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PAPER

Addressing road–river infrastructure gaps using a model-based approach

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Abstract

The world's rivers are covered over and fragmented by road infrastructure. Road–river infrastructure result in many socio-environmental questions and documenting where different types occur is challenged by their sheer numbers. Equally, the United Nations has committed the next decade to ecosystem restoration, and decision makers across government, non-government, and private sectors require information about where different types of road–river infrastructure occur to guide management decisions that promote both transport and river system resilience. Field-based efforts alone cannot address data and information needs at relevant scales, such as across river basins, nations, or regions to guide road–river infrastructure remediation. As a first step towards overcoming these data needs in Great Britain, we constructed a georeferenced database of road–river infrastructure, validated a subset of locations, and used a boosted regression tree model-based approach with environmental data to predict which infrastructure are bridges and culverts. We mapped 110 406 possible road–river infrastructure locations and were able to either validate or predict which of 110 194 locations were bridges ($n = 60\,385$) or culverts ($n = 49\,809$). Upstream drainage area had the greatest contribution to determining infrastructure type: when <10 km^2 our model correctly predicted culverts 73% of the time but only 60% of the time for bridges. Road type and stream gradient also influenced model results. Our model-based approach is readily applied to other locations and contexts and can be used to inform decisions about management of smaller infrastructure that are frequently overlooked worldwide.

1. Introduction

Roads are ubiquitous (Ibisch *et al* 2016), and for almost every road, there is a river, stream, or creek that they cross over, run alongside, or impinge upon (Fleming and Neeson 2020). With roads come makeshift crossings (Leal *et al* 2016) and associated infrastructure, from the obvious bridges to the more cryptic and lesser considered culverts (Januchowski-Hartley *et al* 2013) and fords. While the benefits of connection that roads bring societies are obvious, their negative impacts on nature and people are often overlooked despite continued expansion around the world. Roads disconnect river ecosystems by impeding water flow, and the movement of nutrients, materials, and species (Leal *et al* 2016 and Brajão *et al* 2020). Poorly constructed and ageing bridges, culverts, and fords (from here, collectively called road–river infrastructure) can transform ecological processes (Leal *et al* 2016), exacerbate flooding (Pregnolato 2019), and contribute to declines in fish populations important to subsistence and livelihoods (McIntyre *et al* 2016).

Figure 1. Examples of road–river infrastructure types (from top: bridge, culvert, ford) present in Great Britain. The 'Culvert at Calier - geograph.org.uk - 1938882.jpg' image has been obtained by the author(s) from the Wikimedia website where it was made available by Anne Burgess under a CC BY-SA 2.0 licence. It is included within this article on that basis. It is attributed to Anne Burgess. The 'Ford though the River Lostock, Cuerdon Valley - geograph.org.uk - 1385002.jpg' image has been obtained by the author(s) from the Wikimedia website where it was made available by Ann Cook under a CC BY-SA 2.0 licence. It is included within this article on that basis. It is attributed to Ann Cook.

Documenting where different types of road–river infrastructure occur is a need challenged by sheer numbers along the world's waterways. Increasingly, to better understand associated vulnerabilities (Pregnolato 2019) and impacts (Januchowski-Hartley *et al* 2013 and Fleming and Neeson 2020), road–river infrastructure are inventoried and mapped, including along some of the world's largest freshwater ecosystems. For example, Januchowski-Hartley *et al* (2013) estimated >250 000 occurrences of roads crossing over rivers in the great lakes basin in North America. Pocewicz and Garcia (2016) estimated that along the Curuá-Una River and tributaries, in the Amazon river basin, road–river infrastructure or impoundments linked with agriculture occur every eight kilometres of river, while there are some 10 000 road–river infrastructure on Xingu river, a small tributary of the Amazon river basin. However, to our knowledge, no study has characterized the occurrence of different road–river infrastructure types (e.g. bridges, culverts, or fords) at a national scale. Existing

Table 1. Environmental predictor variables used to build boosted regression tree (BRT) models for occurrences of road–river infrastructure, specifically bridges and culverts, in Great Britain.

Variable	Units	Source
Elevation	m asl	Digital terrain 50 (2019); https://ordnancesurvey.co.uk
Stream gradient	m m^{-1} of stream polyline	Digital terrain 50 (2019) and OS open rivers (2020); https://ordnancesurvey.co.uk
Road type	1 = major public roads (motorway and A road) connecting cities and transport links. 2 = feeder public road connecting to major public roads (B and minor road). 3 = local road (local and local access road) not intended for through traffic. 4 = access road (restricted local and secondary access road) intended for start and end of journey	OS open roads (2020); https://ordnancesurvey.co.uk/business-government/open-map-roads
Upstream drainage area	log km^2 draining to a road–river infrastructure location	Centre for ecology and hydrology integrated hydrological digital terrain model; https://ceh.ac.uk
Land cover	% urban; % grassland; % arable cover in 500 m radius buffer around road–river infrastructure	Centre for ecology and hydrology land cover map (2015); https://ceh.ac.uk

data and knowledge gaps can result in under- or overestimating changes and impacts to freshwater ecosystems by road–river infrastructure, and facilitate environmentally unsustainable interventions (O'Shaughnessy *et al* 2016). Ultimately, there is a role for both predicting infrastructure types from modelling and on-ground assessment and monitoring (Januchowski-Hartley *et al* 2013).

Here, we determine where road–river infrastructure, specifically bridges and culverts, occur across Great Britain (Wales, England, and Scotland), which has some of the highest road densities on Earth. Meijer *et al* (2018) observed 268 709 km of road length in Great Britain, and across their modelled projections estimated a mean expansion of an extra 43 000 km of road by 2050. Efforts to mitigate potential road impacts on species and ecosystems is minimal or non-existent in most countries (Cooke *et al* 2020), including in Great Britain, where the current chancellor announced £27 billion committed to building roughly an additional 6500 km of roads between 2020 and 2025[5]. While several recent studies evaluated road impacts on birds and mammals in Europe (Grilo *et al* 2020) and birds in Great Britain (Cooke *et al* 2020) there remains no systematic survey or database of road–river infrastructure in Great Britain. To address this need, we draw on existing spatial data to determine where roads cross rivers and use a model-based approach to examine whether remotely collected environmental data can be used to predict the occurrence of road bridges and culverts in Great Britain. We distinguish the environmental characteristics and variability in locations of road bridges and culverts on rivers. We discuss the relevance of our findings both in Great Britain and more broadly in other regions in relation to expanding programs to remediate road–river infrastructure to rehabilitate hydrological and ecological connectivity.

2. Methods

2.1. Georeferenced road–river infrastructure, validation, and environmental data

We used two available spatial datasets, ordnance survey (OS) open rivers[6] and open roads[7], to determine where roads cross rivers in Great Britain. To do this, we intersected the OS open rivers (excluding 'canals' and 'lakes') and open roads spatial datasets in ArcGIS 10.5.1[8], which returned 110 406 georeferenced road–river infrastructure locations across Great Britain (SI, figure 1(a)).

[6] OS open rivers 2020 https://ordnancesurvey.co.uk/business-government/products/open-map-rivers.
[7] OS open roads 2020 https://ordnancesurvey.co.uk/business-government/products/open-map-roads.
[8] ESRI, 2017. ArcGIS 10.5.1. Environmental Systems Research Institute, Redlands, CA.

We validated a subset of all georeferenced road–river infrastructure locations. To do this, we randomly selected ∼10% of the 110 406 georeferenced locations (proportional in Wales, England, and Scotland) and determined the type of infrastructure present. One author (JCW) located each of the 10 770 georeferenced road–river infrastructure locations and attributed it to one of five possible categories: bridge, culvert, ford, not a location where a road crosses a river, or not-clear (unable to visually attribute to another category). Bridges are built structures that carry roads over waterways, culverts are built structures that tunnel a waterway under a road, and fords are built at the level of the riverbed and can be made of natural materials or built structures (see figure 1).

The location and attribution of road–river infrastructure was done using the aerial imagery and street views in Google Earth Pro[9]. If unable to categorise road–river infrastructure based on the initial inspection in Google Earth Pro, the author further assessed it in the OS roaming tool in Digimap[10], which visualises road–river infrastructure as vectors and text (e.g., a bridge is depicted differently to a culvert, and often bridges are labelled whereas culverts are not). Of the 10 770 georeferenced locations, there were: 5617 bridges, 4425 culverts, and 134 fords. The remaining locations were not road–river infrastructure (153) or not-clear (441) and were excluded from the training dataset for our model (see below). Due to the low representation of fords (<2% of the attributed road–river infrastructure), we excluded these from our model training dataset.

We limited the selection of environmental variables to those available across Great Britain, and that have been previously shown to influence characteristics of road–river infrastructure (e.g. Januchowski-Hartley *et al* 2014) and of larger structures such as dams and weirs (e.g. Januchowski-Hartley *et al* 2019). We assembled spatial data for five environmental variables that are predictors of infrastructure type (table 1). Upstream drainage area (km^2) and elevation (m asl) values were extracted to georeferenced road–river infrastructure locations using spatial analyst in ArcGIS 10.5.1. The gradient of each stream polyline ($m\ m^{-1}$) was calculated as: (from-node elevation—to-node elevation)/stream polyline length; elevation values were extracted to the from-node and to-node of each stream polyline using spatial analyst in ArcGIS 10.5.1. The type of road was attributed to each georeferenced road–river infrastructure location from the intersection between OS open rivers and OS open roads; it is the 'function' value in OS open roads, and classified into four types: major, feeder, local, and access road. The percentage of urban, grassland, and arable land (derived from a 25 × 25 m resolution land cover dataset; table 1) within a 500 m radius buffer was determined for each georeferenced road–river infrastructure location in ArcGIS 10.5.1. Our reasons for including the five predictors are set out here, in brief. Upstream drainage area was included because it is an indicator of waterway width (McGinnity *et al* 2012) and discharge (Januchowski-Hartley *et al* 2014) and can influence the type of road–river infrastructure installed at a location. We included road type because it relates to road size and traffic volumes and can influence the type of infrastructure installed at a location. We included stream reach gradient, elevation, and landcover because these can influence distribution of infrastructure and types installed at given locations (*sensu* Januchowski-Hartley *et al* 2014 and Januchowski-Hartley *et al* 2019).

We could not attribute upstream drainage area to 985 road–river infrastructure locations, because of the extent of spatial data. Therefore, one author (SRJ) located and attributed a category to infrastructure at each of the 985 locations using the same approach described above, and returned 678 bridges, 248 culverts, 15 fords, and 44 that were not road–river infrastructure. We were able to attribute all environment variables to 109 268 road–river infrastructure, including locations we had validated as bridges or culverts to use as our training dataset as well as remaining locations that we predicted a type for with our model.

2.2. Modelling and predicting road–river infrastructure types

To assess which environmental variables were associated with road–river infrastructure that we validated as being bridges or culverts, we performed BRTs machine learning modelling on these training data ($n = 9936$). We used the gbm.step routine in the *dismo* package[11]. BRTs are an advanced regression technique that sequentially creates many regression trees through fitting with residuals of the previous tree. This allows BRTs to exhibit high predictive performance, because of the ability to fit non-linear relations and allowing for complex interactions (Elith *et al* 2008).

We used a binomial distribution where validated bridges ($n = 5513$; SI, figure 1(b)) were coded as '1' and culverts ($n = 4423$; SI, figure 1(c)) as '0'. Prior to model construction, we used a Spearman's rank test to assess correlations between predictor variables and found no correlations >0.7. To optimize models, we first ran all possible combinations of three model parameters: tree complexity (the number of nodes in a tree, here constrained to 1, 2, 3, 4 or 5); learning rate (the contribution of each tree to the model—0.01, 0.001 or 0.005); bag-fraction (the proportion of data selected during each cross-validation step, either 0.5 or 0.75) and

[9] Google Earth Pro 2020 http://google.co.uk/earth/download/gep/agree.html.
[10] Digimap 2020 https://digimap.edina.ac.uk/.
[11] dismo 2017 http://rspatial.org/sdm/.

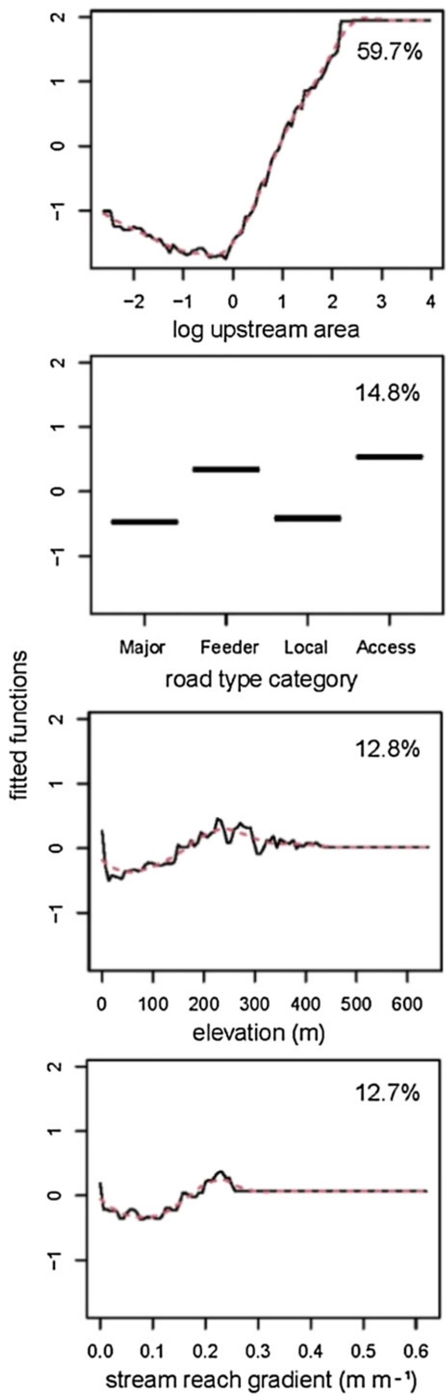

Figure 2. Partial dependency plots for the four most influential environmental variables predicting the occurrence of different road–river infrastructure types (bridges, coded as 1 and culverts, coded as 0). Relative influence of each variable is reported at the top of each graph.

the combination with the lowest deviance selected to fit the final BRT model using the gbm.fixed function in *dismo* package. We then used the *gbm.simplify* routine in *dismo* package to perform a backward selection to drop variables contributing little to model performance (assessed by comparing mean CV error values to decide the number of variables that can be dropped before predictive performance of the model is impacted). This resulted in all land cover variables being dropped from the model, and the final BRT being run with upstream drainage area, gradient, elevation, and road category, a tree complexity of 5, learning rate of 0.01, a bag fraction 0.5 and 1000 trees. We were interested in producing a model that not only identified environmental variables that differentiated bridges and culverts, but that also predicted the probability of a non-validated road–river infrastructure being a bridge or culvert. We used our final BRT model to predict the probability that each of the 109 268 road–river infrastructure were either bridges or culverts.

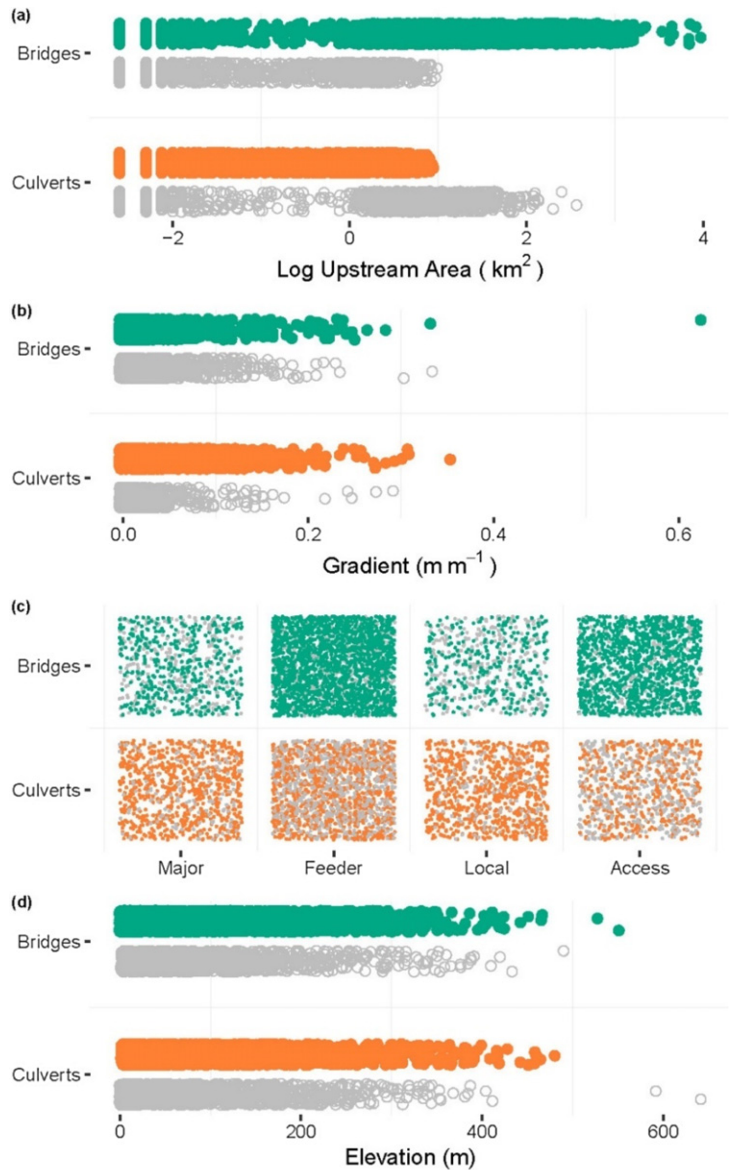

Figure 3. Accuracy of BRT predictions for those validated bridges and culverts ($n = 9936$) in the model training dataset across (a) upstream drainage area; (b) stream reach gradient; (c) road type; and (d) elevation. Accurate predictions are filled circles, inaccurate are open circles.

Model performance was evaluated by ten-fold cross-validation; this tested the model against withheld portions of the data which were not used in model fitting (*sensu* Elith *et al* 2008). We report both the model and cross-validated area under the receiver operating characteristics curve (AUC) as well as per cent deviance explained calculated as one—(residual deviance/total deviance) as measures of model performance. An AUC value of 0.5 corresponds to a predictive ability like what would be expected by chance alone; values are considered 'acceptable' between 0.7–0.8, 'excellent' between 0.8–0.9 and 'outstanding' above 0.9 (Hosmer and Lemeshow 2000). Deviance complements AUC because it expresses the magnitude of the deviations of the fitted values from the validated training data.

To identify a threshold of probability above which a road–river infrastructure was more likely than not to be a bridge (coded as '1' in the model) we used the *optimal.threshold* model with the MaxPCC method in the *PresenceAbsence* package[12]. We used the binomial values determined form the MaxPCC threshold method to calculate the proportion of our validated model training data ($n = 9936$) accurately predicted by the model. We compared the accuracy of these predictions across all the environmental variables. Partial dependency plots were used to visualize the relationships between the most influential predictor variables and the response (road–river infrastructure type). All analyses were conducted in R 4.0.0[13].

[12] PresenseAbsence 2012 https://cran.r-project.org/package=PresenceAbsence.

[13] R 4.0.0 2020 https://cran.r-project.org/.

3. Results

BRT models performed well in predicting whether a road–river infrastructure was a bridge or a culvert. Both bridges and culverts were predicted to occur broadly across all three countries in Great Britain (SI, figures 1(d) and (e)), and our model accurately predicted these infrastructure types in our training dataset 71% of the time. In total, we determined there were 60 385 bridges and 49 809 culverts (90% and 91% of which were predicted by our model, respectively with the remainder from our validated subset) where roads cross rivers in Great Britain (see Januchowski-Hartley *et al* 2020b).

The final model had 19% deviance explained and showed between acceptable and excellent predictive performance (AUC = 0.78; cross-validated AUC = 0.76). Upstream drainage area made the greatest contribution to the model (59.7%) and determining whether a road–river infrastructure was a bridge or culvert (figure 2). Road type, elevation, and stream reach gradient made highly comparable contributions to the model, with road type contributing slightly more (14.8%) to determining whether infrastructure was a bridge or culvert than elevation (12.8%) or stream reach gradient (12.7%) (figure 2).

There were several notable geographical patterns and rules-of-thumb that emerged when comparing the accuracy of predictions for our training dataset in relation to the different environmental variables (figures 3(a)–(d)). When upstream drainage area was $<10\ \mathrm{km}^2$ and our model predicted a bridge, it was correct 60% of the time, whereas it correctly predicted culverts 73% of the time (figure 3(a)). For upstream drainage areas $>10\ \mathrm{km}^2$, our model predicted 15% of road–river infrastructure as culverts, despite our validated dataset not containing any culverts with upstream drainage area of more than $10\ \mathrm{km}^2$ (figure 3(a)). We also found our model to vary in prediction accuracy for bridges and culverts depending on type of road (figure 3(c)). For major and local roads, our model was more accurate for culverts, predicting correctly 84% and 88% of the time respectively, compared to 44% and 46% of the time for bridges. This pattern switched for feeder and access roads, where bridges were predicted correctly 78% and 83% of the time respectively, compared to 59% and 48% of the time for culverts (figure 3(c)).

4. Discussion

Determining environmental variables that explain where different types of road–river infrastructure are likely to occur has great value for decision makers who often work with limited and incomplete data and information. Drawing on a compilation of data from across the three countries of Great Britain, this study presents a first model-based approach to quantify the importance of different environmental variables for explaining and predicting the occurrences of different types of road–river infrastructure. Our resulting database and findings offer new insights into the distribution and abundance of different road–river infrastructure across broad-spatial scales. Given the enormity of the challenge to locate, validate, and attribute road–river infrastructure types via on-the-ground surveys (Januchowski-Hartley *et al* 2014), our findings provide useful rules-of-thumb that decision makers can use to guide and prioritise their efforts. We believe our approach is directly applicable to decisions being made in Great Britain and Europe, and more broadly where datasets to inform cross-scale thinking, planning, and management could be limiting people's understanding of transport and river system resilience (*sensu* Walker 2020). Below, we discuss our key findings and set out ways that these could inform decision making related to management of road–river infrastructure.

We found that upstream area (km^2) draining to a road–river infrastructure made the greatest contribution to determining whether the infrastructure at that location was a bridge or culvert. When upstream drainage areas were $<10\ \mathrm{km}^2$ our model correctly predicted culverts nearly three quarters of the time based on comparison of model predictions with our validated data. This finding is important because smaller infrastructure like culverts are often overlooked by national level policies in Great Britain but can negatively impact both the environment and ecology of watercourses because of ageing and poor installation practices (Januchowski-Hartley *et al* 2020a and Fleming and Neeson 2020). Previous studies have also shown a relationship between upstream drainage area and the occurrence of culverts with certain characteristics. For example, the presence of an outlet drop is characteristic of culverts on streams with smaller upstream drainage areas and steeper gradients and can influence whether a fish can pass through the structure when swimming upstream (Januchowski-Hartley *et al* 2014 and Fleming and Neeson 2020).

Road-type is also highlighted by our work in determining whether a road–river infrastructure is a bridge or culvert. For example, for major and local roads, our model was more accurate for culverts, and the opposite was true for feeder and access roads. The relatively high density of roads in Great Britain could explain why culverts are associated with major roads (such as motorways and A roads), since there is a greater chance for larger roads to intersect smaller waterways (where culverts are more commonly found), as opposed to larger waterways which are less common in the landscape. It is worth noting, however, that our findings related to specific road-types might not directly translate to other areas of the world. There are likely to be relationships between road-type and the type of infrastructure present, but it might not necessarily be reflected in the same way as we have found in Great Britain because of differences in drainage patterns, road densities and construction methods, and environmental policies. We see this as an interesting direction for further study and potential comparison of patterns of road infrastructure in relation to freshwater ecosystems around the globe to determine if patterns observed in one region or at a particular spatial extent scale up or down or are observed across regions. Similar to upstream drainage area, the patterns observed from our results in relation to road type do offer rules-of-thumb to guide validation of road–river infrastructure, where priority should be given to areas that our model likely incorrectly predicted a bridge or culvert (e.g. predicted culverts on feeder roads).

Restoring riverine connectivity aligns with the aspirations of the United Nations upcoming Decade on Ecosystem Restoration (2021–2030)[14], and our approach and findings can inform this restoration, and sustainable use and management of freshwater ecosystems. For instance, our mapping of road–river infrastructure and model findings are directly relevant to initiatives established through the European Union Flood Directive[15]. The Floods Directive aims to determine broad-scale risks associated with flooding, and our work provides the responsible flood authorities (government agencies and local councils) with necessary data to inform those processes. Determining where bridges and culverts occur in our waterscape is critical for quantifying risks to these infrastructures from changing climate and flood conditions (Pregnolato 2019). Our findings can also inform ongoing government and non-government initiatives in Great Britain, such as those pursued by Environment Agency and Scottish Environment Protection Agency as well as environmental charities like Rivers Trusts, to reconnect habitat for fishes and restore hydrological processes. Once we know where different types of infrastructure occur along watercourses we can better understand and predict fiscal and social costs associated with potential failures, and in the case of the culverts, identify more cost-effective solutions than maintaining and repairing structures that have myriad environmental and ecological impacts (O'Shaughnessy *et al* 2016). Finally, our findings can and should be integrated into national- and European-scale initiatives such as the catchment based approach[16] in Great Britain, and the AMBER Atlas[17] that has mapped locations of larger infrastructure to inform planning and management of rivers and infrastructure (Belletti *et al* 2020). While the AMBER Atlas collated locations for >600 000 infrastructure (such as dams and weirs) it overlooked the smaller and more abundant infrastructure associated with transport systems, and our findings can begin to address this while our approach could be applied to other areas of Europe to further fill gaps.

5. Conclusions

This study provided a model-based approach to overcome data and knowledge gaps about road–river infrastructure present along rivers in Great Britain. It is critical to first determine where different types of road–river infrastructure occur to enable quantification and mitigation of vulnerabilities and instream impacts, and to further consider this with road expansion. In Great Britain, further expansion of road networks is on the horizon, despite already globally high densities of roads. Our approach has provided a major step towards a more representative, consistent, and harmonised database that can be used to mitigate current and future impacts to nature and humans from inadequate planning or management of road–river infrastructure in Great Britain. The techniques applied here draw on remotely collected data that are now available at national-scales in many countries or through open global-scale spatial data and platforms such as Google Earth. Therefore, our approach can be extended to other locations and contexts, and we encourage others to perform such analyses to establish if the observations reported here occur elsewhere.

6. Data statement

All data associated with road–river crossings in Great Britain that were mapped and modelled in this study will be made available for download from Figshare upon publication acceptance (Januchowski-Hartley *et al* 2020a).

[14] United Nations Decade on Ecosystem Restoration https://decadeonrestoration.org.
[15] European Union Flood Directive 2007 https://ec.europa.eu/environment/water/flood_risk/implem.htm.
[16] Catchment based approach https://catchmentbasedapproach.org/.
[17] AMBER Atlas 2020 https://amber.international/barrier-atlas/.

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Data availability statement

The data that support the findings of this study are available at the following DOI: https://doi.org/10.6084/m9.figshare.13139492.v4.

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