Research Article

Impact of climate change on the distribution of brown trout, *Salmo trutta* Linnaeus, 1758 (Teleostei: Salmonidae) using ensemble modelling approach in Iran

Hossein MOSTAFAVI*1, Jafar KAMBOUZIA2

1Department of Biodiversity and Ecosystem Management, Environmental Sciences Research Institute, Shahid Beheshti University, GC, Tehran, Iran.

2Department of Agroecology, Environmental Sciences Research Institute, Shahid Beheshti University, GC, Tehran, Iran

*Email: hmostafaviw@gmail.com

Abstract: In recent decades, climate change and other anthropogenic pressures have seriously influenced freshwater biodiversity to decline faster than terrestrial biodiversity. This trend is likely to be continued in the future. We assessed the impact of climate change on the distribution of brown trout in Iran by simulating their conditions under optimistic and pessimistic climate change scenarios (RCP 2.6 and RCP 8.5) in 2050 and 2080 by using species distribution models (SDMs) tool and ensemble forecasting approach. The results showed a significant reduction in the distribution range of this species (100%) in our database in all optimistic and pessimistic climate change scenarios. Moreover, no new potential sites were predicted in those scenarios. These outcomes seriously warn that a conservation and management plans are required to protect this species in future.

Keywords: Brown trout, Species Distribution Modelling, Conservation, Range distribution.

Introduction

Climate change is one of multiple interacting stresses on ecosystems. In last decades, climate change and other anthropogenic pressures have caused freshwater biodiversity to decline faster than terrestrial ecosystems and this trend is likely to continue in future (Dudgeon et al. 2006; Filipe et al. 2013). Freshwaters are particularly vulnerable to climate change because (i) many species within these fragmented habitats have limited abilities to disperse as the environment changes, (ii) water temperature and availability are climate-dependent, and (iii) many systems are already exposed to numerous anthropogenic stressors (Dudgeon et al. 2006; Woodward et al. 2010). Ongoing anthropogenic climate change increases water temperatures, and alters precipitation, evaporation and hydrology patterns, and accordingly affects essential habitat conditions for freshwater species (Schindler 2001; Woodward et al. 2010; Filipe et al. 2013).

Attaining predictive models for the biogeography of riverine fish species in the face of environmental changes is a key scientific goal and a priority for obtaining effective conservation and management (Olden et al., 2010; Filipe et al. 2013). Species distribution models (SDMs) have become important tools in the fields of ecology, biogeography and biodiversity research to model species geographic distributions based on correlations between known occurrence records and the environmental conditions at occurrence localities (Pearson & Dawson, 2003; Mostafavi et al. 2015). A major concern of such models is their inherent uncertainty, particularly the variability of results achieved from different statistical techniques and datasets used (Thuiller 2004; Thuiller et al. 2004a, b; Filipe et al. 2013;
Mostafavi et al. 2014). Therefore, summarising different model types into an ensemble forecasting approach reduces uncertainty of individual techniques (Araújo & New 2007).

Iran is a country with large climatic variability. More than 82% of Iran is located in arid and semi-arid zone of the world. The average rainfall in this country is about 250mm. Another important climatic element is extreme temperature changes that sometimes range from -20 to +50°C (Abbaspour et al. 2009; Amiri & Eslamian 2010). Based on the research and assessment carried out during the Climate Change Enabling Activity Project under UNFCCC and using the scenarios proposed by IPCC, it is estimated that if the CO₂ concentration doubles by the year 2100, the average temperature in Iran will increases by 1.5-4.5°C. The direct adverse impacts of climate change include changes in precipitation and temperature patterns, water resources, sea level rise and coastal zone, drought frequency, etc. (Abbaspour et al. 2009; Amiri & Eslamian 2010).

Brown trout Salmo trutta Linnaeus, 1758 in Iran, are reported from the Caspian Sea basin in the north, from the Urmia basin in the north-west, and the endorheic Namak basin in the northcentral region of Iran (Abdoli 2017; Coad 2018). They inhabit headwaters with high oxygen saturation, steep slope, fast flow, suitable temperature regimes and adequate food (Elliott 1994). Moreover, they are sensitive to environmental changes (Mostafavi et al. 2014). The high recreational and commercial value of this species renders it as a priority for conservation and management efforts, which require accurate and realistic predictions of its future distribution.

The aim of this study is to model the potential impact of future climate change on the geographical distribution of brown trout under optimistic and pessimistic scenarios (RCP 2.6 and RCP 8.5) in 2050 and 2080.

Materials and Methods

Study area and fish data: The study area was the country of Iran. The fish data used in this study collected from several time periods (1970-2000) obtained from databases originating from the previous field samplings, several museums (e.g. Museums of Natural History in Vienna and Canada) and literature (e.g. Berg 1949; Saadati 1977). Finally, 1090 sites were identified for modelling (Fig. 1, Real data).

Environmental/predictor variables: After collecting the fish data, to develop models, a limited number of candidate environmental/predictor variables were selected. These are major descriptors of river habitat at the reach and regional scale and are assumed to be relatively unaffected by human pressures according to Pont et al. (2009). Accordingly, we considered eight environmental variables (elevation (ELE), stream slope (SLO), bank-full width (B_WID), maximum air temperature (Max_TEM), minimum air temperature (Min_TEM), mean air temperature (A_TEM), the range of air temperature (R_TEM) and annual precipitation (PRE)) according to Mostafavi et al. (2014). The ELE and B_WID were extracted from Google Earth (Google Inc. 2009, Version 5). SLO was calculated for a 1km stretch extending upstream of each site. Climate variables (i.e. Max_TEM, Min_TEM, A_TEM, R_TEM and PRE) were extracted from WorldClim data (Hijmans et al. 2005; Hijmans et al. 2007) to characterize annual climate trends based on records for 30 years of monthly means (1970 to 2000), and interpolated at 30 arc-seconds grid extent (~1km²). Moreover, climate variables were extracted in a circular buffer (5km) around each sampling site (Mostafavi et al. 2014). Afterwards, variable redundancy within eight environmental variables was tested by Spearman's rank correlation (r). If two variables were highly correlated (r>0.75) (Filipe et al. 2013; Mostafavi et al. 2014); one of them was excluded to avoid collinearity according to our expert judgement and literatures.

For future climate conditions, we used statistically downscaled climate projections to the same size (~1km²) based on the spatial interpolation of anomalies from 16 available general circulation
models (GCMs) of the fifth assessment report from the Intergovernmental Panel on Climate Change (IPCC 5AR), under RCP 2.6 and RCP 8.5 greenhouse-gas emissions scenarios. These data was downloaded from CCAFS website (Climate Change, Agriculture and Food Security; http://www.ccafs-climate.org). Because climate change impact assessments are associated with a degree of uncertainty (Lindner et al. 2014), we averaged all GCMs in each scenario according to Valavi et al. (2018). In order to model the potential impact of future climate change on the geographical distribution of brown trout, we used optimistic and pessimistic scenarios (RCP 2.6 and RCP 8.5) in 2050 and 2080.

Modelling framework (techniques, calibration, evaluation and ensemble forecasting): BIOMOD2 (BIOdiversity MODelling) package (Thuiller 2003) was used within the R software (R Development Core Team, 2011) for modelling in this study. As above mentioned, our fish data was based on a heterogeneous data set containing information from several sources, therefore the “presence-background modelling” approach was used according to Chefaoui & Lobo (2008) and Barbet-Massin et al. (2012). Then, the following nine modelling techniques were applied: Generalised Linear Models (GLM), Generalized Additive Model (GAM), Classification Tree Analysis (CTA), Artificial Neural Network (ANN), Surface Range Envelops (SRE), Generalized

Fig 1. Distribution of brown trout at different stages of modelling: Real data means where brown trout was really occurred/observed; current prediction means the potential geographical distribution of brown trout where was predicted by models according to the current environmental variables; future prediction means the potential geographical distribution of brown trout where is predicted by models according to the future climate change scenarios (RCP 2.6 in 2050 (2050-2.6), RCP 8.5 in 2050 (2050-8.5), RCP 2.6 in 2080 (2080-2.6) and RCP 8.5 in 2080 (2080-8.5). Colors: Real data: green means sites where the fish were observed, grey means sites where fish were not observed; in current prediction: probability of potential distribution of fish from zero (grey) to 1000 (red); Future prediction: black means sites where have no potential for fish distribution).
Boosting Method (GBM), Random forest (RF), Multivariate Adaptive Regression Splines (MARS), and Flexible Discriminant Analysis (FDA). We applied a cross-validation procedure by randomly splitting the data into calibration (80% of the data) and validating (20%) data sets with 10 repetition runs to assess model performance stability (Mostafavi et al. 2014). Model evaluation was based on the True Skill Statistic (TSS) which corresponds to the sum of sensitivity and specificity minus 1, and is independent of prevalence (Lobo et al. 2008; Thuiller et al. 2009a; Thuiller et al. 2009b). The range of TSS is from 0 to 1. A model with excellent prediction performance has a TSS higher than 0.8, a good model has a TSS between 0.6 and 0.8, and a model is considered as fair and poor if its TSS is below 0.6 (Swets 1988). All nine modelling techniques were combined in an ensemble forecasting framework as recommended by (Araújo & New 2007).

Finally, we projected the models under both the RCP 2.6 and 8.5 scenarios in 2050 and 2080 to generate four future habitat suitability maps for comparison with the contemporary model outputs.

Variable importance was calculated by a permutation procedure used in BIOMOD2, which is independent of the modelling technique (Thuiller et al. 2009a, b). We used the software ArcGIS Desktop 10.3 (ESRI© 1999–2008) to map the spatial pattern of the predicted distributions of the studied fish species at the scale of Iran.

Results

After correlation test, six environmental variables (B_WID, SLO, ELE, A_TEM, R_TEM, and PRE) out of eight, remained as independent variables for the modelling. Table 1 describe their characteristics. Based on the results, brown trout is highly impacted by climate change (Fig. 1, Table 2). Indeed, any suitable habitats were not predicted for brown trout by models under optimistic and pessimistic scenarios (RCP 2.6 and RCP 8.5) in 2050 and 2080. And according to our database, all potential habitats will be loss in future due to climate change effects even at optimistic scenario.

Figure 2 represents that the performance of modelling was excellent (i.e. ensemble>0.8). SRE had an inferior performance compared to the other models (i.e. <0.6 in TSS), whereas RF, GAM and GBM had the highest performance values (i.e. >0.97 in TSS).

Overall, the variables A_TEM and R_TEM had the highest importance values (≥40%), whereas others were less than 30%. Nonetheless, the relative importance of variables was different among

Table 1. Mean and range (minimum- maximum) of environmental variables. (Abbreviations: bank-full width (B_WID), wetted width (W_WID), stream slope (SLO), elevation (ELE), mean air temperature (A_TEM), range of air temperature (R_TEM), annual precipitation (PRE)).

<table>
<thead>
<tr>
<th>Number of sites</th>
<th>B_WID (m)</th>
<th>SLO (%)</th>
<th>ELE (m)</th>
<th>A_TEM (°C)</th>
<th>R_TEM (°C)</th>
<th>PRE (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>112.5</td>
<td>1.6</td>
<td>731</td>
<td>19.1</td>
<td>13.3</td>
<td>384.8</td>
</tr>
<tr>
<td>Range</td>
<td>1.0-3539.8</td>
<td>0.0-28.0</td>
<td>27-2708</td>
<td>5.5-29.5</td>
<td>6.9-18.5</td>
<td>53-1478</td>
</tr>
</tbody>
</table>

Table 2. Percentage of the gain, loss and change of brown trout under optimistic and pessimistic scenarios (RCP 2.6 and RCP 8.5) in 2050 and 2080.

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Gain %</th>
<th>Loss %</th>
<th>Change %</th>
</tr>
</thead>
<tbody>
<tr>
<td>RCP 2.6 in 2050</td>
<td>0</td>
<td>100</td>
<td>-100</td>
</tr>
<tr>
<td>RCP 8.5 in 2050</td>
<td>0</td>
<td>100</td>
<td>-100</td>
</tr>
<tr>
<td>RCP 2.6 in 2080</td>
<td>0</td>
<td>100</td>
<td>-100</td>
</tr>
<tr>
<td>RCP 8.5 in 2080</td>
<td>0</td>
<td>100</td>
<td>-100</td>
</tr>
</tbody>
</table>
Table 3. Relative importance of environmental variables at different models for brown trout (Abbreviations: bankfull width (B_WID), stream slope (SLO), mean air temperature (A_TEM), annual precipitation (PRE), elevation (ELE), range of air temperature (R_TEM)).

<table>
<thead>
<tr>
<th>Model</th>
<th>Ensemble</th>
<th>SRE</th>
<th>CTA</th>
<th>RF</th>
<th>MARS</th>
<th>FDA</th>
<th>GLM</th>
<th>GAM</th>
<th>GBM</th>
<th>ANN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Max-Width</td>
<td>0.07</td>
<td>0.16</td>
<td>0.00</td>
<td>0.01</td>
<td>0.00</td>
<td>0.03</td>
<td>0.02</td>
<td>0.13</td>
<td>0.01</td>
<td>0.29</td>
</tr>
<tr>
<td>Slope</td>
<td>0.21</td>
<td>0.41</td>
<td>0.33</td>
<td>0.14</td>
<td>0.06</td>
<td>0.13</td>
<td>0.17</td>
<td>0.38</td>
<td>0.27</td>
<td>0.03</td>
</tr>
<tr>
<td>Elevation</td>
<td>0.29</td>
<td>0.11</td>
<td>0.00</td>
<td>0.04</td>
<td>0.41</td>
<td>0.00</td>
<td>0.48</td>
<td>0.77</td>
<td>0.03</td>
<td>0.78</td>
</tr>
<tr>
<td>Trange</td>
<td>0.54</td>
<td>0.58</td>
<td>0.62</td>
<td>0.28</td>
<td>0.61</td>
<td>0.40</td>
<td>0.77</td>
<td>0.84</td>
<td>0.52</td>
<td>0.23</td>
</tr>
<tr>
<td>Ave-Tmax</td>
<td>0.40</td>
<td>0.48</td>
<td>0.65</td>
<td>0.23</td>
<td>0.07</td>
<td>0.33</td>
<td>0.32</td>
<td>0.51</td>
<td>0.46</td>
<td>0.57</td>
</tr>
<tr>
<td>Ave-Prec</td>
<td>0.18</td>
<td>0.11</td>
<td>0.00</td>
<td>0.03</td>
<td>0.35</td>
<td>0.28</td>
<td>0.00</td>
<td>0.26</td>
<td>0.00</td>
<td>0.63</td>
</tr>
</tbody>
</table>

![Fig.2](image.png) Evaluating models performance based on TSS index for brown trout.

**Discussion**

The SDMs and predictions built in this study for brown trout are particularly valuable for developing new research suggestions and planning effective conservation and management actions. Managers may initiate plans to protect current and future habitats where the species is likely to occur based in our forecasts (Moss et al. 2009; Filipe et al. 2013). Improving environments for adaptation by protecting critical habitats is better to releasing maladapted captive bred animals – a common practice in commercial exploited freshwater species (McGinnity et al. 2009). If brown trout populations cannot survive with the new environments fast enough, unique genetic variants may be lost.

Usually species can respond to climate change in several ways i.e. move to track climatic conditions, stay in place and adapt to the new climate, or they become extinct (Berteaux et al. 2004; Lovejoy & Hannah 2006). In our study, brown trout distribution will become dramatically reduced in the future in all tested scenarios and no new habitats will be gained which this finding is in line with Filipe et al. (2013). However, by 2080, 100% of the stream reaches sampled will be unsuitable habitats for brown trout in our study while in Filipe et al. (2013) was 64%. This difference might be due to following reasons: first, the number and type of environmental variable used in both studied were different in some cases, for example, in our study we did not use land cover data, Strahler order. Second, in contrast to Filipe et al. (2013), climate variables were extracted in a circular buffer (5km) around each sampling site as a catchment layer similar to CCM2 (Catchment...
Characterization and Modelling database) (Vogt et al. 2003; Vogt et al. 2007; De Jager & Vogt, 2010) is not available for Iran. Third, nine models (GLM, GAM, CTA, SRE, GBM, RF, MARS, and FDA) were used in our modelling while Filipe et al. (2013) they used only four models (GLM, GAM, RF and MARS).

In contrast to our study and Filipe et al. (2013), brown trout has been shown to occupy and acclimate to new accessible habitats (Launey et al. 2010; Valiente et al. 2010). Therefore, future research on the mechanisms of brown trout adaptation to environmental changes could permit more reliable extrapolations across time and space, namely regarding the importance of ecological drivers at various scales, thermal adaptations and energy efficiency (Finstad et al. 2011; Filipe et al. 2013), dispersal, interactions with other species at different life history stages (e.g. Wenger et al. 2011; Filipe et al. 2013) and the time course of the adaptations required (Portner et al. 2010). Such research is essential because biotic homogenization is expected to increase (Filipe et al. 2013), and newly opened niches are probably to become accessible (MacDonald 2005).

In conclusion, our forecasts are quite alarming to managers regarding the future of brown trout in Iran. This is particularly important as human activities over recent decades had huge impacts on brown trout occurrences in Iran which resulted to dramatic decline of native populations of brown trout (Mostafavi et al. 2014). The majority of adequate habitats were destroyed through different human pressure types i.e. land use, connectivity, hydro-morphology and water quality (Mostafavi et al. 2015). Therefore, our results have important implications for conservation activities and management as the models forecasted climate change will intensely influence the suitability of habitats.

Acknowledgements
This study was funded by Shahid Beheshti University, G.C. Special thanks are given to E. Fataei and Gh. Amiri Ghadi for their support during our fish sampling.

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مقاله بژوهشی

اثر تغییر اقلیم بر توزیع گونه قزل آلای خال قرمز، Salmo trutta Linnaeus, 1758 در ایران با استفاده از روش‌های مدل Ensemble (Teleostei: Salmonidae)

حسن مصطفوی*، جعفر کامبوزی
گروه تنویع زیستی و مدیریت اکوسیستم‌ها، پژوهشکده علوم محیطی، دانشگاه شهید بهشتی، تهران، ایران
گروه کشاورزی اکولوژیک، پژوهشکده علوم محیطی، دانشگاه شهید بهشتی، تهران، ایران

چکیده: در دهه‌های اخیر، تغییر اقلیم و سایر فشارهای انسانی بی‌طرف جدی تاثیر سریع تری بر کاهش نسبتی اکوسیستم‌های آبی‌شیرین نسبت خشکی داشته است. این روند احتمالاً در آینده نیز ادامه پایید. ما تاثیر تغییر اقلیم را بر توزیع ماهی قزل آلای خال قرمز در ایران تحت سال‌های خوش و بد بینانه ensemble نرم‌افزاری شبیه‌سازی (SDMs) را در سال‌های 2050 و 2080 با استفاده از نرم‌افزار مدلسازی توزیع گونه (RCP 2.6 و 8.5) و مدل K-spearman کردیم. نتایج نشان داد که توزیع گونه در تمامی سال‌های خوش بینانه و بد بینانه تغییر اقلیم در صورت منعی (100 درصد) بر اساس پایگاه داده‌های ما کاهش خواهد یافت. علاوه براین، هیچ سایت بالقوه جدیدی در این سال‌های پیش بینی نشده است. این نتایج به‌طور جدی به‌صورت مثبت نمایش داده که برای حفاظت از این گونه در آینده، برنامه‌های حفاظتی و مدیریتی لازم است.

کلمات کلیدی: ماهی قزل آلای خال قرمز، مدلسازی توزیع گونه، حفاظت، محدوده توزیع.