Analysing the efficacy of novel barrier prioritisation and management tools

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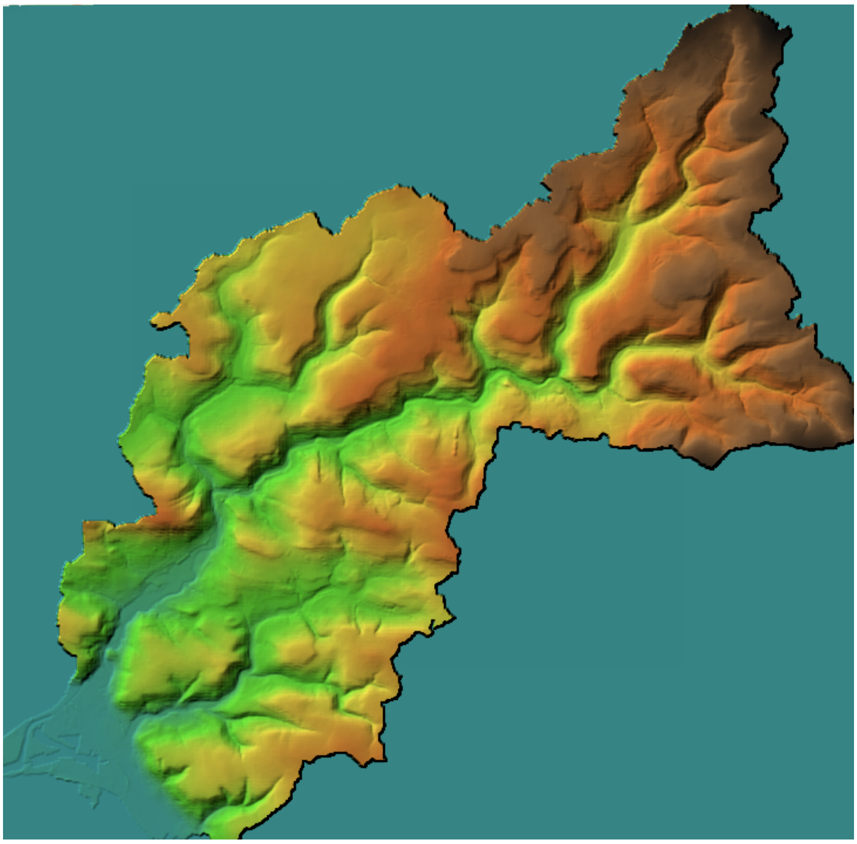

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Summary

Artificial river barriers interrupt the free-flowing nature of rivers, causing habitat fragmentation such as impeding nutrient and sediment delivery and disrupting flow regimes (Lehner et al, 2011; Zarfl et al, 2015). It is important to document and manage river barriers to understand the potential ecological, societal and economic consequences caused by the presence or degradation of an artificial barrier (Zarfl et al, 2015; Fuller et al, 2015). This thesis consists of three chapters, testing novel tools to help, classify and prioritise the removal of barriers.

Chapter one is a repeatability study of barrier classification efficacy. An analysis was conducted on the integrity of a novel 'Barrier ID Protocol', a flowchart that supports easy classifying of river barrier types, with hope of reducing discrepancies around classifying barrier type. The promising results of 'Good' Intraclass Correlation Coefficient (ICC) outcomes when testing repeatability of Rater 1, Rater 2, and Rater 3 and of the inter-rater test, suggests the 'Barrier ID Protocol' potentially reduces the discrepancies between rater observations and thus individual subjectivity.

Chapter two involves the use of desktop surveys for assessing river fragmentation. To address the issues around documentation, I tested the accuracy of using satellite imagery as a viable method in identifying river barriers, with the aim to supersede field work. Using the 'Barrier ID Protocol', observations were recorded and compared with ground-truthed (field) data for a river catchment in South Wales. The results suggested that using satellite imagery should be utilised as a starting point, as we can identify barriers within the Afan catchment and across Wales using remote sensing with a 44% probability of detection. There is a need to supplement with field work, as the findings suggest that environmental predictors (such as forestry cover) play a significant role on the ability to accurately identify artificial river barriers using remote sensing.

Lastly, chapter three explores the parameters used in prioritisation modelling for optimising barrier removal, by creating a prioritised list of barriers to remove based on the habitat gained upstream. The model used to create a prioritised river barrier list for removal was expanded from using the original input of just river 'length', exploring comparisons between model inputs such as river 'length', 'area', fish species and river chemical quality weightings. Results showed the model input 'area' provides the most significant gains for species bullhead at lower budgets (<£10,000,000). All species reached 99%+ habitat gained by prioritised barrier removal at lower budgets when using river 'area' and the results recommend modelling on a species-specific basis as diadromous species (Atlantic salmon) are more susceptible to the fragmentation caused by anthropogenic barriers than to potadromous species (bullhead and brown trout).

The results of Chapters 1 and 2 show using barrier classification and identification tools can save stakeholders time and money whilst creating a standardised approach to barrier documentation. When creating a prioritised list of barriers for removal, Chapter 3 shows an increase in habitat gains when using additional quantitative inputs.

Declaration of Statements

Declaration

This work has not previously been accepted in substance for any degree and is not being concurrently submitted in candidature for any degree.

Signed: [redacted]

Date: 16th February 2022

This thesis is the result of my own investigations, except where otherwise stated. Other sources are acknowledged by footnotes giving explicit reference. A bibliography is appended.

Signed: [redacted]

Date: 16th February 2022

I hereby give my consent for my work, if relevant and accepted, to be available for photocopying and for inter-library loan after expiry of a bar on access approved by the university.

Signed: [redacted]

Date: 16th February 2022

The University's ethical procedures have been followed and, where appropriate, that ethical approval has been granted.

Signed: [redacted]

Date: 16th February 2022

Statement of Expenditure

Student Name: Millicent Parks

Student Number: 2042330

Project Title: Analysing the efficacy of novel barrier prioritisation and management tools

Category	**Item**	**Description**	**Cost (Inc VAT & Delivery)**
Consumables	Wifi Extender	Internet Access	£27.99
Education	Data Analysis with R	A guidebook for scientists	£15
Education	QGIS Short Course for Hydrological Applications		£305.10
Conference	WEEN 2021 Conference	Presenting results and fuel	£112.32
Conference	A0 Poster	Poster for WEEN	£25
Total			**£485.41**

The above expenditures were funded by the students KESS 2 Scholarship.

I hereby certify that the above information is true and correct to the best of my knowledge.

[redacted]

[redacted]

Signature (Supervisor)

Statement of Contributions

MP – Millicent Parks, MRes Candidate

CGL – Prof. Carlos Garcia de Leaniz, Academic supervisor

SC – Prof. Sofia Consuegra, Second academic supervisor

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Conceptualization	CGL, SC
Data curation	MP, PJ, JJ
Formal analysis	MP, JJ
Funding acquisition	CGL, SC
Methodology	MP, CGL, PJ, JJ
Project Administration	MP, CGL
Software	MP, JJ
Supervision	JJ, PJ, CGL, SC
Writing – original draft preparation	MP
Writing- review & editing	MP, CGL, JJ, PJ

Contents

i. Acknowledgements

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Mae'r Ysgoloriaeth Sgiliau Economi Gwybodaeth (KESS 2) yn fenter sgiliau lefel uwch Cymru gyfan a arweinir gan Brifysgol Bangor ar ran y sector AU yng Nghymru. Fe'i cyllidir yn rhannol gan raglen cydgyfeirio Cronfa Gymdeithasol Ewropeaidd (ESF) ar gyfer Gorllewin Cymru a'r Cymoedd.

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Ysgoloriaethau Sgiliau Economi Gwybodaeth
Knowledge Economy Skills Scholarships

UNDEB EWROPEAIDD
EUROPEAN UNION

Llywodraeth Cymru
Welsh Government

Cronfa Gymdeithasol Ewrop
European Social Fund

ii. List of figures

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iv. Definition of abbreviations

AMBER: Adaptive Management of Barriers in European Rivers

AC: Afonydd Cymru/Rivers Trust

AIC: Akaike information criterion

CPLEX: IBM ILOG CPLEX Optimization Studio

CRS: Coordinate reference system

DCI: Dendritic Connectivity Index

DEM: Digital Elevation Model

DEN: Dendritic Ecological Network

GLM: General Linear Model

GOODD: Global Georeferenced Database of Dams

GRanD: Global reservoirs and dam databases

MOE: Margin of error

NRW: Natural Resource Wales

WFD: Water Framework Directive

v. Justification and aims of the thesis

Globally, artificial river barriers continue to go undocumented and thus continue to disconnect streams, impacting longitudinal connectivity and causing a myriad of effects, such as obstructing the free flow of organisms, sediments and nutrients.

Whilst databases have been created to document river barriers, these often focus on large and economically important barriers, such as dams. Documenting river barriers traditionally involves extensive field work and thus considerable resources. My research investigates alternative ways to document river barriers without minimising the need for resource intensive fieldwork. I test the efficacy of novel tools developed to document and prioritise river barriers, in the hopes of increasing the ease and accessibility of doing so.

The aim of chapter 1 is to determine how reliable the newly developed 'Barrier ID Protocol' developed by AMBER (Adaptive Management of Barriers in European Rivers) is and whether all stakeholders using the protocol arrive at the same conclusions. There is currently an absence of a standardised barrier identification methodology, and the 'protocol' is a barrier classification flowchart which aims to become that standard framework. A repeatability study will show the efficacy of this tool compared to sources where it has not been used, and also show classification trends when classifying barriers.

The aim of chapter 2 is to determine the accuracy of remote sensing barriers using primary and secondary data: within the Afan Catchment and across Wales. There is currently a huge underreporting of barriers and there is a need to test to what extent different methods of barrier identification are effective, with the overall aim to achieve more comprehensive documentation of river barriers.

The aim of chapter 3 is to explore the effects different inputs have on a barrier removal prioritisation model. Modelling the removal of river barriers to increase longitudinal connectivity is still in its infancy, with many parameters remaining unexplored. This exercise involves an existing prioritisation model developed by Dr Jesse O'Hanley, which uses river length to create a prioritised list of barriers to remove. The modelling in this chapter aims to compare the existing model inputs of river 'length' with a new input of using river 'area', in the hopes that this refined habitat representation increases efficiency of the prioritisation results. Additionally, habitat quality weightings will be applied to the model and comparisons created to determine if this positively or negatively affects habitat gain results against a predetermined budget range.

1. A Repeatability Study of Barrier Classification Efficacy

1.1. Chapter Summary

A novel 'Barrier ID Protocol' was developed by Jones et el (in prep), which is a flowchart to support individuals when classifying artificial river barrier types. An analysis was conducted on the integrity of the 'Barrier ID Protocol', with the aim of reducing discrepancies around barrier type classifications.

An Intraclass Correlation Coefficient (ICC) (aka repeatability study) is a widely used reliability index that was used to test the reliability of the Protocol. An inter-rater repeatability study using three raters (R1, R2, R3) revealed the efficacy of the 'Barrier ID Protocol' compared to samples where it has not been used (AMBER citizen science data (R4) and Faptic image recognition software (R5)). Using the 'Barrier ID Protocol' shows moderate repeatability (ICC = 0.67) between the three raters. Repeatability is stronger (ICC = 0.789) when it was one rater rating the same photos at different time periods (7 day window). The Intra-rater repeatability with Citizen Science (R1, R2, R3, R4) produced the lowest repeatability ICC score (ICC = 0.559).

Analysis on the Faptic image recognition software, which has been trained to identify river barrier by type, showed varying accuracy in identifying barrier types. There was a slight trend (except for the 'Other' category) that using more barrier photos when training the model results in a more accurate prediction of barrier type.

Preliminary results showed the 'Barrier ID Protocol' reduces discrepancies amongst observers and is a significant first step in standardising the methodology used to classify river barriers by type.

1.2. Introduction

Artificial river barriers have been identified as a significant problem affecting longitudinal connectivity (Grizzetti et al, 2017). 'Longitudinal connectivity' refers to "connections between upstream and downstream sections of the river network" as extracted from Cote et al (2009). For a river to be free-flowing they must allow the unhindered movement of water, organisms and substrate, whilst be predominantly unimpacted by changes in connectivity (Grill et al, 2019). The ability of a river to flow freely is a direct result of the presence of river obstacles, which can cause fragmentation (Grill et al, 2019). These obstacles to longitudinal connectivity can result in a reduction in the free flow of organisms, nutrients and energy and cause physical obstructions in addition to chemical and sediment barriers (Garcia de Leaniz, 2008; Burford et al, 2009 & Boubée et al, 1997). An artificial longitudinal barrier is defined as:

"Any built structure that interrupts or modifies the flow of water, the transport of sediments, or the movement of organisms and can result in longitudinal discontinuity."

(Belletti et al, 2020)

To define the standards for successful river restoration, a global database documenting river barriers must first be created. Barrier inventories are essential for making remediation decisions (Atkinson et al, 2020) and supporting decision makers in restoration efforts (Kemp & O'Hanley, 2010 & Beletti et al, 2020). From a river management perspective, the documentation of river barriers is required to determine the hydromorphological status or a river in alignment with the EU Water Framework Directive (WFD) 2000/60/EC (Atkinson et al, 2020). Improvements thus far in global databases of river barriers has resulted in a more complete assessment of rivers (Lehner & Grill, 2013).

The results of Chapter 2 found a 44.3% accuracy in using satellite data to identify artificial river barriers. One source which could have contributed positively to this result could be the 'barrier ID protocol' (Figure 1.1.) that was used by the raters to classify the artificial river barriers. The tool was created by Jones et al (*in prep*) in an effort to remove subjectivity in the classification process. As mentioned in chapter 2, there is a lack of barrier documentation globally, especially smaller streams in upper catchments (Baletti et al, 2020) and for restoration of river connectivity according to ecological standards, one must know where and what type of barriers are in the river (Palmer, 2005). This is because it is costly and time consuming to ground-truth all artificial barriers, making it unfeasible for many river managers (Garcia de Leaniz et al, 2019 & Jones et al, 2019). For the purposes of this thesis study, bridges are classed as 'road-river' crossings, categorized as culverts.

A big step in this direction has been created by the introduction of the AMBER 'Barrier Tracker' App. The aim was to build the first European Barrier Atlas and it allows the public to document river barriers through a citizen science smartphone application (AMBER, 2021). The data recorded is freely available for anyone to download. In addition to geographical location, barrier details such as width and height are required to determine removal or remediation, which the Barrier Tracker App records (Atkinson et al, 2020). Knowing barrier locations is important in relation to testing river connectivity. Fragmented rivers can still have high connectivity in areas that have barriers spread out along the network. Recording barrier location means experts can assess *in situ* the current state of connectivity and create predictions on cost of barrier removal and efficacy. Currently, 14,748 classifications have been submitted with the barrier tracker app (AMBER Consortium, 2020).

In creating a database of river barriers, we can test different river restoration tools and models. As rivers become increasingly documented and barriers are recorded, experiments can be run which show the ease and efficiency of removing barriers across a variety of financial budgets. The accuracy of testing different software in recording barriers can also be tested, and comparisons of predictions with ground-truthed data can be created. The objective of this chapter is to test the repeatability of the novel 'Barrier ID Protocol' developed by Jones et al (2020). A repeatability study will show the efficacy of this tool compared to sources where it has not been used, and also show behavioural trends when classifying barriers.

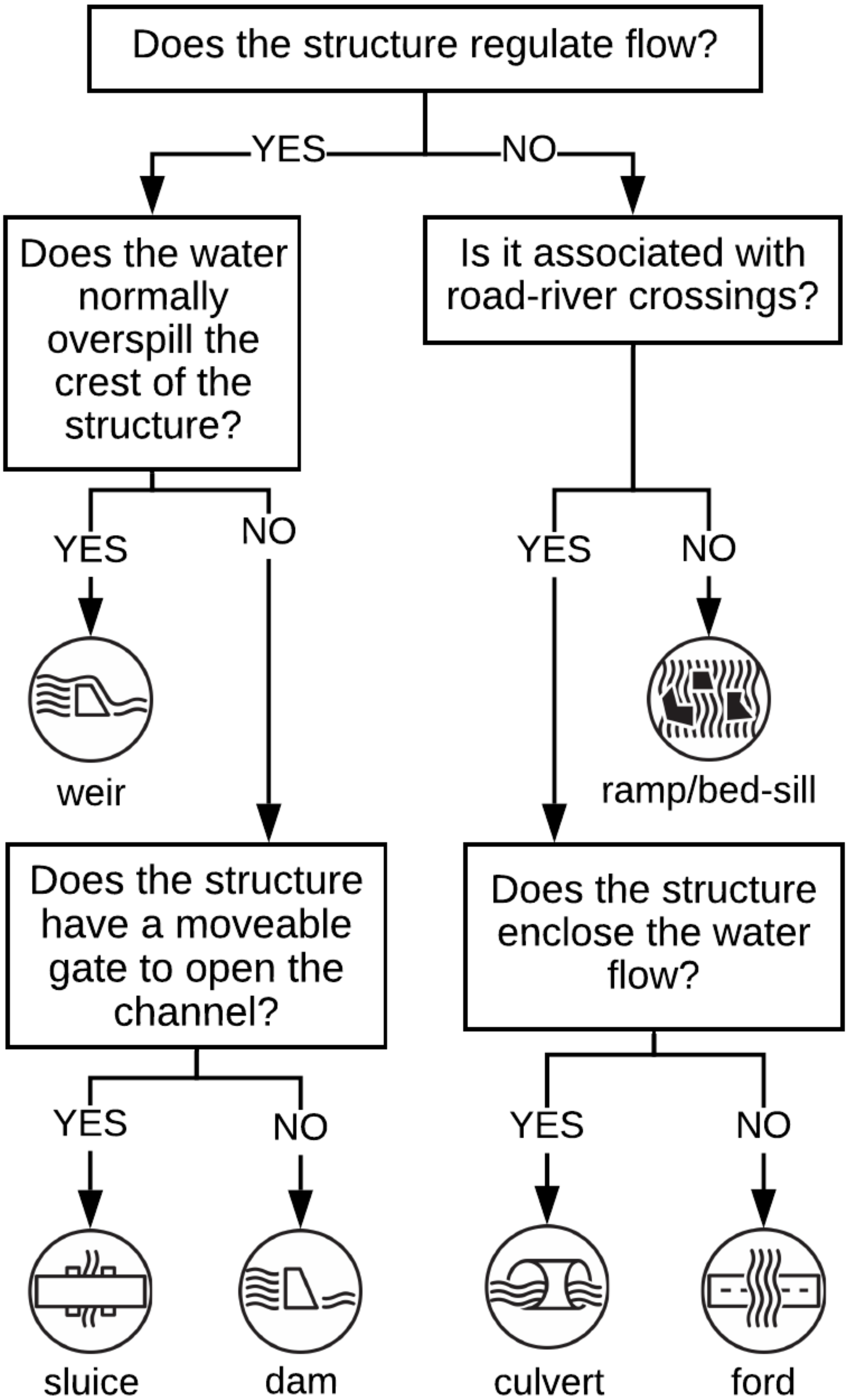


Figure 1.1. 'Barrier ID Protocol' flowchart taken from Jones et al (2020) showing the decision process for artificial barrier type classification.

1.3. Methods

1.3.1. Barrier classification Protocol validation

There is currently no standardised approach for classifying barriers, which can result in interpretation differences between raters (an individual identifying a barrier). The aim of the Barrier ID Protocol (Figure 1.1) is to provide a classification system for anthropogenic barriers on Welsh rivers. In providing this, the aim is to reduce discrepancy between raters due to discrepancies in barrier definition.

To measure the efficacy of the Barrier ID Protocol, a repeatability study was used. To examine this repeatability, river barriers were classified by raters, using the same measurement method (by using the same Barrier ID Protocol and excel form) (Bartlett & Frost, 2008).

1.3.2. Barrier photo database

From the online AMBER database, 360 river barrier photographs were downloaded at random in October 2021. This subset consisted of 60 photos of each barrier type noted in Table 1.1, classified by 3 random raters according to citizen science. Classification information was removed before sending to raters to reduce risk of bias.

1.3.3. Inter-rater reliability study

Three raters (R1, R2, R3) were asked to classify the barrier photographs extracted from the AMBER Barrier Tracker database, using the Barrier ID Protocol as a guide. This was to determine the level of difficulty when classifying barriers and the level of discrepancy between raters. This is a type of method comparison reproducibility study, where the same methods are used for each rater (Bartlett & Frost, 2008). A consensus majority was also calculated from the raw data. This consensus was determined by the majority (2 of 3 raters) answer. An analysis was also run to test how citizen scientists compare to the consensus classification by raters with varying levels of industry knowledge.

An 'other' category was created when raters were asked to categorize barriers according to Figure 1.1, as some photographs did not fit into one of these barrier types. For example, these were photographs of 'natural' river barriers (not man-made, i.e., waterfalls and log jams), duplicates of barrier photos and miscellaneous photos (not of river barriers, potentially uploaded in error). Once images were sorted into categories, this category was removed from analysis as this is not one of the ‘protocol’ (Figure 1.1) barrier classification types, and only the six categories were used in analysis.

When measurements are made by different raters, subjectivity between observers may result in barrier classification differences (Bartlett & Frost, 2008). When testing for inter-rater repeatability, the repeatability tests the scale of the measurement error in observed measurements between subjects. When measurement errors are small, this indicates repeatability is high. The Intra-class Correlation Coefficient (ICC) equals the correlation between measurements recorded on the same data. One area of subjectivity of using an ICC test is that is can be challenging to interpret due to being dimensionless, and thus difficult to determine what creates high reliability (Bartlett & Frost, 2008). For repeatability integrity, the measurements were made using the same methodology, over a 24-hour period by the same rater. Thus, if error occurs, it is most likely due to the measurement process and consequently, we are able to inspect the integrity of the Barrier ID Protocol.

An ICC was also run on the three raters in comparison to the classifications made by citizen scientists when documenting barriers using the AMBER Barrier Tracker App, known as R4. This was done to identify if the classification method used in the app is simple enough for individuals to interpret as they had the same barrier definitions, but no access to the ‘protocol’ flowchart shown in Figure 1.1.

1.3.4. Intra-rater reliability study

Commonly, measurements made by the same observer multiple times are more similar than measurements recorded by different observers (Bartlett & Frost, 2008). This intra-rater reliability study was undertaken to determine if there are any discrepancies between observations. The study consisted of the same rater, measuring the same subset of river barrier photographs (360), with 1 week in between each classification (22/09/2021 and 29/09/2021). The barrier photographs were randomised, and the order was changed again for the second classification session.

1.3.5. Image Recognition reliability study

A potential source of error may be the small sample size of just four raters (R1 – R4), and therefore little can be concluded about how other sources may classify these. Thus, Faptic image recognition software was used as an additional source of rater classification (R5) to compare the abilities of the software. The Faptic software has been trained to identify river barrier by type on 2709 files of river barriers, with 6 barrier classes, shown in Table 1.1. For validation, 676 barrier photos were used, different to the images used in training. The sum of these (2709 + 676) found 3385 files belonging to the 6 barrier classes (this is the total images used for programming the Faptic software): 20% of files for validation, 80% for training. The 2709 training set is used to perform the initial training of the model, initializing the weights of the neural network. The 676 photos in the validation set compare the model results with the actual barrier types and are used for refining the network's parameters and comparing how changes to them affect the predictive accuracy of the model.

Finally, 200 (after 3 ‘other’ barrier photos removed) test images were used to test the predictive accuracy of the trained neural network on previously unseen data, after training and parameter selection with the training and validation datasets were used. The Faptic image recognition software produces individual success rates (%) when correctly predicting barrier type, for each barrier type.

River barrier photos from the Faptic database were cross-referenced with the photos (both photo sets extracted from the AMBER database) used from the inter- and intra- reliability studies and 29 barrier photographs matched (Appendix 4.1). Thus, an ICC was run on this subset of photos with the four raters (R1, R2, R3 and R4) and Faptic as R5. A positive prediction value (PPV) is the probability that Faptic image recognition software correctly predicts river barrier type.

1.3.6. Intraclass Correlation Coefficient

The Intraclass correlation coefficient (ICC) test is a reliability index which reflects both the degree of correlation and agreement between measurements (Koo & Li, 2016). It is commonly used for inter-rater and intra-rater reliability analysis based on the McGraw and Wong (1996) convention dictating ICC types.

As mentioned, there are no standard values for acceptable reliability, however, an ICC result close to 1 commonly indicates high similarity between values from the same group (Gutierrez

Rabadan et al, 2021, Koo & Li, 2016). The ICC should be reported with 95% confidence intervals (Koo & Li, 2016).

A single-rating, absolute-agreement, 2-way random-effects model was chosen as the raters were chosen randomly and not the focus of this study (Shrout & Fliess, 1979 & Gutierrez Rabadan et al, 2021). This study focuses on the conclusions provided by the raters and not the particular raters themselves. As the raters are considered random, the ICC model used treats the raters a random effect (Bartlett & Frost, 2008). The ICC test requires a 95% confidence interval to test if the ICC value significantly exceeds the suggested values in Table 1.2. (Koo & Li, 2016).

The rater barrier type observations were translated into an ordered code system (Table 1.3.) for statistical analysis, using the 'irr' package in R Version 4.0.3 to produce the ICC (script in appendix 4.2). Whilst it makes no difference in the statistical ICC calculations, the barriers have been ordered by height (m).

Table 1.1. The breakdown of the artificial river barrier types within the training dataset, when training the Faptic image recognition software.

Barrier Type	Quantity of Faptic Training Images	Quantity of Faptic Test Images
Ramp	60	17
Sluice	244	37
Weir	749	81
Culvert	821	76
Dam	624	50
Ford	203	38

Table 1.2. ICC score range and value outcomes extracted from Koo & Li (2016).

ICC Score	Suggested Reliability Value Outcome
<0.5	Poor
0.5-0.75	Moderate
0.75-0.9	Good
>0.9	Excellent

Table 1.3. The coding system used for statistical analysis, showing the artificial river barrier types and their corresponding numerical code, ordered by height (m).

River Barrier Type	Numerical Translation
ford	1
culvert	2
ramp	3
sluice	4
weir	5
dam	6

1.4. Results

1.4.1. Faptic image recognition results

Figure 1.2. shows a positive prediction value (PPV) with binomial 95% confidence intervals, showing the percentage (%) of times that Faptic image recognition software correctly predicts river barrier type. This shows the accuracy (%) of Faptic image recognition software when predicting river barrier type. The graph displays the barriers in ascending order, with barrier type 'ramp' at 27% accuracy. Faptic accurately classifies sluice barriers 35% of the time, ford barriers roughly 47% of the time and dams 63% of the time. Faptic image recognition software accurately classifies weirs and culverts approximately 70% of the time, with culverts being slightly easier to classify, according to Figure 1.3. Both these barrier types also have the smallest error bars, indicating the results to be the most accurate of the barrier types listed.

Figure 1.3. shows the results of a confusion matrix of the observed (ground-truthed) barrier classifications versus the barrier types predicted by the Faptic image recognition software. A frequency scale (0-1) shows the rate at which the software is confusing two barrier types. The figure shows that most commonly, Faptic is confusing dams (observed) for sluices (predicted, 0.22 frequency). This is the highest frequency result and shows that overall, the software confusion frequency (misclassification) is low.

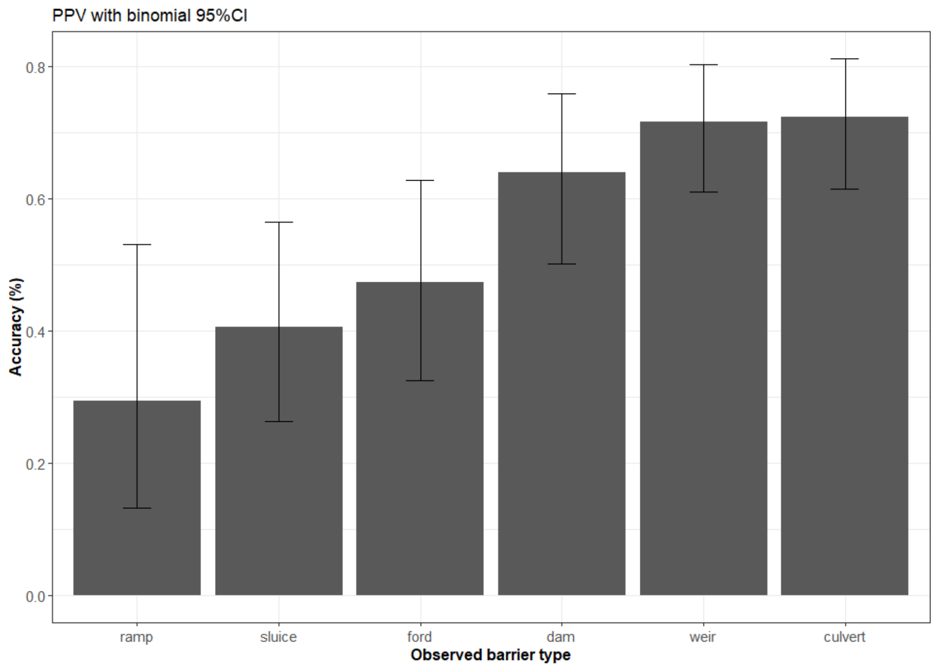


Figure 1.2. Positive prediction value (PPV) with binomial 95% confidence intervals (CI) error bars, showing the accuracy (%) of Faptic image recognition software when correctly predicting river barrier type, using the 299 barriers from the test dataset.

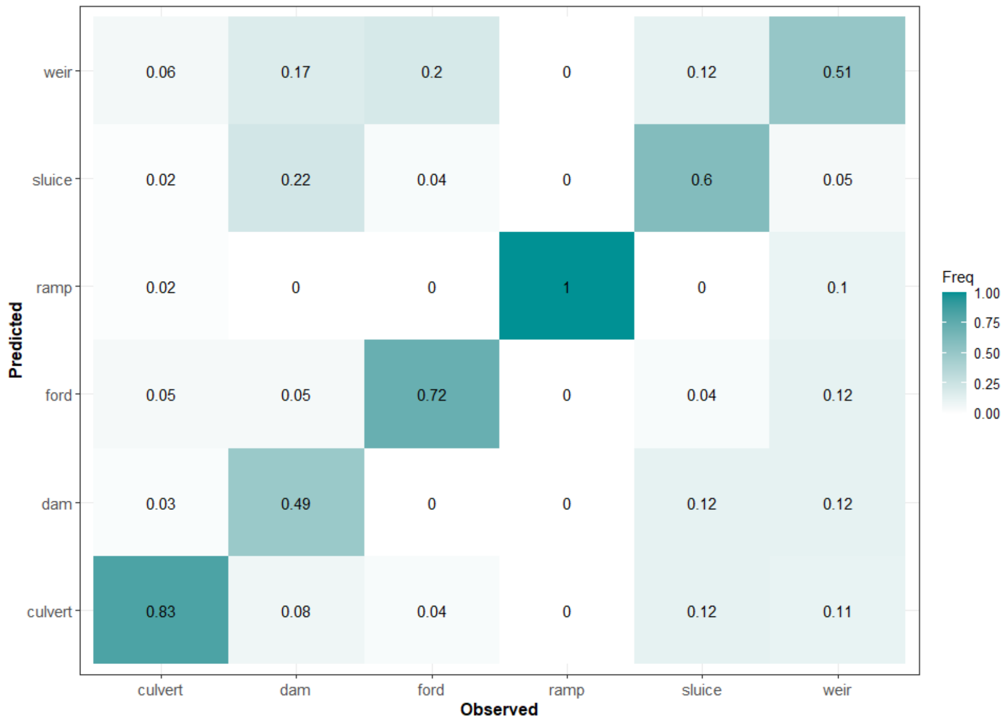


Figure 1.3. Confusion matrix of observed vs predicted barrier types, predicted by Faptic image recognition software using a frequency scale (0-1), using the 299 barriers from the test dataset.

1.4.2. Rater results

Using the Barrier ID Protocol shows moderate (ICC = 0.67) reliability between the three raters who were chosen at random (R1, R2, R3), according to Table 1.4. Repeatability is stronger (ICC = 0.789) when it was one rater rating the same photos at different time periods (7-day window). Using Table 1.2, this is recorded as a having a ‘good’ ICC repeatability outcome and the highest ICC repeatability of the study. The Inter-rater repeatability with Citizen Science (R1, R2, R3, R4) produced the lowest repeatability ICC score (ICC = 0.559) from Table 1.4.

1.4.3. All Raters (R1 – R5) Results

An ICC test was run with the same inputs above, with the addition of the Faptic image recognition software (rater R5) on the 29 river barrier photos that matched between datasets out of the 360 photos used by the raters and the 299 test images (all photos extracted from thr AMBER database. Table 1.5 shows the results comparing ICCs when using raters R1, R2, R3 and R5 and when using raters R1, R2, R3, R4 and R5 to see how they compare with and without the citizen science barrier classifications (R4). Using the Table 1.2. ICC scoring ‘Suggested Reliability Value Outcome’, the results show a ‘poor’ agreement between these different groups and is the lowest result of the entire study. The right column (test using raters 1-5) returned the second lowest ICC result (ICC = 0.388) and using Table 1.2, can also be recorded as having ‘poor’ repeatability.

1.4.4. Faptic Results: observed versus predicted

An Intra-class correlation coefficient (ICC) was run on the Faptic image recognition software results alone. The test was run on the actual ground-truthed ‘observed’ data (extracted from the AMBER database) which had been classified into one of seven barrier types (Table 1.3.) versus the barrier type the Faptic software predicted it would be. Shown in Table 1.6, the ICC test returned a ‘poor’ repeatability outcome (ICC = 0.33, 95% Cl -0.11–0.61) and was the weakest result of the entire study. This shows the software is not useful at correctly predicting barrier type. The raw data is shown in appendix 4.18.

Table 1.4. Repeatability results based on the inter- and intra-class correlation coefficients (ICC) of four rates (R1, R2, R3 and R4) independently classifying 360 river barrier photos.

	Inter-rater repeatability (R1, R2, R3)			Intra-rater repeatability (R1 at time 1 & time 2)			Inter-rater repeatability with Citizen Science (R1, R2, R3, R4)		
	ICC	95 Cl	P	ICC	95 Cl	P	ICC	95 Cl	P
360x AMBER photos	0.67	0.611-0.722	<0.001	0.789	0.746-0.825	<0.001	0.559	0.505-0.612	<0.001

Table 1.5. Repeatability results based on the inter- and intra-class correlation coefficients (ICC) of four raters (R1, R2, R3 and R4) in conjunction with Faptic (R5) independently classifying 29x AMBER river barrier photos.

	Inter-rater repeatability (R1, R2, R3 and Faptic (R5))			Inter-rater repeatability (R1, R2, R3 with Citizen Science (R4) and Faptic (R5))		
	ICC	95 Cl	P	ICC	95 Cl	P
29x AMBER photos	0.374	0.188 – 0.581	<0.001	0.388	0.224 – 0.581	<0.001

Table 1.6. Repeatability results based on the inter- and intra-class correlation coefficients (ICC) of Faptic software comparing the observed (ground-truthed barriers from AMBER) vs predicted. 29 barrier classifications which matched the AMBER photos. The raw data is shown in appendix 4.18.

	Intra-rater repeatability (Faptic Observed (cleaned) vs. Predicted		
	ICC	95 Cl	P
29x AMBER photos	0.33	-0.11 – 0.61	0.0289

1.5. Discussion

From the combined results, the findings suggest that using a standardised barrier classification tool such as the 'Barrier ID Protocol' (Figure 1.1.) is a significant first step in standardising the methodology used to classify river barriers by type. When all raters used the 'Barrier ID Protocol', the ICC returned the strongest repeatability of the study. When other raters were added to the ICC who had not used the 'protocol' (R4 and R5), the ICC repeatability outcome weakened. Table 1.5 shows that adding R4 (Citizen Science) increases the ICC value. This shows a logical trend that humans are better at classifying barriers than image recognition software. This is supported by the results in Tables 1.4 – 1.6., with even the lowest human (R1 – R4) ICC output as 0.559, compared to the Faptic ICC output of 0.33. In theory, the 'Barrier ID Protocol' is a promising start as results show it may have reduced subjectivity amongst raters, shown in Table 1.5.

It is no surprise the intra-class study returned a higher repeatability outcome. As there were only 7 days between each recording, it is unlikely knowledge or barrier classification experience would substantially increase in such a short time frame. An area of further study is to repeat this study at time intervals, for example: 1 week, 6 months, 1 year, to test if repeatability decreases or increases as knowledge in this field develops.

One source of potential discrepancy between observers may be the level of rater experience and expertise, resulting in subjectivity and differences of opinion when classifying barriers. Logically, it is predicted, that with more barrier classification experience, the more accurate the rater should be. The participants (R1 – R3) had a range of experience in this field in order to be representative. Whilst using three raters (R1, R2, R3) is considered acceptable by Koo and Li (2016), the raters had varying degrees of experience in this sector and thus the ICC results cannot properly reflect those results of the general population who have no prior knowledge of river barriers. To overcome this, citizen science data from the AMBER Barrier Tracker App was used as a rater (R4), as I did not wish to generalise the R1 – R3 rater results as a representation of the entire population. Going forward, increasing the sample size with more individual raters may increase precision (Lee et al, 2012).

Table 1.6 shows the lowest ICC score, even when Figures 1.2 & 1.3 show low misclassification from Faptic when predicting barrier type, particularly for dam, weir and culvert. The logical explanation for this low ICC is due to the small sample size. Only 29 photos (out of 2709) were found in the 360 barrier photos downloaded from the AMBER database and thus used in predictions, compared to the 299 barriers used in in the dataset for Figures 1.2 & 1.3. Further ICC testing could be carried out using a more extensive subset of photos. Whilst not the focus of this chapter, the use of image recognition software may be useful in classifying historical barrier images or images where barrier type isn't known, however I acknowledge these to be infrequent occurrences.

As mentioned in the methodology, using the inter-class correlation coefficient is one method of testing the repeatability of a study, however it is important to acknowledge the subjectivity of using ICC as a repeatability test (Koo & Li, 2016), in that there is no concrete threshold, rather just commonly accepted range values from 'poor' to 'excellent'.

The low accuracy of Faptic's capability to predict ramps, fords and sluices is another area of weakness. This may be because in the training dataset, there were fewer photos of these barrier types. As Table 1.1 shows, the training dataset consisted of only 60 photos of ramps, whilst there were 821 photos of culverts and 749 photos of weirs. This could show that using more training photos results in a more accurate barrier type prediction.

Large dams (>10m) are frequently the largest anthropogenic river barrier type and thus easier to spot than smaller barriers, even when using satellite imagery (Belletti et al, 2020, Jones et al, 2019, Van Looy et al 2014). The Global Georeferenced Database of Dams (GOOD) has been created to specifically document dams using Google Earth satellite imagery (Mulligan et al, 2009). One reason as to why dams were not more accurately predicted using Faptic, in addition to training dataset size (Table 1.1. shows barrier type dam was trained on 624 photos) is because of the generally large size of a dam structure. All individual raters (R1 - R3) commented that the barrier photos of dams often did not include the entire dam as it was too large to fit into the frame of the photo. The image recognition software may have difficultly classifying a barrier when its entirety is not in the photo and it is only partially documented. Most dams have a bottom release of water similar to a sluice, raising issue of potential error in classifying photos when there are two barriers in a photo, as in this example there would be a dam and a sluice-like gate.

Using the image recognition software is still useful, especially when predicting dams, weirs or culverts (all over 50% accurate). Increasing the sample sizes of the training photos for fords, sluices and ramps may improve accuracy of correctly predicting these barrier types using image recognition software. Furthermore, if all barrier types were to be trained on the same quantity of barrier photos, it would be interesting to see which barrier types the Faptic software most accurately predicted. This could be done using rarefaction techniques, to account for different sample sizes (Raup, 1975; Simberloff, 1972). Using rarefaction in this study, we would only do the analysis on 60 of each barrier type (as the ramp category has the lowest quantity) to provide an even comparison between barrier types. This was outwith the limits of this chapter as the training required to train the Faptic software was completed in-house by Faptic-Tech themselves.

There are significant underestimations of anthropogenic barrier abundance both nationally and globally, and one reason may be due to discrepancies around defining barrier type (Garcia de Leaniz et al, 2019 & Jones et al, 2019) as there is no standardised framework such as the 'protocol'. The study by Jones et al (2019) found UK databases to underestimate anthropogenic barriers by at least 68%, whilst a study by Sun et al (2020) found only 22.7% of barriers were present in the national database with no culverts documented in the national inventory. As a direct result of the AMBER Barrier tracker, a further 14,748 anthropogenic barriers have been recorded in Europe (AMBER Consortium, 2020) which paves the way for river management plans to restore longitudinal connectivity.

In general, all types of anthropogenic river barriers are under-documented, however large dams are thought to be the most documented and thus widely studied (see Jones et al, 2019, Lehner et al 2011, Van Looy et al, 2014, Vörösmarty et al, 2003, Kummu et al, 2010). Even so, Mulligan et al (2020) report almost 30% of dams as underestimated due to the poor resolution of satellite imagery. Moreover, in the North American Great Lakes, Dr. Stephanie Januchowski-Hartley reported a significant underreporting of smaller structures such as culverts: the number of river/road crossings exceed dams by a factor of 30. Ground-truthing river barriers using fieldwork is time consuming and resource intensive (Januchowski-Hartley et al 2014, Lehner & Grill, 2013). If the 'Barrier ID Protocol' helps even marginally with ground-truthing barriers by saving time (and thus money too) when classifying *in situ*, then this can help increase the global documentation of river barriers via a robust standardised approach.

In a wider context, this study shows a need for a standardised approach when classifying barriers and can be used in conjunction with wider river management tools (Gargan et al, 2011). Examples include the use of set ecological standards proposed by Palmer (2005) which include five criteria for measuring success: restoration design must be with the aim of a healthier river, ecological conditions of the river must improve, riverine system must selfsustain with minimal maintenance required, during construction, no ecosystem harm may occur and all assessment data must be publicly available. Another management method this ‘protocol’ can be combined with is decision making on a catchment-wide scale as opposed to individual barriers, as this can maximise gains in longitudinal connectivity (Kemp and O’Hanley, 2010).

The ‘Barrier ID Protocol’ contains various exclusions as it only focuses on longitudinal connectivity. Excluded from the ‘Protocol’ are natural barriers (examples include log jams and waterfalls), even though these can isolate populations (Whitely et al, 2010). Barriers that are not physical, such as diffuse pollution (examples include agricultural run-off and thermal from industrial outputs), are not included in the ‘Barrier ID Protocol’ and thus the repeatability study. Additionally, structures which affect lateral river connectivity are not addressed in this ‘Protocol’ and are reported to be difficult to identify and thus commonly excluded from river management (Buddendorf et al, 2019 & Atkinson et al, 2020).

1.6. Conclusion

Several studies have reported a substantial underestimation of anthropogenic river barriers, highlighting the need for tools to support barrier documentation (see Jones et al 2019; Sun et al, 2020; Mulligan et al, 2020; Garcia de Leaniz et al, 2019; Januchowski-Hartley et al, 2013 & Grizetti et al, 2017).

The results show a higher repeatability result across raters who all utilised the same classification methodology (R1 – R3), than when all raters did not (ICC with R4 and R5). The promising results of ‘Good’ ICC outcomes when testing repeatability of R1, R2 and R3 and of the intra-rater test, suggests the ‘Barrier ID Protocol’ potentially reduces the discrepancies between rater observations and thus individual subjectivity. With further training of the Faptic image recognition software on a larger quantity of river barrier photos, this will hopefully increase the accuracy of correctly predicting barrier type, particularly for ramps, fords and sluices.

This is a significant initial step in using a standardised approach to classifying river barriers and training image recognition software to classify river barrier types. With additional data, the ‘Barrier ID Protocol’ could be used to classify river barriers and reduce discrepancies and subjectivity. Using the tool along with other measures (see Palmer, 2005; Kemp and O’Hanley, 2010 & Grizetti et al, 2017) is required to increase the global documentation of river barriers, of which the ‘Barrier ID Protocol’ may be able to support during the classification process.

2. The use of desktop surveys for assessing river fragmentation

2.1. Chapter Summary

Documenting river barriers traditionally involves extensive field work and thus considerable resources. Whilst databases have been created to document river barriers, these often focus on large and economically important barriers, such as dams. This chapter investigates alternative ways to document river barriers without the need for such resources, with the aim to determine the accuracy of remote sensing barriers within the Afan catchment and across Wales to establish an effective yet affordable to documenting river barriers. Additionally, we want to know which environmental factors determine whether barriers can be identified or not via remote sensing.

To address the issues around river barrier documentation, I tested the accuracy of using satellite imagery to supersede field work, using two methodologies. Barrier observations were made using Google Earth and a record created, using a novel 'Barrier ID Protocol' (Figure 1.1.) to guide observations. To validate, this record was compared with ground-truthed (field) data for a river catchment in South Wales, or for the pan-Wales validation method, a record of potential barriers was overlayed onto Google Earth and barriers were checked in this way.

The results show that remote sensing (satellite imagery) can be used to identify river barriers across Wales with an overall 43% probability of detection: 39.3% detection of barriers using the Afan field data (majority vote), 50.5% detection using amalgamation of barrier observations and 48.2% detection of barriers using the Afonydd Cymru dataset across 32 Welsh catchments. There was strong agreement (fleiss' kappa = 0.63) between observers when using the 'Barrier ID Protocol', which was used with the aim to reduce subjectivity between observers. Environmental predictors such as forestry cover, Strahler order and 'Distance to mouth' play a statistically significant role in identifying barriers across Welsh catchments. Limitations to this method of barrier identification included the quality of satellite imagery and the presence of forest or clouds covering the river.

To summarise, the results suggested that using satellite imagery should be utilised as a preliminary barrier documentation procedure, but there is a need to supplement with field work, because of the environmental limitations noted.

2.2. Introduction

Freshwater ecosystems are key components of global biodiversity yet often get the short straw in trade-offs with the provision of goods and services (Dudgeon et al, 2005; McGarrigle, 2014). With an 83% decline in freshwater populations between 1983 and 2014, this not only outstrips both marine and terrestrial counterparts, yet is consistently overlooked in the discussion around conservation (Reid et al, 2019; Cooke et al, 2016). Of the five leading causes of freshwater decline (overexploitation, water pollution, invasive species, flow modification and habitat degradation), flow modification and habitat degradation are due to river fragmentation, which can arise from artificial stressors such as barriers (Dudgeon et al, 2005).

Attempts have been made to collate records of river barriers, notably the GOODD (Global Georeferenced Database of Dams) and GRanD (Global Reservoirs and Dams), however these are still dominated by records of larger dams (Mulligan et al, 2020). Smaller, low-head structures (such as weirs) often go undocumented, even though their cumulative impact on river connectivity is more substantial than larger barriers (Januchowski-Hartley et al, 2013; Birnie-Gavin et al, 2017; Belletti et al, 2020).

Freshwater ecosystems, and importantly diadromous species (those that migrate between salt water and fresh water), are adapted to natural river flows and so the presence of artificial barriers negatively impacts the migration of organisms, including fish movements and seed dispersal (Lehner et al, 2011; Atkinson et al, 2018; Jones et al, 2020). Artificial river barriers can also influence behavioural and chemical processes, such as light availability due to turbidity or pH reduction from acid sulphate leachate (Kroon & Phillips, 2014; Kroon, 2005).

Artificial barriers need to be catalogued in order to prioritise barriers for management (Kroon & Phillips, 2014). Similar studies (see Atkinson et al, 2018; Kroon & Phillips, 2014; Januchowski-Hartley et al, 2013) have been carried out in other countries, but there is a distinct lack of research around remote-sensing barriers in Wales.

At present, surveying river barriers via field surveys requires time, money and a dedicated team of surveyors. Due to this investment of resources, many countries have an incomplete account of river barriers, with only larger barriers being recorded, if any (Birnie-Gavin et al, 2017; Lucas et al, 2009). There is also currently no benchmark on how to document barriers cheaply whilst remaining accurate, with substantial variance between barrier identification methods, causing significant subjectivity between recordings (Mulligan et al, 2020).

Satellite imagery can be useful in analysing remote areas which are difficult to access (Kroon & Phillips, 2014) in addition to using significantly less resources than field work. The ease of remote-sensing barriers will lead to a better global documentation of barriers. However, there are disadvantages, notably the unknown accuracy of using satellite imagery to detect artificial barriers.

This chapter aims to establish how reliable remote sensing is in identifying river barriers using three sources of binary data within two datasets, to establish an effective yet economic solution to documenting river barriers. Additionally, I want to know which (if any) environmental factors play a significant role in predicting barrier identification, and to what accuracy (%). This will be done by firstly determining the accuracy of remote sensing against field data collected from the Afan catchment (located in Neath, South Wales) and then compared to data collected by Afonyd Cymru from catchments spread across Wales. The purpose of using multiple datasets was to strengthen the accuracy of our results and allow assessments to be made between both datasets. Using this dataset increased our sample size to n = 661 (n= 292 and n=293) for all remote sensed barriers cross-referenced against known field data.

2.3. Methods

2.3.1. Barrier Identification Protocol for Remote Sensing

There is currently no standardised approach for recording barriers using satellite imagery, which can result in interpretation differences between observers. As discussed in chapter 1, the aim of the 'Barrier ID Protocol' is to provide a classification system for detecting anthropogenic barriers on Welsh rivers. In providing this, we hope to remove any sampling bias caused by problems of definition, enabling us to calculate repeatability of detection within and between observers and assess what determines the probability of barrier detection.

Barrier definitions and key were extracted from the AMBER (Adaptive Management of Barriers in European Rivers) Atlas citizen science project and specifically, the mobile application used to record barriers. Some guidelines and harmonised barrier definitions (Jones et al, 2020) were implemented to reduce discrepancy. Figure 1.1. shows the 'Barrier ID Protocol' decision tree used to determine barrier type. Appendix 4.3 shows the 'Barrier Type ID' table used to support observers.

It is important to note that road/river crossings were assumed to be culverts even if a barrier type was not identifiable from satellite data. This may be a potential error source in relation to quantity of barrier types in Wales.

2.3.2. Predictors of Barrier Detection

The variables, considered as environmental predictors of barrier detection were as followed: forest cover, Strahler order, distance to mouth (d2m), barrier type, barrier height (m) and altitude (m). These were chosen because they are freely available through online databases and websites. Strahler, distance to mouth and altitude were extracted using QGIS software, version 3.10 A Coruña (QGIS, 2021). Appendix 4.25 shows the sources of the environmental parameters collated for the Afan Catchment.

To calculate the forested cover of each barrier, the field dataset was uploaded to Google Earth and for every barrier, a score was given to attribute the coverage of forest. This was 0= unforested, 1= forest present, within a 10m buffer. This is important to document as this may play a role as to whether we can identify a barrier or not. Barriers with immediate forestry were marked as 1 = forest present even if they were visible, along with barriers that only had forestry on one riverbank. Three or more trees grouped together were the minimum threshold for 1 = forest. Whilst some barriers are recorded as 0, unforested, the river was still not identifiable via remote sensing due to other factors such as roads or urban areas.

Strahler stream order starts at 1 with the smallest tributaries and when two streams of the same order join, the Strahler order increases (Strahler, 1957). This is logically linked to altitude and distance to mouth. The smaller streams (with the lowest Strahler) commonly start in the upper catchment of the river network, usually at a higher altitude in the foothills. Following this logic, a barrier with a Stream order of '1' commonly has a larger distance to mouth as these are usually further away from the river mouth at sea level.

Barrier type and height are important parameters to consider as we are interested in whether barrier height can affect detectability using remote sensing. Barrier height and type were attributed using the AMBER 'Barrier Tracker' app for field data, Google Earth and Appendix 4.17 for remote sensed barriers and the Afonydd Cymru (AC) dataset. Height data is commonly continuous, but the app assigns height categories (<0.5m, 0.5m – 1m, 1m – 2m, 2m – 5m, 5m – 10m and >10m) and unknown barrier heights were assigned averages listed in Appendix 4.17, extracted from the AMBER database (Amber consortium, 2020).

2.3.3. Remote-sensing Samples and Analysis

The Afan field data consists of river barriers recorded from a site walkover in 2019 by scientists using the AMBER 'Barrier Tracker' mobile application. In total, 171km of the river was surveyed, with 326 natural barriers recorded and 295 artificial barriers recorded. The mean barrier free length was 4km. This dataset was used as the benchmark to compare remote-sensed barriers with.

Using Google Earth (version 9.136.0.2), 3 observers were asked to record all barriers they could clearly identify on the Afan river at approximately 500 metre (m) viewing distance whilst following the 'Barrier ID Protocol' to note barrier type. A Google Earth viewing distance of ~500m was used to avoid discrepancy between observers, as it had the best image quality with minimal pixelation (example in Appendix 4.26). To ensure an unbiased assessment of potential barriers, similar to Atkinson et al. (2018), a copy of the field data was withheld from the observers, so they did not know where the confirmed barriers were. Potential artificial barriers were marked with a colour coded point. Figure 2.1. shows a completed observer sample of the main stem and tributary networks of the Afan river catchment. Records were not shared or discussed between observers to reduce the risk of bias.

All samples were consolidated into one consensus list, with the majority vote (2 of 3 observations recorded) marking the presence of a barrier or not. For example, if 2 observers had marked the presence of a barrier and one observer had not, the majority is that the barrier had been recorded and thus in the consensus list, we would mark the barrier as present. For the purpose of this study, I have focussed on the majority vote to increase integrity of the results but have also analysed the recordings of when any barrier presences is recorded by any individual observer and the agreements between observer, shown in Figure 2.5.

Two other sources of barrier data were also included in the study to increase sample size when reviewing the accuracy of remote sensing (Figure 2.4a-d). These include data from Natural Resource Wales (NRW) of known culverts in the Afan and data extracted from the AMBER Atlas website of all the barriers recorded using the Barrier Tracker app. However, very few of the NRW culverts (10 of 295) and AMBER Atlas data (25 of 295) were identified using remote sensing and the decision was made to drop these datasets due the small sample sizes.

Once samples were collected, the agreement between observers was analysed to show potential discrepancies and gauge reliability of remote sensing. Fleiss' kappa was computed to assess the agreement between three observers in identifying the presence of river barriers on the Afan using Google Earth. A Fleiss' Kappa is used to measure the observer agreement chance (Landis & Koch, 1977) whilst correcting for accuracy expected to occur by chance (Cohen, 1960). It is important to note that this can be criticised for being inherently dependent on prevalence and the random choice of threshold value (Allouche et al, 2006; Freeman & Moisen, 2008). Our second measure of discrimination therefore was a simple agreement test in R (R script in Appendix 4.4) (Stoffel et al, 2017).

An X^2 test was calculated to test the agreement of observed river barrier types using remote sensing with the expected river barrier types attained from the field or AC datasets (McHugh, 2013). It was used to plot the estimated under reporting error (%) for each dataset, graphed by barrier type.

2.3.4. Preparing datasets for statistical modelling

2.3.4.1. Afan Field Data

Once all environmental predictors were collected, duplicates and errors were removed from the dataset (16 barriers in total). From the observations, the majority vote of each barrier was used, referred to as the 'google consensus majority (referred to henceforth as the 'GCM'). This is when the majority vote for barrier presence was recorded as the confirmed overall decision made by observers. For example, is observers 1 and 2 identify a barrier present (present = 1) and observer 3 does not identify a barrier in that location (not present = 0), the majority vote is that there is a barrier present and thus the overall consensus is that there is barrier present (present = 1).

In QGIS, the 'Google Consensus Majority' (GCM) dataset was split into 0= barrier not verified and 1= barrier verified, confirmed by cross-referencing the barriers with the field data (Figure 2.2. shows an example). An inclusion rule (a buffer of 10m around the field data) was created to reduce situational judgment bias when recording the barrier presence of the 'GCM' barrier dataset against the field data. If barrier buffers overlap, barrier presence was assigned to the closest google sample barrier record. Figure 2.3a - 2.3d shows the GCM, NRW and AMBER Atlas data in QGIS to give an idea of varying barrier distributions within the Afan River catchment according to different sources.

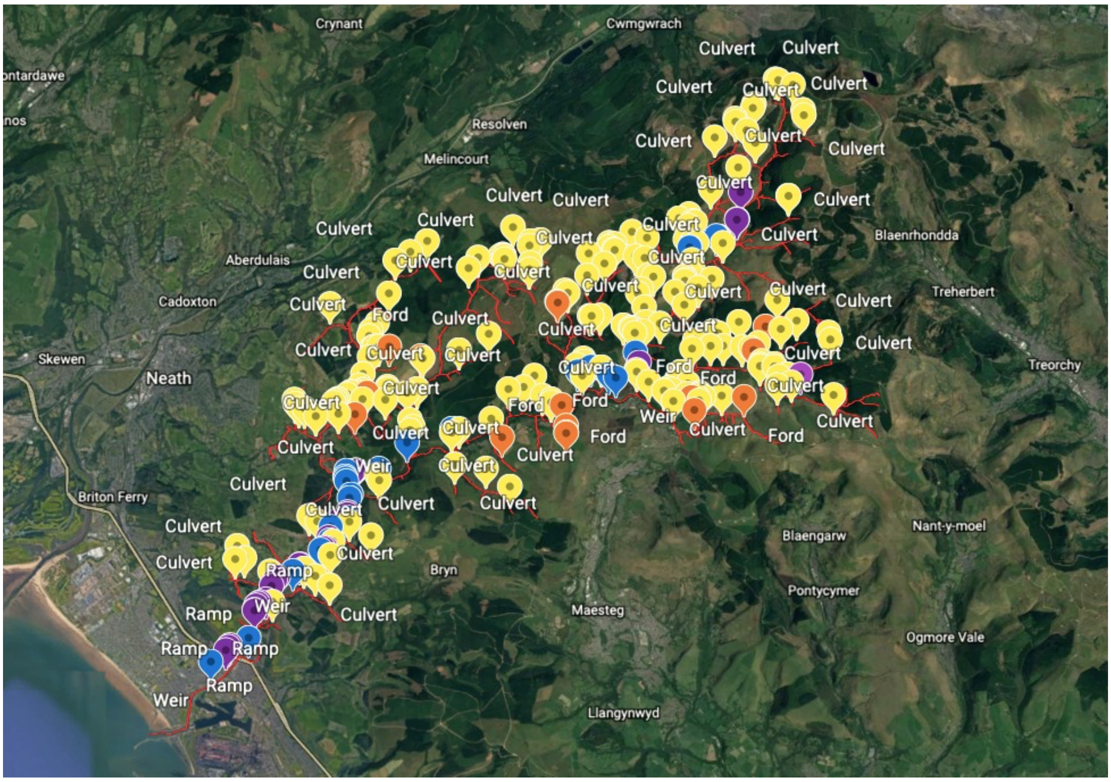


Figure 2.1. An observer sample of the main stem and tributary networks of the Afan river catchment, colour coded by barrier type to match the AMBER 'Barrier ID protocol' shown in Figure 1.1. (Google Earth, 2021). Culverts are marked yellow, fords orange, weirs are blue, and ramps are purple. The red lines show the Afan river.

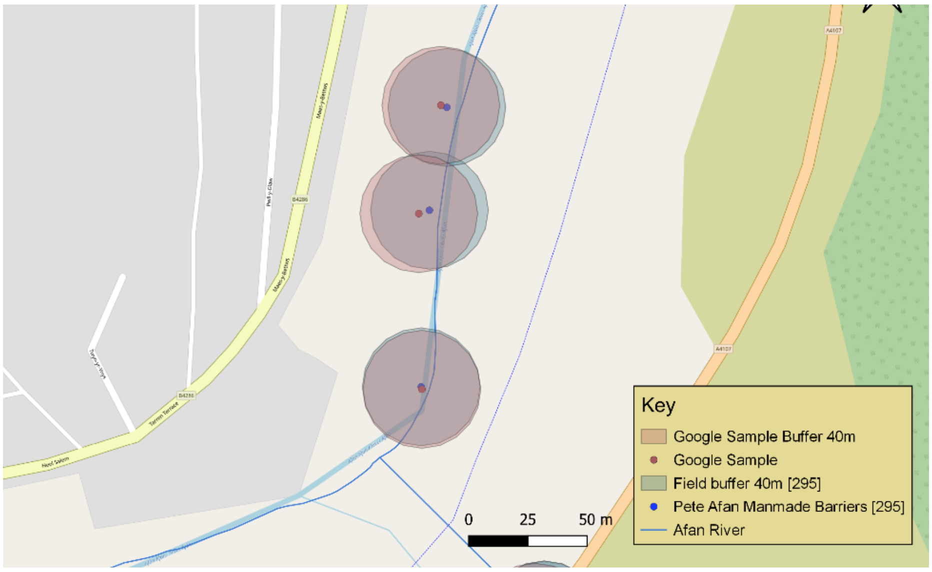
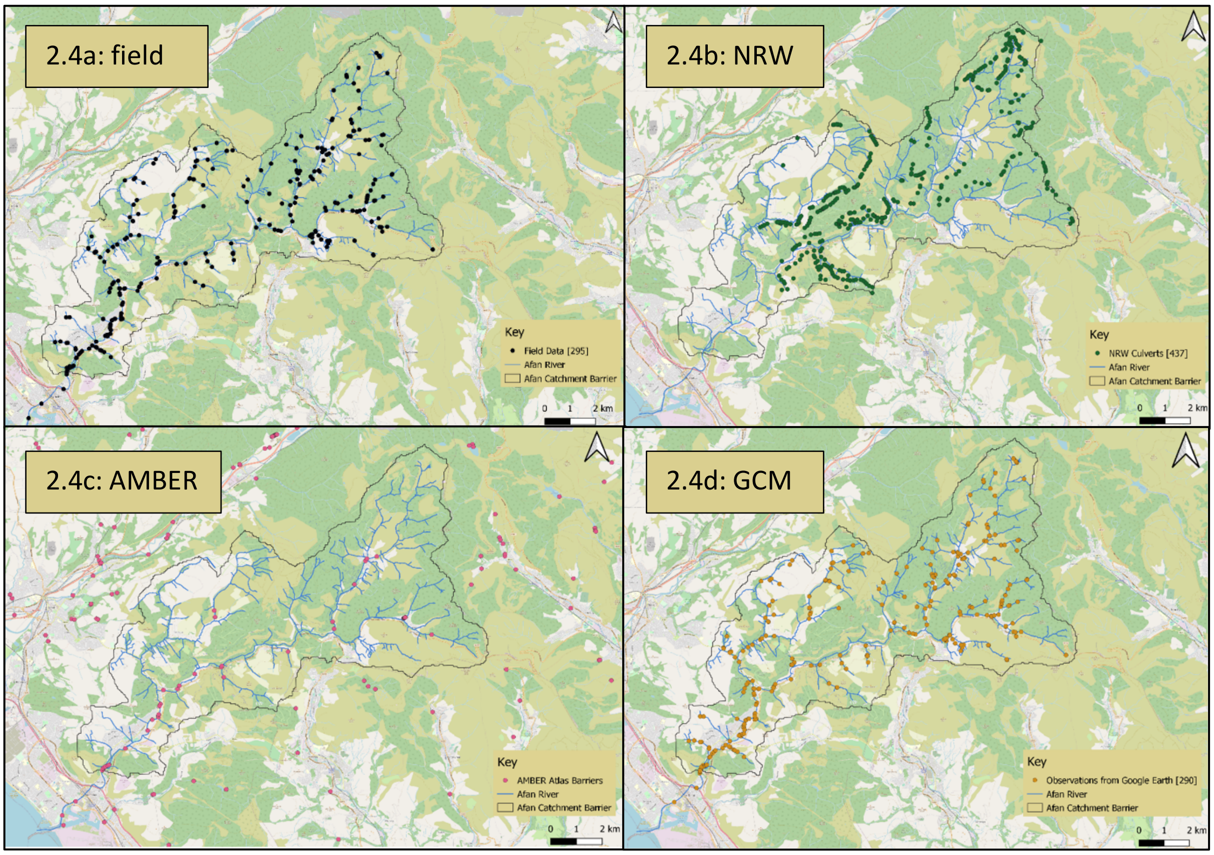


Figure 2.2. Buffer overlap of a Google sample with the field data within the Afan catchment. A 40m buffer was used in this example for clarity but a 10m buffer was used during research. This would then be recorded as 1 = present in an excel table (QGIS, 2021). Contains OS data © Crown copyright and database right 2021.



Figures 2.3a – 2.4d. The field data, the ‘google consensus majority’ (GCM), AMBER Atlas and NRW culvert dataset mapped within the Afan catchment using QGIS version 3.10 A Coruña (QGIS, 2021). Figure 2.4b ‘NRW was dropped from the study. Contains public sector information licensed under the Open Government Licence v3.0.

2.3.4.2. Afonydd Cymru/Rivers Trust Data

The Afonydd Cymru (AC) dataset (Figure 2.3.) is field data extracted from 'Fisheries Habitat Restoration Plan' surveys, undertaken by regional rivers trusts throughout Wales. It was commissioned by Natural Resource Wales, with the aim to identify opportunities for improving riverine habitats for fish species. This dataset shows 390 barriers recorded across 29 river catchments in Wales and 293 of these were barriers for the Afan catchment, shown in Figure 2.4. The purpose of using this dataset was to strengthen the accuracy of our results and allow assessments to be made between both datasets.

To create the AC desktop survey, the data points was uploaded to Google Earth and recorded as 1= verified if a barrier was identifiable from satellite imagery, or 0 = not verified if it was not clearly identifiable. This method was used because it was not feasible to map every artificial barrier in Wales using remote-sensing and then to compare it to the 390 features in the AC dataset across 29 river catchments (Figure 2.4.).

The AC dataset was incomplete and environmental predictors (such as barrier 'height', 'altitude', 'distance to mouth') had to be attributed. Appendix 4.16 shows the sources of the variables collected.

The Strahler stream orders were calculated from the EU Digital Elevation Model (DEM) E30N30 file using 'fill sinks (Wang & Liu, 2006)' followed by using the 'Strahler Order' tool, both found in the QGIS SAGA toolkit (QGIS, 2021). Approximately 70 data points were missing so they were manually added using the nearest river stream order to them. Barrier height data was not available in this dataset so using Appendix 4.17, the average barrier height for each barrier type was attributed. These are barrier heights for each barrier type listed in Figure 1.1., with an average calculated from all barriers uploaded to the AMBER database.

The raw data included details about some of the barriers and combined with Figure 1.1, 355 barrier 'types' were attributed to the dataset, leaving 35 entries with incomplete information. Hybrid barrier types (e.g., culvert/dam) and barriers without 'type' data were validated using satellite data to streamline into the 6 AMBER list of barrier types (Figure 1.1). Data with missing information was removed (removed entries shown in Appendix 4.5).

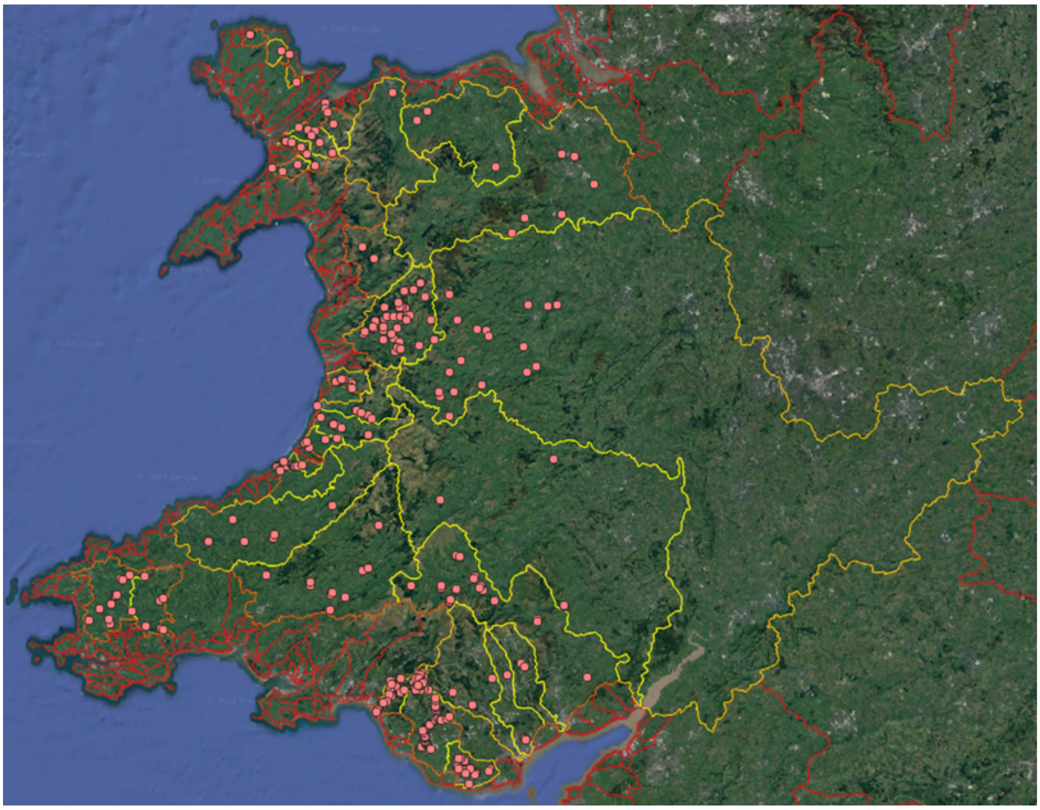


Figure 2.4. A map showing the location of the 390 barriers from the Afonydd Cymru (AC) river barriers as pink dots, which were recorded within 29 river catchments across Wales and England. Highlighted catchments in yellow show the study area.

2.3.5. Statistical Analysis and Model building

The aim was to test if any of the environmental predictors listed in Appendix 4.16 affect the reliability of correctly detecting artificial river barriers. The same statistical methods were used on both the Afan catchment field data and the Afonydd Cymru (AC) dataset.

Before statistical modelling in R version 4.0.3 (R Core Team, 2020), data exploration was carried out on both datasets to highlight potential sources of error or outliers. A binomial logistic GLM was used to examine which attributes significantly predict the probability of barrier detection via remote sensing, using the variables listed in Appendix 4.16.

Collinearity between the environmental predictor variables was checked before the significant variables were identified. Collinearity describes the correlation between predictor variables (Dormann et al, 2012). An assumption of binomial logistical regression is that there is no multicollinearity amongst explanatory variables. The presence of collinearity can falsely influence which environmental predictors display a statistically significant ($p < 0.05$) role in barriers being accurately identifiable via remote sensing and equally hide which are the correct significant parameters.

For testing collinearity, the independent variables were rescaled using the base R rescale function which mutates all numerical data into a scale of 0-1, to make explanatory variables with different scales comparable in exploration (Wickham and Seidel, 2020). Correlations were displayed using a corrplot, in addition to using a Pearson's correlation coefficient. Positive correlations are displayed in blue and negative correlations in red colour. Colour intensity and the size of the circle are proportional to the correlation coefficients.

Variance Inflation Factors (VIF) thresholds are commonly disputed, with some experts stating >10 as an indicator or multicollinearity, and some as low as >2.5. From reviewing the literature, a threshold of VIF>5 was chosen (O'Brien, 2007). Multicollinearity is of greater concern with small datasets (James et al, 2013; Menard, 2001; de Jongh et al, 2015). A VIF value of 1 indicates absolute lack of collinearity but a small degree of collinearity between covariates can typically arise (James et al, 2013). The collinearity results were plotted using the corrplot function (Wei, 2017).

A stepwise deletion (backwards and forwards) was used for model selection after testing for collinearity. No collinear variables were found so no variables were removed due to collinearity. It starts with a model with all variables, sequentially removing least significant variables until a final model is returned with only significant variables (Thomas et al, 2017).

Within the stepwise deletion, the Akaike Information Criterion (AIC) estimates prediction error and was used as the method of model selection. It compares the logged and unlogged models, with the lowest AIC indicating the strongest model. This was used because it reduces the probability of overfitting (Thomas et al, 2017).

To predict the accuracy of remote sensing, the data was split into 75/25 ‘train/test’ sets and the binomial GLM was used on the ‘train’ dataset. The ‘predict’ function in base R is used to predict values based on the independent variables in the final model (Thomas et al, 2017). It was applied to the ‘test’ dataset to calculate the predicted probability of accurately identifying river barriers using remote sensing and results were plotted for each variable. A McFaddens Pseudo R^2 and p-value were calculated to return the significance level of the test.

2.4. Results

2.4.1. Afan Field Data

2.4.1.1. Observer Agreements

The probability of detection by each observer varied when recording artificial barriers within the Afan catchment: observer 1 with 43.4%, observer 2 with 37.9% and observer 3 with 32.5% probability of detection. Fleiss' kappa was computed to assess the agreement between the three observers in identifying the presence of river barriers on the Afan using Google Earth. The kappa = 0.63 (p value < 0.001) which according to literature, means there was substantial agreement (0.61 – 0.81) between the three observers (Landis & Koch, 1977). Fleiss' kappa agreement thresholds are traditionally used in medicine and should thus be interpreted with caution. The secondary observer agreement test which was run in R showed that inter-observer accuracy is approx. 75%, supporting the Fleiss' kappa results. When comparing the observed 'GCM' dataset to the field data, the 'GCM' correctly identified 115 barriers out of 293 when using remote sensing, which equates to 39.3%.

When recording barrier presence from any observer (i.e., not in a consensus majority), 148 barriers out of 293 were correctly recorded, which equates to 50.5%. Figure 2.5. shows a Ven diagram of the breakdown of barrier recordings of each observer, amongst observers and the total quantity of barriers recorded by any observer. Observer 1 recorded 96 barriers, observer 2 recorded 128 barriers and observer 3 recorded 112 barriers. When observer 1 and observer 2 recordings are amalgamated, this equates to 141 barrier observations. Observer 1 and observer 3 record 130 barriers and observer 2 and observer 3 record 141 barriers in total.

2.4.1.2. Data Exploration and Binomial Logistic Regression

Figure 2.6. shows the frequency of barrier type within the Afan River catchment, extracted from the field data. Results show that culverts are the most prevalent barrier type with 50.3% (n= 147). Ramp/bed-sills were the second most common barrier type with 22% (n= 65). Figure 2.7. shows the estimated under reporting error for each barrier type when using remote sensing, calculated using an X^2 test. The largest reporting error was for barrier 'type 'other' as this can be any barrier, artificial or natural that does not fall into the 6 barrier types listed in Figure 1.1. within the AMBER barrier types, 'weir' shows the biggest reporting error of 70%. Barrier type 'ramp' had the lowest reporting error. These are typically found in the lower river catchments near urban areas; thus rivers tend to be larger here and barriers easier

to spot. This figure shows that the probability of detection varies by barrier type. Barriers types with <10 were removed due to insufficient sample sizes: these were sluice (n=0), dam (n= 5) and ford (n= 9).

Data exploration was limited as there are only 3 environmental predictors (‘height’, ‘altitude’ and ‘distance to mouth’), with true continuous numeric data (Zuur et al, 2010). A boxplot and Cleveland plot were created using the field data to detect potential outliers using the numerical environmental predictors of which this dataset has none (appendix 4.21.). It is important to test for outliers as one of the assumptions of a binomial logistical regression is that there are no extreme outliers.

Figure 2.8. shows a multi-panel Cleveland plot of the ‘Distance to Mouth’, ‘Height’ and ‘Altitude’ parameters. The vertical nature of the ‘height’ graph is a result of the approximate heights (Appendix 4.17) extracted from the AMBER Atlas database. The single larger value on the right side of the graph at first looks to be a measurement error but when referring to appendix 4.17, this looks to be a dam with a height of 20.3 meters. No discernible outliers are present in the ‘Distance to Mouth’, or ‘Altitude’ graphs.

Figure 2.9. shows some preliminary plots for the continuous data within the Afan dataset. It shows that a lower altitude may result in more accurately identifiable barriers within the Afan catchment. Similarly, it shows that a smaller ‘Distance to mouth’ may result in a higher presence of accurately identified barriers using remote sensing. The barrier ‘Height’ data here does not show a significant relationship.

A GLM model with family = binomial was used to test potential significance of environmental predictors in influencing whether barriers are identifiable using remote sensing. The data was split into 75/25 train/test to predict the response value of a new observation. The collinearity test revealed a Pearson’s correlation of 0.91 between ‘Altitude’ and ‘Distance to mouth’ variables. The VIF results ‘Altitude’ confirmed this with the highest VIF score (7.5) and Altitude was removed from model. The stepwise deletion shows the significant variables (to <0.05) to be ‘Strahler’ and ‘Distance to mouth’ (D2m), resulting in the variables ‘Altitude’, ‘Height’, ‘Forested’, ‘Type’ to be removed in that order, beginning with least significant.

‘Model0’ was used to calculate the significance of the selected variables on the ‘GCM’ dataset (model summary in Appendix 4.6.). ‘GCM’ barrier presence is the probability of detection using Google Earth (0/1) with ‘Strahler’ and ‘D2m’ as the independent variables:

$$Model0 = 5.440\text{e-}01 + 8.806\text{e-}02x_i + -8.959\text{e-}05x_{ii}$$

Deviance residuals represent the square root of the contribution that each data point has to the overall residual deviance. The summary shows the deviance residuals are approximately symmetrical and centred around the Median. The default dispersion parameters were taken to be 1. Since we are not estimating the variance from the data but deriving it from the mean, it is possible that the variance is underestimated. The number of Fisher Scoring iterations was 4, which tells us how quickly the GLM function converged on the maximum likelihood estimates for the coefficients.

A McFadden's Pseudo R^2 was calculated to interpret the overall effect size (0.068) and the p-value for this using chi-square distribution was calculated to be <0.001, indicating this is not by chance and is indeed significant but with a tiny effect. The corrgram (appendix 4.22) showed no strong correlation between the independent variables of the final model and it is concluded there are no parameters to be excluded from predictive modelling due to correlation as shown.

Figure 2.10. shows that the smaller the 'Distance to mouth', the higher chance for probability of detection using remote sensing. The larger the 'Distance to mouth' (meters), the lesser chance of being accurately remote sensed, with probability of detection tripling from 25000m to 5000m distance. Figure 2.11. shows that the higher the Strahler number, the more likely is it that remote sensing can be used to accurately identify river barriers. The probability of detection doubles from Strahler 1 to Strahler 6. The data points appear stacked as the Strahler order is a categorical variable, from 1 to 6 in this example. A jitter function was used to move the points slightly to show data distribution better.

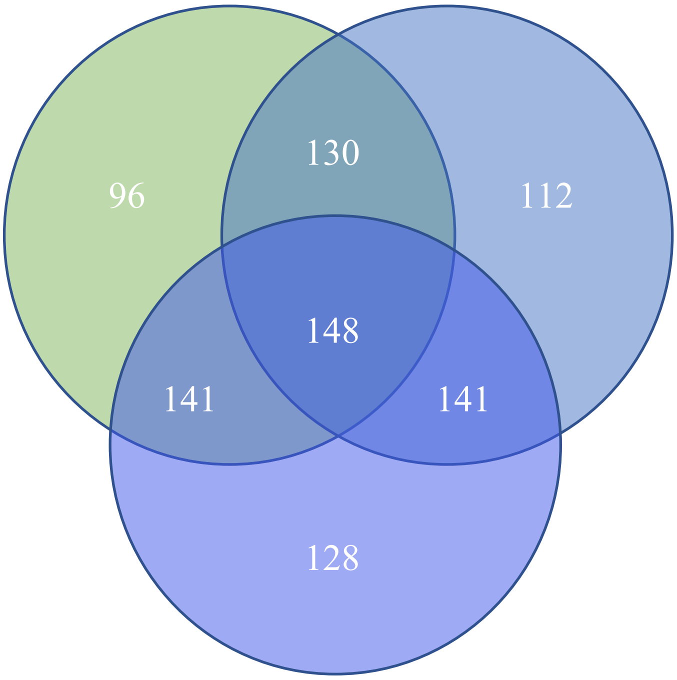


Figure 2.5. Ven diagram of barrier recordings by rater, showing individual recordings, paired recordings and the total quantity of barriers observed in the middle section. The green circle represents observer 1, purple is observer 2 and blue is observer 3.

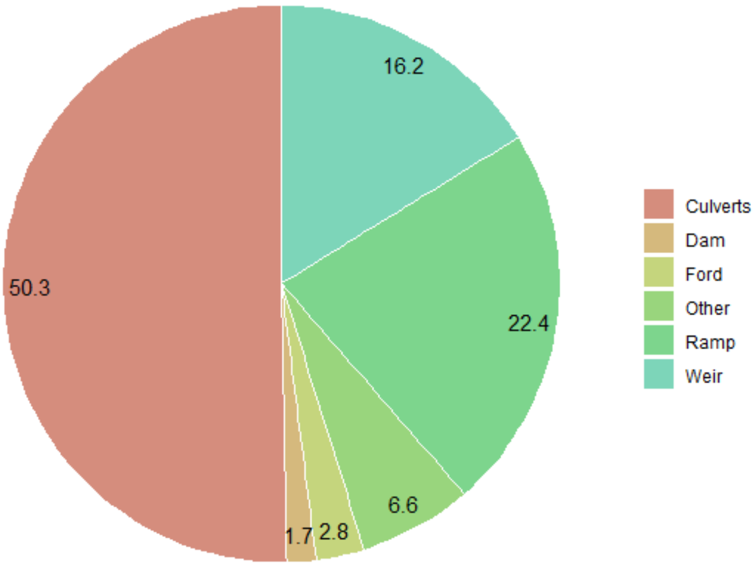


Figure 2.6. Artificial river barrier distribution (%) within the Afan catchment, graphed by barrier type (n = 295).

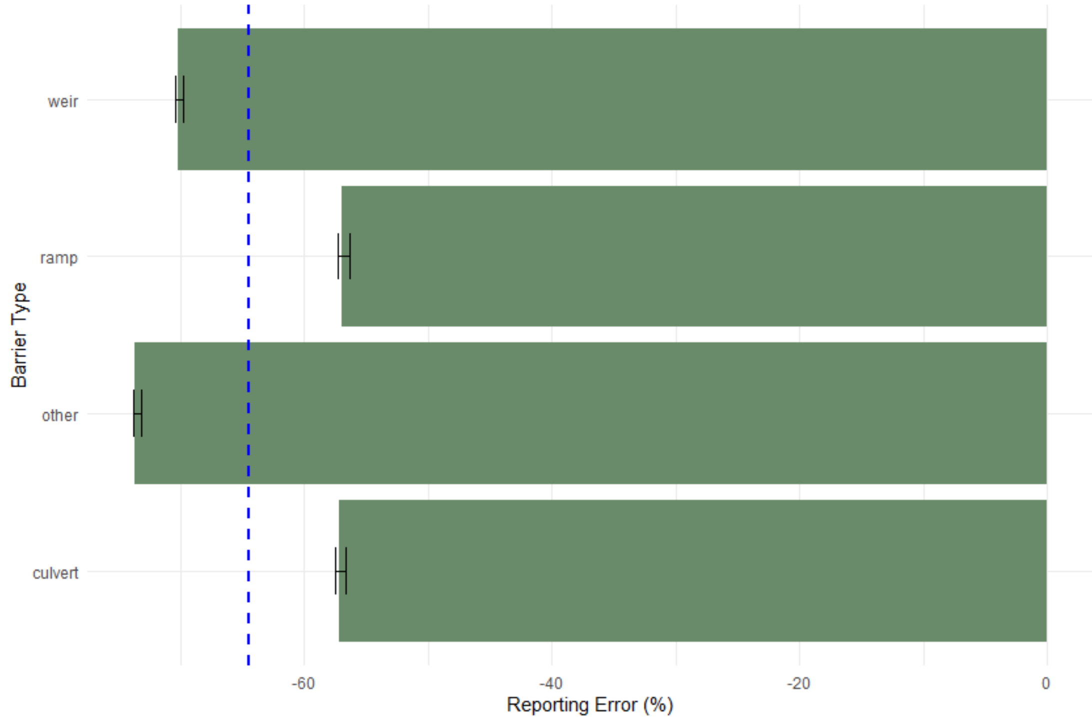


Figure 2.7. The estimated under-reporting error for the Afan dataset (% of barriers that were not identified using remote sensing) is shown for barriers types with standard errors shown in black and the mean reporting error as the dashed blue line. Barrier types with <10 samples within each were removed.

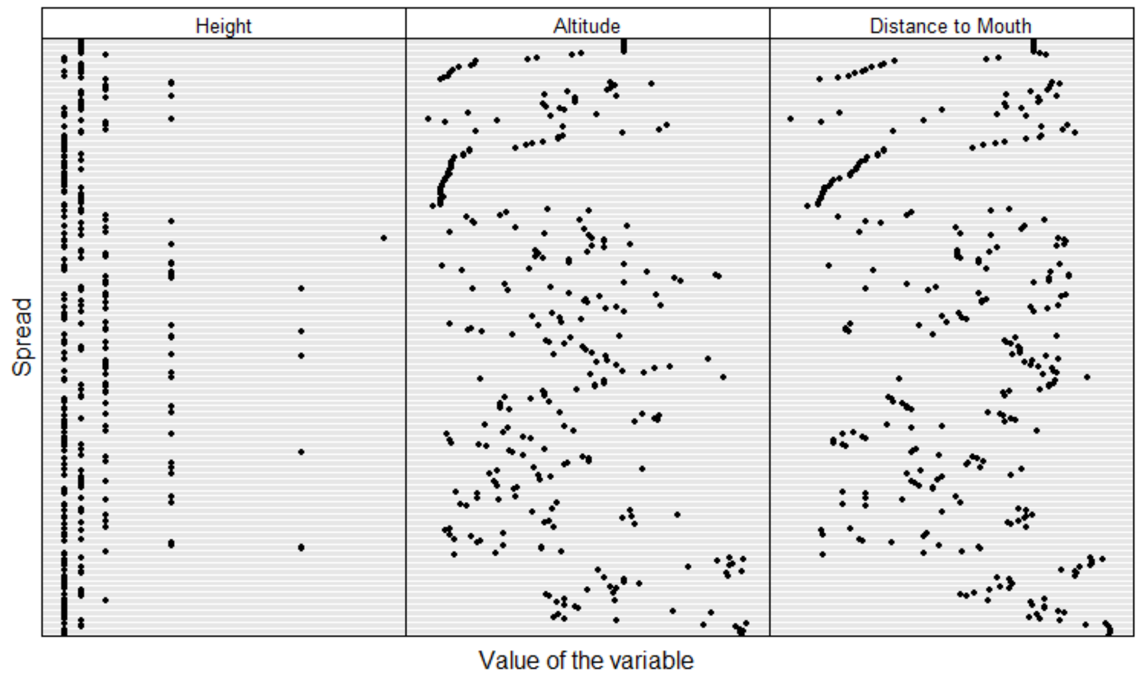


Figure 2.8. Multi-panel Cleveland plot showing the spread of Afan data on the y axis for the continuous environmental predictor variables 'Height', 'Altitude' and 'Distance to Mouth'. The x axis shows the value in meters, with smallest to largest going left to right.

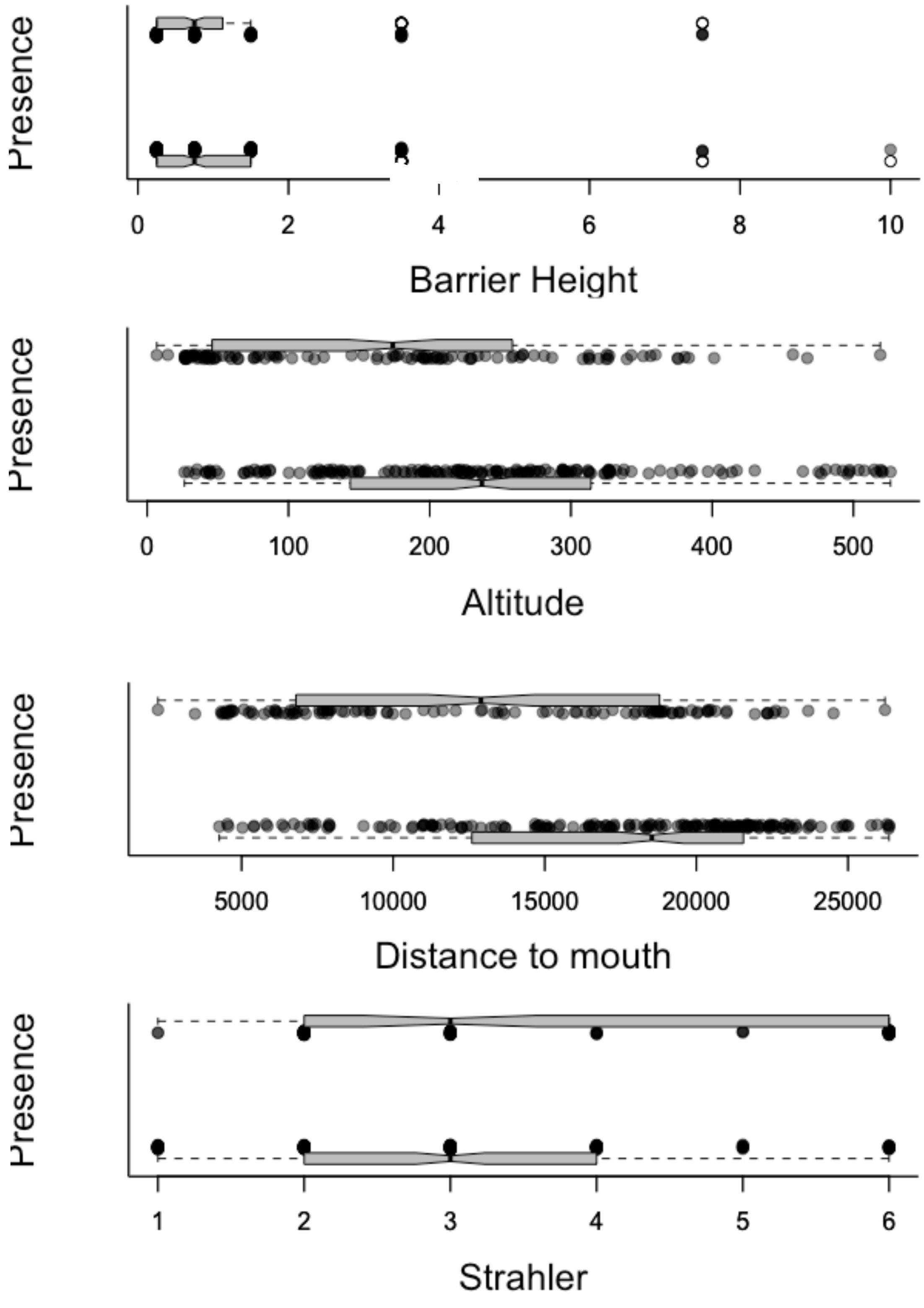


Figure 2.9. Preliminary plots of the continuous data extracted from the Afan dataset, with the upper grey barrier representing a presence and the lower grey barrier representing no presence. Each plot x axis is shown in meters except for ‘Strahler’ which shows the different Strahler levels present in the Afan river catchment.

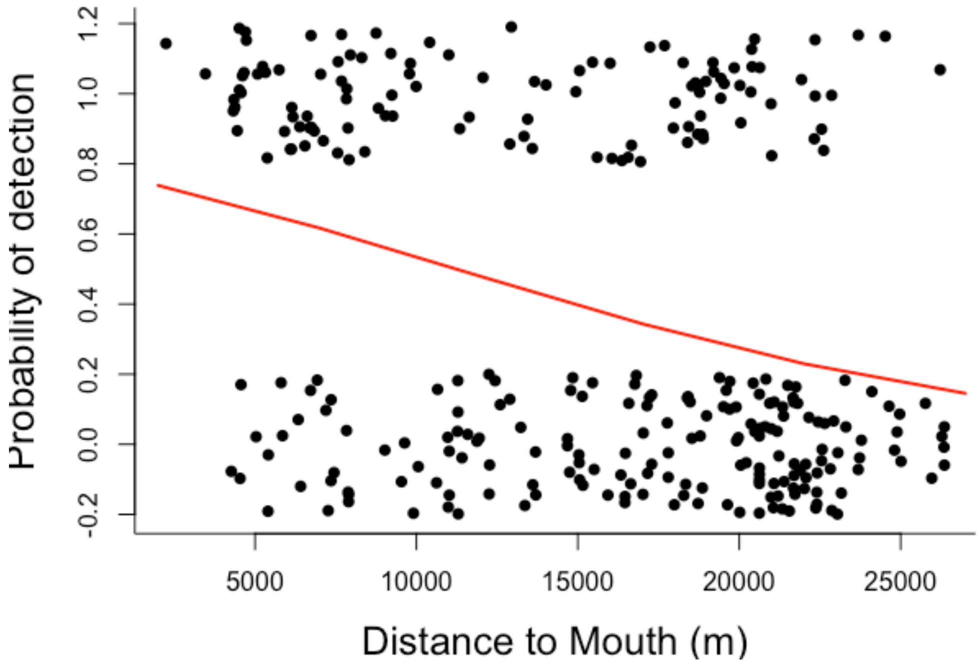


Figure 2.10. The predicted probability plot of identifying barriers using the 'Distance to mouth' variable. The red trend line plots the predicted probability against 'Distance to mouth'. Jitter function was used to show the spread of data around.

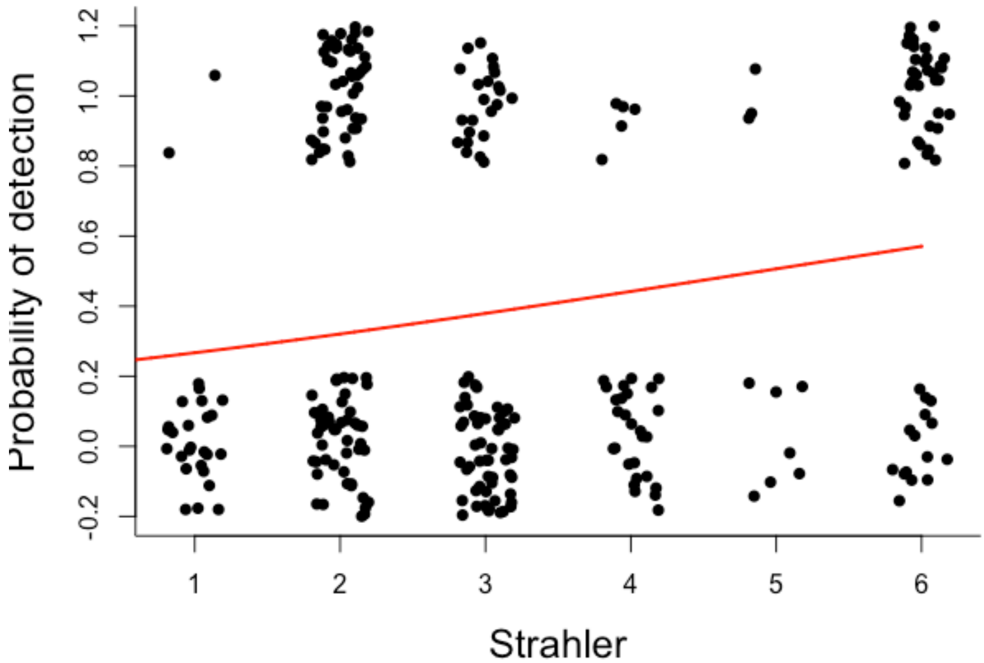


Figure 2.11. Predicted probability plot of identifying barriers using the 'Strahler' variable. The red trend line plots the predicted probability against 'Strahler'. Jitter function was used to show the spread of data around. Note it is a factor variable but was converted to continuous for graphical presentation purposes.

2.4.2. Afonydd Cymru/Rivers Trust data

2.4.2.1. Remote sensing observation accuracy

After removal of natural barriers and missing data, there were 293 Afonydd Cymru (AC) barriers. When compared with the field data, there is an 8.9% increase in the quantity of barriers recorded via remote sensing relative to the Afan dataset. Out of the 293 barriers, 178 barriers were identified using satellite imagery, equating to a 48.2% identification accuracy using remote sensing before we carry out predictive modelling. This may have arisen from the difference in remote sensing protocol (in the Afan, observers recorded barriers without seeing the field data but for the AC dataset, the barrier dataset as a guide to validate the presence of a barrier).

2.4.2.2. Data Exploration and Binomial Logistical Regression

Unlike the barriers recorded in the Afan catchment (Figure 2.6.), weirs are the most prevalent barrier type (Figure 2.12.) recorded across Welsh catchments using the AC data with 41% (n= 150), which may be more indicative of the barrier types across Wales. Figure 2.13. shows the estimated under-reporting error for the AC dataset, calculated using an X^2 test. This is the percentage of barriers that were not identified using remote sensing, split into barrier types. Similar to the Afan plot (Figure 2.7.), ramps showed the lowest estimated report error. Sluices have the highest reporting error in this dataset with 100% under reporting. This is likely because sluices are difficult to spot from satellite imagery as they are small and can often be part of a larger river barrier, such as a dam. They are easiest to spot from a side angle as opposed to a 'birds eye view' used in remote sensing. Barrier type 'other' has the second largest estimated reporting error and was the largest in the Afan, however there are no sluices present in the Afan dataset, so these show similar results. The reporting error percentage is also similar at nearly 70%.

Five potential outliers were shown in the 'Altitude' boxplot (appendix 2.23), but when the data is shown in the Cleveland plot, only 2 potential outliers are obvious as they are outwith the general spread of data. Outliers were double checked using an elevation finder and were found to be correct altitudes, so the decision was made to keep these entries (©Free Map Tools, 2021). The 'Distance to mouth' boxplot shows potential outliers however, the Cleveland graph shows this is not the case and that many entries simply have a larger 'Distance to mouth'.

The Cleveland plot (Figure 2.14) show 4 larger values on the right side of the graph at first looks to be a measurement error but when referring to appendix 4.17, this looks to be a dam with a height of 20.3 meters.

Figure 2.15. shows some preliminary plots for the continuous data within the AC dataset. The barrier 'Height' data here does not show a significant relationship. It shows that potentially a lower altitude may result in more accurately identifiable barriers within the AC dataset and that a smaller 'Distance to mouth' may result in a higher presence of accurately identified barriers using remote sensing.

A corrgram (appendix 4.24) was used to check for correlation in the Afan dataset and show some correlation between the predictors of the final model. The collinearity test revealed a Pearson's correlation of 0.39 between 'Altitude' and 'Distance to mouth' variables and -0.5 between 'Altitude' and 'Strahler'. The VIF results showed 'Altitude' with 1.72, Strahler with 1.75 and D2m with 1.3, which are all below the correlation threshold used in this study of >5 so the variables were kept for the stepwise deletion.

The Stepwise deletion determined 'Forested', 'Strahler' and 'Distance to mouth' (D2m) as the significant environmental predictors for the AC data, dropping barrier 'type', 'height' and 'altitude', with the remaining parameters are statistically significant to <0.05. 'Model1' was used to calculate the significance of the selected variables on the AC data, with 'gv" (google validation) as being the probability of barrier detection using remote sensing and 'Forested', 'Strahler' & 'D2m' the predictor variables:

$$\textit{Model1: } 1.332e{+}00 + -2.023e{+}00x_{i} + 3.526e{-}0x_{ii} + -1.652e{-}05x_{iii}$$

The model summary (appendix 4.7) shows the deviance residuals are approximately symmetrical and centred around the Median. The default dispersion parameters were taken to be 1. Since we are not estimating the variance from the data but deriving it from the mean, it is possible that the variance is underestimated. The AIC shows the Residual Deviance adjusted to the number of parameters in the model and was 356.17 for the full model with all variables and 354.84 after the stepwise deletion, showing a better fitting model. The number of Fisher Scoring iterations was 4, which tells us how quickly the GLM function converged on the maximum likelihood estimates for the coefficients.

A McFadden's Pseudo R^2 was calculated to interpret the overall effect size (0.09986462) and the p-value for this using chi-square distribution was calculated to be <0.001, indicating this is not by chance and is indeed significant.

Figure 2.16. shows that the less forested an area, the higher probability (approx. 90%) of a barrier being correctly identified using remote sensing. The probability of detection decreases when there is forest present near the barrier and thus the lesser chance of being accurately remote sensed. Figure 2.17. shows that the smaller the 'Distance to mouth', the chance for probability of detection using remote sensing approximately doubles. Lastly, Figure 2.18. shows that that the higher the Strahler number, the more likely is it that remote sensing can be used to accurately identify river barriers, with an increase from approximately 40% at Strahler 1 to 70% probability of detection at Strahler 6. A jitter function was used to move the points slightly to show data distribution better.

After modelling, the question arose as to whether it is probable that the presence of forestry affects barrier visibility and that they may interact, depending on stream order. To test this, 4 further models were created:

- *Predictor variables: Forested + Strahler, Forested * Strahler + D2m*
  - ⇒ *model2:* $4.089e\text{-}01 - 6.666e\text{-}01x_i + 7.132e\text{-}01x_{ii} - 1.322e\text{-}05x_{iii} - 4.834e\text{-}01x_{iv}$
- *Predictor variables: Forested + Strahler, Forested * Strahler*
  - ⇒ *model3: 0.1856 - 0.7954 + 0.6772 - 0.4354*
- *Predictor variables: Forested*
  - ⇒ *model4:* $2.0015 - 1.8658x_i$
- *Predictor variable: Strahler*
  - ⇒ *model5:* $-0.4291 + 0.2500x_i$
- *predictor variable: Forested + Strahler*
  - ⇒ *model6* $0.69519 - 0.34687x_i + 0.06002x_{ii}$

Models were compared by examining changes in AIC values (Table 2.1.) via the anova command, starting with a model with three main effects (Forested, Strahler, D2m) and the 2-way 'Forested x Strahler' interaction. The minimal adequate model with the lowest AIC was 'model1' (X2 = 0.038) and contained Forested (p = 0.000001), Strahler (p = 0.012) and D2m (p = 0.03) but did not include the 2-way 'Forested x Strahler' interaction, which was not statistically significant (p = 0.961). As soon as there is a model where 'Forested' isn't a predictor variable, there is a substantial increase in AIC/loss of model performance. Model 1 is most suitable as performance is no worse, but it is a simpler model. This is also supported by the AIC increase between model 4 and model 5. Model 6 shows a weaker model overall compared to model 1, as it has a higher AIC.

Thus, the most plausible model is 'model1' and shows the presence of forestry does not affect barrier visibility depending on stream order. This shows us that forestry does affect the probability of being detected, just not in relation to the Strahler order.

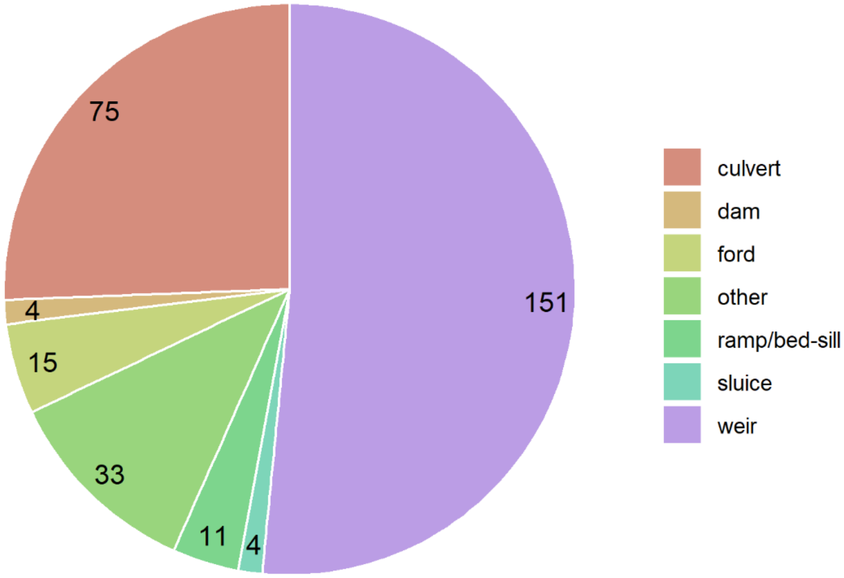


Figure 2.12. Artificial river barrier distribution across Welsh river catchments according to the AC data, graphed by barrier type (n = 293).

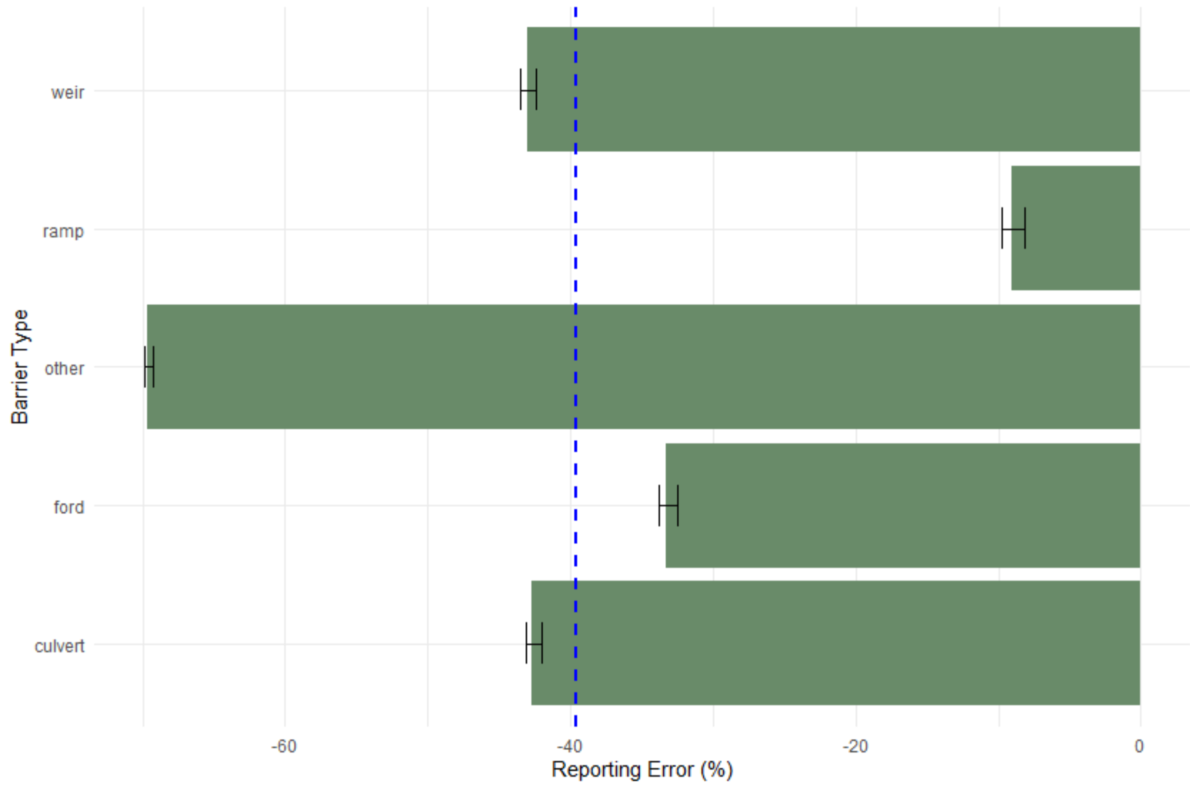


Figure 2.13. The estimated under-reporting error for the AC dataset (% of barriers that were not identified using remote sensing) is shown for barriers types with 95% confidence

intervals shown in black and the mean reporting error as the dashed blue line. Barrier types with <10 samples within each were removed.

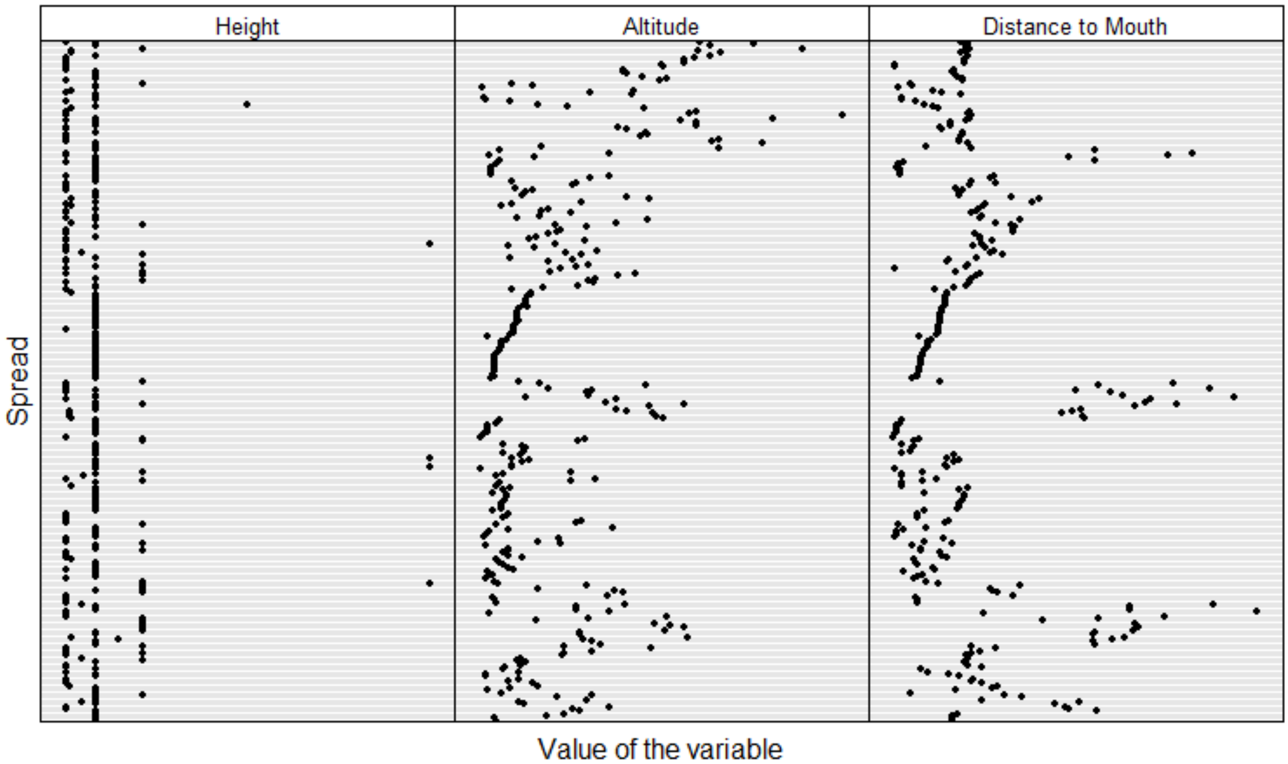


Figure 2.14. Multi-panel Cleveland plot showing the spread of AC data on the y axis for the continuous environmental predictor variables ‘Height’, ‘Altitude’ and ‘Distance to Mouth’. The x axis shows the value in meters, with smallest to largest from left to right.

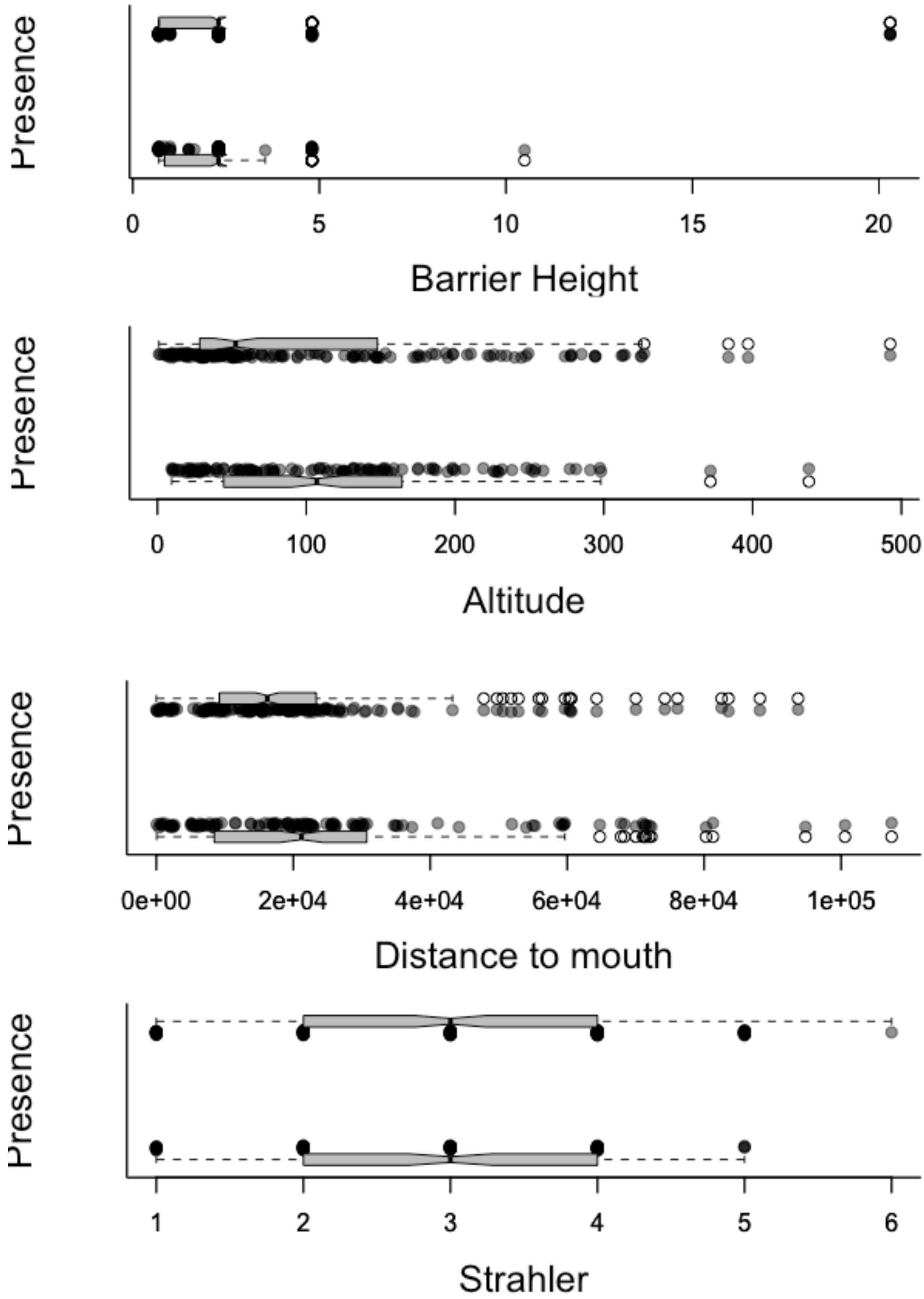


Figure 2.15. Preliminary plots of continuous data extracted from the AC dataset, show in meters (m) for each variable. The upper grey barrier representing a presence and the lower grey barrier representing no presence. Each plot x axis is shown in meters except for 'Strahler' which shows the different Strahler levels present in the Afan river catchment.

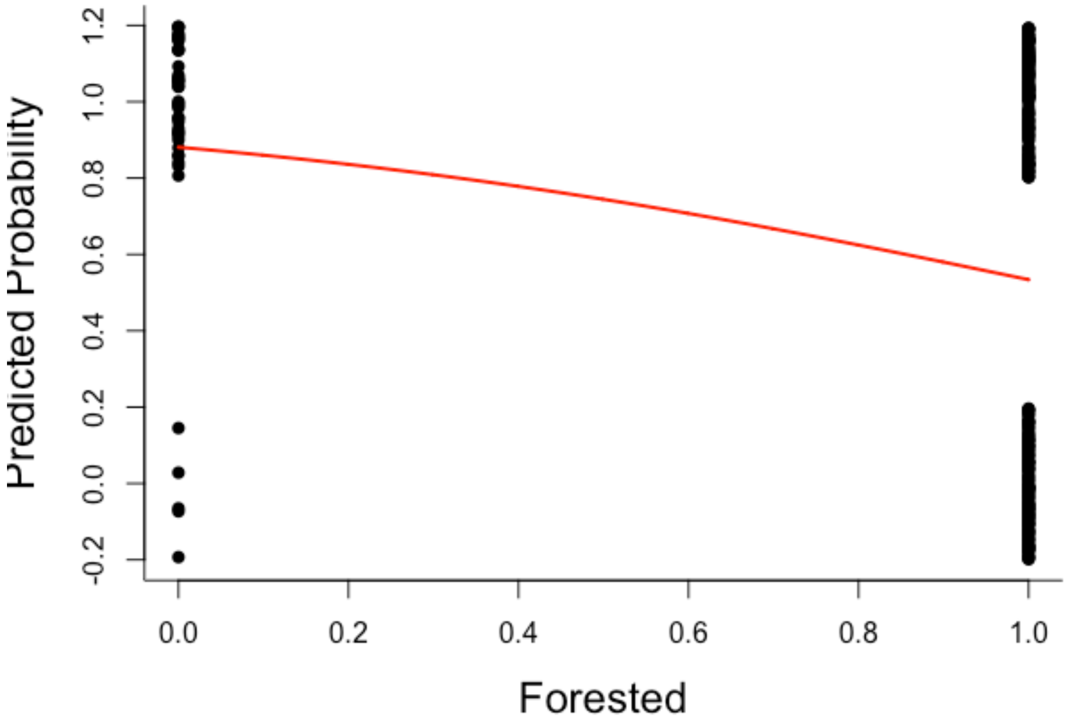


Figure 2.16. The predicted probability of identifying barriers using the 'Forested' variable within the Afonydd Cymru (AC) dataset, independent of the other predictor variables. The red trend line plots the predicted probability against 'Forested'. The jitter function was used to show the spread of data.

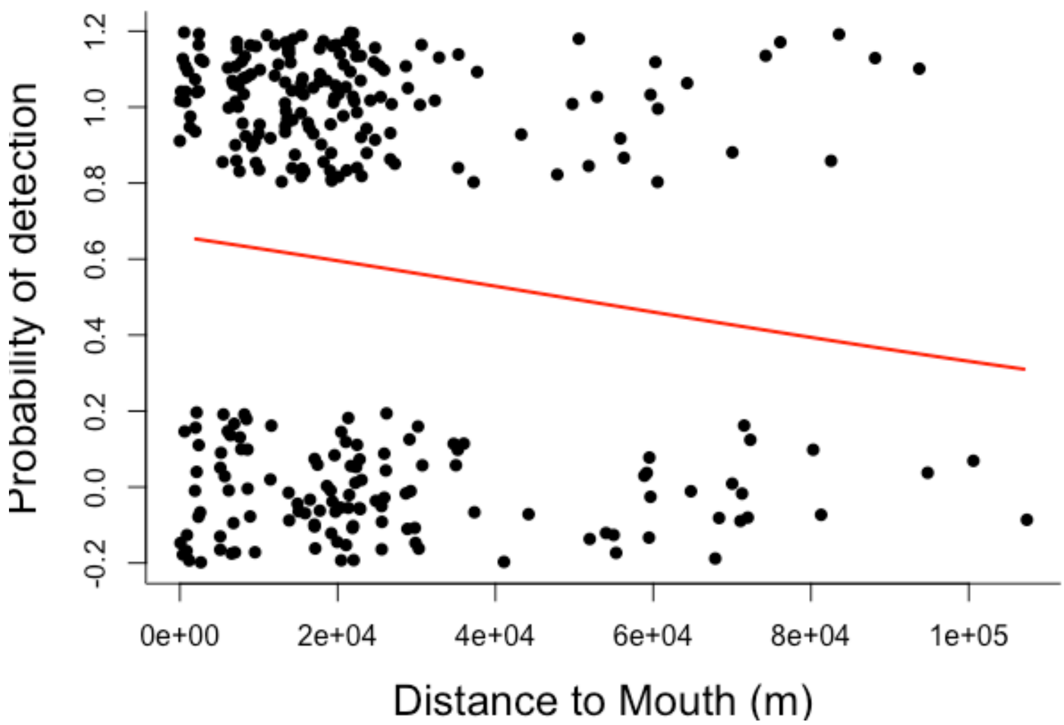


Figure 2.17. The predicted probability of identifying barriers using the 'Distance to mouth variable within the Afonydd Cymru (AC) dataset, independent of the other predictor variables. The red trend line plots the predicted probability against 'Distance to mouth'.

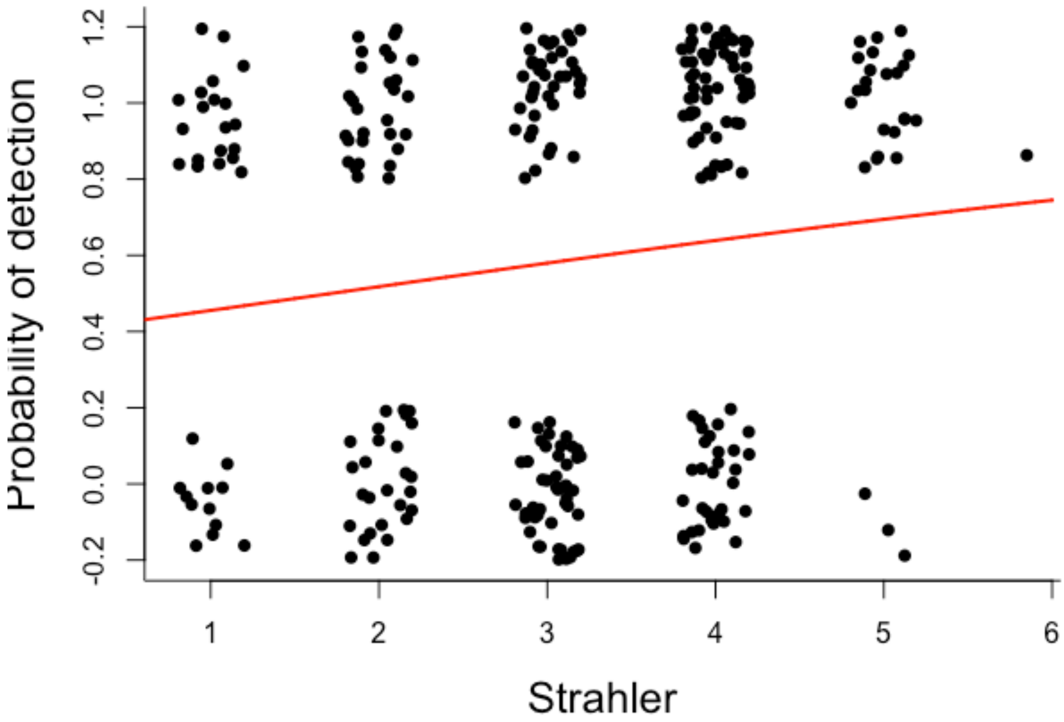


Figure 2.18. The predicted probability of identifying barriers using the 'Strahler' variable within the Afonydd Cymru (AC) dataset, independent of the other predictor variables. The red trend line plots the predicted probability against 'Strahler'. The jitter function was used to show the spread of data.

Table 2.1 Model outputs from testing the interaction between predictors 'Forested' and 'Strahler' using 6 different models.

Model type	**AIC**
Model1: Forested + Strahler + D2m	397.72
Model2: Forested * Strahler + D2m	399.72
Model3: Forested * Strahler	402.43
Model4: Forested	404.6
Model5: Strahler	417.19
Model 6: Forested + Strahler	400.43

2.5. Discussion

2.5.1. Observer agreements

Using the Afan field data, remote sensing can correctly identify artificial barriers in the Afan river to an accuracy of 39.3%, missing 60.7% of river barriers. To address the Wales hypothesis, remote sensing is accurate in identifying artificial barriers across Welsh catchments to 48.2%, missing 51.8% of river barriers. To address the objective of this study we can combine these two results, correctly identify barriers within the Afan catchment and across Wales using remote sensing to a combined accuracy of 43.8%, missing 56.2% of barriers. This is an encouraging outcome, considering the study by Atkinson et al (2018) found 30% of obstacles were located using satellite imagery.

The results showed that the most prevalent barrier type was 'weir' in the Afan and 'culvert' from the AC dataset. This could be a reason for the lower identification result in the Afan, as culverts are harder to identify using satellite imagery than weirs. This differs from the results of Belletti et al (2020) which reported the most common barrier type to be 'ramps'. Barrier type can often be indicative of the location, topography and human population density around the barrier (Clerici et al, 2013; Belletti et al, 2020), and the Afan and AC results can indicate the topography locally and throughout Wales. Weirs are more common in urbanised areas with a higher population density, whilst culverts can be dispersed throughout a river catchment: common in upper catchments due to many tributaries crossing logging roads and in lower catchments due to the increase in urban roads.

2.5.2. Predictors of barrier detection

From the combined results, the findings suggest that certain predictors ('Strahler' and 'Distance to mouth' for the field dataset and 'Forested' and 'Strahler' and 'Distance to mouth' for the AC dataset) determine the ability to detect artificial stream barriers using remote sensing, but that they vary between the Afan field and AC datasets. It is unclear why the barrier predictors were different for each dataset (perhaps as a result of the differing distributions of barrier types within each dataset as a result of topography or urbanisation) as reporting errors showed the probability of detection varies by barrier type. The results also show a preliminary trend that working with larger datasets provides more accurate remote sensing results and this is an area to further explore.

According to Atkinson et al (2018), it is probable that the 'Forested' predictor affects visibility of a river barrier (Atkinson et al, 2018). However, this was tested statistically and found that the presence of forestry does not affect barrier visibility depending on stream order. Thus, the results from both datasets draw similar conclusions in that, the less forested the river is, the closer to the mouth a river is and the larger the Strahler order, the more accurate it is to correctly predict river barriers using remote sensing. This reinforces the idea that the larger a river is, the easier it is to view using satellite data. Nevertheless, satellite imagery is still useful in analysing remote areas with access or topographic difficulties, such as gorges (Kroon & Phillips, 2014).

As the modelling results noted, one issue in this study was the presence of forested areas covering much of the Welsh river catchments, similar to an issue in the Irish study by Atkinson et al (2018). Others have recorded similar issues with cloud cover, which was also present in the satellite data used in this study (Mulligan et al, 2020). One potential limitation is the age of satellite images available on Google Earth and Maps (Atkinson et al, 2018; United States Department of Agriculture, 2005). We do not know if these images are outdated, potentially showing barriers no longer there or missing barriers that are recently built. These reasons above could explain why we did not have a higher probability of detection when using remote sensing river barriers via the GCM 'Afan' method and the AC 'validation' method.

2.5.3. Feasibility

It is uncommon to have a complete field validated dataset like we have used in this example with the Afan catchment (Ovidio, Capra and Philippart, 2007). Without a complete dataset, the ability to complete a validation experiment using remote sensing remains unfeasible for river managers and the wider sector to repeat this study (Januchowski-Hartley et al, 2013). Another constraint is the poor image quality in some regions which made it difficult to interpret the type of barrier present (similar to Atkinson et al, 2018) as a result of low resolution pixelating the imagery. Similarly, within GOODD, there is an estimated 28% underestimation of dam record due to low resolution imagery (Mulligan et al, 2020).

The need for further study is required to determine if the Afan results are unique to that river catchment and that the AC dataset is more representative of Welsh rivers as an entity, or that both results are inaccurate. For example, each dataset results in a different most common barrier type (Afan = culvert, AC = weir). The difference in remote sensing methods of each dataset is a source of potential dispute, in addition to the subsequent different significant variables between datasets, which may be a result of the varying methodology.

This is a significant first step in barrier recording using a desk-based research method and in addressing the issue of remote sensing accuracies within a national and global context. Going forward, the barrier identification protocol should be used to serve as a benchmark when identifying barriers using remote sensing in the future, creating a standardised method and thus generating potentially comparable results (Gargan et al, 2011). As mentioned, road/river intersects were assumed to be culverts, whether they could be correctly identified or not (Atkinson et al, 2018). A ground-truthing exercise could be carried out to test the accuracy of this assumption (Januchowski-Hartley et al, 2013). Lastly, on a local scale, encouraging the use of citizen science (such as the AMBER Barrier Tracker App) and liaising with local stakeholders (such as fishers and kayakers) who know the river best is a good method in confirming potentially present barriers that have been identified using remote sensing.

2.6. Conclusion

In summary, a study was carried out to evaluate the feasibility of correctly identifying artificial river barriers using remote sensing as the first step in a prioritization process seeking to improve river connectivity. The results demonstrate that remote-sensing barriers as a stand-alone resource is not 100% accurate in identifying artificial river barriers due to the limitations discussed. Using satellite imagery to identify river barriers missed 56.2% of barriers overall in this study. I suggest it can be used as a starting point, but there is a need to supplement this process with additional methods to improve accuracy, such as field visits to unknown barriers. The results also indicate that certain environmental predictors play a statistically significant role in a desk-based method of identifying river barriers using remote sensing, however they differed slightly between the two datasets used. Now we know there is strong agreement between raters, only one rater can be used to record barriers via satellite imagery, which will further save resources. Going forward, this study would be ideally recreated with a larger sample size, using a barrier database from either a larger river in Wales, or another country with a larger barrier database than the Afan. This would show the repeatability of the study and allow for comparison between countries. This study gives a wider understanding of the feasibility of a desk-based study of barrier identification and the accuracies involved for those wishing to use remote sensing.

3. Modelling prioritised barrier removal in the Afan Catchment

3.1. Chapter Summary

Modelling can be used to prioritise the artificial barriers which should be removed first, and which will reconnect the most river longitudinal connectivity according to specific financial budgets and fish species. This chapter looks into comparing the results of using river ‘length’ vs river ‘area’ to see which model input gives a more accurate result of the potential reconnected habitat that would be created by barrier removal.

According to the modelling results, when using river ‘area’ as a model input instead of river ‘length’, the results show that at lower budgets, it is better to prioritise barrier removal by ‘area’ as this reconnects the most habitat at most financial budgets. The results showed that specifically using river ‘area’ as a prioritisation input is more effective for barrier removal projects with budgets £1-5million and can be used as a first step in the barrier removal process.

3.2. Introduction

River barriers provide a myriad of societal benefits, such as fresh water supply and agricultural lands, as well as reduced floods and droughts (Grill et al, 2019). As a result of this, their negative impacts are often left unchecked (Januchowski-Hartley et al, 2021).

River barriers break up the free-flowing nature of rivers, impacting reproduction, genetic diversity and migration of fish (see Baras & Lucas, 2001; Kroon & Phillips, 2014; Januchowski-Hartley et al, 2013, Perkin & Gido, 2012; Grant et al, 2007 and Samia et al, 2015) as well as decreasing agricultural productivity from flood plains due to flood attenuation (Lehner et al, 2011).

In addition to the current environmental impacts we are aware of, Fuller et al (2015) believe we may have yet to witness the full impacts of anthropogenic barriers as we begin to observe the impacts of climate change and the role it plays on our freshwater ecosystems. This could take centuries to realise and unforeseen problems may arise that we have not yet considered. There can also exist a time or geospatial lag from when an artificial barrier is introduced to where the effects are seen on the river network (Pringle, 2003). For example, reductions in sediment flow can arise from anthropogenic barriers such as dams, which can lead to river delta sinkage (Lehner et al, 2011), potentially displacing coastal communities who depend on delta ecosystems. A fragmented dendritic network can encourage local extinctions within metapopulations (Levins,1970) of riverine species and create genetic isolation between subpopulations (Labonne et al, 2008).

The boom of the Industrial Revolution saw a steep incline in the quantity of anthropogenic barriers and river infrastructure in the 18^{th} - 20^{th} centuries due to the requirements of transportation and water extraction (Tvedt, 2010), which outpaced the evolution of aquatic species (Fuller et al, 2015).

Longitudinal fish migration is important for accessing feeding, spawning and refuge grounds (Atkinson et al, 2020) and so it is imperative to measure impacts arising from longitudinal fragmentation. For example, in Atlantic salmon, freshwater is vital for spawning and salmon travel thousands of kilometres to return to spawning grounds (Mills, 1991).

Research around aquatic habitat fragmentation is still limited, with most focussing on terrestrial fragmentation. One reason for this is that terrestrial fragmentation is often studied in two-dimensional ‘patch’ dynamics, however this does not translate well into the longitudinal, continuous nature of a river (Fuller et al, 2015). Some researchers have loosely translated 'patch' dynamics into the network segments, for example, a river tributary counting as one 'patch' along the dendritic ecological network (DEN) (Perkin et al, 2012). Abiotic factors (such as the physical nature of a river network: discharge rate, geomorphology) have been identified as an impact to the dispersal and diversity of fish species. (Finn and Poff, 2011; Thornburgh and Gido, 2009). Another reason is that terrestrial habitat connectivity has also been found to be more robust against lower connectivity levels than aquatic habitats, so connectivity modelling is not transferable across habitat types (Cote et al, 2009).

It can be difficult to measure freshwater habitat fragmentation due to the transient nature of barrier height. For example, fragmentation severity changes with river flow rate or seasonal discharge (e.g. a low weir that migratory fish can pass during high flow rates), making it difficult to measure habitat areas due to seasonal changes in stream width. Furthermore, some studies excluding minor and/or ephemeral watercourse whilst some including them (Allen at al 2018, Clerici et al 2013).

Fuller et al (2015) notes another reason could be the lack of a standardised measuring approach of river fragmentation that can be applied across all aquatic species (also Puijenbroek et al 2018). This is because each species has different migration requirements, distribution patterns and habitat demands, even on the same river network (Puijenbroek et al, 2018). As noted in chapters 1 and 2, this is a common theme across research relating to river connectivity and issues arising from artificial barriers.

River fragmentation due to anthropogenic barriers has been noted as a principle threat to the decline in migratory species. Within a hydrological capacity, connectivity is vital for the transfer of abiotic materials through the river system (Pringle, 2003). Some scientists are pioneering research in the area of freshwater habitat fragmentation, such as research by Cote et al (2009), Puijenbroek et al (2018), Perkin et al (2012) and Kemp & O'Hanley (2010). However, where research has been conducted, it often focuses on larger and/or simulated rivers, such as in Puijenbroek et al (2018), Cote et al (2009) and Perkin et al (2012).

The most notable existing model for measuring longitudinal connectivity of rivers is the Dendritic Connectivity Index (DCI), created by Cote et al (2009) to quantify impacts to longitudinal river caused by dams. A limitation of this model is that the DCI does not assess habitat quality, such as the effects to flow regime and fish habitat, as they are not captured by a purely spatially derived index (Shaad et al, 2018). An assumption of current barrier analyses such as the DCI is that spatial structure is predictive of ecological function and exclude the relationship between longitudinal connectivity and ecological restoration, such as metapopulation persistence, chemical quality or gene flow (McKay et al, 2016).

It also used universal passability standards and was not species specific, thus a modelling study on individual species barrier passing abilities is needed. This paper modelled only river length as an input and did not account for river width or subsequently river area. This means that rivers 10cm wide and rivers 10m have equal weighting in these simulations, even though these will be very different habitats available. There is an obvious need here to introduce river width as an input to calculate the area of each river segment.

This connectivity measurement method was further developed by Bourne et al (2011) to assess the significance of both input types (fish species, fish size and hydrological conditions) and barrier assessment methods. The study showed that fish length had the largest impact on DCI results and that barrier passability depends on fish species, size and hydrological conditions, which means it is important to model at a specific species level when modelling longitudinal connectivity (Bourne et al, 2011, Kemp and O'Hanley, 2010). A key finding from this study was that using the DCI as a method in modelling river connectivity is that it is insensitive to swim speed assumptions on different sizes of fish. Another key limitation of this study is that only 2 fish species were used to determine the results and they were both salmonids.

It has also been found that current survey methods for assessing impacts of river barriers is biased towards culverts and economically important fish, specifically salmonids (Kemp & O'Hanley, 2010). Fish barrier modelling on species other than salmonids is therefore needed. A comparison study (Samia et al, 2015) using the DCI versus a matrix model investigating the characteristics of a river barrier impact population growth rate found that the DCI also excludes the influences of mortality caused by river barriers.

Optimizing river barrier removal into a prioritised list is essential for cost-effectiveness removal (O'Hanley & Tomberlin, 2005) and yet tools to model habitat gains to river connectivity from barrier removal remain nascent and in the exploratory stage, resulting in no current industry standard (Cote et al, 2009). Additionally, prominent connectivity models have limitations, notably that previous studies focus on larger rivers and larger barriers as they are easily spotted using satellite data (See Puijenbroek et al 2018 and Cote et al 2009). Studies on small-scale rivers and/or that use species other than salmonids are uncommon within Europe (Lucas et al, 2009) and there is a need to develop barrier modelling at a catchment scale (Kemp & O'Hanley, 2010).

Another issue raised by Labonne et al (2008), is that due to the dendritic nature of river systems, there is usually only one path for species to take. This means that, for example, even if there are good spawning grounds in one river segment, if there are barriers (these can be physical, chemical or biological) between the fish and their target destination, that entire river segment cannot be accessed, no matter how pristine or well-connected the environment beyond the barrier. Exploring the relationship between other barriers to fish migration (for example, chemical) in conjunction with anthropogenic barriers to create a full picture of habitat fragmentation to species is required. As mentioned, the DCI method does not include this so even with current river barrier modelling efforts, there is a need for alternative methods.

As most river catchments will not have a complete dataset of artificial barriers, it can be challenging to calculate complete river connectivity. The Afan catchment in Neath, South Wales has a complete dataset of river barriers. As we have this unique inventory of artificial barriers in the Afan, the aim of this chapter is to extend the parameters of an existing prioritisation model developed by Dr Jesse O'Hanley, which uses river length to model a prioritised list of barriers to remove. The modelling in this chapter aims to compare the existing model inputs of using river 'length' with a new input of using river 'area', in the hopes that this refined habitat representation increases accuracy of the prioritisation results. Additionally, habitat quality weightings will be applied to the model and comparisons created to determine how this affects the prioritisation results against a predetermined budget range (£0 - £13,000,000).

3.3. Methods

For the purposes of this study, ‘habitat connectivity’ can be defined by Turner & Gardner (2001), where the terrestrial definition is “spatial continuity of a habitat or cover type across a landscape” (in this instance, the landscape is a river system). This study focuses only on longitudinal river connectivity as defined in Chapter 1, thus other connectivity types (such as lateral) were out with the scope of this study.

An optimization model algorithm has been developed by Dr Jesse O’Hanley of the University of Kent, using simulation software which assigns cost and impact (i.e. barrier passability) to removing barriers based on species jumping capabilities, depending on the species and their jumping heights. It is currently a generic method which is applicable to any species and uses river ‘length’ to calculate upstream habitat creation as a result of barrier removal. Using river ‘length’ is not an ideal parameter as it does not account for how wide the river is or the river ‘area’, so it may not accurately reflect the amount of habitat gained from barrier removal.

I recognise the model can be optimised further, to include common UK freshwater species, specifically bullhead (*Cottus gobio*), brown trout (*Salmo trutta*), Atlantic salmon (*Salmo salar*), found in the Afan catchment and using alternative river measurements to include river ‘area’. Using a variety of species means we can compare the results, seeing how prioritization of barriers change with the varying needs of each species. For this reason, Atlantic salmon was chosen as the diadromous (migrations between marine and freshwater) species and bullhead and brown trout were chosen as the potadromous (migrations within freshwater) species.

Expanding the model parameters will allow me to create comparisons between the results of using just river length and river area. Results will vary depending on which species as been chosen for the model to run on. Once parameters are extended, different constraints and practical applications using the algorithm can be explored, such as a) the habitat gained across a range of budgets and b) weighting results using different habitat quality parameters extracted from the Water Framework Directive.

Calculating the widths of rivers can be a geographical and technical challenge due to physical access and available data on rivers. The Catchment Characterisation and Modelling (CCM) database is the most comprehensive GIS data set of European freshwater habitat yet contains no data on river width or rivers with a Strahler stream order of < 3 (Vogt et al, 2007), thus excluding smaller river segments commonly found in the upper catchment. Based on the methodology of McGinnity et al (2012) and Allen et al (2018), a predictive model was created using independent variables to predict wetted width.

3.3.1. River Width Surveys

All geographical mapping and analysis were completed using QGIS 3.16 Hannover (QGIS, 2021).

It was unfeasible, due to funding and time constraints, to collect width data on all river segments, so a subset was collected. Using Cochran's sample size formula to calculate the size of the subset (Cochran, 1977), the minimum sample size of river segments to record widths was calculated to be 211 (total number of river segments in drainage network = 464, Cl 95%, margin of error (MOE) +/- 5%), which is 36 for each Afan Strahler order subset (211/6). The database of Afan river widths was completed in July 2021, correlating with the summer low flow of previous measurements recorded by Clement Ricordel (Ricodel, 2019, unpublished). Field river width measurements were considered to be conservative measurements, as they were recorded at lowest flow and ephemeral streams may have dried up. The wetted surface area was considered as the width of the river (McGinnity et al, 2012). No recordings were taking below the Green Park Weir barrier (NGR SS7603589761), as this stretch of the Afan river is tidal. A combination of visual estimations and a mobile measurement application (Apple's 'Measure' for iPhone) was used to record stream widths. Visual estimations were tested 3 times in the upper catchment and found to be within <10cm of the measurement application.

Using QGIS, a random selection of 211 river segments were chosen, as recording all segment widths in situ would require extensive field work, which was outside the financial and time limitations of this study. Following previous methodology (Ricodel, 2019, unpublished), 5 width measurements were taken at varying locations of each river segment and an average for each segment was calculated. The average wetted river width (m) was recorded and individual samples not used to avoid the risk of pseudoreplication (McGinnity et al 2012).

One hundred and thirty one river segment widths were recorded in Google Earth using the inbuilt measurement tool but not all width recordings were possible due to image resolution quality and the presence of tree coverage. Thus, 54 segments were collected in situ. this was 5 per river segment and then averaged to avoid pseudo-replication. Three data sources were combined to result in 219 width recordings. These were extracted from Google Earth (131), field measurements (54) and measurements taken independently by Clement Ricordel (34) in 2019 for a previous study (unpublished).

3.3.2. Stream width predictive modelling

To estimate the width of remaining segments (n = 245), a linear regression model was defined using the known river width data (n = 219). To create the model, Strahler, Altitude, Drained catchment area and Shreve were used as the independent variables to test different models and determine the most accurate model. River reaches (n = 464) were split into two datasets: those with known widths (n=219) and those without known widths (n=245).

3.3.3. Independent variables

To get the altitude (m) for each river reach, the average was calculated from the minimum and maximum values extracted from the EU DEM layer, using the 'profile tool' QGIS plug in. Upstream drainage area for each reach was generated using the 'catchments for points' tool in QGIS (van der Kwast, 2020).

Previous Shreve calculations needed to be revised because it was calculated inclusive of drainage ditches, whereas this study focuses on natural river segments suitable for fish habitation. Three points from the updated file were not located on the Afan river, so were removed. In keeping with the previous study by Ricodel (unpublished), Shreve stream order (Shreve, 1974)) was calculated using the 'Hy2rores0' plug-in (Van der Kwast, 2020) and Strahler (Strahler, 1952) was calculated using the SAGA Strahler Order tool (Conrad & Olaya, 2004).

3.3.4. Statistical methods

All analysis was done in R version 4.0.3 (R Core Team, 2020).

A linear regression model was used to predict the unknown widths as they are a continuous variable and because all assumptions were met by checking kurtosis, skewness and correlation. A forward and backwards stepwise deletion was used to decide the most significant model (appendix 4.19). A forward stepwise is a technique used to build regression models, starting with the null model and iteratively adds predictors, stopping when adding subsequent predictor variables is no longer statistically significant. Similarly, a backwards stepwise deletion starts with a model with all variables, sequentially removing least significant variables until a final model is returned with only significant variables (Thomas et al, 2017). Within the stepwise deletion, the Akaike Information Criterion (AIC) was used as the method of model selection, in comparing the logged and unlogged models with the lowest AIC indicating the strongest model. This was used because it reduces the probability of overfitting (Thomas et al, 2017).

Bootstrapping with 10,000 replicates was used to estimate the remaining river widths (appendix 4.20). Once river widths (m) were obtained, there were multiplied with river length (m) data used in the river length modelling to attain obtained wetted river surface area (m^2) and attributed to the corresponding barrier ID or that stream segment.

3.3.5. Modelling for prioritised barrier removal

All simulations were coded in the OPL modelling language using IBM ILOG CPLEX Optimization Studio (CPLEX), Version 12.10 (IBM, 2021). All experiments were run on the same Viglen VIG830S desktop PC Intel® i7-6700 CPU @ 3.4 GHz with 8 GB of RAM. Optimization modelling was used to prioritize for removal those barriers that provided the greatest increases in habitat availability to species present in the Afan catchment (brown trout, bullhead and Atlantic salmon). CPLEX is an optimization software package which enables decision optimization for improving efficiency and reducing costs and was used to model the prioritization of river barrier removal (IBM, 2021). The current model developed to prioritize barriers for removal uses river 'length' (m) as an input, which does not account for the area of upstream habitat that can be gained and so stream width data from the Afan catchment was used to alter the parameter to river 'area' (m^2).

Similar to the model used in Neeson et al (2015), this model has some limitations. The formula omits deltas, rivers within tidal ranges, braided channels and artificial connections (via drainage channels), as it assumes each barrier has only one downstream barrier.

Mitigation budgets ranging between £0 and £13,000,000 were used to simulate the prioritisation models in CPLEX. According to Dr. Josh Jones, the total cost of removing all 294 artificial barriers in the Afan was estimated to be £13,000,000. Eighteen different prioritisation models were run in total, with the breakdown shown in Figure 3.1, however it was realised that the 'overall ecological status' parameter already included 'fish passability' as a contribution. The areas of the Afan with an ecological status lower than 'good' are failing due to poor fish communities. By using this weighting in the analysis, I would essentially be prioritising barrier removals in areas with good fish communities, while areas with poor fish communities will not be prioritised. To avoid this issue, the results were subsequently omitted from this chapter and instead this section focusses on using class 'chemical' as this removes the related inputs that may adversely influence modelling results. Thus, only 12 models will be discussed.

The habitat quality data was extracted from the Water Framework Directive (WFD) via Water Watch Wales (NRW, 2020). Chemical quality status was parametrised and compared (Table 3.1.) and applied to each river section (Table 3.2.).

Model simulation species include bullhead, brown trout and Atlantic salmon as these are commonly found in the Afan river and jumping height information was readily available, shown in Table 3.3. The migratory behaviour of the selected fish affects the model behaviour. Brown trout and bullhead are both potamodromous species whilst Atlantic Salmon are diadromous and thus migrate between fresh and saltwater. Different formulations were produced to account for this behaviour.

In the model outputs, barrier passability was assigned as 1 = the barrier will be removed with full passability reinstated and 0 = barrier cannot be removed at this budget, in accordance with Neeson et al (2015). Habitat quality was calculated using the following equation:

Habitat Quality = area or length (m2 or km) x WFD weighting

An example of this would be:

10km (river length) x 2 (poor chemical quality) = 20km habitat quality

Table 3.3. shows three fish species commonly found in the Afan river and their associated barrier height jumping range ability. The data was extracted from Table 4 of the '*General principles underlying the ICE protocol*' and Table 10 of the '*Assessment of passability during upstream migration'* documents produced by ONEMA (Baudoin et al, 2014a; Baudoin et al, 2014b). Jump heights are needed to calculate the pre-passability of each barrier in the Afan (R script in appendix 4.27) so we can calculate the post-passability and subsequent habitat gain. The jump height averages of each fish were used in the model to determine passability of each barrier according to jump heights. As the average jump height data was missing for bullhead, the maximum was used instead (Table 3.3).

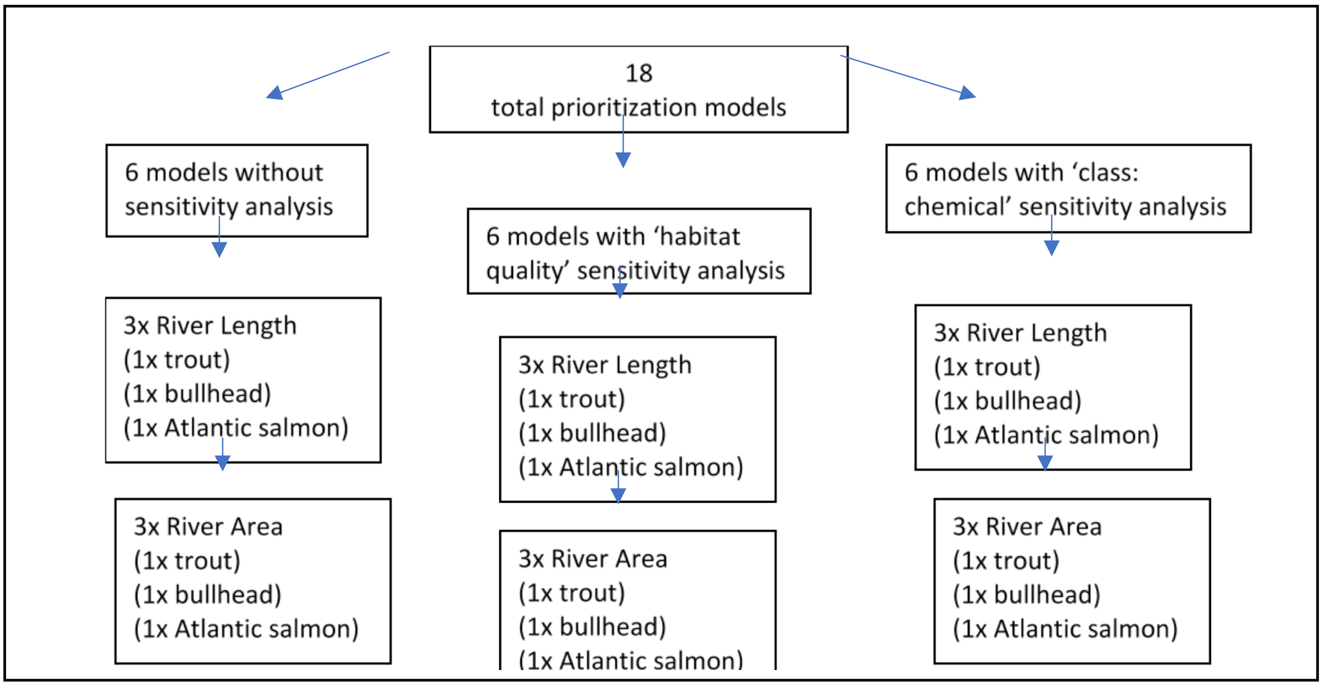


Figure 3.1. A flowchart showing the breakdown of the original 18 prioritization models according to subset. Note that the 6 'habitat quality' models were dropped from analysis.

Table 3.1. 'Chemical Status' quality parameters extracted from the 2018 WFD Cycle 2 classes with the corresponding weighting from 1-4.

Chemical Status	Weighting
fail	1
poor	2
moderate	3
good	4

Table 3.2. Afan river sections with corresponding weighting using the 2018 WFD Cycle 2 classes.

Afan River Section	Chemical Weighting
Corrwg - headwaters to confluence with Afan	4
Afan - headwaters to confluence with Corrwg	4
Afan - conf with Corrwg to confluence with Pelenna	1
Pelenna - headwaters to confluence with Afan	4
Afan - confluence with Pelenna to tidal limit	4

Table 3.3. The barrier jump height capabilities for each species, extracted from Table 4 of the 'General principles underlying the ICE protocol' and Table 10 of the 'Assessment of passability during upstream migration' documents produced by ONEMA (Baudoin et al, 2014a; Baudoin et al, 2014b).

Species	Minimum (m)	Average (m)	Maximum (m)
Atlantic salmon	1	1.5	2.5
Bullhead	-	-	0.2
Brown trout	0.6	1	1.6

3.4. Results

3.4.1. Statistical Analysis

3.4.1.1. Data Exploration

The 'observed widths' dataset was found to be skewed to the left when distribution was checked using a histogram, so the width dataset was log transformed which restored data symmetry by increasing normality. The data was still bimodal (major mode on right and minor mode on left) with a slight negative kurtosis and skewed slightly to the right. This is because the data is from mixed sources.

A correlation plot (Appendix 4.8) was used to test the collinearity of the independent (Strahler order) and dependent variable (observed width). No significant correlation (>1) was determined by the graph. It is important to note that Strahler 5 holds the highest correlation, however individual orders cannot be dropped from the model and so Strahler was kept in the model.

3.4.1.2. Model Selection

The model with the lowest AIC was determined to be the best fitting model. The null model returned an AIC of 40.87 whilst the model with Strahler returned an AIC of -209.1, thus the log transformed model with Strahler was selected to predict river widths. To find the best fitting model, a backwards stepwise deletion was used. This method of model selection automatically stops when no more significant variables are present, removing the variables 'Altitude', 'Area' and 'Shreve'. This left the significant model predictor variable to be 'Strahler' order.

From the linear model output, the adjusted (for number of predictors in the model) R^2 is 0.6863, meaning that the observed and the predicted outcome values have a somewhat positive linear relationship, however the stepwise deletion acknowledged this to be the strongest model type and thus it was used. The F-statistic was 120.2 on 4 and 214 DF with a p-value < 0.05, showing a difference between group means that is statistically significant. The bootstrapping function results returned a decreased prediction error (RMSE) to 0.62 meters and the MAE of 0.45.

Figure 3.2. shows the predicted river widths according to the Strahler stream order. It follows a linear pattern where the higher the Strahler order, the larger river width the model predicts.

This linear pattern makes sense as smaller stream orders are found in the upper catchments, where the river is nearer the source, and larger stream orders are found where the river meets the ocean. The plot correctly predicts the width of Strahler 1, estimated to be 0-1m (meters) in comparison to the observed Strahler 1 width of 0.8m. However, compared to the observed (actual) river widths, the model underestimated the river width for each Strahler level above this. From the observed data, the average width at Strahler 2 is 1.8m, however Figure 3.2. plots it as 0.4m. The observed data shows Strahler 3 as 3.5 meters but predicted as 1.2 meters, whilst Strahler 4 is 5.6m but predicted to be 1.7m. The figure becomes less accurate as Strahler order increases, estimating a river width of 2.5m at a Strahler order of 5, when the average width at Strahler 5 is 11.6m.

3.4.2. CPLEX Length & Area

Twelve model simulations were run using the prioritization model. Six for each chosen species using river length data (3 with and 3 without chemical quality) as an input and river area data (3 with and 3 without chemical quality) as an input. Figures 3.3-3.5. show the simulation results for each species, with ‘spp’ referring to the percentage (%) of habitat that has been gain from removing barriers. There appears to be marginal habitat gains at £0, however this is because of the name given to the output (“available habitat gain”), when in reality this is just the “available habitat (%)” already present in each upstream segment.

The spp difference between using river ‘length’ and ‘area’ for each species was calculated and is shown in Figures 3.3-3.5. The figures show that at low to medium budgets (approx. £1,500,000 - £7,000,000), it's better to run prioritization modelling using the river ‘area’ (m^2) as an input instead of using river length (m), as it is showing that using river ‘area’ over river ‘length’ as a modelling input results in more habitat becoming reconnected and freed from barrier removal. Specifically, the largest difference in habitat gains for salmon is at budget of £2,000,000 with a difference of spp 13.93. For Atlantic salmon, a habitat gain of nearly 100% (spp) is achieved at lower budgets when using river ‘area’ over river length’, with 99.2% habitat gain using ‘area’ and 90.6% habitat gain using ‘length’ at a budget of £8,500,000. For bullhead this is at a budget of £4,000,000 with an spp difference of 28.61. For species bullhead, the differences between using the two types of model input begin to decrease at a budget of £9,000,000 with <5 spp % difference, and from £11,500,000, the differences are <1% spp/habitat gain. Lastly, for brown trout, the largest difference in habitat gains by using input ‘area’ is 23.66% spp at budget £3,500,000. These differences of results decline to <5 spp at a budget of £8,500,000 and decrease to <1 spp at £11,500,000.

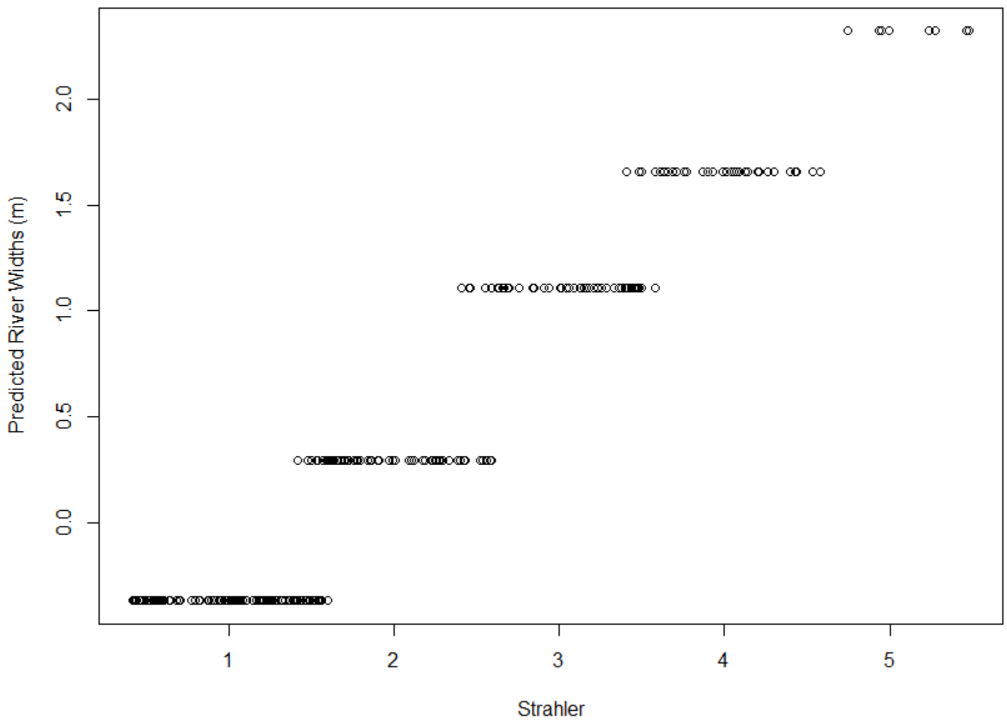


Figure 3.2. shows the predicted river widths according to Strahler stream order.

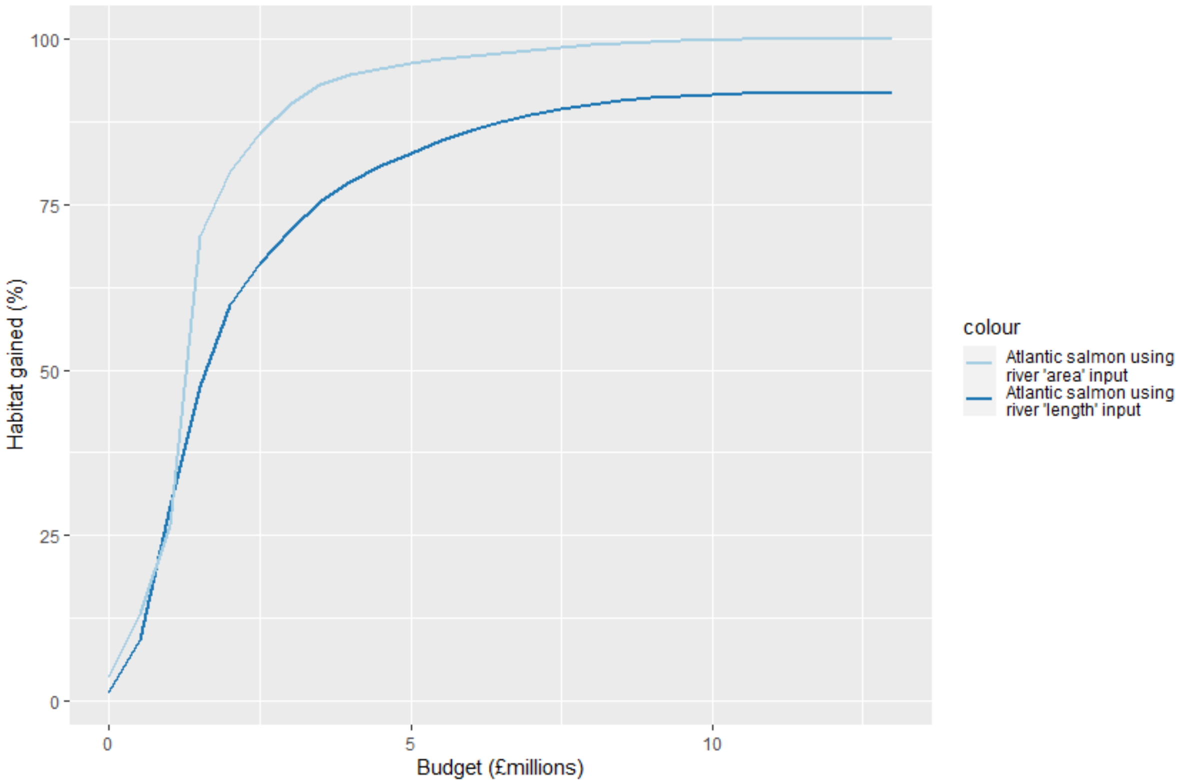


Figure 3.3. The 'spp' (percentage available (%) of habitat gain) value of Atlantic salmon, from £0 to £13million. Information extracted from the length and area model simulations.

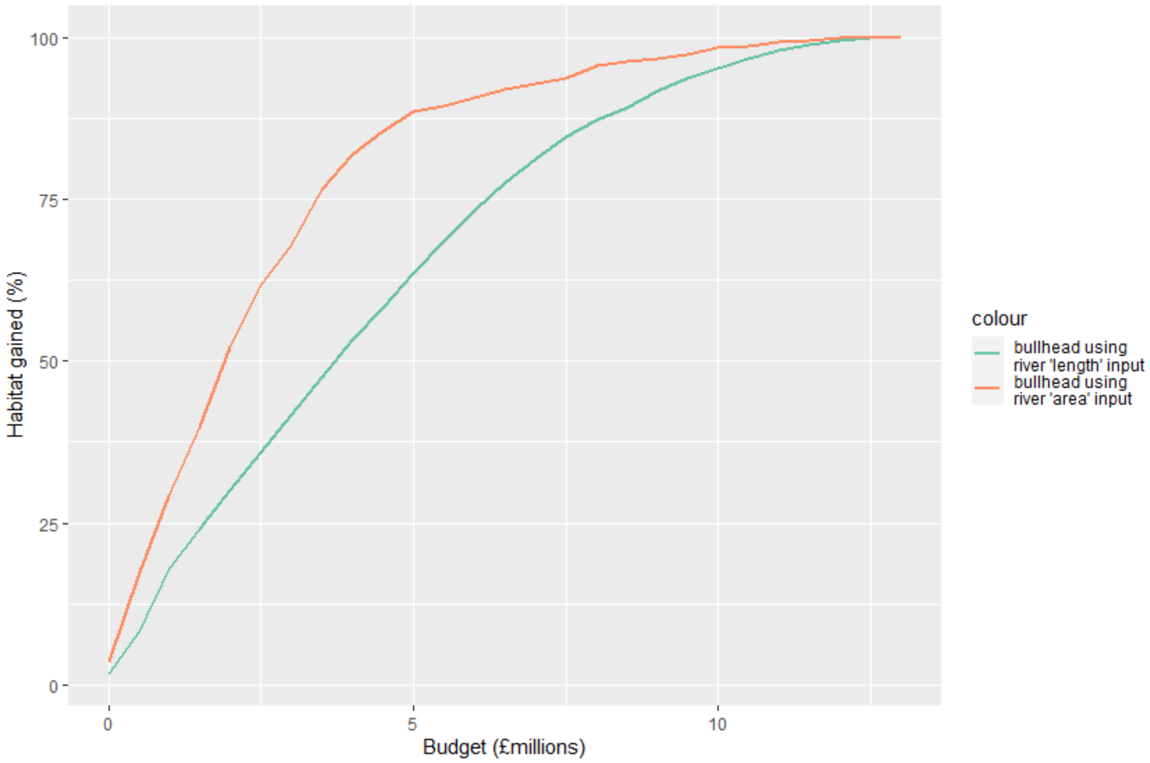


Figure 3.4. The 'spp' (percentage available (%) of habitat gain) value of bullhead from £0 to £13million. Information extracted from the length and area model simulations.

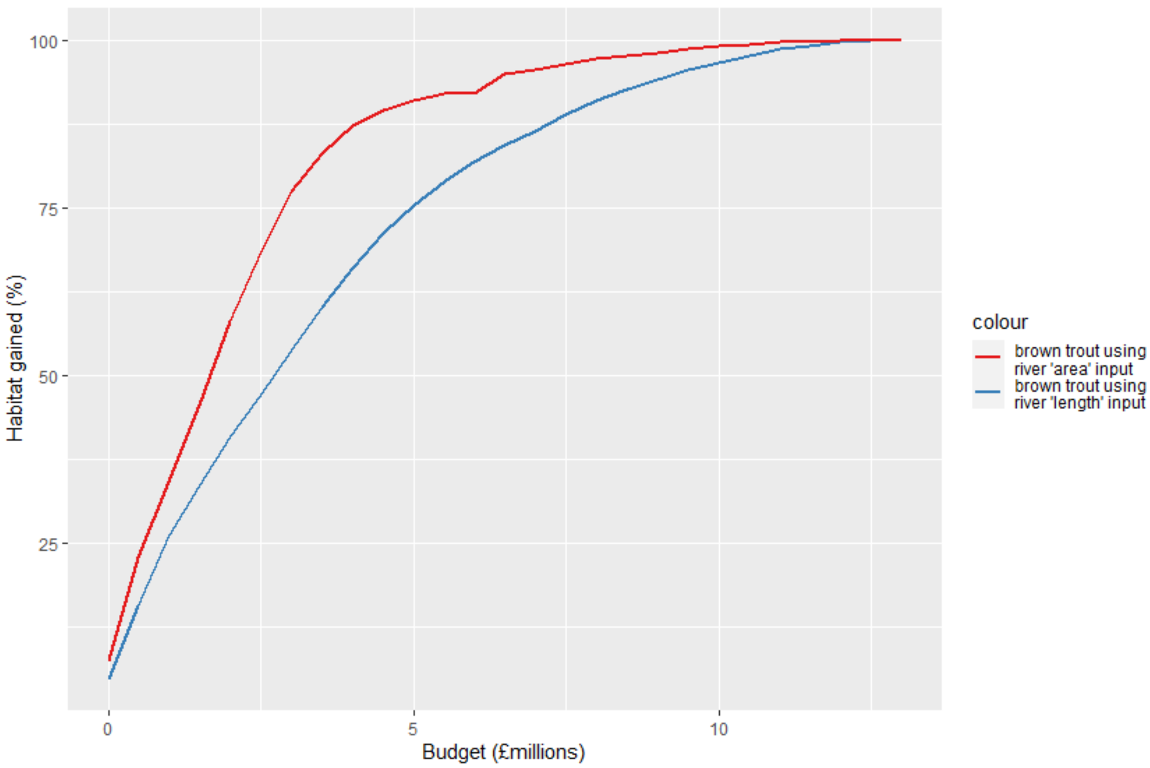


Figure 3.5. The 'spp' (percentage available (%) of habitat gain) value of brown trout from £0 to £13million. Information extracted from the length and area model simulations.

3.4.3. Habitat Quality Analysis

As mentioned in Figure 3.1, habitat sensitivity analysis was originally explored using the Water Framework Directive classes ‘ecological’ and ‘chemical’ from the 2018 cycle. As discussed in Section 2.5, class ‘ecological’ was omitted from the results. The ‘chemical’ class was used for both ‘length’ and ‘area’ inputs and has been presented against previous model types in Figures 3.6. – 3.13.

3.4.3.1. Stream ‘Length’ as a model input

3.4.3.1.1. Atlantic salmon

At budgets between £0 and £1,500,000, Figure 3.6 shows that using the ‘chemical’ habitat quality weighting decreases the returned % of habitat gained (spp) (appendix 4.13 for CPLEX outputs). At a budget of £2,000,000, the difference in spp is <1% and from £2,500,000 to £13,000,000, the use of this weighting positively increases the returns of habitat gained (spp), with the largest difference at £13,000,000 with 8.7%.

3.4.3.1.2. Brown trout

Figure 3.7. shows that there are very little differences in % habitat gained (spp) when using ‘chemical’ habitat quality classes as a weighting when modelling (appendix 4.12 for CPLEX outputs). Between budgets £0 and £4,000,000, the weighting decreases the percentage (%) of habitat gained when using river ‘length’, with no difference at £4,500,000. From £5,000,000 to £13,000,000, using the chemical weighting positively affects river length results, resulting in more habitat gained (% spp). Differences are marginal throughout (<5%), with the largest difference in spp % habitat gained at a budget of £1,000,000 when using chemical weighting on the river ‘length’ input. The results show that at £4,500,000 there is no difference in using the chemical weighting, and that from budgets £5,000,000 to £13,000,000 there is <1% difference.

3.4.3.1.3. Bullhead

Similar to brown trout, Figure 3.8. shows there are marginal differences when applying the ‘chemical’ habitat quality weighting to the river ‘length’ input (<5% spp). The largest differences can be seen at a budget of £1,000,000 with a difference of -2.8% spp. Whilst marginal, differences fluctuate between increases and decreases in % habitat gained (spp), meaning there is no defined benefit or disadvantage when weighting for chemical quality using input river ‘length’ for species bullhead (see appendix 4.9 for CPLEX outputs).

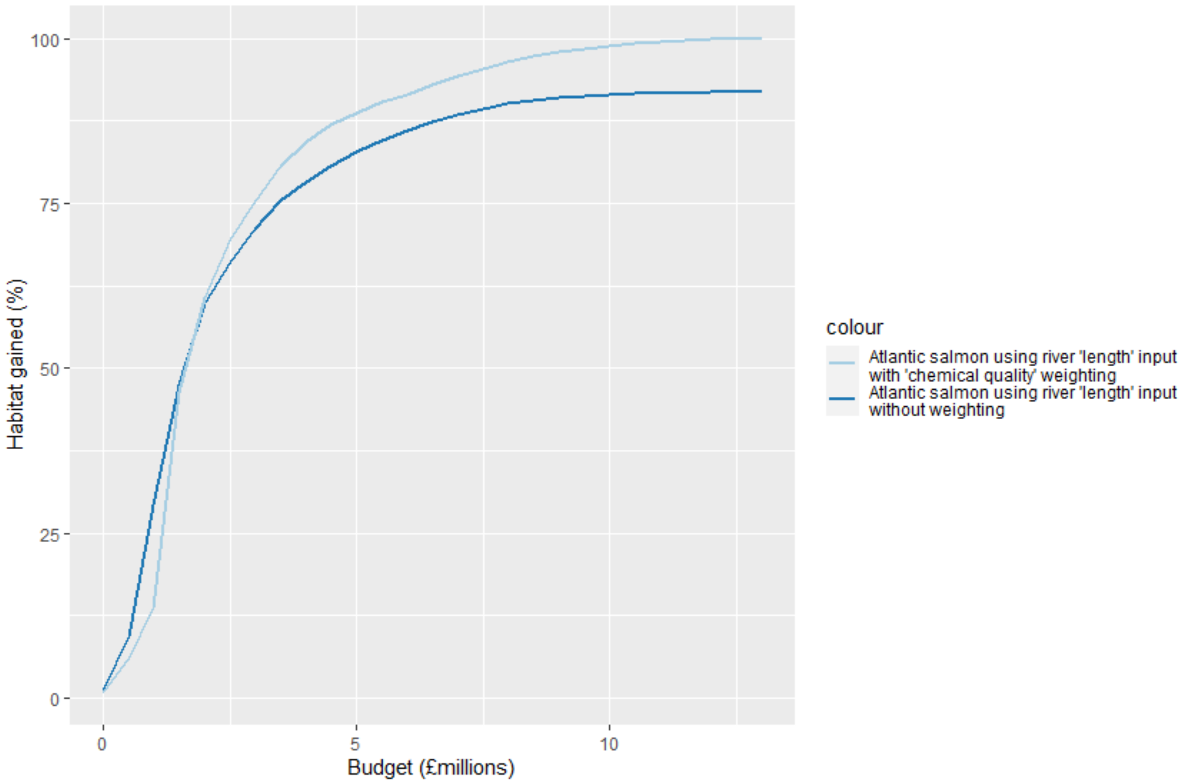


Figure 3.6. Shows the 'spp' (% habitat gain) results of using class 'chemical' as a habitat quality rating for species Atlantic salmon, plotted against the 'spp' results of using no habitat quality weighting.

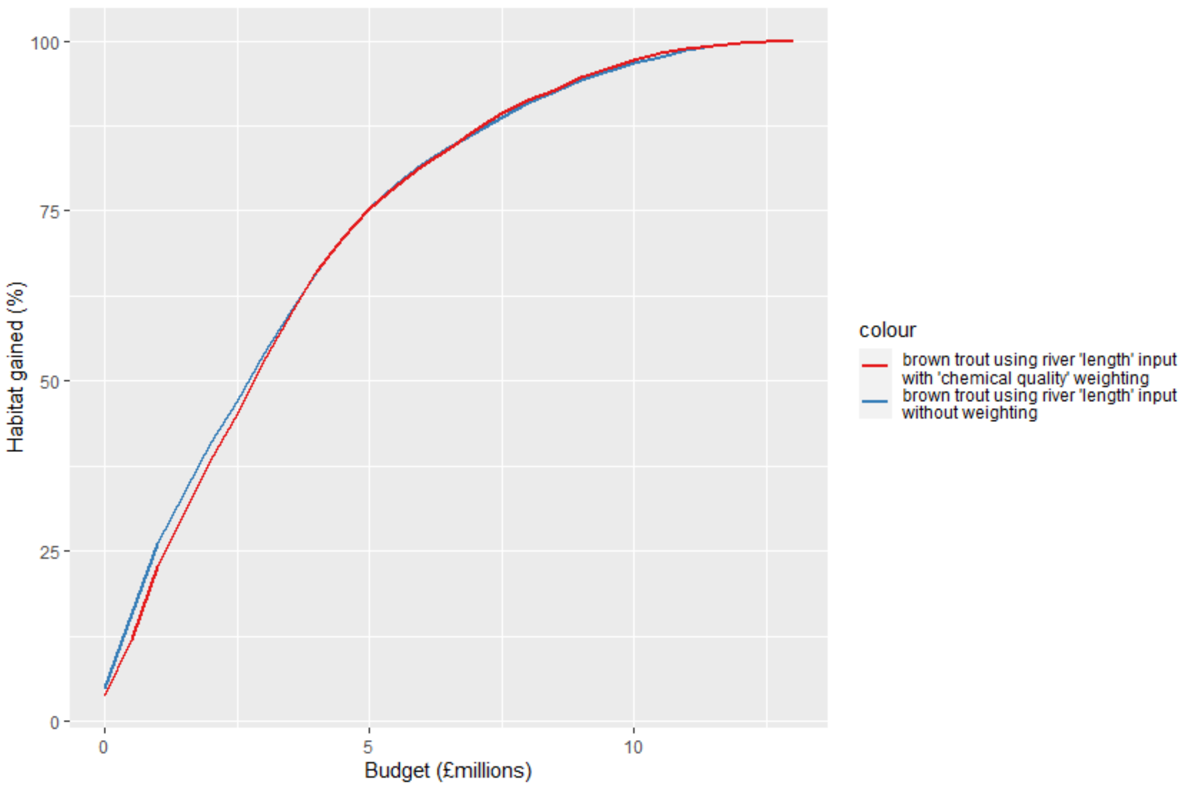


Figure 3.7. The graph shows the 'spp' results of using class 'chemical' as a habitat quality rating for species brown trout, plotted against the 'spp' results of using no habitat quality weighting.

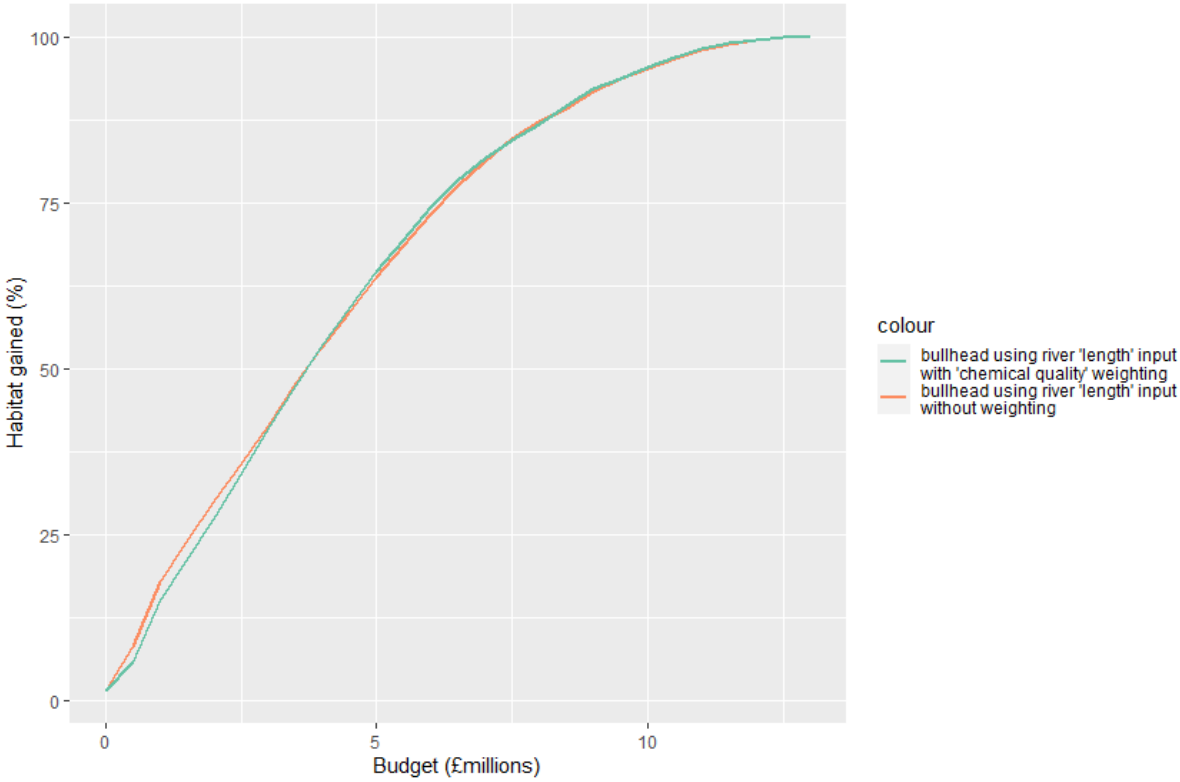


Figure 3.8. The graph shows the 'spp' results of using class 'chemical' as a habitat quality rating for species bullhead, plotted against the 'spp' results of using no habitat quality weighting

3.4.3.2. Stream 'Area' as a model input

The same method as above was also applied to the spp (% habitat gained) model outputs when using river 'area' as an input to create a comparison and identify if weighting for habitat quality affects modelling results.

3.4.3.2.1. Atlantic salmon

When using 'area' as an input for species Atlantic salmon, Figure 3.9. shows that for all weightings the results occur within <5% spp of each other (appendix 4.14 for CPLEX outputs). The largest difference between weightings occurs at a budget of £1,500,000 with a spp difference of 3.89%. The effect that the chemical weighting has when using river 'area' fluctuates between positive and negative throughout the budget range. This is different from using the chemical weighting on river input 'length' as the only negative differences in spp output occurred at budgets £0 - £1,500,000. From budget £11,500,000 onwards, there is no difference in spp when using the chemical weighting or not.

3.4.3.2.2. Brown trout

Compared to the results when using river 'length' as an input (Figure 3.7.), the results for brown trout using river 'area' as an input vary more (Figure 3.10.), with larger differences between each weighting, especially at lower budgets (appendix 4.11 for CPLEX outputs). Using 'chemical' weighting has reduced the percentage of habitat freed (spp) for budgets £0 - £5,500,000. The graph (Figure 3.10) shows that from budget £2,000,000 onwards, there is marginal differences of <5% between the weightings, which reduces to <1% spp from budget £7,500,000. Similar to Atlantic salmon above, the effect that the chemical weighting has when using river 'area' fluctuates between positive and negatives throughout the budget range, with no discernible pattern at low to mid budgets.

3.4.3.2.3. Bullhead

Unlike Atlantic salmon and brown trout above (Figures 3.9. and 3.10.), Figure 3.11. shows that using a chemical weighting for river input 'area' for bullhead (Figure 3.11) creates a visible pattern. Applying the chemical weighting reduced the spp % (habitat gained) for this species until a budget of £11,500,000. From £11,500,00 and £12,000,000 using this weighting increases the habitat gained when using river input ‘area’. There is no difference from using the chemical weighting at budgets £12,500,000 and £13,000,000 (appendix 4.10 for CPLEX outputs).

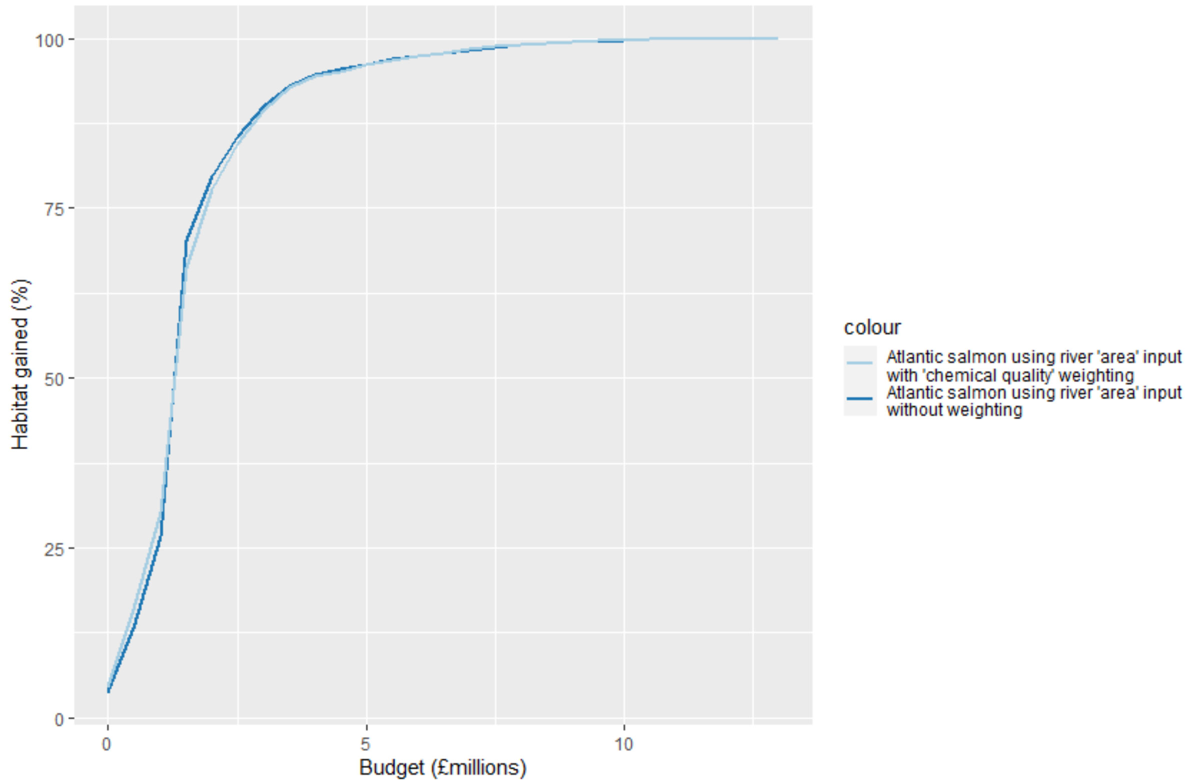


Figure 3.9. The graph shows the ‘spp’ results of using class ‘chemical’ as a habitat quality rating for species Atlantic salmon, plotted against the ‘spp’ results of using no habitat quality weighting.

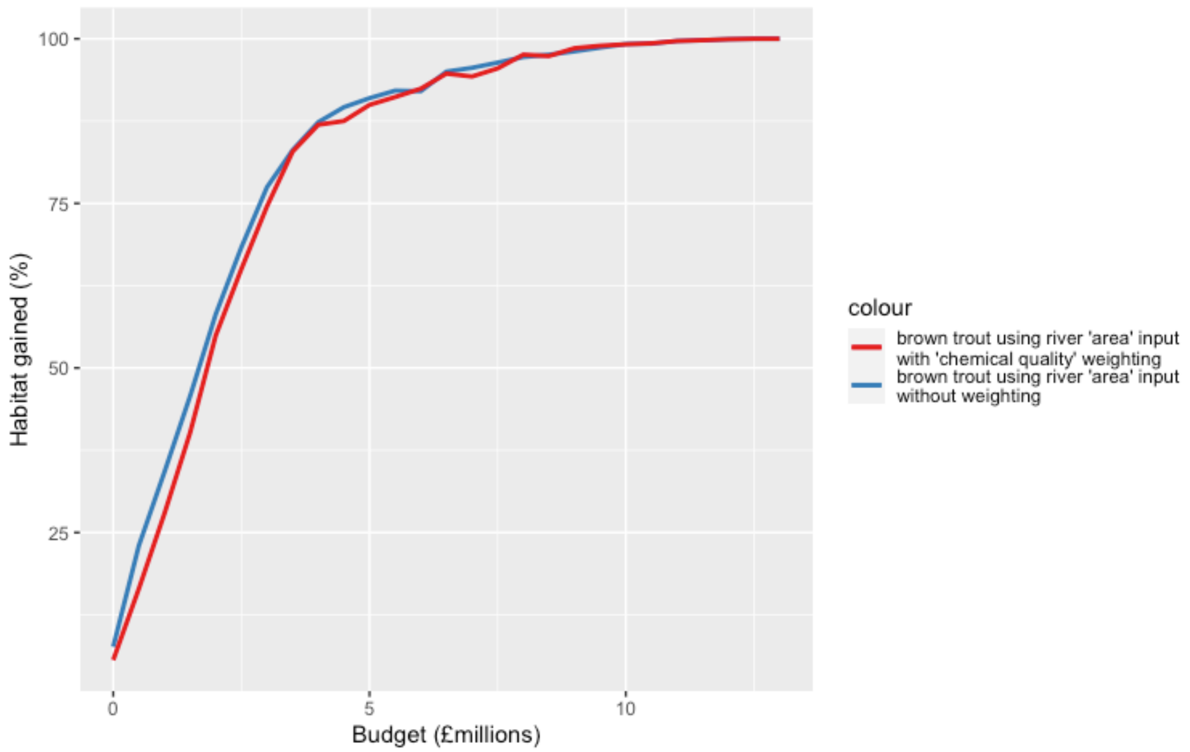


Figure 3.10. The graph shows the ‘spp’ results of using class ‘chemical’ as a habitat quality rating for species brown trout, plotted against the ‘spp’ results of using no habitat quality weighting.

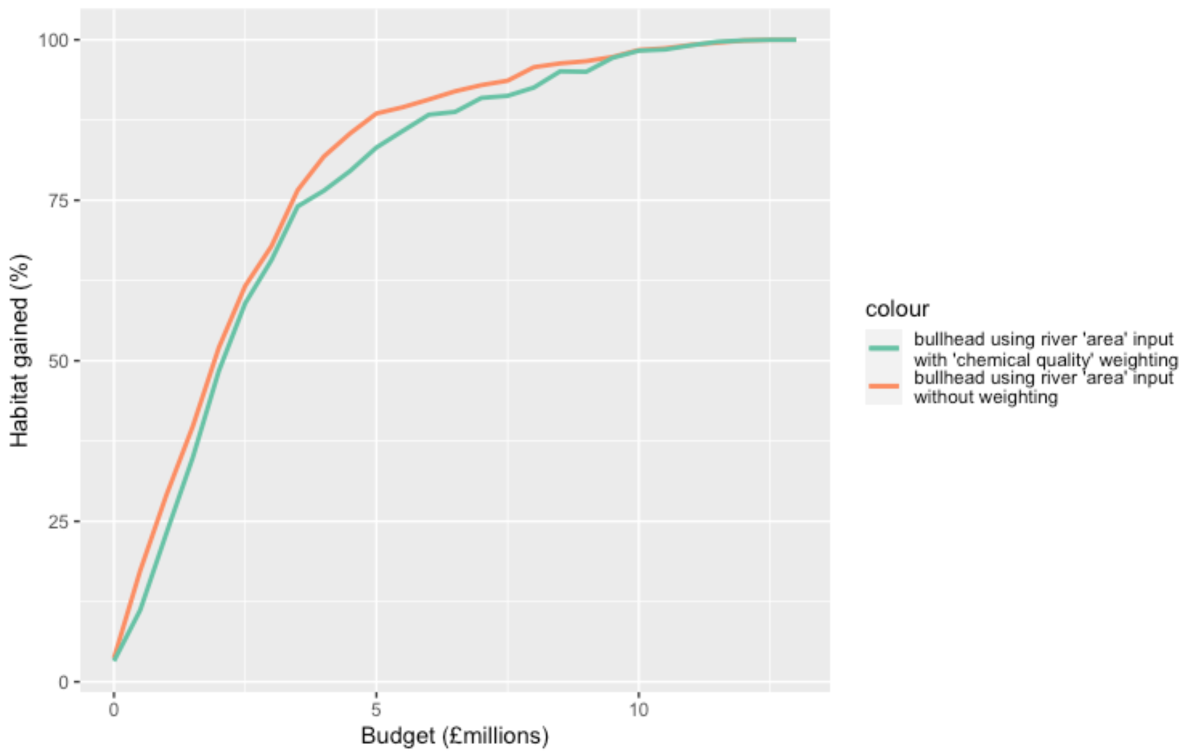


Figure 3.11 The graph shows the ‘spp’ results of using class ‘chemical’ as a habitat quality rating for species bullhead, plotted against the ‘spp’ results of using no habitat quality weighting.

3.5. Discussion

The restoration of freshwater habitats has been recognised as a global goal in the United Nations (UN) decade on restoration 2021-2030, which notes barrier removal as a targeted goal to restore river connectivity by the UN Environmental Programme (UNEP, 2022).

3.5.1. River length vs river area

When using river 'area' as a model input instead of length, the results show that for brown trout and bullhead, at £0 - £10,000,000, it is more cost efficient to prioritise barrier removal by area, particularly lower budgets of (£0 – 5,000,000). This may be because when 'area' is used, lower sections of the river have a larger area and can be more easily reconnected, compared to in the upper reaches where the river is narrower. This is due to the lower barrier density right at the river mouth where, simultaneously, the river is at its widest reach.

One factor that may have influenced this result is the distribution of barriers within the Afan catchment, with more barriers present in the lower Strahler order river segments (resulting in a smaller river area) and less barriers in the higher order segments. Barrier distribution is not random, but commonly clustered (Garcia de Leaniz and O'Hanley, 2021) as shown in the Afan. The results differ for Atlantic salmon in that at budgets £0 - £1,000,000, there is no discernible different in modelling barrier prioritisation by river 'area' over 'length, and the significant benefits begin from £1,500,000. Using river 'area' had the most significant gains to habitat freed for species bullhead, and all species reached 99%+ habitat gained by prioritised barrier removal at lower budgets when using river 'area'.

A subject to address is that when collecting river widths from the field, the widths for each Strahler order were divided equally, however they should have been weighted depending on the frequency of Strahler orders found in the river, as the Afan is not split into an equal amount of Strahler orders.

Similar to the findings of Cote et al (2009) and Puijinbroek et al (2018), this study found that diadromous species (Atlantic salmon) are more susceptible to the fragmentation caused by anthropogenic barriers than to potadromous species (bullhead and brown trout). A reason for this is because commonly, bigger barriers are located nearer the sea. At each budget, more habitat becomes available to Atlantic salmon by removing barriers in comparison to bullhead or brown trout. This finding is supported by the widespread decline of Atlantic salmon in the

UK and Europe, with Puijenbroek et al (2018), de Groot (2002) and Parrish et al (1998) noting the decline a direct result of habitat fragmentation.

3.5.2. Financial budgets

The study shows that financial budgets play a significant role in prioritizing barriers for removal (O'Hanley and Tomberlin, 2005). At higher budgets, differences between inputs and class weightings become marginal, showing the most differences in results at lower budgets. This is because as the budget increases, the more barriers can be removed and thus the margin between using 'area' versus 'length' closes when we reach £13million. This means it is important for river managers and stakeholders to use prioritization models like this one to get the best potential habitat gain results and thus to improve riverine habitat reconnection when using smaller financial budgets.

3.5.3. Chemical weightings

Using the chemical weightings does affect the results, with some significant differences in habitat gained depending on species, budget selection and what input type (length vs area) is being used. There is little difference in using the chemical weighting when using river 'length' on species brown trout and bullhead. This differs for Atlantic salmon, where the weighting reduces habitat gain at budgets for £0-£1,500,000 and then increases habitat gain from budget £2,500,000. Inversely, using the chemical weighting has little effect on habitat gained by barrier removal for salmon when using the river 'area' input, but there is a trend in decreased habitat gained for brown trout and bullhead when using the chemical weighting for model input 'area'. As the chemical weightings do affect the habitat gained, it is important to take habitat quality parameters into consideration when modelling habitat fragmentation (Taylor and Love, 2003; Branco, 2014).

3.5.4. Practical Applications

This model can be used by river manager and stakeholders to increase river restoration efficiency by identifying habitat restoration opportunities, depending on budget. If field work is required to record widths, no specialist training or technology has been used. The software's used (R, QGIS, CPLEX) are free to use but only for educational purposes, which may be a limiting factor. Additionally, the premade model can be easily edited with minimal training, meaning that species can be customized to suit stakeholder requirements and geographical location.

Current habitat fragmentation models calculate barrier removal on an individual scale however, this ignores the cumulative and wider effects on the river system as a whole (Kemp & O'Hanley, 2010, Roni et al, 2000). Prioritisation modelling such as used in this chapter considers all known barriers in the river catchment in relation to financial budgets, so can be used to encourage decision makers to make catchment wide decisions, (Kuby, 2005; Branco et al, 2014).

3.5.5. Future Research

Going forward, an area for future research includes testing the model on rivers with incomplete datasets in comparison with full datasets. The location of every single barrier and associated details such as barrier height have been recorded from a site-walkover, and most river owners do not hold a complete dataset of barriers and thus the accuracy of using incomplete datasets must be determined. In agreement with Januchowski-Hartley et al (2021), it is not feasible to ascertain all barrier information required by field-based efforts alone, especially for larger scale (catchment- or nationwide) documentation. When measuring river widths in the future, it is imperative to use a laser rangefinder for accurate wetted width measurements. Additionally, a river with a larger sample size of barriers may be useful in exploring budget limitations, in addition to testing even smaller budgets (<£500,000).

The methodology found that satellite data cannot be used to accurately document river barriers, especially in the upper catchments, due to forestry cover and varying levels of satellite image quality (Whittemore et al, 2020, Weil, 2018). Additionally, this study used data from a previous study by Clement Ricordel (unpublished) and so summer widths were collected to align with previous methodology. Using summer flow means ephemeral streams may have dried up and river flow is commonly at its lowest. River flow varies significantly in the UK depending on season, and this is an area of potential discrepancy due to changes in wetted width of the river. Data that captures the transient nature of barrier passability (such as seasonal flow) should be attempted to be included (Bourne et al, 2011). To allow for the transient nature of river flow, going forward it would be best to record stream width seasonally to create an average width to be using in modelling, or using hydrological models to predict the seasonal discharge rate rather than basing wetted river width (and thus area) predictions on the lowest seasonal flow. Using either seasonal observations or hydrological models to predict river flow and thus potentially wetted width will allow for seasonal and subsequently annual comparisons of the habitat area, which is useful for recording long-term habitat gains.

Altering the weighting system could be a point of future research, depending on the popularity of a river segment. For example, river segments close to the river mouth will have higher traffic of diadromous species than river segments in the Afan headwaters (Rolls, 2011). Applying a popularity weighting may account for the differentiation between importance of different river segments. Similarly, from previous modelling (Cote et al, 2009, Kemp and O'Hanley, 2010) we know it is important to be as specific as possible to return the most accurate results and that fish species cannot be generalised due to variations in jumping capabilities, however findings from Bourne et al (2011) show that fish length plays a more significant role than fish species. The model also presumes the cause of inaccessibility to fish is solely barrier height and did not explore how the interplay of anthropogenic barriers and other external factors (e.g., dissolved oxygen, pH or sediment) may also influence habitat fragmentation (Nunn and Cowx, 2012).

Management and policy decisions are currently made in the absence of complete understanding of longitudinal connectivity due, in part, to the extent of anthropogenic alterations before the full effects from these changes have been realised (Pringle, 2003). Furthermore, what is required is a change of mindset in riverine management. A move away from hard river engineering (Stanford et al, 1996) to a management system aligned with the principles of natural habitat restoration and encompassing an entire catchment approach will safeguard longitudinal connectivity into the future.

To support the development of future modelling of river connectivity restoration, increasing global barrier documentation (e.g. the AMBER database) will only aid the capabilities of barrier prioritisation modelling (Kemp & O'Hanley, 2010, Atkinson et al, 2018). In conjunction with the research of Chapters 1 & 2, more research is occurring in this sector, notably on smaller river infrastructures too (see Januchowski-Hartley et al, 2021).

If anthropogenic barriers must be introduced (for example for hydropower generation), it is wise to model current habitat connectivity without the barrier and future connectivity with the barrier to compare longitudinal connectivity. Barrier placement can be detrimental to the transient nature of the riverine system, and prudent barrier placement is key (Shi et al, 2018). However, it is also important to consider if the overall global benefit of such barriers to reducing climate change and reliance on fossil fuels outweighs the localised barrier effects. Cote et al (2009) use the example of placing anthropogenic barriers near natural barriers such as waterfalls, or in the upper catchments of the river network. This planning protocol safeguards longitudinal connectivity near the river mouth for diadromous species.

3.6. Conclusion

This research aimed to expand the parameters of a model used to prioritize barriers for removal and restore longitudinal river connectivity. The results show that with a limited financial budget, it is recommended to use as much detail as possible, which includes using river 'area' rather than river 'length', however the use of the chemical weighting to represent habitat quality varies with species and geospatial input.

Similar to Puijenbroek et al (2018), this study showed that modelling river fragmentation and barrier passability remains challenging due to the dynamic nature of river barriers and it is in fact species specific. One size does not fit all when it comes to modelling the habitat gains from barrier removals. Going forward from this study, it is recommended that future modelling should be conducted on a size- or species-specific level and that results cannot be generalised across fish species. Additionally, collecting average river widths from all seasons will represent a more accurate river width for use in the model.

However, agreeing with Cote et al (2009), whilst it has shown it is difficult to create a general model which can be applied to any river due to the unique geospatial nature of a river catchment, the study is reproducible to river stakeholders who wish to prioritize river barriers for removal and increase freshwater habitat restoration efforts. With continued exploratory modelling of habitat restoration by prioritising river barrier removal, a transferable framework can be realised and thus utilised in the management and restoration of river longitudinal connectivity.

4. Appendices

4.1. Faptic Barrier photographs cross-referenced with AMBER Database

Faptic_test
1519041639984_photo.jpg
1519202444029_photo.jpg
1522015179448_photo.jpg
1523639386361_photo.jpg
1523639441453_photo.jpg
1523707904117_photo.jpg
1523854365455_photo.jpg
1524029294307_photo.jpg
1524156536880_photo.jpg
1524160035042_photo.jpg
1524160066425_photo.jpg
1524235589448_photo.jpg
1524827452404_photo.jpg
1525127271758_photo.jpg
1525181566811_photo.jpg
1525348181960_photo.jpg
1525349226105_photo.jpg
1525879190154_photo.jpg
1525959570073_photo.jpg
1526097772068_photo.jpg
1526821789301_photo.jpg
1527704516678_photo.jpg
1528629290043_photo.jpg
1530087866996_photo.jpg
1530088259802_photo.jpg
1534768747255_photo.jpg
1556196691790_photo.jpg
1560333969981_photo.jpg
1560936641298_photo.jpg

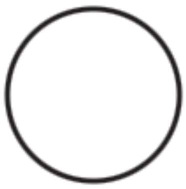
4.2.ICC R Script

```
### Repeatability of barrier categorisation

# all raters

inter_raters <- read.csv("ICC_scorings.csv")

icc(inter_raters, model=c("twoway"), type=c("agreement"), unit=c("single"),
   r0=0, conf.level=0.95)
```

```
library(psych)
# all raters
library(irr)
icc(inter_raters, model = "twoway", type = "agreement", unit = "single")

# me
intra_rater <- read.csv("intra_rater.csv")
library(irr)
icc(intra_rater, model = "twoway", type = "agreement", unit = "single")

# all raters with Faptic
inter_raters_fap <- read.csv("Inter_rater_with_Faptic.csv")
icc(inter_raters_fap, model=c("twoway"), type=c("agreement"), unit=c("single"),
  r0=0, conf.level=0.95)
# experts and Faptic (no cs)
inter_raters_fap_no_cs <- read.csv("Inter_rater_with_Faptic_no_cs.csv")
icc(inter_raters_fap_no_cs, model=c("twoway"), type=c("agreement"), unit=c("single"),
  r0=0, conf.level=0.95)
# Faptic2 (obs vs pred only)
Faptic2 <- read.csv("Faptic2.csv")
icc(Faptic2, model=c("twoway"), type=c("agreement"), unit=c("single"),
  r0=0, conf.level=0.95)
```

4.3. Barrier Type ID

Barrier Type	Barrier Characteristics	ID Protocol
Bed-Sills/Ramp 	A structure aimed at stabilizing the channel bed and reducing erosion. Ramps and bed sills come in many forms. They can be underwater structures (not blocking the flow of water, only acting on riverbed and channel slope).	Classed as ‘boulder’ barriers (do not create pool upstream like a weir) for controlling substrate movement or stabilising channel (note: can be difficult to separate from weirs).
Culverts	A structure which allows a stream or river to flow through/under an obstruction. Often embedded in soil and come in many shapes	Assume road/track-river line intersects contain culverts (even

	and sizes, varying from round and elliptical to box shaped.	where vegetation obscures the feature), except where: **(a)** you can see no stream is present (i.e. dry, no channel depression) **(b)** it looks like a bridge **(c)** where you can see the stream runs over the track/road (ford).
Dam 	A barrier that blocks or constrains the flow of water and raises the water level, forming a reservoir. Often used to provide water supply and for electricity generation. It can cause significant flow alteration, sediment discharges and complete interception of bedload.	Only class as a dam where the barrier creates a reservoir/lake/pond.
Fords 	A structure which creates a shallow place for crossing the river or stream by vehicle or on foot.	Assume road/track-river line intersects contain culverts (even where vegetation obscures the feature), except where you can see the stream runs over the track/road.
Natural	A natural structure formed from bedrock.	Do not record as cannot distinguish things like riffles and rapids from waterfalls.
Other 	Other types of barriers that can impact on longitudinal connectivity include fish traps, lateral groynes or wing dykes.	Any visible manmade structure that looks like a barrier but can't be classed into the above categories.
Sluices 	A movable barrier aimed at controlling water levels and flow rates in rivers and streams. By opening or closing the sluice, water levels and flow rates can be altered. Also used in ship locks to allow ships to navigate passed dams or other obstructions which create uneven levels of water.	Usually positioned near a dam (or other obstruction such as ship lock) so use this to guide you.
Weirs	A barrier aimed at regulating flow conditions and water levels, at intercepting sediment or reducing the channel slope for stabilizing the channel bed of a river or stream. Water often flows freely over the top of a weir. Weirs come in many shapes and	Usually concrete structures that create a water level change. (note: can be difficult to separate from bed-sills/ramps).

	sizes (e.g. in mountain areas: retention and consolidation check dams; in lowland areas: consolidation or abstraction weirs).	

4.4. R scipt for raters agreement

```
Data<-read.csv("GoogleSurveyRepeatability.csv")

attach(Data)

library(rptR)

head(Data)

BarrierID

rpt1<-rpt(PresAB ~ (1 | BarrierID), grname = "BarrierID", data = Data, datatype = "Binary",

   nboot = 1000, npermut = 0)

print(rpt1)

####

Repeatability for BarrierID

--------------------------------

Link-scale approximation:

R  = 0.754

SE = 0.054

CI = [0.613, 0.81]

P  = 1.08e-58 [LRT]

#### Suggests inter-observer accuracy (repeatability/reproducability) is 75%
```

4.5. Removed entries from AC dataset

Catchment	Lat	Long
Clwyd	53.207434	-3.6371327
Usk	51.921926	-3.4613433
Usk	51.884404	-3.4907837
Usk	51.893799	-3.4894816
Usk	51.895262	-3.4875098
Usk	52.014753	-3.4635944
Usk	51.839384	-3.1073601
Usk	51.933406	-3.3579481
Usk	51.930968	-3.661573
Taff	51.686196	-3.3003827
Seiont	53.146173	-4.1374832

Rheidol	52.385247	-3.8652741
Severn	52.69255	-3.0386313
Severn	52.454608	-3.5549025
Dyfi	52.567301	-3.7303237
Afon Dee	52.886593	-3.2472342

4.6. Stepwise script summary for Afan

Coefficients:

(Intercept) Strahler D2m

6.697e-01 2.554e-02 -2.308e-05

Degrees of Freedom: 291 Total (i.e. Null); 289 Residual

Null Deviance: 69.71

Residual Deviance: 61.69 AIC: 382.7

4.7. Stepwise script summary for AC

Coefficients:

(Intercept) Forested Strahler D2m

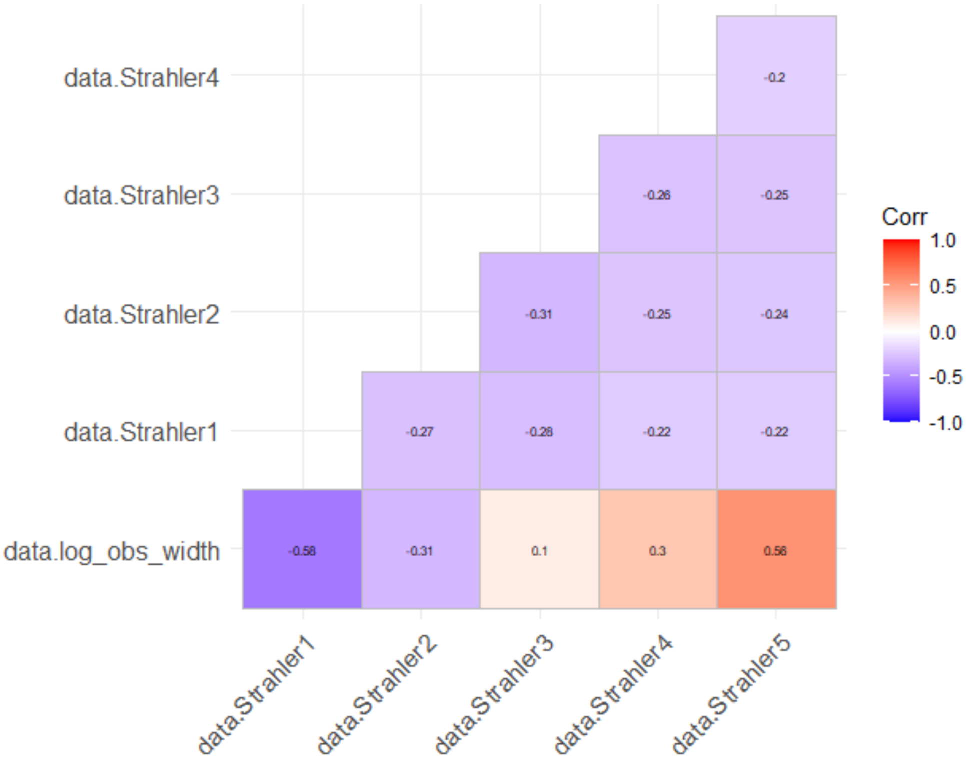
7.655e-01 -3.389e-01 5.669e-02 -2.861e-06

Degrees of Freedom: 292 Total (i.e. Null); 289 Residual

Null Deviance: 71.2

Residual Deviance: 64.43 AIC: 397.7

4.8. Results of the R corrplot function



4.9. CPLEX results for Length bullhead (no weighting 'normal' and chemical weighting 'spp' % habitat gain results)

	normal	chemical	
budget	**spp**	**spp**	**diff**
0	1.66	1.54	-0.12
0.5	8.26	5.88	-2.38
1	17.91	15.13	-2.78
1.5	24.11	21.42	-2.69
2	30.14	27.66	-2.48
2.5	35.82	34.34	-1.48
3	41.65	41.08	-0.57
3.5	47.58	47.21	-0.37
4	53.22	53.34	0.12
4.5	58.32	58.94	0.62
5	63.68	64.57	0.89
5.5	68.56	69.34	0.78
6	73.32	74.3	0.98
6.5	77.48	78.5	1.02
7	81.26	81.66	0.4
7.5	84.61	84.49	-0.12
8	87.26	86.8	-0.46
8.5	89.19	89.68	0.49
9	91.75	92.11	0.36

9.5	93.74	93.66	-0.08
10	95.12	95.4	0.28
10.5	96.61	96.99	0.38
11	97.92	98.27	0.35
11.5	98.92	99.05	0.13
12	99.48	99.59	0.11
12.5	99.95	99.97	0.02
13	100	100	0

4.10. CPLEX results for area bullhead no weighting 'normal' and chemical weighting 'spp' % habitat gain results)

	normal	chemical	
budget	**spp**	**spp**	**diff**
0	3.68	3.24	-0.44
0.5	17.33	11.18	-6.15
1	29.12	23.17	-5.95
1.5	39.75	34.9	-4.85
2	52.1	48.46	-3.64
2.5	61.66	58.96	-2.7
3	67.85	65.67	-2.18
3.5	76.58	74.05	-2.53
4	81.83	73.5	-8.33
4.5	85.42	79.57	-5.85
5	88.52	83.22	-5.3
5.5	89.49	85.79	-3.7
6	90.7	88.34	-2.36
6.5	91.98	88.77	-3.21
7	92.94	90.94	-2
7.5	93.63	91.27	-2.36
8	95.73	92.56	-3.17
8.5	96.32	95.08	-1.24
9	96.67	95.02	-1.65
9.5	97.32	97.19	-0.13
10	98.41	98.3	-0.11
10.5	98.67	98.48	-0.19
11	99.2	99.14	-0.06
11.5	99.55	99.7	0.15
12	99.89	99.9	0.01
12.5	99.99	99.99	0
13	100	100	0

4.11. CPLEX results for Length brown trout (no weighting 'normal' and chemical weighting 'spp' % habitat gain results)

	normal	chemical	(1-4 weighting)

budget	spp	spp	diff
0	4.87	3.75	-1.12
0.5	15.72	12.05	-3.67
1	26.1	22.72	-3.38
1.5	33.57	30.7	-2.87
2	40.79	38.27	-2.52
2.5	47.18	45.27	-1.91
3	53.8	52.78	-1.02
3.5	60.15	59.8	-0.35
4	65.94	66.06	0.12
4.5	71.19	71.19	0
5	75.37	75.28	-0.09
5.5	78.94	78.67	-0.27
6	81.86	81.66	-0.2
6.5	84.4	84.1	-0.3
7	86.36	86.82	0.46
7.5	88.88	89.38	0.5
8	90.93	91.28	0.35
8.5	92.64	92.82	0.18
9	94.2	94.61	0.41
9.5	95.53	95.97	0.44
10	96.68	97.24	0.56
10.5	97.72	98.19	0.47
11	98.65	98.79	0.14
11.5	99.2	99.32	0.12
12	99.68	99.73	0.05
12.5	99.98	99.97	-0.01
13	100	100	0

4.12. CPLEX results Area brown trout (no weighting 'normal' and chemical weighting 'spp' % habitat gain results)

	normal	hq adjusted	
budget	**spp**	**spp**	**diff**
0	7.64	5.63	-2.01
0.5	23.01	16.46	-6.55
1	34.21	27.89	-6.32
1.5	45.72	40.17	-5.55
2	58.16	54.93	-3.23
2.5	68.33	65.02	-3.31
3	77.46	74.55	-2.91
3.5	83.09	82.86	-0.23
4	87.33	86.94	-0.39
4.5	89.61	86.21	-3.4
5	90.98	89.96	-1.02

5.5	92.12	91.15	-0.97
6	92.04	92.42	0.38
6.5	95.01	94.71	-0.3
7	95.59	94.27	-1.32
7.5	96.38	95.5	-0.88
8	97.23	97.59	0.36
8.5	97.58	97.38	-0.2
9	98.09	98.57	0.48
9.5	98.66	98.94	0.28
10	99.2	99.16	-0.04
10.5	99.26	99.31	0.05
11	99.68	99.66	-0.02
11.5	99.78	99.79	0.01
12	99.93	99.93	0
12.5	99.99	100	0.01
13	100	100	0

4.13. CPLEX results length Atlantic salmon (no weighting 'normal' and chemical weighting 'spp' % habitat gain results)

	normal	chemical	
budget	**spp**	**spp**	**diff**
0	1.35	0.88	-0.47
0.5	9.43	6.05	-3.38
1	29.3	13.74	-15.56
1.5	47.55	46.39	-1.16
2	59.87	60.78	0.91
2.5	66.16	69.51	3.35
3	71.01	75.3	4.29
3.5	75.37	80.61	5.24
4	78.32	84.24	5.92
4.5	80.63	86.88	6.25
5	82.76	88.7	5.94
5.5	84.65	90.29	5.64
6	86.1	91.54	5.44
6.5	87.36	93.08	5.72
7	88.49	94.36	5.87
7.5	89.37	95.48	6.11
8	90.08	96.54	6.46
8.5	90.66	97.28	6.62
9	91.07	97.95	6.88
9.5	91.36	98.47	7.11
10	91.55	98.9	7.35
10.5	91.68	99.24	7.56
11	91.75	99.51	7.76

11.5	91.8	99.75	7.95
12	91.82	99.9	8.08
12.5	91.83	99.99	8.16
13	91.83	100	8.17

4.14. CPLEX results area Atlantic salmon (no weighting 'normal' and chemical weighting 'spp' % habitat gain results)

	normal	chemical	
budget	**spp**	**spp**	**diff**
0	3.73	4.52	0.79
0.5	13.16	15.92	2.76
1	26.67	30.23	3.56
1.5	70.21	66.32	-3.89
2	79.8	77.85	-1.95
2.5	85.61	84.59	-1.02
3	90.07	89.43	-0.64
3.5	92.97	92.77	-0.2
4	94.64	94.4	-0.24
4.5	95.5	95.16	-0.34
5	96.18	96.21	0.03
5.5	96.94	96.88	-0.06
6	97.45	97.41	-0.04
6.5	97.88	97.91	0.03
7	98.28	98.38	0.1
7.5	98.67	98.78	0.11
8	98.99	99.04	0.05
8.5	99.23	99.27	0.04
9	99.44	99.45	0.01
9.5	99.61	99.63	0.02
10	99.75	99.73	-0.02
10.5	99.84	99.83	-0.01
11	99.91	99.9	-0.01
11.5	99.95	99.95	0
12	99.98	99.98	0
12.5	100	100	0
13	100	100	0

4.16. Data sources of the variables collated for the AC barriers across Wales

Variable	Data extracted from:
Latitude	Natural Resource wales
Longitude	Natural Resource wales

Average barrier height	AMBER Atlas
Strahler (stream order)	EU DEM E30N30 (from Copernicus)
Forested area	Google Earth
Barrier Type	Natural Resource wales/Google Earth
Distance to mouth (m)	Manually calculated in QGIS
Altitude (m)	EU DEM E30N30 (from Copernicus)

4.17. Average barrier heights extracted from the AMBER database (Amber consortium, 2020).

Barrier Type	Height (meters)
Culvert	0.7
Ford	1.0
Sluice	1.5
Ramp	0.7
Weir	2.3
Dam	20.3
Other	4.8

4.18. Raw data of Table 1.6: Repeatability results based on the inter- and intra-class correlation coefficients (ICC) of Faptic software comparing the observed (ground-truthed barriers from AMBER) vs predicted. 29 barrier classifications which matched the AMBER photos.

Observed barriers	Predicted barriers
sluice	dam
sluice	sluice
ford	culvert
ford	ford
ford	culvert
sluice	sluice
ford	ford
sluice	sluice
ford	weir
ford	ford
ford	ford
sluice	dam
ford	ford
ramp	weir
ramp	weir
ford	ford
ford	ford
sluice	sluice

ford	ford
sluice	sluice
ford	weir
culvert	weir
sluice	weir
ford	weir
ford	ford
ramp	ramp
ford	weir
weir	weir
weir	weir

4.19. Chapter 2 model selection using stepwise deletion R script

```
library(tidyverse)

library(caret)

library(leaps)

library(MASS)

data <- read.csv("observed_widths.csv", header = TRUE)

data$Strahler <- as.numeric(data$Strahler)

data$Strahler <- as.factor(data$Strahler)

data$Shreve <- as.factor(data$Shreve)


# need to log as not normal distribution: natural log

hist(data$obs_width)

data$log_obs_width <- log(data$obs_width)

hist(data$log_obs_width)


#intercept only model (null model)

data2 <- data.frame(data$log_obs_width, data$Strahler, data$Altitude, data$Area,
data$Shreve)

null.model <- lm(data.log_obs_width ~ 1, data = data2)

summary(null.model)


#model with all predictors (make new data frame with just independent variables)

data2 <- data.frame(data$log_obs_width, data$Strahler, data$Altitude, data$Area,
data$Shreve)

all <- lm(data.log_obs_width ~., data=data2)
```

```
summary(all)

# stepwise deletion to find simplest model
step.model <- stepAIC(all, direction = "both",
                      trace = FALSE)
summary(step.model)
plot(step.model)

# also check using a forward stepwise deletion
forward <- step(null.model, direction='forward', scope=formula(all), trace=0)
forward$anova
forward$coefficients

# final model
lm(data.log_obs_width ~ data.Strahler, data=data2)
```

4.17. Chapter 2 bootstrapping and predicting river widths R script

```
data4 <- read.csv("observed_widths.csv", header = TRUE)
newdata <- read.csv("unknown_widths2.csv", header = TRUE)

data4$log_obs_width <- log(data4$obs_width)
data4$Strahler <- as.factor(data4$Strahler)
newdata$Strahler <- as.factor(newdata$Strahler)

# OLS using bootstrap method ####
library(finalfit)
library(dplyr)
library(caret)
library(boot)

# bootstrapping ####
set.seed(101)
```

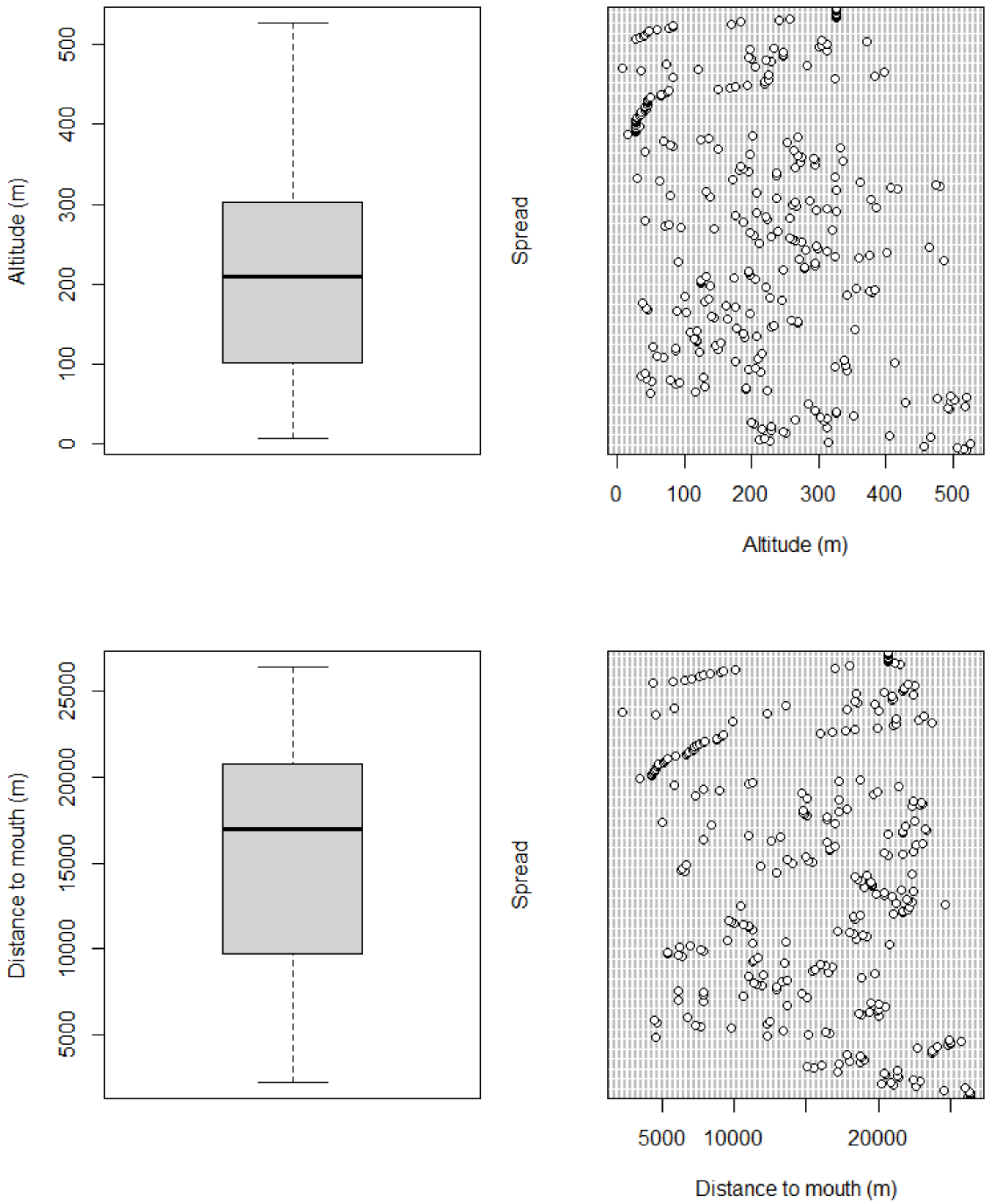
```
#train model
train.control <- trainControl(method = "boot", number = 10000)
model2 <- train(log_obs_width ~ Strahler, data = data4, method = "lm",
          trControl = train.control)

#make prediction and get residuals
library(tidyverse)
depVar = data4$log_obs_width
indepVars <-rename(indepVars, Strahler=newdata.Strahler)
ols.pred = predict(model2, indepVars)
residuals = ols.pred - data4$log_obs_width

#unlog ols.pred
unlogd.pred <- exp(ols.pred)

# Model performance ####
# (a) Compute the prediction error, RMSE
RMSE(ols.pred, data4$obs_width)
# (b) Compute R-square
R2(ols.pred, data4$obs_width)
# save width predictions
write.csv(unlogd.pred, "predicted.widths2.csv")

#### jitter ####
 newdata$Strahler <- as.numeric(newdata$Strahler)
# adding ols.pred as column in newdata
pred.widths2 <- read.csv("predicted.widths2.csv", header = TRUE)
newdata$pred.widths2 <- pred.widths2
pred.widths2 <- select(pred.widths2, -X)
x_jitter <- jitter(newdata$Strahler, factor = 3)
plot(x= x_jitter, y=ols.pred,
```

xlab="Strahler",

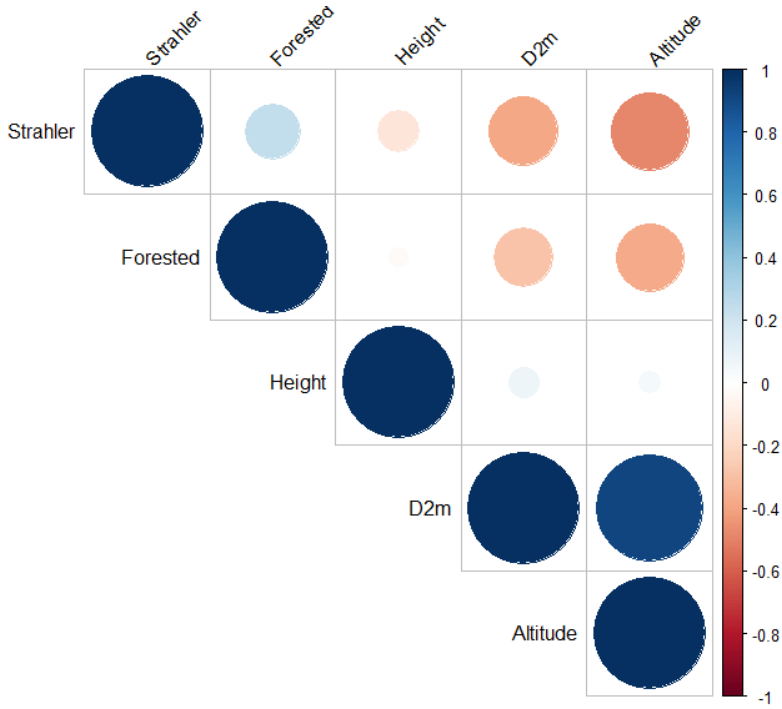
ylab="Predicted River Widths (m)",

main="Predicted River Widths according to Strahler")

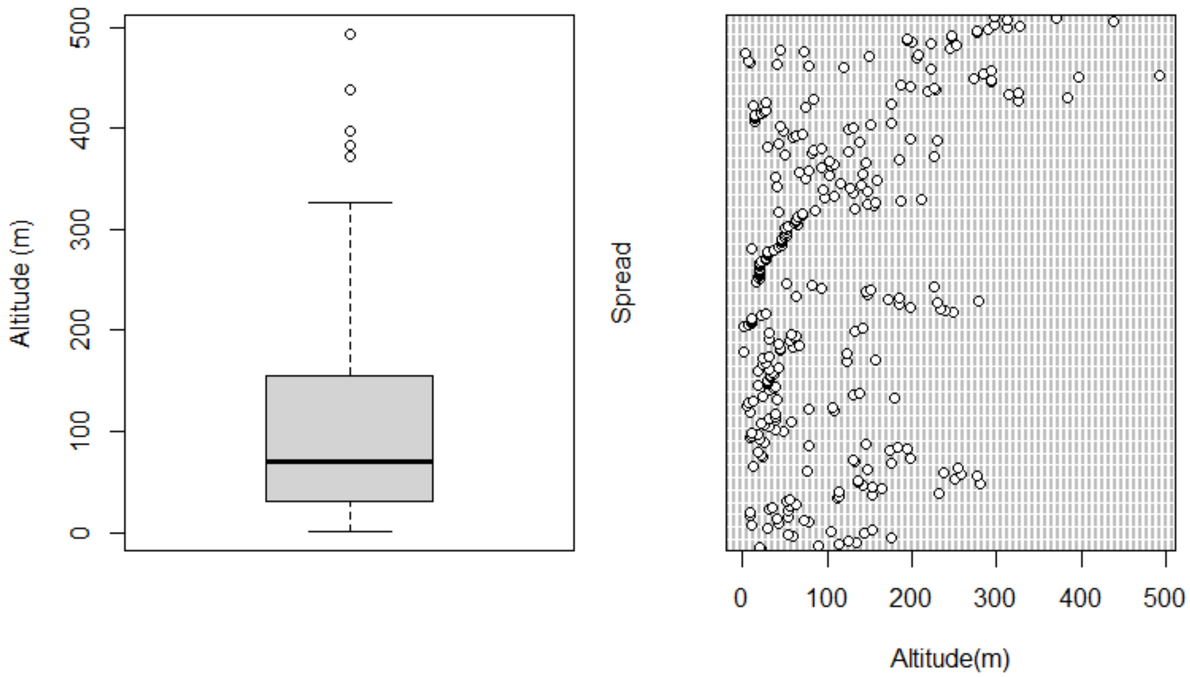
4.18. Boxplot and Cleveland plots used in data exploration for predictors 'altitude' and 'distance to mouth' using the field data

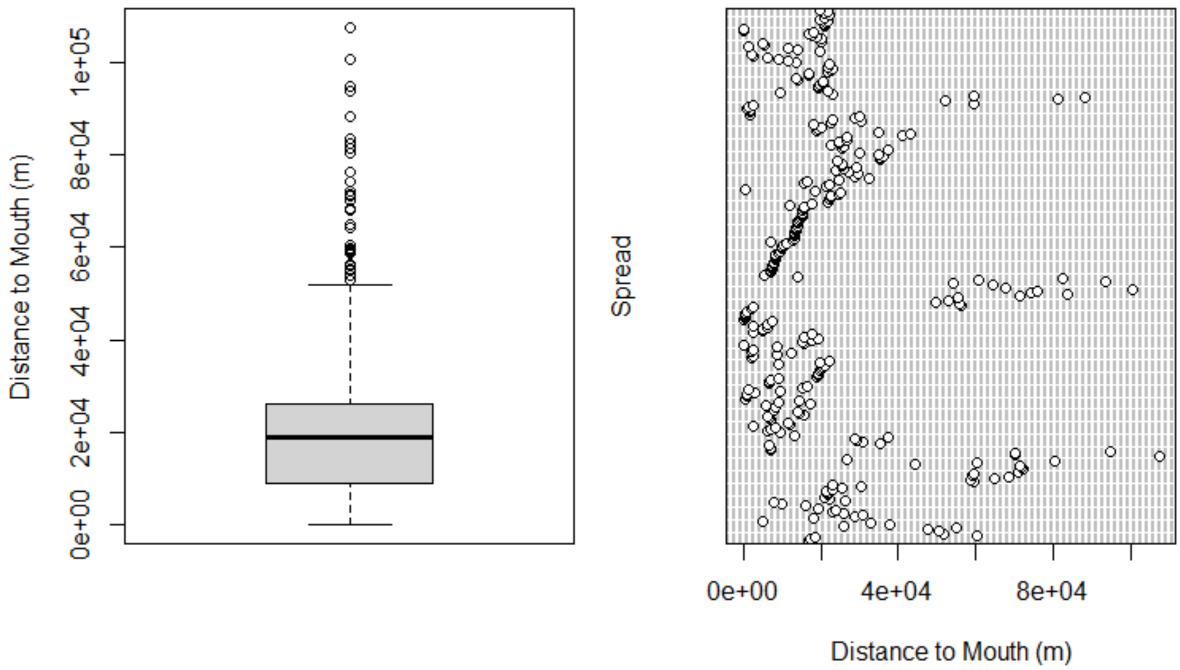


4.19. Corrgram of predictors using the field data

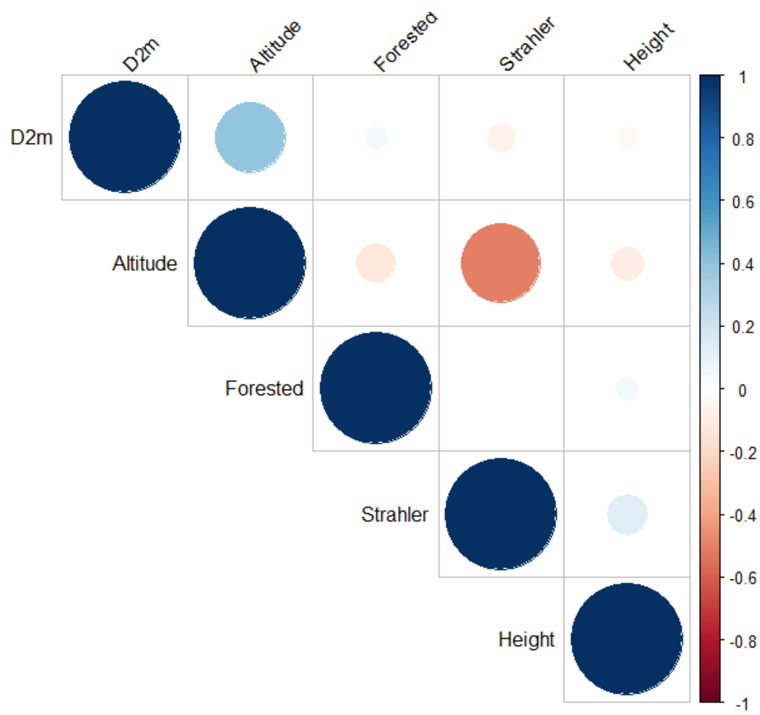


4.20. Boxplot and Cleveland plots used in data exploration for predictors 'altitude' and 'distance to mouth' using the AC data





4.21. Corrgram of predictors using the AC data



4.22. Data sources of the variables collated for the AC barriers across Wales

Variable	Data extracted from:
Latitude	Fieldwork
Longitude	Fieldwork

Average barrier height	Fieldwork
Strahler (stream order)	EU DEM E30N30 (from Copernicus)
Forested area	Google Earth
Barrier Type	Fieldwork/Google Earth
Distance to mouth (m)	Fieldwork
Altitude (m)	EU DEM E30N30 (from Copernicus)

4.23. Example of Camera: 505m viewing distance using on Google Earth

4.24. R script to calculate barrier passability based on jump heights

```
# sigmoid function
barrierImpact = function(x, maxHeight = 4, a = maxHeight/2, b = (a-0.01)/3) {
 if ((a <= 0 | b <= 0 | maxHeight <= 0))
  return("Wrong parameters entered!")
 else{
  impact <- 1 / (1 + exp((a - x)/b))
  return(impact)
 }
}
```

```
# bullhead test
maxH <- 4
barrierImpact(x=4, maxHeight = maxH)
# result: 0.9827137

hdata <- read.csv("Afan_heights.csv", header = TRUE)

# barrier height
x <- hdata$height

# minus 1 for passability
maxH <- 0.2
bullpass <- 1-barrierImpact(x, maxH)
maxH <- 2.5
salpass <- 1-barrierImpact(x, maxH)
maxH <- 1.6
btroutpass <- 1-barrierImpact(x, maxH)

pass <- c(bullpass, salpass, btroutpass)
spp <- c(rep("Bullhead"),
        rep("Atlantic salmon"),
        rep("Brown trout"))
 h <- c(x,x,x)

data <- data.frame(pass, spp, h)

ggplot(data, aes(x = h, y = pass, colour = spp)) +
  geom_line(size = 1.5) +
  xlab("Barrier height (m)") +
  ylab("Probability of passage success")  +
  scale_x_continuous(breaks = seq(0, 3, by = 0.5))+
```

```
scale_colour_manual(name = "",
                    values = cbp2) +
scale_shape(name = NULL, solid = TRUE) +
theme(legend.position = c(0.75, 0.8),
      legend.text = element_text(size=11,
                                 face="bold"))
```

5. Bibliography

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