Ecosystem-based environmental flow assessment in a Greek regulated river with the use of 2D hydrodynamic habitat modelling

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Abstract - Despite the long-term research on the use of hydraulic-hydrodynamic habitat models (HHMs) for predicting the response of aquatic biota to habitat alteration, their practical application in model-based environmental flow assessments (EFAs) has been limited due to reasons mainly associated with cost-effectiveness, time-efficiency, required expertise and availability of hydro-ecological information. In this study, we demonstrate a cost-effective and time-efficient application of a benthic-invertebrate, two-dimensional, fuzzy rule-based EFA in a 277-m long reach in the downstream route of a regulated river in western Greece. Apart from developing ecosystem-based environmental flow (eflow) scenarios, we highlight the valuable features of HHMs, comment on their disadvantages and propose working solutions to overcome them. The results of the study show that the hydrology-based environmental flow of 0.2 m³/s, initially proposed by the managing authorities, is not sufficient to ensure the long-term functionality of the downstream benthic communities, as the ecosystem-based eflow ranged between 0.6 and 2 m³/s. As social resilience relies heavily on ecological resilience, ecosystem-based approaches can ensure the sustainability of aquatic ecosystems. This study demonstrates, inter alia, that HHMs-based EFAs can be implemented cost-effectively and time-efficiently to serve as an accurate scientific basis for water managers and stakeholders, in search of the fine balance between anthropogenic water demand and long-term ecosystem integrity and functionality.

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1. Introduction
The use of hydrodynamic habitat models (HHMs) to quantify and predict the response of freshwater biota to gradients of hydrological/hydraulic conditions has been excessively researched since the mid-1970s. HHMs
integrate computational fluid dynamics and ecological knowledge into a two-module modelling framework; a hydrodynamic module provides information on the change of physical habitat as a function of flow by predicting water depths (D) and depth-averaged flow velocities (V) at multiple discharges in a computational grid that simulates the area under investigation. A coupled habitat module compares the predicted values of V and D with information on the habitat preferences of aquatic biota to calculate habitat suitability at each simulated discharge (Acreman and Dunbar, 2004; Gopal, 2013).

During the 1990s, habitat availability and suitability were closely related with the concept of environmental flows, i.e. the quantity, timing, and quality of water flows required to sustain freshwater and estuarine ecosystems and the human livelihoods and well-being that depend on these ecosystems (Brisbane Declaration, 2007). And since HHMs predict habitat suitability over a range of discharges, they have been considered powerful tools - but also criticized accordingly - for implementing accurate, ecosystem-based environmental flow assessments (EFAs) in the downstream route of hydrologically altered river systems (Maddock, 1999; Tharme, 2003; Sedighkia et al., 2017).

Over the years and within much ‘constructive’ debate between researchers (Orth, 1987; Booker et al., 2004; Holm et al., 2001; Lancaster and Downes, 2010; Lamouroux et al., 2010) new methods have been incorporated in HHMs to improve the predictive accuracy of their hydrodynamic and habitat modules. Since the early one-dimensional concept of habitat suitability curves (HSCs) (Bovee, 1986) implemented in the PHABSIM software (Milhous et al., 1989; Waddle, 2001), the hydrodynamic module of HHMs advanced from 1D cross-sectional interpolations to 2D/3D unsteady- and steady-flow simulations of enhanced accuracy (e.g. open TELEMAC-MASCARET - Galland et al., 1991; CASiMiR 2D - Schneider et al., 2001; River2D - Steffler and Blackburn, 2002). The habitat module simultaneously advanced from the initial HSCs concept; habitat suitability is currently modelled based on multivariate statistical methods, machine-learning, fuzzy-logic or fuzzy rule-based Bayesian algorithms (Van Broekhoven et al., 2006; Dakou et al., 2007; Vezza et al., 2015; Theodoropoulos et al., 2018).

In the European Union, the potential of HHMs to be used for implementing accurate, ecosystem-based EFAs has been officially acknowledged in the Guidance Document No. 31 (WFD CIS, 2015) of the Water Framework Directive 2000/60/EC (WFD - European Union Council, 2000). A three-class hierarchy of EFA methodologies has been suggested, with HHMs being considered as ‘level 3’, potentially applicable in situations where a high degree of certainty is required to provide water managers with defensible environmental flow recommendations. But despite the excessive long-term research, the improved predictive accuracy and the wide recognition of their effectiveness in providing accurate EFAs, the practical application of HHMs in EFAs in Europe remains disproportionately limited compared to their hydrology-based alternatives (Dunbar et al., 2012; Linnansaari et al., 2013; Rivaes et al., 2017) and is primarily focused on fish (Waddle and Holmquist, 2011; Artthington, 2012; Leitner et al., 2017). The low percentage (18%) of European HHMs-based case studies in the relevant WFD Guidance Document is also indicative of this gap between theoretical research/knowledge and practical application of HHMs. Particularly in Greece, HHMs have only recently been incorporated into EFAs and are currently focused solely on fish (Muñoz-Mas et al., 2016; Papadaki et al., 2017), while the legal framework on environmental flows is still based on simplistic and rather arbitrary hydrological criteria (Ministry of Environment, Energy and Climate Change, 2011).

The reasons for this limited application of HHMs in EFAs are mainly associated with cost-effectiveness, time-efficiency, required expertise and availability of hydroecological data (Jorgensen and Bendoricchio, 2001; Conallin et al. 2010). HHMs-based EFAs inevitably require a costly and time-consuming collection of hydraulic and hydrometric data to calibrate and validate the hydrodynamic module (Spense and Hickley, 2000) and usually, additional, carefully designed field visits are necessary to calculate the habitat preferences of aquatic
biota (Heggenes et al., 1990). Moreover, the developed hydrodynamic habitat model is usually restricted to an area of 200 or 300 meters, whereas the effects of hydrological alteration may be geographically widespread (Boeker, 2016). In addition, most HHMs focus on the habitat preferences of specific (fish) species, while it has long been acknowledged that accurate EFAs, within a holistic framework, must be based on the ecological requirements of different biological communities (Acreman et al., 2009).

The purpose of this article is to present an application of a 2D hydrodynamic habitat model for the development of ecosystem-based environmental flow recommendations in the downstream route of a regulated river in Western Greece. Using benthic macroinvertebrates as the target aquatic community and a fuzzy rule-based Bayesian algorithm to accurately assess their habitat preferences, we demonstrate a cost-effective and time-efficient 2D hydrodynamic habitat modelling application. For this reason, we additionally include an analysis of the costs and time required to implement our case study. Our main intention is (i) to highlight the under-valued features of HHMs that make them ideal candidates for ecosystem-based EFAs, (ii) to discuss on their disadvantages and propose working solutions on how to properly overcome them and (iii) to point out that HHMs-based environmental flow assessments can be cost-effective and time-efficient and should be preferred over other options by water managers when searching for the fine balance between anthropogenic water demand and long-term ecosystem functionality and integrity.

2. Materials and methods

2.1. Study area and site selection

Our study site is located in western Greece, at the downstream route of the river Parapeiros (Fig. 1). Parapeiros is a large tributary of the Peiros River, with which they share a common basin, covering an area of 578 km². Parapeiros originates in the mountainous upper parts of the basin and after a distance of 25 km it converges with Peiros and empties in the Patraikos Gulf. The basin has a temperate Mediterranean climate with temperatures ranging from 0°C to 35°C. The flow regime is highly seasonal; increased runoff occurs between October and April, while July, August and September are the driest months of the year. Average maximum precipitation over a 30-year period (1961 - 1990) has been recorded in December (121.8 mm) and minimum in August (4.8 mm).

The river basin is currently ungauged. Existing rainfall-runoff models (Digga, 2012) calculate daily discharges, based on average annual values, ranging from 1.22 m³/s to 1.73 m³/s, while daily discharge values from a gauged site in a neighboring basin of similar hydrological and climatological characteristics (Glafkos River - Mechleri, 2008) range from 0.3 m³/s (from June to October) to above 3 m³/s (from November to May), reaching higher than 6 m³/s during floods and varying between the years. Two dams have been constructed and will soon be operative in order to supply the city of Patras with drinking water. The largest one is the earthen dam located at the mid-course of the Parapeiros River, with a height of 68 m and a storage capacity of 38.8 x 10⁶ m³. According to the relevant environmental impact assessment, an environmental flow (baseflow) of 0.2 m³/s, calculated based on a combination of limited hydrological records and hydrological modelling, will be released during summer to maintain the integrity of the downstream aquatic ecosystem (Digga, 2012).

2.2. Hydrodynamic modelling

2.2.1. Topographic data

The 2D hydrodynamic simulation was carried out in a 277-m long reach, situated 8 km downstream of the major dam location. Channel topography was mapped with 863 points recording longitude (X), latitude (Y) and bottom elevation (H). We used a Real-Time Kinematic (RTK) GPS consisting of the ‘Spectra Precision SP60 GNSS Receiver’ (http://www.spectraprecision.com/eng/sp60.html) and the ‘MobileMapper 10 GIS - GPS Receiver’
We mapped slope breaks and similar areas with rapid relief changes with higher density of points, allocating fewer points in flat surfaces. The topographic data (X,Y,H points) were afterwards imported into the BlueKenue software to linearly interpolate channel topography and generate a triangular computational mesh representative of the study reach.

2.2.2. Hydrometric data

Hydrometric data were collected at two different discharges (Q) (0.3 m³/s and 1 m³/s). Depth (D) was measured using a water-depth measurement rod. Depth-averaged flow velocity (V) was measured using the Swoffer 2100 current velocity meter at 0.6 x D when D ≤ 0.75 m and by averaging 0.2 x D and 0.8 x D when D > 0.75 m according to Nolan and Shields (2000). Longitude, latitude (using the RTK-GPS) and field measurements of V and D were recorded at 15 randomly selected points at each discharge and used to calibrate-validate the hydrodynamic model. The type of substrate (S) was visually estimated according to the categories defined by Schneider et al. (2010) and used as a basis to adjust the Manning’s roughness coefficient (n) for model calibration based on the values suggested by Chow (1959). At each survey, according to the model's requirements, Q was measured at the upstream boundary and water surface elevation (Z) was measured at the downstream boundary. To reduce the required number of field visits, a rating curve was developed for the downstream boundary following the suggestions of the US National...
Resources Conservation Service (2012): V was measured at selected points through the cross section; from these V values and their associated cross-sectional areas, Q was computed for various Z values on the rising and falling side of an elevated flow and the stage-discharge curve was developed.

2.2.3. Hydrodynamic simulation

The FUDAA-PREPRO pre-processor (http://prepro.fudaa.fr) was used to define boundary and initial conditions prior to running the 2D hydrodynamic simulation. Q was prescribed at the upstream boundary and Z was prescribed at the downstream boundary based on the developed stage-discharge curve. TELEMAC-2D v6.2 (Galland et al., 1991) was used to simulate D and depth-averaged V in various discharge scenarios.

The model was calibrated using the data (V and D) from the first hydrometric survey (Q = 0.3 m$^3$/s) and validated using the hydrometric data from the second survey (Q = 1 m$^3$/s). Calibration was applied by properly adjusting the Manning’s n values at different sections of the study reach (based on the initial visual assessment of the substrate types) until an acceptable combination of $R^2$ between the predicted and observed V and D values was achieved. The validated model was used to simulate 11 discharge scenarios ranging from 0.01 m$^3$/s to 7 m$^3$/s.

2.3. Habitat suitability modelling

Benthic invertebrates were used as the target aquatic community. Their habitat preferences were assessed using the ‘benthos-GR’ dataset (https://github.com/chtheodoro/benthos-GR), consisting of 380 microhabitat observations collected from nine sampling sites in Greece (Theodoropoulos et al., 2018). Each microhabitat is a combination of V, D and S corresponding to a habitat suitability value ($\kappa$), calculated using BM-community metrics commonly applied to assess the quality-suitability in relevant studies (Englund and Malmqvist 1996; Monk et al. 2006; Waddle and Holmquist 2011; Holmquist et al. 2015). Each metric was weighted based on a combination of expert judgment and previous literature to reflect its relevant contribution-significance to the calculation of $\kappa$ and the following equation was used:

$$\kappa = 0.4 \frac{n_{ij}}{n_{jmax}} + 0.3 \frac{H_{ij}}{H_{jmax}} + 0.2 \frac{EPT_{ij}}{EPT_{jmax}} + 0.1 \frac{a_{ij}}{a_{jmax}}$$

where,

$\kappa$ is the calculated habitat suitability of the $i^{th}$ microhabitat of the $j^{th}$ site, ranging from 0 to 1

$n_{ij}$ denotes the number of BM taxa (families) found at the $i^{th}$ microhabitat of the $j^{th}$ site

$H_{ij}$ denotes the Shannon’s diversity index for the $i^{th}$ microhabitat of the $j^{th}$ site

$EPT_{ij}$ is the number of EPT taxa found at the $i^{th}$ microhabitat of the $j^{th}$ site

$a_{ij}$ is the abundance of benthic macroinvertebrates found at the $i^{th}$ microhabitat of the $j^{th}$ site

$n_{jmax}, H_{jmax}, EPT_{jmax}$ and $a_{jmax}$ denote the maximum value of the relevant variables observed at the $j^{th}$ site

The benthos-GR dataset was used to train and cross-validate a fuzzy rule-based Bayesian algorithm (FRB) based on Brookes et al. (2010), described in detail in Theodoropoulos et al. (2018) and implemented in the HABFUZZ software (Theodoropoulos et al., 2016). In the FRB, the numerical values of the input variables (V, D and S) are converted to overlapping, trapezoidal-shaped, membership functions called fuzzy sets (van Broekhoven et al. 2006). By this process, called fuzzification, each numerical value is assigned to one or more fuzzy sets with a membership degree ranging from zero to one; $\kappa$ values are also classified in five classes (0 ≤ bad ≤ 0.2; 0 < poor ≤ 0.4; 0.4 < moderate ≤ 0.6; 0.6 < good ≤ 0.8; 0.8 < high ≤ 1). The training dataset (benthos-
GR), with a priori calculated κ values, is used to develop sets of data-driven IF-THEN rules, relating the input fuzzy sets with a specific κ class. The fuzzy membership degree (MD) of each input variable (V, D and S) is considered as the probability of occurrence of the particular fuzzy set, such as ‘IF V is low with a membership degree of 1 AND D is moderate with a MD of 1 AND S is gravel with a MD of 1 THEN κ is high with a MD of 0.3 and good with a MD of 0.7’. The IF-THEN rules are then combined using the Bayesian joint probability, so that (referring to the previous example) the probability of the specific microhabitat’s κ being high is the joint probability that V is low AND D is moderate AND S is gravel AND κ is high (1 x 1 x 1 x 0.3 = 0.3), while the probability of κ being good is the joint probability that V is low AND D is moderate AND S is gravel AND κ is good (1 x 1 x 1 x 0.7 = 0.7). Based on a utility function (Brookes et al., 2010), a score is assigned to each κ class (bad: 0.2, good: 0.4, moderate: 0.6, good: 0.7, high: 0.9) and the habitat suitability for each microhabitat is predicted using the following equation:

\[ K = \sum M_{ij} S_{ij} \]

where,

- \( K \) is the predicted habitat suitability
- \( M_{ij} \) denotes the joint probability of occurrence of each κ class
- \( S_{ij} \) denotes the score of each κ class

For the previous example, \( K \) equals to 0.7 x 0.9 + 0.3 x 0.7 = 0.84 (high).

Since our study site, typologically belongs to the RM-2 (100-1000 km²; altitude <600 m.a.s.l.; mixed geology) European intercalibration type (van de Bund, 2009), we trained the model using two datasets, (i) the whole benthos-GR dataset (380 microhabitats) that includes microhabitats from the RM-1, RM-2 and RM-4 river types (T-BGR) and (ii) the microhabitats of the benthos-GR dataset corresponding to samples collected from two reference sites in the same river, upstream of the study site (T-PAR). The output of the hydrodynamic model (D and depth-averaged V values) at each simulated discharge was used as input to the FRB habitat model, which calculated \( K \) at each node of the computational mesh of the hydrodynamic model (resulting in 5170 \( K \) values x 11 discharge scenarios x 2 training alternatives). The habitat suitability of the study reach at each Q was visualized using the BlueKenue software.

2.4. Environmental flow calculation and selection

The selection of the best Q scenario for each training option (environmental flow) was based on the optimal combination of the below-mentioned calculated parameters/indicators:

i. Overall Suitability Index (OSI):

\[ OSI = \sum_{i=1}^{w} K_i \]

ii. Normalized OSI (nOSI):

\[ nOSI = \frac{OSI}{w} \]

where,

- \( K_i \) (from 0 to 1) denotes the habitat suitability
- \( w \) denotes the total No. of wetted nodes in the computational mesh at each Q scenario

iii. Certainty of prediction (COP): The ratio of the No. of microhabitat combinations actually found in the training dataset to the total No. of nodes in the computational mesh; Habfuzz applies a trick when a
microhabitat combination is not found in the training dataset and instead of returning some arbitrary K value for a particular node (e.g. -1), it uses the K value of its neighboring node in the domain.

iv. Percentage of wetted nodes in the computational mesh at each Q scenario (w).

v. Habitat connectivity (C): The ratio of connected (neighboring) nodes with K>0.6 to the total number of wetted nodes with K>0.6.

vi. Habitat availability (A): The ratio of connected (neighboring) nodes with K>0.6 to the total number of nodes in the study reach (wetted and dry).

The optimal combination of the indicators was numerically expressed for each simulated Q using the Optimal Flow Scenario index (OFSi) (with ‘i’ denoting the different Q scenarios) as follows:

\[ OFS_i = nOSI_i \times w_i \times C_i \times A_i \times COP_i \]

All OFSi values were normalized in a 0-1 scale by dividing each OFSi with the maximum OFS observed. A useful illustration of the process followed in our case study is shown in Fig. 2.

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**Fig. 2.** The steps followed to implement the hydrodynamic habitat modelling case study (modified from Theodoropoulos et al., 2015). Step 1 has been already implemented and discussed in Theodoropoulos et al. (2018).
3. Results

The computational mesh generated for the study reach is composed of 9,875 elements and 5,170 nodes with a 1 m spatial resolution. The Manning’s roughness coefficient in the calibrated model ranged from 0.03 to 0.05. The coefficient of determination ($R^2$) between the predicted and observed $D$ and depth-averaged $V$ values was greater than 0.8 and ranged from 0.9317 ($D$) to 0.9338 ($V$) ($p<0.01$) for the calibration dataset and from 0.8879 ($D$) to 0.9328 ($V$) ($p<0.01$) for the validation dataset (Fig. 3), suggesting strong, statistically significant correlations and an acceptable model performance. Depths in the wetted nodes of the study reach ranged from 0.1 m to 0.92 m for the lowest discharge (0.01 m$^3$/s) and from 0.3 m to 3.17 m for the highest discharge simulated (7 m$^3$/s). Depth-averaged $V$ values, respectively ranged from 0.05 m/s to 0.5 m/s ($Q = 0.01$ m$^3$/s) and from 0.05 m/s to 3.2 m/s ($Q = 7$ m$^3$/s).

![Calibration dataset (0.3 m$^3$/s) vs Validation dataset (1 m$^3$/s)](image)

**Fig. 3.** Correlation between observed and simulated data in 15 randomly selected points during calibration ($Q = 0.3$ m$^3$/s) and validation ($Q = 1$ m$^3$/s). $V$: flow velocity, $D$: water depth

The predicted habitat suitability at each of the 5,170 nodes of the study reach for the various simulated $Q$ scenarios and for each training option (T-BGR) and (T-PAR) is depicted in Fig. 4. In addition, table 1 shows the suitability indicators calculated for each scenario at each training option. According to the results, the selection of the optimal flow scenario should focus on the $Q$ range between 0.6 m$^3$/s and 2 m$^3$/s, since the highest values of the indicators used for the quantification of habitat suitability for both training options were observed in this range. The highest OSI was calculated in $Q = 2$ m$^3$/s (T-BGR) and $Q = 5$ m$^3$/s (T-PAR); the maximum nOSI was observed in $Q = 0.6$ m$^3$/s and $Q = 0.8$ m$^3$/s for the T-BGR and the T-PAR training option, respectively; the highest number of wetted nodes was found at $Q = 7$ m$^3$/s; maximum connectivity was calculated for $Q = 2$ m$^3$/s (T-BGR) and $Q = 3$ m$^3$/s (T-PAR); maximum availability was observed in $Q = 0.8$ m$^3$/s (T-BGR) and $Q = 0.6$ m$^3$/s (T-PAR). The certainty of prediction was also maximum for $Q = 0.6$ m$^3$/s and $Q = 0.8$ m$^3$/s in T-BGR and for $Q = 2$ m$^3$/s and $Q = 5$ m$^3$/s. The visual representation of $K$ in Fig. 4 also indicates that, in $Q$ scenarios lower
than 0.6 m$^3$/s and higher than 2 m$^3$/s, the number of unsuitable habitats ($K < 0.6$) becomes disproportionately increased and habitat availability reaches unacceptable levels, especially for the T-BGR training option.

According to the OFS values (Fig. 5), the optimal flow scenario for freshwater macroinvertebrates corresponds to $Q = 2$ m$^3$/s, followed by $Q = 0.8$ m$^3$/s (see the discussion for the environmental flow selection). The OFS decrease observed in $Q = 1$ m$^3$/s can be explained through an integrated interpretation of table 1, Fig. 4 and Fig. 5. As the quantity of the water in the study reach increases (from $Q = 0.01$ m$^3$/s to 0.8 m$^3$/s) the habitat indicators increase due to the increase in $V$ and $D$ values until a peak of most indicators is observed from $Q = 0.6$ m$^3$/s to $Q = 0.8$ m$^3$/s. At $Q = 1$ m$^3$/s, the further increase in $D$ and $V$ becomes temporarily suboptimal for benthic invertebrates; the most downstream part of the river becomes deeper while the midparts are still too shallow to support high number of optimal habitats. As the discharge increases to 2 m$^3$/s, new wetted cells are introduced into the reach (mainly in the upper part), with suitable combinations of $D$ and $V$ and the habitat quality indicators increase again (still the most downstream part is continuously deepening and remains unsuitable). In discharges higher than 2 m$^3$/s the $D$ and $V$ values continuously increase to unsuitable levels.

### Table 1. The indicators calculated at each simulated discharge and for each training dataset (T-BGR and T-PAR) to facilitate the selection of the optimal flow scenario. The highest values for each indicator have been shaded grey.

**T-BGR**

<table>
<thead>
<tr>
<th>$Q$ (m$^3$/s)</th>
<th>OSI</th>
<th>nOSI</th>
<th>$w$ (%)</th>
<th>$C$ (%)</th>
<th>$A$ (%)</th>
<th>COP (%)</th>
</tr>
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<td>0.572</td>
<td>46.83</td>
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<td>89</td>
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<td>88</td>
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<td>90</td>
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<td>0.529</td>
<td>99.21</td>
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**T-PAR**

<table>
<thead>
<tr>
<th>$Q$ (m$^3$/s)</th>
<th>OSI</th>
<th>nOSI</th>
<th>$w$ (%)</th>
<th>$C$ (%)</th>
<th>$A$ (%)</th>
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<td>79</td>
</tr>
</tbody>
</table>

$Q$: discharge, OSI: overall suitability index, nOSI: normalized OSI, $w$: wetted cells, $C$: habitat connectivity, $A$: habitat availability, COP: certainty of prediction
Fig. 4. Habitat suitability values for the various simulated discharge scenarios. Values higher than 0.6 are considered acceptable based on the requirements of the Water Framework Directive 2000/60/EC. (a) Model trained using the whole benthos-GR dataset; (b) Model trained using the T-PAR data.
4. Discussion

4.1. Environmental flow selection

The results of the study indicate that the hydrology-based environmental flow (eflow) of \( Q = 0.2 \text{ m}^3/\text{s} \), proposed in the relevant environmental impact assessment (EIA) for the Parapeiros River dam, is not sufficient to provide optimal habitat conditions for supporting a functional benthic community. According to the ecosystem-based approach applied in our study, the EIA-proposed eflow ranked between seventh and ninth, based on the OFS values of the two training options (0.521 and 0.348 for the T-BGR and T-PAR, respectively). Habitat suitability was highest at \( Q = 2 \text{ m}^3/\text{s} \) for both training alternatives, while acceptable values (OFS \( \geq 0.6 \)) included \( Q = 0.8 \text{ m}^3/\text{s} \), \( Q = 0.6 \text{ m}^3/\text{s} \), \( Q = 1 \text{ m}^3/\text{s} \) and \( Q = 3 \text{ m}^3/\text{s} \) in the T-BGR dataset, extending up to \( Q = 5 \text{ m}^3/\text{s} \) in the T-PAR dataset. While optimal BM-habitat can be obviously ensured by providing a 1-m\(^3\)/s or 2-m\(^3\)/s eflow, water managers and stakeholders may decide to apply another eflow scenario, in search of the fine balance between human and ecosystem water demand. According to the 5-class quality system adopted in the Water Framework Directive 2000/60/EC, for both training options, the eflow scenario of \( Q = 0.6 \text{ m}^3/\text{s} \) can be considered acceptable (\( K > 0.6 \)) to allow for the continuation of the specified use (drinking water supply and water for irrigation), without compromising the long-term functionality of the aquatic ecosystem (WFD CIS, 2003). Since the environmental flow is a negotiated value (Dyson et al., 2003), HHMs provide the most valuable feature in the process, in comparison to their hydrology-based alternatives; the ability to accurately map habitat suitability in various discharge scenarios and offer a simplified visualization of the information required by water managers and stakeholders to reach a consensus.

4.2. Cost-effectiveness and time-efficiency of HHMs-based EFAs

As mentioned previously, the application of HHMs-based EFAs is disproportionately limited compared to their hydrology-based alternatives, due to reasons mainly associated with time-efficiency, cost-effectiveness, required expertise and availability of hydroecological information (Jorgensen and Bendoricchio, 2001; Conallin et al. 2010).

Fig. 5. Optimal Flow Scenario (OFS) index values for each discharge (Q) and for each training dataset (T-PAR and T-BGR). Acceptable Q values based on the WFD requirements are indicated.
The expertise required to implement the specific case study may be considered minimal (OWRB, 2011), as all steps of this study including the collection and identification of BM samples, the assessment of their microhabitat preferences and the 2D hydrodynamic habitat simulation were successfully implemented by a small team of aquatic ecologists and hydraulic-hydrodynamic engineers. All fieldwork and data treatment was implemented by two individuals; computer simulations and results interpretation were supervised by three experts in ecology and hydrodynamics. Hydrology-based EFAs require teams of almost-equal size and a similar level of expertise to be adequately implemented and interpreted (Efstratiadis et al., 2014; Zhang et al., 2014).

Hydrodynamic habitat models are considered costly to implement (Lamouroux and Jowett, 2005; Booker, 2016), since they require multiple field visits at the river reach under investigation prior to applying the hydrodynamic habitat simulation. The most cost-intensive step in such implementations is the collection of the hydroecological reference dataset. Indeed, we (two-person team) spent more than 20 days (three seasonal one-week visits) to collect BM data (microhabitat samples) from 9 sites in Greece (Table 2) (Theodoropoulos et al., 2018). However, once the hydroecological dataset has been collected and the reference conditions are established, the hydrodynamic simulation can be carried out by two on-site visits; one visit to collect topographical information and hydrometric data to calibrate the hydrodynamic module and one additional visit to collect a second set of hydrometric data for the validation of the hydrodynamic module.

Regarding time and based on our application (Table 2), we argue that once an adequate hydroecological reference dataset is collected, the actual HHM-implementation requires less than two months to obtain an adequate topographical representation of the river channel, apply the hydrodynamic simulation and reach robust conclusions. This period of time may be considered rather short, taking into account the valuable final visual representation of an HHM-application, which offers a scientific base for trade-offs between scientists, water managers and stakeholders during the decision-making process. Again, the most time-consuming step is the determination of the hydroecological reference conditions. It took us (two persons) 178 days in total to collect, analyze and prepare accurate BM data to train the HHM’s habitat module (Theodoropoulos et al., 2018). However, multiple environmental flow applications can be implemented using the same reference hydroecological dataset in reaches with similar environmental and hydraulic properties. This reduced the time required for our application to 45 days and could be further minimized elsewhere by utilizing advanced surveying and mapping technologies, such as remote sensing, total stations, or LiDAR (light detection and ranging). As Pasternack and Senter rightfully indicated (2011) these ‘tools’ can currently provide a detailed characterization of physical habitat at the 0-0.1 m spatial scale for long river reaches in a very short period of time.

4.3. Transferability of reference conditions
Based on the aforementioned, the acquisition of a detailed, robust hydroecological dataset is a key step to the application of HHMs-based EFAs. Either as habitat suitability curves or fuzzy rules, habitat preferences of aquatic biota (mainly fish or benthic invertebrates) have been developed worldwide. However, the generalization of these habitat preferences and their transferability to river reaches other than those for which they were developed, has been questioned (Heggenes, 1990; Holm et al., 2001; Lancaster and Downes, 2010) and recently, generalized approaches attempted to overcome this limitation (Lamouroux and Jowett, 2005; Booker, 2016). Based on our application, a useful approach to overcome this ‘obstacle’ would require:

i. Collection of reference samples (microhabitat observations) from river reaches of the same typology, i.e. similar environmental and hydraulic properties (temperature, flow variability, substrate types). In Greece for example, most rivers belong to the RM-2 (100-1000 km² - altitude < 600 m - mixed geology)
and RM-4 (10 - 1000 km² - altitude between 400 -1500 m - mixed geology) intercalibration types. A reference hydroecological dataset collected from these river types would have a wide application in instream flow studies in Greece.

ii. Calculation of habitat suitability ($\kappa$) based on BM metrics and not using specific BM taxa (Theodoropoulos et al., 2018); as not all BM taxa are found in all river reaches, calculating $\kappa$ using BM metrics can be a valuable option.

iii. Normalization of habitat suitability per season and per site (by dividing the calculated $\kappa$ of each microhabitat with the maximum $\kappa$ found at each site at each season); this is a key step to eliminate (at least partially) any seasonal and geographical variation; as our results suggested, despite the small variation between the two training datasets, the same environmental flow ($Q = 0.6 \text{ m}^3/\text{s}$) would be probably selected regardless of the training option applied.

Table 2. Time taken to carry out the Parapeiros River hydrodynamic habitat simulation. All fieldwork and data treatment was applied by two persons. Computer simulations and results interpretation were supervised by three experts in ecology and hydrodynamics.

<table>
<thead>
<tr>
<th>HHM step</th>
<th>Days required</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Habitat module</strong></td>
<td></td>
</tr>
<tr>
<td>Collection of microhabitat BM samples (380)</td>
<td>21</td>
</tr>
<tr>
<td>Identification of BM samples (380 - family level)</td>
<td>125</td>
</tr>
<tr>
<td>Data treatment (calculation of $K$)</td>
<td>2</td>
</tr>
<tr>
<td><strong>Total (Habitat)</strong></td>
<td><strong>178</strong></td>
</tr>
<tr>
<td><strong>Hydrodynamic module</strong></td>
<td></td>
</tr>
<tr>
<td>Channel topography mapping (863 points - 277-m long reach)</td>
<td>1</td>
</tr>
<tr>
<td>Prepare data for hydrodynamic simulation</td>
<td>1</td>
</tr>
<tr>
<td>Hydrodynamic model calibration</td>
<td>7</td>
</tr>
<tr>
<td>Hydrodynamic model validation</td>
<td>30</td>
</tr>
<tr>
<td><strong>Total (Hydrodynamic)</strong></td>
<td><strong>39</strong></td>
</tr>
<tr>
<td><strong>Hydrodynamic habitat model</strong></td>
<td></td>
</tr>
<tr>
<td>Hydrodynamic simulation</td>
<td>3</td>
</tr>
<tr>
<td>Habitat simulation</td>
<td>2</td>
</tr>
<tr>
<td>Data treatment (visualization and presentation of results)</td>
<td>1</td>
</tr>
<tr>
<td><strong>Total (HHM)</strong></td>
<td><strong>6</strong></td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>223</strong></td>
</tr>
</tbody>
</table>

5. Conclusion
Ecosystem-based approaches are required to ensure ecosystem integrity and functionality in the long term. Based on the results, the hydrology-based environmental flow of $0.2 \text{ m}^3/\text{s}$ is not considered suitable to maintain functional benthic communities downstream of the dam; the habitat suitability in $Q = 0.2 \text{ m}^3/\text{s}$ was lower than the ecologically-acceptable limit ($\text{OFS} \leq 0.6$) and all BM-community metrics were suboptimal (Table 2). Cost-effective and time-efficient HHMs-based EFAs can be implemented using advanced surveying-mapping methods and by following specific methodological steps during the process. The establishment of a robust reference hydroecological dataset is of paramount importance, but once such a dataset has been developed, there are options available to properly treat the dataset and enable its use (as a habitat-module training dataset) in multiple model-based EFAs.
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