Predicting the occurrence of stoneflies (Plecoptera) on the basis of water characteristics, river morphology and land use

Koen Lock and Peter L. M. Goethals

ABSTRACT

Stoneflies are macro-invertebrates that are sensitive water quality indicators. Here, their occurrence was modelled based on physical–chemical water characteristics, river morphology and land use with five different modelling techniques. In a case-study in Flanders, stoneflies were found in 219 samples and two sets of absence data were gathered: 219 random samples from sites without stoneflies and 219 samples from sites downstream of each sampling site where stoneflies were observed. With both random and downstream absences, logistic regressions, artificial neural networks, support vector machines, random forests and classification trees could all successfully predict stonefly occurrence. For most environmental parameters, significant differences were found between sites with and without stoneflies. As stoneflies were only detected in a few percent of the samples, the ecological water quality is obviously still too low in most watercourses. Based on planned water quality improvement measures, an ensemble forecast using the five mentioned modelling techniques predicted that stonefly prevalence will only increase marginally by 2015 and 2027. To meet the European Union Water Framework Directive requirements, which states that all surface waters should obtain a good ecological quality, a more ambitious management plan is needed to decrease nutrient concentrations and improve habitat quality.

Key words | ecological water quality, ensemble forecasts, Flanders, Water Framework Directive

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INTRODUCTION

Achieving a good ecological status of groundwater and surface water in Europe by 2015 is the main objective of the European Union Water Framework Directive (WFD; European Council 2000). To assess water quality, the WFD requires the use of biotic indicators such as macrobenthic fauna, fish fauna and aquatic flora. All member-states have to develop methods that are concurrent with the WFD. In Flanders, where the presented case-study was performed, the Multimetric Macroinvertebrate Index Flanders (Gabriels *et al.* 2010) was developed in order to meet the requirements of the WFD. In this index, stoneflies are recognised as the most sensitive group of water invertebrates, which only occur in waters with a high ecological water quality. Despite their importance as water quality indicators, stoneflies only recently received attention in Flanders (Lock & Goethals 2008).

Flanders (the northern, Dutch speaking part of Belgium) has a population of 6.2 million inhabitants and a high population density of 456 citizens/km^2. About 87% of the households are connected to a sewage system, however only 70.3% are actually treated (VMM 2009a). As rainwater is often not collected separately, untreated water is regularly discharged after heavy rains, which results in problematic drops in dissolved oxygen concentration and high levels of substances such as ammonium. Flanders is also heavily industrialised and the intensive agriculture causes a heavy pressure as 53% of the land is used for agriculture (VMM 2009a). In addition, thousands of weirs have been built for

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flood control, hundreds of kilometres of artificial banks have been installed and the majority of the river channels have been straightened. Although the situation in Flanders is probably more problematic than in most other countries in Europe due to the high population density, the other member-states have to deal with similar problems.

As is the case in most European countries, river management in Flanders has been conducted at the river basin level using wastewater treatment plants and imposed standards of effluent concentrations. Although these measures resulted in a significant improvement of the chemical and ecological water quality since the early 1990s (VMM 2010), many Flemish watercourses still lack the 'good' ecological status required by the European Union WFD. This is also reflected by the scattered distribution of the different stonefly species in Flanders (Lock & Goethals 2008).

Ameliorating water quality from bad to poor or moderate did not help populations of sensitive organisms such as stoneflies. Recently, most waterbodies that had a bad or poor ecological water quality for macroinvertebrates have improved due to the installation of waste water treatment plants and the more stringent effluent standards; however, more than half of the locations that had a very good score for macroinvertebrates have declined (VMM 2009a). A first step should therefore be to protect the sites which still have a high ecological water quality and contain sensitive organisms such as stoneflies. As most suitable habitats are now isolated, populations are extremely vulnerable to extinction and recolonisation possibilities might be limited (Lock & Goethals 2008). Therefore, intentional interventions are also needed in order to connect isolated populations by solving the present bottlenecks that prevent the expansion of remaining populations. To efficiently allocate restoration efforts, ecological models are useful for the assessment of these bottlenecks in the river basin (Mouton *et al.* 2008).

Any given modelling technique might be efficient for one dataset, however it might fail for another, thereby rendering the identification of 'the' best modelling technique impossible. Another difficulty with the use of species distribution models is that the number of available techniques is large and keeps rising, making it difficult to select the most appropriate methodology. Recent analyses also demonstrated that discrepancies between different techniques can be very large, making the choice of the appropriate model even more difficult, which is especially true when models are used to project distributions of species under future scenarios. Therefore, Thuiller *et al.* (2009) proposed that ensemble forecasts with several modelling techniques should be made and that the resulting range of predictions should be analysed rather than relying on the results of a single model. In the present study, five modelling techniques were applied to predict stonefly occurrence: logistic regressions (LR), artificial neural networks, support vector machines (SVM), random forests and classification trees (CT). With the exception of SVM, which only recently became popular for modelling ecological data (Ambelu *et al.* 2010; Hoang *et al.* 2010; Pino-Mejias *et al.* 2010), all these modelling techniques have been frequently used for habitat suitability modelling.

The aim of the present study was to predict the presence or absence of stoneflies in Flemish watercourses in order to provide insights useful for water quality management. Not only the traditional physical–chemical parameters were used to model the occurrence of stoneflies with the five mentioned modelling techniques, but it was also investigated whether other parameters such as land use type and river morphology could improve model performance. To evaluate the influence of the planned measures for quality improvement, an ensemble forecast using the same five modelling techniques was subsequently performed to predict stonefly prevalence (a fraction of samples where stoneflies are present) in 2015 and 2027 based on modelled future oxygen and nutrient concentrations.

METHODS

Macroinvertebrate data

In the context of water quality monitoring by the Flemish Environment Agency, macroinvertebrates have been sampled at several thousand sampling points in Flanders since 1989. Sites are usually sampled every three years between April and October. During monitoring, macroinvertebrates are sampled by kicksampling using a standard handnet, as described by Gabriels *et al.* (2010). Stoneflies were identified to species level during a previous study

(Lock & Goethals 2008); however, most species were very rare in Flanders, which makes it unfeasible to develop species specific habitat suitability models. Therefore, it was decided to model the presence/absence of stoneflies in general during the present study.

Environmental parameters

Conductivity, pH and dissolved oxygen were always measured in the field during macroinvertebrate sampling. Other chemical parameters (Table 1) were retrieved from monitoring data of the chemical water quality database of Flemish surface waters. As the chemical monitoring, which was usually performed on a monthly basis, was not carried out simultaneously with the macroinvertebrate sampling, measurements from the last date before macroinvertebrate sampling were used. The structural parameters included slope, sinuosity and river morphology. The slope of a watercourse was determined based on the difference in height between two points 1,000 m apart using GIS (geographic information system) software applied on the Flemish Hydrographic Atlas (AGIV 2006). The same data were used to determine the sinuosity on a stretch of 100 m. River morphology was evaluated based on pictures of the sampling sites: pool-riffle pattern and meandering were both categorised from 0 (absent) to 5 (well developed) (Figure 1) and summed, which yielded a score from 0 to 10. Aerial photographs were used to distinguish five different land use types. Along a stretch of 500 m upstream of the sampling point, the main land use type along the watercourse was assigned to forest, meadow, arable land, urban or industry. All parameters of the locations used during the present study are given in the supporting material. Differences in environmental parameters between sites where stoneflies were present and absent were analysed using Mann–Whitney U tests (StatSoft 2004). Chi-square tests were used to test the difference in land use types between sites with and without stoneflies.

Modelling

In total, stoneflies were found in 219 samples from Flemish watercourses. To obtain a prevalence of 50%, the same number of absences was used for modelling. Two sets of absence data were retrieved. The first set contained 219 samples randomly selected from sampling sites where no stoneflies had been found. These samples were randomly selected from the database of the Flemish Environment Agency, which contains about 10,000 samples distributed

Table 1 | Median values (with 10 and 90 percentiles) of the assessed environmental parameters in samples where stoneflies were present, in samples downstream of samples where stoneflies were present and in random samples where stoneflies were absent (BOD: biological oxygen demand; COD: chemical oxygen demand). Parameters differing significantly with the samples where stoneflies were present are indicated with * in the absence columns

Parameter	Unit	Present	Absent (downstream)	Absent (random)
pH		7.44 (6.47–8.20)	7.46 (6.52–8.07)*	7.71 (7.28–8.04)
Conductivity	μS/cm	321 (139–625)	340 (209–758)*	805 (434–1390)*
Oxygen	mg/L	9.50 (7.65–11.1)	8.46 (3.64–10.8)*	6.58 (3.04–10.7)*
BOD	mg/L	2.5 (2.0–3.0)	3.0 (2.0–13)*	5.0 (2.2–13)*
COD	mg/L	23 (8.6–52)	24 (11–200)*	32 (13–77)
Ammonium	mg N/L	0.318 (0.0880–0.536)	0.640 (0.195–2.33)*	1.50 (0.229–7.22)*
Nitrite	mg N/L	0.029 (0.011–0.070)	0.057 (0.023–0.13)*	0.16 (0.030–0.39)*
Nitrate	mg N/L	3.13 (0.546–8.84)	2.88 (0.360–6.00)	3.65 (0.372–9.14)
Kjeldahl nitrogen	mg N/L	1.32 (0.800–2.54)	2.05 (1.10–4.97)*	3.30 (1.60–9.14)*
Phosphorus	mg P/L	0.50 (0.091–0.60)	0.50 (0.16–1.1)*	0.68 (0.30–1.9)*
Orthophosphate	mg P/L	0.080 (0.028–0.16)	0.15 (0.060–0.31)*	0.30 (0.097–1.0)*
Slope	m/1,000 m	2.59 (0.716–20.5)	1.91 (0.563–6.64)*	0.888 (0.133–3.67)*
Sinuosity		1.04 (1.00–1.25)	1.02 (1.00–1.13)*	1.02 (1.00–1.22)
River morphology	Classes from 0–10	5 (3–8)	4 (0–6)*	3 (0–5)*

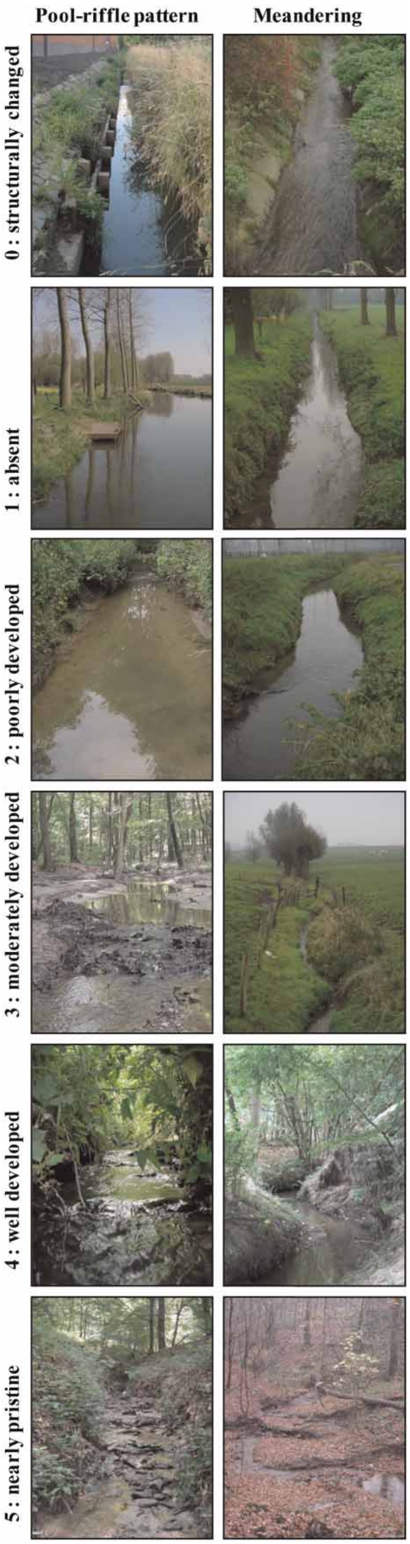

Figure 1 | Pool-riffle pattern and meandering were categorised from 0 to 5 based on pictures of the sampling sites.

across Flanders. In the second set, samples were selected from sites immediately downstream of each of the 219 sampling sites where stoneflies were observed. These downstream samples were specifically chosen in order to determine why stoneflies were no longer present downstream from sites containing stoneflies. Because the monitoring network in Flanders is quite dense, the downstream samples were situated on average only 2.4 km (standard deviation: 1.6 km) from the sites containing stoneflies.

Each of the three datasets was randomly split into two thirds for training and one third for validation. During calibration, a 10-fold cross-validation was used to avoid overfitting. Five modelling techniques were used to model the presence/absence of stoneflies: LR, CT, random forests, artificial neural networks and SVM. LR are used for the prediction of the probability of occurrence of an event by fitting data to a logit function logistic curve. Here, a multinomial logistic regression with ridge estimator was used as a generalised linear model. The ridge value of the log-likelihood was set to 10^{-8}. Coefficients and odds ratios were derived for the attributes. CT summarise the relationships between explanatory variables and the response variable (presence/absence of stoneflies) in a dichotomously branching tree. Each bifurcation is defined by a certain value of one of the explanatory variables dividing the dataset in two more homogenous subsets. CT were grown automatically using the J48 algorithm that minimises the impurity of the subsets (Witten & Frank 2005). A fully grown tree would explain the training data with a high accuracy, but it would fail for unseen data because of overfitting. CT generality was increased by pruning, which usually yields simpler trees that result in better classification of unseen data (Dakou *et al.* 2007). The confidence factor was set to 0.25 and the minimum number of instances per leaf was set to 2. A dichotomous J48 tree was generated with an indication of the number of leaves and the tree size. Random forests (RF) are an ensemble learning alternative to CT: many trees are constructed, with classes that are predicted by majority vote. An RF is grown by a procedure called bagging, which is short for bootstrap aggregating, where each tree is independently constructed by using a bootstrap sample (with replacement) of the entire dataset. Each node of the trees is split using only a subset of the explanatory variables chosen randomly for each tree. Ten trees were generated and one was used as a random seed number. The output included the number of random features and the out of bag error. Artificial neural networks (ANN) are non-linear statistical data modelling tools that are based on the architecture of biological neural networks and consist of a group of interconnected computing units or neurons. During a learning phase, connection weights among the neurons are adapted by backpropagating training data through the net. The number of hidden layers was set to (attributes + classes)/2, the learning rate was set to 0.3 and the momentum to 0.2, the randoms seed to 0, the training time to 500 epochs and the validation threshold to 20. The weights of the threshold, the nodes, the inputs and the attributes were derived. SVM are developed from a linear classifier using a maximum hyperplane to separate two classes. In a non-linear case, the central idea of classification with SVM is to map training data into a higher-dimensional feature space and to compute separating hyperplanes that achieve maximum separation between classes. The maximum separation hyperplane is only a function of the training data that lie on the margin and are called support vectors. Platt's sequential minimal optimisation algorithm (Keerthi *et al.* 2001) was used for training a support-vector classifier, which replaces all missing values, transforms nominal attributes into binary ones and multi-class problems are solved using pairwise classification. The complexity parameter was set to 1, the tolerance parameter to 0.001, epsilon to 10^{-12}, the random seed to 1, the polykernel had a cache size of 250,007 and an exponent value of 1. The attribute weights were derived, with an indication of the number of kernel evaluations.

All modelling techniques were performed using WEKA software (Witten & Frank 2005). Changing the settings of the models hardly resulted in better accuracies of the models, which was probably due to the large differences in environmental variables between samples with and without stoneflies. It was therefore decided to use the default settings provided by WEKA (Witten & Frank 2005) for all modelling techniques, which also assured uniformity of the performed analyses. Four sets of models were developed, which were either based on physical–chemical parameters, land use types, structural characteristics of the watercourses or all these parameters together. To evaluate the performance of each method, the percentage of correctly classified instances (% CCI) and Cohen's kappa statistics (K) were used (Witten & Frank 2005). Percentage CCI is the sum of the % true positive and true negative predictions. K measures the proportion of all possible presences or absences that are predicted correctly by a model after accounting for chance (Manel *et al.* 2001). For N data points, K is given by

$$K = \frac{(a+d) - (((a+c)(a+b) + (b+d)(c+d))/N)}{N - ((a+c)(a+b) + (b+d)(c+d))/N)}$$

where a is the number of true positive predictions, b is the number of false positive predictions, c is the number of false negative predictions and d is the number of true negative predictions.

Ensemble forecast

The PEGASE water quality model (Deliège *et al.* 2009) was used to simulate the improvement of the water quality in Flanders by the years 2015 and 2027 (Ronse & D'heygere 2007). The PEGASE model is a detailed hydrodynamic, deterministic water quality model that consists of three submodels: a hydrological and hydrodynamic submodel, a thermal submodel and a biological submodel. In the first scenario (2015), the standard policy as well as the proposed measures in the first period of the district plans are implemented. In the second scenario (2027), all proposed restoration measures are implemented and the water received from the neighbouring countries is expected to be of a good quality. Based on the planned measures, especially collecting and treating a higher fraction of the domestic waste water, oxygen and nutrient concentrations were modelled using the water quality model PEGASE (VMM 2009b). More specifically, models were developed using the five mentioned techniques based on the concentration of oxygen, biological oxygen demand, nitrate, ammonium, Kjeldahl nitrogen, phosphorus and orthophosphate. River morphology and land use were not included in these models because these are not likely to change substantially by 2027, especially because there are no large scale plans to change these parameters. An ensemble forecast based on the five techniques was used to model stonefly prevalence in a reference situation in 2006 and the two future scenarios in 2015 and 2027.

RESULTS

Environmental parameters

Median values as well as 10 and 90 percentiles of all environmental parameters are listed in Table 1. Mann–Whitney U tests indicated that most parameters differed significantly between samples with and without stoneflies (Table 1). Also the land use type differed significantly (Chi-square, $p < 0.001$) between samples with and without stoneflies. While stoneflies were mainly found in forests, downstream sites contained more meadow and urban area and random sites without stoneflies contained more arable land, urban and industrial areas (Figure 2).

Modelling

The presence and absence of stoneflies could be accurately modelled based on physical–chemical parameters with all five modelling techniques when random samples without stoneflies were used (Table 2). Although somewhat less accurate, presence and absence could still be modelled based on the type of land use or based on structural parameters (slope, sinuosity and river morphology). When all variables were used simultaneously, the accuracy of the models was even higher with most cases more than 90% CCI and Cohen's kappa higher than 0.8, only CT performed slightly less accurately. When downstream samples were used as absence data, model performance was still good, but the accuracy was always somewhat lower. When downstream data were used to validate the models with random absences (called inter-group validation in Table 2), the developed models did not perform as well. However, when random data were used to validate the models with downstream absences, model performance remained good.

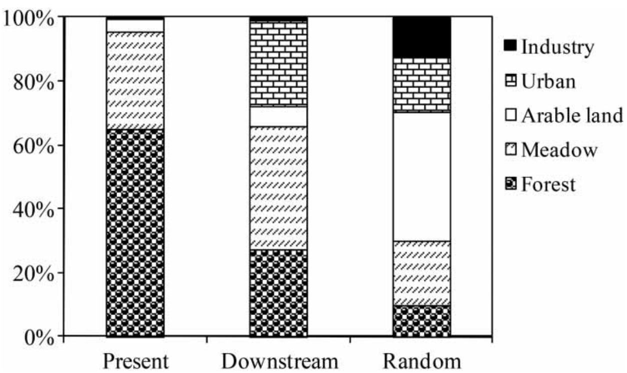

Figure 2 | Dominant land use in the samples where stoneflies were present as well as downstream samples and random samples where stoneflies were absent.

Ensemble forecast

On the basis of the modelled oxygen and nutrient concentrations, the five mentioned modelling techniques were used to make an average ensemble forecast of the stonefly prevalence. The modelled prevalence, which was about 13% in the reference year 2006, increased minimally in 2015 and slightly increased to about 16% in 2027 (Figure 3). Models developed on the basis of random and downstream absences resulted in very similar predictions.

DISCUSSION

Stoneflies can occur in all types of watercourses in Flanders, from small streams to very large rivers (Lock & Goethals 2008). However, due to human impact, stoneflies now only occur in a few percent of the sampled watercourses, which are almost exclusively small streams. In the part of Belgium south of the rivers Samber and Meuse, where the human impact is less severe, stoneflies are still present in nearly all watercourses, even in large rivers.

In the present study, all applied modelling techniques resulted in reliable models, only the performance of CT was slightly less accurate (Table 2). The high accuracy of the developed models indicates that stoneflies were present in the majority of the suitable watercourses. Hardly any additional watercourses have become suitable for stoneflies recently. If the water quality would have become suitable at locations that were not yet colonised by stoneflies, this would have resulted in a higher fraction of false positive predictions and the model accuracy would have been lower. In a great number of watercourses, an improvement of the water quality could easily be followed by the recolonisation

Table 2 | CCI and Cohen's kappa statistics (*K*) for calibration, validation and inter-group validation when using all variables or only physical–chemical data, land use or structural characteristics with five different models: logistic regressions (LR), artificial neural networks (ANN), support vector machines (SVM), random forests (RF) and classification trees (CT)

			Calibration		Validation		Inter-group validation	
Included variables	**Absences**	**Model**	**CCI (%)**	***K***	**CCI (%)**	***K***	**CCI (%)**	***K***
All variables	Random	LR	95	0.90	95	0.90	70	0.38
		ANN	96	0.92	95	0.89	66	0.33
		SVM	91	0.83	95	0.89	69	0.38
		RF	93	0.86	93	0.86	71	0.41
		CT	88	0.77	89	0.78	61	0.22
	Downstream	LR	77	0.54	76	0.52	85	0.70
		ANN	84	0.68	82	0.63	85	0.70
		SVM	77	0.54	78	0.56	90	0.81
		RF	89	0.78	83	0.66	87	0.74
		CT	85	0.70	79	0.59	78	0.56
Physical–chemical (pH, conductivity, oxygen, BOD, COD, nutrients)	Random	LR	86	0.73	88	0.77	65	0.30
		ANN	90	0.80	89	0.78	60	0.21
		SVM	86	0.72	86	0.71	59	0.18
		RF	86	0.72	88	0.75	60	0.19
		CT	83	0.66	80	0.60	64	0.27
	Downstream	LR	71	0.41	77	0.55	82	0.63
		ANN	76	0.53	74	0.48	82	0.63
		SVM	71	0.42	77	0.53	82	0.64
		RF	78	0.57	79	0.58	78	0.56
		CT	75	0.51	75	0.49	79	0.59
Land use (one parameter with five types)	Random	LR	82	0.63	86	0.71	66	0.32
		ANN	81	0.61	78	0.56	67	0.34
		SVM	82	0.63	86	0.71	66	0.32
		RF	82	0.63	86	0.71	66	0.32
		CT	82	0.63	86	0.71	66	0.32
	Downstream	LR	70	0.40	67	0.34	78	0.56
		ANN	64	0.28	67	0.34	78	0.56
		SVM	70	0.40	67	0.34	78	0.56
		RF	70	0.40	67	0.34	78	0.56
		CT	70	0.40	67	0.34	78	0.56
Structural (slope, sinuosity, river morphology)	Random	LR	75	0.51	75	0.49	67	0.34
		ANN	86	0.73	83	0.66	51	0.01
		SVM	75	0.51	73	0.45	68	0.36
		RF	86	0.72	87	0.74	75	0.49
		CT	77	0.54	79	0.58	73	0.45
	Downstream	LR	65	0.30	64	0.27	70	0.40
		ANN	65	0.29	64	0.29	67	0.34
		SVM	66	0.32	60	0.21	67	0.34
		RF	89	0.77	81	0.62	69	0.38
		CT	79	0.59	77	0.53	64	0.27

by stoneflies, due to passive distribution from upstream populations.

In Figure 4, a strongly pruned classification tree is presented (that was not used in the analysis), which indicates that stoneflies are present in waters with a low conductivity, but are only present in waters with a higher conductivity when the slope is steep. This example illustrates that CT can be easily understood and communicated and therefore, this technique is very suitable to show to river managers, decision makers or even the public (Boets *et al.* 2010; Dominguez-Granda *et al.* 2011). This ease of understanding more than makes up for the small loss of predictive power.

The occurrence of stoneflies in Flanders could not only be predicted based on the physical–chemical water

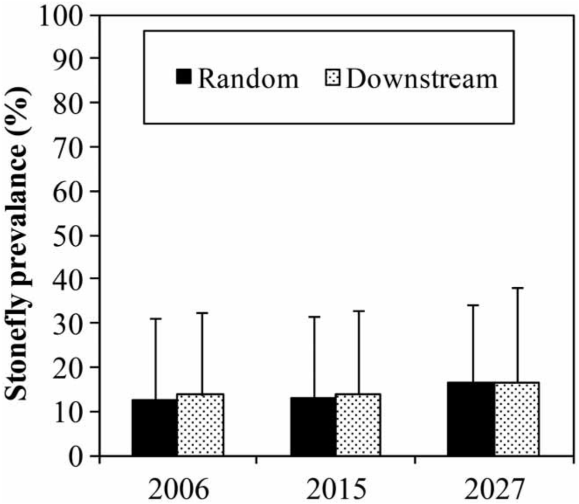

Figure 3 | Average ensemble forecast of the stonefly prevalence (with indication of the standard deviation) in 2006, 2015 and 2027 based on water characteristics modelled with PEGASE, for models developed with random as well as downstream absences.

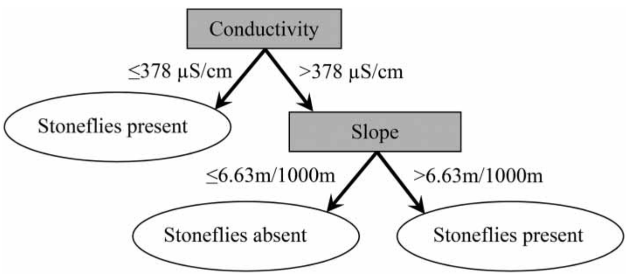

Figure 4 | Strongly pruned classification tree predicting the presence or absence (in random samples) of stoneflies in Flemish watercourses (correctly predicted instances 86%, Cohen's kappa 0.73).

characteristics, but also based on the land-use or the river morphology. Also in other regions, land-use appears to be a key factor influencing macroinvertebrate community composition among sites (Sponseller *et al.* 2001; Strayer *et al.* 2003; Compin & Cereghino 2007; Collier 2008). Urban and industrial sites in the river basin represented the pressure with the most negative impact on macroinvertebrate indices, while forests and pastures had a positive effect (Wasson *et al.* 2010). An advantage of the parameters describing land use and river morphology is that they are quite stable in time. On the other hand, physical–chemical parameters can strongly fluctuate, which can easily lead to erroneous conclusions regarding habitat suitability. Including land use and river morphology can therefore improve the accuracy of habitat suitability models, as was also observed during the present study.

The developed models could accurately distinguish suitable from unsuitable habitats for stoneflies, especially with random absences (CCI 88–96%; K 0.77–0.92). This was not surprising since almost all environmental parameters differed significantly between samples where stoneflies were present and random samples where they were absent (Table 1). Although models developed using samples downstream from locations with stoneflies as absence data were slightly less accurate, they were still able to predict the occurrence of stoneflies with high confidence (CCI 77–89%, K 0.54–0.78). These data suggested that the physical–chemical water characteristics of most watercourses in Flanders are still not good enough to allow the occurrence of stoneflies. In order to obtain a good water quality in all Flemish water bodies, which should be the case by 2015 according to the WFD (European Council 2000), there is thus still a lot of improvement required. De Cooman *et al.* (2007) indicated that these goals could only be achieved by implementing small-scale efforts such as natural bank restoration, fish passage construction or river channel re-meandering, which affect physical and chemical habitats both locally and at the basin scale. Although these kinds of measures are undoubtedly beneficial, they are also very expensive. Especially, re-meandering is costly and our models even indicated that sinuosity has only a minor effect on the occurrence of stoneflies. Jahnig *et al.* (2010) concluded that habitat restoration within a small stretch is generally not sufficient to realize changes in benthic invertebrate community composition and that restoring habitat on a larger scale, using more comprehensive measures and tackling catchment-wide problems (e.g. water quality, source populations) are required for a recovery of the invertebrate community.

More cost-effective measures might therefore be the installation of constructed wetlands for small-scale waste water treatment and the creation of buffer zones. Currently, agricultural land in Flanders usually extends up to the river banks and a buffer zone is rarely present although these are known to decrease the runoff of nutrients and pesticides (Sahu & Gu 2009; Tran *et al.* 2010). Wasson *et al.* (2010) indicated that riparian corridors are manageable areas and their creation along European watercourses should receive priority in order to achieve a good ecological status. On the other hand, constructed wetlands are considered as a cost-effective alternative for the treatment of point-sources that cannot easily be connected to a sewage treatment plant (Meers *et al.* 2008; Boets *et al.* 2011).

Despite the improvement of the water quality since the beginning of the 1990s (VMM 2010), stoneflies still occur only in a few percent of the sampled watercourses. Obviously, a further improvement of the ecological water quality is needed for sensitive species such as stoneflies. Nonetheless, an ensemble forecast with the five modelling techniques indicated that stonefly prevalence will only increase from 13% in 2006 to 16% in 2027 when all the planned measures are carried out (Figure 3). These measures thus clearly indicate a lack of ambition to reach the goals of the WFD, which is to achieve a good ecological quality in all surface waters by the year 2015, especially when it is taken into account that plans are rarely completely carried out as intended. The modelled prevalence in 2006 was even an overprediction since in reality, stoneflies were observed in <2% of the sampled watercourses in 2006. However, it should be taken into account that due to the rarity of stoneflies in Flanders, their prevalence strongly fluctuates from year to year, depending on the sampled watercourses, but has never surpassed 10% during the last two decades. In the same reference year 2006, <10% of the surface waters reached a good ecological water quality for macroinvertebrates (VMM 2009b), indicating that stoneflies are not too sensitive to be used as ecological indicators and that their prevalence actually gives a good reflection of the ecological status of the Flemish watercourses.

CONCLUSIONS

Despite an improvement of the water quality since the beginning of the 1990s, stoneflies are still rare in Flanders. Most environmental parameters differed significantly between samples with and without stoneflies, which suggests that not only morphological river characteristics such as meandering and bank structure, but also physical–chemical water characteristics of most watercourses in Flanders are still not good enough to allow the presence of stoneflies. LR, artificial neural networks, support vector machines, random forests and CT could all successfully predict stonefly occurrence. Models using random absences and downstream absences both resulted in reliable predictions. Based on the measures planned by the Flemish government, which mainly consist of improved waste water treatment, an ensemble forecast using the five mentioned modelling techniques predicted that stonefly prevalence in Flanders will increase only marginally by 2027. More efforts will thus be needed to effectively reach a good ecological quality in all surface waters as required by the WFD.

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