Impact of water development on river flows and the catch of a commercial marine fishery

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Citation: Broadley, A., B. Stewart-Koster, R. A. Kenyon, M. A. Burford, and C. J. Brown. 2020. Impact of water development on river flows and the catch of a commercial marine fishery. Ecosphere 11(7):e03194. 10.1002/ecs2.3194

Abstract. The growing demand for freshwater resources has led to dam construction and water diversions in a majority of the world’s large rivers. With an increasing demand for freshwater, trade-offs between water allocations and the preservation of ecological connections between terrestrial and marine ecosystems are inevitable. The ecological links formed by rivers flowing into the ocean benefit many commercially fished species. The degree to which different species and the livelihoods of fishers are negatively impacted by changes in river flows due to water extraction or diversion is important for management across terrestrial and marine boundaries. Our objective was to predict how changes in freshwater flows from three wet–dry tropical rivers in northern Australia, that is, the Mitchell, Gilbert, and Flinders rivers, affect the commercial banana prawn (Penaeus merguiensis) catch. We used a novel spatiotemporal Bayesian approach to model the effects of river flows and key climate drivers on banana prawn catch. We then predicted how the loss of flow due to water extraction or diversion affected prawn catch. Our analyses of three water development scenarios found that catch was most impacted by water extraction during low flows. The impact of water extraction was greatest for a scenario with dams on the Mitchell River, where we predicted catch would decline by 53% during a year with low flow. Overall, our results imply that maintenance of low-level flows is a crucial requirement for sustained fishery yields. We suggest that water managers must balance agricultural demand for water during drier years against the impact of water extraction on prawn fisheries during low-flow years. Protecting low-level flows during drier years is a priority for maintaining terrestrial–marine linkages for adjacent marine fisheries.

Key words: coastal ecology; estuaries; estuarine ecology; fisheries dynamics; fisheries management.

INTRODUCTION

The connections between terrestrial and marine ecosystems are a critical interface for ecological dynamics and have important implications for fishery management (Hughes et al. 2015, Brown et al. 2019). Productivity of the world’s coastal fisheries is dependent on ecological links to freshwater and terrestrial ecosystems, such as nutrient inputs from floods that boost primary production (e.g., Bianchi 2007, Saeck et al. 2013) and altered physio-chemical environments (e.g., MacCready and Geyer 2001, Stacey et al. 2001). The disturbance of terrestrial freshwater pathways from changes in climate, river flows, and land use has led to habitat destruction and loss of biodiversity in recipient coastal marine ecosystems (Vörösmarty and Sahagian 2000,
of commercial fi
dictability and contribute to better management in the environment may improve mounting evidence that accounting for changes in the environment may improve fish stock predictability and contribute to better management of commercial fisheries (Szuwalski et al. 2015).

Environmental factors affecting coastal wild capture fish stocks extend far beyond the management boundaries of fisheries (Oczkowski et al. 2009, Szuwalski et al. 2015). The absence of integrated management across terrestrial–marine boundaries has seen the decline and collapse of fish stocks from the construction of dams and water diversions (Oczkowski et al. 2009). The Australian government is currently investigating opportunities for water resource development in northern Australia (Petheram et al. 2018). However, unlike most tropical rivers that have distinctive seasonal patterns of flow, wet–dry tropical rivers such as those in northern Australia have highly variable flows (Warfe et al. 2011). In the wet–dry tropics, rivers may only flow for short periods of time during the wet season and are often followed by long periods of low flow or cease to flow in the dry season (Warfe et al. 2011). The extreme climatic variability of the region raises concerns about how water extraction in low-flow years will impact marine fisheries. It is important to evaluate the scale of impacts of proposed water resource development projects on river flows and their effects on the catch and effort of adjacent coastal marine fisheries.

Both spatial and temporal changes in freshwater flows are known to have important implications for fish and invertebrate species in coastal, estuarine, or freshwater habitats, particularly in northern Australia (Vance et al. 1985, Robins et al. 2005). For example, the construction of the Ord River Dam in northern Australia led to a reduction in the banana prawn (Penaeus merguiensis) population by changing the river’s flow regime from wet–dry tropical to a perennial flow system (Warfe et al. 2011). Similar to the banana prawn, many other marine species respond to changes in freshwater flows by shifting their location to avoid unfavorable conditions such as changes in salinity, while others may take advantage of changed conditions to reproduce or search for prey (Grimes and Kingsford 1996). This behavior is reflected in a species distribution in space and time and is often constrained by their physiological adaption to environmental changes that have occurred throughout their life history (Vance et al. 1985, Taylor and Loneragan 2019). Species that spawn or spend their early life stages in estuarine or freshwater habitats are particularly vulnerable to changes in the timing and magnitude of freshwater flows (Vance et al. 1985). Fluctuations in seasonal patterns of freshwater flows are known to affect the survival, growth, migration, and recruitment to fisheries of many commercially important marine fish and invertebrates (e.g., Drinkwater and Frank 1994, Hilborn et al. 2003, Duggan et al. 2014). Changes in freshwater flows can affect an individual’s physiology either directly through variations in salinity and temperature, or indirectly through changes in habitat or food availability, but regardless of the mechanism, changes in flow are expected to affect fishery yields (Drinkwater and Frank 1994).

In the Australian Northern Prawn Fishery, change in the osmoregulation capability of juvenile banana prawns combined with reduced salinities from seasonal freshwater flows is an important mechanism forcing banana prawns to emigrate from estuarine nurseries to coastal waters (Vance et al. 1985, Dall et al. 1990). There is concern that growing development pressure on freshwater flows, particularly in low-flow years, will reduce the emigration cue and thus impact the fishery. One of the first stages in the process of planning for major water resource development involves using simulation models to evaluate the impact of upstream development on downstream needs, such as the water needs of fisheries species (Gippel et al. 2009). Predicting the impact of such water resource development on fishery catch requires a modeling framework that can simultaneously account for the natural spatial and temporal variability in the environment that also affects catch. The aims of this research were to (1) characterize interannual flow variability for three wet–dry tropical rivers in northern Australia, the Mitchell, Gilbert, and Flinders rivers; (2) determine how climate and environmental variables affect prawn catch; and
(3) predict how scenarios for water extraction and diversion from the three rivers may affect the commercial banana prawn catch. We examined the influence of river flows on the annual catch using a spatiotemporal Bayesian model. The model development process considered different climate covariates and river flow scenarios over a 28-yr period and the impact of flow extraction and diversion on the banana prawn fishery.

**Methods**

**Study area**

Situated in northern Australia, the Gulf of Carpentaria is a large semi-enclosed body of water covering an area of approximately 400,000 km² (Fig. 1). The Gulf of Carpentaria’s open boundary extends into the Arafura Sea and is connected to the Coral Sea across the Torres Strait (Condie 2011). The bathymetry of the entire region is relatively flat and shallow with water depths ranging from 20 m near the coast to 70 m toward the center (Rothlisberg and Burford 2016). The focus of this study was on the southeastern region covering around 150,000 km² of coastal waters (Fig. 1). Within this region, the Mitchell, Gilbert, and Flinders rivers drain vast catchment areas that remain largely undisturbed from human impact (Petheram et al. 2008, Rothlisberg and Burford 2016).

**Northern Prawn Fishery**

The Northern Prawn Fishery has operated within some sections of the Gulf of Carpentaria from the late 1960s (Kompas et al. 2010). Since this time, it has expanded to become Australia’s largest multi-species prawn fishery covering an area of around 900,000 km² in the coastal waters around northern Australia (Kompas et al. 2010). The banana prawn is one of the most commercially important species targeted by fishers in Northern Prawn Fishery. Adult banana prawns spawn offshore, generally in the warmer tropical and subtropical waters. The resultant larvae are then transported by currents toward settlement locations in shallow water habitats within estuarine and coastal areas. After growing for a period of 4–6 months, ontogenetic changes in their osmoregulation combined with reduced salinities from wet season river flows cue their emigration offshore. Once in the ocean, banana prawns continue to grow, mature, spawn, and recruit to the fishery (D. J. Vance and P. C. Rothlisberg, unpublished manuscript).

At the time of the study, the majority of the banana prawn catch was harvested in the southeastern region of the Gulf of Carpentaria, where 80% of the catch was usually taken within the first few weeks of the fishing season opening. This typically begins at the transition from wet to dry seasons in April each year. At the beginning of the fishing season, banana prawns form large aggregations and fishers look for discoloration in sediments as a guide for large schools of banana prawns. Light aircraft are also used to identify and direct the location of banana prawn aggregations to fishers (Die and Ellis 1999). The aggregating behavior of the banana prawn and its effect on fisher behavior meant the likelihood of catch had a strong influence on effort. This was evidenced both by a strong correlation between catch and effort, \( r = 0.77 \), and from the majority of the trawl tows being under 3 h in duration (Die and Ellis 1999).

Weekly catch and effort data for the banana prawn fishery from 1984 to 2011 on a six nautical mile (~11 km²) grid resolution covering the entire study area were obtained from the Commonwealth Scientific and Industrial Research Organisation (CSIRO). The catch and effort data were based on information recorded by fishers in daily log sheets (Dichmont et al. 2014). When the catch and effort data were analyzed spatially, some areas of low catch and very low effort were found. These areas produced a high catch per unit effort (CPUE) that was comparable to areas of much larger catch and higher effort. Targeting banana prawn aggregations early in the season meant CPUE was likely to be decoupled from the true abundance distribution, with short trawls able to yield very low or very high catch, depending on the size of the aggregation. We also did not have access to individual trawler location data and were therefore unable to verify fishing effort. We assumed catch data were correct because fishers logged the location of each shot of the net, which is verified with landed weights from processing companies and trawler owners (Bishop and Die 2001). For these reasons, we decided that using catch data only would provide a better spatial
representation of banana prawn distribution than CPUE.

**Regional climate and weather**

The Gulf of Carpentaria is an area of extreme climatic variability that is characterized by wet and dry seasons (Petheram et al. 2009). In this study, the wet season was defined as the months between October and April, and the dry season, from May through to September, based on gauged river flow data. Each season is influenced by global-scale changes in atmosphere–ocean circulation patterns that generate substantial modes of climatic variability (Wheeler and Hendon 2004, Ghelani et al. 2017). The influence of different climate modes on regional rainfall flux provided an opportunity to analyze how substantial interannual changes in river flows related to the catch of banana prawns. The relationship between river flow regimes and banana prawn catch was used to infer how altered flows from water extraction, that is, water diversion or construction of dams, might impact the fishery.

The long-term average rainfall in the Gulf of Carpentaria showed a strong north–south gradient with most rain falling in the northern catchments. The Mitchell River located in the northernmost catchment of the study had the highest average annual flow of 13,000 GL/yr. Average annual flows in the Gilbert (5304 GL/yr) and Flinders (1982 GL/yr) rivers were considerably less than the Mitchell River. The large difference in size of the Flinders catchment (109,000 km²) compared to the Gilbert and Mitchell (46,354 and 73,230 km², respectively) did not appear to be an important factor influencing the annual volume of river flows in this study.

The variation in climate is mainly caused by interactions between shifts in phase of the El Niño Southern Oscillation (ENSO) and the strength of activity from the Madden Julian Oscillation (MJO; Ghelani et al. 2017). The ENSO is the dominant mode of climatic variability measured on interannual timescales, and the MJO operates intra-seasonally approximately every
30–80 d (Wheeler and Hendon 2004). Changes in the ENSO and MJO have been linked to the frequency and severity of tropical storms and cyclones occurring in northern Australia (Ghe- lani et al. 2017).

We captured the interannual effects of El Niño, La Niña, and neutral phases of ENSO by calculating the average Southern Oscillation Index (SOI) for each wet season from 1984 to 2011 using data from the Australian Bureau of Meteorology (BOM; http://www.bom.gov.au/climate). An SOI value below −8 indicated an El Niño, above +8 indicated La Niña, or values between −8 and +8 implied neutral conditions.

In the Gulf of Carpentaria, tropical cyclones are an important component of extreme changes in weather conditions (Klingaman et al. 2013). During the wet season each year, it is common for more than one tropical cyclone to form or make landfall in northeastern Australia (Ramsay et al. 2008). As cyclones move across the coast and into the Mitchell, Gilbert, and Flinders catchments, they have the potential to cause floods or overbank flows that occur over very short periods of time (Klingaman et al. 2013, Ndehedehe et al. 2020). A composite index based on each cyclone’s mean wind speed (km/h), representing its severity, and the day of year it first appeared in the region, including catchment areas, was created using principal components analysis (PCA). The first component of the PCA was used as the index, which accounted for 76% of the variation in the wind speed and timing of all cyclones. Information on tropical cyclone wind speed, track, and timing used in this study was obtained from the Australian BOM.

Both the SOI and cyclone index captured important large-scale and local elements of annual climatic variability. We accounted for additional regional-scale climate effects by creating an index of the outgoing longwave radiation (OLR) measured at 850 hPa in the atmosphere directly above the Gulf of Carpentaria. The index was developed from daily interpolated 1° latitude by 1° longitude OLR data from the Physical Sciences Division of the National Oceanic and Atmospheric Administration (NOAA). The mean OLR between 138° and 144° east and −13° and −20° south was computed for each wet season from 1984 to 2011. Lower values of the OLR index indicated greater convection in the atmosphere above the Gulf of Carpentaria’s coastal and river catchment areas.

The SOI, cyclone, and OLR indices were created to capture the nonlinear effects of environmental conditions in the ocean and atmosphere that influence the catch of banana prawns. The SOI represented large-scale changes in ocean water temperatures and rainfall that are known to affect spawning patterns and migration of many marine species (Meynecke and Lee 2011). The cyclone index was created because the timing of severe weather events can positively or negatively affect catch from increased river flows, damage to habitat, or reduced fishing effort from fishers seeking safe harbor (Callaghan 2011, Loneragan et al. 2013). The OLR index captured the effects of both the ENSO and cyclones by focusing on atmospheric conditions directly above the Gulf of Carpentaria. OLR has been used in many climate studies and forms the basis of indices such as the MJO (Wheeler and Hendon 2004).

Rivers

The end-of-system (EOS) river flow data were available for the Mitchell, Gilbert, and Flinders rivers from the CSIRO using river models configured in the eWater Source software (Lerat et al. 2013). The modeled CSIRO flow data covered a period in time from 1900 to 2011. Annual wet season flows for each river were created by summing daily EOS flow data between October and April. Because the annualized wet season flows crossed years, they were associated with the end of wet season year that aligned with the fishing season. All of the flow data were standardized.

Collinearity between river flows was investigated using a Pearson correlation test in R (R Core Team 2018). The results of the Pearson test identified a strong correlation between the Flinders and Gilbert rivers (86%), and the Gilbert and Mitchell rivers (75%). Evidence of collinearity does not always present issues for model stability or prediction, but early testing of our model indicated collinearity was causing instability and spurious results. To reduce model instability, a PCA was used in R (R Core Team 2018) to create two new variables (PC1 and PC2) that each accounted for 80% and 18% of the variability for all river flows. The results of the PCA were verified with a biplot (Appendix S1:
The parameter values of PC1 and PC2 were not directly interpretable and had to be back-transformed by projecting onto the PCA coordinate system using the same rotation matrix as the observed river flows.

**Model development**

**Modeling approach.**—The model development process considered the life history of the banana prawn with particular focus on how changes in river flows influence the spatial distribution of commercial catch. Exploratory analysis revealed the banana prawn catch had a distinct spatial structure with a high concentration of banana prawns found near the coast (Fig. 2). It was also evident that the extreme interannual variability in climate meant there was little temporal autocorrelation between seasonal river flows (Appendix S1: Fig. S2). The development of an appropriate model would need to account for the spatial dependency of banana prawn catch, seasonal changes in river flows, and nonlinearities associated with interannual changes in climate.

**Model structure.**—We used a hierarchical spatiotemporal Bayesian model to predict how changes in the distribution of the banana prawn catch vary with annual freshwater flows from the Mitchell, Gilbert, and Flinders rivers. A gamma distribution was chosen because the banana prawn catch data only contain positive values. Following the integrated nested Laplace approximation (INLA) modeling framework (www.r-inla.org), the gamma function $\Gamma(\cdot)$ was parameterized in terms of its mean $\mu$, a fixed scaling parameter $s > 0$, and hyperparameter $\phi$ (Rue et al. 2009, Lindgren et al. 2011),

$$y_{ij} | \mu_{ij}, \theta \sim \Gamma(\mu_{ij}, s\phi),$$

where $y_{ij}$ represents banana prawn catch at location $i$ in year $j$ that depends on an unobserved process $\mu_{ij}$ with hyperparameters $\theta$. A log link was used to link the linear predictor to $\mu$. The unobserved process $\mu_{ij}$ was modeled by,

$$\log(\mu_{ij}) = \eta_{ij} = \beta_0 + \beta_1 \text{PC1}_{ij} + \beta_2 \text{PC2}_{ij} + \sum_{l=1}^{L} f_l(\text{clim}_l) + x_i,$$

where $\eta_{ij}$ is the linear predictor, $\beta_0$ is the intercept, both $\beta_1$ and $\beta_2$ are coefficients used to quantify the effect of river flows represented by PC1$_{ij}$ and PC2$_{ij}$ from the PCA axes for flows, $L$ refers to the total number of climate covariates, $f(\cdot)$ were first-order random walks on clim$_l$ used to evaluate the temporal trends of SOI, OLR, and cyclones on the fit and predictive power of the model, and $x_i$ refers to a Gaussian random field (GRF) with a zero mean and Matérn covariance matrix, $x_i \sim \text{GRF}(0, \Sigma)$. Using a GRF enabled any latent factors, such as the availability of habitat or coastal primary productivity, influencing the spatial distribution of the banana prawn catch to

![Fig. 2. Spatial distribution of the mean banana prawn catch with discharge from the Mitchell, Gilbert, and Flinders rivers for years grouped by (a) low flows and (b) high flows.](image)
be represented in the covariance structure of the model.

The spatial effect was modeled using INLA’s stochastic partial differential equation (SPDE) approach. Here, the smoothness, range, and marginal variance of the Matérn function were parameterized for use with the penalized complexity (PC) prior framework (see Fuglstad et al. 2019). INLA’s finite element method was used to approximate the solution of the SPDE (Lindgren et al. 2011). The spatial domain of the banana prawn catch was divided into a constrained refined Delaunay triangulation or mesh of non-intersecting triangles (Appendix S1: Fig. S3). The vertices within the mesh were mapped to basis functions with an associated weighting factor for linear interpolation of values in each of the triangles (Lindgren et al. 2011).

**Priors.—** Bayesian priors were assigned to regression coefficients and hyperparameters. We used the default Gaussian prior distributions with 0.0001 for the coefficients that were associated with river flows. PC priors were incorporated into the gamma distribution, random walk, and Matérn GRF components of the model (see Simpson et al. 2017, Fuglstad et al. 2019). PC priors are weakly informative priors that shrink model components from more flexible to simpler base models and so are useful to avoid overfitting the model to the data (Simpson et al. 2017). Probability statements were used to specify parameters of the PC priors, thus setting the magnitude (λ) of the penalty for deviating from base models. PC priors for the precision (τ) of the gamma distribution and random walks were set to have a high probability their standard deviation would be between 0 and 1, P(σ > 1) = 0.01, calculated as

\[ \lambda = \frac{-\ln(0.01)}{1} \]

\[ \pi(\tau) = \frac{\lambda}{2\tau^{3/2}}\exp\left(-\lambda\tau^{-1/2}\right). \]

A joint PC prior for the range and variance was used to shrink the Matérn GRF toward a base model of infinite range and 0 marginal variance (Fuglstad et al. 2019). This approach avoids overfitting of the Matérn GRF by using the range and variance parameters to control the correlation and magnitude of the spatial field. In this setting and because many penaeid species are mobile and able to move distances over 100 km, we assumed there was a low probability the spatial range parameter would be smaller than 10 km, \( P(\rho < 10 \text{ km}) = 0.01 \) (García 1988, Dall et al. 1990). We also set the standard deviation of the spatial field so it was unlikely to exceed 1.5, \( P(\sigma > 1.5) = 0.01 \). The joint prior for the Matérn GRF with a fixed smoothness \( v = 1 \) and dimensions \( d = 2 \) was calculated as

\[ \tilde{\lambda}_1 = -\log(0.01)10^{d/2} \text{ and } \tilde{\lambda}_2 = -\frac{\log(0.01)}{1.5} \]

\[ \pi(\sigma, \rho) = \frac{d\tilde{\lambda}_1\tilde{\lambda}_2\rho^{-d/2}}{\sqrt{2\pi}\tilde{\lambda}_1\tilde{\lambda}_2\rho^{-d/2}} \cdot \exp\left(-\frac{\tilde{\lambda}_1\sigma^{-d/2}\tilde{\lambda}_2\rho^{-d/2}}{2}\right). \]

**Model comparison and cross-validation.—** In order to compare the fit and predictive quality of different combinations of SOI, OLR, and cyclones on the model, we used the widely applicable information criterion (WAIC), logarithm of the pseudo-marginal likelihood (LPML). We also ran out-of-sample cross-validation using the root mean square error (RMSE) as the evaluation metric to compare models. The WAIC was calculated by INLA during model runs with lower values indicating improved model performance. The LPML summarizes the conditional predictive ordinate (CPO) that was computed by INLA into a single value, a greater number indicates better predictive quality of the model,

\[ \text{LPML} = \sum_{i=1}^{n_{\text{te}}} \log(CPO_i). \]

We conducted the cross-validation process by randomly dividing data into training and test sets, with randomization stratified by year. This process tests the ability of the model to predict catch across years, assuming the fixed spatial structure is known. Each training set contained 22 yr or ~80% of data, and the remaining 6 yr of data became the test set. Each model was initially fitted to the training data while omitting the test data. The fitted model was then used to predict catch in each location and year from the previously omitted test data. RMSE was calculated to measure the quality of fit between the observed data and predicted values for each model run, smaller values indicated a better fit,

\[ \text{RMSE} = \sqrt{\frac{1}{n_{\text{obs}}} \sum (\text{obs} - \text{pred})^2}. \]
The cross-validation process was repeated 100 times for each model, and the mean RMSE values from the training and test data sets were used to compare different models. We evaluated the sensitivity of the RMSE to the hold-out set by stratifying the cross-validation by flow scenarios. The flow covariates were included in all model comparisons. Testing flow would be a trivial null hypothesis because its importance in the life cycle of banana prawns was already well established (Vance et al. 1985). Once we found which environmental covariates were important, we applied the model to different flow scenarios to predict the catch of banana prawns under changed river flows.

Predicting catch from changes in river flows.—We used the fitted Bayesian model to predict annual catch when the flow of each river was reduced according to three water extraction scenarios (Table 1). Water extraction scenarios were based on recent Queensland Government Water Resource Plans and Assessments for the Flinders, Gilbert, and Mitchell catchment areas. Scenario A had the least extraction of any scenario and assumed that all surface water entitlements granted as part of the water planning process were fully utilized (DNRME 2017). These included extractions for town, indigenous, and industrial use. Scenario B assumed current and future allocations were fully utilized (DNRME 2018a, b). Scenario C had the greatest water extraction from the potential development of major instream dams in the Mitchell catchment (Petheram et al. 2018).

To account for covariance in river flows, we ran the extraction scenarios for multiple flow regimes. The EOS flow data from 1900 to 2011 were analyzed to determine a common set of flow-level patterns for the Flinders, Gilbert, and Mitchell rivers. Flow-level patterns were identified using k-means cluster analysis by classifying annual wet season flows for each river into low, medium, high, and very high categories using the Cluster package in R (Maechler et al. 2018, R Core Team 2018). We then predicted catch when each river’s flow was altered for each flow-level pattern and water extraction scenario.

RESULTS

Climatic context

Here, we consider the environmental context throughout the 28-yr study period and examine potential confounding influences between climate predictors. These results were an important component of model development and were used to better understand model limitations and behavior.

A majority of cyclones (59%) appeared in the region during neutral ENSO conditions (Fig. 3a, b). The number of cyclones in both El Niño and La Niña years was much lower with nine cyclones occurring in each phase. The average intensity of cyclones was 25% stronger during El Niño years compared to that in La Niña. Similar to the difference in intensity was the average timing of cyclones where during El Niño years, cyclones first appeared in January, while in La Niña, they appeared later in February. There was also a noticeable shift in the timing of cyclones in neutral to El Niño conditions (between 1990 and

| Scenario Description | Flinders | Gilbert | Mitchell |
|----------------------|----------|---------|----------|
| (A) Granted entitlements | Full use of all surface water entitlements that have been granted as part of the water planning process. In this scenario, surface water is mainly pumped to locations throughout each catchment | 206 | 126 | 20 |
| (B) Planned allocations | Full use of all future planned surface water allocations including those licenses already granted. Surface water could be extracted by either pumping or building instream dams | 266 | 489 | 70 |
| (C) Mitchell instream dams | The construction of multiple major instream dams in the Mitchell River could release 2800 GL of water for consumption. Water extraction at this level would see total EOS flows reduced by around 3425 GL. This scenario includes the full use of all planned and granted water allocations | 266 | 489 | 3425 |
OLR was below 253 watts (Fig. 3a, c). Out of the five lowest OLR years, three recorded an OLR of 245 watts/m², which coincided with the presence of at least one Category 3 or higher cyclone in the region. More generally, the observed trends in OLR reflected cycles of ENSO where La Niña conditions had an average OLR of 250 watts/m², neutral years averaged 255 watts/m², and El Niño years had the highest average OLR of 260 watts/m². When comparing OLR and SOI at 10- to 15-yr timescales, there was a small difference, 256 watts/m² from 1984 to 1998, compared to 253 watts/m² from 1999 to 2011. The difference in OLR did match a similar scale shift in SOI, from −4.2 to 4.3, over the same period of time. Along with the possible existence of a low-frequency cycle associated with OLR, there also was evidence of a higher frequency 3- to 7-yr cycle.

The temporal patterns found in the ENSO and OLR climate predictors were also evident in the observed river flows (Fig. 4). In the last 13 yr of the study, there was a 30% increase in total river flows, from 244,949 to 349,757 GL. The increase in total flow could be attributed to above-average flows in all three rivers that only occurred during neutral or La Niña phases of ENSO. There were also some notable patterns at shorter timescales between rivers and OLR. For instance, the 3- to 7-yr periods of below-average flows mostly occurred when OLR was above 255 watts/m². A similar threshold existed when OLR was below 253 watts/m² with at least one of the rivers having above-average flows.

The strength and number of cyclones did not always translate into years of substantial river flows. For example, both 2005 and 2006 were seasons influenced by strong Category 3–5 cyclones, but generated very different patterns in river flows. Despite the presence of two cyclones in 2005, the total flow of freshwater was around 50% below average, 10,960 GL. Below-average flows were more likely to be associated with El Niño-type conditions, an SOI of −8.3, and the absence of convective conditions in the atmosphere for a majority of the wet season, shown by a high OLR of 262 watts/m². In 2006, the presence of two cyclones coincided with close to La Niña conditions, SOI 7.1, and a very low OLR of 245 watts/m², indicating strong convection in the atmosphere throughout the wet season. These conditions were associated with above-average flows in the Flinders (3104 GL) and Mitchell (17,883 GL), and below-average flows in the Gilbert (3015 GL).

Overall, these environmental patterns indicated some, but not complete, covariance between each climate predictor, which may confound model interpretation. Therefore, outlined below we focused on identifying the subset of climate predictors providing the most accurate predictions of catch.

Classification of river flows

There were some common patterns of flow found with the k-means classification of the river flow time series of the three rivers (Table 2). Less than half (n = 29) of all 64 possible combinations of low, medium, high, and very high flows occurred between 1900 and 2011 (Table 3). When only considering the 28-yr study period, the number of river flow combinations was reduced to 16. Within the study period, the top six flow patterns occurred more than once, and these accounted for 64% of all study years. Low flows in all three rivers (flow-level pattern 1) was the most frequently occurring pattern, found in 18% of study years and 22% of all years. The number of medium-flow (flow-level pattern 4) years during the study period was nearly half, 7%, that of all years, 12%, whereas flow-level pattern 3 (low, medium, and high), occurred more frequently, 11%, during the study period compared to 6% in all years.

Model comparison, verification, and fit

The performance of each model was evaluated using different combinations of climate predictors (Table 4). The WAIC did not vary greatly between most models except that models 1 (no climate covariates) and 4 (cyclones) had higher (worse) values. There was less difference among the predictive quality of models measured by the LPML, with all models, except 1 and 4, ranging from −12,406 to −12,415. The top three models having the smallest difference between the
observed annual catch vs. the fitted training data (Fig. 5a, d, g), and the observed annual catch vs. predictions from the hold-out data (Fig. 5b, e, h) were models 1 (24.6 t/yr), 3 (134.3 t/yr), and 4 (120.8 t/yr). Further analysis revealed that throughout the cross-validation, Model 3 (OLR) had produced the best predictive performance (Fig. 5f), having the lowest variance in catch predictions of 223 t/yr.

Model 3 (OLR) was selected due to its consistent performance across evaluation measures compared to other models. The OLR model performed well compared to other models having similar WAIC and LPML scores (Table 4), and importantly a consistently lower variance in prediction accuracy during cross-validation (Fig. 5f). The performance of the OLR model was related to how the OLR index captured changes in atmospheric conditions that were confounded with elements of both the SOI and the presence of cyclones (Fig. 3a, b, c). The confounded elements of the SOI were linked to large-scale changes in ocean–atmosphere circulation patterns, whereas the effects of cyclones were more likely confounded at a much smaller catchment scale. Overall, the OLR model demonstrated it would provide the most reliable predictions of banana prawn catch from changes in flow.

The cross-validation process was sensitive to the mix of low, medium, high, and very high flows included in the training data. Sensitivity analyses revealed a range in RMSE\textsubscript{Test}, for all 8 models, from 223 to 1083 t/yr (Appendix S1: Fig. S4). In general, the RMSE\textsubscript{Test} was lower when the training data included the rare years with very high river flows (200–500 t/yr). When
the training data excluded high- and very-high-flow years, the RMSE_{Test} was higher (500 and 650 t/yr), because these models were extrapolating catch predictions to high-flow years.

A review of marginal posterior parameters for all models (Appendix S1: Table S2) showed the fixed, random, and spatial effects were all important to explain the variability in catch. Back-transforming PC1 and PC2 for each model (Appendix S1: Table S3) revealed similar parameter values for each river, ranging from 2457 to 2794 GL/yr in the Flinders, 4642 to 4819 GL/yr in the Gilbert, and 17,011 to 19,146 in the Mitchell. The \( \rho \) (range) of the spatial field indicated the distance where spatial correlation was reduced to around 0.13. All of our models had a similar value of \( \rho \) from between 99 and 113 km, indicating a diminishing spatial autocorrelation of catch for distances over 113 km.

**Model predictions for water extraction scenarios**

The following results show catch predictions from the OLR model for each of the three water extraction scenarios, (A) granted entitlements, (B) planned allocations, and (C) Mitchell instream dams. For each water extraction scenario, the predicted decline in catch was shown for the four most common flow-level patterns (patterns 1–4), with the addition of rare patterns 8 (all rivers high) and 10 (all rivers very high). These six flow-level patterns accounted for 56% of all possible combinations of low to very high

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**Fig. 4.** The end-of-system river flow during the wet season from October to April from 1984 to 2011 and average annual flow, indicated by the red dashed line, for the (a) Mitchell, (b) Gilbert, and (c) Flinders rivers.
categories of flow that occurred in the three rivers over a 112-yr period (Table 4).

In scenario A, we assumed that all surface water entitlements granted as part of the water planning process were fully used and therefore flow reductions were minimal (Fig. 6a, d). The predicted change in catch for all flow-level patterns was less than 5%. Flow patterns 1–4 had a decline in catch of between 34 and 57 t (95% CI, 30–65 t). The decline in catch was lower for the higher flows associated with patterns 8 and 10, with a predicted reduction in catch of between 5 and 22 t (95% CI, 3–35 t).

The planned allocations scenario B assumed full use of all future planned surface water allocations including those entitlements already granted (Fig. 6b, e). Model predictions indicated water extracted during low- to medium-flow years (patterns 1–4) at the level of planned allocations could potentially reduce catch between

Table 2. Descriptive statistics generated from the k-means classification of the Flinders, Gilbert and Mitchell river flows from 1900 to 2011.

| River     | Category | Range (GL) | Mean (GL) | Median (GL) |
|-----------|----------|------------|-----------|-------------|
| Flinders  | Low      | 0–1602     | 540       | 335         |
|           | Medium   | 1743–4216  | 2883      | 2758        |
|           | High     | 5120–9772  | 7113      | 6876        |
|           | Very high| 13,435–24,918| 18,234   | 16,349      |
| Gilbert   | Low      | 55–2410    | 1221      | 1399        |
|           | Medium   | 2506–5689  | 3734      | 3591        |
|           | High     | 6131–10,966| 8231      | 7915        |
|           | Very high| 16,167–34,735| 22,716   | 17,246      |
| Mitchell  | Low      | 2095–8503  | 4975      | 4691        |
|           | Medium   | 9262–16,654| 12,946    | 12,525      |
|           | High     | 17,049–25,130| 21,022   | 20,642      |
|           | Very high| 30,220–54,255| 38,467   | 38,282      |

Table 3. Categorized flow patterns identified by using k-means clustering on the 1900 to 2011 EOS flow data set for the Flinders, Gilbert, and Mitchell rivers.

| Flow pattern | Flinders | Gilbert | Mitchell | All years | Study years |
|--------------|----------|---------|----------|-----------|-------------|
|              |          |         |          | 1900–2011 | 1984–2011   |           |
| 1            | Low      | Low     | Low      | 25        | 5           | 18        |
| 2            | Low      | Low     | Medium   | 11        | 4           | 14        |
| 3            | Low      | Medium  | High     | 7         | 3           | 11        |
| 4            | Medium   | Medium  | Medium   | 13        | 2           | 7         |
| 5            | Low      | Medium  | Low      | 6         | 2           | 7         |
| 6            | Medium   | Medium  | High     | 5         | 2           | 7         |
| 7            | Low      | Medium  | Medium   | 9         | 1           | 4         |
| 8            | High     | High    | Medium   | 5         | 1           | 4         |
| 9            | Low      | High    | Medium   | 2         | 1           | 4         |
| 10           | Very High| Very high| Very high| 2         | 1           | 4         |
| 11           | Medium   | Low     | Low      | 1         | 1           | 4         |
| 12           | High     | Low     | Low      | 1         | 1           | 4         |
| 13           | Medium   | High    | Medium   | 1         | 1           | 4         |
| 14           | Very high| Very high| High     | 1         | 1           | 4         |
| 15           | Medium   | High    | Very high| 1         | 1           | 4         |
| 16           | Medium   | Very high| Very high| 1         | 1           | 4         |
| Total        |         |         |          | 91        | 28          | 100       |

Note: The number of years each flow pattern occurred, and percentage of total years are shown for flow data from 1900 to 2011 and the study period from 1984 to 2011.
12.4% and 17.3% or 178 and 226 t (95% CI, 155–257 t). Changes in flow during high- and very-high-flow years (patterns 8 and 10) appeared to have little effect on catch, 1.2% (39 t) and 0.7% (26 t), respectively.

Scenario C included the construction of multiple major instream dams in the Mitchell River that would have had a major impact on EOS flows (Fig. 6c, f). During low-flow conditions (pattern 1), the model predicted a decline in catch of 53.2% or 568 t (95% CI, 498–646 t). The modeled decline in catch across flow patterns 2–4 was similar, ranging from 371 to 426 t (95% CI, 313–482 t). During high and very high flows, the predicted catch was lower in terms of percentage, 9%, but the larger observed catch associated with years of high flows meant predicted catch declined between 305 and 349 t (95% CI, 223–524 t), respectively.

DISCUSSION

We investigated the potential impact of water extraction scenarios on the commercial catch of banana prawns in the economically important Northern Prawn Fishery in northern Australia. The scenarios modeled water extraction-induced changes in seasonal river flows within three catchments in a wet-dry tropical region. Using a novel approach to model the effects of river flows and climate predictors, we found a greater decline in banana prawn catch across all extraction scenarios in years with low to medium river flows than those with high and very high flows. Previous research in this region has linked the variation in catch by using rainfall as proxy for flow or modeled temporal changes in flow from only one or two rivers (e.g., Vance et al. 1985, 2003, Staples and Maliel 1994, Venables et al. 2011, Duggan et al. 2019). Despite differences in statistical approaches between previous studies and our Bayesian spatiotemporal model, we found some similarities in results. For example, a technical report that focused only on the Flinders and Gilbert rivers and a larger geographical catch area found that a reduction in total flows of 852 GL resulted in a decline in catch from 3 to 13% (Bayliss et al. 2014). We predicted a decline in catch from between 0.7% (high flows) and 17.3% (low flows) in scenario B when a total 825 GL of water was extracted from the Mitchell, Gilbert, and Flinders rivers. Overall, our results show that managing equitable water extraction during periods of extended low flows or drought conditions, like those seen in the region from 1985 to 1990, will be particularly challenging for sustaining fishery yields.

Flow and catch

One of the most important findings of this study was the predicted proportional decline in banana prawn catch with decreasing flow levels due to water extraction. In this fishery, annual profits are closely tied to the quantity of banana prawn catch, because market prices for banana prawns are exogenous to the fishery (Kompas et al. 2010). Our analyses of six flow-level patterns across three rivers, delineating low, medium, high, and very high flows, showed that proportionally, catch was most impacted by water extraction during low flows (Fig. 6d, e, f). Low-catch years are when the economic viability
of the fishery may be most sensitive to catch reductions (Kompas et al. 2010). For instance, we predicted that extracting water during low flows would see a year of already poor catch (~1070 t) drop by 53% (Fig. 6c, f). With the current 52 licensed vessels fishing in the Northern Prawn Fishery, a predicted catch of less than 10 t per vessel would adversely impact the livelihoods of many fishers.

We also found the catch of banana prawns was driven by different patterns in wet season river flows both across years and across the three rivers (Table 3). When two or more rivers had medium to very high flows, regional catch was...
higher. The current understanding is that in years with high flows, combined with the Gulf of Carpentaria’s shallow coastal bathymetry, salinity levels are reduced to below the physiological tolerance for banana prawns within both estuarine and near-shore areas (Staples and Vance 1986, Vance et al. 1998). It is also possible that periods of sustained low salinity due to high freshwater flows may prevent recently emigrated juvenile banana prawns from returning to their preferred near-shore habitats. The food supply for banana prawns (benthic animals) in the estuaries is also impacted by low salinity, resulting in major reductions in food availability (Duggan et al. 2019). The estuarine benthic community only re-establishes as salinity increases during the dry season. These conditions are likely to force banana prawns to grow and mature in deeper waters where they are available to the fishery. High flows may also benefit banana prawns in deeper waters by stimulating coastal production at the base of the food web and providing protection from many predators as a result of increased levels of turbidity (Griffiths et al. 2007, Burford et al. 2009). The opposite was also true, low flows in two or more rivers produced lower catch. Within marine-equivalent estuaries, it is likely that without a low salinity mechanism triggering or forcing emigration, banana prawns remained in estuarine or near-shore coastal areas or were simply inaccessible to the fishery (Haywood and Staples 1993, Wang and Haywood 1999, Burford et al. 2010).

The predicted decline in catch in scenario C (Mitchell instream dams) was surprising because many years of catch data have consistently shown relatively low catch in the vicinity of the Mitchell River, suggesting that flow from the

![Graphs and diagrams showing the relative decline in flow and catch](https://www.esajournals.org/doi/fig/10.1890/19-1431.1)
Mitchell River had a limited influence on catch (Laird 2018). Past analyses have had difficulty demonstrating a relationship between Mitchell River flow and adjacent banana prawn catch, or have shown a low contribution of flow (using rainfall as a proxy) to eventual commercial catch (Vance et al. 1985, 2003). Alternatively, it could be that juvenile banana prawns from the Mitchell River are being transported significant distances away from the river mouth. In the southeastern region, seasonal river flows produce large jets of freshwater that interact with Coriolis forces, and tidal and wind-driven currents, and generate salinity-driven currents that move and mix lower salinity water in a southerly direction (Wolanski 1993). We therefore hypothesize that juvenile banana prawns emigrating from the Mitchell River were forced toward the Gulf of Carpentaria’s southern coastal boundary as a result of a low salinity water mass moving south. Thus, banana prawn catch near the Mitchell estuary will be low because juvenile banana prawns that used it as a nursery are potentially recruited to the fishery over 100 km away. Further research is required to fully understand the effect of river flows on regional hydrodynamics, the migration of juvenile banana prawns, and the spatial distribution of catch.

Management implications

In the Gulf of Carpentaria, it is common for years of higher flows to be separated by 4–7 yr of low flows or periods of drought (Fig. 4). This variability in river flow has considerable management implications in balancing the needs of upstream agricultural development and downstream industries, such as the Northern Prawn Fishery. Under all of the modeled water resource development scenarios, water extraction from wet season high and very high flows would have minimal impact on banana prawn catch. Extracting water during periods of high flows could sustain the needs of upstream agriculture over all years if there was enough storage capacity to last through periods of low flows or drought. The protection of low flows, in conjunction with water extraction from high flows, has the capacity to serve the needs of both current users of catchment flows (such as fisheries) and irrigated agriculture, should it become established within the catchments. One of the methods used to protect low flows is to set a minimum flow or trigger level below which water extraction must reduce or cease (Kenyon et al. 2018). Trigger levels should be set quantitatively, deploying the latest empirical studies and modeling to define a rigorous flow level that supports ecosystem stability in each river and catchment (see Bayliss et al. 2014, Petheram et al. 2018, Pollino et al. 2018, Duggan et al. 2019).

Model testing and limitations

A novel component of this study was the use of SOI, cyclones, and OLR climate indices as nonlinear predictors of ocean–atmosphere interactions that influence banana prawn catch. We compared multiple models with different climate covariates, but in general, there was little difference between these models (Appendix S1: Fig. S4, Table S2). The relatively small difference in model performance indicated possible confounding between climate predictors (Fig. 3). Confounded climate predictors could also explain the poor predictive performance of models with two or more climate covariates from increased model instability. The main source of confounding was likely related to climate patterns operating at local and regional scales, captured by the cyclones and OLR indexes, and the ENSO (SOI) oscillating over larger spatial scales. We found some evidence of a 10- to 15-yr oscillation where a negative SOI was correlated with a 25% increase in the intensity of cyclones that occurred one month earlier in the season, and a decrease in regional atmospheric convection measured by an increase in OLR of 10 W/m².

The frequent presence of cyclones and tropical storms in the Gulf of Carpentaria was another potential confounding factor, due to their effect on fisher behavior influencing catch. However, the potential effects of changes in fishing effort due to cyclones and tropical storms were largely minimized because the banana prawn fishing season starts at the transition from wet to dry seasons, when extreme weather events are rare (Fig. 3b). Though cyclones occur less frequently at this time of year, there were two fishing seasons, 1984 and 2006, that were interrupted by cyclones. Both the 1984 and 2006 fishing seasons were included in our models because the two late-season cyclones that were present in the Gulf of Carpentaria were tracked 500 km away from
our study region (BOM 2020). We assumed the effects of cyclones far away had a lower impact on banana prawns and fishing in the southeastern region of Gulf of Carpentaria.

It is likely that including flow data from other major rivers in the Gulf of Carpentaria would improve the model’s predictive power and reduce the variability associated with predictions. Using catch data, instead of CPUE, was not ideal, and unfortunately, it was not possible to obtain better data, due to its commercial sensitivity. We also did not consider the possibility of banana prawn population collapse resulting from one or more years of low flows. Future studies would benefit from a more complete data set where spatial discrepancies with fishing effort could be accurately resolved.

Future Directions

Further exploring the links between climate and the spatiotemporal dynamics of banana prawn populations may be an area of future research that could provide valuable insights into the impact of climate change on fisheries in the region. The model could also be extended to other fishing areas, species, and environmental covariates. While these points identify avenues for future research, this current modeling provides managers and decision makers with substantial information about the implications of potential development that can be integrated into water planning processes.

Acknowledgments

Andrew Broadley was supported by an Australian Government Research Training Program Scholarship and a Northern Australia Environmental Resources/ Northern Environmental Sciences Programme scholarship. Christopher Brown was supported by a Discovery Early Career Researcher Award (DE160101207) from the Australian Research Council. Support was also provided from project 1.4: Contribution of rivers to the productivity of floodplains and coastal areas of the southern Gulf of Carpentaria within the Northern Australia Environmental Resources/Northern Environmental Sciences Programme. We would also like to thank CSIRO for providing access to the Northern Prawn Fishery catch and effort data, and river flow data.

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**Supporting Information**

Additional Supporting Information may be found online at: http://onlinelibrary.wiley.com/doi/10.1002/ecs2.3194/full