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Analysing the effect of Environmental and Hydrological Variability on Fish Growth Rates in Queensland's Dryland Rivers

# Abstract

This project aims to investigate the complex relationships between hydrological and environmental factors, and the growth rates of three key lotic fish species, Golden Perch (*Macquaria ambigua*), Bony Bream (*Nematalosa erebi*), and Common Carp (*Cyprinus carpio*), within South and West Queensland's dryland river systems. Utilizing otolith-derived incremental growth data, along with river flow metrics and annual temperature readings, this research delves into how spatial and temporal variations in streamflow and thermal regimes influence fish growth. The methodology encompasses the extraction and analysis of data via a Power BI Solution developed collaboratively by La Trobe University and the Department of Environment and Science (DES), Queensland, followed by rigorous statistical modeling using R. The predictor variables, including flow volume, duration, temperature accumulation (degree days), and events of drought and flood, will be evaluated for their impacts on annual growth rates. This research aims not only to shed light on the growth dynamics of lotic fish in response to environmental stresses, but also to contribute to the sustainable management and conservation of riverine ecosystems amid increasing climatic and anthropogenic pressures. By exploring the relationships between these predictive factors and fish growth, this project aims to provide valuable insights for ecosystem management and policy formulation and contribute to the long-term resilience of aquatic biodiversity in changing environments.

# Background

There is a complex interplay between spatial and temporal variability in fish migratory behaviour, and their influence on fish morphology (Chapman et al., 2015) and growth (Clausen et al., 2015; Tattam et al., 2017). In lotic habitats such as riverine ecosystems, these influences are compounded by inherent environmental variability, such as streamflow variability and temperature. Research indicates that for some species, stable low-flow periods that follow periods of sudden and increased flow rates tend to yield higher growth rates, especially if coupled with warmer temperatures (Haworth & Bestgen, 2016; Tonkin et al., 2017). These findings have significant implications for the monitoring and management of riverine ecosystems. For instance, relationships between flow variability and growth of fish highlights how regulatory measures that modify the flow of water in lotic ecosystems could be detrimental to the growth of certain species. These effects are also subject to much temporal variability, with higher growth rates not only being associated with periods of warmer temperature, but also higher hydrological variability during critical life stages (Tonkin et al., 2017). Therefore, species management interventions must carefully consider not only the environmental factors that serve as predictor variables, but also their spatio-temporal scales. Monitoring the growth of species during drought conditions is also a important way of understanding how the response to such disturbance changes with frequency and severity of such disturbance events (Magoulick & Kobza, 2003). For the purposes of this research, the term refugia, is used as defined by Lancaster & Belyea (Lancaster & Belyea, 1997); ‘places (or times) where the negative effects of disturbance are lower than in the surrounding area (or time)’. Prior research on isolated habitats that are relatively small also suggest that food web interactions, including predator prey interactions are heightened during such cases (Gido et al., 2015; Jackson et al., 2001; Magoulick & Kobza, 2003), in particular where species are present in high densities, and prey refuges are few? (prey refuges? Is this an important point?). Research also shows that smaller water bodies, such as the islotated refuges in this instance, exacerbate the biotic and abiotic stressors. For example, smaller water bodies exhibit a higher degree of temporal variation in oxygen and temperature (Jackson et al., 2001). Aside from changes wrought from extreme events such as drought s and floods, the biogeographically insular nature of the refuges themselves can alter much of the physico-chemical and biological properties of the habitat. The increased evaporation and low water flow associated with such water bodies can cause increased sedimentation, salinity and turbidity (Pettit et al., 2012; Wager & Unmack, 2000). There is also a significant impact on biotic processes and interactions, such as predator-prey interactions, exposure to disease and parasites, competition and migration. Sudden and often severe changes in these processes have been associated with fish mortality in such dryland refuges (Balcombe et al., 2005; Magoulick & Kobza, 2003; Turschwell et al., 2019; Wager & Unmack, 2000)

Within this context, the distinctive hydrological characteristics of South and West Queensland's dryland rivers serve as a compelling case study to better understand the impacts of environmental variability on fish migration, growth and survival. The Bureau of Meteorology classifies large swathes of this region of Queensland as arid and semi-arid (Bureau of Meteorology, 2007), where habitats are typically characterised by either low rainfall throughout the year, or by wet summers and low rainfall winters. Dryland rivers, which are a critical aquatic habitat in this region, experience cyclic conditions of “booms” in productivity due to episodic floods and “bust” periods after the waters recede, leaving behind perennial and semi-perennial waterholes that serve as drought refuges for many aquatic species (Arthington & Balcombe, 2011; Sheldon et al., 2010). These refuges play a central role in shaping the ecological dynamics of intermittent (dryland) riverine species, influencing key processes such as growth and resilience (Marshall et al., 2016).

This project aims to look at the impact of various environmental and hydrological factors on, growth rate of golden perch (*Macquaria ambigua*), Bony bream (*Nematalosa erebi*) and Common carp (*Cyprinus carpio*) populations in local riverine systems that experience flow intermittency. Otoliths are Otolith biochronology will be used as a means of examining the impact of these factors and their spatiotemporal variability, on incremental growth rates in these three species across 11 sites in rivers in the Northern Murray-Darling Basin. Why otoliths, why is it valid. Who has used before. How

Monitoring growth and movement in fish populations can be challenging, particularly when the species in question exhibit migratory behaviour. Sclerochronological studies, which analyse incremental marks on calcified structures, are one method utilised to address this issue. In particular, otolith (ear bone) growth rings are widely researched and recognised as effective proxies for tracking fish growth, as well as the impact of pertinent environmental parameters such as temperature (Dunlop et al., 2023; Gillanders et al., 2012; Martino et al., 2019; Morrongiello et al., 2019).

While a number of factors such as diet, temperature and age of the fish does impact how closely otolith size may reflect growth rate (Ashworth et al., 2017; Fey, 2006),

This project not only aims to answer specific research questions regarding the magnitude and effect of various predictive factors such as temperature and flow variability on growth, but also to contribute to the broader discourse on sustainable water resource management in the face of increasing climate variability and anthropogenic disturbance. All research outputs will be transparent and accessible via a GitHub repository, facilitating further research and application.

# Methods and Approach

## 2.1 Data Sources

A range of ecological and environmental datasets will be utilised for this project, including data on otolith-derived incremental growth rates, from age 1 to age 2 for the three fish species, river flow metrics, and annual average temperature readings. These datasets will be accessed and extracted via a Power BI Solution developed by La Trobe University, with input from the Department of Environment and Science (DES), Queensland. The streamflow data and temperature data contained therein will be sourced from stream gauges installed within the study area. The raw datasets will be collated and organized via R, to create a consolidated dataset that will be used for subsequent data analysis.

## 2.2 Predictor Variables

The primary focus of the analysis will be to evaluate the impact of various environmental and hydrological factors on the annual growth rates (via otolith growth rings) of three lotic fish species. The predictor variables, derived from the data sourced through the Power BI dashboard, will include:

* Flow Volume: The mean, minimum, maximum water levels, to reflect the dynamics of water flow within the habitat.
* Flow Duration: The length of time for which water flow is sustained at various levels, affecting connectivity and movement.
* Bank full Flow Conditions: Indicates the maximum carrying capacity of the river, without overflowing, and consequently disrupting sediment transportation and habitat structure.
* Flow Days: The number of days with significant water flow, potentially affecting feeding opportunities and other interactions within the food web.
* Water Temperature (Annual Average): Indicating the thermal conditions experienced at the study sites annually.
* Temperature Accumulation (Degree Days): A cumulative measure of heat exposure over time, which influences fish metabolic rates and growth cycles.
* Drought and Flood Events: Instances of extreme low and high waterhole volume, affecting habitat quality and food availability.

Additional variables might be considered depending on their availability and relevance to the growth patterns observed in the otolith data. These could encompass environmental features such as habitat composition, water quality parameters, and anthropogenic influences. The inclusion of these variables will be adaptive and, contingent upon their statistical significance to the models, the insights they provide into the growth rates of the species being studied and the convergence properties of the models themselves.

## 2.3 Modeling

The primary final product will be a comprehensive analytical script prepared with the programming language R that tidies, prepares for analysis and thoroughly explores the dataset to examine the impact of the various environmental and hydrological factors outlined above, on the otolith growth patterns in Golden perch, Bony bream, and Common carp. The initial steps will involve data visualisation and generation of descriptive statistics to guide the modeling process. Following this, a methodologically iterative approach will be taken to explore the relationships between environmental factors and otolith growth patterns. This means starting with simpler models to understand basic relationships, then progressively incorporating more complex models to incorporate more nuance. This phased approach allows for a thorough exploration of the data, ensuring that the final model(s) provide insightful and reliable predictions about the impact of hydrological factors on fish growth rates. The aim is not only to identify significant environmental influences on individual fish growth but also to understand the magnitude of their effects, contributing to informed management strategies for riverine ecosystems. Some of the model types that will be considered include the following:

**Multiple Linear Regression:**

* Overview: A foundational method to quantify and model the relationship between fish growth and one or more of the independent variables.
* Implementation: The lm() function will be used to estimate model parameters, starting with a base model and iteratively adding potential predictors.
* Evaluation: Model diagnostics such as residual plots, QQ-plots, and the variance inflation factor (VIF) will be employed to check the assumptions and fit of the model. The R-squared value will be used to provide insight into the explanatory power of the model.

**Mixed Effects Models:**

* Overview: These models will consider both fixed and random effects of the predictor variables on otolith growth and are predicted to be especially useful where there is spatial or temporal nesting within the data.
* Implementation: Implementation will be using the lmer() function from the ‘lme4’ package in R, fixed effects of predictors will be analysed while accounting for the random variations across catchments and sites.
* Evaluation: Model fit will be evaluated using likelihood ratio tests, and AIC and BIC criteria. As with multiple linear regression, model assumptions will be checked via residual plots.

**Generalized Linear Models (GLMs):**

* Overview: These models will extend linear regression to allow for response variables that have error distributions other than a normal distribution.
* Implementation: The glm() function will be employed, and Gaussian GLMs will be the primary focus, but the project will explore variations, adjusting fixed and random effects, and trying different link functions based on data distribution.
* Evaluation: Deviance and residuals will be the key evaluation metrics. The goodness of fit will be evaluated using the AIC and BIC.

**Advanced Techniques (Tentative):**

Random Forest and Artificial Neural Networks (ANNs) may be explored for their ability to capture non-linear relationships and complex interactions within the data. The choice to use these techniques will depend on initial findings from simpler models and the complexity of the data.

## 2.4 Data Splitting and Model Validation

Prior to modeling, the dataset will be divided into training and testing sets to validate model performance on unseen data.

**Training Set:** This subset will include 80% of the original dataset, and will be used for model development and training, enabling algorithms to learn the relationship between the dependant and independent variables.

**Testing Set:** This subset will comprise the remaining 20% of data, it will be used to evaluate the performance of each model on ‘unseen’ data, to prevent overfitting.

An additional validation set will be used specifically for Artificial Neural Networks, to fine-tune the model parameters without impacting the test set, ensuring it remains an unbiased measure of model performance.

# 3.0 Schedule

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  |  |  | April | | May | | | |
| Milestone description | Start | Days |  | 3 | 4 | 1 | 2 | 3 | 4 |
| **Literature Review and Finalisation** | | | | | | | | | |
| Review background literature. | 15/04/24 | 2 |  |  |  |  |  |  |  |
| Finalize objectives and expected outcomes of the project. | 17/04/24 | 1 |  |  |  |  |  |  |  |
| **Accessing and Preparing Data** | | | | | | | | | |
| Combine datasets to create a comprehensive and consolidated dataset for modeling | 18/04/24 | 1 |  |  |  |  |  |  |  |
| Identify missing data points and inconsistencies | 19/04/24 | 1 |  |  |  |  |  |  |  |
| Preliminary data exploration and creating a tidy dataset | 20/04/24 | 3 |  |  |  |  |  |  |  |
| Data preprocessing: Normalize, standardize, or transform data as necessary. | 23/04/24 | 2 |  |  |  |  |  |  |  |
| Split data into training and testing sets (and validation set for ANNs). | 25/04/24 | 1 |  |  |  |  |  |  |  |
| **Modeling** | | | | | | | | | |
| Initiate modeling process with Multiple Linear Regression Models and Polynomial Regression Models. | 26/04/24 | 2 |  |  |  |  |  |  |  |
| Fit models, test assumptions, and evaluate initial results. | 28/04/24 | 2 |  |  |  |  |  |  |  |
| Continue modelling process with Generalized Linear Models (GLMs). | 30/04/24 | 2 |  |  |  |  |  |  |  |
| Evaluate the GLMs using AIC and BIC. | 02/05/24 | 2 |  |  |  |  |  |  |  |
| Start Random Forest modeling. | 04/05/24 | 2 |  |  |  |  |  |  |  |
| Evaluate predictor importance and model performance. | 06/05/24 | 2 |  |  |  |  |  |  |  |
| Start developing Artificial Neural Networks (ANNs). Adjust architectures and activation functions as needed | 08/05/24 | 2 |  |  |  |  |  |  |  |
| Validate models using the dedicated validation set to prevent overfitting | 10/05/24 | 1 |  |  |  |  |  |  |  |
| Evaluate the ANN models using MAE and RMSE | 11/05/24 | 1 |  |  |  |  |  |  |  |
| Compare all models side-by-side and identify the most accurate and efficient model(s) for predicting growth. | 12/05/24 | 1 |  |  |  |  |  |  |  |
| **Report Drafting** | | | | | | | | | |
| Draft a comprehensive report detailing methodologies, results, findings, and recommendations. | 13/05/24 | 5 |  |  |  |  |  |  |  |
| Review, edit, and finalize the report | 18/05/24 | 5 |  |  |  |  |  |  |  |
| **Seminar Preparation** |  |  |  |  |  |  |  |  |  |
| Synthesize key points from report | 18/05/24 | 2 |  |  |  |  |  |  |  |
| Develop visual aids and prepare PowerPoint presentation | 20/05/24 | 3 |  |  |  |  |  |  |  |

# 4.0 Project Deliverables

The completion of this project will yield a suite of deliverables which are designed to provide insight into how various environmental and hydrological factors affect growth and movement in lotic fish species. These outputs will inform management interventions and conservation efforts, so that they can be better guided to reflect these relationships.

**Predictive Models and R Script:**

The outcomes will include code including a collection of rigorously developed models, such as Multiple Linear Regression, Mixed Effects Models, and Generalized Linear Models (GLMs), Random Forest, and Artificial Neural Networks (ANNs), all geared towards exploring how various factors affect growth in lotic species. In the interest of ensuring transparency and reproducibility, the full R code for each of these modeling processes will be shared via GitHub and other agreed means.

**Visualisation and Model Evaluation:**

Detailed visual representations will be used to illustrate the dynamics between fish growth and environmental factors, complemented by graphical representations and plots showing the predictive abilities of each model. Where Artificial Neural Networks are utilised, architecture diagrams will also be included, depicting layers and activation functions.

Detailed statistical evaluations of each model's performance, including R-squared values, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) will be presented.

**Final Report:**

This document will compile the research findings, outlining the methodology, data analysis, and interpretations of how environmental and hydrological conditions influence lotic fish species. Recommendations for management actions and potential areas for further investigation will be highlighted, aiming to contribute to sustainable ecosystem management.

**Seminar Presentation:**

The key findings of the research will be synthesized into a PowerPoint presentation and will be designed to encourage dialogue on the practical applications of the research and prospective directions for advancing current knowledge and practices in riverine ecosystem conservation.

These deliverables collectively aim to provide stakeholders, researchers, and policymakers with the knowledge and tools necessary to predict and respond to the impacts of environmental changes on the growth and population dynamics of riverine fishes, thereby supporting informed decision-making for ecosystem management and conservation.

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