

Key management rules for agricultural alpine newt breeding ponds based on habitat suitability models

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Abstract

- 1 The alpine newt, *Ichthyosaura alpestris*, is very sensitive to habitat destruction and alteration which has led to declining populations across Europe. As this species is protected through the Bern Convention, it is essential to have a comprehensive understanding of its habitat requirements to ensure proper conservation measures. This research provides quantitative insights, which are generally lacking for this species.
- 2 To fill in this knowledge gap, we trained, validated and optimized classification tree models based on data on local aquatic habitat conditions from 125 farmland ponds scattered over Belgium where the alpine newt commonly occurs. To obtain user-friendly and representative models, data was pre-processed and stratified after which different degrees of pruning were applied for model optimization. We assessed the models' technical performance via the percentage of correctly classified instances (%CCI) and Cohen's κ . In order to check the model's applicability for management, we predicted alpine newt occurrence with an independent dataset.
- 3 The most robust and reliable model revealed that fish presence was the major driving factor predicting the occurrence of alpine newts followed by the thickness of the sludge layer. The threshold value for the sludge layer below which habitats were suitable was found to be 15 cm, thereby providing quantitative information for decision makers. Furthermore, our results indicated that the amount of sludge was associated with the level of eutrophication rather than being a result of natural succession.

4 Regarding management practices, it is first and foremost advised to assure the absence of fish in ponds designated for the conservation of alpine newts. Temporary ponds are therefore considered to be suitable ponds as they are generally fish-less. Moreover, sludge accumulation in ponds that periodically dry out is reduced compared to permanent pond ecosystems, thereby mitigating eutrophication effects in an agricultural landscape. Finally, we promote to install buffer strips around the freshwater body to reduce nutrient run-off from the terrestrial environment.

Keywords

Alpine newt, habitat suitability models, classification tree, machine learning, independent validation, integrated pond management

1 **Introduction**

2 Across Europe, salamander or urodelan populations are facing dramatic declines and
3 extinctions. Almost 30% of all European urodelan species are categorized as
4 vulnerable, endangered or critically endangered which is the second highest of all
5 European vertebrates (cf. 37% for freshwater fishes, 19.4% for reptiles, 16.5% for
6 mammals, 12.6% for birds and 7.5% for marine fishes) (BirdLife International, 2015;
7 Cox & Temple, 2009; Freyhof & Brooks, 2011; Nieto et al., 2015; Temple & Cox,
8 2009; Temple & Terry, 2007). Urodeles are exposed to several threats. Human induced
9 habitat loss and degradation are the most prominent stressors at present (Hof et al.,
10 2011). Many of the European salamanders require stagnant water bodies, such as ponds,
11 for their reproduction (Temple & Cox, 2009). Besides, the presence of such ecosystems
12 in for example farmland, which covers approximately half of the European territory,
13 contribute significantly to general regional biodiversity (Scheffer et al., 2006).
14 Agricultural intensification and urbanisation are major causes for pond loss and
15 degradation due to e.g. eutrophication or pesticide pollution (Curado et al., 2011;
16 Temple & Cox, 2009). Furthermore, the destruction of ponds and other small landscape
17 elements, such as shrubs, hedges and rough vegetation enhances spatial
18 homogenization and fragmentation of a landscape, thereby reducing connectivity
19 amongst habitats, which is essential for sustaining healthy salamander populations
20 (Hehl-Lange, 2001). Next to habitat alteration, urodelans are threatened by the fungal
21 disease caused by the species *Batrachochytrium dendrobatidis* (hereafter: Bd) and
22 *Batrachochytrium salamandrivorans* (hereafter: Bsal). Note that the severity of the
23 disease depends on the affected species. For example, fire salamanders, *Salamandra*
24 *salamandra*, are lethally susceptible to Bsal, independent of the dose, while alpine

25 newts, *Ichthyosaura alpestris*, shows a dose-dependent Bsal disease course, making
26 them moderately susceptible. Due to their dispersal abilities and their frequent co-
27 occurrence with the highly susceptible fire salamander, alpine newts are seen as notable
28 vectors of chytridiomycosis (Stegen et al., 2017). On top of that, they are considered to
29 be the most consistently infected species in the wild for Bd, thus further enhancing their
30 disease carrying and transmission potential (Spitzen-Van Der Sluijs et al., 2014).

31 The alpine newt is currently listed as a “least concern” species in the IUCN Red List of
32 Threatened Species owing to its wide distribution, low specificity in habitat
33 requirements and presumed large populations. The species and its habitat are also
34 lawfully protected by the Bern Convention, a European treaty aiming at conserving
35 Europe’s natural heritage. Nonetheless, a continuously decreasing trend is observed for
36 European populations (Arntzen et al., 2009). Habitat destruction and fish introduction
37 are the most prominent factors responsible for the population declines (Arntzen et al.,
38 2009).

39 The alpine newt requires both suitable terrestrial and aquatic habitats. Generally, they
40 are absent from large water bodies and rivers, which often contain fish. Most other
41 water bodies, such as (garden) ponds, temporary pools, ditches, fens, (concrete) cattle
42 drinking basins and even ruts can be occupied for reproduction. On land, they are
43 present in a wide variety of habitats ranging from forests over pastures and gardens to
44 heavily disturbed lands where they use rocks, wood and trash as hiding places during
45 hibernation. They seem to avoid large cultivated agricultural areas and prefer deciduous
46 forested zones owing to the presence of multiple hiding places (Arntzen et al., 2009;
47 van Delft, 2009). Even though knowledge is available about the habitat this species

48 inhabits, quantitative information, which is useful for management strategies of natural
49 environments, is lacking.

50 Decision tree models have widely been used for quantitative habitat suitability analyses,
51 owing to their ease of interpretation and reliability (Boets et al., 2010; Everaert et al.,
52 2011; Hoang et al., 2010; Zarkami et al., 2010). The classification tree is a purely data-
53 driven ecological model describing the non-linear statistical relationship between a
54 nominal response variable and numerical predictors that are split according to certain
55 threshold values (Van Echelpoel et al., 2015). In this way, the occurrence of a certain
56 species can be linked to environmental conditions.

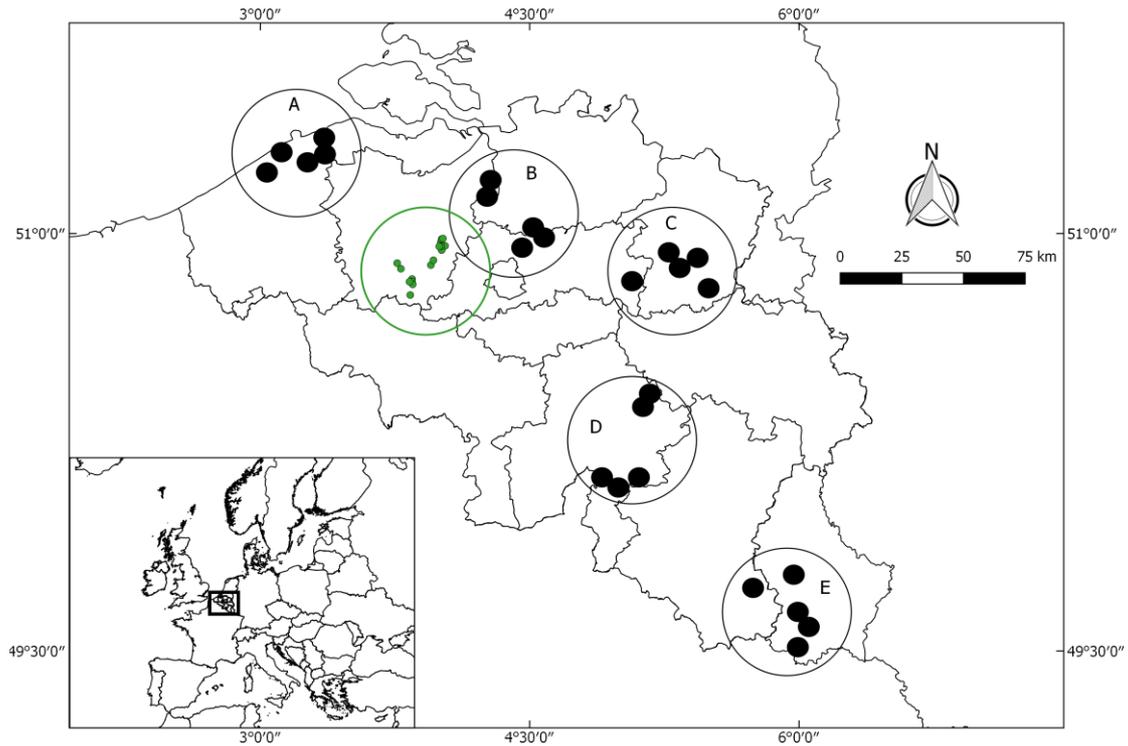
57 Here, we aim to: (1) develop a classification tree based habitat suitability model relating
58 local pond conditions (predictor variables) to alpine newt presence/absence (response
59 variable); (2) evaluate the obtained model using a combination of technical criteria,
60 expert knowledge and validation with independent field data; (3) provide practical
61 information for decision makers regarding the implementation of the model in
62 management.

63 **Materials and Methods**

64 **Study area**

65 A habitat suitability decision tree model was trained, optimized and validated using
66 available data from 125 farmland ponds in Belgium and Luxemburg that were sampled
67 in 2008 (cf. Lemmens et al., 2018). Ponds were distributed over five biogeographical
68 regions (i.e. Gutland, Chalk region, Sand region, Polders and Loam regions). Each
69 region had 5 clusters (within 38 km²) of 5 randomly selected ponds. In this way, ponds
70 within each cluster shared a similar regional species pool.

71 Additional field data were collected from 18 ponds in the province of East Flanders
72 between 8 and 13 May 2017 (**Figure 1**). The purpose of this new data was to
73 independently test the model's applicability. For the latter, ponds were selected based
74 on information on newt presence obtained from local stakeholders (land owners and
75 nature conservation organisations). We aimed to equally include ponds with and
76 without alpine newts in order to test the model's prediction power for both situations.
77 Four of the selected ponds were located in rural urban areas and nine ponds were
78 situated in nature reserves. These natural areas are characterised by wet meadows,
79 brushwood and swampy forests. Furthermore, we selected five ponds in a more
80 agricultural environment (i.e. arable land and pasture).



81

82 **Figure 1: Map of the study area with the sampling regions Polders (A), Sand**
 83 **region (B), Loam region (C), Chalk region (D) and Gutland (E) each containing**
 84 **five clusters represented by the black dots. Every cluster comprises five sampling**
 85 **sites (ponds). The sites that were additionally sampled in 2017 are indicated in**
 86 **green.**

87 **Field data collection and sample analyses**

88 Decision tree model training data consisted of morphometric, physical-chemical, and
 89 biological data. These were collected once for each of the 125 farmland ponds during
 90 the summer of 2008 based on the methodology of Declerck et al. (2006). A detailed
 91 description can be found in Appendix S1 in the *Supporting Information*. Pond sampling
 92 started with visually gathering information about pond characteristics. The model
 93 excluded data from land use and structural pond connectivity (i.e. number of nearby

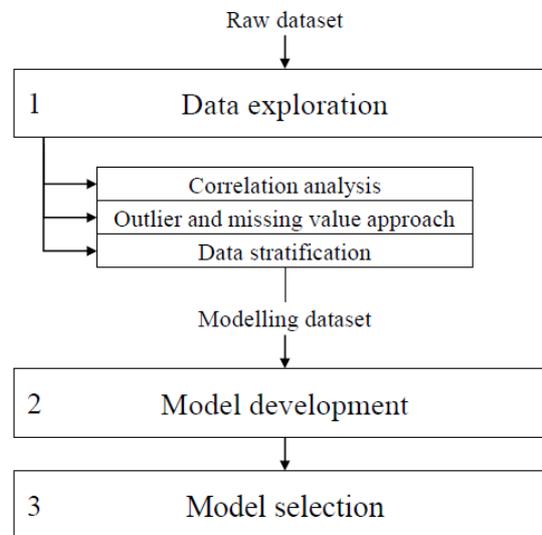
94 ponds) thereby focusing solely on the suitability of the aquatic habitat for alpine newt.
95 Afterwards, pond water was sampled for the measurement of pH, water transparency,
96 electrical conductivity (EC), dissolved oxygen (DO), temperature (T), suspended solids
97 (SS), chlorophyll a (Chl_a), total nitrogen (TN), total phosphorous (TP), alkalinity,
98 hardness and ions of calcium (Ca²⁺), sulphate (SO₄²⁻) and chloride (Cl⁻). For assessing
99 the fish community, the Point Abundance Sampling by electrofishing (PASE) was
100 applied as this method is suitable for catching small juvenile fish (body size > 6 to 7
101 mm) in standing water bodies (Garner, 1996; Perrow et al., 1996). The amount of
102 sampling locations varied according to the pond size. Per acre, 6 to 8 anode immersions
103 were done randomly, and fish were collected with a hand net, identified, counted and
104 returned to the pond. The presence of amphibian species was determined through direct
105 visual observation and capture during sweep net sampling (25 cm x 25 cm; mesh size:
106 250 µm) in the open water areas and vegetated zones. The total sweep net sampling
107 time varied with pond size and the time spent in each zone was adapted according to
108 their respective percentage. Additionally, these vertebrates might have been
109 accidentally caught whilst electrofishing. All caught amphibians were identified,
110 counted and released back to their natural environment.

111 The data required for the model testing (the additional 18 samples) consisted of less
112 variables as indicated by the trained model. The presence of fish and amphibians was
113 determined using floating fikes (50 cm x 30 cm x 25 cm) that were placed in the ponds
114 during one night. The number of fikes depended on the pond size and varied from two
115 to eight aiming at a catching effort of 3 to 4 fikes per are. They were equidistantly
116 placed close to the shores. All species were identified and release back to the pond. This
117 sampling procedure differed from the one from 2008 as the purposes of both studies

118 were not the same. For the present research, solely amphibian and fish occurrences were
119 required for which both methods provided accurate information, despite their different
120 sampling strategies. Finally, sludge depth was determined according to the procedure
121 described in Appendix S1.

122 **Data pre-processing**

123 In order to quantitatively investigate the relationship between the occurrence of alpine
124 newt in pond ecosystems and local pond conditions, classification tree models were
125 built. The modelling procedure consisted of three parts (**Figure 2**). As this type of
126 black-box model is purely data-driven, its quality is highly depending on the data. We
127 therefore checked all data for missing values, any type of error and skewed distributions
128 prior to model development and selection (**Figure 2 – Step 1**).



129

130 **Figure 2: Overall modelling procedure for classification tree construction. Data**
131 **pre-processing via correlation, outlier, missing value and stratification analyses**
132 **(step 1) preceded model development (step 2) and model selection (step 3).**

133 The raw data was converted into an optimized modelling dataset in three steps based
134 on Van Echelpoel et al. (2015). We conducted a *correlation analysis* aiming at finding
135 strongly correlated variables characterized by a correlation coefficient ρ of at least 0.7
136 (Dancey & Reidy, 2004). Oxygen and temperature were excluded from the dataset as
137 the measurements can strongly fluctuate during the day and were therefore considered
138 not representative (e.g. Andersen et al., 2017; Whitney, 1942). In case of collinearity
139 between variables, we decided to retain the most direct predictor variable. This decrease
140 in dataset dimension is favourable as it results in a lower computation time and reduces
141 model complexity. Associations among environmental variables were also investigated
142 via a Principal Component Analysis (PCA) using R software and the *vegan* package.
143 All records containing *missing entries* were retained during the entire modelling
144 procedure in order to incorporate as much information as possible from the available
145 dataset. For the PCA, missing values were beforehand statistically imputed via the
146 expectation-maximization algorithm (EM-PCA) after which a biplot was constructed
147 from the completed dataset. Similarly, *outliers* were considered to be an inherent and
148 valuable part of the data, as argued by Orr et al. (1991). Decision trees in general are
149 quite robust against skewed distributions due to outliers, especially models built with
150 the C4.5 algorithm, which was used for model development in the present research
151 (John, 1995).

152 The classification tree model has to be able to predict both presence and absence of
153 alpine newts with an equal accuracy. Our data however contained less presence records
154 than absences. To achieve a balanced design, we *stratified the dataset* by removing
155 absence records, thereby making the urodelan species distribution uniform. The
156 elimination procedure was done geographically so that every region (**Figure 1: A – E**)

157 occurred in the subset. Per region, an equal number of ponds with and without alpine
158 newts were randomly selected. This fraction was equal to the proportion of the total
159 amount of presence records to the total absences. A major drawback of this procedure
160 is the loss of data. The manipulation was repeated ten times and optimal classification
161 tree models were developed for each data subset to verify the model robustness against
162 data manipulation.

163 **Model development and selection**

164 Decision trees are suitable models when it comes to small datasets, which is the case in
165 the present research (Everaert et al., 2011). After data pre-processing, model building
166 (**Figure 2 – Step 2**) was done with the software Waikato Environment for Knowledge
167 Analysis (Weka, version 3.8.3) for all ten stratified datasets using the J48 algorithm,
168 which is the Java implementation of the C4.5 algorithm (Witten & Eibe, 2005). The
169 software accounts for missing values by classifying them with weights proportional to
170 frequencies of the observed non-missing values. As model parameterization can
171 considerably influence the model outcome and thus the applicability towards end-users,
172 we tested different settings related to the size and growth of the classification tree
173 (Everaert et al., 2016). Data overfitting during model training often leads to large and
174 complex trees at the expense of predictive power. Pruning is a means to prevent
175 overfitting by removing knowledge rules that contribute little and thus limiting tree size
176 (Witten & Eibe, 2005). The degree of pruning was verified via the pruning confidence
177 factor PCF ('confidenceFactor' in Weka) and the minimum number of instances per
178 leaf ('MinNumObj' in Weka). PCF is a post-pruning parameter as it compares model
179 reliability of a classification tree with its subtrees after replacing branches by leaves,

180 thereby affecting the error estimates in each node. More specifically, increasing PCF
181 values decreases the difference between the error estimate of a parent node and its splits.
182 We therefore tested PCF values of 0.05, 0.10, 0.15, 0.25 and 0.35 for each of the ten
183 datasets during model training. Pre-pruning was also applied by varying the minimum
184 amount of instances a leaf should contain before it is split (test settings of MinNumObj:
185 2, 5, 7, 10, 12).

186 Regarding model validation, we applied a ten-fold cross-validation, as recommended
187 by Han et al. (2011). Parameter testing led to the construction of 25 classification tree
188 models per stratified set, i.e. the sum of all PCF combinations per MinNumObj element
189 without repetition. For each array of models, we identified the most optimal parameter
190 set by assessing the classification trees mainly on the models' technical performance.
191 The percentage of correctly classified instances (%CCI) and Cohen's kappa (κ) served
192 as criteria for testing the models' fit. The %CCI corresponds to the percentage of ponds
193 that were classified correctly as a pond with or without alpine newts, i.e. true positive
194 and true negative predictions, respectively. κ accounts for all correctly predicted
195 presences and absences adjusted to the amount of agreement expected by chance
196 (Cohen, 1960; Hoang et al., 2010; Manel et al., 2001). Models with a CCI higher than
197 or equal to 70% and a Cohen's kappa exceeding 0.4 were considered to be sufficiently
198 reliable (Goethals et al., 2007). In addition to technical criteria, model selection (**Figure**
199 **2 – Step 3**) also depended on: (1) the complexity of the model (less complex trees are
200 more user-friendly); (2) model robustness (being the frequency of recurrence of a
201 specific model over all models and stratified subsets); and (3) ecological relevance. For
202 the latter, which expert-knowledge was used to check if the observed patterns were
203 likely from an ecological point of view. This selection assessment eventually led to the

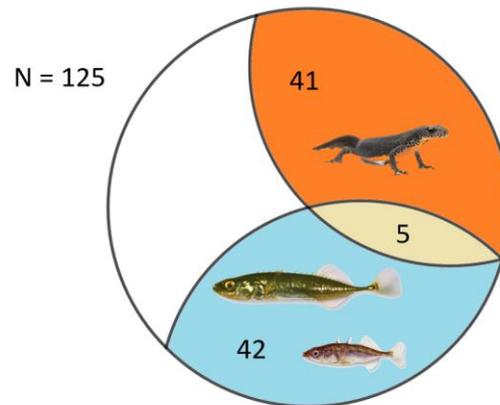
204 proposal of one model that was tested with the independent data as collected in 2017.
205 The if/then rules were implemented in Excel, after which %CCI and κ were calculated
206 and evaluated by comparing predictions with observations via a confusion matrix.

207 **Results**

208 **Data optimization**

209 The initial dataset consisted of 41 predictor variables, of which 9 were nominal and 32
210 were numerical (Appendix S2). The dimension of the dataset was reduced by
211 conducting multiple correlation analyses to detect collinearity between predictor
212 variables and by selecting the most direct variable in case of significant correlations
213 (Appendix S3). The percentages of shade, overhanging trees and trees on the margin of
214 the pond were found to be highly correlated. We therefore decided to only include the
215 percentage of shade as a proxy for the light entering the pond in subsequent analyses.
216 Similarly, we decided to retain surface area of the pond above other dimension variables
217 (i.e. length, width, volume) due to their high mutual correlation. The average bank angle
218 was chosen over minimum and maximum bank angle. Five records had missing values,
219 i.e. three with unavailable data for the variables hardness, sulphate and chloride, and
220 two other instances did not have data about fish presence. The total dataset contained
221 information on 125 ponds of which 41 with only alpine newts with no fish, while 42
222 were solely inhabited by fish and contained no alpine newts. The most commonly
223 encountered fish were *Pungitius pungitius* (ninespine stickleback), *Gasterosteus*
224 *aculeatus* (three-spined stickleback) and *Carassius gibelio* (Prussian carp), occurring
225 in 71.1%, 26.1% and 21.7% respectively of the ponds with fish. There were only 5
226 ponds in which both alpine newt and fish were present (**Figure 3**). The PCA biplot
227 indeed shows that alpine newt presence and fish occurrence are strongly negatively
228 associated (Appendix S4). Additionally, alpine newts seem to be positively associated

229 with the percentage of vegetation and dead plant material and show a negative
230 association with variables linked to eutrophication such as sludge, TN, TP, SS and Chl_a.



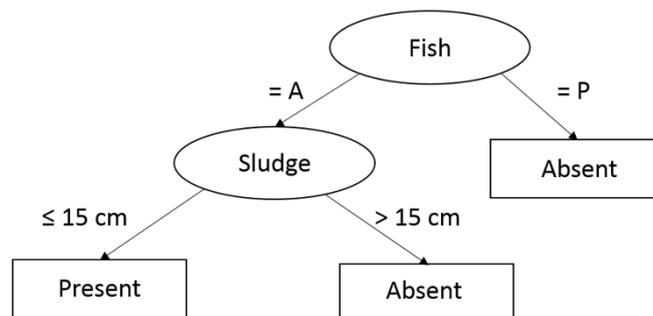
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232 **Figure 3: Venn diagram of the prevalence of fish and alpine newt in the optimized**
233 **dataset containing 125 ponds (N).**

234 **Model development, selection and testing**

235 All constructed models were first assessed on their technical performance, calculated
236 via %CCI and Cohen's κ . An extensive overview of the results of all parameterizations
237 and stratifications is provided in Appendix S5. There were 220 models of 250 possible
238 combinations (88.0%) that fulfilled the requirements of a %CCI and Cohen's κ of at
239 least 70% and 0.40 respectively. A total of 42 different classification trees could be
240 distinguished. The model that returned most frequently, i.e. in 32.3% of all cases, was
241 also amongst the most simple of models (maximum of two nodes) and robust as it
242 recurred in 6 out of 10 stratified datasets. The key factors in this model were the
243 dichotomous variable fish occurrence (absence/presence) followed by sludge thickness
244 split at 15 cm (**Figure 4**). If fish are present in a pond ecosystem, alpine newts are
245 predicted absent by the model, and in fishless ponds the species tend to be absent when

246 the sludge layer is > 15 cm thick. The second most common model, i.e. in 14.1% of all
 247 reliable models, was the same as the one described in **Figure 4**, apart from the threshold
 248 value for sludge thickness, which was set at 22 cm. Furthermore, in 9.6% of all reliable
 249 models, water transparency, measured via sneller depth (root node), and fish (internal
 250 node) determined habitat suitability. A pond characterised by a sneller depth smaller
 251 than or equal to 10 cm, is predicted to contain no alpine newts. In less turbid ponds (i.e.
 252 sneller > 10 cm), alpine newts are likely to be absent in case the pond is inhabited by
 253 fish. Both models were present in 3 and 4 out of 10 stratifications, respectively. Due to
 254 this lower model robustness, we deemed the model in **Figure 4** to be a more accurate
 255 representation of alpine newt occurrence in ponds in our data. All other reliable models
 256 occurred rather sporadically (< 4.6%), were less robust as they were all the result from
 257 a specific subset, and were more complex consisting of 3 to 6 nodes. Note that the most
 258 simple models occurred at higher levels of pre-pruning, while more complex and lower
 259 performing models on average could be linked to less pre-pruning.



260

261 **Figure 4: Most consistently returning model of all reliable classification trees**
 262 **(%CCI ≥ 70% and $\kappa \geq 0.40$). Fish presence results in absence of alpine newts, while**
 263 **in fishless ponds sludge depth is considered to be the most decisive factor.**
 264 **A=absent; P=present.**

265 The obtained model described in **Figure 4** was tested with independent newly collected
266 field data. Alpine newts were present in 8 out of 18 sampled ponds and we found two
267 fish species in 5 of the ponds, namely *Pungitius pungitius* and *Gasterosteus aculeatus*.
268 Sludge depth varied from 1 cm to 42 cm with an average of 10.9 cm and a standard
269 deviation of 12.2 cm. The model was able to correctly classify 72.2% of all cases and
270 combined with a κ statistic of 0.46 this indicated a satisfactory model performance in
271 an ecological context (Goethals et al., 2007).

272 **Discussion**

273 **Model relevance**

274 The alpine newt is a urodelan species which is generally believed to have only few
275 specific habitat requirements (van Delft, 2009). This idea is supported by the relatively
276 simple structure of the best performing model from the present study (**Figure 4**), which
277 only contains fish presence/absence and sludge thickness as major steering variables
278 determining the presence/absence of alpine newts. This classification tree is user-
279 friendly, due to its simplicity and reliability ($\kappa > 40\%$ for test data). We thus propose
280 that the model can be used for management purposes.

281 The proposed model indicates a lack of co-occurrence between alpine newts and fish.
282 Indeed, fish compete for the same resources and/or directly predate on the amphibian
283 community in the same habitat (Winandy et al., 2015). For example, Pearson & Goater
284 (2009) observed an almost complete extinction of *Ambystoma macrodactylum* larvae
285 (long-toed salamander) and a 39% reduction in salamander survival in the presence of
286 the predatory fish *Oncorhynchus mykiss* (rainbow trout). In another example, the non-
287 piscivorous *Pimephales promelas* (fathead minnows) outcompeted the urodele for
288 zooplankton as a food resource. Several other authors have reported similar outcomes
289 on the effect of fish presence on newt communities (e.g. Cabrera-Guzmán et al., 2017;
290 Monello & Wright, 2001; Pagnucco et al., 2011). The most commonly encountered
291 fishes in the assessed ponds of the present study were sticklebacks that can predate on
292 newt egg masses and larvae. They are also strong competitors as they feed on similar
293 resources, such as zooplankton and macroinvertebrates (Jakubavičiūtė et al., 2017).
294 Fish presence can also induce behavioural changes in newts and have non-consumptive

295 effects. For example, Winandy & Denoël (2013) reported that alpine newts use shelters
296 (micro-habitats) more frequently and significantly reduce their sexual activity in the
297 presence of *Carassius auratus* (goldfish). Multiple non-predatory fish can have
298 detrimental impacts on aquatic vegetation and can increase water turbidity, thereby
299 impeding foraging and signalling efficiency during mating (Richardson et al., 1995;
300 Secondi et al., 2007). Furthermore, fish have a substantial negative effect on newt
301 paedomorphs, i.e. a non-metamorphosized alternative adult phenotype with larval traits
302 such as gills (Denoël et al., 2005). This uncompleted form of transformation is common
303 amongst alpine newts, smooth newts and palmate newts, making them even more
304 susceptible to fish co-occurrence (Denoël et al., 2009).

305 In fishless ponds, our data suggest that sludge thickness determines alpine newt
306 occurrence. The amount of sludge is not necessarily a causal factor, as it can be linked
307 to several processes. Firstly, sludge thickening occurs during the natural succession of
308 pond ecosystems. Unmanaged shallow ponds will gradually fill up, through sediment
309 influx from streams or rivulets after heavy rains, thereby reducing pond depth and
310 allowing vegetation to gradually colonize the entire ecosystem (Chauchan, 2008). Our
311 PCA results (Appendix S4), however, show that alpine newt presence is positively
312 correlated with the percentage of vegetation cover, making it rather unlikely that natural
313 succession always decreases pond habitat suitability. Indeed, this urodelan species
314 commonly occurs in vegetated pools where they fold eggs in leaves to protect them
315 from predation (van Delft, 2009). In our dataset, sludge is strongly associated with
316 levels of total nitrogen, total phosphorous, chlorophyll a and suspended solids. This
317 suggests that the degree of eutrophication, translated via sludge thickness in the model,
318 is likely to have a major influence on the occurrence of alpine newts. Eutrophication

319 leads to algae-dominated systems with sparse submerged vegetation. The lack of
320 submerged vegetation reduces the amount of suitable egg depositing habitats, while
321 high turbidity affects the feeding and mating behaviour of newts (Secondi et al., 2007).

322 **Implications for management**

323 Regarding management practices for alpine newt conservation in an agricultural
324 landscape, our results suggest that ponds which from time to time fall dry might be
325 highly suitable habitats. Recurrent dry-stands not only ensure fish absence, but also
326 reduce eutrophication. Ponds that periodically dry out have less sludge accumulation
327 due to organic oxidation during the dry phase. It is advisable that such ponds dry out
328 earliest in late summer, by which time offspring of alpine newts have left the pond
329 (Hermy & De Blust, 1997). Larval growth rate can, however, vary depending on a
330 pond's hydroperiod due to developmental plasticity (Griffiths, 1997). Temporary ponds
331 often contain unique biological communities resulting in a high pond conservation
332 value (Biggs et al., 1994; Collinson et al., 1995). In addition to regular dry-stands,
333 buffer strips consisting of e.g. reed, soft rush and water plantain should be encouraged
334 as a protective measure against nutrient input from surrounding land, especially in case
335 of cattle drinking ponds. This can also reduce the negative impact of agricultural
336 contaminants, such as pesticide residues and heavy metals (Hermy & De Blust, 1997).
337 Patches of dense, high grass can be added to the buffer zone so that adult newts can
338 forage and find shelter. The herb layer then preferably gradually evolves to shrubs and
339 forest as these elements provide excellent hibernation and shelter places, such as
340 mouldered branches and trunks (Hermy & De Blust, 1997).

341 Sludge accumulation can also be countered by dredging and vegetation removal, mainly
342 to control natural succession and to preserve the aquatic ecosystem. However, it is
343 inadvisable that all ponds in a landscape be dredged simultaneously because this could
344 lead to a significant decrease in habitat hence reduced aquatic gamma diversity (Biggs
345 et al., 1994; Hassall, 2014). Teurlinx et al. (2018), for example, promote successional
346 stage heterogeneity via the Cyclic Rejuvenation through Management (CRM)
347 approach, where aquatic water bodies are periodically and asynchronously reset.
348 Related to this, managers should invest in connecting ecologically diverse ponds to
349 maximize landscape-wide biodiversity (Biggs et al., 2000). Connectivity of different
350 ponds plays a major role in maintaining a healthy gene flow amongst amphibian
351 metapopulations (Stevens et al., 2006). Functional connectivity, related to the newt
352 dispersal capabilities and colonization of ponds, is even more crucial as it is the actual
353 connectivity from the perspective of the animal. As newts have a dispersal capacity of
354 around 400 meters, ponds should be closer to each other than for the common toad,
355 which migrates in a radius of 2 200 meters (Hermy & De Blust, 1997). Ecological
356 corridors play an essential role in pond connectivity. For the alpine newt, Emaresi et al.
357 (2011) identified forests to be major corridors, while urban areas act as significant
358 dispersal barriers.

359 **Conclusions**

360 The present research provides a reliable and user-friendly classification tree model as a
361 management tool to assess the habitat suitability of farmland ponds for alpine newts.
362 The major steering variables within local habitats are the presence of fish and the
363 thickness of the sludge layer. Ponds without fish provide suitable habitat for alpine
364 newts, while the species also prefers a sludge thickness less or equal to 15 cm. As the
365 latter is often linked to the degree of eutrophication, we advise decision makers to create
366 ponds that dry out annually to reduce the impact of eutrophication and to eliminate fish.
367 In addition, construction of a buffer zone around ponds further limits the nutrient input
368 from land to the aquatic ecosystem, especially in agricultural areas where fertilization
369 is widely applied.

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371

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