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# Marine Scotland

# THE POTENTIAL INFLUENCE OF ROBIN RIGG WIND FARM ON THE ABUNDANCE OF ADULT AND JUVENILE ATLANTIC SALMON

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## FINAL REPORT

## FEBRUARY 28, 2013

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# Executive summary

- Data on the abundance of adult (rod catch) and juvenile (electrofishing surveys) Atlantic salmon were analysed to assess the potential impact of offshore wind farm construction and operation on local stocks.
- Given the available data and assumptions of the models (including choice of treatment and control rivers) no significant effect of wind farm construction was detected on the abundance of either adult or juvenile salmon.
- The findings of this analysis should be interpreted in the context of the limited power of both the rod catch (adult abundance) and electrofishing (juvenile abundance) data to detect change. Specifically, there is a 1 in 5 chance that the wind farm could be depressing Atlantic salmon abundance in potentially affected rivers by as much as 40% without being detected.
- In the current situation, where there is not an opportunity for obtaining greater pre-development baseline information, the collection of additional electrofishing data does not improve the chances of detecting an effect of the wind farm beyond that already provided by the rod catch data (a freely available resource collated by Marine Scotland Science).
- Given the associated costs, it is suggested that the collection of additional electrofishing data is therefore unwarranted at the present time.
- Given the remaining uncertainty and the (small) improvements in statistical power provided by longer runs of data, it is suggested that the rod catch data should continue to be monitored and assessed.
- If, in the future, rod catch data suggest a substantial decline in adult numbers returning to the rivers to the north-east of the wind farm relative to those on the Irish Sea side, then collection of supplementary electrofishing data may be justified.
- It is recommended that prior to a future offshore development situational-specific power analyses should be performed and a decision made with regard to the amounts and types of data to be collected.

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# Introduction

The Scottish Government has a target for 100% of Scottish demand for electricity to be met by renewable energy production by 2020. The Robin Rigg wind farm development was the first major offshore wind farm development in Scotland. The development can produce approximately 180 Megawatts of electricity from 60 turbines. Robin Rigg wind farm was constructed between December 2007 and February 2010 and has been operational since February 2010 (Natural Power 2011). It is located on the Scottish side of the Solway Firth (Figure 1), 11 km from the nearest landfall at Balcary Point on the coast of Dumfries and Galloway, and 13 km from the Cumbrian coast. Each of the 60 turbines is connected to offshore substations by subsea cables. These substations are connected to the local electricity distribution system by two 132 kV cables. The cables come ashore near Seaton, Cumbria, where they run about 2 km inland to a new onshore substation. It is possible that wind farm developments could affect migratory fish through barrier effects caused by the introduction of new structures, electromagnetic fields and noise to the development area

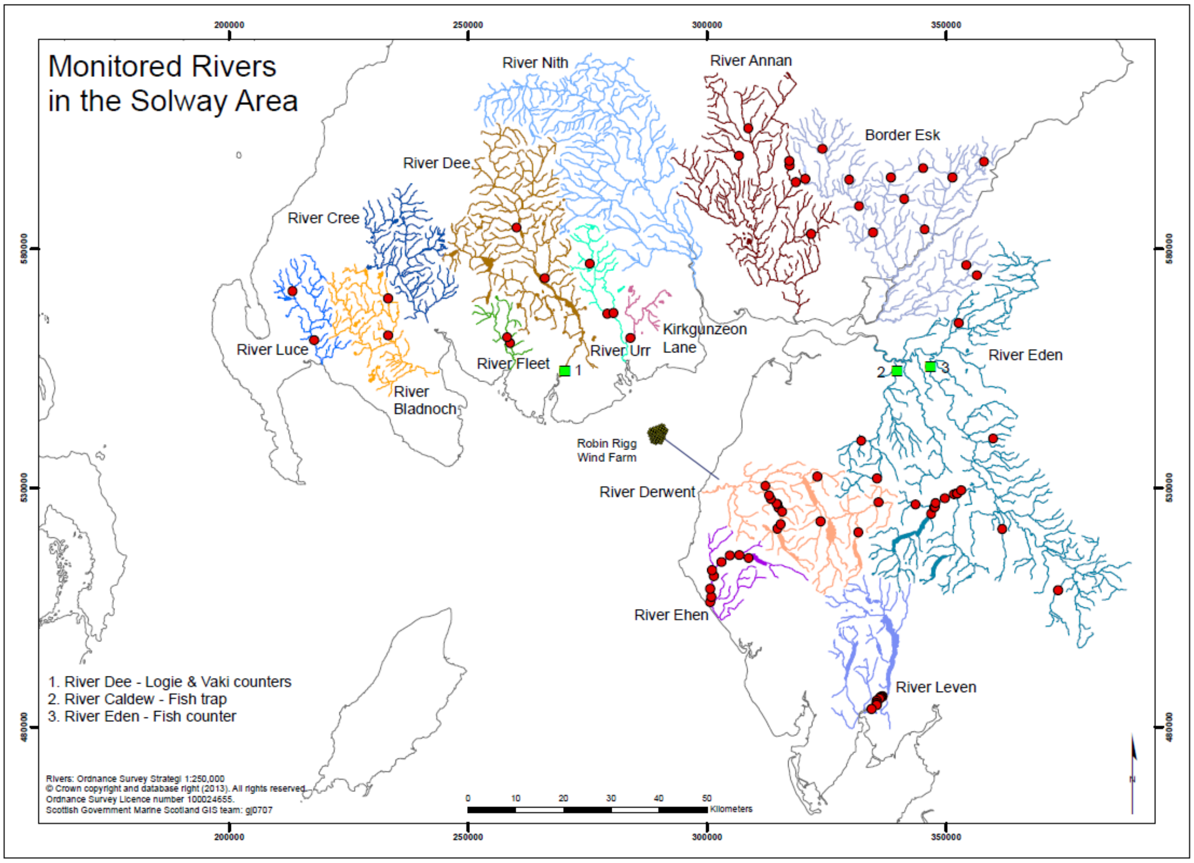

Figure 1.The major rivers in the Solway Area showing the locations of electrofishing sites and counters/fish traps.

A monitoring plan was established for Robin Rigg to try and assess the potential impacts of the development on birds, marine mammals and fish. In the case of diadromous fish (fish spending part of their life cycle in both marine and fresh water environments) a decision was taken to largely rely on pre-existing data for the Solway area that was collected for other purposes, supplemented by a small amount of additional data collection, specifically associated with this development. This report analyses available data for the Solway area in an effort to determine whether there is any evidence of an impact from the wind farm. Importantly, because there is a strong desire to apply lessons learned from Robin Rigg to inform the design of future monitoring plans power analyses are also performed to determine the magnitude of effect that would have been required for it to have been detectable given available data. Some recommendations are then made given the findings of the analysis.

The potential effects of the wind farm on Atlantic salmon abundance were determined from adult rod catch data (as a surrogate for adult abundance) and juvenile electrofishing data using hierarchical Bayesian models. Power analyses were performed on simulated rod catch and electrofishing data to determine the suitability of the available data to detect an effect. Adult returns from three counters were also examined qualitatively.

# Methods

The rod catch and electrofishing data were analysed using hierarchical Bayesian Before-After Control-Impact (BACI) models (Smith et al. 1993). Given the lack of detailed local knowledge on salmon migratory routes and the potential for interaction with the wind farm it was necessary to make a pragmatic decision over which rivers would constitute controls and treatment rivers. For the purposes of this analysis, those rivers where the river mouth lay to the Irish Sea side of the wind farm and allowed for direct migration without passing perpendicular to the wind farm or cable routings were considered controls while the River Urr and other rivers to the north-east of the wind farm were considered to be treatments (potentially impacted rivers) (Table **1**).

Table 1. The major rivers in the Solway Area and their status with respect to the Robin Rigg wind farm

| River | Status |
|---|---|
| Luce | Control |
| Bladnoch | Control |
| Cree | Control |
| Fleet | Control |
| Dee (Kirkcudbright) | Control |
| Urr | Treatment |
| Nith | Treatment |
| Annan | Treatment |
| Esk | Treatment |
| Eden | Treatment |
| Derwent | Control |
| Ehen | Control |
| Leven | Control |

The before period (period prior to construction) was considered to be pre-2008. The estimated influence of the wind farm on abundance was expressed in terms of the estimated percent change in abundance with 95% credibility intervals (Bradford et al. 2005). The model structure and parameters from the rod catch and electrofishing analyses were then used to simulate data with a known impact spanning different magnitudes and different numbers of years. The simulated data sets were analysed using the original model and the probability of detecting an effect (the power) estimated (Peterman 1990).

## Adult Abundance

The effect of the wind farm on adult abundance was estimated from rod catch data for the Scottish rivers collated and provided by Marine Scotland Science. Both fish which are retained and fish which are released are included. The model, a generalized linear BACI model with autocorrelation, and modelling approach, are described in Appendix A. In short, the annual log catches were modelled as a linear function of year where the regression was allowed to vary by river and sea-age. Year was also modelled as a first-order autoregressive (AR1) random effect to account for region-wide influence and a AR1 term was included to account for autocorrelation in the log-normally distributed residuals. The effect of the wind farm was modelled by a single parameter that described a fixed change in the log rod catches in the treatment rivers from 2008 onwards. The significance of the fixed change was determined using the Bayesian equivalent of a two-sided p-value (Appendix A).

In order to estimate the power of the data and fitted models, the probability of detecting a decline in abundance from 10 control and 6 treatment rod catch time series following 56 before years (equivalent to the current situation) was estimated via power analysis. The magnitude of the simulated impact (decline of 10%, 25% and 40%) and the number of years of data post-impact (5, 10 and 25) were varied.

In addition, to the rod catch data, annual upstream counts were plotted and examined for three counters/traps, two of which were in the River Eden which is a treatment river. In 2007 the resistivity counter at Tongland on the River Dee, which is a control river, was replaced by an infra-red counter with both counters being run from July to December 2007. To facilitate comparisons the plotted results for Tongland are the annual upstream counts by counter type from July to December.

## Juvenile Abundance

The effect of the wind farm on juvenile abundance was estimated from multi-pass electrofishing data supplied by the Galloway Fisheries Trust (GFT), Annan District Fishery Board and the Environment Agency (EA) and collated by the GFT. The July to September electrofishing data were analysed using a hierarchical Bayesian removal model similar to those of Wyatt (2002, 2003) with a BACI component. The model, which was fitted to the electrofishing data for age-0 (fry) and age-1 (parr) separately, is described in Appendix A. In summary the log lineal density (fish/m) was modelled as a function of river, site, river within year and site within year. The capture efficiency, which was assumed to be constant for passes within a site visit, was permitted to vary among site visits. As was the case for the rod catch data, the effect of the wind farm was modelled by a single parameter that described a fixed change in the log lineal density in the treatment rivers from 2009 onwards for age-0 fish and from 2010 onwards for age-1 fish. The significance of the fixed change was determined using the Bayesian equivalent of a two-sided p-value (Appendix A).

Preliminary analysis included the effect of day of the year and log wetted width on the log lineal density but both explanatory variables were dropped from the final models as they were insignificant ($p > 0.05$) for both fry and parr. The effect of parr density on fry density was also examined and although significant it was dropped from the final model as the positive relationship was not thought to be causal i.e. low fry densities can be associated with low parr densities simply because annual spawner counts are autocorrelated. The probability of detecting a decline in abundance given the current sampling data (7 control and 4 treatment rivers with irregular sampling of a total of 80 sites) and the probability of detecting a decline in abundance with an additional year of data from all 80 sites was estimated via power analysis.

# Results

## *Adult Abundance*

The model provided a reasonable fit to the rod catch data (Figure 2) although as a result of the high variability in the rod catches some structuring remained in the residuals (Figure 3) despite the inclusion of an autocorrelation parameter that was permitted to vary between time series. The residual structuring was not sufficient to invalidate the model's conclusions. The effect of year, which was also considered to be autocorrelated, indicates area-wide influences (Figure 4) that are likely due to common drivers such as variation in ocean survival and rod exploitation rates. The model failed to detect a significant effect ($p > 0.05$) of the wind farm on the rod catches in the control rivers (Figure 5), although the importance of this finding should be considered in the context of the power of the data to detect changes.

The power analysis indicates that the number of years of data post-treatment has a relatively minor influence on the probability of detecting an effect compared to the magnitude of the impact and that in order to achieve 80% power the treatment must result in a decline of approximately 40% (Figure 6), i.e. there would have to be a reduction in adult numbers of 40% in each of the treatment rivers relative to the control rivers for an effect to be detected even at the relatively modest 80% level.

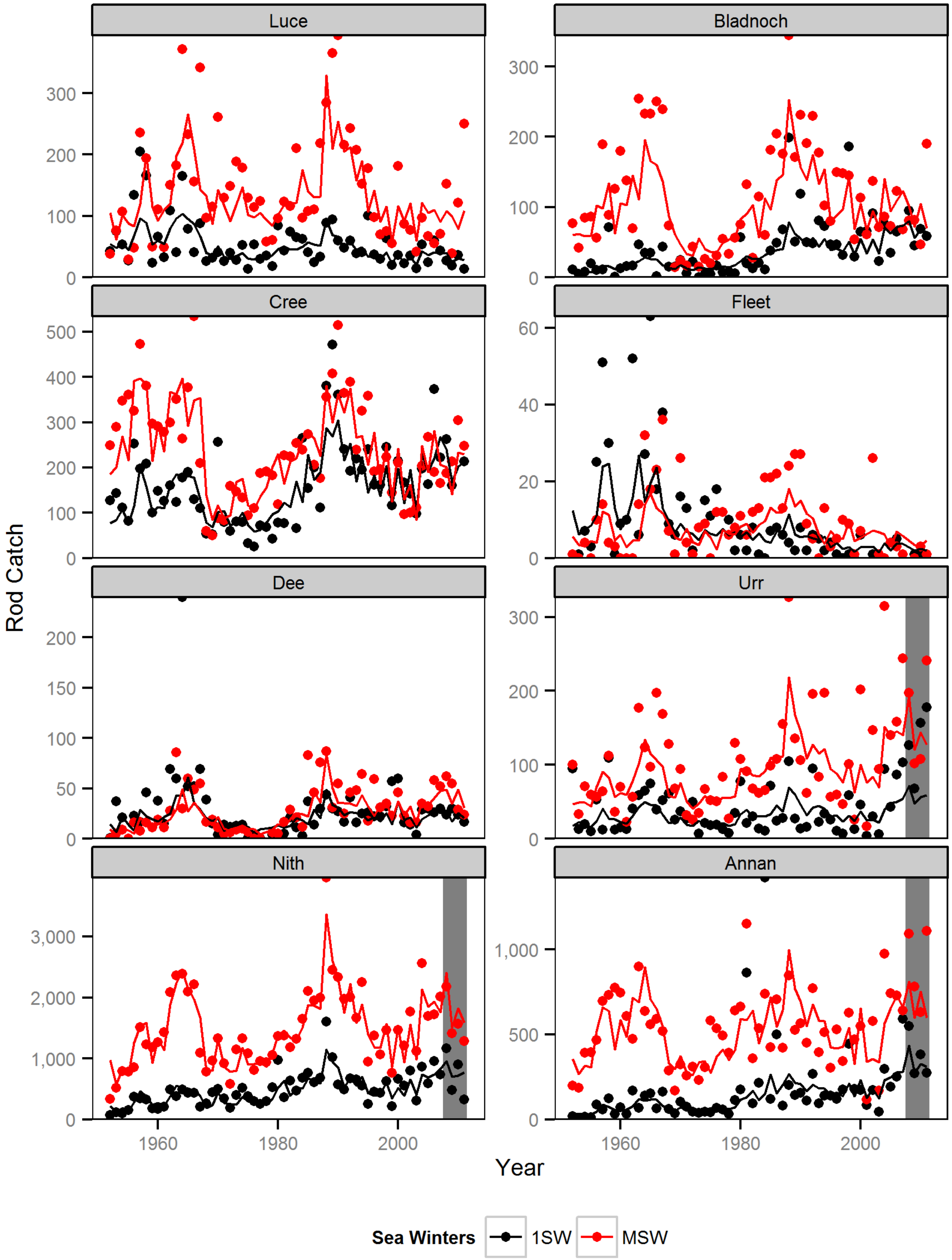

Figure 2.Annual rod catches by time series (river (panels) and sea-age (colour)) together with the model fits (lines). The vertical grey bands indicate the treatment period.

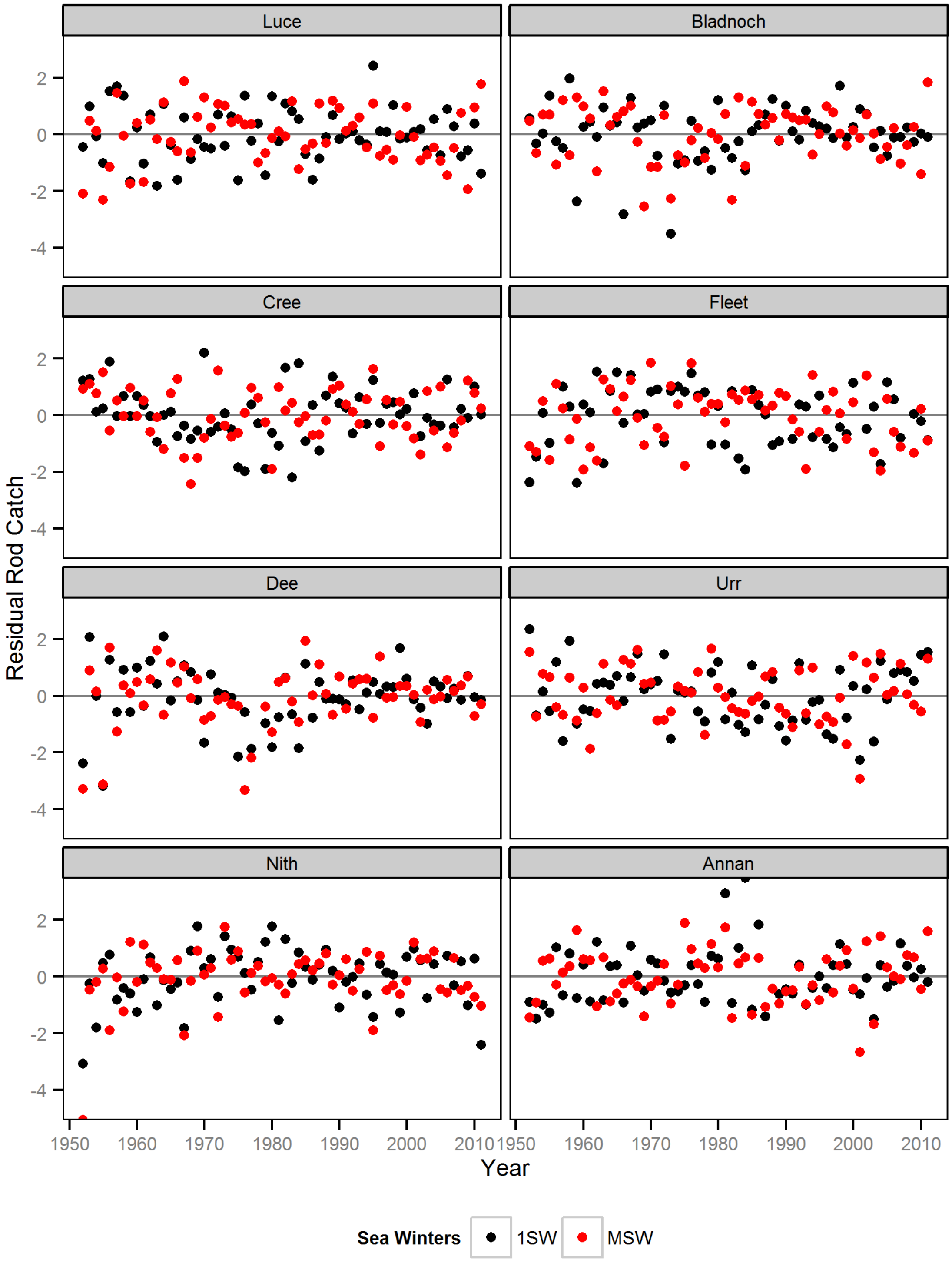

Figure 3.The standardized residual rod catches by time series (river and sea-age).

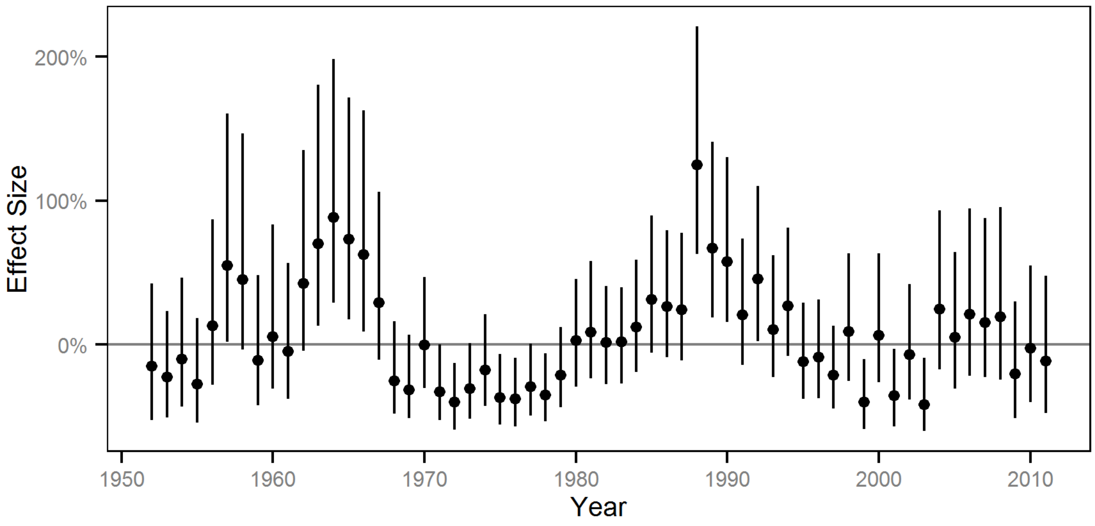

Figure 4.The effect of each year on adult abundance expressed as the percent change in the rod catch in a typical time series. The bars represent 95% credibility intervals.

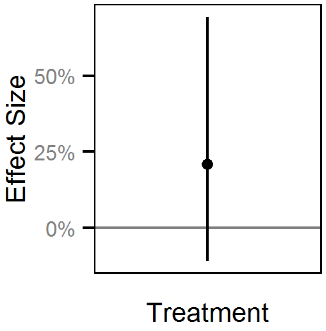

Figure 5.The estimated effect of the wind farm on adult abundance expressed as the percent change in the rod catch in a typical time series. The bars represent 95% credibility intervals. As the 95% credibility intervals include no change (0%), the effect is not significant ($p > 0.05$).

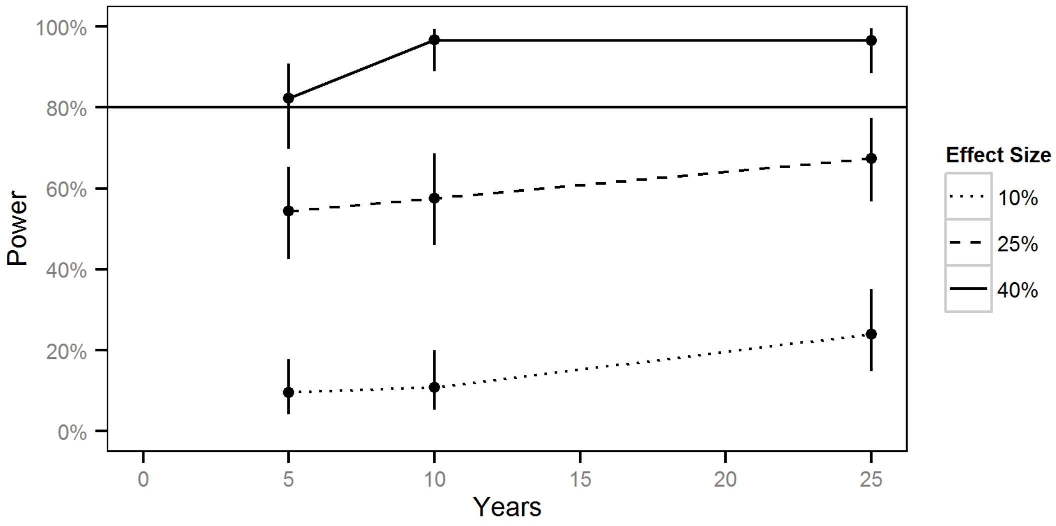

Figure 6.The probability of detecting an effect (the power) by magnitude of effect (% decline in abundance) and number of years post-treatment for the simulated rod catch data. The bars represent 95% credibility intervals.

The switch from a resistivity to infra-red counter at Tongland on the River Dee appears to have resulted in an approximate doubling of the number of upstream counts, assuming that the short cross-calibration period is representative of the wider data (Figure 7). The counts at the Caldew Fish Trap on the River Eden, which is a treatment river, have declined since the wind farm was installed. However three counter-related observations indicate that factors other than the wind farm may be primarily responsible for the decline: 1) the start of the decline at the Caldew Fish Trap predates the wind farm by approximately four years; 2) with the exception of 2011 the counts at the Corby fish counter which is also on the River Eden remained stable during the same period; and 3) the counts at the Tongland fish counter on the River Dee which is a control river declined over the same period. Given these observations formal analysis of the counter data was considered unnecessary.

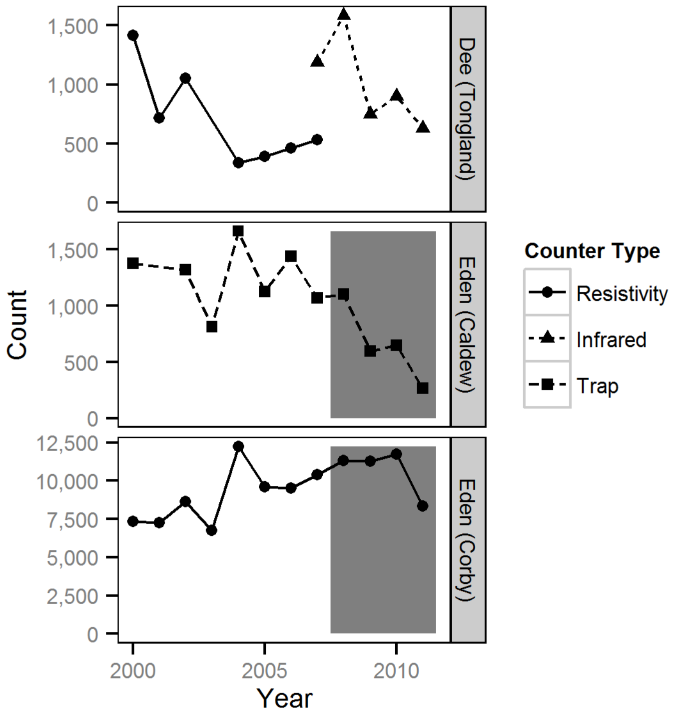

Figure 7.The counter time series by counter and year from 2000 to 2011. The grey band indicates the treatment counts.

## *Juvenile Abundance*

A total of 80 electrofishing sites have been sampled in the seven control and four treatment rivers since 1997 (Figure 8). Analysis of the electrofishing data indicates substantial differences in fish densities by river (Figure 9) although it should be noted that unless the sites represent a random sample the estimated densities may not be indicative of those throughout the river. The expected (median) capture efficiency estimated from the removals was 61% of the remaining fish per pass for fry and 66% for parr (Figure 10). In common with the rod catch analysis no significant effect of wind farm construction / operation was detected on the electrofishing densities of fry or parr (Figure 11). However, these findings should again be interpreted in the context of the statistical power of the data, which was broadly comparable to that of the rod catch data and indicated that even a 40% reduction in numbers was unlikely to be detected with currently available data. The power analysis also indicates that an additional year of sampling for all 80 electrofishing sites has a relatively minor influence on the power (Figure 12).

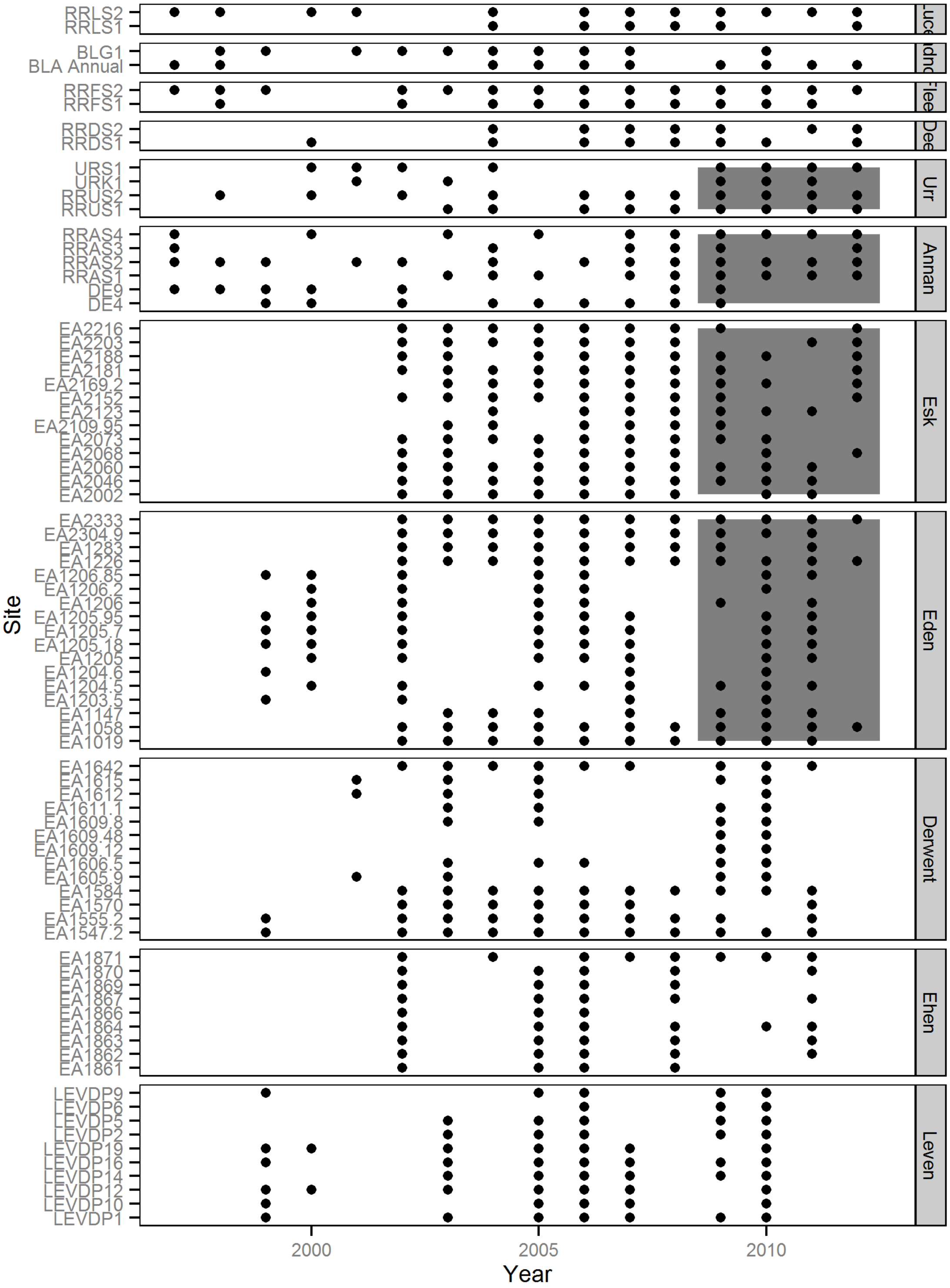

Figure 8.The sampling of electrofishing sites by river and year. The grey band indicates the treatment sites for fry (for parr the treatment period starts a year later). The first four rivers are the Luce, Bladnoch, Fleet and Dee, respectively.

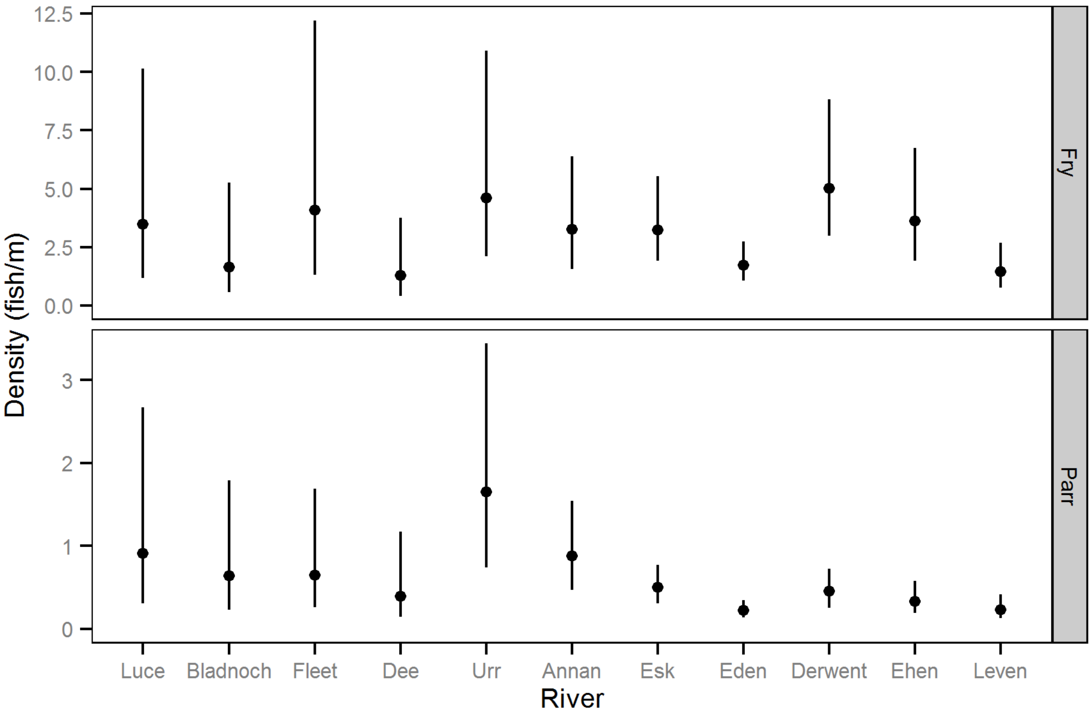

Figure 9.The estimated lineal fish densities for fry (age-0) and parr (age-1) in a typical year and at a typical site by river. The bars represent 95% credibility intervals.

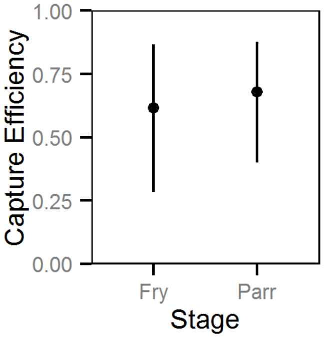

Figure 10.The estimated capture efficiencies for fry (age-0) and parr (age-1). The bars represent 95% credibility intervals.

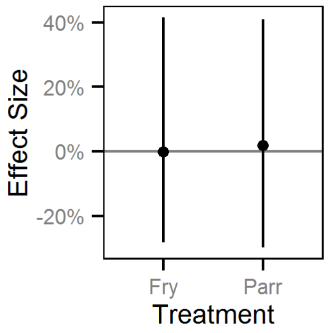

Figure 11.The estimated effect of the wind farm on juvenile densities expressed as the percent change in the lineal fish density at a typical site. The bars represent 95% credibility intervals. As the 95% credibility intervals include no change (0%), the effect is not significant (p > 0.05).

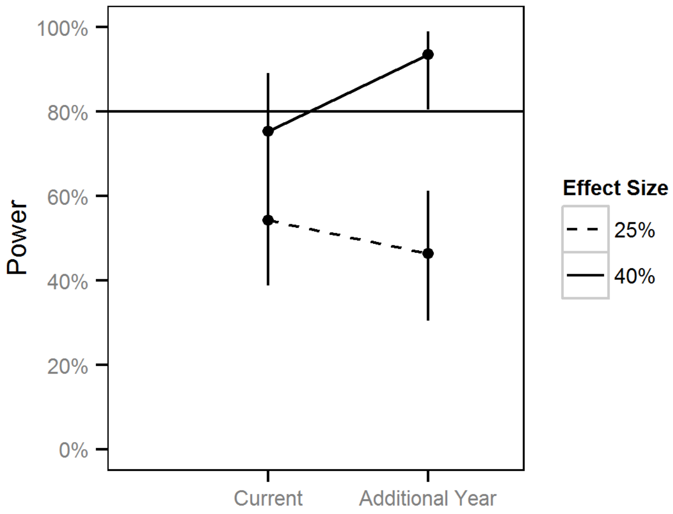

Figure 12.The probability of detecting an effect (the power) by magnitude of effect (% decline in density) given the current data and with an additional year of data from all sites for the electrofishing data. The bars represent 95% credibility intervals

# Discussion

The current analyses did not detect a significant effect of the wind farm on adult (rod catch data) or juvenile (electrofishing data) Atlantic salmon abundance in the Solway area. However the sensitivity of both the rod catch and electrofishing data is limited and there is a 1 in 5 chance that the wind farm could depress adult Atlantic salmon abundance in the treatment rivers by as much as 40% without being detected. In the case of the electrofishing data the chance of failing to detect an impact is even higher as the non-linear nature of stock-recruitment relationships means adult abundance can vary substantially with little to no effect on juvenile abundance, depending on the position of stocks on the local stock-recruitment relationship. Furthermore it is important to note that the analyses assume that an effect of the wind farm will result in a step change in abundance associated with the treatment rivers. If an effect was more spatially or temporally graduated then the power of the analyses to detect it would be further reduced.

Given the uncertainty it would be desirable to work towards a more definite answer. However, the power analyses indicate that the collection of additional post-construction electrofishing data will not substantially improve the ability to detect an impact beyond that already provided by the rod catch data. Given the costs of electrofishing, the collection of additional data is therefore considered unwarranted at the present time. Nonetheless if the rod catch data indicate a significant decline in the rivers to the north-east of the wind farm relative to the controls then this should be revisited.

The current report examines three types of information about Atlantic salmon abundance in the Solway Firth: rod catches, juvenile electrofishing and counter/trap data. The relative value and cost of these three types of data are discussed in more detail by Youngson et al. (2007) who state that “no single category of information is sufficient to provide all the insights that are required for management in all the various forms in which it might be practiced.” In the current situation the power analyses indicate that the available electrofishing data does not provide additional power beyond that provided by the rod catch data. However it is important to note that this conclusion is context specific and depends on the number and size of the control and treatment rivers as well as the amount of baseline electrofishing data, counter data and stability of the rod fisheries. Consequently, it is recommended that prior to a future offshore development situational-specific power analyses should be performed and a decision made with regard to the amounts and types of data to be collected.

# Closure

This report is to the best of my knowledge accurate and correct. If you have any questions regarding its contents please contact the undersigned.

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# Appendix A

# Bayesian Analyses

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28 February 2013

## 1 General Approach

Bayesian models were fitted to the data using the software packages R 2.15.2[9] and JAGS 3.3.0[7] which interfaced with each other via the rjags R package. In general the models assumed low information uniform or normal prior distributions. The posterior distributions were estimated from a minimum of 1,000 samples thinned from the second halves of three Gibbs sampling chains. Model convergence was confirmed by ensuring that R-hat (the Gelman-Rubin-Brooks potential scale reduction factor) was less than 1.1 for each of the parameters in the model[3, 5, 4]. Where relevant, the statistical significance of particular parameters was calculated using two-sided Bayesian p-values[1, 6].

Following Bradford et al. (2005)[2], the influence of particular variables was, where informative, expressed in terms of the effect size (i.e., percent change in the response variable) with 95% credibility intervals with the other variables held constant. When additional variables were random effects, the percent change in the response was quantified with respect to the typical value, i.e., the expected value of the underlying distribution from which the observed values represent random draws. Plots were produced using the ggplot2 R package [10].

## 2 JAGS Distributions, Functions and Operators

JAGS distributions, functions and operators are defined in the following two tables. For additional information on the JAGS language, which is a dialect of the BUGS language, see the JAGS User Manual[8].

| JAGS Distribution | Description |
|---|---|
| dlnorm(mu, sd^-2) | Log-normal distribution |
| dnorm(mu, sd^-2) | Normal distribution |
| dunif(a, b) | Uniform distribution |

| JAGS Function or Operator | Description |
|---|---|
| <- | Deterministic relationship |
| ~ | Stochastic relationship |
| 1:n | Vector of integers from 1 to n |
| for (i in 1:n) {...} | Repeat ... for 1 to n times incrementing i each time |
| log(x) | Logarithm of x |
| T(a, b) | Truncation of a distribution between a and b |
| x - y | x minus y |
| x * y | x multiplied by y |
| x + y | x plus y |
| x[1:n] | Subset of first n values in x |
| x^y | Power where x is raised to the power of y |

# 3 JAGS Models

The following sections provide the variable and parameter definitions and JAGS model code for each of the analyses.

## 3.1 Rod Catch

### 3.1.1 Variables and Parameters

| Variable/Parameter | Description |
|---|---|
| bAR1[sr] | First order autoregressive correlation in log catch for srth series |
| bAR1MU | Mean of first order autoregressive correlations on log catches among series |
| bAR1SD | SD of first order autoregressive correlations on log catches among series |
| bCorYear | First order autoregressive correlation of effect of year on log catch |
| bIntercept[sr] | Log catch intercept for srth series |
| bInterceptMU | Mean of log catch intercepts among series |
| bInterceptSD | SD of log catch intercepts among series |
| bsCatchMU | Mean of SDs of residual log catches among series |
| bsCatchSD | SD of SDs of residual log catches among series |
| bTheta[sr, yr] | Expected log catch for srth series in yrth year with autocorrelation |
| bTime[sr] | Effect of time (standardized year) on log catch for srth series |
| bTimeMU | Mean of effect of time (standardized year) on log catches among series |
| bTimeSD | SD of effect of time (standardized year) on log catches among series |
| bTreatment[tm] | Effect of tmth treatment on log catch |
| bYear[yr] | Effect of yrth year on log catch |
| CatchA[sr, yr] | Catch in srth series in yrth year |
| eLogCatch[sr, yr] | Expected log catch for srth series in yrth year without autocorrelation |
| sCatch[sr] | SD of residual log catch for srth series |
| sYear | SD of effect of year on log catch |
| TimeA[sr, yr] | Time (standardized year) of srth series in yrth year |
| TreatmentA[sr, yr] | Treatment of srth series in yrth year |

### 3.1.2 Model Code

```
model {
```

```
  bInterceptMU ~ dnorm(0, 5^-2)
  bInterceptSD ~ dunif(0, 5)

  bTimeMU ~ dnorm(0, 5^-2)
  bTimeSD ~ dunif(0, 5)

  bAR1MU ~ dnorm(0, 1^-2)
  bAR1SD ~ dunif(0, 1)

  bsCatchMU ~ dnorm(0, 5^-2)
  bsCatchSD ~ dunif(0, 5)

  bTreatment[1] <- 0
  for (tm in 2:nTreatment) {
    bTreatment[tm] ~ dnorm(0, 5^-2)
  }

  bCorYear ~ dunif(-1, 1)
  sYear ~ dunif(0, 1)
  bYear[1] ~ dnorm(0, sYear^-2)
  for (yr in 2:nYear) {
    bYear[yr] ~ dnorm(bCorYear * bYear[yr-1], sYear^-2)
  }

  for (sr in 1:nSeries) {
    bIntercept[sr] ~ dnorm(bInterceptMU, bInterceptSD^-2)
    bTime[sr] ~ dnorm(bTimeMU, bTimeSD^-2)
    bAR1[sr] ~ dnorm(bAR1MU, bAR1SD^-2) T(-1, 1)
    sCatch[sr] ~ dlnorm(bsCatchMU, bsCatchSD^-2)

    eLogCatch[sr, 1] <- bIntercept[sr]
      + bTime[sr] * TimeA[sr, 1]
      + bTreatment[TreatmentA[sr, 1]]
      + bYear[1]

    bTheta[sr, 1] <- eLogCatch[sr, 1]

    for (yr in 2:nYear) {
      eLogCatch[sr, yr] <- bIntercept[sr]
        + bTime[sr] * TimeA[sr, yr]
        + bTreatment[TreatmentA[sr, yr]]
        + bYear[yr]

      bTheta[sr, yr] <- eLogCatch[sr, yr]
        + bAR1[sr] * (log(CatchA[sr, yr - 1]) - eLogCatch[sr, yr - 1])

      CatchA[sr, yr] ~ dlnorm(bTheta[sr, yr], sCatch[sr]^-2)
    }
  }
}
```

## 3.2 Electrofishing Data

### 3.2.1 Variables and Parameters

| Variable/Parameter | Description |
|---|---|
| bDensityIntercept | Log density intercept |
| bEfficiencyIntercept | Logit efficiency intercept |
| bEfficiencySite[st] | Effect of stth site on logit efficiency |
| bEfficiencyVisit[vt] | Effect of vtth site on logit efficiency |
| eAbundance[i] | Expected number of fish at ith site visit |
| eEfficiency[i] | Expected efficiency on ith site visit |
| eLogDensity[i] | Expected log density on ith site visit |
| ePresent[i] | Estimated number of fish at ith site visit |
| eRemaining[i, ps] | Estimated number of fish at ith site visit prior to psth pass |
| Length[i] | Site length on ith site visit |
| Pass[i, ps] | Fish caught at ith site visit on psth pass |
| sDensitySite | SD of effect of site on log density |
| sDensitySite[st] | Effect of stth site on log density |
| sDensityYear | SD of effect of year on log density |
| sDensityYear[yr] | Effect of yrth year on log density |
| sEfficiencySite | SD of effect of site on logit efficiency |
| sEfficiencyVisit | SD of effect of visit on logit efficiency |
| Site[i] | Site of ith site visit |
| Year[i] | Year of ith site v isit |

### 3.2.2 Model Code

```
model {
    bEfficiencyIntercept ~ dnorm(0, 2^-2)

    sEfficiencyVisit ~ dunif(0, 2)

    sDensitySite ~ dunif(0, 2)
    sDensitySiteYear ~ dunif(0, 2)
    for (st in 1:nSite) {
      bDensitySite[st] ~ dnorm(0, sDensitySite^-2)
      for (yr in 1:nYear) {
        bDensitySiteYear[st, yr] ~ dnorm(0, sDensitySiteYear^-2)
      }
    }

    sDensityRiverYear ~ dunif(0, 2)
    for (rv in 1:nRiver) {
      bDensityRiver[rv] ~ dnorm(0, 2^-2)
      for (yr in 1:nYear) {
        bDensityRiverYear[rv, yr] ~ dnorm(0, sDensityRiverYear^-2)
      }
    }

    bTreatment[1] <- 0
    for (tr in 2:nTreatment) {
```

```
    bTreatment[tr] ~ dnorm(0, 2^-2)
  }

  for (i in 1:nrow) {
    eLogitEfficiency[i] ~ dnorm(bEfficiencyIntercept, sEfficiencyVisit^-2)
    logit(eEfficiency[i]) <- eLogitEfficiency[i]
    log(eDensity[i]) <- bDensityRiver[River[i]]
      + bTreatment[Treatment[i]]
      + bDensitySite[Site[i]] + bDensityRiverYear[River[i], Year[i]]
      + bDensitySiteYear[Site[i],Year[i]]
    eAbundance[i] <- eDensity[i] * Length[i]
    ePresent[i] ~ dpois(eAbundance[i])
    eRemaining[i, 1] <- ePresent[i]
    for (ps in 1:nPass) {
      Pass[i, ps] ~ dbin(eEfficiency[i], eRemaining[i, ps])
      eRemaining[i, ps + 1] <- eRemaining[i, ps] - Pass[i, ps]
      ePass[i, ps] ~ dbin(eEfficiency[i], eRemaining[i, ps])
      bResidual[i, ps] <- Pass[i, ps] - ePass[i, ps]
    }
  }
}
```

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