes in the Queensland Snapper line fishery.

6.2 Spanner Crab Specific Conclusions

The environmental variables that were found to have significant associations include (but are not limited to): GSLA, SST, Chl-a, SOI, components of ocean current velocity and MHW. There were indications that some of the differences in these associations are based on the large latitudinal gradient across the Spanner Crab management regions as well as on the cross-shelf depth gradient of the surveyed locations within each management region.

Perhaps, fortunately, in the most productive Region 4, the FIS catch rate of legal-size crabs was found to be relatively insensitive to fluctuations in the following important environmental variables: Chl-a, GSLA, SST, and MHW. FIS catch rates in Region 4 were found to be positively correlated with bottom current speed during the month of capture which was seen to be related to catchability. This association may be of interest to fishers, as there seems to be a consensus that the East Australian Current is accelerating (e.g. Cai *et al.* 2005).

We also concluded that, based on the data used in our study, Chl-a was significantly associated with the catch rate of legal-size crabs in four of the five Queensland regions. Significant positive correlations in Regions 2, 3, 5 and 6 were present at multiple monthly lag times ranging from 1 to 48 months. Given that Spanner Crabs captured in the fishery are likely at least four years old, mechanisms by which Chl-a influence catch rates the following year are unclear. Moreover, Chl-a is a proxy for primary productivity at the ocean surface, which is expected to be beneficial to higher trophic levels in the plankton, such as larval Spanner Crabs.

GSLA was found to be negatively associated with the catch rate of legal-size crabs in Queensland Spanner Crab Regions 2, 3 and 6, at multiple monthly lag times. Sea level anomalies are indicative of eddies, upwelling, downwelling events and current speed. The negative correlation with spanner crab catch rates indicates that downwelling is deleterious and upwelling is beneficial to subsequent Spanner Crab catch rates. Upwelling typically triggers primary productivity blooms.

The direction of significant associations in the NSW Spanner Crab Region 7 was found to be generally opposite to those in Regions 2, 3 and 6. This applies to the correlations of the catch rates of legal-size crabs with GSLA, Chl-a and SST. While the biological mechanism is unclear, it is conceivable that in this southernmost region the long-term warming trend could be beneficial rather than detrimental. This is in concordance with recent findings for Queensland saucer scallop fishery in Courtney *et al.* (2021) who report that increased catch rates have been observed in the southern most part of the fishery off Fraser Island in recent decades. Alternatively, these associations may be an artefact of large reductions in commercial fishing effort in this region in recent years improving local catch rates, coincidentally during the same period that GSLA and SST has been increasing and Chl-a has been decreasing.

6.3 Pearl Perch Specific Conclusions

There was no fishery independent survey done for Pearl Perch to permit similarly detailed analyses to those conducted on Snapper and Spanner Crab. However, CFISH logbook data for the Queensland's commercial Pearl Perch line fishery were analysed for associations with SST, Chl-a and GSLA.

In particular, GSLA had a significant negative association with the commercial standardised CPUE in Queensland, lagged by 0 – 6 years. This suggested presence of long-term delayed effects of the GSLA variable. There were also statistically significant positive correlations between Pearl Perch CPUE and Chl-a, lagged by 0, 1 and 2 years. The current year (lag 0) yielded the strongest degree of association, suggesting a positive effect of Chl-a on Pearl Perch catchability, although a biological mechanism for this is unclear.

7 Implications

Our three target species - Spanner Crabs, Snapper and Pearl Perch – were selected by Fisheries Queensland based on their categorisation as depleting or depleted in the national Status of Australian Fish Stocks Reporting (SAFS 2018). As a result, these species are of key interest to the management agencies in Queensland and NSW. Findings of this project inform fishery managers, industry stakeholders and the public about: (a) The environmental associations of the three targeted fishery species, (b) The possible impacts of environmental drivers on these fishery stocks, and (c) The impacts of environmental drivers on predictive modelling of fishery stocks, including the evaluation of different management strategies.

The main implication of our study is cautionary in the following ways:

- A. Fishery stakeholders need to be cognisant of possible, near term, adverse scenarios if the observed increasing trends in sea level anomalies and seas surface temperature and decreasing trends in Chl-a continue.
- B. Some of these long-term trends are consistent with literature on climate change and, as such, unlikely to self-correct in the near term, except for intermittent oscillations such as La Niña episodes.
- C. Short-term surplus model forecasts indicate that historical levels of harvest of these three species are unlikely to be achievable in the future.

A secondary, more optimistic, implication stems from the following findings which, however, require ongoing monitoring, or further research, to confirm their persistence:

- D. Presence of certain, counterintuitive, significant associations between catch rates and key environmental drivers and (in some cases) absence of the same, may indicate opportunities for stable future harvests.
- E. For Spanner Crabs, D would be consistent with the observed relative resilience of Region 4 and observed associations in Region 7.
- F. For Snapper, D would be consistent with the observed relative resilience of trap fishery in NSW.

Finally, the results from this project indicate that environmental variables can be used to inform future harvest strategy development through setting of reference points and should be considered for incorporation into performance measures that are used to set harvest limits via harvest strategies. Further work is required to determine the most appropriate method for forecasting the effects of environmental variables on biomass into the future.

8 Recommendations

Several recommendations follow directly from the findings of this study.

1. Continue annual fishery independent abundance surveys of Snapper and Spanner Crabs to validate stock status and to optimise management procedures. Consider developing fishery independent monitoring of Pearl Perch recruitment using methods similar to those used to monitor Snapper recruitment. As the time series for the FIS abundance indices are relatively short, confidence in the study's main findings should improve with additional annual survey data.
2. Consider key environmental variables (GSLA, Chl-a, and SST) and their forecasts when developing harvest strategies.
3. Ideally, undertake targeted investigations which distinguish the effects of fishing from environmental effects, for example whether environmental associations are detectable in areas not subject to recent fishing pressure (protected or unfished area).
4. Investigate underlying causes of the relative resilience of Spanner Crab catch rates in Region 4 to environmental fluctuations, possibly with greater focus on oceanographic processes specific to that region.
5. Continue monitoring those identified, unexplained, associations between catch rates (both FIS and commercial) and key environmental drivers that may be indicators of enhanced, or stable, future harvests. For instance, in Regions 7 and 4 of the Spanner Crab fishery.
6. Regularly update the biomass ratio trajectories of Kobe plots in surplus production models as a, simple, diagnostic tool of progress towards goals of MSEs.
7. Further explore the incorporation of environmental effects into the CPUE standardisation procedure for each species. The current procedure incorporates a categorical "year" factor, which likely absorbs much of the interannual variability potentially stemming from environmental conditions. Explicit and iterative replacement of the "year" factor, as well as seasonality parameters, with different environmental variables could identify and quantify the environmental conditions affecting catch rates. "Logbook grid" is a spatial explanatory term in the CPUE standardisation procedure in many Queensland fished species, which is also likely correlated with environmental influence. Hence, if environmental influences are incorporated in the standardisation GLM, inclusion of potentially redundant temporal (e.g. year) and spatial (e.g. grid) factors requires further consideration.
8. Empirically quantify fishing power for use in the CPUE standardisation procedures for Snapper and Pearl Perch.

8.1 Further Development

Constraints of time and resources – that included the onset of COVID-19 restrictions - prevented us from carrying out certain analyses that, ideally, we would have wanted to complete. In this section we mention three tasks that fall into this category.

The first of these concerns the list of potentially meaningful environmental variables presented in Table 1. Not all of these were analysed in this project even if their data were pre-processed for such analyses. For instance, wind speed and direction or variables related to eddy activities were not covered. It would be desirable for analyses on these important variables to be completed. This would encourage researchers to further explore potential impacts of environmental drivers. In addition, there are other variables beyond the scope of the current project which merit investigation, in particular regarding habitat availability and changes. For example, Spanner Crabs prefer coarse sandy sediments which enable them to bury themselves, but large flood or storm events may locally deposit fine sediments, which could result in increased Spanner Crab natural mortality due to predation, or Spanner Crab

movement away from affected areas. Note that recently, Courtney *et al.* (2021) modelled the distribution of sediment types and saucer scallops on the Queensland coast.

The second task is related to the timing of intermittent episodes such as MHWs or El Niño/La Niña events. The biological impact of these events may be amplified, or reduced, depending on the season at which they occur (e.g. winter spawning of Snapper), or the life history stage of the species of interest (e.g. pelagic larval phase) that they coincide with. This would require more detailed analyses tailored to each species. It would also potentially reduce the number of episodes such as MHWs qualifying for consideration.

The third task concerns our objective (2) as stated in Section 2. It was determined that surplus production models offered the most promising pathway of incorporating the impact of environmental factors into stock assessments – in a unified fashion – for all three target species. There was a threefold rationale for this determination. Firstly, there is no age-structured stock assessment model of Spanner Crabs and surplus production models were the only option. Secondly, our attempts to exploit CPUE standardisation models did not yield useful results. Thirdly, DAF is currently updating its age-structured stock models for Snapper and Pearl Perch, so it would not be appropriate to work with the models that will soon be replaced. However, we feel that incorporation of environmental drivers into age-structured stock assessment models is an important task that should be undertaken. In fact, we have considered the methodology for tackling this task which we, briefly, outline below.

Incorporating environmental indices into age-structured models

Consider a traditional age-structured population model with an annual time step measured in years. The population dynamics input is total annual catch and fitted to standardised annual catch rates and age-frequency data. Generally, the number of individuals at age $a + 1$ at time $t + 1$ is described by the system of recursive equations

$$N_{a+1}(t + 1) = \begin{cases} N_a(t)e^{-M}(1 - sel_a \cdot d_a \cdot U(t)), & a = 1, \dots, a_{max-1} \\ \frac{E(t)}{\alpha + \beta E(t)}, & a = 0 \end{cases} \quad (28)$$

where t is the year, a denotes age of the fish in years, a_{max} is the oldest modelled age, M is the annual instantaneous natural mortality rate, sel_a is the gear-selectivity at age a , d_a is the discard mortality at age a , $U(t) = \hat{C}(t)/B(t)$ represents the harvest rate at time t , where $\hat{C}(t)$ is the recorded total annual catch (in t) and $B(t)$ is the exploitable biomass at time t (in tons). Finally, $E(t)$ is the number of recruits (or egg production) and α, β are parameters of the associated Beverton-Holt type recruitment relation (Beverton and Holt 1957).

There are several, natural, ways to modify (28) to account for the impact of the environmental index z_t depending on whether such index is deemed more likely to impact recruitment, survival or growth rates. For instance, we intend to consider modified models of the form

$$N_{a+1}(t + 1) = \begin{cases} N_a(t)e^{-M}e^{v_a z_t}(1 - sel_a \cdot d_a \cdot U(t)), & a = 1, \dots, a_{max-1} \\ \frac{E(t)e^{\eta z_t}}{\alpha + \beta E(t)e^{\eta z_t}}, & a = 0 \end{cases} \quad (29)$$

where we have the options of eliminating the influence on either the recruits (by setting $\eta = 0$), or on subsequent cohorts (by setting $v_a = 0$).

9 Extension and adoption

To date the research team has been focusing on the scientific aspects of the study and there has been very limited opportunity for extension activities. Nonetheless, the process of disseminating the objectives and findings of this project has begun and will continue in order to reach diverse groups of end users including fishery managers, industry, pertinent research communities and the public at large. The following is the list of extension activities have either taken place or are still pending:

1. UQ News media release on 20/01/2020 entitled “How do environmental factors impact Queensland’s fisheries”, see <https://www.uq.edu.au/news/article/2020/01/how-do-environmental-factors-impact-queensland%E2%80%99s-fisheries>
2. Results communicated to stakeholders at Spanner Crab working group on 5/3/2021 by team’s Dr S. Williams, and to stakeholders at the Rocky Reef Fishery working group on 14/7/2021 by team’s Dr S. Leahy. These groups represent all relevant stakeholders including recreational fishers, commercial fishers, charter fishers, scientists, and conservationists.
3. Progress and findings were presented to representatives of our main stakeholder groups comprising the project Steering Committee. Three, half day long meetings were held on 27/03/2020, 12/10/2020 and 5/03/2021.
4. Results communicated to Fisheries Queensland fishery managers and stock assessment team via copy of this report once reviewed by FRDC.
5. The RAPT software and instruction files can be found in the project’s repository directory on <https://cloudstor.aarnet.edu.au/plus/s/8Hb3kHOAhcWJCSZ>.
6. Provide model support online.
7. News release scheduled to coincide with FRDC’s acceptance of the final report. Future media engagement and extension will be overseen by project PI (Filar) and CI (Leahy) and coordinated among the co-investigating agencies composed of UQ, QDAF, FRDC and AIMS. Advance notice will be given to FRDC of any planned media releases.
8. Presentation at WFC 2021 in Adelaide entitled “Environmental-Based Quantitative Assessments: A Case Study of the East Coast Spanner Crab and Snapper Fisheries”, to be presented by team’s Dr W.-H. Yang.
9. Training of two UQ PhD students: Ms M. Mendiolar and Mr Y. Lei who, upon graduation, will be well qualified to work in fisheries modelling.
10. Training of one post-doctoral research fellow: Dr L. Gibson who, upon completion, will be well qualified to work in fisheries modelling.
11. Planned international journal publications:
 - a. “Associations between environmental drivers and three Queensland species”, based on selected material from Sections 4.1-4.3 and targeting Fisheries Research.
 - b. “Incorporating environmental variables into surplus production models”, based on material from Sections 4.1, 4.5 and targeting Fisheries Research.
 - c. “Environmental indices capturing memory, intermittence, persistence, thresholds and periodicity”, based on material from Sections 3.3, 4.1.5, 4.1.7, 4.1.8, 4.2.5, 4.2.6 and 4.3 targeting Natural Resource Modeling.
12. Project staff have extended results from the present study to researchers associated with the FRDC-funded project Development of a user-friendly MSE framework for Queensland’s rocky reef fishery (2019/020).
 - a. Specifically, the negative correlation between SST in offshore areas during June and July and the density of snapper recruits in Moreton Bay was incorporated into the MSE via the recruitment deviation parameter. The incorporation of this parameter allows the user to test the effects of decreasing recruitment on biomass, resulting from increasing SST, in the forecasted period.

- b. Further, the positive correlation between Chl-a and pearl perch SCPUE may imply a negative correlation to SST given the trajectories of Chl-a and SST (see Figure 57 and Figure 58), despite the absence of direct correlations between SCPUE and SST (Table 12). As with snapper, the effect of variable pearl perch recruitment on biomass, resulting from changing SST, can be quantified using the recruitment deviation parameter.
- c. In the MSE forecast period for both snapper and pearl perch, the recruitment deviation parameter varies according to a user-specified standard deviation parameter with a default log value equal to zero.

9.1 Project Materials Developed

A project directory on AARNET cloudstor <https://cloudstor.aarnet.edu.au/plus/s/8Hb3kHOAhcWJCSZ> has been created storing results – but not the data - of extensive statistical and modelling analyses and experiments carried out in the course of this project.

The RAPT app is also available in that directory together with a readme file on how to run it.

When the planned publications, outlined in Section 9, are accepted hyperlinks to their journals and DOIs will be added to this directory.

When PhD theses of Ms Mendiolar and Mr Lei are completed, they will also be added to this repository. This is because components of their theses are related to their involvement in this project.

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11 Appendices

11.1 List of Researchers and Project Staff

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Dr Nan Ye, Lecturer, School of Mathematics and Physics, The University of Queensland.

11.2 Intellectual Property

It is unlikely that any IP will eventuate from this project.

11.3 Local Trendlines for Key Environmental Variables

In this appendix we provide plots of time series of the three key environmental variables, GSLA, SST and Chl-a, calculated for local fishery areas that featured in this report. These plots display both actual and modelled data colour coded in black and red, respectively. Importantly, their mean trendlines are indicated as straight lines, in green. After the year 2020 only the estimated model curves and their trendlines are extrapolated up to the year 2030. Finally, these plots are accompanied by tables listing the two key properties of the trendlines: their gradients and standard errors.

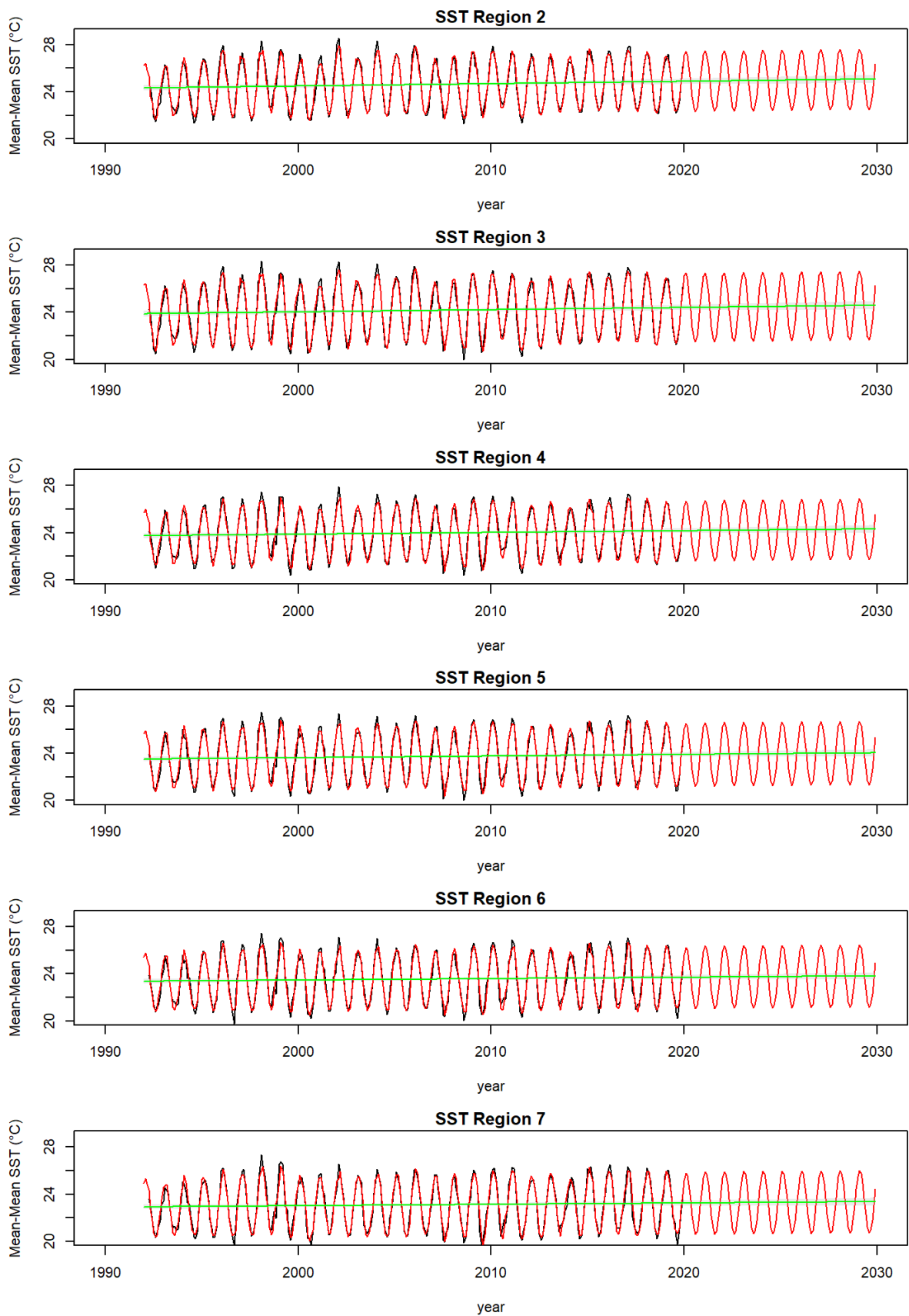


Figure 84: Time series of SST for Spanner Crab Regions 2-6. Actual data (black), modelled data (red) and trendlines (green). After 2020 only the estimated model curves and their trendlines are displayed.

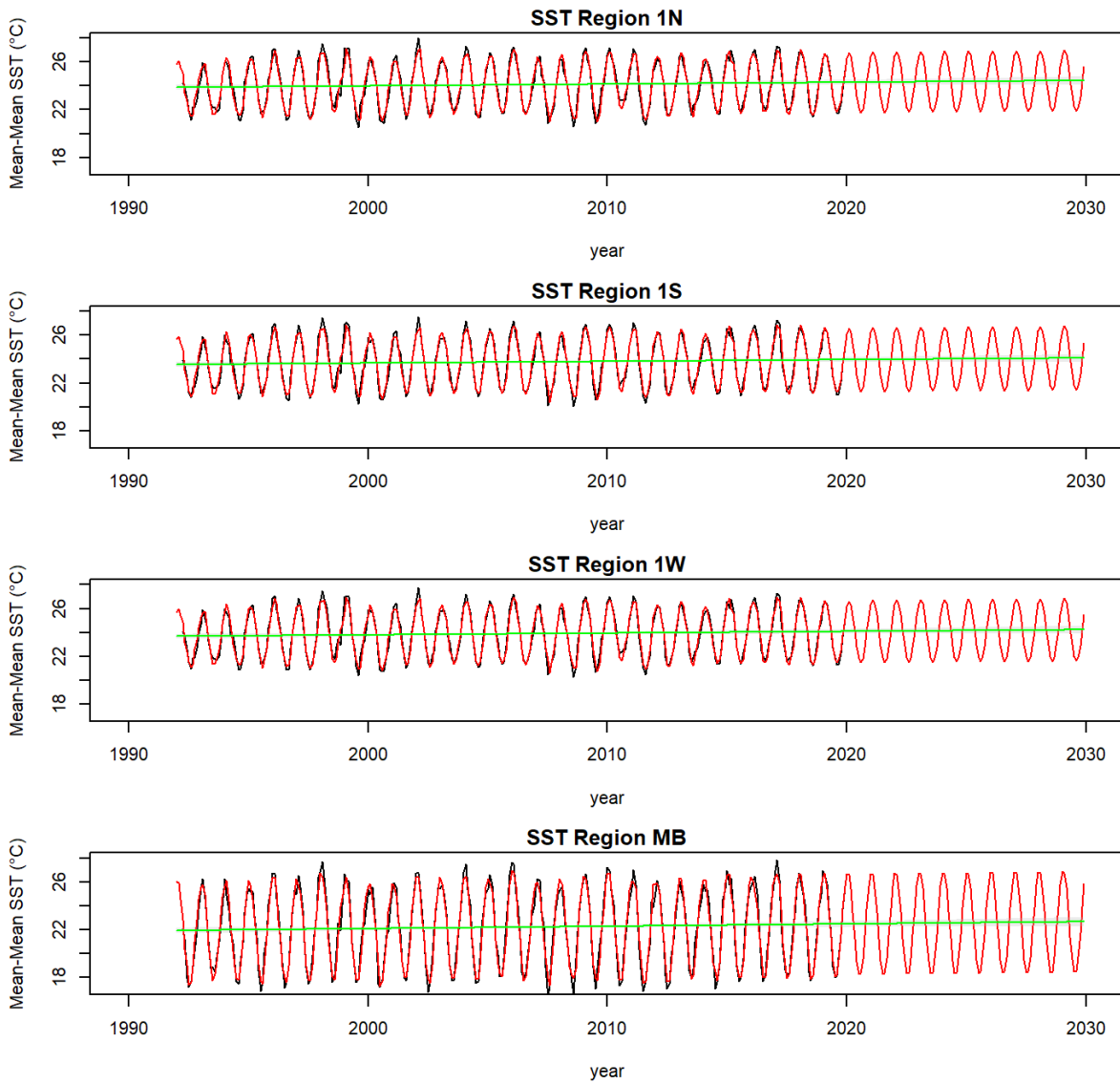


Figure 85: Time series of SST for Snapper Regions 1N, 1S, 1W and MB. Actual data (black), modelled data (red) and trendlines (green). After 2020 only the estimated model curves and their trendlines are displayed.

Table 26: Gradients and standard errors of SST trendlines across all regions considered.

Region	Gradient (°C per decade)	Standard Error
2	0.199	0.071
3	0.187	0.073
4	0.150	0.064
5	0.139	0.058
6	0.119	0.058
7	0.116	0.063
1N	0.151	0.065
1S	0.143	0.060
1W	0.147	0.063
MB	0.194	0.075

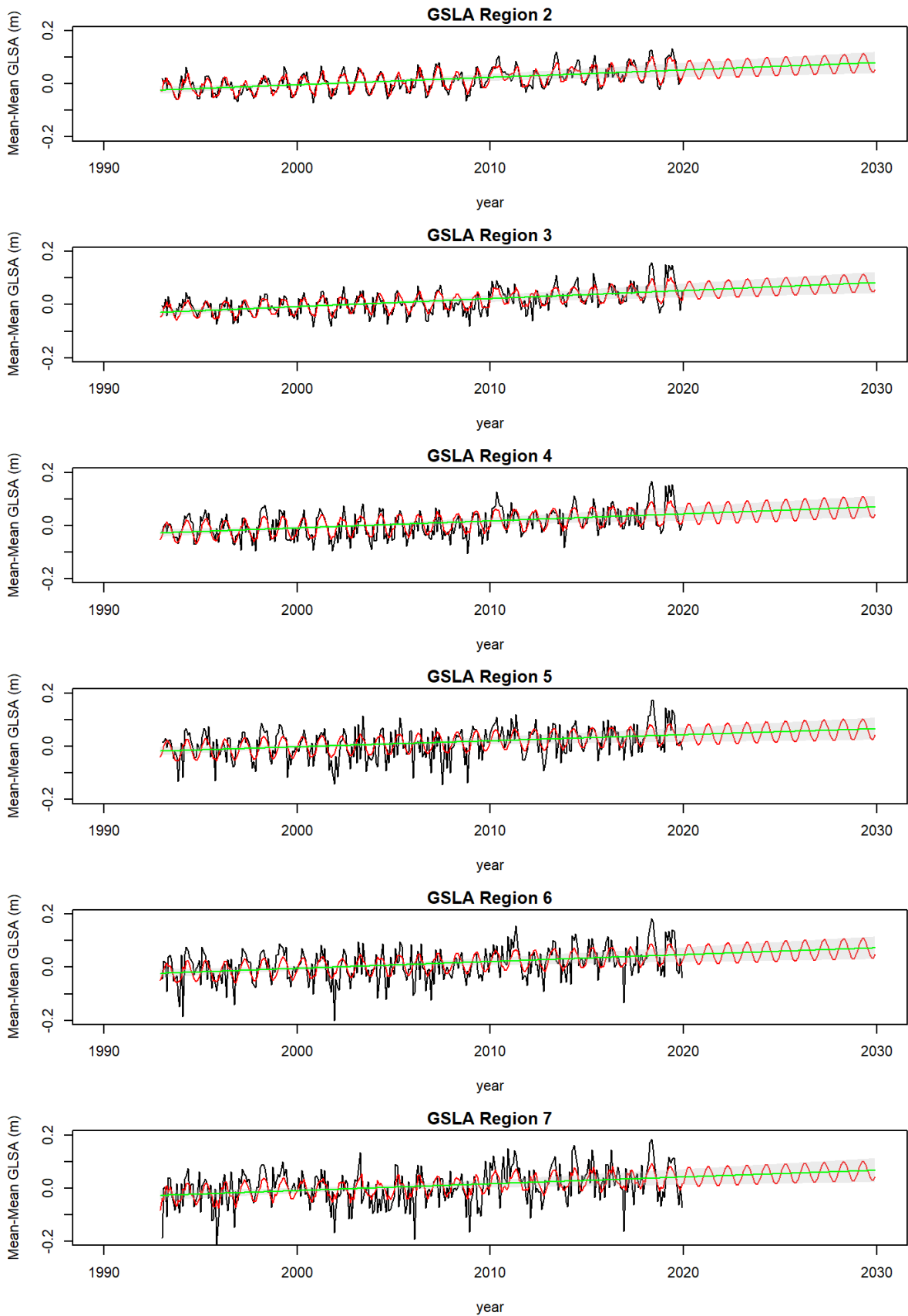


Figure 86: Time series of GSLA for Spanner Crab Regions 2-6. Actual data (black), modelled data (red) and trendlines (green). The shaded area represents the 95% uncertainty band around the mean trend. After 2020 only the estimated model curves and their trendlines are displayed.

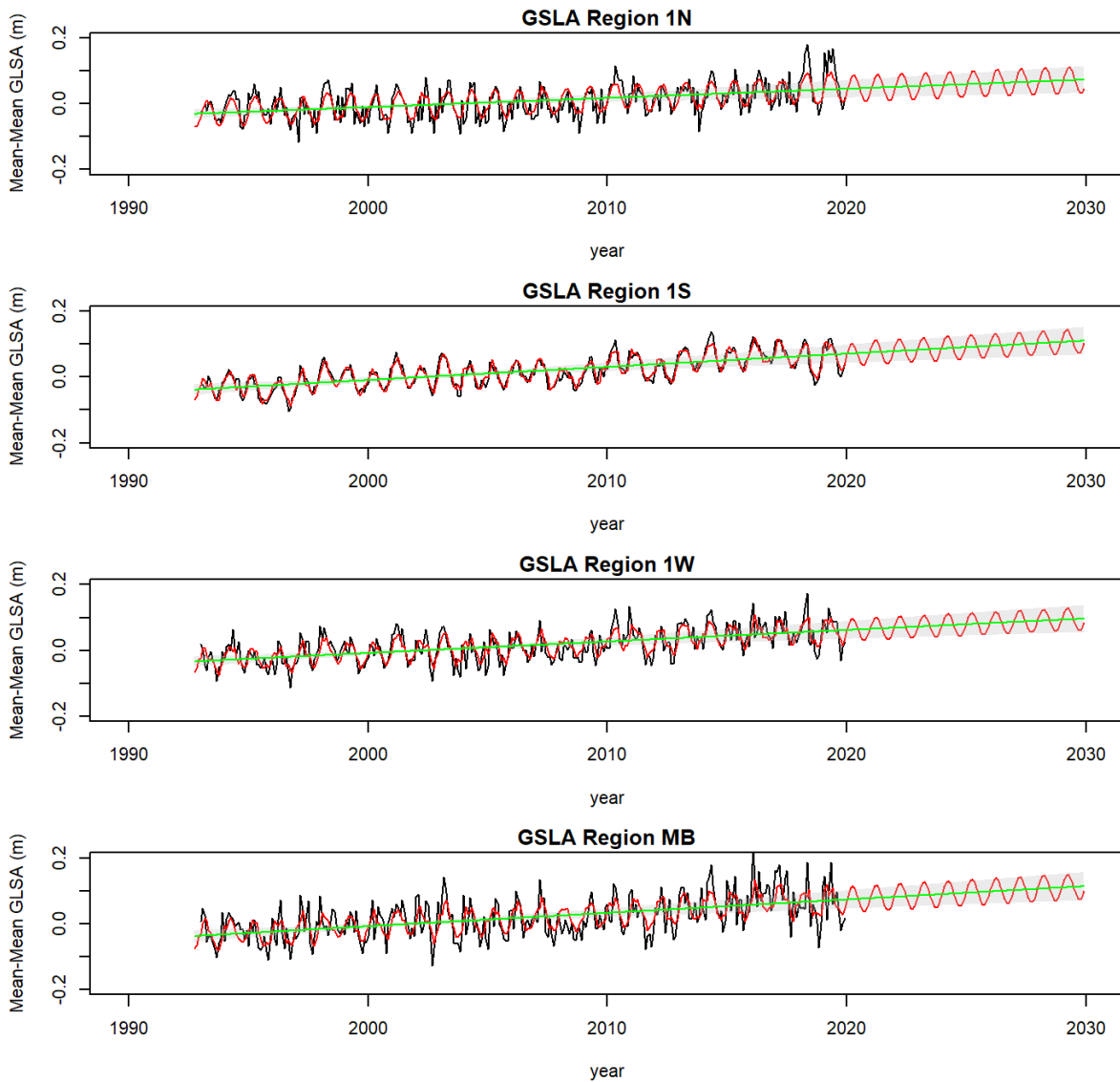


Figure 87: Time series of GSLA for Snapper Regions 1N, 1S, 1W and MB. Actual data (black), modelled data (red) and trendlines (green). The shaded area represent the 95% uncertainty band around the mean trend. After 2020 only the estimated model curves and their trendlines are displayed.

Table 27: Gradients and standard errors of GSLA trendlines across all regions considered.

Region	Gradient (cm per decade)	standard error
2	2.78	0.73
3	3.02	0.72
4	2.65	0.73
5	2.27	0.75
6	2.59	0.77
7	2.55	0.84
1N	2.79	0.73
1S	4.00	0.77
1W	3.50	0.75
MB	4.07	0.79

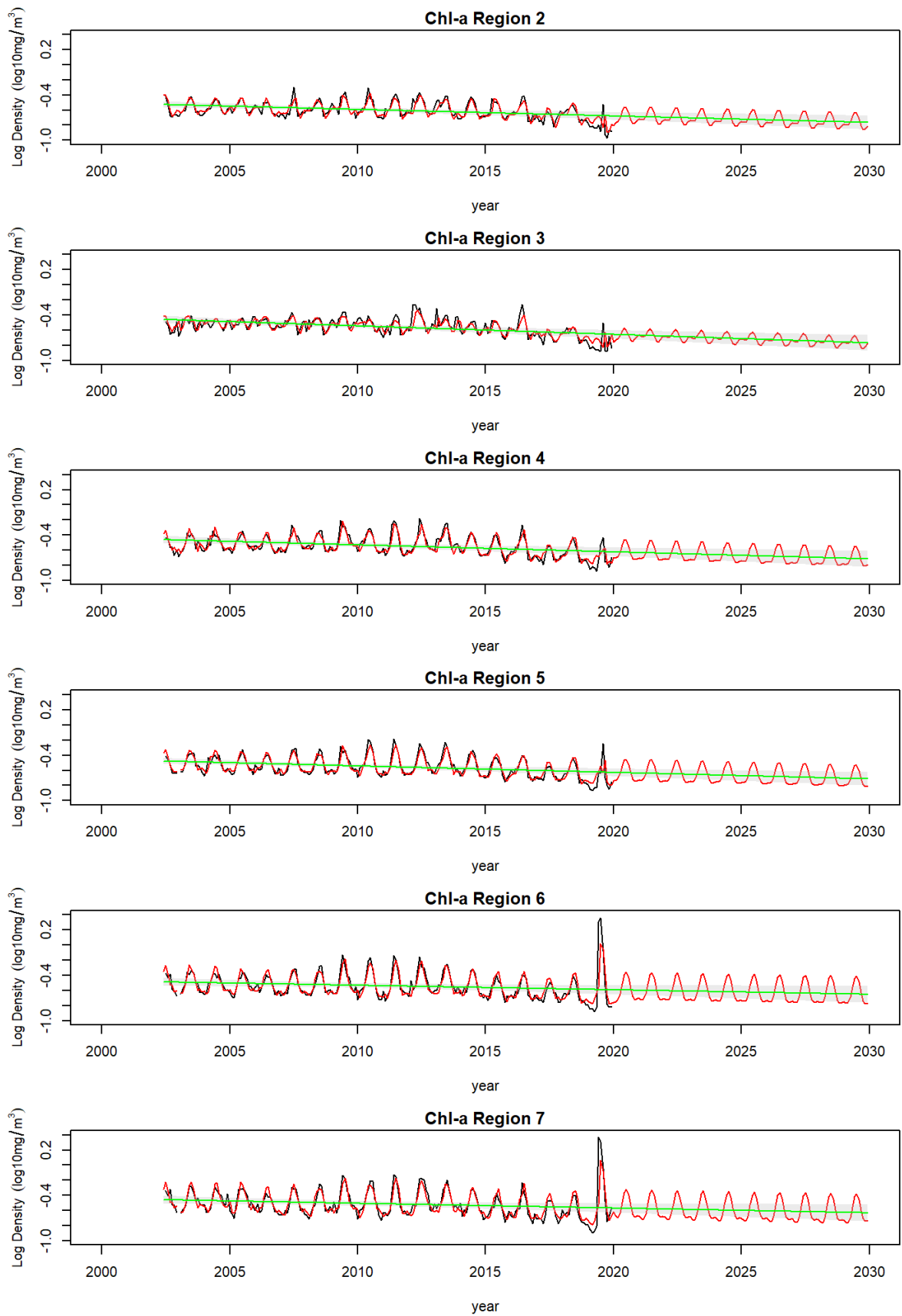


Figure 88: Time series of Chl-a for Spanner Crab Regions 2-6. Actual data (black), modelled data (red) and trendlines (green). The shaded area represents the 95% uncertainty band around the mean trend. After 2020 only the estimated model curves and their trendlines are displayed.

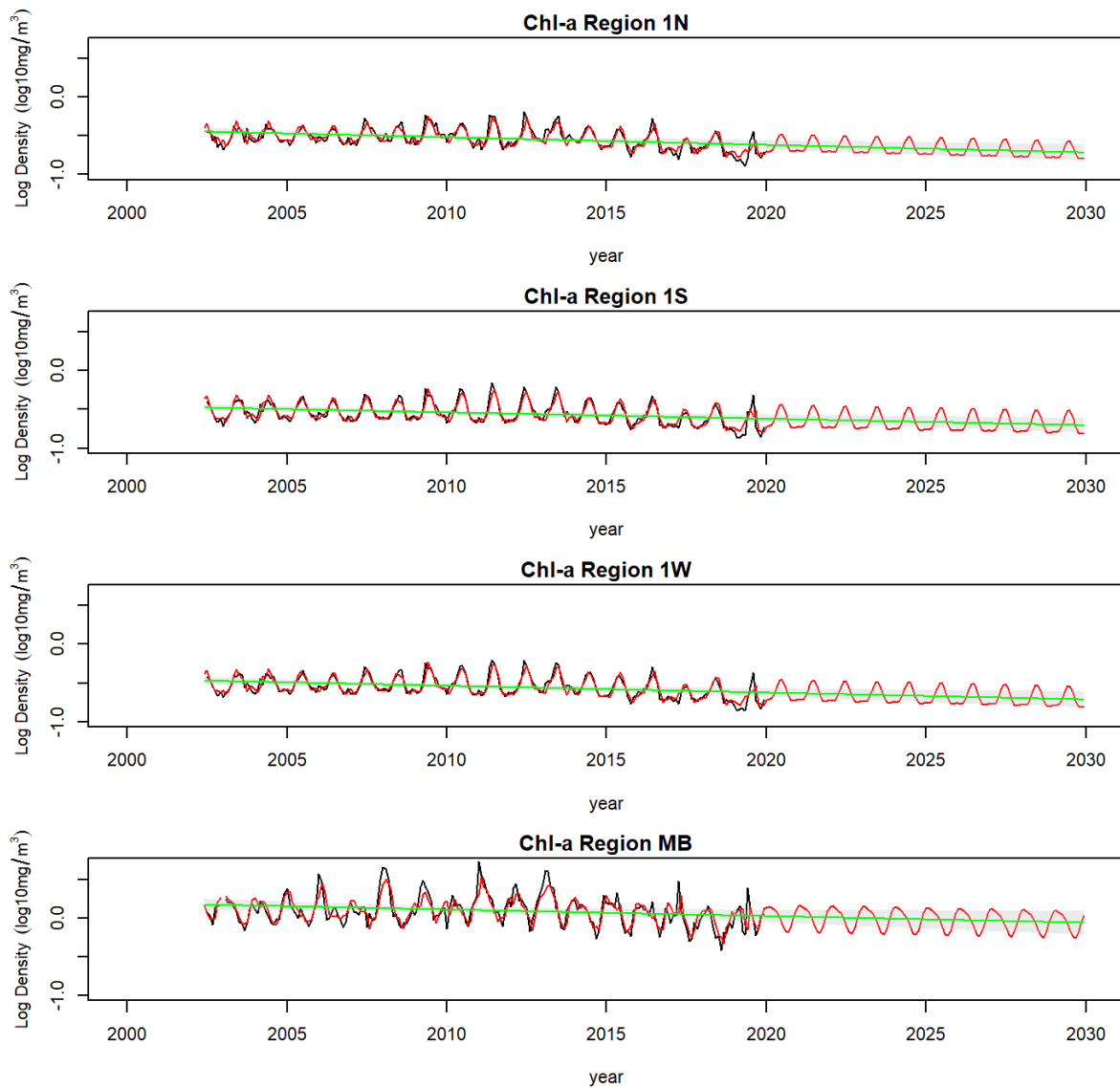


Figure 89: Time series of Chl-a for Snapper Regions 1N, 1S, 1W and MB. Actual data (black), modelled data (red) and trendlines (green). The shaded area represents the 95% uncertainty band around the mean trend. After 2020 only the estimated model curves and their trendlines are displayed.

Table 28: Gradients and standard errors of Chl-a trendlines across all regions considered.

Region	Gradient (% per decade)	standard error
2	-18.0	5.3
3	-22.7	6.0
4	-19.1	6.2
5	-17.9	5.1
6	-12.7	6.6
7	-13.4	6.6
1N	-20.2	6.3
1S	-17.2	5.3
1W	-18.3	5.9
MB	-17.7	9.4