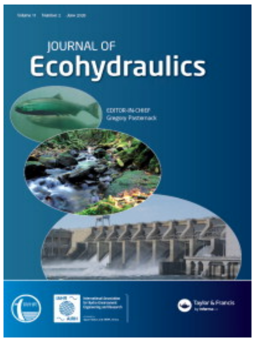

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How parameter weighting influences hydraulic unit mapping and fluvial mesohabitat assessment in Rivers

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ABSTRACT

Mesoscale habitat approaches are increasingly popular and all rely on a definition and delineation of geomorphic (GU) and hydraulic (HU) units. Traditionally, experts perform GU–HU delineation in the field, but unsupervised algorithms are increasingly being developed. Such algorithms typically assume that the parameters selected for HU delineation (mostly water depth and flow velocity) are of equal importance. This study challenges that assumption by investigating the consequences of weighting parameters in the automatic delineation of HU. Using simulated hydraulic variables, we applied algorithmic HU delineation under various conditions and tested different parameter weightings. The resulting HU were compared to GU delineated using a field-based field approach. Additionally, a synthetic habitat suitability criterium was used to evaluate how parameter weights influence final habitat assessments. We found that weighting parameters influences the algorithmic HU delineation and the amount of predicted habitat; assuming equal importance for all parameters can lead to inaccurate conclusions in habitat assessments. We show that field- and algorithmic-based approaches used for mesohabitat delineation are not interchangeable, but rather are complimentary. This work contributes towards the integration of field- and algorithmic-based approaches.

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Unsupervised clustering; mesohabitat delineation; parameter weighting; fluvial habitat assessment; hydraulic units; river patch classification; hydrodynamic modelling; geomorphic units

1. Introduction

In recent decades mesohabitat methods have gained popularity in the investigation of fluvial environments, especially for fish and macroinvertebrate habitat (Yi et al. 2017; Negro et al. 2021; van Rooijen et al. 2021; Farò et al. 2022; Pinna et al. 2024). These approaches assume that the habitat choice of an individual fish or macroinvertebrate depends on its surroundings and not just the point where it is observed. The results of these methodologies yield important ecological data on a scale that is relevant for river managers and scientists alike (Newson and Newson 2000; Gosselin et al. 2010; Belletti et al. 2017).

An important step in mesoscale habitat approaches is the delineation of the geomorphic and hydraulic units (GU and HU) (Belletti et al. 2017). These units form the basis on which the mesohabitat approach is built. A geomorphic unit (e.g. pool, riffle or rapid) is defined as an area containing a landform created by erosional and/or depositional processes (Belletti et al. 2017). A geomorphic unit may contain one to several hydraulic units. A hydraulic unit is a spatially distinct patch of relatively (in relation to its surroundings) homogeneous surface flow and substrate character (Belletti et al. 2017). Note that this is independent of any erosional or depositional processes. Both geomorphic and hydraulic units are generally associated with the mesohabitat scale and are suitable for mesohabitat suitability evaluation, while smaller spatial units (like river elements, e.g. small patches of rock, plant or homogeneous substrate) comprise the microhabitat scale (Belletti et al. 2017). Meso and microhabitats can be analyzed on different scales, each with their own patch types, which are hierarchically nested (Frissell et al. 1986; Gurnell et al. 2016; Belletti et al. 2017).

Multiple methodologies exist which aim to analyze habitat at the mesoscale. They can broadly be categorized into two groups: field-based approaches and algorithm-based approaches. Field-based approaches (e.g. Parasiewicz 2001, 2007; Eisner et al. 2005;

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Schneider et al. 2005) rely on experts delineating GU or HU, using data collected in the field and visual observation of the unit's spatial extent. Parameters that are usually considered for unit delineation are water depth, flow velocity, substrate size, spatial distribution of substrate, local water surface level gradient and local bed slope, but ultimately depend on the applied methodology. After the GU or HU are delineated, habitat suitability criterium (HSC) are used to evaluate the physical habitat suitability for a specific ecological target (commonly macroinvertebrate or fish preferences).

Algorithm-based approaches delineate HU using an algorithm, based on data obtained from a numerical hydrodynamic model or remote sensing. These algorithms can be supervised or unsupervised and fall in the category of machine learning; often clustering algorithms are applied (van Rooijen et al. 2021). In supervised algorithms an expert identifies the thresholds of certain parameters where one patch changes into another, an algorithm then applies these thresholds to identify HU (often with an additional smoothing or filtering step, see e.g. Hauer et al. 2009; Wyrick et al. 2014; Wegscheider et al. 2024). Unsupervised algorithms require less input from an expert, and may be less biased by subjective parameter or threshold definitions. They automatically identify HU based on the spatial distribution of water depth and flow velocity values in a reach (and possibly other parameters), often obtained using a numerical hydrodynamic model (e.g. Tamminga and Eaton 2018; van Rooijen et al. 2021; Farò et al. 2022), but may also use data obtained using aerial images (e.g. O'Sullivan et al. 2021). Other parameters (such as substrate characteristics) are only rarely considered in scientific literature, but see Inoue and Nakano (1999) as a rare example.

The standard procedure for using unsupervised clustering algorithms is to normalize the input data to avoid that the identification of clusters is based on one parameter more than another (Jain 2010). Ever since these algorithms have been used to identify HU, this has also been the standard procedure for these algorithms (e.g. Tamminga and Eaton 2018; O'Sullivan et al. 2021; Farò et al. 2022; van Rooijen et al. 2024, 2021). This is also needed to ensure that the results are not dependent on the units in which the parameters are expressed. However, the inherent assumption is then thus made that all parameters are equally important for the delineation of HU. This may not be accurate or ecologically sound. The assumption implies that an ecosystem or species are equally dependent on several parameters, this is arbitrary. Species and ecosystems are complex and therefore one would expect it is more likely that they would be more sensitive to one parameter than another rather than be equally sensitive to all investigated parameters. Despite this, the aforementioned assumption has to the author's knowledge never been tested, justified, or discussed.

The goal of this work is to challenge this assumption and investigate the main consequences of unequal importance of parameters in the clustering step to identify HU. As such, we formulate the following research question: how does the delineation of fluvial habitat patches change when the parameters they are based on are not weighted equally? Specifically, we will discuss how changing parameter weighting influences the unit locations and extents as well as possible effects on habitat analysis procedures. To do this, we gathered topographical data and constructed numerical hydrodynamic models for two reaches in the Alpine region. We adopted the algorithm of van Rooijen et al. (2021) to delineate fluvial patches using different weighting factors. In these reaches we also delineated patches using a field-based approach, which served as a reference against which to compare modelled results. We then compared the algorithm-derived HU with the field-delineated GU and identified how their relative spatial extent changes with changing weights. By means of a synthetical yet realistic HSC, we evaluated the effects of the weights on the results of a habitat assessment. The predicted habitats were also compared to those predicted by the more conventional field-based approach. Changes in the shape and extent of identified patches under different weightings indicate that patch delineation is sensitive to the choice of weights. A change in predicted habitats would infer that a habitat analysis is sensitive to these choices.

2. Methods

2.1. Study site

We investigated two gravel-bed Alpine reaches (Figure 1) in the Moesa river (Switzerland) and in the Mareta (Mareit) river (Italy). The reach of the Moesa river is located in canton Grisons, Switzerland near the village of Cabbiolo. The Moesa river is a 5th Strahler order Alpine stream which at this site has not been channelized but does have lateral side embankments for flood protection. The study reach is approximately 800 m long and the total width of the floodplain is between 100 and 200 m. It has a longitudinal slope of approximately 0.012 m/m. Gravel (2–64 mm) and sand (0.0625–2 mm) dominate the substrate composition. Brown trout (*Salmo trutta*) and bullhead (*Cottus gobio*) are dominant the fish species present there. More information on this fieldsite can be found in van Rooijen

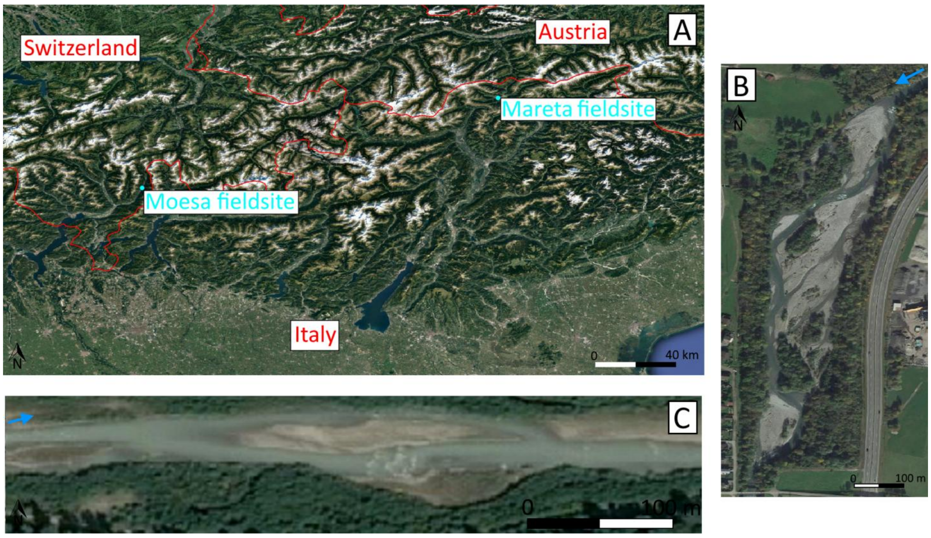

Figure 1. An overview of the investigated field sites. Panel A shows the location of the two field sites, and panels B and C show a close up of the Moesa and Mareta field sites, respectively. Map data originates from google maps.

et al. (2024), van Rooijen (2022) and Caponi et al. (2025).

The second study site of Mareta (Mareit) river is located between the villages of Stanghe and Casateiain in South Tyrol, Italy. The investigated part of the reach is approximately 500 m long and the total width of the floodplain is between 30 and 60 m, after a restoration intervention in 2009. It has an approximate longitudinal slop of 1%. The substrate composition is also gravel and sand dominated. This field site was used for further comparison e.g. to identify if patterns found at the Moesa also hold elsewhere. Information about data acquisition and modelling at this field site can be found in Baumgartner (2020) and Farò et al. (2022).

2.2. Field-based GU delineation

As a reference also field-based patch delineations were obtained. Geomorphic units were identified and classified following the standardized procedures of the Geomorphic Units survey and classification System (Rinaldi et al. 2015; Belletti et al. 2017) which identify flow stage dependent units. The identification process relied on field validation surveys which were supplemented at the Moesa by the interpretation of high-resolution aerial orthophotos. Units were delineated based on distinct morphological features (e.g. breaks in slope, changes in bed material and flow patterns) and categorized according to the GUS hierarchical typology, which distinguishes between macro-units (channel and floodplain), units (e.g. pools, riffles and rapids), and sub-units (e.g. substrate elements and flow patterns).

At the Moesa field site, the GU were delineated using a handheld RTK GPS and the GU type was annotated. In QGIS software (QGIS Development Team 2021) the GU were then reconstructed from the measured vertices. GU were delineated on 12 March 2020 and 4 March 2021. The GU were delineated at comparatively low discharges: 2.2 m^3/s (pre-flood) and 1.37 m^3/s (post-flood), respectively, as measured at the nearest gauging station at Soazza Al Pont (Amt für Natur und Umwelt 2006–2021) located approximately 4 km upstream of the field site. These values correspond to baseflow. Delineating GU at high discharges proved difficult at this field site due to generally worsening safety conditions.

At the Mareta field site, GU were delineated on an approximately 500 m long stretch of the field site. The GU were mapped using a portable GPS system connected to a rangefinder. GU were delineated on 20 March 2017, 11 April 2018 and 21 June 2018 under three different discharge conditions: 1.7, 3.2 and 10.4 m^3/s. These discharge conditions represent the range of winter low flow conditions (1.7 m^3/s) to summer high flow conditions (10.4 m^3/s). The survey was conducted at multiple flow stages to capture the temporal variability of habitat conditions, enabling subsequent analyses of habitat turnover and supporting applications such as habitat modelling and environmental flow assessments. More information on the expert-delineation of GU at the Mareta field site can be found in Farò et al. (2022).

2.3. Algorithm-based HU delineation

2.3.1. Topographical measurements

At the Moesa, the topography was measured by a combination of structure from motion technique based on RGB imagery and individually measured GPS points using handheld GPS devices Trimble R10 GNSS, Trimble R8 swipos RTK and Leica GS16. Drone flights were carried out, of which the photographs were used to determine the topography using structure from motion. These flights were carried out close in time to the field-based GU delineation (22 January 2020 and 4 March 2021). Structure from motion does not measure the topography below the water surface well though, therefore the area that was wetted during the drone flight was sampled using handheld RTK GPS devices. These two datasets were combined to obtain a digital terrain model (DTM) of the whole low-flow channel and floodplain area. For more information, see van Rooijen et al. (2024). The topography between the two measurement campaigns had changed due to several floods, the largest of which had a discharge of approximately 150 m^3/s (van Rooijen 2022). We therefore constructed two DTMs corresponding to the two topographical states. At the Mareta, the topography was measured using an airborne water penetrating laser in December 2016. The acquired points were georeferences and classified into water surface, river bathymetry and dry channel classes. Bathymetric points were corrected for refraction using Snell's law, using constant refraction coefficients (1.33 for water and 1.00029 for air). The corrected wetted-channel points were then merged with the dry channel data to generate a uniform raster grid with a 50 cm resolution, with the heights of each cell computed as the mean of the surrounding points. For more information on the topographical data collection at the Mareta, see Farò et al. (2022) and Baumgartner (2020).

2.3.2. Hydrodynamic models

A depth-averaged 2D hydrodynamic model was set-up and run for the same hydro-morphological conditions as during the field-based patch surveys. For the Moesa field site, the BASEMENT software (version 3.1, Vanzo et al. 2021) was used. Five different hydraulic roughness categories (coarse sediment, fine sediment, vegetated, blockramp and boulders) were considered, with Strickler roughness coefficients of 30, 50, 5, 45 and 20 $m^{1/3}/s$, respectively. At the downstream boundary a water level was imposed, calculated based on the discharge and local slope by the BASEMENT software, assuming uniform flow conditions. At the inflow boundary a discharge was imposed, the discharges were set to the discharge registered during the delineation of the patches in the field (2.20 or 1.37 m^3/s). For more information on the set-up of the model, see van Rooijen et al. (2024). For the Mareta fieldsite, the HYDRO_AS-2D hydrodynamic model was used (Nujić 2014). Simulations were run using a regular triangulated mesh with grid resolution of 50 cm, derived from the DTM, generated using the software Surface-Water Modelling System (SMS; by Aquaveo). Calibration was performed at a constant discharge of 1.7 m^3/s by minimizing the root mean square error (RMSE) between simulated and LIDAR-derived water surface elevations (WSE). This was achieved by adjusting spatially variable Gauckler–Strickler roughness coefficients, assigned to represent different macro-roughness classes within the channel, over the range $k_{st} = 17 - 30m^{1/3}/s$. Model performance at higher discharges was evaluated by comparing simulated and observed water extents at $Q = 10.4m^3/s$, using water edges derived from the GU survey. For more information on the set-up and calibration of the model, see Baumgartner (2020). At the upstream boundary, three discharges were imposed, the same as those which occurred during the field delineation of patches at this field site. At both fieldsites the flow is mostly subcritical with small areas with supercritical flow under the low discharge conditions. Note that the point of this work is not to compare numerical solutions to each other but rather to investigate the delineation algorithm which requires data obtainable from such solutions.

2.3.3. Algorithmic HU delineation

Hydraulic units were identified using the BASEmeso clustering algorithm (van Rooijen et al. 2021), based on water depth and flow velocity values obtained from the numerical hydrodynamic models. The BASEmeso algorithm is an agglomerative hierarchical clustering algorithm with a hard spatial contiguity constraint. It identifies contiguous, homogeneous and distinct patches based on the local distributions of the clustering parameters, in this case water depth and flow velocity.

The water depth and flow velocity were normalized, as usual in unsupervised algorithms (Jain 2010); z-scores were applied. This recast the parameter values into similar ranges and causes the algorithm to not weight one parameter more strongly than the other by equalizing the distance between points in the parameter space (Figure 2). This is because a clustering algorithm identifies which elements should be part of the same patch by minimizing the Euclidean distance between the elements in the multidimensional parameter space. The normalization ensures that the Euclidean distance is equally influenced by all parameters. If, however, we do not want each parameter to have the same influence, we can artificially weight the parameters by changing the distance along one axis between points in the parameter space (Figure 2). These weights were applied after the normalization, to ensure that we know the magnitude at which the parameters were weighted.

Using weights is analogous to using hyperparameters for an algorithm. In this study, we weighted the parameters according to:

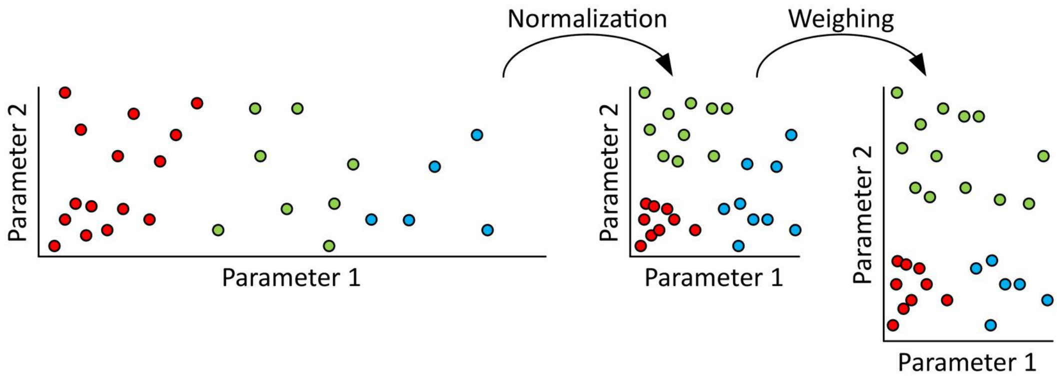

Figure 2. The distance between elements in the multi-dimensional parameter space affects how elements are grouped together when using a clustering algorithm. The above figures represent a hypothetical case where the dots represent elements in the multi-dimensional parameter space. The colours represent the groups in which these could be clustered by a clustering algorithm. By normalization the distances between the elements are made equal in the different parameter-dimensions, making the groups less dependent on a single parameter. Weights can be added by changing the distances between the elements.

$$P_{weighted} = w_p * (P - P_{\min})^{1/r}, \quad (1)$$

where $P_{weighted}$ is the weighted parameter value, w_p is the weight for the parameter compared to other parameters $[1, \infty]$, P is the normalized parameter value, $P_{\min}$ is the smallest normalized value of that parameter and r is the relative weighting factor $[1, \infty)$.

Essentially, two types of weights (w_p and r were applied. The first (i) weights the two clustering parameters (depth and velocity) with respect to one another. All values of one parameter after normalization were multiplied by a value higher than 1 (w_p). This increases the distances between the elements in the parameter space in either the direction of depth or velocity (Figure 2). Since the distances in the multiplied direction have increased, elements with similar values of this parameter are considered less similar by the algorithm than before. As a result, this parameter is more likely to differentiate between units, thereby increasing its weight in the delineation of units. The multiplication factor thus could be considered a weighting factor. The second (ii) type of weight reflects a relative weighting of the parameters. Instead of weighting one parameter against another, this weighting factor weights distances in one direction of the parameter space. For example, it allows the difference between 0.1 and 0.2 m of water depth to be weighted more strongly than the difference between 1.1 and 1.2 m of water depth, despite a difference in water depth of 0.1 m in both cases. This is done by increasing the distance in the parameter space between low values, and decreasing the distance between high values. To do this, the normalized values are shifted so that the lowest value is at 0 (by subtracting the smallest normalized value $P_{\min}$), then an exponentiation with an exponent between 0 and 1 is performed. The value of the exponent then determines how strong the relative weighting is considered. With an exponent with a value of 1 no relative weighting is applied, while with lower values this relative weighting is stronger. To obtain a more intuitive weighting factor we chose the exponent as 1/r where r is the relative weighting factor. Higher r values will correspond to lower exponent values.

2.4. Evaluation of HU location and extent with varying weights

Depending on the weights chosen for the clustering algorithm, the HU delineation will change. We therefore ran the clustering algorithm using different sets of weights to investigate how they changed. Both water depth and flow velocity were weighted with respect to one another with the following values: 1 to 2 with steps of 0.1, then 2.5, 3, 5 and 10. In addition, for the sake of testing, we consider an ‘extreme’ weighting scenario, where one of the parameters was multiplied by 0, making the clustering algorithm fully dependent on the other parameter (i.e. infinitely weighting it). This leads to 31 different absolute weighting scenarios; this will allow the effect of weights to be visualized. With exception of the infinite weighing, the same values listed above were also used for the relative weighting (r). For the sake of testing the methodology, we tested also the relative weighting with values below 1, namely 0.6 and 0.8 (yielding a total of 17 relative weighting scenarios in total). Note, however, that weights $r < 1$, as used in our tests have no practical relevance. They impose that the same absolute differences in parameter value are more important when the parameters are at a high value as opposed to a low value. These cases were included solely to examine and discuss the behaviour of the adopted metric. With this setup, we defined and investigated a total of 527 (31×17) weighting scenarios.

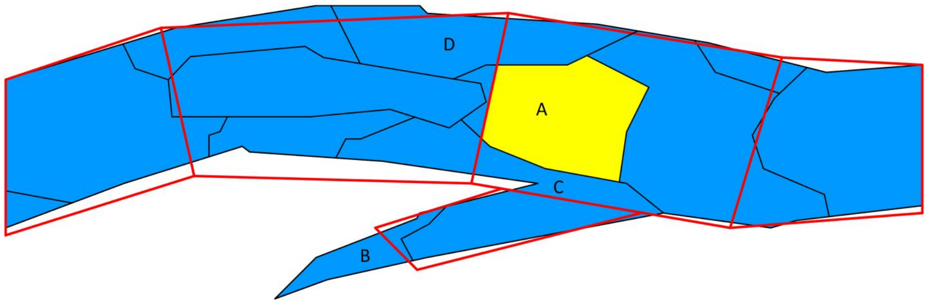

Figure 3. A hypothetical river section with patches delineated. The red lines delineate field-delineated patches, while the black lines delineate algorithm-derived patches. The patches A, B, C and D are referred to in the text. The yellow part of patch a is the part of patch a that is in the GU with which patch a overlaps the most.

The resulting algorithm-derived HU were compared with the field-delineated GU, to identify how well they overlapped. This not to maximize the overlapping, but to find a pattern. An important challenge of this comparison is that the field-based and algorithm-based approaches generally do not delineate the same types of units. The algorithm identifies hydraulic units (HU), which are smaller and more complex in shape than the geomorphic units (GU) which were used in the field-based approach. This is due to the algorithm identifying patches based on the spatial distribution of the parameters and therefore creating shapes which follow the spatial elements on which these parameters are defined, such as pixels of an aerial photograph or grid cells of a hydrodynamic model. In contrast, GU delineated in the field often follow lines, which can be straight for simplicity and to save time. Furthermore, the field operators often identify channel-spanning units (see Belletti et al. 2017), while the algorithm will consider the channel margins to be substantially different from the area around the thalweg and thus not part of the same unit.

Comparing the two patches is however possible since HU are subpatches of GU (Belletti et al. 2017). The two approaches used are thus hierarchically linked. This makes a comparison between the two possible; a perfect match between the two patch approaches is obtained when one or several algorithm-derived units together form one field-delineated GU. Although a perfect agreement between the two is unlikely to ever be achieved due to the aforementioned differences between the patches, a general trend of similarity between the two can be obtained and quantified.

The following procedure was followed to evaluate how well the two approaches overlapped. For each algorithm-derived HU, the field-delineated GU with which it overlapped the most was identified. Then the total overlapping area was computed between these two units, for example for patch A in Figure 3 the yellow area. This was computed for all HU that were at least for 80% in the area where GU were identified. HU that were in side-channels where GU were not delineated were thus not taken into account for the analysis, like patch B in Figure 3. There are several reasons why the exact area where GU and HU were both delineated did not match. Areas with much dense vegetation were avoided due to the lower accuracy of the GPS equipment. Some areas which are predicted as wetted by the numerical model were not wetted during the field-delineation of the GU, likely due to water infiltrating into the ground and inaccuracies in both the model and field-survey procedure. Please note that the borders (or perimeter) of the field-delineated GU were characterized by a number of georeferenced points to speed up the field survey. Therefore, this spatial comparison of overlapping areas can be biased by the coarse spatial resolution of the field survey. The computed overlapping areas were summed and divided by the total area where both types of patches were delineated. A perfect but in reality unobtainable overlap would be represented by a value of 1, which is also the theoretical maximum value. The aim is not to obtain this value, but to see under which conditions it increases.

2.5. Analysis of changes to predicted habitat availability

We applied synthetic HSC, based on real fish preferences, to evaluate physical habitat suitability in the HUs and GUs. This to further show how weighting parameters might impact the results of habitat assessments. The implemented HSC for adult bullhead and juvenile and adult marble trout (*Salmo marmoratus*), were derived from literature and empirical-data, and have been previously applied to habitat assessments of the Mareta field site. For more information on this habitat model, see Farò et al. (2022). Marble trout is present at the Mareta field site but not at the Moesa field site. As we are not aiming to identify real habitats for the species, but rather identify only the differences due to changes in weighting factors, this is irrelevant for our approach and has no practical relevancy for the field case. For each unit, we applied the rules to the water depth and flow velocity distributions of the patch to identify whether the patch constituted suitable habitat. The same set of rules was applied to both the algorithm-derived and field-delineated units.

3. Results

3.1. Comparison between the algorithm-derived and field delineated approach

At the Moesa field site, four different GU types were identified using the field-based approach: pool, riffle, glide and backwater (Figure 4A and Supplementary Material). At the Mareta field site also rapids and steps habitat type were identified from the field-based field survey (see Supplementary Material). With higher discharges the habitats shifted more towards fast flowing types. Of all identified GU types, glides were most abundant at both field sites. The modelled water depth (1–2.5 m) and flow velocity (0–3.5 m/s) have values similar to other Alpine rivers (c.f. Argyrakis and Skourtis 2018) (Figure 4 and Supplementary Material).

In the algorithm-based approach the weights change the way the algorithm delineates HU (Figure 5). At some locations an HU boundary is repetitively identified, while at others, HU boundaries will depend on the chosen weights. In other words, the border between some HU is independent of the chosen weights, likely because it represents a very crisp clear border between two spatially distinct patches of relatively homogeneous surface flow. In other cases, where the transition from one patch to another is smoother, the location of the border will depend on the chosen weights. Each set of weights thus will lead to a unique HU assemblage for the field site. As a result, for some weights the HU identified by the algorithm will match better with the field-delineated GU (Figures 6 and 7).

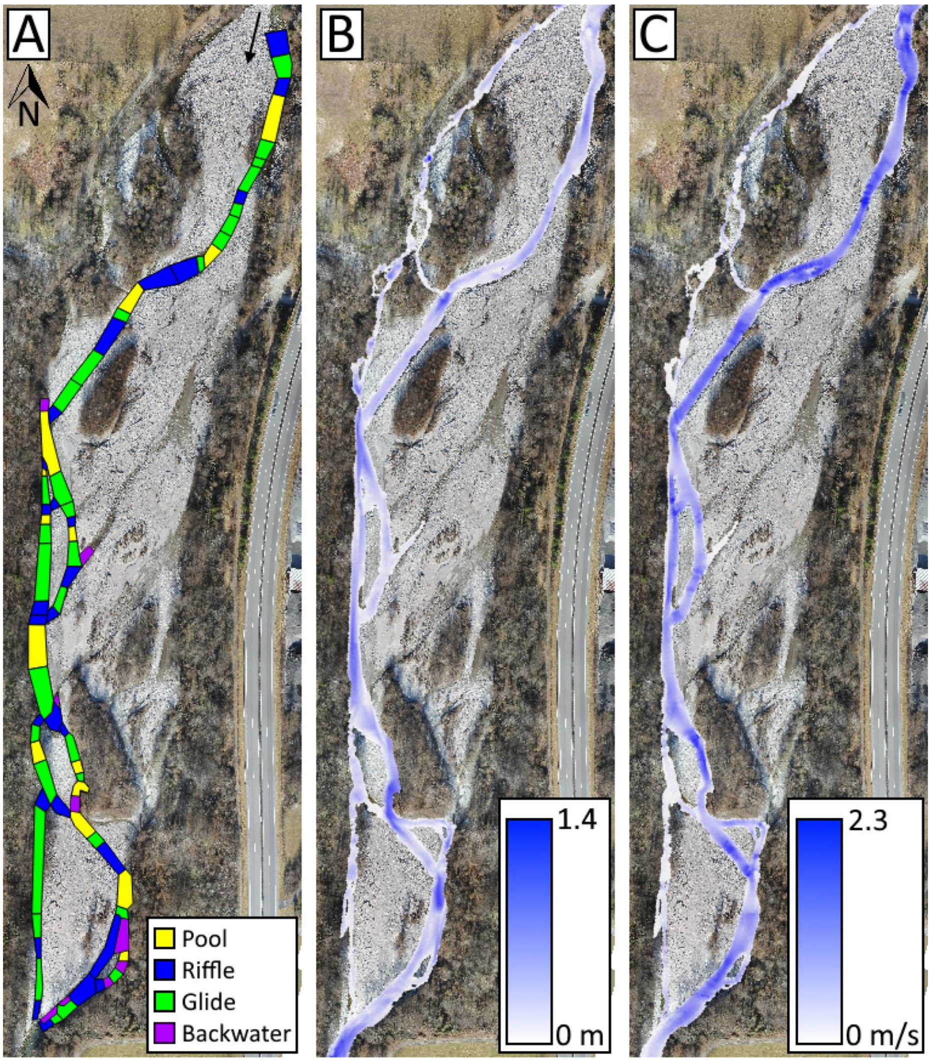

Figure 4. Results of the GU-delineation in the field and the hydrodynamic model for the Moesa field site with a discharge of 2.2 m^3/s. Panel A shows the delineated GUs. Panels B and C show the modelled water depths and flow velocities, respectively. Note that GU were not delineated throughout the entire field site. Areas with much dense vegetation were avoided due to the lower accuracy of measuring equipment. Some areas which are predicted as wetted by the numerical model were not wetted during the field-delineation of the patches, likely due to water infiltrating into the ground and inaccuracies in both the model and measurements. Background imagery recorded on 22 January 2020.

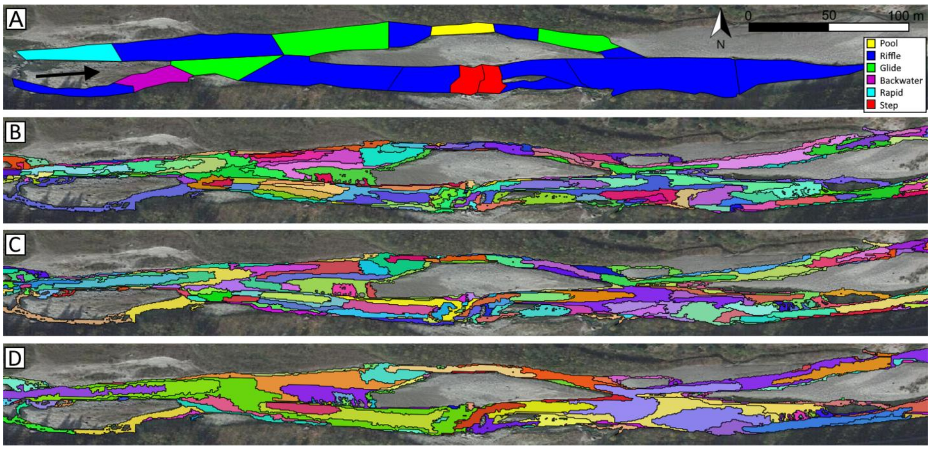

Figure 5. Results of the patch-delineation in the field and the patch-delineation based on the hydrodynamic model for the Mareta field site with a discharge of 3.2 m^3/s. Panel A shows the units delineated in the field. The panels B, C and D show the patch delineations by the algorithm (different random colors) where velocity is weighted 1, 1.4 and 5 times more strongly than depth, and the relative weight is 1, 1.5 and 5, respectively.

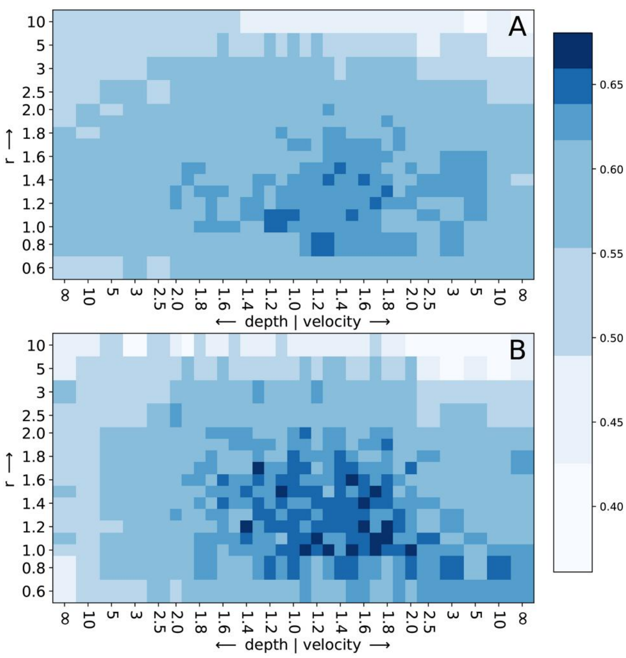

Figure 6. How well algorithm-derived and field-delineated units compare as a function of the used weights for the Moesa fieldsite. The darker the colour, the better the two types of units compare. Panels A and B correspond with the pre-flood and post-flood morphological configurations, respectively. The horizontal axis shows the weights compared to other parameters and the vertical axis shows the relative weighting factor.

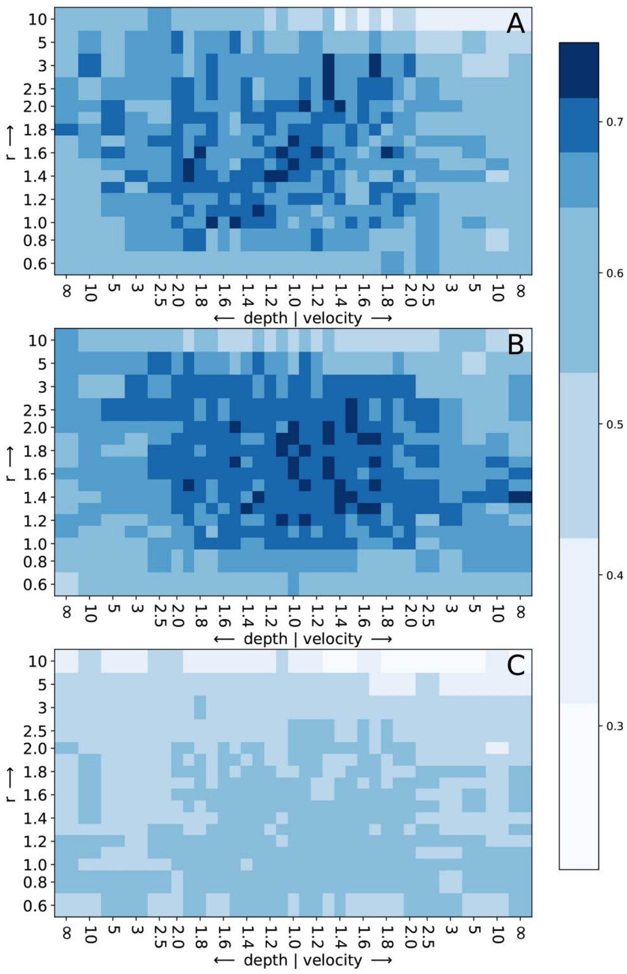

Figure 7. How well algorithm-derived and field-delineated units compare as a function of the used weights for the Mareta fieldsite. The darker the colour, the better the two types of units compare. Panels A, B and C correspond with the discharge scenarios of 1.7, 3.2 and 10.4 m^3/s, respectively. The horizontal axis shows the weights compared to other parameters and the vertical axis shows the relative weighting factor.

In the two investigated morphological configurations of the Moesa reach we see that the pattern that emerges from comparing the field and algorithm-derived units, is similar between the two scenarios. In both scenarios the two types of units compare best by weighting the flow velocity slightly more (approximately 1.3 times) than the water depth and by employing a small relative weighting factor (approximately 1.3; see Figure 6). An exact optimum cannot be identified though.

At the Mareta field site (Figure 7) no exact optimum can be identified either. The relative weighting factor with which the algorithm-derived and field-delineated units correspond best does not change noticeably between the investigated discharge scenarios

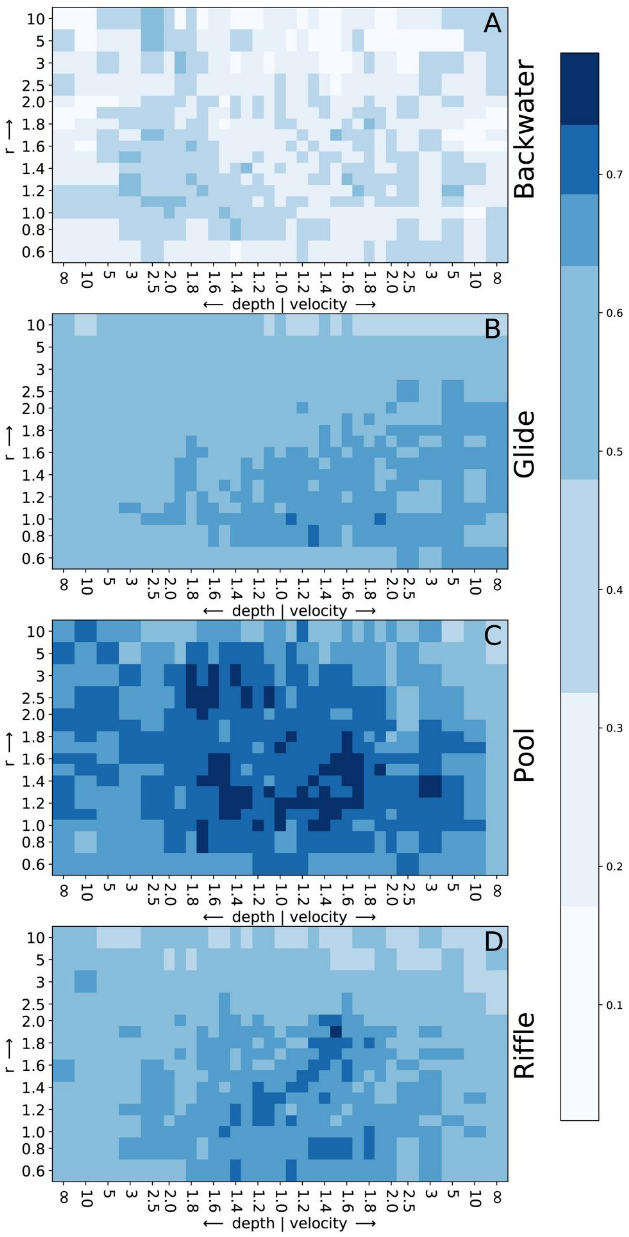

Figure 8. How well algorithm-derived and field-delineated units compare as a function of the used weights for the Moesa field site in the pre-flood morphological configuration (2.2 m^3/s), by GU type. The darker the colour, the more suitable habitat there is. Panels A, B, C and D correspond to backwaters, glides, pools and riffles, respectively. The horizontal axis shows the weights compared to other parameters and the vertical axis shows the relative weighting factor.

(between 1.3 and 1.5). However, the other weights under which the GU compare best with the HU do change between the investigated discharge scenarios. With increasing discharge, flow velocity becomes increasingly more important for the delineation of units with respect to water depth. Furthermore, under the highest discharge condition, the congruity between the two types of units is lowest.

A comparison of the spatial overlap between each field-based GU type and the modelled HUs (see Figure 8) indicates that substantial variability in agreement. The highest overlap is observed for pools and riffles and the lowest for backwaters.

3.2. Predicted habitat suitabilities under different weighting scenarios

Since the patch locations and extents change with changing weights, it is possible that the weights affect the amount of predicted habitat as well. Figures 9 and 10 show the delineated units and their habitat suitabilities for two river states for the field-delineated GU and several algorithm-derived HU under different weighting scenarios. Suitable habitat is mostly predicted at similar locations for the field- and algorithm-based approach. Specifically, within every GU that is identified as suitable, there is at least some area which is also considered suitable by the algorithmic-approach. At each of the areas where suitable habitat is predicted, the amount of suitable HU and their sizes can however vary depending on the weighting scenario.

Comparing the field- and algorithm-based approaches quantitatively (Table 1) shows that GU that are considered unsuitable are mostly also considered unsuitable by the algorithmic approach. Overall, a good agreement between the two approaches exists; in Table 1 the areas where the two approaches agree on whether habitat is suitable or unsuitable are far greater than the areas where the two approaches disagree, for all cases. If the two approaches disagree whether a certain area is suitable or not, it occurs more often that the field-based approach considers it suitable while the algorithm considers it unsuitable compared to vice versa. Multiple HU make up one GU, and in each GU that is suitable at least one HU is suitable.

The weights affected the predicted amount of suitable habitat (Figures 11 and 12). For example, at the Moesa before the flood, approximately 25% more suitable habitat is predicted when weighting the velocity more than the depth. Furthermore, when the topography changed, the weights also impacted how much habitat was lost or gained (Figure 11). However, weights have a smaller impact when the discharge changes (Figure 12). Clearly, the discharge impacts the predicted amount of habitat more than the chosen weights, although the weights can still influence the predicted amount of suitable habitat. For bullhead, at the middle discharge (panel B) the most habitat is predicted for a large relative weighting factor and weighting water depth more strongly than flow velocity, while at the high discharge (panel C), the least amount of suitable habitat is predicted with these weights.

4. Discussion

4.1. The effects of parameter weighting in patch delineation

The results show that when weights are included into the approach, the HU size and spatial extent, as

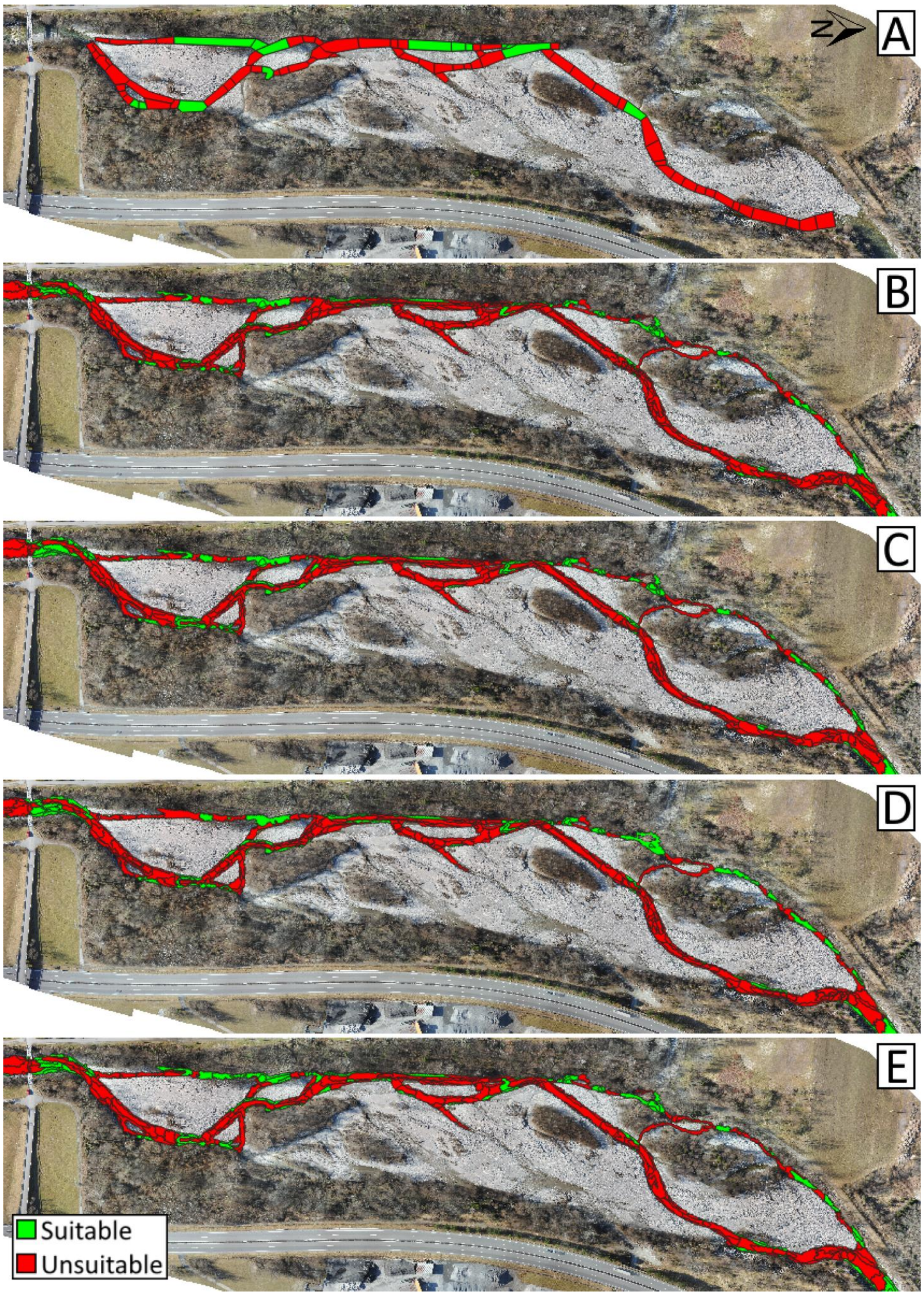

Figure 9. The obtained units and their suitability for juvenile marble trout for the Moesa field site in the pre-flood morphological configuration (discharge of 2.2 m^3/s). Panel A shows the field-based delineated GUs. Panels B, C, D and E show the modelled HU for the following weighting scenarios, respectively: no weights (e.g. all weights 1), relative weighting factor 1.9, velocity weighting factor 1.6, velocity weighting factor 1.6 and relative weighting factor 1.9.

well as the amount of predicted habitat change. This shows that the choice for how to weight parameter values is important and cannot be ignored. Moreover, also the habitat quantification and habitat changes upon external change are dependent on the used weights (Figures 11 and 12). Figure 11 shows that the difference in amount of habitat between the two morphological states, will be considered larger if the velocity is weighted more than the depth. Although not as pronounced, the opposite is true for Bullhead at the Mareta (Figure 12).

The fact that weights impact the change in habitat under varying conditions, is arguably even more important than just a different amount of habitat predicted by the methodology when using weights. This is because these methods are mostly used to identify how a system change would affect habitats. Generally, habitat-streamflow rating curves are used to identify how a change in discharge affects the amount of habitat in a river. These curves would thus be affected (see also the Supplementary Material for an example). Weights thus have the potential to lead to different conclusions.

In this work we used z-scores to normalize the parameter values. Other choices for normalization also exist, such as min–max scaling. Min–max scaling has the disadvantage that the normalized parameters can become strongly dependent on single outliers in the dataset. This could then inadvertently weight one

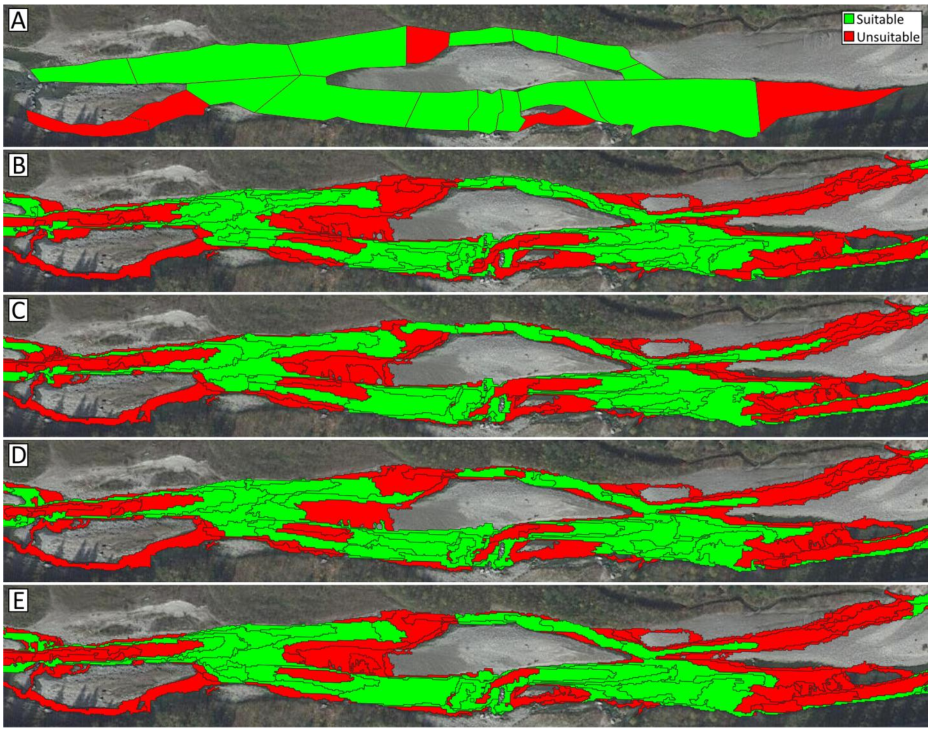

Figure 10. The obtained units and their suitability for adult bullhead for the Mareta field site with a discharge of 3.2 m^3/s). Panel A shows the field-based delineated GUs. Panels B, C, D and E show the modelled HU for the following weighting scenarios, respectively: no weights (e.g. all weights 1), relative weighting factor 1.9, velocity weighting factor 1.6, velocity weighting factor 1.6 and relative weighting factor 1.9.

Table 1. Agreement in habitat suitability between the two approaches shown are the percentages of area where the field- and algorithm-based approaches both consider habitat to be suitable, both consider habitat to be unsuitable and where one considers them suitable and the other unsuitable. This is shown for all five scenarios and the three ecological targets. For example: in the Moesa in the pre-flood condition for adult marble trout, 6.3% of the area is considered suitable by both approaches, 75.8% of the area is considered unsuitable by both approaches, 9.2% of area is considered suitable by the field-based approach but not by the algorithmic approach and 8.6% is considered unsuitable by the field-based approach and suitable by the algorithmic approach. For the algorithm-based approach the weights which yielded the best similarity to the field-based approach were used.

			Field					
			Suitable			Unsuitable		
			Adult marble trout	Juvenile marble trout	Bullhead	Adult marble trout	Juvenile marble trout	Bullhead
Algorithm	Suitable	Moesa pre-flood	6.3	9.5	29.5	8.6	6.1	4.4
		Moesa post-flood	1.3	8.3	35.7	1.5	5.0	1.7
		Mareta 1.7 m^3/s	0.0	40.5	65.2	1.4	3.4	2.3
		Mareta 3.2 m^3/s	1.3	7.2	54.9	2.9	11.3	2.5
		Mareta 10.4 m^3/s	33.1	0.55	37.6	3.2	5.3	2.2
	Unsuitable	Moesa pre-flood	9.2	12.6	23.3	75.8	71.8	42.8
		Moesa post-flood 2	4.5	3.0	28.3	92.7	83.7	34.2
		Mareta 1.7 m^3/s	0.0	33.4	21.9	98.6	22.7	10.6
		Mareta 3.2 m^3/s	3.0	12.5	30.1	92.8	69.0	12.5
		Mareta 10.4 m^3/s	30.3	2.2	43.8	33.4	92.0	16.4

parameter more than the other, as if one were to use weights without wanting to. The only effect of using a different approach for normalization would therefore be that the optimum set of weights could be different, because in a way the parameters are already weighted against one another. Care should thus be taken that weights obtained can only be used if the same normalization approach is used.

4.2. How to choose weights

It has been shown that considering weights influences the outcomes of habitat analysis. An important question then becomes: which weights should be chosen? This question will usually be difficult to answer due to a lack of data. It is conceivable that the optimal weights, are different between different types of rivers and discharge regimes. More research is going to be needed to answer what a good set of weights is for different conditions. Notwithstanding, our data shows that a relative weighting factor of approximately 1.3 optimizes the match between the field-based and algorithm-based approaches in the two field sites. Using a relative weighting factor with this value is thus recommended for Alpine river

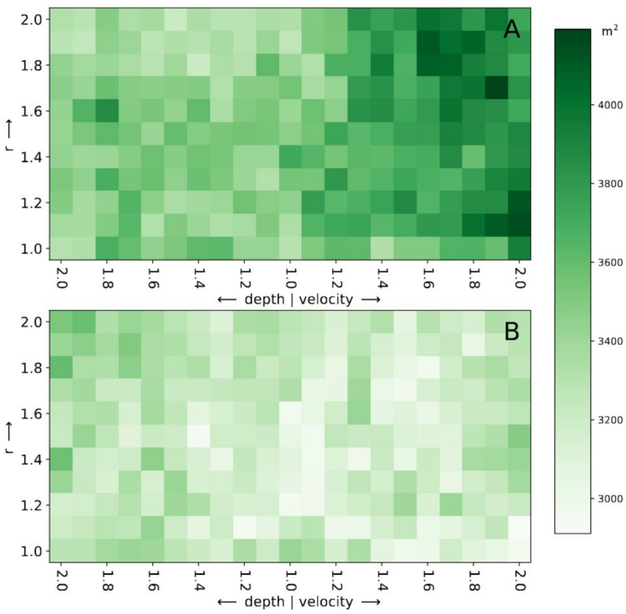

Figure 11. Amount of predicted suitable juvenile marble trout habitat using the algorithm-based approach at the Moesa field site as a function of the used weights. The darker the colour, the more suitable habitat there is. Panels A and B correspond to the Moesa pre- and post-flood morphological configurations, respectively. The horizontal axis shows the weights compared to other parameters and the vertical axis shows the relative weighting factor.

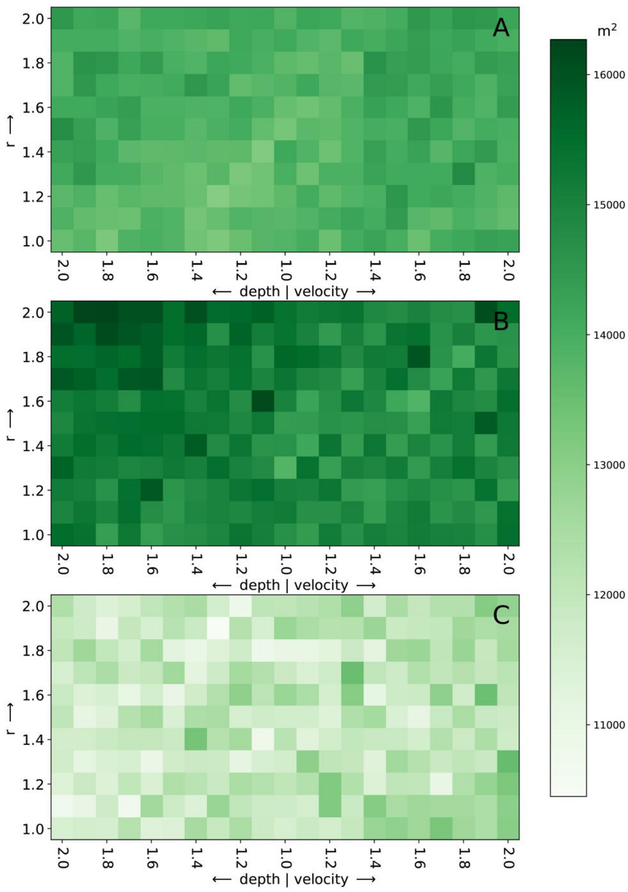

Figure 12. Amount of predicted suitable bullhead habitat at the Mareta field site using the algorithm-based approach as a function of the used weights. The darker the colour, the more suitable habitat there is. Panels A, B and C correspond to the discharge 1.7, 3.2 and 10.4 m^3/s, respectively. The horizontal axis shows the weights compared to other parameters and the vertical axis shows the relative weighting factor.

channels until a more in depth analysis has been undertaken. We hypothesize that experts in the field not only consider absolute changes in parameter values but also relative ones. Further research can shed light on this.

Furthermore, we are able to propose a way in which a set of weights can be estimated for a specific river site. Making figures such as Figures 6 and 7 which show for which weights the patch assemblage is most similar to that delineated in the field, would aid in choosing which weights to use. By choosing weights in the area with highest similarity ensures that the knowledge of experts (conscious or subconscious) is utilized, and therefore makes a reasonable and defendable choice. This could be considered hyperparameter tuning of the algorithm by using data obtained by experts.

4.3. Limitations

In this analysis, the algorithm-derived HU are compared with the field-delineated GU to identify a suitable set of weights that could be used in habitat analysis. This analysis still has some limitations. The first is that it relies on field-delineation. Many different mesohabitat mapping classification systems exist and the choice for the mapping system can influence the delineated units (Milan et al. 2010). All systems rely on field surveys to delineate GU, where mapping by different operators can cause differences in delineation (Jowett 1993; Poole et al. 1997; Mouton et al. 2011). If one were to choose the weights by comparing to field delineated units, the choice could be impacted by the field survey.

Furthermore, some of the environmental conditions can impact how well patches can be delineated. At the Mareta under the highest discharge condition (Figure 7C), the agreement between the two types of units is lowest. This is likely because GU are easier to identify under lower discharge conditions, due to improved visibility, weadability and increased differences in hydraulic characteristics. Wyrick et al. (2014) found a similar trend for different types of mesohabitat units. Both the field- and algorithm-based approaches may be impacted by this.

The difference in unit type between the field-based and algorithm-based approach (GU vs. HU) may lead to further limitations. Although an HU is by definition a subunit of a GU, an algorithm based on water depth and velocity only may not always identify them as such, since it has no information on the other parameters required to delineate GU. Two adjacent HU with similar hydraulic characteristics in different GU are different units, but an algorithm is likely to consider these two HU as one. This is likely to occur in the channel margins (patches C and D in Figure 3 are examples). Since this identified HU is covering multiple GU, the overlap with one GU is low. As such this HU will lower the metric value for comparison. This behaviour should grosso modo occur at equal rates for all weighting scenarios. Therefore, although it will lower the metric values, it is unlikely to influence the overall trend in the metric values.

Another limitation of the comparison is that some patches are more difficult to identify, both in the field as well as for an algorithm. The two approaches mapped better onto one another for the units that the field operator defined as pools or riffles (Figure 8). These two GU types are the types which have characteristics on the extreme end of water depth and flow velocity, respectively. This has likely helped both methodologies to more accurately delineate them, increasing the overall similarity. For backwaters the two approaches delineated patches that barely agreed. Many backwaters at this site were formed by woody debris or boulders affecting the local flow. Since the hydrodynamic model does not consider the hydraulic effects of these elements due to their absence or limited representation in the model, the identification of backwaters based on hydrodynamic modelling results may generally be underestimated. Another potential reason for the low agreement for backwaters, is that some of the backwaters have similar characteristics to channel margins of adjacent GU, not allowing the algorithm to distinguish between the channel margins of one GU and the adjacent GU defined as backwater.

The fact that within a suitable GU there is always also a suitable HU indicates that the HU show in greater detail which parts exactly make a certain location suitable. This was also observed by Farò et al. (2022).

4.4. The next steps

So far, algorithmic approaches have never considered weighting the parameters for the delineation of units. Essentially, they have always used weights with values of 1, for both the parameter weights and the relative weighting factor. Since weighting parameters affect the outcome of a habitat analysis we should ask ourselves the question if we should continue with this procedure. There are good reasons to weight the parameters. The species living in a habitat may for example be more sensitive to one of the parameters, which means that the habitat identification should reflect this. Furthermore, field operators (consciously or subconsciously) also do not weight depth and flow velocity equally when delineating the units, either because they also consider other parameters, or because one is more important to delineate certain units. Algorithms would improve if they also consider this. Although weighting the parameters adds an additional step in the analysis which might require field-data to be collected to define an appropriate set of weights, the increased resulting accuracy should make it appropriate to weighting the parameters going forward.

In order to do this, the correct weights for a specific situation must be able to be determined. In this work we proposed a methodology on how to do this. The methodology however still requires further development as it is currently only able to identify an area in the weight parameter space in which the correct weights must lie, as opposed to finding these weights directly. More research is thus needed to identify the optima for multiple field sites and river morphologies, which could broaden our understanding and allow us to identify what elements impact the location of the optimum which could then be used. It would also ensure that no inherent assumption is used in the approach, but rather that there is a reason for the choice taken.

The methodology set out to identify the weights in the algorithm by comparing the HU to GU identified in the field could also be used to quantify possible inconsistencies between field surveys carried out by different operators. Multiple operators can delineate slightly different GU at the same location and conditions, and the comparison method can be used for each set of field-delineated GU. When the weights for which the algorithm and operator are most similar differ significantly between operators, a relative bias between the two operators has been found and quantified. Research identifying an operators bias is limited (but see Jowett (1993); Mouton et al. (2011); Poole et al. (1997); Farò et al. (2023)). The analysis provided here can supply an objective and repeatable way of identifying the differences between operator GU delineation and will thus allow many further studies.

4.5. Discussing the assumption

Currently, algorithm-based approaches cannot be considered to be ecologically relevant alone, as they comprise an inherent assumption which cannot be defended. Similarly, field-based approaches also cannot be considered to be fully reliable due to, for example, the limitations when applied at higher discharges or possible inconsistency between different field operators. Thus, a unique and comprehensive delineation of both HU and GU is not possible at this moment. This does not mean that trying to obtain a more comprehensive delineation is not going to be worthwhile. In order to do so, most likely, the field- and algorithm-driven approaches should be combined. In this way, the limitations inherent to both can be reduced. For example, the algorithmic approach can be used on very large, non-wadable rivers under multiple discharge conditions and can be used to analyze potential future conditions. A field-based approach is usually too time-consuming to employ for large river reaches under many different discharge conditions, but can identify more ecologically relevant GU. A methodology in which both field and algorithm-based approaches are combined would be able to identify ecologically relevant patches on long river stretches under many discharge conditions.

A combination of the two approaches may also improve the fundamental basis of fluvial habitat modelling. GU and HU are the most relevant scale to identify fluvial habitats (Belletti et al. 2017), because mesohabitats are strictly linked to the life cycle of several communities, such as fish (Gosselin et al. 2010; Vezza et al. 2014; Negro et al. 2021; Pinna et al. 2024). Therefore, this spatial scale is deemed representative to establish links between physical and biological river elements. HUs are the fundamental building blocks of habitat. However, similar HU in different GU will probably have different biotic assemblages (Thomson et al. 2001). Thus, the understanding of habitat use at the mesoscale may be obtained with a methodology that considers both HU and GU.

In this work, we compared the two approaches, identifying their strengths and where they can supplement each other. This can be considered a first step towards combining the two approaches. Multiple steps are required for this to become a reality. In addition to an algorithmic approach for HU, an algorithmic approach that identifies GU based on the output of a hydrodynamic model and on the riverbed and shoreline characteristics could prove beneficial. This would require the inclusion of more parameters like for example the substrate size and distribution, and the surface gradient. In addition, more research is needed to identify in which other ways the delineation of ecologically relevant units may be achieved, other than parameter weighting.

5. Conclusions

This study demonstrates that the inherent assumption that all parameters for hydraulic unit (HU) delineation when using clustering-based approaches carry equal weight is untenable. Variations in both absolute and relative parameter weighting lead to substantial differences in the spatial delineation of HUs and thus directly influence habitat assessment outcomes. The choice of weighting not only determines the configuration of the final HU assemblage, but also the quantity and distribution of predicted suitable habitat, making the ecological interpretation of model results dependent on this prior decision.

The comparison with field-based geomorphic units (GUs) shows that algorithmic and field-based approaches capture different aspects of mesohabitat structure and are not interchangeable, but rather complementary. In both studied river systems, a limited relative weighting ($r = 1.3$) corresponded most closely with field observations, while absolute weighting terms varied by river site and situation. This suggests that experts in practice do not treat parameters equally. This underscores that the traditional normalization procedure, which reduces parameters to equal influence, does not constitute an ecologically neutral standard but rather an arbitrary choice with significant consequences.

To achieve more ecologically relevant HU delineations, an explicit and well-founded definition of parameter weights is necessary, preferably aligned with field knowledge and system characteristics. Further development of algorithms – such as through the integration of additional physical variables – and closer integration between field- and model-based approaches represent logical next steps towards an integrated methodology for mesohabitat delineation. This paper can be considered a first step towards this future.

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The authors report there are no competing interests to declare.

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