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Well known indicator groups do not predict the decline of insects

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ABSTRACT

In decision making for insect conservation, one depends largely on knowledge of the relationship between changes in environmental factors and abundance of a very limited number of species. The species we have knowledge on cannot be regarded as a representative sample of all insects. How accurately do changes in the abundance of these species predict the changes in other species? To answer this question, we studied 373 insect species belonging to the Apidae (bees), Lepidoptera (butterflies), Orthoptera (grasshoppers), Ephemeroptera (mayflies), Trichoptera (caddisflies), Odonata (dragonflies), and Plecoptera (stoneflies), with known population trends and attributes in the Netherlands. The 78 attributes included morphological and demographic trait values, as well as habitat requirements of species. We trained Random Forests (RFs) with random samples and with taxonomic groups to predict the decline of the species based on their attributes. Then we used the trained RFs to predict the decline of the species outside the training groups and checked the accuracy of the predictions. The results showed that accuracy of the predictions of the RFs trained by the random samples increased from 0 to 0.20 (maximum 0.40, on a scale of 0 to 1) with sample size increasing from 10 to 90% of the insects. Moreover, we found that the accuracy of the predictions by the RFs trained with the taxonomic groups were zero in case of butterflies and grasshoppers, and low in other groups (maximum 0.37, in case of bees predicting terrestrial insects). Accuracy depended significantly on the size of the taxonomic group. Large over- or underestimation of number of declining species occurred in all cases. Further, we found that the taxonomic groups had few attributes important for predicting in common. The attribute 'Active dispersion' had the highest importance when all insects were used for training the RF. Using 'indicator groups' for predicting the decline of insects has a high risk of over- or underestimating the actual number of declining species and should therefore be advised against unless the indicator group is sure to be representative.

1. Introduction

In 2017, Hallmann et al. published a 75 % decline of terrestrially flying insect biomass in 27 years in German nature conservation areas. The study inspired much follow-up research (Wagner et al., 2021), and, based on 166 long-term surveys spanning the period 1925–2018, Van Klink et al. (2020a, 2020b) performed a *meta*-analysis showing a decline of terrestrial insect abundance by about 10.6 % per decade, but an increase of freshwater insect abundance by about 12.2 % per decade. Recently, no net decline in insect abundance could be detected in the US (Crossley et al., 2023). These results show that it is important to acknowledge the fact that insects are an heterogenous class of organisms. In fact, insects are the most species rich class on earth (Mora et al., 2011), but the conservation status of species is only known for very few of them, even in well studied countries. Because it is often not feasible to study all insects, policy-makers and nature managers generally focus on specific species groups (Halme et al., 2009; Siddig et al., 2016). Species groups are selected according to several criteria, among which: data availability, relations with environmental pressures and management, ease of identification, and resonance with the wider public (Gregory et al., 2005; Pryke et al., 2015; Siddig et al., 2016). Ideally, the selected species groups should also be informative about biodiversity in general (Gaspar et al., 2010). However, although studies are available of specific insect groups as potential indicators for changes in abundance of insects in general, for example butterflies (Thomas, 2005) and dragonflies (Bush et al., 2013; Hassall, 2015; Pryke et al., 2015), the latter criterion

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is often more hoped for than tested thoroughly. Some authors have been warning against the use of organism groups as 'diversity surrogates' (e.g., Gaspar et al., 2010 in case of spatial diversity). For example, butterflies could not be used to predict the declining species insects and are no robust indicator for pollinating insects in the Netherlands (Musters et al., 2013; Segre et al., 2023).

Here, we explore the possibilities to find a subgroup that could be used to predict the number of declining species in a wider group of insects. Ideally this subgroup, that we will call an indicator group, should be small, i.e., contain a limited number of species. After all, the less species in the indicator group, the less effort it will take to assess the trend in the wider group.

2. Theory

The term 'indicator species' in ecology can be defined in a number of different ways (Dufrêne and Legendre, 1997; McGeoch, 1998; De Cáceres et al., 2010; Niemi and McDonald, 2004; Fleishman et al., 2005; Halme et al., 2009; Ricotta et al., 2015; Siddig et al., 2016; Soldaat et al., 2017; Buckland and Johnston, 2017). Here, we define an indicator species group as a group of species of which the change in abundance over time can be used to accurately predict the trends in a wider group of species.

Since the causes of change in abundance may be different for different species and depend on the properties of species, accurate prediction of the trends in the wider group seems only possible when the distribution of the relevant properties over the species in the indicator group can be assumed to be equal to the distribution of those properties in the wider group. In that case, the indicator group can be called a representative subgroup of the wider group of species (Boyd et al., 2023). A random sample of species from the wider group approaches representativeness with increasing sample size (Boyd et al., 2023).

The above reasoning is in essence trait-based (Violle et al., 2007; Webb et al., 2010; Murray et al., 2011; Musters and van Bodegom, 2018; Chichorro et al., 2022). The basic idea is that, because trait modalities, or 'attributes' as we will call them here, are the evolutionary outcome of adaptions to the environment, the relationship between attributes and environmental change can assumed to be universal among a wide group of species (Musters and van Bodegom, 2018; Chichorro et al., 2022). So, species with the same attributes are supposed to react in the same way to environmental changes. For example, if fragmentation is the cause of the decline of certain species, the dispersion ability of species will predict which species will decline and which not.

A trait-based approach seems needed, because pragmatic candidates for indicator groups are seldom known random samples of the wider focal group (Siddig et al., 2016; Boyd et al., 2023). Taxonomic subgroups, such as butterflies or dragonflies for insects, certainly are not. In theory, this problem could be solved when the relationship between the attributes and the trends of species in the indicator group is known, as well as the distribution of attributes in the wider group. In that case, the trend of the wider group could be predicted by the trend of the indicator group, weighted according to the distribution of the relevant attributes in the wider group.

Here, we have applied this 'model-based inference' (Boyd et al., 2023) and assessed the accuracy of prediction by comparing the results of the prediction with the actual known trends in the wider group. For that, the indicator group was first used to quantify the relationship between attributes and trends of species, resulting in a predicting model parameterized with the indicator group species, and then this model was used to predict the trends in the wider group. The universality of the relationship between the attributes and the trend in the indicator group was tested in this way.

A possible explanation for the poor performance of a candidate indicator group, therefore, could be the low universality of the relationship between the attributes and trends because insects are a too heterogeneous group. If we would reduce this heterogeneity by subdividing insects in more homogeneous groups, a candidate group might become a good indicator for one of those homogeneous subgroups. An obvious subdivision in insects is that in species that are exclusively terrestrial and those that are spending at least part of their lifecycle in aquatic systems, because terrestrial and aquatic species have shown to have different trends (Van Klink et al., 2020a).

Here we examine this possible explanation. We assessed 78 intrinsic attributes of insects and trained Random Forests (RFs) to predict the decline of species within six taxonomic groups of which we had information of more than 35 species (Breiman, 2001; Musters et al., 2013; Musters and van Bodegom, 2018). Then, we used each of these trained RFs to predict the decline of either terrestrial or aquatic insects in general. The reversed Normalized Brier score (rNBs), which is a strictly proper score of the accuracy of a prediction (Brier, 1950; Ishwaran and Lu, 2019; Musters and de Snoo, in prep), together with associated type I and type II errors, were our criteria for deciding whether a group was a suitable indicator group. Our results made us also assess the accuracy of any combination of one terrestrial and one aquatic group in predicting the decline of all insects. Next, we checked whether the attributes that were important for predicting decline per group, did correspond between the groups (Fig. 1).

3. Material and methods

3.1. Dutch red lists

In the Netherlands, Red Lists have been assessed for seven insect species groups: six orders [Lepidoptera (butterflies), Orthoptera (grasshoppers), Ephemeroptera (mayflies), Trichoptera (caddisflies), Odonata (dragonflies) and Plecoptera (stoneflies)] and one family [Apidae (bees)] (Table 1). These seven groups were divided in either terrestrial or aquatic species whose trends we want to predict using only one of the species groups. According to the Dutch Red List criteria, a species' threat status is determined by the long-term trend since 1950 and its current rarity (for details see De Iongh and Bal, 2007). In the present study we used the information on the trend per species in 2015. So, 'decline' is a binary indicating whether or not the species range or abundance is declining in the Netherlands since the fifties of the last century according to the latest Red List assessment. A total of 738 insect species were evaluated for the Red Lists. From these, 373 species were randomly selected within each group to get a more or less equal representation of the groups in our dataset (Table 1). Of our selected insects 48 % are declining, i.e., 51 % of the terrestrial and 44 % of the aquatic insects.

3.2. Attributes

To identify traits predicting decline of species across taxonomic groups, we made a 'universal' list of 61 traits that is supposed to cover all aspects of life history based on ecological theory, including morphological and demographic traits as well as habitat requirements of species (Musters et al., 2013). The modalities of these traits per species were obtained from species group experts (Musters et al., 2013). In accordance with classification tree literature (Breiman, 2001), we called these trait modalities the attributes of the species. In several cases more than one attribute could be regarded as reflecting a certain trait. All attributes were transformed into categorical variables in order to avoid the influence of cardinality on the importance of attributes (Deng et al., 2011). In the case of scale variables, the scale was divided into five equal parts, leading to a five-point ordinal attribute. When needed, the original values were log-transformed for approaching a normal distribution before transforming into an ordinal attribute. We did our analyses based on all 78 intrinsic attributes available for insects, i.e., the attributes that can be regarded as independent of the environment (Table S1 in Supplementary Information). So, attributes depending on the distribution of the species within the Netherlands, such as preference for certain Dutch habitats, were excluded.

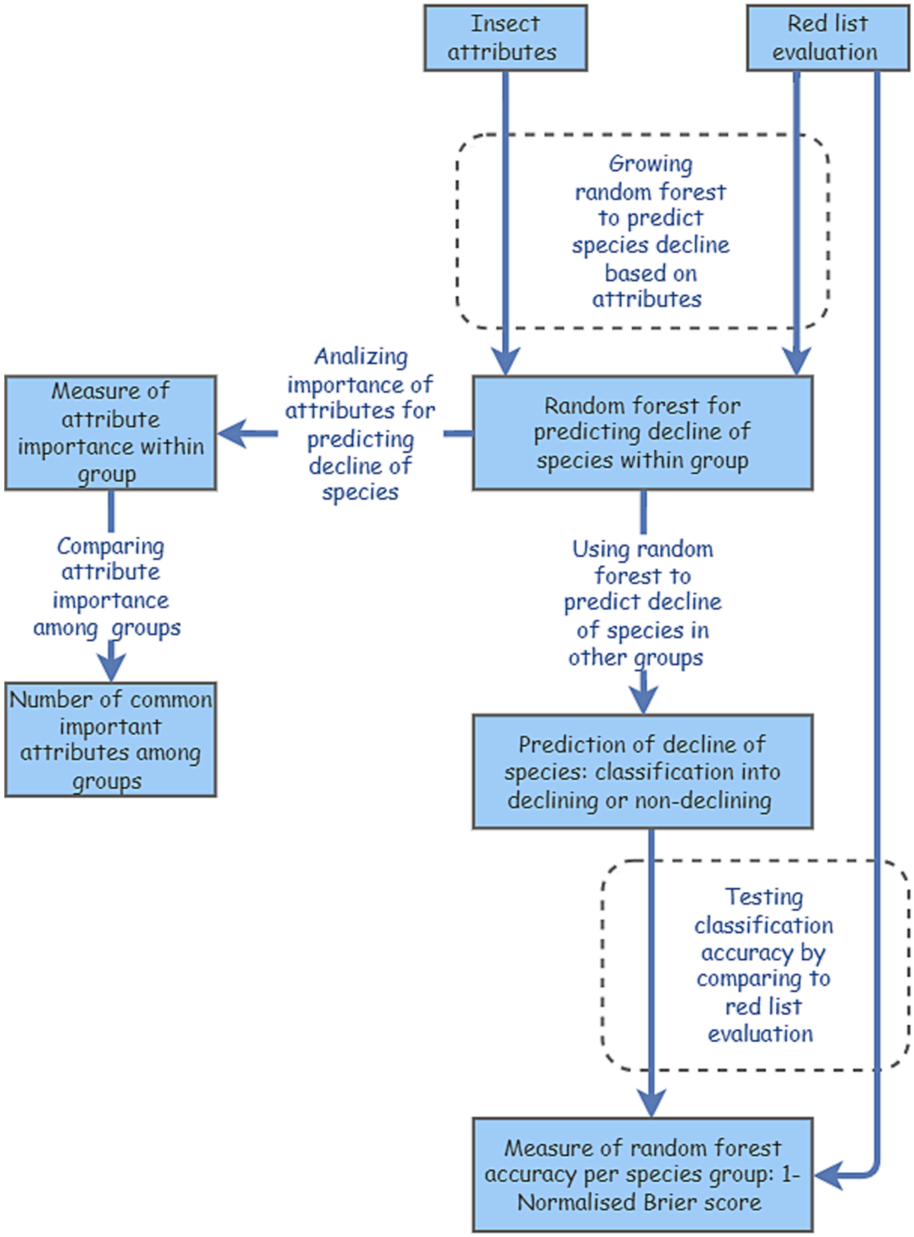

Fig. 1. Procedure for testing the accuracy of predicting the decline of species with a Random Forest trained by an indicator group and assessing the importance of attributes for the prediction.

Table 1
Most recent Dutch red lists of insects used in this study. N spec.: estimated number of Dutch species; Eval.: number of species evaluated for the Red List; Sel.: number of species selected for this study; Frac. hab.: fraction of terrestrial or aquatic selected species; Frac. all: fraction of all selected species; Prev.: prevalence of declining species in selected species, i.e., number of declining species divided by total number of selected species.

Group		N spec.	Eval.	Sel.	Frac. hab.	Frac. all	Prev.	Published by
Apidae	Bees	359	331	116	0.59	0.31	0.48	Reemer, 2018
Lepidoptera	Butterflies	71	71	49	0.25	0.13	0.76	Van Swaay, 2006
Orthoptera	Grasshoppers	64	44	35	0.18	0.09	0.26	Reemer, 2012
Ephemeroptera	Mayflies	60	52	41	0.23	0.11	0.41	Verdonschot et al., 2003
Trichoptera	Caddisflies	175	155	69	0.39	0.18	0.38	Verdonschot et al., 2003
Odonata	Dragonflies	65	65	47	0.27	0.13	0.38	Termaat and Kalkman, 2011
Plecoptera	Stoneflies	27	20	18	0.10	0.05	0.89	Verdonschot et al., 2003
All	Insects		738	373			0.48	
Of which	Terrestrial		446	198		0.53	0.51	
	Aquatic		292	175		0.47	0.44	

3.3. Random forests

For studying the suitability of the groups as indicator group, we grew Random Forests for predicting whether a species was declining or not with attributes as predictors (Breiman, 2001; Breiman and Cutler, 2012). We used the function *rfsrc()* of the *randomForestSRC* package in R (Ishwaran and Kogalur, 2007; Ishwaran et al., 2008; R Development Core Team, 2015) for the classification.

The accuracy of the prediction is our criterion for assessing the suitability of the groups as indicator: this should be as high as possible. It was calculated as 1 – Normalized Brier score, i.e., the reversed Normalized Brier score (rNBs; Musters and de Snoo, in prep). The Normalized Brier score is a strictly proper score of the accuracy of a prediction, but it runs from 0 (perfect accuracy) to 1 (zero accuracy, i.e., when the prediction is not different from throwing a coin). By subtracting it from 1, the rNBs indicates a high accuracy with a high score.

3.3.1. Random samples of all insects

We started our analysis by training RFs with random samples of all insect species, and then trying to predict the number of declining species in all species. We did this analysis with a random sample of size 0.1, 0.2, etc. times the total number of insect species ($n = 373$). Since these random samples can be regarded as representative for all insects, we expect optimal accuracy of the predictions, and therefore we can use the results as a kind of standard of the results in the next analyses. We performed the predictions ten times with each sample size in order to assess the variation in accuracy resulting from the randomness of the sample. Because one can expect that the accuracy of the prediction increases with the percentage of species used for training in the total number of species, we assessed the accuracy for both the prediction of all species and for all non-trained species.

3.3.2. Indicator groups

We trained RFs with the following six indicator groups: bees, butterflies, grasshoppers (terrestrial species); mayflies, caddisflies, dragonflies (aquatic species). We then used these RFs to classify our sample of the terrestrial and aquatic insects, respectively, into either declining or non-declining species and assessed the accuracy of the prediction (Fig. 1).

A high accuracy does not exclude a high chance of either type I (the chance of a false positive) or type II (the chance of a false negative) errors. These chances were therefore also taken into consideration and regarded as significant when lower than 0.05. Since we have no *a priori* idea on which of these two types of errors is worse, we assume that both should be as low as possible, i.e., both should be as close to zero as possible. A good measure for this is the Euclidean distance to the origin in the two-dimensional space with type I and type II errors as axes: Eucl. $D = \sqrt{(\text{type I})^2 + (\text{type II})^2}$. But both should also be as equal as possible, because if the type I is larger than the type II error, the number of declining species will be overestimated, while it will be underestimated in case of type I is smaller than type II errors. The percentage over- and underestimation [(100*Predicted prevalence of declining species/Actual prevalence of declining species)-100] was used to check this. In all cases, we trained the RFs ten times so that we could assess the effect of the stochastic parts of procedure on the results. Tables and figures show the averages of these ten runs. The tables also give standard deviation, but the figures give the 95 % confidence interval.

3.3.3. Importance of attributes

Of the last of the ten RF trainings, we calculated the mean and confidential interval of the importance per attribute with the delete-d-jackknife subsampling procedure as recommended by Ishwaran and Lu (2019), using the *subsample()* and *extract.subsample()* functions of *randomForestSRC* package of R. Attributes that had an importance that was significantly higher than zero were considered to contribute significantly to the prediction of the decline of species.

4. Results

4.1. Random samples of all species

The accuracy of the prediction of the decline of all species by RFs trained with a random, i.e., with a representative, sample of species could be as high as 0.73 rNBs, but showed a dependency on the fraction of species that was taken as sample size (Fig. 2). Also, the accuracy was clearly lower when the prediction was only made for the species that were not in the training group (Fig. 2). The predicted prevalence of declining species is independent of the fraction and on average slightly lower than it actually is, but the variance in prediction decreases with the fraction is (mean predicted prevalence = 0.44, sd = 0.050; actual prevalence = 0.48; p-value actual prevalence is higher than predicted < 0.001; Table 1; Fig S1 in Supplementary Information). When the complete dataset of insects is used to train the RF, 46 out of all 78 attributes turn out to have an importance higher than zero, with the attribute 'Active dispersion' having the highest importance (Table S1).

4.2. Indicator groups

The RFs trained by the different taxonomic groups resulted in a highest accuracy of 0.37 rNBs in predicting declining terrestrial species when trained by the bee dataset and of 0.23 rNBs in predicting declining aquatic species when trained by the dragonfly dataset (Table 2, Fig. 3). RFs trained by butterflies or grasshoppers were not able to predict terrestrial insects at all (accuracy not different from zero). The accuracy as compared to the accuracy of a representative sample with the same fraction of species shows that in all groups the accuracy is lower than that of the representative group (Fig. S2). In case of the grasshoppers, caddisflies, and dragonflies, the chance for type I error was significant; for all the groups the chance of type II was never below 0.05, although for butterflies it was nearly significant (Table 2 and 3). In all cases, either the type I or type II error was higher than 0.5, except for the RFs trained by the bees (Fig. S3) and, therefore, the Euclidian distance to the origin was large (Table 2 and 3). Also, the number of declining species was always significantly over- or underestimated (Fig. 4). The least deviation of the estimated number of declining species from the actual number was found in using bees for training the RF for predicting the number of declining terrestrial species (10.6 % overestimation, Table 2).

Calculations of the accuracy of predicting the decline and prevalence of declining species in all insect species using one taxonomic group or any combination of one terrestrial and one aquatic group for training the RFs showed the same low accuracies and high over- or underestimations as in the previous results and no large difference between single groups and combinations of two groups (Fig. 5, S11, S12, S13). However, the accuracy showed a clear positive correlation with the number of species in the indicator group ($F_{[1,16]} = 32.55$, $p < 0.001$; Fig. 5).

4.3. Importance of attributes

The number of attributes that significantly contributed to the prediction of declining species, that is, that had an importance significantly higher than zero, varied between three and fifteen per taxonomic group (Table S2). Only one attribute was important in four of our seven species groups, viz. CQ46: Active dispersion, the attribute that also had the highest importance when all insects were used for training the RF (Table S1). Two attributes were important in three groups, viz. CLogQ1: Number of European species in the genus, and Q11c: Species that have their Western border through the Netherlands, i.e., Eastern species. Figs. S4-S10 give the relationship between the attribute value and the probability of decline of all the important attributes. Usually, the number of important attributes per group that groups have in common is low (Table 4). Only in case of the dragonflies and the stoneflies, the two

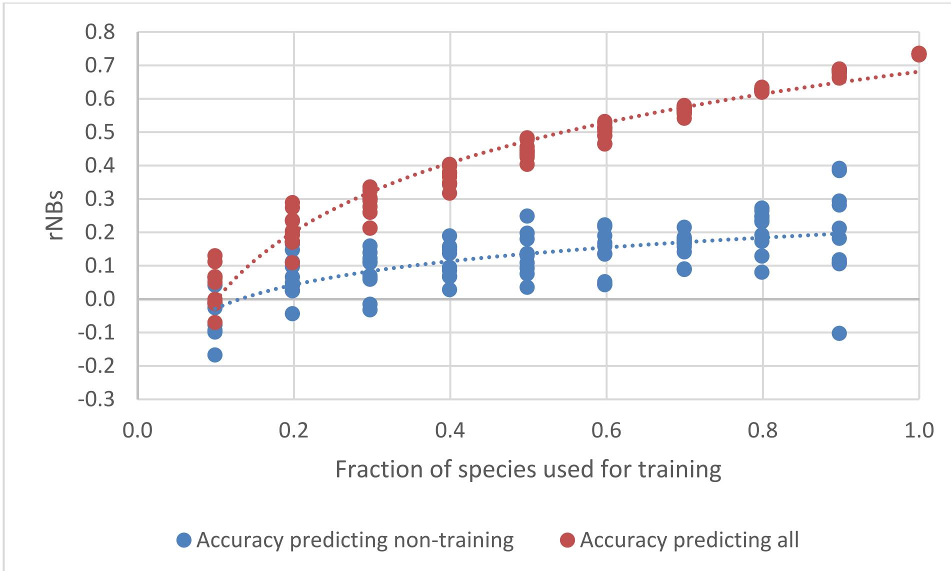

Fig. 2. Relationship between the fraction of species and the accuracy of predicting the decline of all species and of the species outside the training group. All species: rNBs = 0.2968 * ln(Fraction of species) + 0.681; Non training species: rNBs = 0.1019 * ln(Fraction of species) + 0.2067.

Table 2
Results predictions terrestrial insects. Accuracy: reversed Normalized Brier score (rNBs); Err I: chance of type I error; Err II: chance of type II error; Eucl D: Euclidian distance to the origin of the Fig. 2; Pred. prev.: predicted prevalence of the declining species, i.e., number of declining species divided by total number; Overest. %: percentage of overestimated number of declining species, negative values are underestimations.

Group	rNBs	Err I	Err II	Eucl D	Pred. prev.	Overest. %
Bees	0.373 ± 0.007	0.351	0.130	0.374	0.616 ± 0.010	10.6
Butterflies	−0.018 ± 0.019	0.806	0.056	0.808	0.876 ± 0.026	36.6
Grasshoppers	−0.050 ± 0.027	0.007	0.846	0.846	0.082 ± 0.008	−42.7

Table 3
Results predictions aquatic insects. Accuracy: reversed Normalized Brier score (rNBs); Err I: chance of type I error; Err II: chance of type II error; Eucl D: Euclidian distance to the origin of the Fig. 2; Pred. prev.: predicted prevalence of the declining species, i.e., number of declining species divided by total number; Overest. %: percentage of overestimated number of declining species, negative values are underestimations.

Group	rNBs	Err I	Err II	Eucl D	Pred. prev.	Overest. %
Mayflies	0.097 ± 0.005	0.152	0.609	0.628	0.257 ± 0.015	−18.3
Caddisflies	0.188 ± 0.009	0.029	0.674	0.675	0.159 ± 0.006	−28.1
Dragonflies	0.231 ± 0.004	0.035	0.571	0.573	0.208 ± 0.006	−23.2

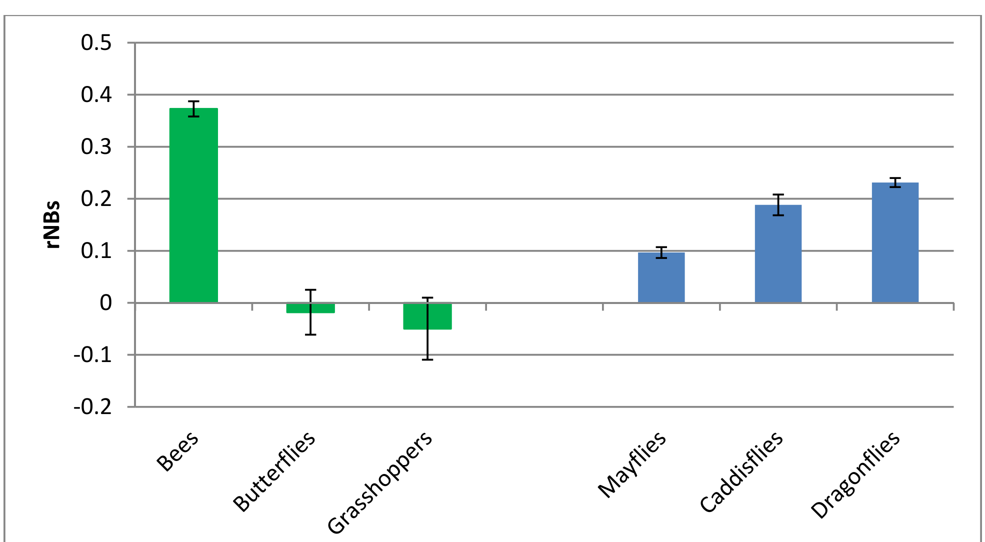

Fig. 3. Accuracy of prediction of declining terrestrial (green) and aquatic insects (blue) by using the Random Forest trained by bees, butterflies, grasshoppers, mayflies, caddisflies, and dragonflies. Error bars indicate the 95% confidence interval based on ten Random Forests. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

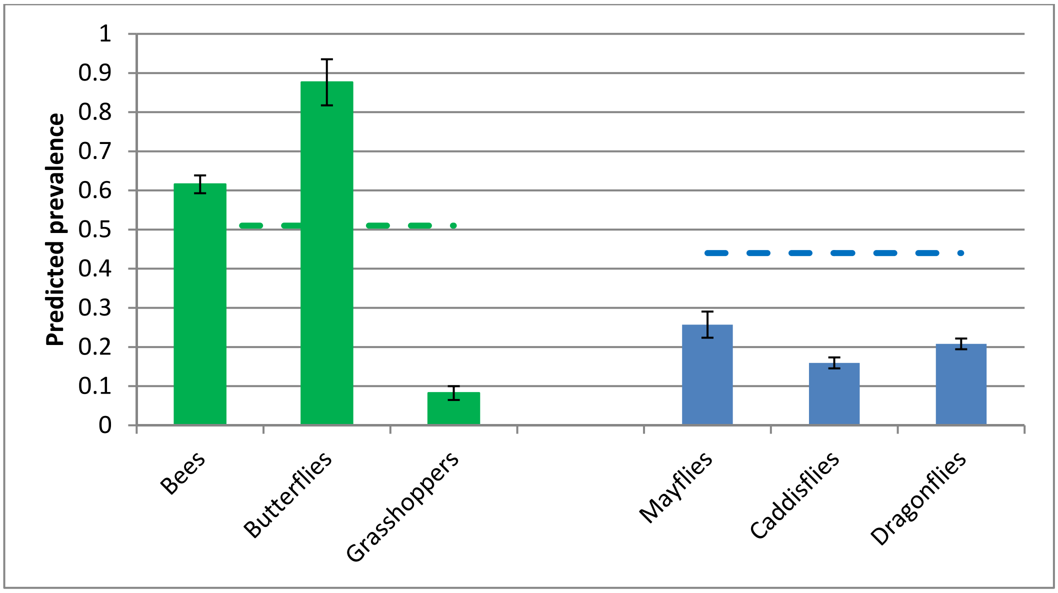

Fig. 4. The predicted prevalence of the declining terrestrial (green) and aquatic (blue) species by using the Random Forest trained by bees, butterflies, grasshoppers, mayflies, caddisflies, and dragonflies. The dashed green line shows the actual percentage of declining terrestrial species and the dashed blue line that of declining aquatic species. Error bars indicate the 95% confidence interval based on ten Random Forests. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

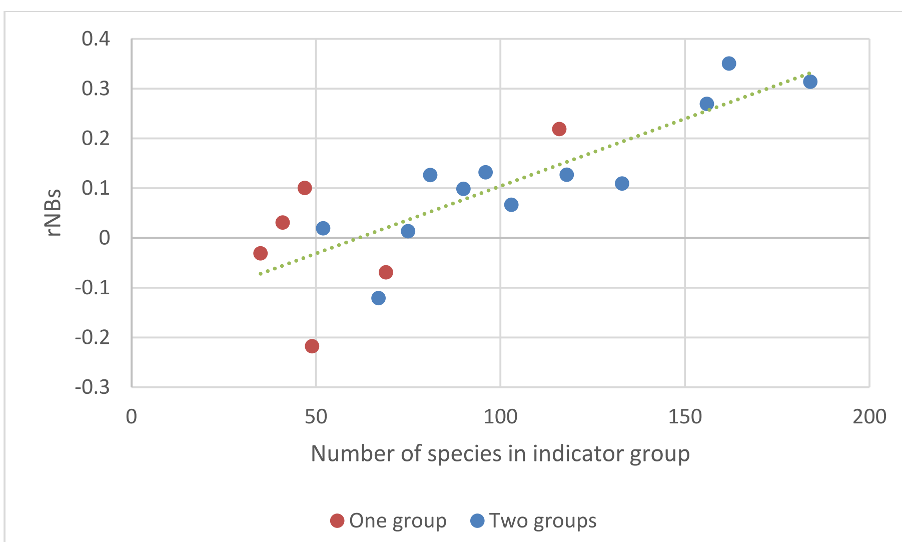

Fig. 5. Relationship between number of species in the indicator group and the accuracy of predicting the decline of all species with RFs trained with either one or two groups. Regression line: rNBs = 0.0027 * Number of species – 0.1668.

Table 4
Number of important attributes in common between groups of species.

	Bees	Butterflies	Grasshoppers	Mayflies	Caddisflies	Dragonflies	Stoneflies
Bees		Q29	Q11c	Q10	CLogQ1	CLogQ1, Q11c	
Butterflies	1		Q17d, CQ46				CQ46
Grasshoppers	1	2			Q22d, Q12	CQ46, Q11c	CQ46
Mayflies	1	0	0		Q22a	Q38c	
Caddisflies	1	0	2	1		CLogQ1	
Dragonflies	2	0	2	1	1		CQ46, Q25, Q18c
Stoneflies	0	1	1	0	0	3	

groups had three important attributes in common. In all other combinations of groups this number was lower.

5. Discussion

High accuracy of predicting the decline of insect species could only be reached by training the RF with a random sample that includes a large fraction of all the species to be predicted. But even in the case that all the species are used for training, the accuracy of prediction was not higher than 0.73 rNBs. More importantly, our results showed that the high accuracy was not found when only the decline of species was predicted that were not used for training. In that case, the accuracy was not above 0.4 rNBs, but usually around 0.2 rNBs. Based on knowledge of declining species, the decline of other species seemed never to be predicted very accurately, even when that knowledge was based on a representative sample of the species.

The accuracy of the prediction of decline of both terrestrial and aquatic species was low when using the RF trained by the taxonomic species groups and lower than that of a representative group of the same size. In case of the highest accuracy, the prediction of terrestrial insects using the RF of the bees, the accuracy was below 0.4 rNBs. Further, the number of important attributes for predicting decline that have species groups in common was low, never exceeding three. So, in case of the Dutch insects that were well studied, we were not able to recommend any taxonomic species group as an indicator group for predicting the decline of insects in general.

Our results support the idea that each taxonomic group of insects has its own specific set of attributes that predict their decline and none of the species groups is a good indicator group for other insects. This seems to be in line with the results of a study of traits and the environmental responses of aquatic macroinvertebrate (Pilière et al., 2016).

Moreover, the general pattern of a positive relationship between the accuracy of the prediction of the decline of species and the size of the indicator group we found (Fig. 5) can easily be explained by the relationship in the accuracy of prediction and the number of species in the training group as proportion of all species (Fig. 2).

The fact that when using all species for training the RF, the prediction of the RF has an accuracy of only 0.73 rNBs shows that our method has fundamental uncertainties. Potential sources of these uncertainties are numerous, such as uncertainties in the RF procedure which includes random sampling steps, in the assessment of the attributes of species, in the completeness of our attribute list (Musters and van Bodegom, 2018) and in the assessment of declining species (Porszt et al., 2012; Soldaat et al., 2017; Buckland and Johnston, 2017). But, most importantly, we think that changes in natural populations are largely indeterministic. In that light, an accuracy of 0.73 rNBs might even be regarded as high.

In general, our study shows that one should be careful in claiming that a species group acts as indicator group. We have found little evidence for the idea of the existence of indicator groups and warn against their use without doing an accuracy check, such as the one we performed here. Selecting one species group to inform about the trend in wider biodiversity in an area may easily over- or underestimate the latter trend. Also, the selection of at least more than one species group and to combine several groups, may not solve this problem.

Contrary, our results seem to suggest that for assessing the general trend in at least the insects, trying to find an indicator group among the species of which presently information is available is not the way forward. The only reliable approach seems to be to select a random sample of all species, and then monitor these selected species (Boyd et al., 2023). This does not solve the present need for information on species trends, bares no guarantee for high accuracy of the prediction of the general trend in insects, and is probably very costly. Cost may in the future be reduced, though, by collecting massive data combined with automatic identification techniques, as are now in development for eDNA sampling and automatic photo-identification (Zenker et al., 2020; Kirkeby et al., 2021; Bjerge et al., 2023).

If such an approach is chosen, the question how large a random sample should be becomes emergent. Our study gave little information on that: Fig. 2 showed almost straight regression lines between the relative number of random species and accuracy of prediction. Besides, our study included only 373 out of at least 19,244 established insect species in the Netherlands (Noordijk et al., 2010).

We call for careful and extensive evaluation of all studies where researchers claim that the state of a specific group of species is indicating the state of a wider group of species, both within and outside the insects (Gaspar et al., 2010). Only with more attention for generalization in ecology, we can hope to develop ecology into a predictive science (Spake et al., 2022). Increasing the accuracy of forecasting in ecology is urgently needed to justify the use of ecological knowledge in nature conservation and policy making (Musters et al., 2023).

6. Conclusion

Selecting a taxonomic subgroup to inform about the trends of the species in the wider taxon in an area may easily lead to over- or underestimation of the number of declining species. Furthermore, selecting more than one subgroup and/or combining several groups may not accurately address this problem. The only reliable approach seems to be to select an as large as possible random sample of all species of the taxon, but that bares no guarantee for high accuracy of the prediction of the trends, even when a large number of the trait values of the species are known.

Author contributions

CM and GdS conceived the ideas. CM and HPH performed the statistical analyses. CM wrote the first draft. All authors improved the drafts and gave final approval for publication. None of them had conflicts of interests.

CRediT authorship contribution statement

C.J.M. Musters: Conceptualization, Formal analysis, Investigation, Methodology, Supervision, Visualization, Writing – original draft, Writing – review & editing. **Hans Peter Honkoop:** . **Geert R. de Snoo:** Conceptualization, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2023.111458.

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