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INFERRING PRESENCE AND ABUNDANCE FROM THE YEAR OF LAST OBSERVATION

Travail de Maîtrise universitaire ès Sciences en comportement, évolution et conservation
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par

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Summary

1. Being acquainted about the population status is paramount in prioritizing conservation managements and efforts. Many methods were developed in order to predict extinction based on sighting data. The aim of the thesis was to assess whether it is possible to predict current presence and/or abundance based on a sighting record, in particular based on the year of last observation (YLO) of the species.

2. We use data on YLO and data from re–surveys of multiple sites (i.e. populations) where the species was known to occur in the past to predict current occupancy and abundance. Therefore, if one knows the relationship between YLO and occupancy and/or abundance, one could then predict occupancy/abundance for sites that were not surveyed.

3. The analysis was done using site–occupancy and abundance models developed by MacKenzie *et al*. (2002) and Royle (2004). Two independent data sets of detection/non–detection records of amphibians were used, the Red List and the "VD/FR" data sets. We used the explanatory variable YLO to assess whether it can predict current occupancy. We used "VD/FR" data to assess whether additional explanatory variables could improve the prediction capacity of YLO. Using the same data set, we tested whether YLO can be used to predict abundance.

4. The main result was that, for eight in fourteen species, YLO was present in the best selected models. YLO had a positive effect on occupancy probability for ten species and on abundance for two species. Additional explanatory variables

(habitat characteristics) led in some cases to better predictions of occurrence probability and abundance based on YLO.

5. The site–occupancy and the abundance analysis of the two independent data sets showed that YLO can be used to predict presence and abundance respectively. The prediction ability, however, varied among species. This ability to predict is positively linked with the decline of the species and can be improved by habitat characteristics. Depending on the species, YLO was shown to be a tool to predict presence and abundance across many populations, providing information about the current population state even for unvisited sites for which an YLO was recorded.

Résumé

1. Se tenir informé de l'état d'une population d'une espèce est primordial afin de poser des priorités dans la gestion et les efforts de conservation. Plusieurs méthodes ont été développées à partir de données d'observation afin de prédire une extinction. Le but de cette thèse était de déterminer s'il est possible de prédire la présence actuelle et/ou l'abondance en fonction d'une donnée d'observation, plus précisément en fonction de la dernière date d'observation (YLO) d'une espèce.

2. Afin de prédire la présence actuelle et l'abondance d'une espèce, nous avons utilisé des données d'YLO ainsi que celles obtenues lors des visites de multiples sites (i.e. populations) où l'espèce a été antérieurement observée. Ainsi, en connaissant la relation entre YLO et la probabilité de présence et/ou l'abondance, nous pourrions alors prédire la probabilité de présence/abondance pour des sites qui n'ont pas été surveillés.

3. L'analyse a été faite avec les modèles de présence et d'abondance développés par MacKenzie *et al*. (2002) et Royle (2004). Deux bases de données indépendantes de détection/non–détection d'amphibiens ont été utilisées, celle de la Liste Rouge et celle de "VD/FR". Nous avons utilisé la variable d'explication YLO afin de déterminer si elle permet de prédire la présence actuelle. Nous avons ensuite utilisé les données de "VD/FR" afin de tester si des variables explicatives supplémentaires pouvaient améliorer la capacité de prédiction de YLO. En utilisant la même base de données, nous avons également testé si YLO peut être utilisée afin de prédire l'abondance.

4. Nous avons démontré que pour huit espèces sur quatorze, YLO était présente dans les meilleurs modèles sélectionnés. YLO a eu un effet positif sur la probabilité de présence pour dix espèces et sur l'abondance pour deux espèces. Une des variables explicatives supplémentaires (le type d'habitat) a permis dans certains cas d'obtenir une meilleur prédiction de la probabilité de présence en fonction de YLO.

5. L'analyse des deux bases de données indépendantes a montré que YLO peut être utilisée comme outil de prédiction de probabilité de présence et d'abondance. Cependant, cette capacité de prédiction varie en fonction des espèces. Elle est positivement liée avec le déclin des espèces et a pu être améliorée par la variable description des habitats. En fonction des espèces, YLO a montré être un outil afin de prédire la probabilité de présence et l'abondance sur plusieurs populations. Cet outil permet ainsi de fournir des informations sur l'état actuel des populations, et cela sans avoir visité des sites pour qui une YLO a été enregistrée.

Key−words Abundance, *Alytes obstetricans*, *Bombina variegata*, extinction, habitat characteristics, *Lissotriton helveticus*, occupancy probability, prediction across many populations, population trend, sighting record.

Introduction

Inferring species extinction is a major concern in conservation biology (Vitousek 1994; Reed 1996). However, extinction can never be inferred with certainty. While the presence of a species may be proven with detection of at least one individual, failure to detect individual at a site does not equate to the absence of the species (McArdle 1990; Kéry 2002). The case of the rediscovered Hula painted frog is an example. The last recorded sighting data of these species, *Discoglossus nigriventer*, was in 1955 in the Hula Valley in Israel. Surveys after 1955 failed to detect the species. In 1996 the species was formally declared as extinct by the IUCN. However, many years later, in October 2011, the species was rediscovered in the Hula Nature Reserve (Biton *et al*. 2013). If a species had not been recorded for many years, the usual approach was to declare a species extinct if it had not been seen for 50 years (Smith *et al.* 1993). However, this approach is not satisfactory. This is especially true for endangered species for which there are occasional sightings (Burgman, Grimson & Ferson 1995). Only a probabilistic statement about the likelihood of absence can be made. In the absence of targeted surveys, for presumably extinct species, multiple methods have been proposed based on the sighting record of the species (Solow 1993; Burgman, Grimson & Ferson 1995; McCarthy 1998; Solow 2005; Rivadeneira, Hunt & Roy 2009). Given the characteristics of sighting record, these models allow generating estimation of the probability and timing of extinction of the species. This can be used in order to evaluate whether these species, which have not be seen from some time, are likely to be truly extinct and to evaluate the year when the species went extinct.

The approach we would like to assess is quite different in the sense that we wanted to know whether the species is still present; and if so, what is the probability of its presence given the sighting records. Additionally, another variable which could be quite interesting to predict is abundance. Indeed, abundance might provide additional information on population status, the trend of its declining across the time and its changes (i.e. changes in population size) might to be good predictors of extinction risk (O'Grady *et al.* 2004).

Moreover, these models are made for a single spatial unit (i.e. on single populations or the global population of a species). An interesting aspect could be about the assessment of extinction prediction across multiple populations. Can the prediction of these sighting data be extended through space and time? If the last sighting data would not only prove to be a tool to predict occupancy and/or abundance but also be able to do prediction in a general way (i.e. in space), this could be very useful for conservation and management of these species. Indeed, this method, with the combination of presence–records data bases and prediction across multiple sites, might provide general information about population status without doing the surveys. In other words, this method might provide a tool in order to, in a certain measure, get acquainted about the population trend and to anticipate the extinction of species and thus improve management and conservation objectives and efforts (McPherson & Myers 2009).

Another interesting aspect is about the sighting records themselves. Indeed, there are many data bases of animals and plants that have presence–records of species (but no absence records, as a species cannot with certainty be considered as so). All these records have attached a year of last observation (YLO), which represents a kind of sighting data. And these data bases are not regularly updated (or only partially updated) such that one does not know whether a species is still present, or not, at a place where it was recorded in the past. These sighting records, the year of last observation YLO, could thus represent potential valuable and accessible information in order to infer presence and abundance.

In this thesis, we wanted to assess, in a first place, whether it is possible to predict current presence and/or abundance of a species from a large number of sites in a large scale of time with the variable "year of last observation" YLO. For this, we used occupancy and abundance models to make an extinction statement across multiple populations, and this within the scale of time recorded, then each YLO recorded for each population (i.e. site).

In a second place, we wanted to assess whether the prediction using YLO can be improved using site characteristics. To do so, we added variables describing habitat characteristics to the models. The goal of this second part was as well to assess whether year of last observation YLO is a good predictor. Indeed, habitat characteristics could serve as well as control. Then, we expect that the model selection will reveal that YLO is a better predictor than habitat characteristics.

First of all, we used data bases with detection/non–detection records on amphibians with their YLO attached from the Red List data base. Data from amphibian monitoring program and surveys should be suitable because most species (i.e. frogs and toads) vocalize, contrary to others (newts) (Tanadini & Schmidt 2011). We could thus expect that, for vocalizing species, occurrence and abundance should have been well detected. In contrast, concerning newts, a particular attention and active researches had to be provided. Secondly, surveys have been performed with focus on the species common midwife toad, the yellow−bellied toad and the palmate newt. These three species have been selected because of their differing ecology (Duguet & Melki 2003; Meyer *et al*. 2009), the number of sites available where they have been recorded in the past and the good spread of variable “year of last observation” YLO. Each of these criterions is important, whether it is for the general predictive aspect we want to assess, or for an efficient statistical analysis.

Materials and methods

Red List Data base

Detection/non–detection data for 14 species was recorded during field work for the update of the Swiss amphibian Red List. During field work, experienced herpetologists visited randomly selected sites four times and recorded detection/non−detection data for all species (Schmidt & Zumbach 2005). The number of sites varied among species. For site occupancy modelling, only "year of last observation" YLO was used as the explanatory variable for occupancy probability. For each species, the year of the visits and the last year of observation ranged from: *Alytes obstetricans*: 2002 to 2004 and 1974 to 2004; *Bombina variegata*: 2002 to 2003 and 1974 to 2004; *Bufo bufo*: 2002 to 2004 and 1901 to 2004; *Bufo calamita*: 2002 to 2004 and 1977 to 2004; *Hyla arborea*: 2003 to 2004 and 1974 to 2004; *Hyla intermedia*: 2003 to 2004 and 1984 to 2002; *Ichthyosaura alpestris*: 2002 to 2004 and 1901 to 2004; *Lissotriton helveticus*: 2002 to 2004 and 1974 to 2004; *Lissotriton vulgaris*: 2003 to 2004 and 1978 to 2003; *Pelophylax esculentus* complex: 2003 to 2004 and 1974 to 2004; *Rana dalmatina*: 2003 to 2004 and 1974 to 2003; *Rana temporaria*: 2002 to 2004 and 1901 to 2004; *Triturus carnifex*: 2003 to 2004 and 1977 to 2003; *Triturus cristatus*: 2003 to 2004 and 1911 to 2003.

Study area

Populations of the study species common midwife toad, the yellow−bellied toad and the palmate newt were surveyed in the cantons Vaud and Fribourg in western Switzerland (center of the study area: 46°37'N; 6°41'E). The study areas covered about 780 km^2 and 44 km^2 respectively. These areas are characterized by forests, agricultural lands, inhabitations and/or human activities (Camenzind & Stalder 2011). Breeding sites, where the three study species were known to occur syntopically in the past, were selected from the amphibian distribution data base of karch. Very large (such as lake shores) or inaccessible sites were removed from the selection such that the number of the study sites was 34 in the end. Selected sites predominantly situated between 400 and 800 m in elevation and classified into three habitat types: ponds (in the number of 14), gravel pits (15) and others (5), the latter corresponding to neither of the both first types. In these sites, the year of last observation YLO varied from 1981 to 2012 for *Alytes obstetricans* and *Bombina variegata* and from 1981 to 2011 for *Lissotriton helveticus*.

Field methods and explanatory variables

From mid−April to mid−July 2013, each site was visited 3 times in a total number of 39 nights. During every visit, detection and non−detection of all species was noted. In order to assess the presence and the abundance of the population, detection methods included both visual encounter surveys and call surveys. The site visits began at sundown and each survey went on 14 to 80 min (mean = 50.10 min) depending on the size and the type of the sites. The suitable habitats were systematically searched and the number of calling and seeing individuals of each species were counted. From that data, detection histories (MacKenzie *et al*. 2002) and point count data (Royle 2004) for the three studied species were constructed such that, occupancy and abundance respectively, could be estimated.

During the site visits, we measured several variables on the field that may explain detection probability. Descriptions about these variables (i.e. scale, signification, etc.) are shown in Table 1. Temperature was obtained by leaving a thermometer outside at the beginning of the visit and picking up the air temperature in the end of the visit. The variables “rain” and "wind" consisted in taking into account the fact that it was raining/winding (1) or not (0) during the field. In order to test the effect of the moon on detectability, 4 states of the moon cycle were measured: new moon, first quarter, full moon and last quarter, which may provide changes in amphibian behaviour. Water clarity was estimated visually as well as the presence of vegetation in the water. The other variables were taken apart from the field. Climate data such as the amount of rain and humidity were obtained from MeteoSwiss (http://www.meteosuisse.admin.ch) and MeteoCentrale (http://www.meteocentrale.ch) from the nearest weather station. The variable "amount of rain" represented the rainfall during the day of the visit (mm), which may influence amphibian activity. Proportions of searched and accessible shoreline were visually determined from topographical maps (map.geo.admin.ch). The altitude was calculated as the mean (in m) from 3 measurements on the site taken on Google Earth.

There were three explanatory variables for site occupancy probability (Table 2). "Year of last observation of the target species" (YLO) and "year of last observation of other amphibians on the same selected sites" (which indicates whether the site was visited between the year of last observation of the target species and current year) were obtained from the karch data base. The "kind of site" (i.e. three kinds: ponds, gravel pits or other) was determined on the field.

Data analysis

The goal of using site−occupancy and abundance models, developed by MacKenzie *et al*. (2002) and Royle (2004) respectively, was to evaluate if the variable "last year of observation" YLO predicted current occupancy (or, its complement local extinction) or current abundance. We fitted the models using the package unmarked in the program R (R Core Team 2012). Model selection was done using AIC.

The analysis of the data of the amphibian Red List used only the explanatory variable “year of last observation” YLO to estimate current occupancy. The aim of the “VD/FR” data analysis was to test whether additional explanatory variables can improve the prediction of current occupancy based on YLO. In addition, the goal was to assess whether YLO can also predict abundance. The data from the Red List analysis and from the “VD/FR” analysis came from different data sets. For the analysis of the Red List data, three candidate models with constant detection probabilities were fit to the data. The models were (1) $\psi(.)p(.)$, which served as a null model, (2) $\psi(YLO)p(.)$ and (3) with a quadratic term $\psi(YLO+YLO^2)p(.)$. We expected that variable “year of last observation” YLO had a positive effect on site occupancy. Indeed, it is know that sighting data can infer current presence (Solow 1993; Burgman, Grimson & Ferson 1995; McCarthy 1998; Solow 2005; Rivadeneira, Hunt & Roy 2009). One should thus expect that recent observations should predict reasonably high presence probability while earlier observations should predict a lower probability of current presence. However, how the relation between observations and presence could be, into a scale of time, remain to assess.

For the “VD/FR” data set, a two–step process has been used to analyse the data, for both occupancy and abundance modelling. For occupancy modelling, the first–step consisted to determine the covariates which best explained detection probability. The aim of this first–step was to control for variation in detectability before modelling occupancy (i.e. the second–step). Thus the number of observers, the duration of the visit (time), temperature, the amount of rain during the day, the shoreline searched and accessible, humidity and the moon state were used as explanatory variables for detection probability. The phenology was modelled using a day–reference (i.e. first day of field work = day 1). In order to allow for a pic, we included models with a quadratic day effect ($DATE+DATE^2$). Variables water−clarity, vegetation and wind were not included in the analysis because of the large number of missing data. There were candidate models with a single explanatory variable for detection and candidate models with all pair−wise combinations. While modelling detection, occupancy probability was held constant (i.e. ψ(.)p(COVARIATE) or ψ(.)p(COVARIATE1+COVARIATE2)). The best model for detection probability was next used for the second–step in which occurrence covariates were included.

For the second–step, three covariates were used to build candidate models. The habitat variable (KINDSITE) which was a categorical variable with 3 levels: gravel pit, pond and other. It permitted to examine whether the effect of “the year of last observation” YLO depends on the type of habitat. Additionally, KINDSITE served as control (i.e. if the models with KINDSITE are better than those with YLO, YLO is not a useful predictor). The year of last observation (YLO) and the year of last observation of other amphibian species (LAST_SPECIES). The latter was used only in combination with YLO in the sense that it is linked with YLO. For this variable we expected positive effect on site occupancy. Indeed it may improve the prediction capacity of YLO in the sense that other amphibian sites which were not visited between YLO and current year may give greater site occupancy probability than other amphibian sites which have been visited but the interest species data were not recorded. The reason is because it is not possible to know, for the second case, whether the cause of this non−recorded data was the absence of the interest species on the site or the non−detection of it. Finally, the last model integrated in the selection was ψ(.) as a control, in order to evaluate whether the covariates described above were well supported by the data.

Abundance modelling were analysed in the same way. The same set of candidate models was used. The first–step consisted as well to determine the covariates which best explained detection probability. Candidate models were tested with the same explanatory variables for detection, single or with all pair−wised combinations (i.e. λ(.)p(COVARIATE) or λ(.)p(COVARIATE1+COVARIATE2)). The best model for detection probability was next used for the second–step in which abundance covariates were included. For the second–step, the same three variables were used in the candidate models, then "the year of last observation" YLO, LAST_SPECIES and KINDSITE. The last model $\lambda(.)$ served as a null model.

Results

Red List Data

Alytes obstetricans was detected in 37 of 77 sites where it had been recorded in the past, *Bombina variegata* in 39 of 86 sites, *Bufo bufo* in 117 of 161 sites, *Bufo calamita* in 21 of 48 sites, *Hyla arborea* in 28 of 57 sites, *Hyla intermedia* in 25 of 32 sites, *Ichthyosaura alpestris* in 138 of 159 sites, *Lissotriton helveticus* in 61 of 89 sites, *Lissotriton vulgaris* in 23 of 52 sites, *Pelophylax esculentus* complex in 121 of 156 sites, *Rana dalmatina* in 37 of 55 sites, *Rana temporaria* in 178 of 202 sites, *Triturus carnifex* in 12 of 22 sites and *Triturus cristatus* in 23 of 55 sites.

The analysis of the Red List data demonstrated that with the three candidate models tested (i.e. (1) $\psi(.)p(.)$, (2) $\psi(YLO)p(.)$ and (3) $\psi(YLO+YLO^2)p(.)$), models with $\psi(YLO+YLO^2)$ gave results that made no biological sense. Therefore they were removed from the analysis which had thus been based on the two other second candidate models only. The model selection results for occurrence probability are shown in Table 4, detection probability estimates under these models are shown in Table 3.

For 6 species the model $\psi(.)p(.)$ was best supported by the data, and for 8 species it was the model $\psi(YLO)p(.)$ (Table 4).

For the 6 species, for which the best model was $\psi(.)p(.)$, occurrence probability was best predicted without the variable "year of last observation" YLO (Table 4). For models including

YLO, the latter had a positive effect on occupancy probability for species *B. calamita* and *L. helveticus* (Table 4 & Fig 1). Compared to the second–best model, the first model had an evidence ratio of 2.704, 2.125, 2.448, 1.632, 1.941 and 2.704 for *B. bufo*, *B. calamita, H. intermedia*, *L. helveticus, R. temporaria* and *T. carnifex* respectively. Given the best model, occurrence probability ± SE was (on the probability scale) for *B. bufo*: ψ=0.796 ±0.038, *B. calamita*: ψ=0.486 ±0.081, *H. intermedia*: ψ=0.899 ±0.091, *L. helveticus*: ψ=0.723 ±0.052, *R. temporaria*: ψ=0.914 ±0.023 and *T. carnifex*: ψ=0.669 ±0.134.

For 8 species, occurrence probability was best predicted with the variable "year of last observation" YLO in the model ψ(YLO)p(.) (Table 4). For each species, YLO had a positive effect (with confidence intervals that did not overlap zero, except for *A. obstetricans* and *I. alpestris*) on occupancy probability (Table 4 & Fig 1). Compared to the second model, the first model had an evidence ratio of 2.125, 39, 232558.1, 1.857, 5.657, 12.699, 4 and 82.334 for *A. obstetrican*, *B. variegata*, *H. arborea*, *I. alpestris, L. vulgaris, P. esculentus, R. dalmatina* and *T. cristatus* respectively. Occurrence probability was on median (on the probability scale) for *A. obstetricans*: ψ=0.510 ±0.079, *B. variegata:* ψ=0.417 ±0.076, *H. arborea*: ψ=0.183 ±0.065, *I. alpestris*: ψ=0.890 ±0.029, *L. vulgaris:* ψ=0.403 ±0.108, *P. esculentus:* ψ=0.773 ±0.044, *R. dalmatina:* ψ=0.380 ±0.118 and *T. cristatus:* ψ=0.240 ±0.086 (Fig 2).

Study species

Common midwife toad

Alytes was detected in 15 of the 34 sites where it had been recorded in the past. The mean number of individuals seen was 1.571 ±0.203 and the mean number of individuals heard was 3.334 ±0.402.

Concerning the site occupancy modelling, detection probability was best modeled with the combination of covariates NUMBER OF OBSERVERS and SHORELINE SURVEYED. The model selection results for detectability and occupancy are shown in Table 5. Based on the model ψ(.)p(NbObs+ShorSurv), variable NUMBER OF OBSERVERS had a positive effect on detection probability while variable SHORELINE SURVEYED had a negative effect on detection probability (Table 5).

Occurrence probability was best explained by the model including variable "year of last observation" YLO alone (Akaike weight = 49%). Second and third best models included as well the variable YLO. Second, in combination with AFTER.ALOB had an Akaike weight of 18.4% and the third, in combination with KINDSITE had an Akaike weight of 14.9%. The first model had an evidence ratio of 2.663 compared to the second best, and of 3.288 compared to the third. In the best model, ψ(YLO)p(NbObs+ShorSurv), YLO had a significant positive effect on site occupancy probability (Table 5 & Fig 3).

Concerning the abundance modelling, as for site occupancy modelling, the model including the two covariates NUMBER OF OBSERVERS and SHORELINE SURVEYED best explained the data (Akaike weight = 35%). As for occupancy model, in λ(.)p(NbObs+ShorSurv) variable NUMBER OF OBSERVERS had a positive effect on detection probability and variable SHORELINE SURVEYED had a negative one (Table 6).

Abundance was best predicted with the model including variables “year of last observation” YLO, LAST.ALOB and KINDSITE (Akaike weight = 55%). The model including YLO and KINDSITE came second with an Akaike weight of 45%. Third came the model assuming a relationship between occurrence probability and KINDSITE with a much lower Akaike weight of 0.24%. The first model had an evidence ratio of 1.22 compared to the second best, and of 229.16 compared to the third. In the best model, λ(YLO+After.ALOB+KindSite)p(NbObs+ShorSurv), variables YLO and KindSite GRAVEL had a significant positive effect on abundance, while covariates AFTER.ALOB, KindSite OTHER and KindSite POND had a negative effect on the abundance (Table 6 & Fig 4).

<u>Yellow bellied toad</u>

During the site visits, *Bombina variegata* was detected in 17 of the 34 sites where it had been recorded in the past. The mean number of individuals seen was 9.354 ±2.036 and the mean number of individuals heard was 2.769 ±0.601.

Concerning the occurrence probability modelling, detection probability was best predicted with the combination of covariates TIME and TEMPERATURE. The model selection results for detectability and occupancy are shown in Table 7. Single−handedly, this model explained 65% of the Akaike weight and had the lowest AIC values for all candidate models. Based on model ψ(.)p(Temp+Time), both covariates had a positive effect on detection probability (Table 7).

Site occupancy probability was best predicted by the model including variables “year of last observation” YLO and KINDSITE (Akaike weight = 45%). In the second model, when in combination with YLO, variables AFTER.BOVA and KINDSITE also explained information on the data well with an Akaike weight of 32%. The model assuming the relationship between occurrence probability and YLO alone came third with an Akaike weight of 15%. The first model had an evidence ratio of 1.406 compared to the second, and of 3 compared to the third. In the best model, ψ(YLO+KindSite)p(Temp+Time), variables YLO, KindSite GRAVEL and KindSite OTHER had a positive effect on occurrence probability, while variable KindSite POND had a negative effect on occurrence probability (Table 7 and Fig 5).

Concerning the abundance modelling, the model including the two covariates DATE+DATE^2 and TIME best explained the data (Akaike weight = 95%). The covariates in the model λ(.)p(Date2+Time) had significant positive impact on detection probability (Table 8).

As for occurrence modelling, abundance was best explained with the model including the two covariates year of last observation YLO and KINDSITE (Akaike weight = 72%). The model assuming relationship between abundance, YLO, AFTER.BOVA and KINDSITE came second with an Akaike weight of 28%. Third, but with a much lower Akaike weight of 0.021%, came the model including variable YLO alone. The first model had an evidence ratio of 2.571 compared to the second, and of 3428.571 compared to the third. In the best model, λ(YLO+KindSite)p(Date2+Time), each covariate had a positive impact on the abundance except variable KindSite POND (Table 8 & Fig 6).

Palmate newt

During the site visits, *Lissotriton helveticus* was detected in 11 of the 34 sites where it had been recorded in the past. The mean number of individuals seen was 7.121 ±5.530.

Concerning the occurrence probability, detection probability was best supported by the variable SHORELINE ACCESSIBLE (Table 9). This model accounted for an Akaike weight of 8.5% and had the lowest AIC values for all candidate models. This is the first model which best explain detection probability with only one variable and not a combination of two, as for the others species. Based on the model ψ(.)p(ShorAcc), variable SHORELINE ACCESSIBLE had a positive impact on detection probability (Table 9).

Four models explained site occupancy probability reasonably well, with an Akaike weight greater than 0.1 (Table 9). Together they account for almost 90% of the Akaike weight. The model assuming constant occurrence probability was best supported by the data (Akaike weight = 34.2%). The variable "year of last observation" YLO appeared in the second model with an Akaike weight of 24.1%. Third, with an Akaike weight of 18.6%, came the model with a constant detection and occurrence probability. The first model had an evidence ratio of 1.419 compared to the second, and of 1.839 compared to the third. In order to assess and visualize the effect of YLO on the occurrence probability, the second model was chosen. In this model, ψ(YLO)p(ShorAcc), YLO had a positive effect on site occupancy probability (Table 9 & Fig 7).

Concerning the abundance modelling, the two covariates MOON and TIME best explained the data (Akaike weight = 97%). Thus, this model p(Moon+Time) has been used for further analysis. Based on the model λ(.)p(Moon+Time), covariates MOON STATE 2, MOON STATE 4 and TIME had a positive effect on the detection probability, while covariates MOON STATE 1 and MOON STATE 3 had a negative impact on detection probability (Table 10).

For abundance modelling, the model including variables "year of last observation" YLO and KINDSITE was the best supported by the data (Akaike weight = 56%). Second model, assuming relationship between abundance, YLO, AFTER.LIHE and KINDSITE, had an Akaike weight of 35%. The first model had an evidence ration of 1.6 compared to the second. In the best model, λ(YLO+KindSite)p(Moon+Time), covariates KindSite GRAVEL and KindSite POND had a positive impact on abundance. On the contrary, the other covariates YLO and KindSite OTHER had a negative impact on abundance (Table 10 & Fig 8).

Discussion

The site–occupancy analysis of the two independent data sets (i.e. the Red List data and the "VD/FR" data) showed that YLO can be used to predict current occupancy. The ability to predict occupancy, however, varied among species. The expectation was that for recent YLO, occupancy would be 100% and when YLO was old occupancy would be 0%. For the species *Hyla arborea*, *Lissotriton vulgaris*, *Rana dalamatina* and *Triturus cristatus*, we obtained the expected estimates of occupancy when using the Red List data. Estimates of occupancy were near 100% for recent YLO and close to 0% when YLO was from decades ago (Fig 1). One can thus infer an "absolute occupancy". Indeed, the totality of the occupancy probability (i.e. from 100% to 0%) is predicted by YLO. Thus, knowing the year of last observation of a species, one can directly use the curve in order to get information about the current occupancy, i.e. how likely a species is to be still present at a site where it was recorded in the past. For other species, such as *Alytes obstetricans*, *Bombina variegata*, *Bufo calamita*, *Ichthyosaura alpestris*, *Lissotriton helveticus* and *Pelophylax esculentus* complex, the curves with positive slopes predict occupancy in a lower range of percentage than for the other species (Fig 1, Fig 3, Fig 5 & Fig 7). For example, for *Alytes obstetricans*, occupancy in 2013 is around 70% when YLO=2012 and around 10% when YLO=1981 (Fig 3). This does not mean that the species went extinct in 30% of the sites within a year (i.e. from 2012 to 2013). This means that the effect of variable year of last observation YLO on occupancy is less predictive for these species. Nevertheless, one can still infer a "relative occupancy". Indeed, still for *Alytes obstetricans*, knowing that the occupancy is estimated at 35% in 1999 and at 70% in 2012 (Fig 3), one could get the relative occupancy for 1999 by dividing the two estimates of occupancy: 35/70=0.5. This means that *A. obstetricans* is half as likely to occur in a site with YLO=1999 than in a site with YLO=2012. Finally the effect of year of last observation YLO on occupancy seemed to be not predictive at all for species *Bufo bufo*, *Hyla intermedia*, *Rana temporaria* and *Triturus carnifex,* with slopes which were flat or slightly negative (Fig 1).

Variation among species in the ability of YLO to predict occupancy depends on the magnitude of decline except for *Hyla intermedia* and *Triturus carnifex* (Fig 2). YLO predicts occupancy well for species with strong declines but it does not do so for species with small declines. This decline is linked with the species status in the Red List as shown in Figure 2. Indeed, according to the IUCN criteria determining the status classification of species into a category (Schmidt & Zumbach 2005), species with endangered status (EN) have a more important decline than species with another status (i.e. least concern (LC), near threatened (NT) or vulnerable (VU)). The question is, for species with another status than endangered (EN), are their curves less important because these species are simply declining in a less quickly way or because YLO is not sufficient unto oneself in order to predict presence. In the first case, this would mean that YLO is sufficient unto oneself and can be used as a predictor of occupancy. And in order to get the absolute occupancy, one could for example extend the range of time. In the second case, one has to test whether additional explanatory variables can improve the prediction of current occupancy based on YLO.

The analysis of the "VD/FR" data set showed that the models can be improved by habitat characteristics. This is for true for some, but not all species (Fig 3, Fig 5 & Fig 7). For example, for species *A. obstetricans* and *L. helveticus* variable habitat characteristics were not selected into the best models and thus did not improve the prediction of YLO. While for *B. variegata*, adding habitat characteristics led to higher estimates of occupancy when YLO was close to 2013 and to lower estimates occupancy when YLO was old. For this species, the range of occupancy probability across the range of YLO was thus increased, given therefore a better prediction of occupancy. Quite unexpectedly, the other additional variable "after.species" (i.e. information whether another species than focal were detected between YLO and current year) did not improved the prediction of YLO on occupancy. There were good reasons to think that it could be important but apparently it was not.

In addition to predicting occupancy, YLO can also be used to predict abundance. YLO had a positive effect on predicted abundance. Populations with recent YLO were predicted to be larger whereas populations with old YLO were predicted to be small. As with occupancy, the ability to predict abundance, however, varied among species (Fig 4, Fig 6 & Fig 8). The expectation was that the predicted abundance based on YLO would give additional information on population status to the predicted occupancy. Indeed, if YLO predicts occupancy, then it predicts lower occupancy if YLO is old. For some species, occupancy is zero when YLO is old, meaning that the species is extinct. If a species goes extinct, then the abundance will decline from many, to few, to none individuals. Species *Alytes obstetricans* and *Bombina variegata* gave expected trend of abundance in function of YLO. By comparison between the graphs, one can get additional information about the population state of the species (Fig 3 vs Fig 4 & Fig 5 vs Fig 6). For example, for *B. variegata*, in the gravel pit habitat, estimated occupancy in 2013 was 70% when the species was last observed in 2005. The species is thus 70% as likely to be present when last observed in 2005 in gravels. And within these 70%, the population might be of 10 individuals. In conclusion, if YLO is old, then for most species this means that the species has a low occupancy probability and if it occurs, then abundance is likely to be low.

The use of variable year of last observation YLO showed to be an alternative to the theory that sighting data can be used in order to infer site–occupancy (or its complement, species extinction) (Solow 1993; Burgman, Grimson & Ferson 1995; Solow 2005). The manner that occupancy and abundance are computed here with these sighting records is quite different than previous cited methods. While using many sighing data of one local species or population to infer extinction, the goal was here to test whether the last year of observation YLO can be predictive across many sites, and thus across many populations. Indeed YLO was predictive, then if one has the species–specific YLO–occupancy curve, one can then predict occupancy for a site that was not surveyed. This may provide, depending on the YLO recorded for this unvisited site, information about its current population status and thus allowing action for conservation if needed. However, it is important to precise that the YLO–curves are species–specific but they are probably also specific to the particular presence–only data base. Thus, the estimated effects of YLO could probably not be transferred to data in another data base. This is probably why the YLO–curves for focal species *A. obstetricans* and *L. helveticus* from the two data sets gave the same pattern (i.e. positive effect of YLO on occupancy estimates) but were different although the selected models were quite the same (i.e. ψ(YLO)p(.) for the Red List data and ψ(YLO)p(Covariates) for the "VD/FR" data) (Fig 1, Fig 3 & Fig 7). With every data base, the curve will have to be calibrated. Thus, one could randomly select some sites and then do re–surveys. Based on the results, one can predict occupancy or abundance for all the sites in the data base. Implement appropriate statistical analysis in order to infer presence or absence of species given sighting records was the mutual aim of the previous cited methods (i.e. Solow 1993; Burgman, Grimson & Ferson 1995; Solow 2005) and this analysis. Indeed these sighting records represent a real potential for assessing species conservation status and providing wildlife management as there are many data base at our disposal (i.e. Museum and Herbarium collections, Institution data bases, etc.). The insights of all these historical data, the implementing methods and tools developed with them are too important to ignore the valuable information they might provide for conservation.

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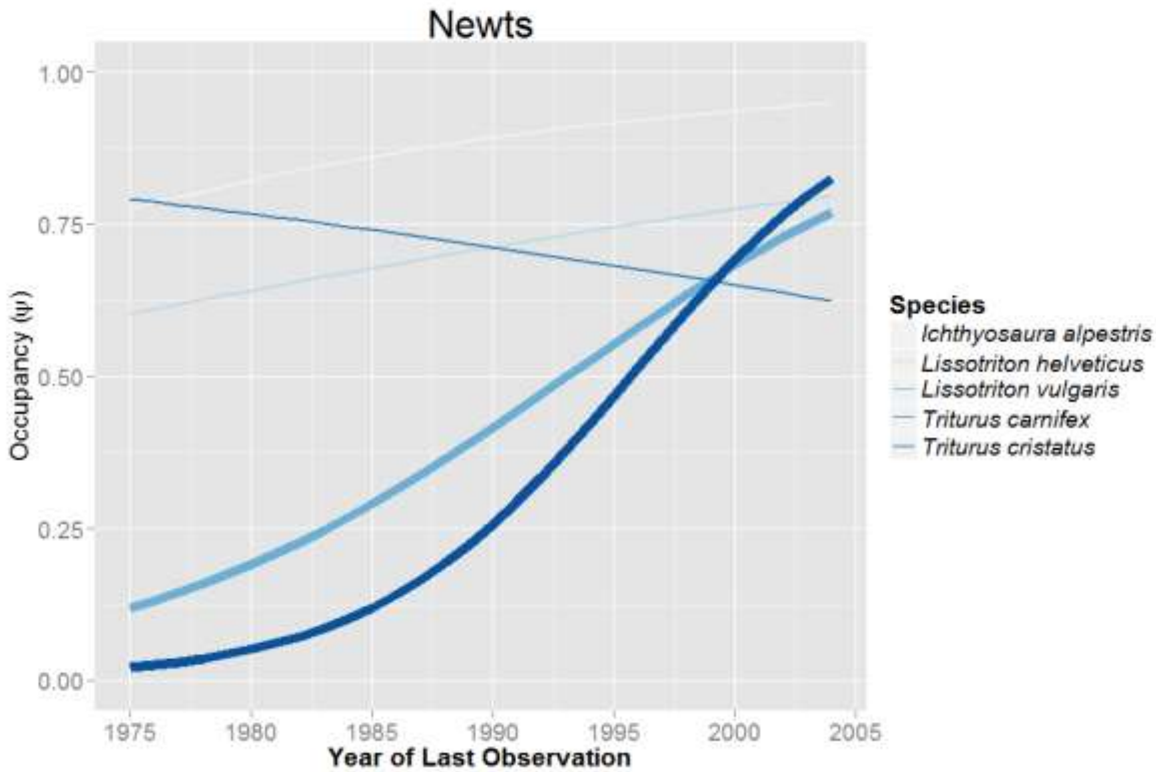
Figures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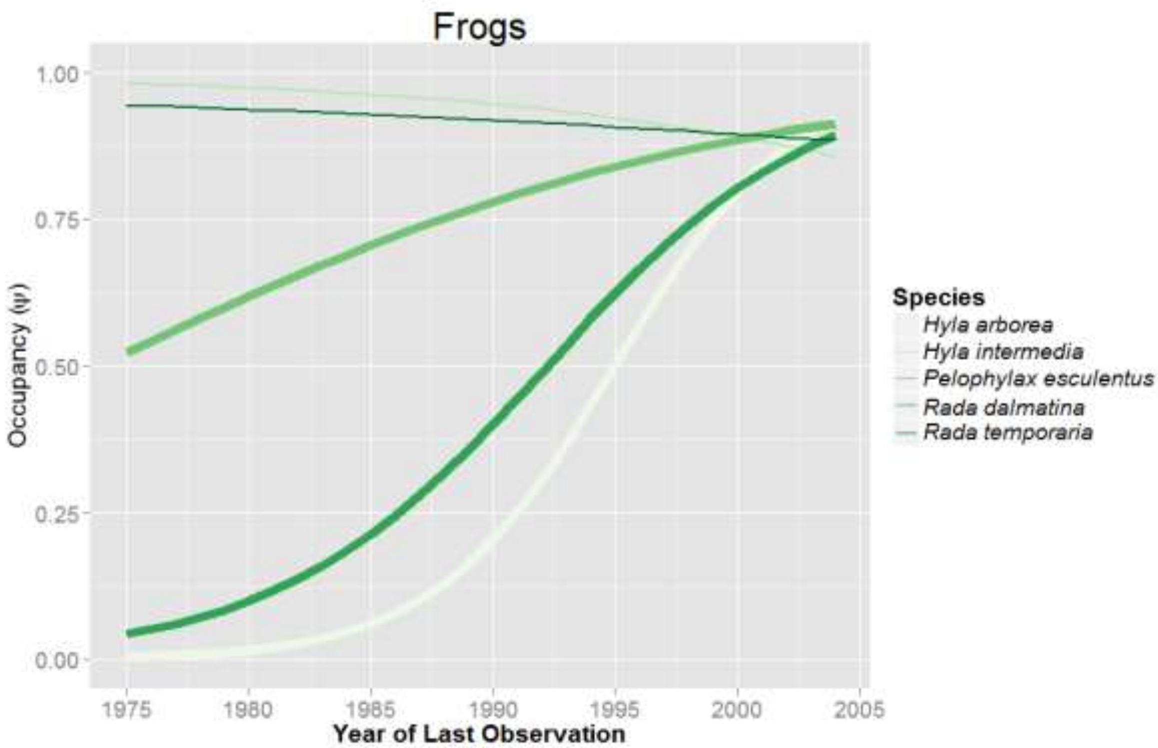
Occupancy (ψ)
1.00
0.75
0.50
0.25
0.00
1975
1980
1985
1990
1995
2000
2005
Year of Last Observation
Species
Ichthyosaura alpestris
Lissotriton helveticus
Lissotriton vulgaris
Triturus carnifex
Triturus cristatus


Frogs
Occupancy (ψ)
1.00
0.75
0.50
0.25
0.00
1975
1980
1985
1990
1995
2000
2005
Year of Last Observation
Species
Hyla arborea
Hyla intermedia
Pelophylax esculentus
Rada dalmatina
Rada temporaria

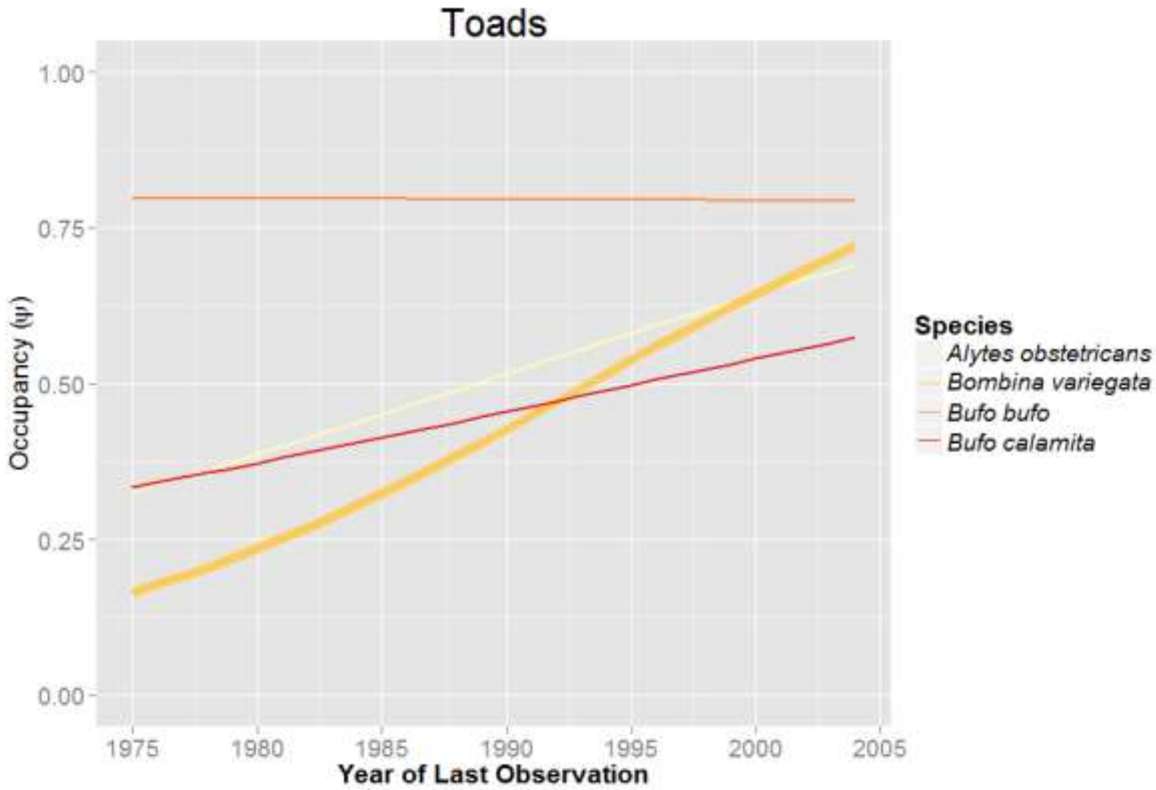


Figure 1 The effect of "year of last observation" YLO on occupancy probability (based on the model ψ(YLO)p(.)) for each species when using the Red List data. Bold lines represent curves for which confidence intervals did not include zero.

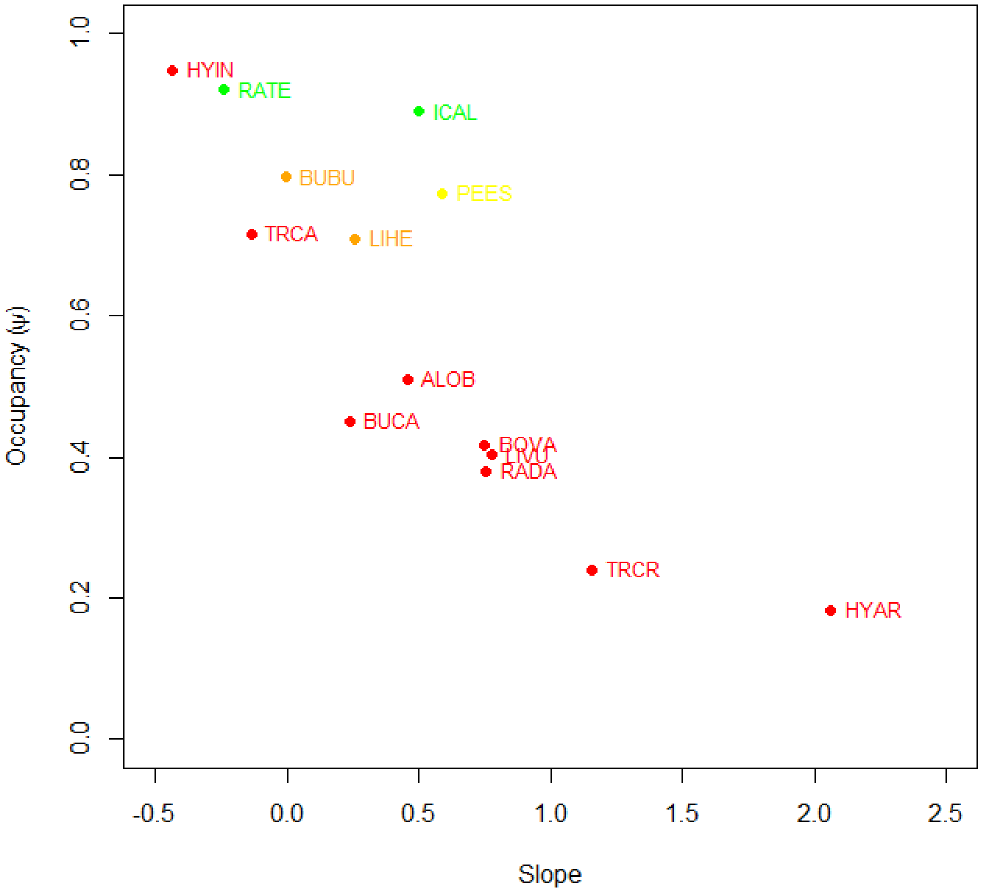


Figure 2 Relation of the Red List status of each species with the interaction between the slope and the median results of occupancy modelling, both based on model ψ(YLO)p(.) when using the Red List data. Median results have been calculated on the predicted values of occupancy for each year, from 1975 to 2004. Colors correspond to the Red List status of the species: EN (Endangered, red), VU (vulnerable, orange), NT (Near Threatened, yellow), LC (Least Concern, green).

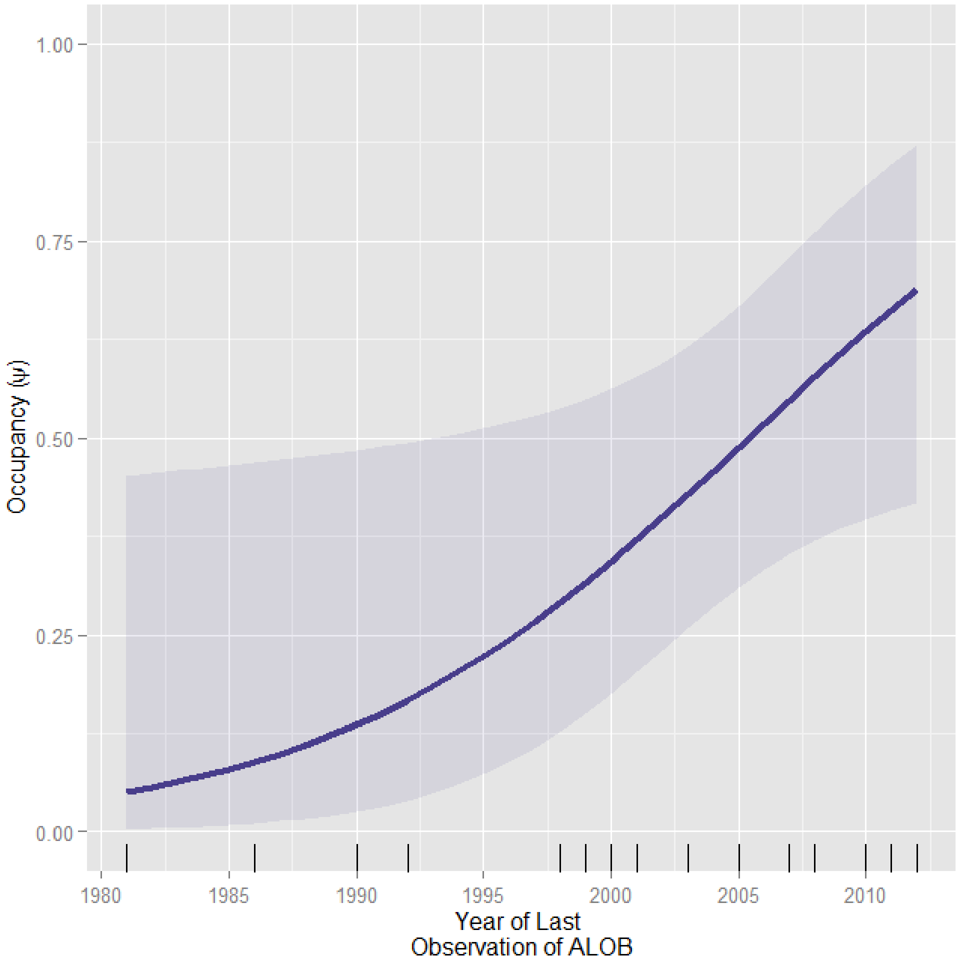


Figure 3 Site occupancy probability (95% confidence interval) as a function of year of last observation YLO for *Alytes obstetricans,* based on the best model ψ(YLO)p(NbObs+ShorSurv) when using the "VD/FR" data. Small black ticks in the graphs represent YLO.

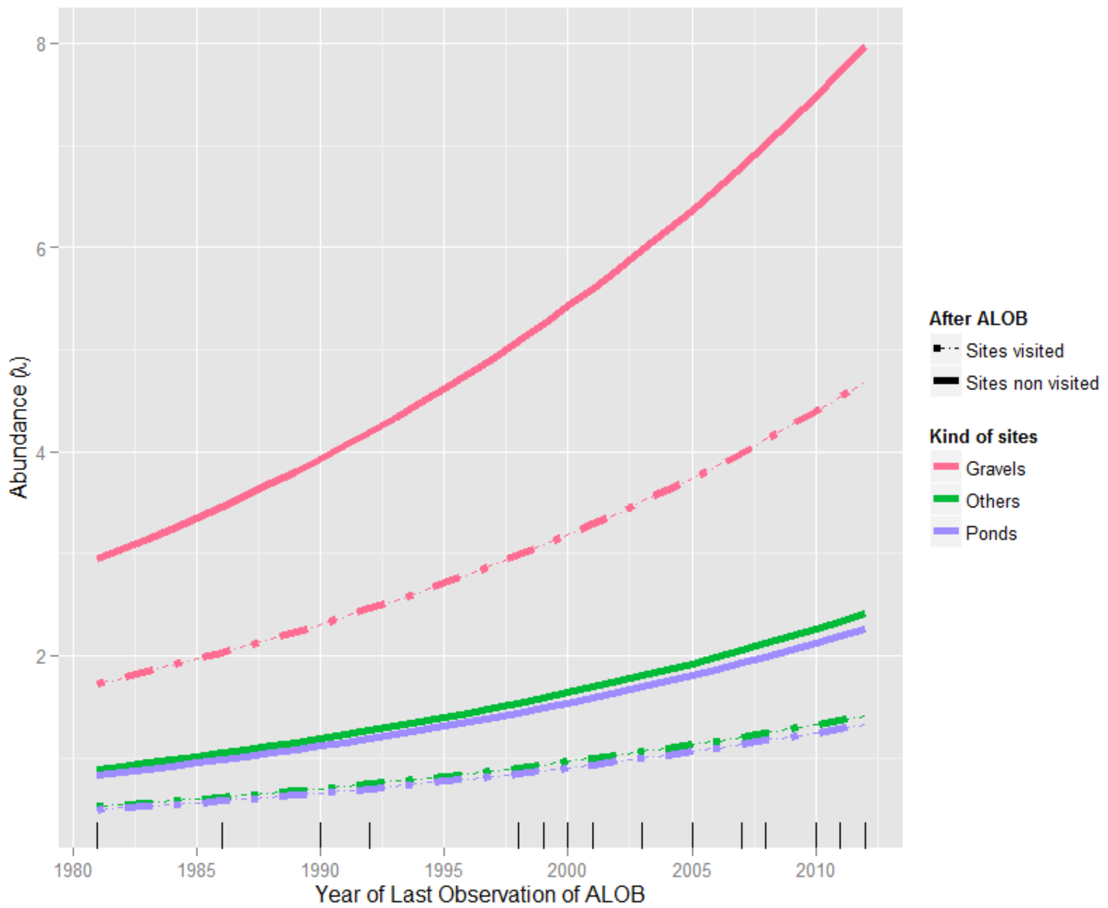


Figure 4 The relationship between the variable year of last observation YLO of *Alytes obstetricans* and its current abundance, based on the best model λ(YLO+After.ALOB+KindSite)p(NbObs+ShorSurv) when using the "VD/FR" data. Small black ticks in the graphs represent YLO.

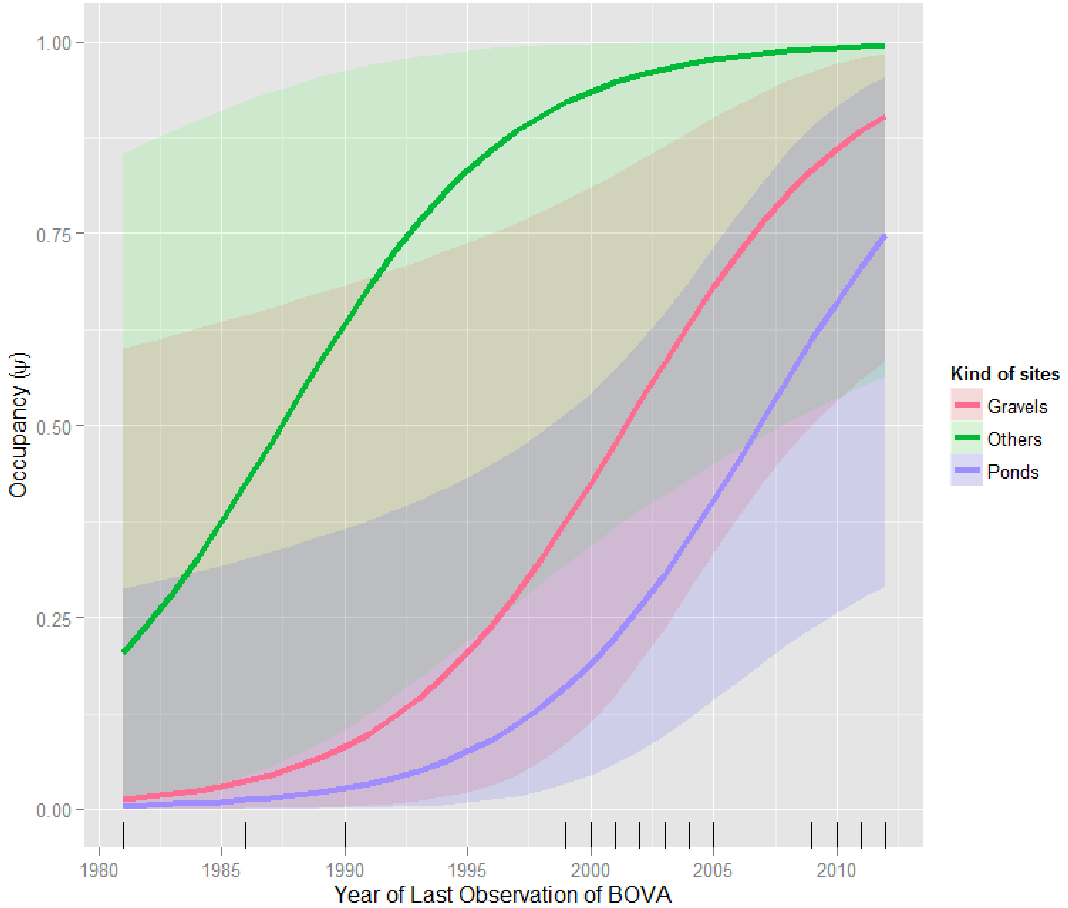


Figure 5 Site occupancy probability (95% confidence interval) as a function of year of last observation YLO for *Bombina variegata*, based on the best model ψ(YLO+KindSite)p(Temp+Time) when using the "VD/FR" data. Small black ticks in the graphs represent YLO.

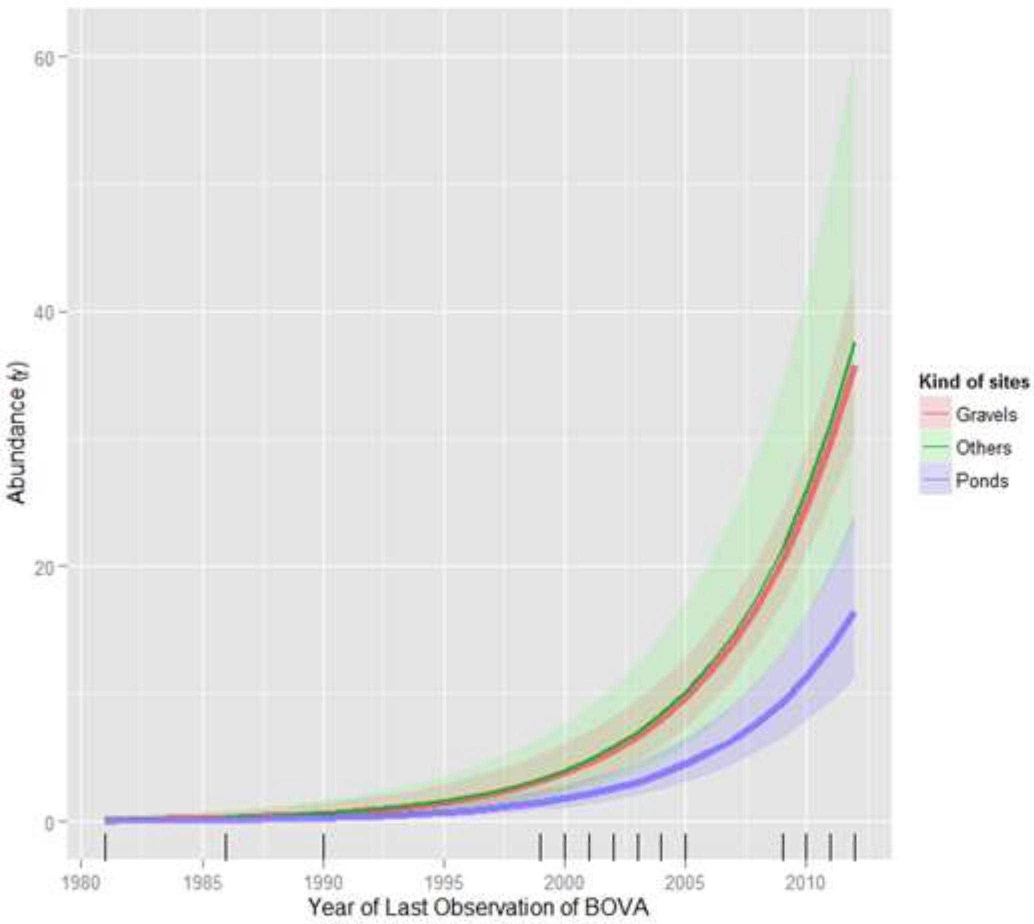


Figure 6 The relationship between the variable year of last observation of *Bombina variegata* and current abundance (95% confidence interval), based on the best model λ(YLO+KindSite)p(Date2+Time) when using the "VD/FR" data. Bold lines represent curves for which confidence intervals did not include zero. Small black ticks in the graphs represent YLO.

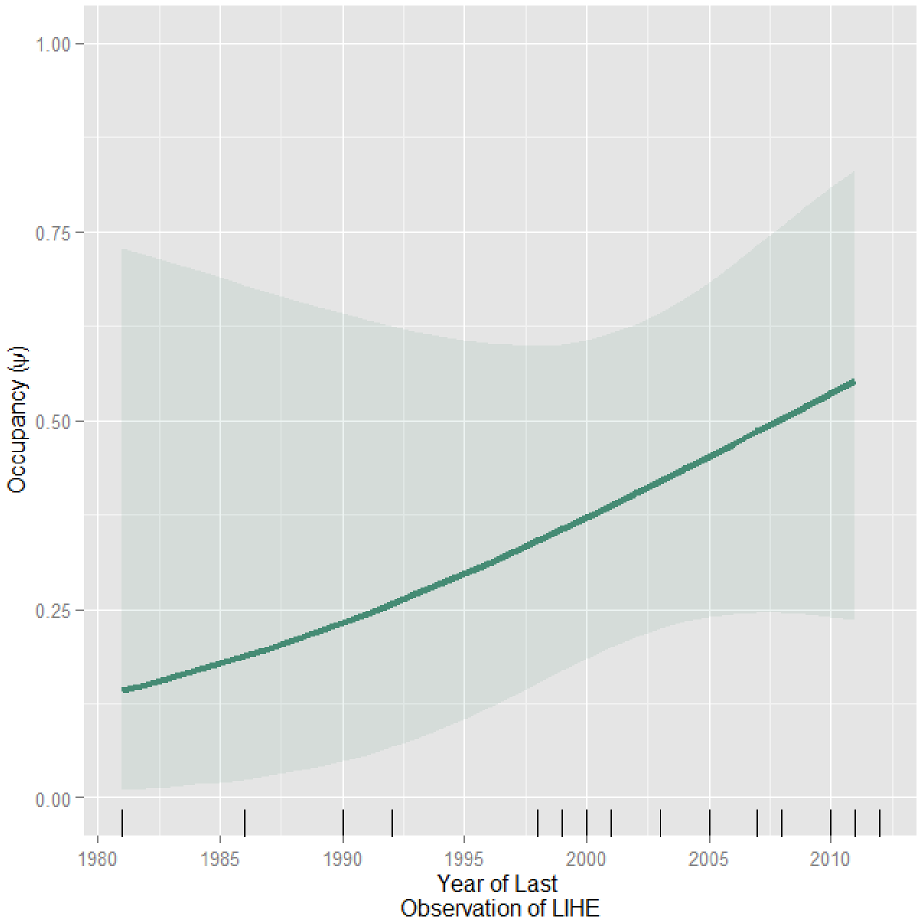


Figure 7 Site occupancy probability (95% confidence interval) as a function of year of last observation YLO for *Lissotriton helveticus*, based on the model ψ(YLO)p(ShorAcc) when using the "VD/FR" data. Small black ticks in the graphs represent YLO.

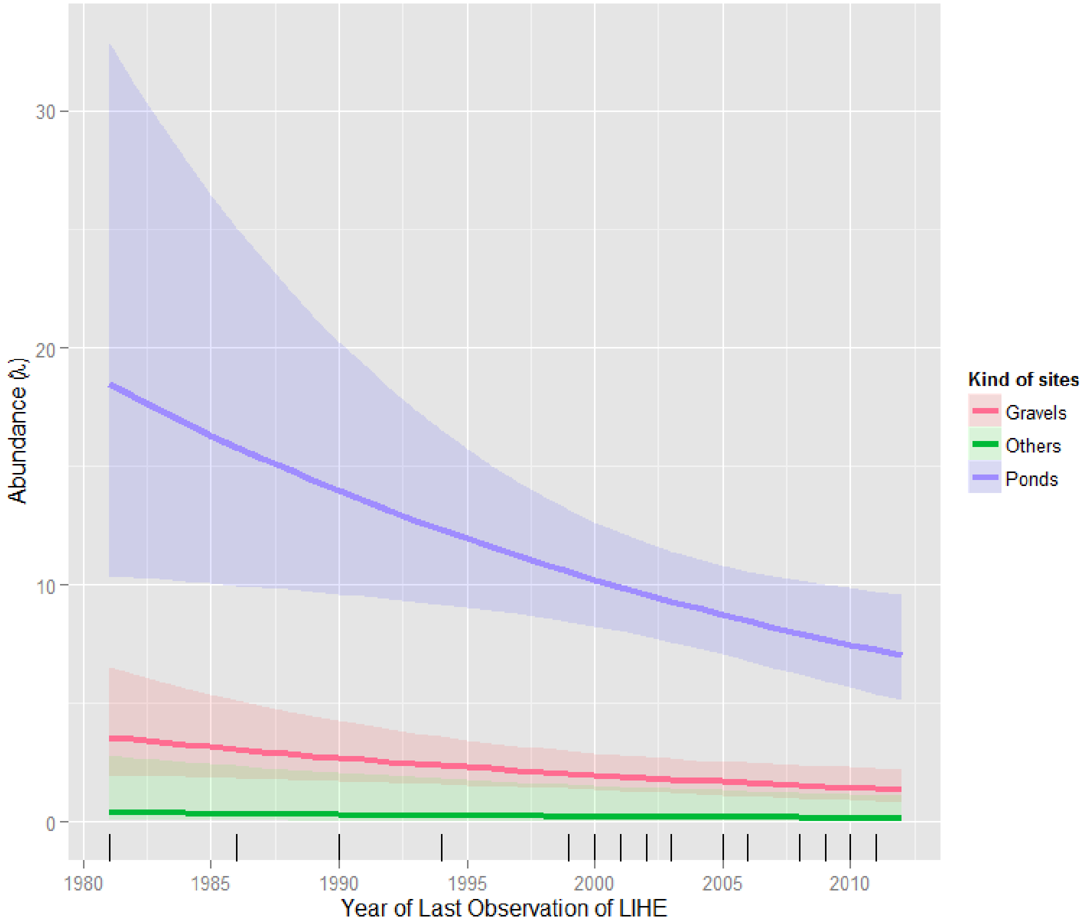


Figure 8 The relationship between the variable year of last observation YLO of *Lissotriton helveticus* and its current abundance (95% confidence interval), based on the best model λ(YLO+KindSite)p(Moon+Time) when using the "VD/FR" data. Small black ticks in the graphs represent YLO.

Tables

Table 1 Variables measured for each site visit which may explain detection probability of *Alytes obstetricans*, *Bombina variegata* and *Lissotriton helveticus*.

Variables	Description	Mean (range)	Probable explanation for
DATE	Date of the visit (day 1 = first day of field work)	59.42 (1−94)	Detection
DATE+DATE^2	Quadratic term of phenology	4483 (2−8930)	Detection
OBSERVERS	Number of observers during the visit	1.99 (1−3)	Detection
TIME	Visit duration (min)	50.1 (14−80)	Detection
TEMPERATURE	Air temperature during the visit (T°C)	13.83 (4−23)	Detection
AMOUNT−OF−RAIN	Rainfall during the day of the visit (mm)	0.614 (0−7.5)	Detection
RAIN	Presence of rain during the visit (1 or 0)	0.009 (0−1)	Detection
WATER CLARITY	Scale of water clarity (1: bottom visible, 2: bottom visible in shallows, 3: bottom not visible, 4: no water)	2.197 (1−4)	Detection
SHORELINE SEARCHED	Proportion of each site visited	2.936 (1=0−25%, 4=76−100%)	Detection
SHORELINE ACCESSIBLE	Proportion of each site accessibility (%)	3.388 (1=0−25%, 4=76−100%)	Detection
HUMIDITY	Proportion of humidity during the visit (%)	67.94 (43−91)	Detection
MOON	State of the moon	2.96 (1−4)	Detection
VEGETATION	Presence of vegetation in the water (0: no vegetation, 1: vegetation, 2: no vegetation because no water)	0.8723 (0−2)	Detection
WIND	Presence of wind during the visit (1 or 0)	0.3789 (0−1)	Detection

Table 2 Variables measured for each site visit which may explain site occupancy probability or abundance of *Alytes obstetricans*, *Bombina variegata* and *Lissotriton helveticus*.

Variables	Description	Mean (range)	Probable explanation for
KINDSITE	Classification of habitat type: pond, gravel or other	–	Occupancy/ Abundance
ALOB YLO	Last year of observation of *Alytes obstetricans*	2003 (1981–2012)	Occupancy/ Abundance
BOVA YLO	Last year of observation of *Bombina variegata*	2003 (1981–2012)	Occupancy/ Abundance
LIHE YLO	Last year of observation of *Lissotriton helveticus*	2002 (1981–2011)	Occupancy/ Abundance
AFTER_ALOB	Detection or not of another species than *Alytes obstetricans* between YLO and current year (1 or 0)	0.4706 (0–1)	Occupancy/ Abundance
AFTER_BOVA	Detection or not of another species than *Bombina variegata* between YLO and current year (1 or 0)	0.5 (0–1)	Occupancy/ Abundance
AFTER_LIHE	Detection or not of another species than *Lissotriton helveticu*s between YLO and current year (1 or 0)	0.6765 (0–1)	Occupancy/ Abundance

Table 3 Model results for detection probability (on the logit scale) for the 14 species of the Red List data base. For the 6 first species the best model was ψ(.)p(.), for the 8 following species, the best model was ψ(YLO)p(.).

Model	Intercept
Bufo bufo	
ψ(.)p(.)	0.319 ± 0.106
ψ(YLO)p(.)	0.318 ± 0.106
Bufo calamita	
ψ(.)p(.)	0.697 ± 0.305
ψ(YLO)p(.)	0.702 ± 0.305
Hyla intermedia	
ψ(.)p(.)	1.140 ± 0.423
ψ(YLO)p(.)	1.130 ± 0.411
Lissotriton helveticus	
ψ(.)p(.)	0.437 ± 0.146
ψ(YLO)p(.)	0.440 ± 0.146
Rana temporaria	
ψ(.)p(.)	0.903 ± 0.091
ψ(YLO)p(.)	0.902 ± 0.091
Triturus carnifex	
ψ (.)p(.)	0.653 ± 0.399
ψ(YLO)p(.)	0.655 ± 0.399
Alytes ostetricans	
ψ(YLO)p(.)	0.409 ± 0.184
ψ(.)p(.)	0.403 ± 0.185
Bombina variegata	
ψ(YLO)p(.)	0.767 ± 0.227
ψ(.)p(.)	0.787 ± 0.226
Hyla arborea	
ψ(YLO2)p(.)	2.310 ± 0.486
ψ(.)p(.)	2.210 ± 0.480
Ichthyosaura alpestris	
ψ(YLO)p(.)	0.785 ± 0.100
ψ(.)p(.)	0.778 ± 0.101
Lissotriton vulgaris	
ψ(YLO)p(.)	0.085 ± 0.250
ψ(.)p(.)	0.083 ± 0.253
Pelophylax esculentus	
ψ(YLO)p(.)	0.622 ± 0.105
ψ(.)p(.)	0.621 ± 0.106
Rana dalmatina	
ψ(YLO)p(.)	0.298 ± 0.197
ψ(.)p(.)	0.293 ± 0.198
Triturus cristatus	
ψ(YLO)p(.)	0.348 ± 0.271
ψ(.)p(.)	0.389 ± 0.269

Table 4 Model selection results for occurrence probability (on the logit scale) for the 14 species of the Red List data base. For the 6 first species the best model was ψ(.)p(.), for the 8 following species, the best model was ψ(YLO)p(.).

Model	ΔAIC	Akaike weight	Intercept	Slope
Bufo bufo				
ψ(.)p(.)	0.00	0.73	1.360 ± 0.233	
ψ(YLO)p(.)	2.00	0.27	1.360 ± 0.233	−0.008 ± 0.216
Bufo calamita				
ψ(.)p(.)	0.00	0.68	−0.057 ± 0.323	
ψ(YLO)p(.)	1.48	0.32	−0.067 ± 0.325	0.236 ± 0.327
Hyla intermedia				
ψ(.)p(.)	0.00	0.71	2.180 ± 0.997	
ψ(YLO)p(.)	1.80	0.29	2.330 ± 1.200	−0.438 ± 1.150
Lissotriton helveticus				
ψ(.)p(.)	0.00	0.62	0.961 ± 0.259	
ψ(YLO)p(.)	0.94	0.38	0.969 ± 0.262	0.256 ± 0.250
Rana temporaria				
ψ(.)p(.)	0.00	0.66	2.360 ± 0.290	
ψ(YLO)p(.)	1.30	0.34	2.396 ± 0.302	−0.241 ± 0.296
Triturus carnifex				
ψ (.)p(.)	0.00	0.73	0.704 ± 0.605	
ψ(YLO)p(.)	1.94	0.27	0.701 ± 0.605	−0.137 ± 0.573
Alytes ostetricans				
ψ(YLO)p(.)	0.00	0.68	0.130 ± 0.248	0.454 ± 0.249
ψ(.)p(.)	1.51	0.32	0.131 ± 0.242	
Bombina variegata				
ψ(YLO)p(.)	0.00	0.975	−0.088 ± 0.249	0.749 ± 0.261
ψ(.)p(.)	7.31	0.025	−0.043 ± 0.235	
Hyla arborea				
ψ(YLO2)p(.)	0.00	1.00	−0.195 ± 0.367	2.065 ± 0.547
ψ(.)p(.)	24.69	4.3e−06	0.034 ± 0.276	
Ichthyosaura alpestris				
ψ(YLO)p(.)	0.00	0.65	2.240 ± 0.310	0.498 ± 0.278
ψ(.)p(.)	1.27	0.35	2.180 ± 0.294	
Lissotriton vulgaris				
ψ(YLO)p(.)	0.00	0.85	0.095 ± 0.349	0.775 ± 0.362
ψ(.)p(.)	3.45	0.15	0.087 ± 0.324	
Pelophylax esculentus				
ψ(YLO)p(.)	0.00	0.927	1.639 ± 0.262	0.589 ± 0.226
ψ(.)p(.)	5.09	0.073	1.530 ± 0.236	
Rana dalmatina				
ψ(YLO)p(.)	0.00	0.80	1.183 ± 0.419	0.753 ± 0.352
ψ(.)p(.)	2.75	0.20	1.080 ± 0.372	
Triturus cristatus				
ψ(YLO)p(.)	0.00	0.988	−0.193 ± 0.352	1.157 ± 0.424
ψ(.)p(.)	8.78	0.012	−0.188 ± 0.296	

Table 5 The model selection results for *Alytes obstetricans*, for detection and occurrence probability (site occupancy model) when using the "VD/FR" data. K is the number of parameters. For detection probability, only the best model is shown. The entire model selection results are shown in the Supporting Information section (Table 11). Values in the first section ("Detection probability") are results of detection probability modelling, values in the second section ("Occurrence probability") are results of occupancy modelling when using the best model for detection (i.e. ψ(.)p(NbObs+ShorSurv)).

Model	**K**	**ΔAIC**	**Akaike weight**	**-2log-likelihood**	**Intercept**	**Slope**	**Slope2**	**Slope3**	**Slope4**
Detection probability									
ψ(.)p(NbObs+ShorSurv)	4	0.00	0.350	80.41	1.760 ± 0.579	1.550 ± 0.634	−1.010 ± 0.560		
Occurrence probability									
ψ(YLO)p(NbObs+ShorSurv)	5	0.00	0.490	74.65	−0.314 ± 0.393	1.006 ± 0.480			
ψ(YLO+After.ALOB)p(NbObs+ShorSurv)	6	1.96	0.184	74.61	−0.305 ± 0.395	0.951 ± 0.575	−0.077 ± 0.470		
ψ(YLO+KindSite)p(NbObs+ShorSurv)	7	2.38	0.149	73.02	0.226 ± 0.586	0.941 ± 0.507	−0.914 ± 1.390	−1.003 ± 0.825	
ψ(.)p(NbObs+ShorSurv)	4	3.76	0.075	80.41	−0.207 ± 0.351				
ψ(YLO+After.ALOB+KindSite)p(NbObs+ShorSurv)	8	4.37	0.055	73.01	0.264 ± 0.599	0.826 ± 0.617	−0.153 ± 0.494	−1.003 ± 1.405	−1.025 ± 0.834
ψ(KindSite)p(NbObs+ShorSurv)	6	4.74	0.046	77.39	0.420 ± 0.532	−1.742 ± 1.252	−0.995 ± 0.772		
ψ(.)p(.)	2	13.27	6.4e−4	93.92	−0.210 ± 0.350				

Table 6 The model selection results for *Alytes obstetricans*, for detection probability and abundance (point count model) when using the "VD/FR" data. K is the number of parameters. For detection probability, only the best model is shown. The entire model selection results are shown in the Supporting Information section (Table 12). Values in the first section ("Detection probability") are results of detection probability modelling, values in the second section ("Abundance") are results of abundance modelling when using the best model for detection (i.e. λ(.)p(NbObs+ShorSurv)).

Model	**K**	**ΔAIC**	**Akaike weight**	**-2log-likelihood**	**Intercept**	**Slope**	**Slope2**	**Slope3**	**Slope4**
Detection probability									
λ(.)p(NbObs+ShorSurv)	4	0.00	0.35	359.71	−0.231 ± 0.242	0.465 ± 0.121	−0.363 ± 0.166		
Abundance									
λ(YLO+After.ALOB+KindSite)p(NbObs+ShorSurv)	8	0.00	0.55	315.33	1.529 ± 0.193	0.269 ± 0.209	−0.270 ± 0.178	−1.198 ± 0.581	−1.261 ± 0.294
λ(YLO+KindSite)p(NbObs+ShorSurv)	7	0.39	0.45	317.72	1.489 ± 0.190	0.499 ± 0.156	−0.994 ± 0.527	−1.232 ± 0.292	
λ(KindSite)p(NbObs+ShorSurv)	6	10.83	2.4e−3	330.16	1.670 ± 0.166	−1.450 ± 0.511	−1.300 ± 0.289		
λ(YLO)p(NbObs+ShorSurv)	5	18.89	4.3e−5	340.23	0.993 ± 0.170	0.606 ± 0.154			
λ(YLO+After.ALOB)p(NbObs+ShorSurv)	6	19.57	3.1e−5	338.91	0.997 ± 0.170	0.467 ± 0.185	−0.183 ± 0.159		
λ(.)p(NbObs+ShorSurv)	4	36.38	6.9e−9	359.71	1.140 ± 0.149				
λ(.)p(.)	2	51.31	3.9e−12	378.64	1.050 ± 0.133				

Table 7 The model selection results for *Bombina variegata*, for detection and occurrence probability (site occupancy model) when using the "VD/FR" data. K is the number of parameters. For detection probability, only the best model is shown. The entire model selection results are shown in the Supporting Information section (Table 13). Values in the first section ("Detection probability") are results of detection probability modelling, values in the second section ("Occurrence probability") are results of occupancy modelling when using the best model for detection (i.e. ψ(.)p(Temp+Time)).

Model	K	ΔAIC	Akaike weight	-2log-likelihood	Intercept	Slope	Slope2	Slope3	Slope4
Detection probability									
ψ(.)p(Temp+Time)	4	0.00	0.65	71.69	1.630 ± 0.568	1.390 ± 0.627	2.290 ± 0.654		
Occurrence probability									
ψ(YLO+KindSite)p(Temp+Time)	7	0.00	0.45	57.73	0.258 ± 0.780	1.837 ± 0.820	2.965 ± 2.150	−1.149 ± 1.020	
ψ(YLO+After.BOVA+KindSite)p(Temp+Time)	8	0.72	0.32	56.45	0.413 ± 0.835	2.401 ± 1.065	0.720 ± 0.669	3.772 ± 2.562	−1.669 ± 1.165
ψ(YLO)p(Temp+Time)	5	2.19	0.15	63.92	0.153 ± 0.435	1.225 ± 0.524			
ψ(YLO+After.BOVA)p(Temp+Time)	6	4.06	0.060	63.79	0.148 ± 0.433	1.125 ± 0.576	−0.177 ± 0.486		
ψ(KindSite)p(Temp+Time)	6	7.31	0.012	67.04	0.811 ± 0.585	0.315 ± 1.341	−1.593 ± 0.844		
ψ(.)p(Temp+Time)	4	7.96	8.5e−3	71.69	0.194 ± 0.372				
ψ(.)p()	2	26.68	7.3e−7	94.42	0.015 ± 0.346				

Table 8 The model selection results for *Bombina variegata*, for detection and abundance (point count model) when using the “VD/FR” data. K is the number of parameters. For detection probability section, only the best model is shown. The entire model results are shown in the Supporting Information section (Table 14). Values in the first section (“Detection probability”) are results of detection probability modelling, values in the second section (“Abundance”) are results of abundance modelling when using the best model for detection (i.e. λ(.)p(Date2+Time)).

Model	**K**	**ΔAIC**	**Akaike weight**	**-2log-likelihood**	**Intercept**	**Slope**	**Slope2**	**Slope3**	**Slope4**
Detection probability									
λ(.)p(Date2+Time)	5	0.00	0.95	915.25	−1.882 ± 0.185	1.477 ± 0.133	0.275 ± 0.098	1.992 ± 0.171	
Abundance									
λ(YLO+KindSite)p(Date2+Time)	8	0.00	0.72	664.61	1.833 ± 0.188	1.620 ± 0.186	0.047 ± 0.245	−0.779 ± 0.191	
λ(YLO+After.BOVA+KindSite)p(Date2+Time)	9	1.92	0.28	664.53	1.803 ± 0.191	1.580 ± 0.192	−0.083 ± 0.102	0.023 ± 0.246	−0.718 ± 0.205
λ(YLO)p(Date2+Time)	6	16.31	2.1e−4	684.92	1.480 ± 0.185	1.880 ± 0.191			
λ(YLO+After.BOVA)p(Date2+Time)	7	16.55	1.8e−4	683.16	1.473 ± 0.182	1.705 ± 0.198	−0.235 ± 0.094		
λ(KindSite)p(Date2+Time)	7	170.46	7.0e−38	837.07	2.961 ± 0.081	−0.459 ± 0.244	−1.411 ± 0.185		
λ(.)p(Date2+Time)	5	244.64	5.4e−54	915.25	2.640 ± 0.081				
λ(.)p(.)	2	559.10	2.8e−122	1237.71	2.320 ± 0.077				

Table 9 The model selection results for *Lissotriton helveticus*, for detection and occurrence probability (site occupancy model) when using the "VD/FR" data. K is the number of parameters. For detection probability section, only the best model is shown. The entire model selection results are shown in the Supporting Information section (Table 15). Values in the first section ("Detection probability") are results of detection probability modelling, values in the second section ("Occurrence probability") are results of occupancy modelling when using the best model for detection (i.e. ψ(.)p(ShorAcc)).

Model	**K**	**ΔAIC**	**Akaike weight**	**-2log-likelihood**	**Intercept**	**Slope**	**Slope2**	**Slope3**	**Slope4**
Detection probability									
ψ(.)p(ShorAcc)	3	0.00	0.085	82.11	−0.324 ± 0.450	0.869 ± 0.506			
Occurrence probability									
ψ(.)p(ShorAcc)	3	0.00	0.342	82.11	−0.365 ± 0.450				
ψ(YLO)p(ShorAcc)	4	0.70	0.241	80.81	−0.413 ± 0.467	0.511 ± 0.478			
ψ(.)p(.)	2	1.22	0.186	85.33	−0.457 ± 0.448				
ψ(YLO+After.LIHE)p(ShorAcc)	5	2.05	0.123	80.16	−0.247 ± 0.823	1.516 ± 1.660	−1.607 ± 1.798		
ψ(KindSite)p(ShorAcc)	5	3.57	0.057	81.67	−0.409 ± 0.622	−0.576 ± 1.352	0.299 ± 0.899		
ψ(YLO+KindSite)p(ShorAcc)	6	4.57	0.035	80.68	−0.446 ± 0.650	0.470 ± 0.494	−0.307 ± 1.400	0.196 ± 0.921	
ψ(YLO+After.LIHE+KindSite)p(ShorAcc)	7	6.00	0.017	80.10	−0.210 ± 0.872	1.330 ± 1.429	−1.536 ± 1.395	−1.015 ± 1.741	0.157 ± 1.177

Table 10 The model selection results for *Lissotriton helveticus*, for detection and abundance (point count model) when using the "VD/FR" data. K is the number of parameters. For detection probability, only the best model is shown. The entire model selection results are shown in the Supporting Information section (Table 16). Values in the first section ("Detection probability") are results of detection probability modelling, values in the second section ("Abundance") are results of abundance modelling when using the best model for detection (i.e. λ(.)p(Moon+Time)).

Model	**K**	**ΔAIC**	**Akaike weight**	**-2log-likelihood**	**Intercept**	**Slope**	**Slope2**	**Slope3**	**Slope4**
Detection probability									
λ(.)p(Moon+Time)	6	0.00	0.97	815.85	−0.160 ± 0.751	1.650 ± 0.782	−2.056 ± 0.798	0.089 ± 0.748	1.168 ± 0.172
Abundance									
λ(YLO+KindSite)p(Moon+Time)	9	0.00	0.56	714.48	0.627 ± 0.199	−0.239 ± 0.098	−2.230 ± 1.023	1.643 ± 0.223	
λ(YLO+After.LIHE+KindSite)p(Moon+Time)	10	0.93	0.35	713.41	0.623 ± 0.199	−0.265 ± 0.101	−0.097 ± 0.093	−2.335 ± 1.029	1.658 ± 0.225
λ(KindSite)p(Moon+Time)	8	3.60	0.092	720.08	0.652 ± 0.197	−2.020 ± 1.020	1.575 ± 0.220		
λ(.)p(Moon+Time)	6	95.36	1.1e−21	815.85	1.500 ± 0.091				
λ(YLO)p(Moon+Time)	7	97.31	4.1e−22	815.79	1.501 ± 0.091	0.021 ± 0.088			
λ(YLO+After.LIHE)p(Moon+Time)	8	99.10	1.7e−22	815.59	1.501 ± 0.091	0.017 ± 0.088	0.040 ± 0.090		
λ(.)p(.)	2	189.74	3.5e−42	918.22	1.510 ±0.094				

Supporting Information

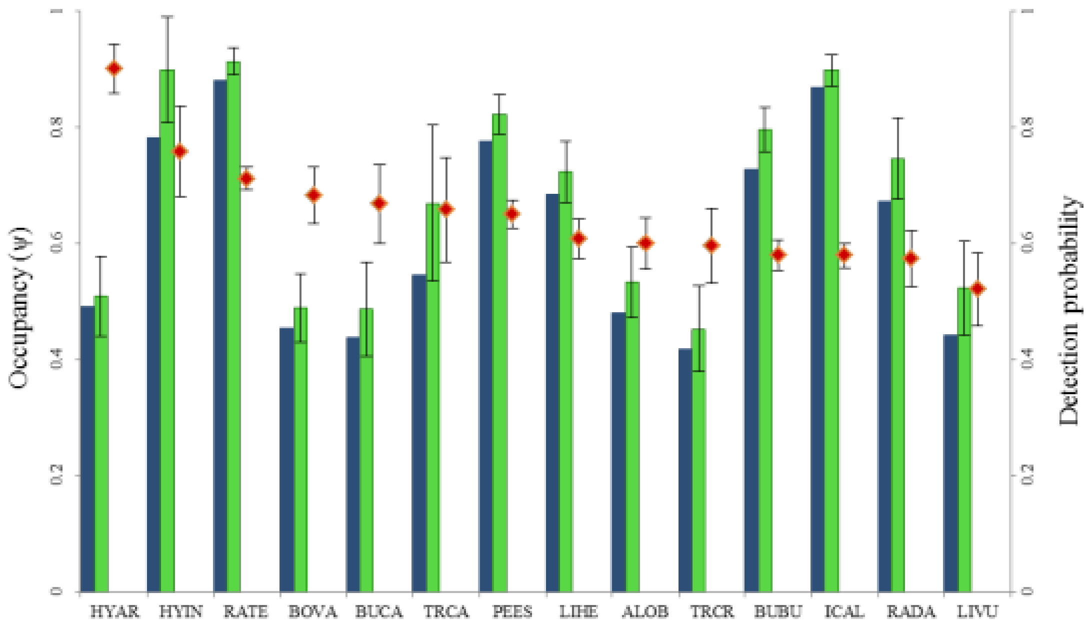


Figure 9 Comparison between naïve occupancy (dark blue bars) and estimated occupancy ± SE (light green bars) based on the model ψ(.)p(.) for each species (on the probability scale). Detection probability ± SE (red circles) is based on the model ψ(.)p(.).

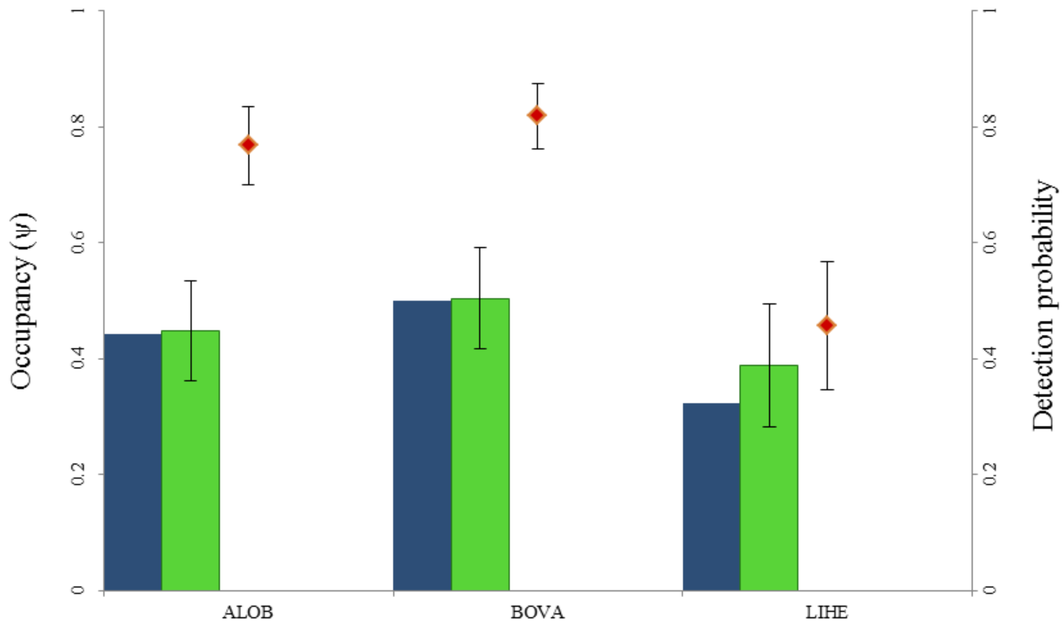


Figure 10 Comparison between naïve occupancy (dark blue bars) and estimated occupancy ± SE (light green bars) based on the model ψ(.)p(.) for species *Alytes obstetricans*, *Bombina variegata* and *Lissotriton helveticus* (on the probability scale). Detection probability ± SE (red circles) is based on the model ψ(.)p(.).

Table 11 The model selection results for *Alytes obstetricans*, for detection and occurrence probability (site occupancy model) when using the "VD/FR" data. K is the number of parameters. Values in the first section ("Detection probability") are results of detection probability modelling, values in the second section ("Occurrence probability") are results of occupancy modelling when using the best model for detection (i.e. ψ(.)p(NbObs+ShorSurv)).

Model	**K**	**ΔAIC**	**Akaike weight**	**-2log-likelihood**
Detection probability				
ψ(.)p(NbObs+ShorSurv)	4	0.00	0.350	80.41
ψ(.)p(NbObs)	3	2.31	0.110	84.72
ψ(.)p(Rain+NbObs)	4	3.41	0.064	83.82
ψ(.)p(NbObs+Temp)	4	3.84	0.051	84.25
ψ(.)p(NbObs+AmountRain)	4	4.02	0.047	84.43
ψ(.)p(NbObs+ShorAcc)	4	4.20	0.043	84.60
ψ(.)p(Date+NbObs)	4	4.24	0.042	84.64
ψ(.)p(NbObs+Time)	4	4.28	0.041	84.68
ψ(.)p(NbObs+Humid)	4	4.30	0.041	84.71
ψ(.)p(Date+ShorSurv)	4	5.06	0.028	85.47
ψ(.)p(Temp+ShorSurv)	4	5.67	0.020	86.07
ψ(.)p(Date2+NbObs)	5	6.00	0.017	84.41
ψ(.)p(Date2+ShorSurv)	5	6.42	0.014	84.83
ψ(.)p(Rain+Temp)	4	6.85	0.011	87.26
ψ(.)p(Temp)	3	7.06	0.010	89.47
ψ(.)p(Moon+NbObs)	6	7.44	8.48e−3	83.85
ψ(.)p(Temp+ShorAcc)	4	7.89	6.77e−3	88.30
ψ(.)p(ShorSurv)	3	8.05	6.26e−3	90.46
ψ(.)p(Temp+Time)	4	8.16	5.92e−3	88.57
ψ(.)p(Date+Rain)	4	8.24	5.69e−3	88.65
ψ(.)p(Temp+Humid)	4	8.81	4.29e−3	89.21
ψ(.)p(Date)	3	8.99	3.92e−3	91.40
ψ(.)p(ShorSurv+ShorAcc)	4	9.01	3.88e−3	89.41
ψ(.)p(Temp+AmountRain)	4	9.03	3.84e−3	89.43
ψ(.)p(Date+Temp)	4	9.05	3.80e−3	89.45
ψ(.)p(Date+ShorAcc)	4	9.41	3.18e−3	89.81
ψ(.)p(Date2+Rain)	5	9.43	3.14e−3	87.84
ψ(.)p(Rain+ShorSurv)	4	9.43	3.14e−3	89.84
ψ(.)p(.)	2	9.51	3.02e−3	93.92
ψ(.)p(Date2+Temp)	5	9.61	2.87e−3	88.02
ψ(.)p(ShorAcc)	3	9.62	2.86e−3	92.02
ψ(.)p(Time+ShorSurv)	4	9.93	2.45e−3	90.33
ψ(.)p(AmountRain+ShorSurv)	4	9.94	2.43e−3	90.35
ψ(.)p(Humid+ShorSurv)	4	10.05	2.30e−3	90.46
ψ(.)p(Date+Time)	4	10.14	2.20e−3	90.55

ψ(.)p(Rain+ShorAcc)	4	10.23	2.11e−3	90.64
ψ(.)p(Rain)	3	10.42	1.91e−3	92.83
ψ(.)p(Date2)	4	10.85	1.54e−3	91.26
ψ(.)p(Date+Humid)	4	10.97	1.46e−3	91.37
ψ(.)p(Date+AmountRain)	4	10.99	1.44e−3	91.39
ψ(.)p(AmountRain)	3	11.16	1.32e−3	93.57
ψ(.)p(Time+ShorAcc)	4	11.22	1.29e−3	91.62
ψ(.)p(Date2+ShorAcc)	5	11.23	1.28e−3	89.63
ψ(.)p(Time)	3	11.33	1.22e−3	93.73
ψ(.)p(Moon+Temp)	6	11.42	1.16e−3	87.82
ψ(.)p(AmountRain+ShorAcc)	4	11.46	1.14e−3	91.86
ψ(.)p(Humid)	3	11.46	1.14e−3	93.87
ψ(.)p(Moon+ShorSurv)	6	11.54	1.10e−3	87.94
ψ(.)p(Humid+ShorAcc)	4	11.60	1.06e−3	92.00
ψ(.)p(Rain+AmountRain)	4	11.93	9.0e−4	92.34
ψ(.)p(Date2+Time)	5	12.08	8.4e−4	90.48
ψ(.)p(Rain+Time)	4	12.19	7.9e−4	92.60
ψ(.)p(Rain+Humid)	4	12.31	7.5e−4	92.71
ψ(.)p(Date2+Humid)	5	12.79	5.8e−4	91.20
ψ(.)p(Date2+AmountRain)	5	12.85	5.7e−4	91.26
ψ(.)p(Moon)	5	12.85	5.7e−4	91.41
ψ(.)p(AmountRain+Time)	4	13.01	5.3e−4	93.41
ψ(.)p(AmountRain+Humid)	4	13.14	4.9e−4	93.55
ψ(.)p(Time+Humid)	4	13.29	4.6e−4	93.69
ψ(.)p(Date+Moon)	6	13.30	4.5e−4	89.71
ψ(.)p(Moon+ShorAcc)	6	13.92	3.3e−4	90.33
ψ(.)p(Date2+Moon)	7	14.17	2.9e−4	88.58
ψ(.)p(Moon+Humid)	6	14.30	2.8e−4	90.70
ψ(.)p(Rain+Moon)	6	14.31	2.7e−4	90.72
ψ(.)p(Moon+Time)	6	14.68	2.3e−4	91.09
ψ(.)p(Moon+AmountRain)	6	14.95	2.0e−4	101.36
Occurrence probability				
ψ(YLO)p(NbObs+ShorSurv)	5	0.00	0.490	74.65
ψ(YLO+After.ALOB)p(NbObs+ShorSurv)	6	1.96	0.184	74.61
ψ(YLO+KindSite)p(NbObs+ShorSurv)	7	2.38	0.149	73.02
ψ(.)p(NbObs+ShorSurv)	4	3.76	0.075	80.41
ψ(YLO+After.ALOB+KindSite)p(NbObs+ShorSurv)	8	4.37	0.055	73.01
ψ(KindSite)p(NbObs+ShorSurv)	6	4.74	0.046	77.39
ψ(.)p(.)	2	13.27	6.4e−4	93.92

Table 12 The model selection results for *Alytes obstetricans*, for detection probability and abundance (point count model) when using the "VD/FR" data. K is the number of parameters. Values in the first section ("Detection probability") are results of detection probability modelling, values in the second section ("Abundance") are results of abundance modelling when using the best model for detection (i.e. λ(.)p(NbObs+ShorSurv)).

Model	**K**	**ΔAIC**	**Akaike weight**	**-2log-likelihood**
Detection probability				
λ(.)p(NbObs+ShorSurv)	4	0.00	0.35	359.71
λ(.)p(NbObs+Humid)	4	0.98	0.21	360.69
λ(.)p(NbObs)	3	2.74	0.089	364.45
λ(.)p(NbObs+Time)	4	3.50	0.061	363.22
λ(.)p(Rain+NbObs)	4	3.69	0.055	363.41
λ(.)p(NbObs+ShorAcc)	4	4.11	0.045	363.83
λ(.)p(Date+NbObs)	4	4.50	0.037	364.22
λ(.)p(NbObs+AmountRain)	4	4.57	0.036	364.28
λ(.)p(NbObs+Temp)	4	4.61	0.035	364.33
λ(.)p(Moon+NbObs)	4	4.74	0.033	364.45
λ(.)p(Date2+NbObs)	5	6.07	0.017	363.79
λ(.)p(Date+ShorSurv)	4	9.54	3.0e−3	369.25
λ(.)p(Date2+ShorSurv)	5	9.56	2.9e−3	367.28
λ(.)p(Date2+Rain)	5	9.60	2.9e−3	367.31
λ(.)p(Date+Time)	4	10.03	2.3e−3	369.75
λ(.)p(Temp+ShorSurv)	4	10.58	1.8e−3	370.30
λ(.)p(Date+Rain)	4	11.19	1.3e−3	370.90
λ(.)p(Temp+Time)	4	11.22	1.3e−3	370.93
λ(.)p(Date2+Humid)	5	11.49	1.1e−3	369.20
λ(.)p(Date+Humid)	4	11.71	1.0e−3	371.43
λ(.)p(Date2+Time)	5	11.74	9.8e−4	369.46
λ(.)p(Rain+Temp)	4	11.77	9.7e−4	371.48
λ(.)p(Temp)	3	12.14	8.1e−4	373.86
λ(.)p(Date)	3	12.35	7.2e−4	374.07
λ(.)p(Date2+Moon)	5	12.62	6.3e−4	370.34
λ(.)p(Temp+Humid)	4	12.69	6.1e−4	372.41
λ(.)p(Moon+ShorSurv)	4	12.89	5.5e−4	372.60
λ(.)p(Date2)	4	12.92	5.5e−4	372.63
λ(.)p(Date+Moon)	4	13.15	4.9e−4	372.87
λ(.)p(Moon+Humid)	4	13.40	4.3e−4	373.11
λ(.)p(Moon+Temp)	4	13.65	3.8e−4	373.37
λ(.)p(Date2+Temp)	5	13.68	3.7e−4	371.40
λ(.)p(Date+Temp)	4	13.84	3.4e−4	373.56
λ(.)p(Temp+AmountRain)	4	13.99	3.2e−4	373.70
λ(.)p(Moon+Time)	4	14.01	3.2e−4	373.73

λ(.)p(Moon)	3	14.05	3.1e−4	375.76
λ(.)p(Temp+ShorAcc)	4	14.14	3.0e−4	373.85
λ(.)p(Date+ShorAcc)	4	14.21	2.9e−4	373.92
λ(.)p(Date+AmountRain)	4	14.27	2.8e−4	373.98
λ(.)p(ShorSurv)	3	14.45	2.5e−4	376.17
λ(.)p(Date2+AmountRain)	5	14.66	2.3e−4	372.37
λ(.)p(Date2+ShorAcc)	5	14.78	2.2e−4	372.50
λ(.)p(Humid)	3	14.84	2.1e−4	376.56
λ(.)p(.)	2	14.93	2.0e−4	378.64
λ(.)p(Humid+ShorSur)	4	14.99	1.9e−4	376.70
λ(.)p(Moon+AmountRain)	4	15.35	1.6e−4	375.07
λ(.)p(AmountRain+ShorSurv)	4	15.39	1.6e−4	375.10
λ(.)p(Time+ShorSurv)	4	15.48	1.5e−4	375.19
λ(.)p(AmountRain)	3	15.76	1.3e−4	377.47
λ(.)p(Rain+Moon)	4	15.78	1.3e−4	375.49
λ(.)p(Rain+Humid)	4	15.81	1.3e−4	375.52
λ(.)p(Moon+ShorAcc)	4	15.91	1.2e−4	375.63
λ(.)p(Time)	3	15.91	1.2e−4	377.63
λ(.)p(Rain+ShorSurv)	4	15.97	1.2e−4	375.68
λ(.)p(AmountRain+Humid)	4	16.22	1.0e−4	375.94
λ(.)p(Rain)	3	16.31	1.0e−4	378.02
λ(.)p(ShorSurv+ShorAcc)	4	16.37	9.7e−5	376.08
λ(.)p(Time+Humid)	4	16.43	9.5e−5	376.14
λ(.)p(Humid+ShorAcc)	4	16.44	9.4e−5	376.15
λ(.)p(ShorAcc)	3	16.46	9.3e−5	378.17
λ(.)p(AmountRain+Time)	4	16.64	8.5e−5	376.35
λ(.)p(Rain+AmountRain)	4	16.66	8.4e−5	376.37
λ(.)p(Rain+Time)	4	17.25	6.3e−5	376.97
λ(.)p(AmountRain+ShorAcc)	4	17.34	6.0e−5	377.05
λ(.)p(Rain+ShorAcc)	4	17.72	4.9e−5	377.44
λ(.)p(Time+ShorAcc)	4	17.84	4.7e−5	377.56
Abundance				
λ(YLO+After.ALOB+KindSite)p(NbObs+ShorSurv)	8	0.00	0.69	314.06
λ(YLO+KindSite)p(NbObs+ShorSurv)	7	1.66	0.30	317.72
λ(KindSite)p(NbObs+ShorSurv)	6	12.10	1.6e−3	330.16
λ(YLO+After.ALOB)p(NbObs+ShorSurv)	6	17.14	1.3e−4	335.20
λ(YLO)p(NbObs+ShorSurv)	5	20.17	2.9e−5	340.23
λ(.)p(NbObs+ShorSurv)	4	37.65	4.6e−9	359.71
λ(.)p(.)	2	52.58	2.7e−12	378.64

Table 13 The model selection results for *Bombina variegata*, for detection and occurrence probability (site occupancy model) when using the “VD/FR” data. K is the number of parameters. Values in the first section (“Detection probability”) are results of detection probability modelling, values in the second section (“Occurrence probability”) are results of occupancy modelling when using the best model for detection (i.e. ψ(.)p(Temp+Time)).

Model	**K**	**ΔAIC**	**Akaike weight**	**-2log-likelihood**
Detection probability				
ψ(.)p(Temp+Time)	4	0.00	0.65	71.69
ψ(.)p(Time+Humid)	4	3.50	0.11	75.19
ψ(.)p(NbObs+Time)	4	4.52	0.067	76.22
ψ(.)p(Time)	3	5.15	0.049	78.84
ψ(.)p(Date+Time)	4	6.60	0.024	78.29
ψ(.)p(Time+ShorSurv)	4	6.95	0.020	78.64
ψ(.)p(AmountRain+Time)	4	7.12	0.018	78.81
ψ(.)p(Rain+Time)	4	7.13	0.018	78.82
ψ(.)p(Time+ShorAcc)	4	7.14	0.018	78.83
ψ(.)p(Date2+Time)	5	8.35	9.9e−3	78.05
ψ(.)p(Moon+Time)	6	9.29	6.2e−3	76.98
ψ(.)p(Date2+Temp)	5	10.97	2.7e−3	80.66
ψ(.)p(Date+Temp)	4	11.35	2.2e−3	83.04
ψ(.)p(Moon+ShorAcc)	6	14.86	3.8e−4	82.55
ψ(.)p(Date2+NbObs)	5	15.07	3.5e−4	84.76
ψ(.)p(Humid+ShorAcc)	4	15.33	3.0e−4	87.03
ψ(.)p(NbObs+Humid)	4	15.50	2.8e−4	87.19
ψ(.)p(Date+NbObs)	4	15.51	2.8e−4	87.20
ψ(.)p(Humid)	3	15.71	2.5e−4	89.41
ψ(.)p(Date+Humid)	4	16.52	1.7e−4	88.21
ψ(.)p(ShorAcc)	3	16.54	1.7e−4	90.23
ψ(.)p(Rain+Humid)	4	16.93	1.4e−4	88.62
ψ(.)p(Temp+Humid)	4	17.08	1.3e−4	88.77
ψ(.)p(Moon+NbObs)	6	17.18	1.2e−4	84.87
ψ(.)p(Date+ShorAcc)	4	17.24	1.2e−4	88.93
ψ(.)p(Temp+ShorAcc)	4	17.52	1.0e−4	89.21
ψ(.)p(AmountRain+Humid)	4	17.55	1.0e−4	89.24
ψ(.)p(Humid+ShorSurv)	4	17.69	9.3e−5	89.38
ψ(.)p(NbObs+ShorAcc)	4	17.72	9.2e−5	89.42
ψ(.)p(Temp)	3	17.90	8.4e−5	91.59
ψ(.)p(AmountRain+ShorAcc)	4	18.24	7.1e−5	89.93
ψ(.)p(ShorSurv+ShorAcc)	4	18.31	6.8e−5	90.01
ψ(.)p(NbObs)	3	18.36	6.7e−5	92.05
ψ(.)p(Date2+Humid)	5	18.47	6.3e−5	88.17
ψ(.)p(Rain+ShorAcc)	4	18.51	6.2e−5	90.20

ψ(.)p(.)	2	18.72	5.6e−5	94.42
ψ(.)p(Rain+Temp)	4	19.09	4.6e−5	90.78
ψ(.)p(Date2+ShorAcc)	5	19.21	4.4e−5	90.91
ψ(.)p(NbObs+Temp)	4	19.29	4.2e−5	90.98
ψ(.)p(Temp+ShorSurv)	4	19.69	3.4e−5	91.38
ψ(.)p(Temps+AmountRain)	4	19.80	3.2e−5	91.50
ψ(.)p(Date)	3	19.84	3.2e−5	93.53
ψ(.)p(Moon+Temp)	6	19.87	3.1e−5	87.56
ψ(.)p(Rain+NbObs)	4	19.94	3.0e−5	91.64
ψ(.)p(Moon+Humid)	6	20.08	2.8e−5	87.77
ψ(.)p(NbObs+ShorSurv)	4	20.11	2.8e−5	91.80
ψ(.)p(Moon)	5	20.11	2.8e−5	89.80
ψ(.)p(Rain)	3	20.33	2.5e−5	94.03
ψ(.)p(NbObs+AmountRain)	4	20.35	2.5e−5	92.04
ψ(.)p(AmountRain)	3	20.67	2.1e−5	94.36
ψ(.)p(ShorSurv)	3	20.71	2.1e−5	94.40
ψ(.)p(Date+AmountRain)	4	21.46	1.4e−5	93.15
ψ(.)p(Date+Rain)	4	21.65	1.3e−5	93.34
ψ(.)p(Date+Moon)	6	21.74	1.2e−5	89.43
ψ(.)p(Date2)	4	21.80	1.2e−5	93.49
ψ(.)p(Rain+Moon)	6	21.82	1.2e−5	89.51
ψ(.)p(Date+ShorSurv)	4	21.83	1.2e−5	93.52
ψ(.)p(Moon+AmountRain)	6	21.99	1.1e−5	89.68
ψ(.)p(Moon+ShorSurv)	6	22.09	1.0e−5	89.78
ψ(.)p(Rain+AmountRain)	4	22.24	9.6e−6	93.94
ψ(.)p(Rain+ShorSurv)	4	22.31	9.2e−6	94.00
ψ(.)p(AmountRain+ShorSurv)	4	22.63	7.9e−6	94.33
ψ(.)p(Date2+Moon)	7	23.37	5.5e−6	89.06
ψ(.)p(Date2+AmountRain)	5	23.44	5.3e−6	93.13
ψ(.)p(Date2+Rain)	5	23.63	4.8e−6	93.33
ψ(.)p(Date2+ShorSurv)	5	23.79	4.4e−6	93.48
Occurrence probability				
ψ(YLO+KindSite)p(Temp+Time)	7	0.00	0.50	57.73
ψ(YLO+After.BOVA+KindSite)p(Temp+Time)	8	1.48	0.24	57.21
ψ(YLO)p(Temp+Time)	5	2.19	0.17	63.92
ψ(YLO+After.BOVA)p(Temp+Time)	6	3.98	0.068	63.72
ψ(KindSite)p(Temp+Time)	6	7.31	0.013	67.04
ψ(.)p(Temp+Time)	4	7.96	9.4e−3	71.69
ψ(.)p()	2	26.68	8.1e−7	94.42

Table 14 The model selection results for *Bombina variegata*, for detection and abundance (point count model) when using the "VD/FR" data. K is the number of parameters. Values in the first section ("Detection probability") are results of detection probability modelling, values in the second section ("Abundance") are results of abundance modelling when using the best model for detection (i.e. λ(.)p(Date2+Time)).

Model	**K**	**ΔAIC**	**Akaike weight**	**-2log-likelihood**
Detection probability				
λ(.)p(Date2+Time)	5	0.00	0.95	915.25
λ(.)p(Date+Time)	4	5.94	0.049	923.19
λ(.)p(Temp+Time)	4	40.35	1.6e−9	957.60
λ(.)p(Temp+ShorAcc)	4	52.94	3.0e−12	970.19
λ(.)p(Date+ShorAcc)	4	60.71	6.2e−14	977.96
λ(.)p(Date2+ShorAcc)	5	61.86	3.5e−14	977.11
λ(.)p(NbObs+ShorAcc)	4	64.28	1.0e−14	981.53
λ(.)p(NbObs+Time)	4	70.00	6.0e−16	987.25
λ(.)p(Moon+Temp)	6	124.69	8.0e−28	1037.94
λ(.)p(Time+ShorAcc)	4	127.64	6.7e−29	1044.90
λ(.)p(NbObs+AmountRain)	4	129.64	6.7e−29	1046.90
λ(.)p(NbObs+Temp)	4	139.28	5.4e−31	1056.54
λ(.)p(Rain+ShorAcc)	4	141.26	2.0e−31	1058.51
λ(.)p(Moon+ShorAcc)	6	142.71	9.8e−32	1055.96
λ(.)p(AmountRain+ShorAcc)	4	145.28	2.7e−32	1062.53
λ(.)p(NbObs+Humid)	4	145.93	1.9e−32	1063.18
λ(.)p(Date+NbObs)	4	147.77	7.8e−33	1065.02
λ(.)p(Date2+NbObs)	5	149.39	3.5e−33	1064.64
λ(.)p(Humid+ShorAcc)	4	154.24	3.1e−34	1071.49
λ(.)p(Date2+Temp)	5	155.96	1.3e−34	1071.21
λ(.)p(ShorSurv+ShorAcc)	4	156.81	8.5e−35	1074.06
λ(.)p(Moon+Time)	6	159.52	2.2e−35	1072.77
λ(.)p(Date2+Humid)	5	159.66	2.0e−35	1074.91
λ(.)p(Moon+NbObs)	6	160.20	1.6e−35	1073.46
λ(.)p(Date+Humid)	4	160.59	1.3e−35	1077.46
λ(.)p(Date+Temp)	4	163.85	2.5e−36	1081.11
λ(.)p(Rain+NbObs)	4	164.32	2.0e−36	1081.57
λ(.)p(Temp+Amou tRain)	4	167.18	4.7e−37	1084.44
λ(.)p(ShorAcc)	3	168.26	2.8e−37	1087.51
λ(.)p(NbObs+ShorSurv)	4	168.41	2.6e−37	1085.66
λ(.)p(Temp+ShorSurv)	4	168.90	2.0e−37	1086.15
λ(.)p(Temp)	3	171.87	4.5e−38	1091.12
λ(.)p(Rain+Temp)	4	172.16	3.9e−38	1089.42
λ(.)p(Temp+Humid)	4	172.60	3.2e−38	1089.85
λ(.)p(NbObs)	3	172.61	3.1e−38	1091.86

λ(.)p(AmountRain+Time)	4	178.33	1.8e−39	1095.58
λ(.)p(Date+ShorSurv)	4	182.85	1.9e−40	1100.10
λ(.)p(Date2+ShorSurv)	5	184.74	7.3e−41	1100.00
λ(.)p(Date+Moon)	6	186.20	3.5e−41	1099.46
λ(.)p(Date2+Moon)	7	188.17	1.3e−41	1099.42
λ(.)p(Date+AmountRain)	4	194.17	6.5e−43	1111.42
λ(.)p(Date)	3	194.96	4.4e−43	1114.21
λ(.)p(Date2+AmountRain)	5	196.05	2.5e−43	1111.30
λ(.)p(Date+Rain)	4	196.69	1.9e−43	1113.94
λ(.)p(Date2)	4	196.83	1.7e−43	1114.09
λ(.)p(Rain+Time)	4	197.29	1.4e−43	1114.54
λ(.)p(Date2+Rain)	5	198.20	8.7e−44	1113.45
λ(.)p(Time+ShorSurv)	4	200.72	2.5e−44	1117.97
λ(.)p(Moon+Humid)	6	200.86	2.3e−44	1114.11
λ(.)p(Time+Humid)	4	207.21	9.6e−46	1124.47
λ(.)p(Time)	3	217.68	5.1e−48	1136.93
λ(.)p(Humid+ShorSurv)	4	234.16	1.4e−51	1151.41
λ(.)p(AmountRain+ShorSurv)	4	241.11	4.2e−53	1158.36
λ(.)p(Rain+ShorSurv)	4	242.35	2.2e−53	1159.61
λ(.)p(Moon+AmountRain)	6	252.75	1.2e−55	1166.01
λ(.)p(Rain+Moon)	6	259.41	4.4e−57	1172.66
λ(.)p(Rain+Humid)	4	265.89	1.7e−58	1183.14
λ(.)p(Moon+ShorSurv)	6	266.16	1.5e−58	1179.42
λ(.)p(AmountRain+Humid)	4	268.35	5.1e−59	1185.61
λ(.)p(Rain+AmountRain)	4	275.09	1.7e−60	1192.34
λ(.)p(ShorSurv)	3	277.57	5.1e−61	1196.82
λ(.)p(Humid)	3	279.83	1.6e−61	1199.08
λ(.)p(AMountRain)	3	281.20	8.2e−62	1200.45
λ(.)p(Moon)	5	285.79	8.3e−63	1201.04
λ(.)p(Rain)	3	285.88	7.9e−63	1205.13
λ(.)p(.)	2	314.46	4.9e−69	1235.71
Abundance				
λ(YLO+KindSite)p(Date2+Time)	8	0.00	0.72	664.61
λ(YLO+After.BOVA+KindSite)p(Date2+Time)	9	1.92	0.28	664.53
λ(YLO)p(Date2+Time)	6	16.31	2.1e−4	684.92
λ(YLO+After.BOVA)p(Date2+Time)	7	16.55	1.8e−4	683.16
λ(KindSite)p(Date2+Time)	7	170.46	7.0e−38	837.07
λ(.)p(Date2+Time)	5	244.64	5.4e−54	915.25
λ(.)p(.)	2	559.10	2.8e−122	1237.71

Table 15 The model selection results for *Lissotriton helveticus*, for detection and occurrence probability (site occupancy model) when using the “VD/FR” data. K is the number of parameters. Values in the first section (“Detection probability”) are results of detection probability modelling, values in the second section (“Occurrence probability”) are results of occupancy modelling when using the best model for detection (i.e. ψ(.)p(ShorAcc)).

Model	**K**	**ΔAIC**	**Akaike weight**	**-2log-likelihood**
Detection probability				
ψ(.)p(ShorAcc)	3	0.00	0.0846	82.11
ψ(.)p(Date2+ShorAcc)	5	1.17	0.0471	79.28
ψ(.)p(.)	2	1.22	0.0459	85.33
ψ(.)p(NbObs+ShorAcc)	4	1.28	0.0445	81.39
ψ(.)p(Date+ShorAcc)	4	1.51	0.0397	81.62
ψ(.)p(Temp+ShorAcc)	4	1.66	0.0370	81.76
ψ(.)p(Humid+ShorAcc)	4	1.66	0.0369	81.77
ψ(.)p(Rain+ShorAcc)	4	1.77	0.0348	81.88
ψ(.)p(Time+ShorAcc)	4	1.89	0.0328	82.00
ψ(.)p(ShorSurv+ShorAcc)	4	1.91	0.0326	82.01
ψ(.)p(AmountRain+ShorAcc)	4	1.93	0.0322	82.03
ψ(.)p(Time)	3	2.39	0.0256	84.50
ψ(.)p(Date2)	4	2.71	0.0218	82.82
ψ(.)p(ShorSurv)	3	2.72	0.0217	84.83
ψ(.)p(AmountRain)	3	2.85	0.0203	84.96
ψ(.)p(Rain)	3	2.92	0.0196	85.03
ψ(.)p(Humid)	3	2.95	0.0193	85.06
ψ(.)p(Date)	3	3.01	0.0188	85.11
ψ(.)p(Temp)	3	3.15	0.0175	85.25
ψ(.)p(NbObs)	3	3.21	0.0170	85.31
ψ(.)p(Date2+AmountRain)	5	3.56	0.0143	81.66
ψ(.)p(Time+ShorSurv)	4	3.76	0.0129	83.87
ψ(.)p(Time+Humid)	4	4.04	0.0112	84.14
ψ(.)p(Rain+Time)	4	4.07	0.0111	84.17
ψ(.)p(AmountRAin+Time)	4	4.11	0.0108	84.21
ψ(.)p(Date2+ShorSurv)	5	4.17	0.0105	82.28
ψ(.)p(Date2+Time)	5	4.17	0.0105	82.28
ψ(.)p(Humid+ShorSurv)	4	4.19	0.0104	84.30
ψ(.)p(Date+Time)	4	4.30	0.0099	84.40
ψ(.)p(AmountRain+Humid)	4	4.33	0.0097	84.43
ψ(.)p(Temp+Time)	4	4.38	0.0095	84.48
ψ(.)p(Moon+ShorAcc)	6	4.39	0.0094	80.49
ψ(.)p(NbObs+Time)	4	4.39	0.0094	84.49
ψ(.)p(Date2+Temp)	5	4.41	0.0093	82.51
ψ(.)p(AmountRain+ShorSurv)	4	4.42	0.0093	84.52

ψ(.)p(Date+AmountRain)	4	4.43	0.0092	84.54
ψ(.)p(Rain+ShorSurv)	4	4.44	0.0092	84.55
ψ(.)p(Date2+Rain)	5	4.53	0.0088	82.63
ψ(.)p(Rain+AmountRain)	4	4.60	0.0085	84.71
ψ(.)p(Date2+Humid)	5	4.61	0.0085	82.71
ψ(.)p(Temp+ShorSurv)	4	4.62	0.0084	84.72
ψ(.)p(Rain+Humid)	4	4.63	0.0084	84.74
ψ(.)p(Date+Rain)	4	4.64	0.0083	84.75
ψ(.)p(Date+ShorSurv)	4	4.65	0.0083	84.75
ψ(.)p(Date+Humid)	4	4.65	0.0083	84.76
ψ(.)p(Date2+NbObs)	5	4.67	0.0082	82.78
ψ(.)p(NbObs+ShorSurv)	4	4.71	0.0080	84.81
ψ(.)p(Temp+AmountRain)	4	4.72	0.0080	84.83
ψ(.)p(NbObs+AmountRain)	4	4.80	0.0077	84.91
ψ(.)p(Rain+Temp)	4	4.82	0.0076	84.93
ψ(.)p(Rain+NbObs)	4	4.90	0.0073	85.01
ψ(.)p(Temp+Humid)	4	4.94	0.0071	85.05
ψ(.)p(NbObs+Humid)	4	4.95	0.0071	85.05
ψ(.)p(Date+NbObs)	4	4.98	0.0070	85.08
ψ(.)p(Date+Temp)	4	5.01	0.0069	85.11
ψ(.)p(NbObs+Temp)	4	5.15	0.0065	85.25
ψ(.)p(Moon)	5	5.62	0.0051	83.72
ψ(.)p(Moon+ShorSurv)	6	6.51	0.0033	82.61
ψ(.)p(Date+Moon)	6	7.12	0.0024	83.22
ψ(.)p(Date2+Moon)	7	7.26	0.0022	81.37
ψ(.)p(Moon+AmountRain)	6	7.27	0.0022	83.38
ψ(.)p(Moon+Time)	6	7.48	0.0020	83.59
ψ(.)p(Rain+Moon)	6	7.50	0.0020	83.61
ψ(.)p(Moon+NbObs)	6	7.53	0.0020	83.63
ψ(.)p(Moon+Humid)	6	7.57	0.0019	83.67
ψ(.)p(Moon+Temp)	6	7.59	0.0019	83.69
Occurrence probability				
ψ(.)p(ShorAcc)	3	0.00	0.342	82.11
ψ(YLO)p(ShorAcc)	4	0.70	0.241	80.81
ψ(.)p(.)	2	1.22	0.186	85.33
ψ(YLO+After.LIHE)p(ShorAcc)	5	2.05	0.123	80.16
ψ(KindSite)p(ShorAcc)	5	3.57	0.057	81.67
ψ(YLO+KindSite)p(ShorAcc)	6	4.57	0.035	80.68
ψ(YLO+After.LIHE+KindSite)p(ShorAcc)	7	6.00	0.017	80.10

Table 16 The model selection results for *Lissotriton helveticus*, for detection and abundance (point count model) when using the "VD/FR" data. K is the number of parameters. Values in the first section ("Detection probability") are results of detection probability modelling, values in the second section ("Abundance") are results of abundance modelling when using the best model for detection (i.e. λ(.)p(Moon+Time)).

Model	**K**	**ΔAIC**	**Akaike weight**	**-2log-likelihood**
Detection probability				
λ(.)p(Moon+Time)	6	0.00	0.97	815.85
λ(.)p(Date2+ShorAcc)	5	8.12	0.017	825.97
λ(.)p(Moon+ShorAcc)	6	8.28	0.015	824.13
λ(.)p(Date+Moon)	6	17.43	1.6e−4	833.28
λ(.)p(Date+ShorAcc)	4	19.14	6.8e−5	838.98
λ(.)p(Date2+Moon)	7	19.37	6.0e−5	833.21
λ(.)p(Moon+Temp)	6	21.81	1.8e−5	837.66
λ(.)p(Date2+ShorSurv)	5	40.56	1.5e−9	858.41
λ(.)p(Moon+NbObs)	6	41.31	1.0e−9	857.16
λ(.)p(NbObs+ShorAcc)	4	41.63	8.8e−10	861.48
λ(.)p(Temp+ShorAcc)	4	41.79	8.1e−10	861.64
λ(.)p(Moon+ShorSurv)	6	42.05	7.1e−10	857.90
λ(.)p(Date2+Humid)	5	45.66	1.2e−10	863.50
λ(.)p(Date2+Rain)	5	49.31	1.9e−11	867.16
λ(.)p(Time+ShorAcc)	4	50.14	1.3e−11	869.98
λ(.)p(Humid+ShorAcc)	4	50.71	9.4e−112	870.56
λ(.)p(ShorAcc)	3	51.16	7.5e−12	873.01
λ(.)p(Moon+AmountRain)	6	51.38	6.8e−12	867.22
λ(.)p(Rain+ShorAcc)	4	51.51	6.3e−12	871.36
λ(.)p(Rain+Moon)	6	52.32	4.2e−12	868.16
λ(.)p(Date2)	4	52.48	3.9e−12	872.22
λ(.)p(Moon)	5	52.62	3.6e−12	870.47
λ(.)p(Date2+AmountRain)	5	52.88	3.2e−12	870.73
λ(.)p(ShorSurv+ShorAcc)	4	52.99	3.0e−12	872.83
λ(.)p(AmountRain+ShorAcc)	4	53.10	2.8e−12	872.95
λ(.)p(Date2+Time)	5	54.47	1.4e−12	872.31
λ(.)p(Date2+NbObs)	5	54.47	1.4e−12	872.32
λ(.)p(Date2+Temp)	5	54.48	1.4e−12	872.33
λ(.)p(Moon+Humid)	6	54.56	1.4e−12	870.41
λ(.)p(Date+Humid)	4	58.01	2.5e−13	877.85
λ(.)p(Date+ShorSurv)	4	58.58	1.8e−13	878.42
λ(.)p(Date+AmountRain)	4	61.76	3.8e−14	881.61
λ(.)p(Date+Rain)	4	62.49	2.6e−14	882.34
λ(.)p(Date+Temp)	4	63.65	1.5e−14	883.50
λ(.)p(Date)	3	65.11	7.0e−15	886.96

λ(.)p(Date+Time)	4	65.58	5.6e−15	885.42
λ(.)p(Date+NbObs)	4	67.08	2.6e−15	886.92
λ(.)p(Temp+Humid)	4	81.92	1.6e−18	901.76
λ(.)p(Rain+Temp)	4	84.06	5.4e−19	903.91
λ(.)p(Temp)	3	85.12	3.2e−19	906.96
λ(.)p(Temp+AmountRain)	4	85.26	3.0e−19	905.11
λ(.)p(Temp+Time)	4	85.43	2.7e−19	905.27
λ(.)p(Temp+ShorSurv)	4	86.30	1.8e−19	906.14
λ(.)p(NbObs+Time)	4	86.33	1.7e−19	906.18
λ(.)p(Time+Humid)	4	86.95	1.3e−19	906.80
λ(.)p(NbObs+Temp)	4	87.06	1.2e−19	906.91
λ(.)p(Rain+Time)	4	87.77	8.4e−20	907.62
λ(.)p(Time)	3	88.37	6.3e−20	910.21
λ(.)p(AmountRain+Time)	4	88.63	5.5e−20	908.48
λ(.)p(NbObs+AmountRain)	4	89.33	3.9e−20	909.18
λ(.)p(Time+ShorSurv)	4	89.88	2.9e−20	909.73
λ(.)p(Rain+NbObs)	4	90.10	2.6e−20	909.95
λ(.)p(NbObs+Humid)	4	90.24	2.5e−20	910.09
λ(.)p(NbObs)	3	90.54	2.1e−20	912.38
λ(.)p(NbObs+ShorSurv)	4	91.75	1.2e−20	911.60
λ(.)p(AmountRain+Humid)	4	92.00	1.0e−20	911.85
λ(.)p(Rain)	3	94.12	3.5e−21	915.97
λ(.)p(Rain+Humid)	4	94.22	3.4e−21	914.07
λ(.)p(Humid)	3	94.28	3.3e−21	916.13
λ(.)p(.)	2	94.37	3.1e−21	918.22
λ(.)p(Rain+AmountRain)	4	95.23	2.0e−21	915.08
λ(.)p(AmountRain)	3	95.30	2.0e−21	917.14
λ(.)p(Humid+ShorSurv)	4	95.47	1.8e−21	915.32
λ(.)p(Rain+ShorSurv)	4	96.10	1.3e−21	915.94
λ(.)p(ShorSurv)	3	96.28	1.2e−21	918.13
λ(.)p(AmountRain+ShorSurv)	4	97.07	8.1e−22	916.91
Abundance				
λ(YLO+KindSite)p(Moon+Time)	9	0.00	0.56	714.48
λ(YLO+After.LIHE+KindSite)p(Moon+Time)	10	0.93	0.35	713.41
λ(KindSite)p(Moon+Time)	8	3.60	0.092	720.08
λ(.)p(Moon+Time)	6	95.36	1.1e−21	815.85
λ(YLO)p(Moon+Time)	7	97.31	4.1e−22	815.79
λ(YLO+After.LIHE)p(Moon+Time)	8	99.10	1.7e−22	815.59
λ(.)p(.)	2	189.74	3.5e−42	918.22