Modelling impacts of climate variability on the commercial barramundi (*Lates calcarifer*) fishery of north-eastern Queensland

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EXTENDED ABSTRACT

Barramundi (*Lates calcarifer*) is an important Queensland commercial fishery that exhibits dramatic inter-annual fluctuations in catch which, according to fishers, are explained in part by variations in the climate. Traditionally, modelling of fisheries harvest has focussed on the development of surplus production/yield models which use catch and effort data, and more complex age-structured models. More recently, however, the effect of climate variability has been shown to have a significant impact on the catch of fisheries such as anchovies, and so techniques to incorporate climate parameters into fisheries modelling and management are being developed. This paper explores, through correlation and cross validated regression modelling techniques, the possible impact of climate variability on the commercial barramundi fishery harvest in Princess Charlotte Bay (PCB) far north Queensland which varies on a year-to-year basis. Results suggest a strong relationship between tested climate variables two years prior and annual barramundi landings.

A conceptual model explaining the life history of the barramundi was constructed to reduce the number of variables used in the analysis. Selected climate variables (air temperature, sea surface temperature (SST), evaporation, fresh water flows), and climate forecasting indices (Southern Oscillation Index (SOI) and Madden Julian Oscillation (MJO)), were initially correlated against local commercial catch data for PCB. Forward stepwise ridge regression (FSRR) analysis was then used in constructing models to quantify the effects of climate on barramundi.

Zero-lagged correlations support the well established theory that early wet season fresh water flow affects the catchability of barramundi in PCB. This is because fish in the fresh water reaches are flushed into the estuary (and fishing grounds) in these years.

Next, a FSRR model was developed from climate variables and selected: rainfall July - September^{-2} (lagged two years), annual evaporation^{-2} and October – December SOI (no lag) and explained 67.6% of the variance in catch adjusted for effort. A second model using climate forecasting indices explained only 53.1% of the variance in catch adjusted for effort. However, because each of these models required data collected in the year of fishing, they did not allow sufficient time for a response from fisheries managers or operators.

A third FSRR model using climate variables known to impact on spawning and early juvenile development 2-3 years earlier, included rain July – September^{-2}, evaporation annual^{-2} and average January – March SST^{-2} and explained 62.7% of the variance in catch. When the predictive capacity of the model was tested using a cross validated "leave-one-out" regression analysis, 48.1% of the variance in future catch was explained (Figure 1).

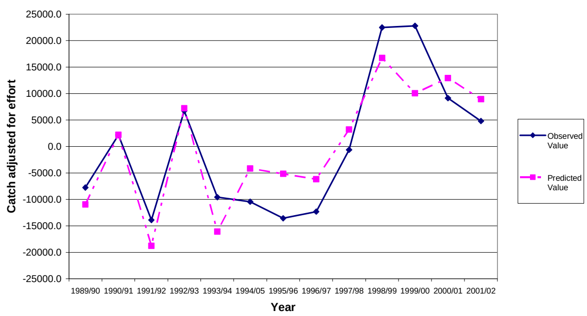

Figure 1: Predicted vs Observed values from the Lagged Model.

1. INTRODUCTION

In order to develop guidelines for the sustainable harvest of a fishery, modelling of the resource traditionally focussed on the development of surplus production/yield models which use catch and effort data (e.g. Fox 1970), and more complex age-structured models which require age class data including recruitment and mortality (e.g. Fournier and Archibald 1982). More recently, the effect of variations in climate (most notably sea surface temperatures and upwelling) have been shown to have a significant impact on the catch of fisheries such as anchovies (e.g. Glantz and Feingold 1990). In cases where there is an absence of age class data, analysis is restricted to correlative and regression modelling procedures to quantify the possible impact of various climate parameters on a fishery. The validity of using these techniques is discussed in a comparative paper by Stergiou and Christou (1996) who tested a suite of eight regression, univariate and multivariate time series modelling techniques to forecast annual commercial fisheries catch. They conclude that a simple multiple regression model incorporating climate variables performed better in terms of fitting accuracy than other techniques tested.

Earlier publications which have considered the impact of climate on barramundi populations in Australia have focussed on regions other than the Queensland north-east coast, and used a variety of techniques and variables including the seasons (Davis 1988), rainfall (Griffin 1986, 1993; Magro *et al.* 1997), and fresh water flow (Griffin 1986; Sawynok 1998; Staunton-Smith *et al.* 2004). However, to date no studies have considered the possible impact of a range of climate variables or climate indices as a measure of more complex interactions with barramundi landings. This study considers the commercial barramundi fishery of Princess Charlotte Bay (PCB) in far north-east Queensland, the landings from which fluctuate on a year-to-year basis. This phenomena is believed by many fishers to be the result of climatic variability. Maximum and minimum air temperature, sea surface temperatures (SSTs), evaporation, rainfall, fresh water flow and indices of the Southern Oscillation (SOI) and Madden Julian Oscillation (MJO) are included in a life cycle model and multiple regression modelling techniques to quantify the impact of climate on the commercial barramundi catch in the PCB region.

2. STUDY AREA

The PCB region lies approximately 340 km north of Cairns on the east coast of Cape York Peninsula (Figure 2) with a climate typical of a tropical, monsoonal area. The foreshore and river estuaries are dominated by extensive saline flats which front dense mangrove forests, and are subject to a low tidal range (0.1 – 4.0 m). The Bay is fed by a number of large rivers and many smaller streams which coalesce during the wet season to form extensive wetlands and swamp areas. Original vegetation and ecosystems have remained relatively undisturbed and the catchment as a whole is classified as near pristine / relatively undisturbed. There are very few of the anthropogenic impacts seen in other areas along the east coast of Queensland such as habitat degradation, impediments to fresh water flow, stocking of fish fingerlings and urban / agricultural development. As a result, “noise” from man-induced factors that may impact on the fishery is minimal. In addition, the barramundi populations in the Bay are part of a discrete genetic strain (Shaklee *et al.* 1993) and so may be assumed to be homogeneous in biological aspects.

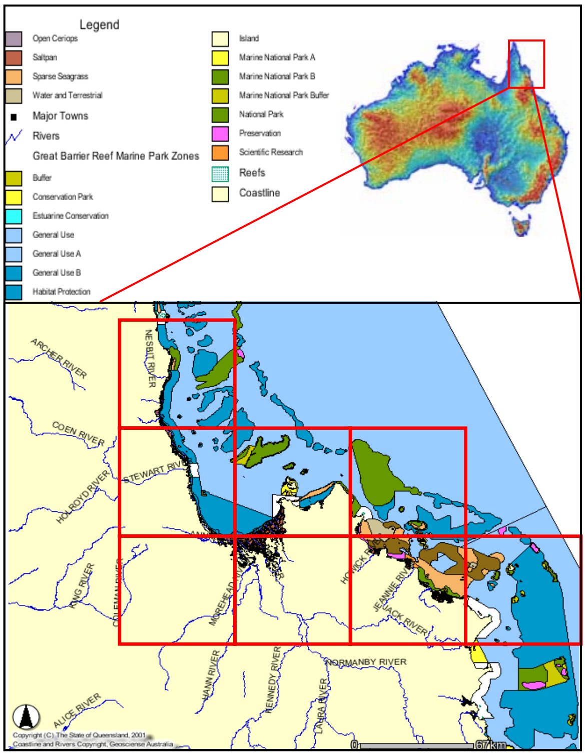

Figure 2. PCB region showing barramundi habitats, adjacent coral reefs and CFISH data grid squares.

3. DATA AND METHODOLOGY

Barramundi have a complex life cycle which is detailed elsewhere (e.g. Garrett 1986). Adults generally spawn prior to, or at the beginning of, the wet season from October – January in salt water estuarine environments. Postlarve move into wetland, mangrove and shallow supralittoral nursery habitats before migrating into tidal creeks and further upstream as the end of the wet season approaches. Juveniles mature in freshwater habitats as males over 2-4 years before migrating downstream to congregate with females to spawn. Protandrous hermaphrodites, they undergo a sex reversal from male to female after spawning. As recommended in a number of other studies (e.g. Shepherd *et al.* 1984) a conceptual life history model of the barramundi was developed to link climate influences known to affect the fish, with the timing of the species life cycle (Figure 3). This reduces the number of variables used in the analysis and errors associated with indiscriminate selection of parameters.

Climate data were collated from a number of sources, selected for critical times according to the life cycle model and formatted accordingly (Table 1). Seasons were defined as per Vance *et. al.* (1998): pre-wet (October – December); wet (January – March); early dry (April – June) and dry (July – September) so as to capture the majority of the wet season rainfall in one season (January – March).

Barramundi catch and effort data were sourced from the mandatory Commercial Fisheries Database System (CFISH) for eight 30 minute grid squares from the northern extremity of PCB south to Cape Flattery (Figure 2) for the thirteen year time-series from 1989 to 2001. Totals for the financial year were calculated in order to align with the fishing season. Although catch and effort were not significantly correlated at the $p<0.05$ level, catch adjusted for effort was used (residuals from the catch versus effort regression), in order to reduce any signal from effort and to normalise the data. Residuals were tested for serial autocorrelation using the Box and Ljung test for lags up to three years and found to be marginally significant at the one year lag ($r=0.488$; $p=0.049$; $Q=3.865$). However, removing autocorrelation can increase the risk of a type II error, or bias results if the source of autocorrelation is due to covariance (Pyper and Peterman 1998). Because of this analyses were undertaken without adjusting either the fisheries or climate data for autocorrelation. The resulting 19 climate data sets selected as relevant were checked for normality using the Shapiro-Wilks test and histograms and transformed where necessary prior to analysis.

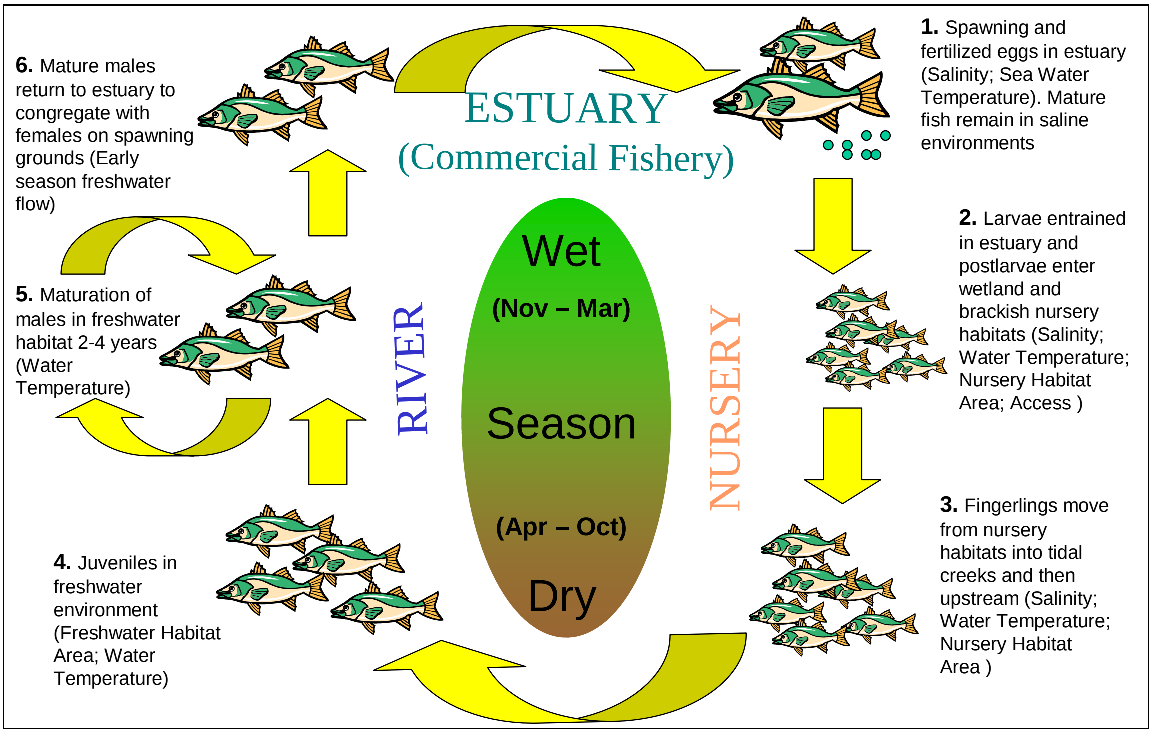

Figure 3. Conceptual model of PCB barramundi life cycle and climate influences.

Table 1: Climate and fisheries data sources and formats for PCB.

Variable	Source	Notes	Life cycle stage
Total catchment seasonal fresh water flows	QDNRM&E Stream gauge	Sum of 8 gauges	1-6
Total seasonal rainfall	BoM SILO database	Average 5 stations	1-6
Average December maximum air temp	BoM SILO database	Single point	1-3
Average July minimum air temp	BoM SILO database	Single point	4-6
Total annual evaporation	BoM SILO database	Single point	2-4
Seasonal average sea surface temps (SSTs) for Oct-Dec and Jan-Mar	NCEP Reynolds Optimally Interpolated SSTs	Single point	6 and 1
Total number of days in Madden Julian Oscillation (MJO) phase	BoM Research Centre website	Phases 1, 4 and 6	6-3
Average seasonal Southern Oscillation Index (SOI) for July–Sep, Oct-Dec and Jan-Mar	QDPI and QDRNME Longpaddock website	Base period 1887-1989	6-3
BoM=Bureau of Meteorology; CFISH=Queensland Commercial Fisheries Database System; NCEP= National Center for Environmental Prediction (US); QDNRM&E=Queensland Department of Natural Resources, Mines and Energy			

4. MODELLING

A correlation matrix of all relevant climate variables (lagged up to three years) against catch adjusted for effort was generated to identify significant relationships and possible collinearity between variables. Some of the independent variables were found to be significantly correlated with each other (e.g. rainfall October – December and fresh water flow October - December). However, as each describes a mechanism which affects the fishery in a different biological way (e.g. flow in the river bed versus rainfall replenishing wetland habitat separate from the river), it was considered valid to include all the variables selected. Collinearity between independent variables was compensated for through the use of forward stepwise ridge regression (FSRR) modelling (Staunton-Smith *et al.* 2004; StatSoft. Inc. 2005). As not all of the variables were collineated and correlations where they did exist were varied, the ridge regression constant *l* (lambda) was initially set at 0.1.

Three different FSRR models were built. The first used each of the climate variables which showed a significant correlation to catch in the correlation matrix, including lagged variables (Climate Variables Model). The second model incorporated each of the indices of the SOI and MJO for all lags (Climate Indices Model), and the third model used only significantly correlated climate variables lagged by two and three years (Lagged Model) in order to capture impacts on early life cycle stages of the fish. The first two allowed for a comparison between the use of climate variables and climate indices in describing catch. The third explored the possibility of generating predictions of future catch with sufficient time for a response from fisheries managers and / or operators. Models were limited to three steps, as the use of more variables in the model risks an artificially high level of the variance being accounted for, and a corresponding decrease in forecasting skill due to the increased degrees of freedom (Shepherd, *et al.* 1984). Residuals were checked for normality using a normal probability plot and for autocorrelation using the Durbin-Watson statistic. Adjusted coefficients of determination (R^2) values which take into account the degrees of freedom in the model were calculated (StatSoft. Inc. 2005).

The predictive capability of regression-based models has been questioned by several authors such as Stergio and Christou (1996) and Myers (1998). However we suggest that the robustness of a regression model can be enhanced by using cross validation (as per Wilkes 1995 and the data-splitting concept recommended by Myers 1998). Therefore the Lagged Model was cross validated using a "leave-one-out" (LOO) technique (Wilkes 1995) which results in a Predictive R^2 value as per Equation 1.1. This cross validated R^2 value is used as a measure of the model's predictive capability.

$$\text{Predictive } R^2 = 1 - \frac{SSEdeleted}{SST} \qquad (1.1)$$

where $SSEdeleted = \sum_{i=1}^{n} (y_i - \hat{d}_i)^2$

where y_i is the ith observed value

$\hat{d}_i$ is the predicted value when y_i is not included in the analysis.

Table 2. Barramundi catch adjusted for effort vs selected climate variables (0–3 year lags. Correlations (r) significant at the p<0.05 level*).

Variable	0 lag	1 year lag	2 year lag	3 year lag
Climate variables				
Minimum temp Jul (°C)	0.10	-0.16	-0.25	**-0.62***
Maximum temp Dec (°C)	-0.55	-0.25	-0.02	0.06
Rain Jul-Sept (mm)	-0.01	0.02	**0.77***	0.46
Rain Oct-Dec (mm)	**0.56***	0.30	0.38	0.15
Rain Jan-Mar (mm)	**0.56***	0.31	**0.62***	0.12
Rain Apr-Jun (mm)	0.37	0.40	-0.02	0.14
Flow Jul-Sep (Ml)	0.36	0.41	0.33	0.18
Flow Oct-Dec (Ml)	**0.71***	0.37	0.29	-0.02
Flow Jan-Mar (Ml)	0.52	0.35	**0.76***	0.36
Flow Apr-Jun (Ml)	0.33	0.33	0.13	0.27
Evaporation Annual (mm)	**-0.73***	-0.48	**-0.62***	-0.34
Average Oct-Dec SST (°C)	0.12	0.25	0.40	0.46
Average Jan-Mar SST (°C)	0.32	0.17	**0.58***	0.03
Climate forecasting indices				
MJO Phase 1	-0.55	0.00	-0.26	-0.08
MJO Phase 4	0.04	-0.39	-0.18	0.05
MJO Phase 6	0.38	0.50	0.16	0.21
Average July- Sep SOI	0.47	0.12	0.29	0.13
Average Oct-Dec SOI	**0.62***	0.19	0.29	0.14
Average Jan-Mar SOI	0.47	-0.18	0.10	0.19

Table 3: Comparison of forward stepwise ridge regression models (Variables significant at the p<0.05 level*).

Climate Variables (Adjusted R²= .6756)			
Variable	**Regression Coefficient**	**Standard Error**	**p-level**
Intercept	27524.44	19494.78	0.19
Rain Jul-Sept (2yr lag)*	6453.33	2348.22	0.02
Evap Annual (2yr lag)	-0.01	0.00	0.07
Av Oct-Dec SOI (no lag)	377.36	234.08	0.14
Climate Indices (Adjusted R²= .5308)			
Variable	**Regression Coefficient**	**Standard Error**	**p-level**
Intercept	18929.36	7768.18	0.04
Av Oct-Dec SOI (no lag)*	813.71	255.66	0.01
MJO Phase 4 (1 yr lag)*	-668.69	288.47	0.05
Av Jul-Sept SOI (2 yr lag)	462.87	246.61	0.09
Lagged Climate Variables (Adjusted R²= .6268)			
Variable	**Regression Coefficient**	**Standard Error**	**p-level**
Intercept	-132042.32	156562.77	0.42
Rain Jul-Sept (2yr lag)*	6552.84	2635.84	0.03
Evap Annual (2yr lag)	-0.01	0.00	0.07
Av Jan-Mar SST (2yr lag)	5671.57	5452.42	0.33

5. RESULTS

The correlation matrix between selected climate variables and barramundi catch adjusted for effort identified 11 significant correlations (Table 2). The FSRR Climate Variables Model (as shown in Table 3) included rain July-September^{-2} (two years previous); evaporation annual^{-2} and average October-December SOI (no lag), and explained 67.6% of the variance in catch adjusted for effort. The Climate Index Model explained 53.1% of the variance with average October - December SOI (no lag), MJO Phase 4^{-1} and July - September SOI^{-2}. The Lagged Model contained rain July - September^{-2}, evaporation annual^{-2} and average January - March SST^{-2} and explained 62.7% of the variance (Table 3). Residuals for all models were normally distributed, independent (Durbin-Watson statistic; p<0.05) and fell within ± 2 standard deviations of the mean indicating an absence of outliers.

Predicted versus observed values of catch were plotted for the Lagged Model with all but four points falling within the 95% confidence limits (Figure 1). Cross validation of the Lagged Model returned an adjusted R^2 value of 0.481 compared to the R^2 value of 0.627 initially calculated. This shows the robustness of the model and indicates that even when used in a predictive capacity, the Lagged Model is explaining nearly half the variance in catch adjusted for effort in PCB.

6. DISCUSSION

Zero-lagged correlations support the well established theory that early wet season fresh water flow (r = 0.71) affects the catchability of barramundi in PCB as fresh water connections to the commercial fishery in tidal waters are enhanced. In early wet years, male fish residing in fresh water reaches return to the estuary in large numbers and are caught later that same year as rainfall and flow are high and connectivity to these areas is good. As would be expected, the October - December SOI as an indicator of seasonal rainfall, and hence flow, was also significantly correlated with catch in the same year (r = 0.62).

Lagged correlations indicate that conditions which maintain optimum nursery habitat, and therefore improved survival of young-of-year barramundi such as high rainfall and fresh water flows in January - March, high rainfall in July - September, high January - March SSTs and low levels of evaporation, are significantly affecting catch two years later. Annual evaporation, a parameter that has not been considered in earlier studies, gives a highly significant inverse relationship with barramundi catch. The impact of this on the fishery is explained by research in the Northern Territory which has shown that the size /area of available wetland nursery habitat appears to be the strongest measure of population fluctuations in barramundi (Griffin 1985).

These findings also suggest that barramundi are growing to commercial size within 2-3 years depending on birth date and time of capture. Significant correlations with minimum temperatures three years prior may be identifying the effect of temperature on gonad activity / maturation, and hence spawning success in subsequent years (R. Garrett *pers. comm.. August 2005*, Principal Fisheries Biologist, DPI&F). Growth rates for the species range considerably between genetic stocks and even from one river to the next (Shaklee, *et al.* 1993). Male barramundi in river systems north of 15°S on both the east and west coasts of Cape York Peninsular have been found to be breeding at age one or two years (Davis and Kirkwood 1984; Garrett 1986), and more recent work using sagittal otoliths to age barramundi are showing fish as young as 1 and 2 years old are entering the commercial fishery (Staunton-Smith, *et al.* 2004).

Variables selected in the Climate Variables Model capture this influence from climatic conditions two years prior to catch (rain July – September^{-2} (+), evaporation^{-2} (-)). Catchability of barramundi in the year of fishing is explained by the inclusion of the October – December SOI (+) (no lag). This is also the first parameter selected for the Climate Indices Model, followed by phase 1 of the MJO^{-1} (-) a measure of suppressed rainfall, and a possible indicator of shallow habitat maintenance, and July - September SOI^{-2} (+) a predictor of early wet season rainfall.

Interestingly, rain from July – September^{-2} is the first variable selected in both the Climate Variables Model and Lagged Model which is somewhat surprising as PCB rainfall at this time of year, although variable, is minimal (0.1 – 21.3 mm). It may be that this rain maintains juvenile habitats which would otherwise dry out, resulting in the death of all fish. There may also be the secondary benefit of establishing a suitable nursery habitat for the arrival of early spawned fish in September - October. Again, research in the Northern Territory has shown that spawning commences in the very early months of the wet season, before the regular monsoon rains, and that the success of this early spawning significantly depends on the amount of rain which falls to replenish water levels in supralittoral nursery swamps (Griffin 1985).

The importance of conditions at the time of spawning and early development is clearly shown by the Lagged Model which includes rain July – September, annual evaporation and January – March SST (all lagged two years) and explains 62.7% of the variation in catch with a cross validated R^2 squared value of 0.48.

7. CONCLUSION

The impact of climate variability on the year-to-year variation of commercial barramundi landings in the PCB region was explored using correlation and regression modelling techniques. A range of climate parameters including fresh water flow, rainfall, evaporation, air and sea surface temperatures and indices of the SOI and MJO, selected to coincide with critical life stages of the species, were analysed against local barramundi catch adjusted for effort. Zero-lagged correlations support the hypothesis that connectivity to estuarine habitats and subsequent catchability of fish is enhanced in wetter seasons. Lagged correlations indicate that conditions which maintain optimum nursery habitats (high July - September and January – March rainfall, high January – March freshwater flows and SSTs, and low annual evaporation) result in higher catches two years later.

A FSSR model built from significantly correlated lagged climate parameters explained 62.7% of the variance in catch adjusted for effort in the Bay two years prior to catch. Despite the high level of physical significance of this particular model, there are well known caveats with regression based models in general (as highlighted by Myers 1998 and Walters and Collie 1988). Hence, we tested the predictive capacity of the model using a cross validated “LOO” regression analysis, which adjusted the R^2 value to 0.481. These results highlight the critical importance of climate on various aspects of the barramundi life cycle which must be accounted for in management strategies, especially in this era of looming climate change and vulnerable fish stocks.

8. ACKNOWLEDGEMENTS

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