Identifying future protection gaps in Amazon floodplains: a dual-season forecasted distribution of the world’s largest scaled freshwater fish

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Abstract

The Amazon floodplains represent important surfaces of highly valuable ecosystems, yet they remain neglected from protected areas. While the efficiency of the protected area network of the Amazon basin may be jeopardised by climate change, floodplains are exposed to important consequences of climate change but are omitted from species distribution models and protection gap analyses. We modelled the current and future (2070) distribution of the giant bony-tongue fish *Arapaima* sp. accounting for climate and habitat requirements, with consideration of dam presence (already existing and planned constructions) and hydroperiod (high- and low-water stages). We further quantified the amount of suitable environment which falls inside and outside the current network of protected areas to identify spatial conservation gaps. We predict climate change to cause the decline of environmental suitability by 16.6% during the high-water stage, and by 19.4% during the low-water stage. We found that about 70% of the suitable environments of *Arapaima* sp. remain currently unprotected, which is likely to increase by 5% with future climate change effects. Both current and projected dam constructions may hamper population flows between the central and the Bolivian and Peruvian parts of the basin. We highlight protection gaps mostly in the southwestern part of the basin and recommend the extension of the current network of protected areas in the floodplains of the upper Ucayali, Juruà and Purus Rivers and their tributaries. This study showed the importance of taking into account hydroperiods and dispersal barriers in forecasting the distribution of freshwater fish species, and stresses the urgent need to integrate floodplains to the protected area networks.

**Keywords**: Arapaima, Climate change, Hydroperiod, Species Distribution Models, Water colour, Dams
Introduction

The Amazon basin is the world’s largest basin and hosts the highest freshwater fish species richness on Earth (Oberdorff et al., 2019; Jézéquel et al., 2020a). Its ichthyologic fauna is currently under multiple threats such as habitat fragmentation by dams, deforestation, urban/agricultural pollutants and overexploitation (Reid et al., 2019; Duponchelle et al., 2021). Climate change may exacerbate these threats by increasing water temperatures and changing precipitation patterns, leading to increasing precipitations in the western part of the basin and to more severe and longer droughts in its eastern portion (Sorribas et al., 2016; Marengo et al., 2018) potentially affecting the Amazon’s fauna (Tedesco et al., 2013).

During The IUCN WC (Marseille, France 05.09.2021), indigenous groups urged the world leaders to take actions in order to protect 80% of the Amazon basin by 2025, stating that bold action is needed to halt the deforestation that is pushing the world's largest rainforest beyond the point of no return. The current network of protected areas (including indigenous lands) of the Amazon basin was mainly designed for terrestrial species, which has downplayed the importance of aquatic ecosystems (Dagosta et al., 2020). Protected areas and indigenous lands cover 52% of the basin surface (Jézéquel et al., 2020b), a surface sufficient to encompass the current distribution of a majority of large-range fish species (Frederico et al., 2021). However, the network’s capacity to protect freshwater biodiversity remains limited (Azevedo-Santos et al., 2019; Jézéquel et al., 2020b). In addition, following future climate change projections, the proportion of species with a sufficient area under protection status will significantly decrease by 2050 as a result of species distribution shifts (Frederico et al., 2021). The highest protection gaps are located in large rivers and their floodplains, which calls the need to focus conservation efforts in these habitats and identify areas where species are predicted to shift (Frederico et al., 2021). Fish species represent a substantial part of the Amazonian diversity (>2200 species described; Jézéquel et al., 2020a) and play major roles in Amazo-
nian ecosystems. The omission of aquatic areas, especially floodplains, from protected area networks may severely increase the basin’s vulnerability to ongoing changes.

The giant bony-tongue fish *Arapaima* sp., also known as *pirarucú* in Brazil or *paiche* in Peru and Bolivia, is an obligate air-breathing species complex (but see Torati et al., 2019) omnivorous with piscivorous tendencies (Carvalho et al., 2018). *Arapaima* sp. represents the world’s largest scaled freshwater taxon and one of the most charismatic fish of the Amazon. The species migrates laterally for feeding and reproduction between river channels and floodplain habitats following hydrodynamics (Castello, 2008). Lateral migrant species are considered as vulnerable to climate change because floodplain lakes are highly exposed to temperature changes (Duponchelle et al., 2021). *Arapaima* sp. is therefore a good model species to better understand the effects of climate change on lowland Amazonian fish species. It is also a key fishing resource eliciting a high economic value in the region (Castello et al., 2009; Macnaughton et al., 2015). Hence, the protecting their range would enable to encompass an important component of biodiversity (e.g. floodplain-dwelling species) and food resource for local communities (Petersen et al., 2016).

After decades of harvesting pressure, the species complex was considered overexploited (Castello et al., 2011; Isaac et al., 1993). Conservation measures were then undertaken in various regions, consisting in banning fishing activities in selected oxbow lakes (Mcgrath et al., 1993). These measures were proven effective (Petersen et al., 2016) but the fishing pressure persisted (Castello et al., 2015; Cavole et al., 2015). Conservation recommendations for management usually account for the species habitat requirements (Arantes et al., 2013, 2010). However, conservation areas may be appropriate under current conditions, but not in the future (Frederico et al., 2021; Leroy et al., 2014). Therefore, there is a need to assess the representativeness of protected areas for *Arapaima* sp. in regard to potential distribution shifts driven by future climate change. To date, only two studies have examined the potential effects of future climate change on *Arapaima* sp. distribution (Oberdorff et al., 2015; Oliveira et al., 2020). However, the first one used a reduced set of species occur-
rence points and only one climatic variable (Oberdorff et al. 2015) while the other was mainly fo-
cused on historical demography and genomic diversity (Oliveira et al., 2020). Hence, there is a need
to develop forecasting models that are dedicated to the design of conservation actions for *Arapaima*
sp and floodplain-dwelling species.

Climate change effects are commonly predicted using Species Distribution Models (SDMs; also
called ecological niche or habitat suitability models; (Guisan et al., 2017). This approach has often
proven effective in conservation planning (e.g. providing recommendations for translocation, habi-
tat restoration or the design of protected areas; Leroy et al., 2014; Dubos et al., 2021b). Species dis-
brution models can be misleading in regard to decision-making depending on the data input and
methodological choices (Araújo et al., 2019; Guisan et al., 2013; Sillero et al., 2021; Sofaer et al.,
2019)). However, in a context of urgent decision-making, ideal conditions for reliable modelling
may hardly be reached (Guisan et al. 2013). Here we aim to provide guidelines for the design of
protected areas on the basis of acceptable methodological considerations for decision-making, using
all the most recently available data, careful environmental variables choice, sample bias treatments,
consideration of hydroperiod and dispersal barriers, integration of a range of algorithms and dealing
with model complexity. So far, floodplains were omitted from species distribution models, which
prevents from quantifying the suitable area available during both water-stage seasons. We apply a
combination of recently developed methods to provide projection maps at high resolution (30 arc
seconds) for both water-stage seasons and identify conservation gaps in Amazon floodplains. We
further assess whether conservation gaps are likely to increase in the future (2070). We eventually
provide guidelines for the design protected areas integrating floodplains and accounting for climate
change.
Methods

Study species and area

The giant bony-tongue fish *Arapaima* sp. is naturally distributed in the sub-basins of the Amazon, Tocantins-Araguaia and Essequibo Rivers, which cover Brazil, Ecuador, Colombia, Guyana and Peru (Castello & Stewart, 2010). Within the Amazon River Basin and according to available data (Jézéquel et al., 2020a), *Arapaima* sp. is naturally evenly distributed in highly productive Amazonian floodplain nutrient-rich whitewaters (Fernandes, Podos & Lundberg, 2004), at the notable exception of the upstream section of the Madeira River (Bolivian Amazon), where a series of rapids probably historically acted as barriers to colonisation (Miranda-Chumacero et al., 2012). However, *Arapaima* sp. colonised Bolivian waters (where it is now considered an invasive species) following an unintentional introduction around the late seventies via the Peruvian side of the Madre de Dios River (Miranda-Chumacero et al., 2012).

Occurrence data

We retrieved 172 occurrence records available from a recent fish occurrence database gathering all information available in published articles, books, gray literature, online databases, foreign and national museums, and universities (Jézéquel et al., 2020a). To reduce spatial autocorrelation, we selected one occurrence per pixel of the environmental variables (30 arc sec), resulting in 162 presence points (i.e. data thinning; Steen et al., 2021; Vollering et al., 2019).

Climate data

We used the 11 bioclimatic variables of temperature at 30 arc sec resolution (approximately 900 m) of the current climate data and the 2070 projections from CHELSA (Karger et al., 2017). We only took temperature variables because (1) freshwater fishes are particularly sensitive to temperature because of direct effects on their metabolism, development and reproduction (Buisson et al., 2008), and because precipitation data tend to be less accurate in riverine systems. We used three Global
Circulation Models (GCMs – i.e. BCC-CSM1-1, MIROC5 and HadGEM2-AO) and two greenhouse gas emission scenarios (Shared Socio-economic Pathways, SPP; also called Representative Concentration Pathways, RCP), the most optimistic RCP2.6 and the most pessimistic RCP8.5. In the case of aquatic species, climate variables can be used as satisfactory surrogates for unavailable instream variables (i.e. water temperature and hydrology) to model their distributions because water and air temperatures are correlated (Frederico et al., 2014; McGarvey et al., 2018).

Distribution modelling

We modelled and projected species distributions with the Biomod2 R package (Thuiller et al., 2009), using 10 modelling techniques: generalised linear and generalised additive models (GLM and GAM; Guisan, Edwards, & Hastie, 2002), classification tree analysis (CTA; Prasad, Iverson, & Liaw, 2006), artificial neural network (ANN; Manel, Dias, & Ormerod, 1999), surface range envelop (SRE, also known as BIOCLIM; Booth et al., 2014), flexible discriminant analysis (FDA; Manel, Dias, & Ormerod, 1999) and random forest (RF; Prasad, Iverson, & Liaw, 2006), Multiple Adaptive Regression Splines (MARS; Leathwick et al., 2005), Generalised Boosting Model (GBM; J. Elith, Leathwick, & Hastie, 2008) and Maximum Entropy (MaxEnt; Phillips, D., & Schapire, 2006). We generated five different sets of randomly-selected pseudo-absences (Wisz and Guisan, 2009). For each individual baseline climate data, we selected one variable per group of inter-correlated variables to avoid collinearity (Pearson’s r > 0.7, Dormann et al., 2013) using the removeCollinearity function of the virtualspecies R package (Leroy et al., 2016) and assessed the relative importance of each variable kept with 10 permutations per modelling technique and pseudo-absence sets (see below; total = 500 permutations). The variables included in the final models were those with a relative importance > 0.2 across at least 50% of model runs. We predicted species distributions with an ensemble of small models approach (ESM; Lomba et al., 2010; Breiner et al., 2015). We ran sets of bivariate models, i.e. including all pairwise combinations of the selected
variables, and produced an ensemble model with the mean predictions across all models weighted by their respective Boyce index (see below). This method is advocated for data-poor species and enables to reduce model complexity without reducing the explanatory power. We took the Amazon Basin as a background, defined as basin boundaries of the major tributaries to the Amazon main stem excluding the Rio Tocantins (Mayorga et al., 2005). Ideally, the background extent should represent the area within which the species is able to disperse, i.e. wetlands. However, we chose to take the whole Amazon Basin as a background and not only the wetlands because this would require either (1) to downscale the climatic data at the resolution of wetland variables, inducing interpolations which are not recommended in most cases (Sillero and Barbosa, 2020) or (2) to aggregate wetland data, which would represent a significant loss of information (i.e. most tributaries would be removed because they cover the minority of the pixels’ surface). Therefore, we accounted for aquatic habitat by post-filtering our projections to remove strickly terrestrial areas (see Habitat data section below). We randomly generated five sets of 10000 pseudo-absences from the background, down-weighted to equal presence data (setting prevalence to 0.5).

**Accounting for sampling bias**

Most occurrence data were obtained from dedicated local studies and may be subject to sample bias. To account for potential sample biases, we produced five additional sets of pseudo-absences generated around the original (unthinned) presence points (Phillips et al., 2009). We used a geographic null model (Hijmans, 2012) and used it as a probability weight for pseudo-absence generation. We spatially partitioned the data for performance evaluation, using 5-folds for block-cross validation (generated with the blockCV R package, Valavi et al., 2019; Fig S1). We quantified the effect of sample bias correction (non-random pseudo-absence generation) using the Relative Overlap Index (ROI; Dubos et al., 2021c). This index informs how sample bias corrections affected spatial predictions (mean Schoener’s D between uncorrected and corrected individual models) relative to inter-model variability (mean overlap between all pairwise combinations of model
replicates). A value of 1 indicates a strong effect of correction across all model replicates (pseudo-absence and block cross-validation runs), while a value below 0 indicates that correction effect is lower than the variability between model replicates. We computed this index independently for each modelling technique and ESM and give the mean value.

Model evaluations – We assessed model performance using the Area Under the Curve of a receiver operating characteristic plot (AUC; Swets, 1988), a maximisation of the True Skill Statistics (maxTSS; (Allouche et al., 2006) and the Boyce index (Hirzel et al., 2006)). For ensemble models, we excluded models for which predictions were worse than random (Breiner et al., 2015; Scherrer et al., 2019), i.e. when the Boyce index was below 0.

We provide clamping masks showing the areas where climates are novel in the future (similar to a MESS analysis; Elith, Kearney & Phillips, 2010) to determine whether models are well informed for predictions on future data.

Habitat data

We accounted for non-climatic habitat requirements of our model species by applying a filter to the projected climate suitability based on land use and land cover data (e.g. Gillard et al., 2017). This enabled to account for habitat without increasing model complexity while remaining biologically realistic and relevant for conservation applications. One challenge in modelling lateral-migrant Amazon fish species is that their distribution is highly variable within the year, as a result of important differences in hydrological regimes and behavioural adaptations. During the high-water period, *Arapaima sp.* colonise the flooded forests before returning to the lakes and the main river channel during the low-water period. Floodplain lakes provide key habitats for *Arapaima sp.* and must be prioritised for conservation (Richard et al., 2018). On the other hand, the habitat types of the main channel (e.g. water colour; Junk, Wittmann, Schöngart, & Piedade, 2015) are also important determinants of fish diversity due to differences in nutrient contents (Oberdorff et al.,
According to the database used the bony-tongue fish seems almost exclusively found in white waters, which are nutrient rich, with high rates of biological production, sustaining large prey fish populations and favourable for omnivore-piscivorous fishes like arapaima. Note that *Arapaima* sp. can be occasionally found in black waters, but in very low densities. We first removed all terrestrial lands and produced a set of projections for the flooded and the dry periods. We retrieved high-resolution data (3 arc-seconds) on wetland areas for the flooded and the dry season from (Hess et al., 2015). We resampled model predictions at the resolution of the wetland data to prevent any information loss. We also used water type data (Venticinque et al., 2016) to remove the black and clear waters from the predictions, to retain only white waters (*Arapaima* is commonly found in nutrient-rich turbid waters). Since data on water colour are linear (vector, i.e. no superficial data), we produced a 0.5° buffer around lines and filtered model predictions falling outside of the buffer.

**Accounting for uncertainty**

To identify priority areas for conservation, we provide a map for each period (dry and wet seasons, current and future) showing the areas that are the most consistently identified as suitable between model replicates and scenarios. Following (Kujala et al., 2013), we computed the weighted mean predictions discounted with inter-model variability (standard deviation) for current and future predictions separately.

**Accounting for dispersal barriers**

We considered spatial features that would prevent potential distribution shifts. We used typological data on dams obtained from (Anderson et al., 2018) and ANA Brazil (2018), and waterfall locations from Oberdorff et al. (2019). We projected these features on predictions maps to examine their potential impact.

**Conservation gap analysis**
We assessed the extent of protected and unprotected suitable environments for the species for both flooded and dry periods, and for current and future conditions (2070). We obtained information on the protection status from the World Database on Protected Areas (UNEP-WCMC, 2019). Protection gap analyses usually involve binary transformations to be able to quantify the area potentially occupied by the species (e.g., Ahmadi et al., 2020; Bosso et al., 2018; D. L. De Carvalho et al., 2017; Hoveka, van der Bank, & Davies, 2020). However, binary transformations are not recommended, since they are strong drivers of uncertainty (Muscatello et al., 2020). Therefore, we rather show the frequency distribution of suitability scores inside and outside protected areas (e.g. Mod et al., 2020). As an indicator of overall suitability, we also provide the proportion of total environmental suitability inside and outside protected areas.

**Results**

*Current distribution modelling*

Model reliability varied with the variables included in small model modalities (Fig. S2), with a median Boyce index of 0.30 before, and 0.47 after sample bias correction. We discarded 498 poorly performing models in the uncorrected group and 408 in the corrected group (out of 1500 per group). The effect of sample bias correction was moderate, slightly higher than the variability between model replicates (ROI = 0.06). We selected four uncorrelated variables, all showing potentially high importance (Fig. S3). The selected variables were, for both uncorrected and corrected groups, annual mean temperature (bio1), isothermality (bio3), temperature seasonality (bio4) and temperature annual range (bio7; Fig. S4). The species is found in the warmest places of the Amazon basin, where annual mean temperature $> 21^\circ$C with an optimum near 28°C (i.e., the maximum annual mean temperature of the study area; Fig. S4). Occupied areas are also characterised by high
diurnal variation in temperature, low seasonality and intermediate temperature annual range relative to the Amazon Basin (Fig. S4).

Future climate suitability

Future predictions mostly depended on the emission scenario (RCP26 versus RCP85; Fig. 1). In all cases, we predict an important decline in climate suitability in most parts of the current range of the species. Models suggested a shift in the suitable climate conditions south-east. The most suitable conditions will be met towards the state of Acre, in the south of the state of Amazonas in Brazil and in southern Peruvian Amazon. These areas correspond mostly to the upper part of the Ucayali, Juruà and Purus rivers and their tributaries. Despite the apparent variability between models, predictions penalised by uncertainty were in agreement with unpenalised predictions (Fig. 2). The clamping masks show an important area extrapolated for RCP85, mostly driven by bio1 (Fig. S5).

Figure 1. Current (a) and future 2070 (b) climate suitability for *Arapaima* sp. in the Amazon basin.
Suitability scores were estimated from Ensemble of Small Models for two emission scenarios and three global circulation models and corrected for sample bias. Black points represent occurrence records. Axes represent the coordinates (WGS84).
Figure 2. Current (a) and future 2070 (b) predicted climate suitability for *Arapaima* sp. accounting for uncertainty. Bottom panels are the result of mean predictions discounted with inter-model variability (standard deviation SD, as an indicator of uncertainty related to model settings and climate data).

**Accounting for habitat**

After removing all non-wetland and keeping only white waters, we found that the total environmental suitability will decrease by 16.6% on average by 2070 during the high water stage, 19.4% during the low water stage (Fig. 3).
Figure 3. Current and future environmental suitability for *Arapaima* sp. projections accounted for hydrological period (high versus low water stage) and water colour (white waters only). Black lines represent the administrative borders.

**Gap analysis**

Under current conditions, 31.4% of the total suitable environment is included within protected areas during the high water stage, 30.7% during the low water stage. In the future, the proportion of protected suitable areas will decrease by approximately 5%, with 26.3% and 25.9% of suitable environments within protected areas for the high and low water stages, respectively (Fig. 4–7). The frequency distribution of suitability scores shows that the majority of the most suitable areas (score > 300) remains unprotected (see grey area in Fig. 4). The most important gap in regard to future environmental suitability is located between the upper parts of the Ucayali, Juruà and Purus rivers.
Figure 4. Predicted environmental suitability for *Arapaima* sp. for current (top) and future 2070 (bottom) conditions at two stages of water levels, with protected areas (blue). We show the frequency distribution of environmental suitability scores inside (blue) and outside (grey) protected areas.
Figure 5. Projected future environmental suitability for *Arapaima* sp. at two stages of water levels (left: high-stage; right: low-stage), with protected areas (blue) for the upper Ucayali river.
Figure 6. Projected future environmental suitability for *Arapaima* sp. at two stages of water levels (top: high-stage; bottom: low-stage), with protected areas (blue) for the upper Juruà river.
Figure 7. Projected future environmental suitability for *Arapaima* sp. at two stages of water levels (top: high-stage; bottom: low-stage), with protected areas (blue) for the upper Purus river.
Accounting for dispersal barriers

Most dams and dam projects are localised towards the edges of the Amazon Basin, near the Andes Mountains. One dam is located East of the Amazon, potentially preventing movements between central Amazon and Peruvian Amazon (i.e. between the Amazon main stem and the Ucayali and Marañón rivers). Population movements will be mostly hampered in the Madeira river, where five dams or dam projects and waterfalls are located. These may represent dispersal barriers between central and Bolivian Amazon (Fig. 8).

Figure 8. Current environmental suitability for Arapaima sp. with dispersal barriers (blue diamonds: waterfalls; black triangles: dams). Red dots are the occurrence points.
Discussion

We used a robust approach for species with scarce distribution data (ensemble of small models), based on climate as predictors and habitat as filters, accounting for sample bias, hydroperiod and dispersal barriers, and integrating uncertainty by discounting inter-model variability from predictions, and successfully modelled the distribution of *Arapaima* sp. We found that the species complex may face important environmental degradation driven by climate change by 2070, and further identified significant conservation gaps in the coverage of suitable environments, which are likely to worsen with climate change.

*Drivers of Arapaima sp. distribution*

*Arapaima* sp. is found in the hottest areas of the Amazon basin, with high daily variation and intermediate variability in annual temperatures overall. Our predictions fit well the known distribution of the species complex, apart from the populations located in the extreme north-west of the Amazon basin (corresponding to the Ecuadorian and Columbian Amazon), where we found climate conditions to be suboptimal. Overall, our models based on temperature identified well the riverine areas (Fig. 1), a sign of good model performance. The minimum annual mean temperature where the species can be found (21°C) is consistent with the findings of (Lawson et al., 2015) who found that *Arapaima gigas* ceased feeding at an average temperature of 20.8°C. The high daily variation may be related to heavy rain episodes which is consistent with the dependence of *Arapaima* sp. on floodplains. The low seasonality corresponds to equatorial regions where the species will not be exposed to low temperatures (detrimental to *Arapaima* sp.) during any period of the year.

We found suitable conditions throughout the Amazon river, but the species is highly restricted to specific habitats (deep and large waters that are connected to other water bodies; Arantes et al., 2013). Those variations could not be perceived at the resolution of our environmental variables (3
arc-seconds, approximately 100 m). Therefore, our predictions must be regarded as regions where the climate is suitable, but local habitat requirements must be considered in future sampling campaigns (e.g. the species is found in deep waters).

The future of Arapaima sp.

We predict a shift in suitable climatic conditions by 2070 in the most optimistic scenario, and a generalised decline of climate suitability in the worst-case scenario. In the optimistic scenario (RCP-SSP 2.6), suitable conditions will be met towards the upper part of the Ucayali, Juruà and Purus rivers and their tributaries, where large floodplains are located. In the most pessimistic scenario (RCP-SSP 8.5), the same region was identified as the most suitable, but conditions will be largely suboptimal. Models also predict a southward shift for the populations from the Amazon main stem, and a northward shift for Bolivian populations. These potential shifts may be hampered by dispersal barriers (waterfalls and dams), for instance between the upper and the lower Madeira river. Our results differ overall from the ones obtained by Oliveira et al. (2020) who found that climate conditions may remain suitable in the western part of the Amazon basin. Note that our predictions are nevertheless in agreement with the potential decline of suitable conditions in central Amazon, and for the shift of suitable conditions at the extreme southwestern part of the Amazon basin (but remaining suboptimal in our case). Differences may have been partly driven by the occurrence data (we used all the recently available data from the AmazonFish database). The input climate data (baseline and GCMs) used can be a strong driver of uncertainty as well (Baker et al., 2016; Dubos et al., 2021a). In their study, Oliveira et al. (2020) used Worldclim baseline data with the CCSM4 GCM while we used CHELSA with three different GCMs. The use of multiple GCMs is highly recommended as it represents an important source of uncertainty in model projections (Buisson et al., 2011; Dubos et al., 2021a). This also applies to our case study, with notable differences throughout the Amazon basin (Fig. 1b, 2b). Our results also differ for the southwestern part of the Amazon basin, where Oliveira et al. (2020) projected a high suitability in the future. In
our case, this region was discarded by the absence of white waters, which is a key habitat feature for Arapaima.

The certainty of our future projections was limited by novel climate conditions (mostly driven by bio1) for which models were uninformed, inducing extrapolations. Given the shape of the response curve to bio1 (higher suitability in the hottest conditions; Fig. S4), extrapolated predictions may result in an overestimation of climate suitability when bio1 is above current conditions. Hence, in the case where future conditions are beyond the thermal tolerance of Arapaima, the decline in climate conditions may be even worse than expected here. Further studies should assess the upper limit of thermal tolerance for Arapaima sp.

Recommendations for management

The majority of suitable environments of Arapaima sp. remain currently unprotected and the proportion of unprotected suitable areas is likely to increase with climate change. This may apply to the wider freshwater fish community inhabiting floodplains (Frederico et al., 2021). The existing protection gap downplays the importance of freshwater species but also an important terrestrial biodiversity during the terrestrial phase corresponding to the low-water stage (Piedade et al., 2010). The most important gap with regard to future environmental suitability is located between the upper parts of the Ucayali, Juruà and Purus rivers. We recommend the extension of the existing protected areas (e.g. Vale do Javi southward, Kanamari do Rio Juruà, El Sira and the protected area network surrounding the Reserva Extrativista Do Médio Purus) to the floodplains surrounding those rivers and their tributaries.

Concluding remarks

The giant bony-tongue fish is currently threatened by overfishing (Castello et al., 2015), as well as deforestation through indirect effects on trophic chains (Carvalho et al., 2018). Here, we have shown that climate change will bring an additional extinction risk to this species of high economic
value, which may be further worsened with future dam building (e.g. Winemiller et al., 2016). This might be the case for most large fish species from the Amazon river, including species that are highly caught by fishermen. The Amazon region is affected by poverty and limited food security. With more than 30 million people depending on floodplain fish for food (Petersen et al., 2016), conservation actions require integrative approaches to ensure biodiversity conservation to prevent conflict and ensure human well-being (Castello et al., 2013).

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Author contribution

All authors designed the study, ND, ML and AG designed the methods, ND analysed the data and led the writing of the manuscript, all authors contributed significantly to the interpretation of the results and the writing of the manuscript. All authors gave final approval for publication.
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Supporting information

Figure S1. Block-cross validation folds for the modelisation of Arapaima sp.
Figure S2. Model reliability (Boyce indices) for each ESM, with (blue) and without (red) sampling bias correction.
Figure S3. Variable importance for the species distribution model of Arapaima sp.
Figure S4. Response curve to bio1 (annual mean temperature), bio3 (isothermality), bio4 (temperature seasonality) and bio7 (temperature annual range) for uncorrected models. Black lines represent predicted values for each individual model. The blue line represents the smoothed response across all models.
Figure S5. Response curves to bio1 (annual mean temperature), bio3 (isothermality), bio4 (temperature seasonality) and bio7 (temperature annual range) for corrected models. Black lines represent predicted values for each individual model. The blue line represents the smoothed response across all models.
Figure S5. Clamping mask for the distribution model of *Arapaima* sp. showing novel climate conditions for 2070. Novel conditions are mainly driven by temperature annual range (bio1).