

Lorenzo Tanadini

February 08-March 09

Master Thesis



Effects of habitat management on amphibian patch occupancy

Supervised by

Dr. Benedikt Schmidt

&

Prof. Dr. Heinz-Ulrich Reyer

**Ecology Group
Institute of Zoology
University of Zurich**

1) <u>Abstract</u>	1
2) <u>Introduction</u>	1
2.1 Amphibian decline and counter-measures	1
2.2) Assessment of effectiveness of conservation	2
2.3) Thesis aim	2
3) <u>Materials and Methods</u>	3
3.1) Study area	3
3.2) Study species	3
3.3) Data sources	4
3.3.1) <i>Amphibian Populations</i>	4
3.3.2) <i>Pond Characteristics</i>	5
3.3.3) <i>Landscape</i>	6
3.3.4) <i>Connectivity</i>	6
3.3.5) <i>Management</i>	7
3.3.6) <i>Weather</i>	8
3.4) Data analysis	9
3.4.1) <i>Step 1: Determining the factors best explaining detection probability</i>	10
3.4.2) <i>Step 2: Determining the factors best explaining occupancy</i>	11
3.4.3) <i>Step 3: Determining the factors best explaining colonization and extinction</i>	11
3.4.4) <i>Step 4: Considering management</i>	12
4) <u>Results</u>	13
4.1) Detection probability	13
4.2) Site occupancy	16
4.3) Colonization and extinction probability	20
4.3.1) <i>Colonization probability</i>	21
4.3.2) <i>Local extinction probability</i>	23
4.4) Colonization and extinction probabilities with management	24
5) <u>Discussion</u>	28
5.1) Detection probability	28
5.2) Occupancy, colonization and extinction probability	29
5.2.1) <i>Past Population size</i>	29
5.2.2) <i>Connectivity</i>	30
5.2.3) <i>Landscape</i>	31
5.2.4) <i>Pond vegetation</i>	31
5.2.5) <i>Pond surface</i>	31
5.2.6) <i>Triturus vulgaris – Occupancy</i>	32
5.2.7) <i>Constant extinction and colonization probabilities</i>	32
5.3) Occupancy, colonization and extinction probabilities with management	32
6) <u>Conclusions</u>	34
7) <u>Future research</u>	34
8) <u>Acknowledgments</u>	35
9) <u>Literature cited</u>	36

1) Abstract

Habitat management and restoration are vital actions for the global conservation of amphibians. Assessing the success of management actions is thus indispensable in conservation, but is not yet common practice. As a consequence, in the most cases we still ignore whether conservation actions reached their goals. Here, we used data from a nine-year monitoring program in northern Switzerland to model and quantify the effects of three different types of habitat management on the presence of eight amphibian species at the landscape scale. In addition to the assessment of management effects, we evaluated the contribution of biotic and abiotic variables acting at local and landscape scale on the presence, colonization, and extinction, again at a landscape scale. Models that included a measure of connectivity and past population size explained patch occupancy and local extinction well. Colonization was best modeled either as constant or with connectivity as an explanatory variable. Management played a role for five out of eight species. Management usually affected local extinction probabilities. The most influential type of management was management of the terrestrial habitat in the vicinity of the ponds. Newts responded to terrestrial habitat management with a decrease in local extinction probabilities, whereas frogs and toads responded with an increased local extinction probability. Second-most influential was the management of the aquatic habitat, which increased local extinction for all species concerned. When management affected the colonization probability, both the management of the terrestrial and the aquatic habitat increased colonization probability. Thus, while habitat management affected amphibian populations, it did not always do so in the expected way.

2) Introduction

2.1) Amphibian decline and counter-measures

Halting and reversing the global amphibian decline (Houlahan et al. 2000, Stuart et al. 2004) is probably the greatest challenge that conservation biologists have ever faced. Habitat management and restoration of former habitat are two types of conservation action that are important for amphibians in human-dominated landscapes (Lee et al. 2006, Stumpel & van der Voet 1998, Brodman et al. 2006). In fact, the persistence of many species seems to depend upon the effectiveness of conservation strategies in human-dominated landscapes (Daily 2001). In addition, both disciplines, conservation biology and ecological restoration, require continuous direct human intervention and maintenance once established (Allison 2007). For all these reasons, conservation and restoration efforts are fundamental to preserve amphibian diversity.

2.2) Assessment of effectiveness of conservation

Assessing the success of ecological management is vital and an indispensable step in iterative conservation and restoration efforts (Barrows & Allen 2007, Barrows et al. 2008). Regrettably, there are extremely few studies that scientifically investigate the success of conservation projects. Clewell and Rieger (1997) could instead illustrate the common tendency to repeat previous restoration protocols for new projects without assessing their efficacy. The lack of this kind of investigation is preoccupying, since we basically do not know what we are doing (see Miller & Hobbs (2007), for the field of habitat restoration).

The few assessments conducted highlight how every design of a monitoring program with the ambition of measuring the success of management is hampered by several difficulties (e.g. McCoy & Mushinsky 2002). Usually, these assessments are done at the level of a single conservation projects or conservation objects. Due to this fact, it is impossible to determine what would have been the success of the management actions without management because there is no control. Additionally, small scale conservation projects generally do not incorporate other similar experimental units in the analysis, such that there is no replication. Also, assessments that focus on single objects may neglect population dynamics and other aspects that may influence the outcome of management actions (Marsh & Trenham 2001, Petranka & Holbrook 2006, Denoël & Lehmann 2006).

An appeal for applying evidence-based practice in conservation management has been given in the past years (Pullin & Knight 2001, Edgar et al. 2004, Stewart et al. 2005), but a change of mentality has not yet occurred. The consequence of this development is that we still ignore whether conservation actions reached their goals. Consequently, we do not know which measures are the most appropriate in what situation. After all, conservation budgets are always limited and often small: asking for the best conservation possible is self-evident.

2.3) Thesis aim

Having seen that amphibian species are suffering an alarming global decline, that conservation efforts are inalienable, and lastly that scientific assessing of the success of conservation programs through monitoring is needed, I am glad to devote this master thesis to the goal of bringing new elements in the field of conservation assessment and statistical-based analysis of effectiveness. In fact, it is fundamental to understand which management actions influence the distribution and abundance of amphibians and why they are successful or unsuccessful. This knowledge is the key to develop effective management in the context of conservation biology.

Here, I modeled the presence of eight amphibian species based on a long-term data set from an amphibian monitoring program. I evaluated the explanatory power of three classes of management (construction of a new pond, pond management, terrestrial habitat management) in modeling persistence, colonization, and extinction at the landscape scale. The goal of the project is to demonstrate whether these management action classes do indeed affect persistence, colonization, and extinction. In addition, this approach allows us to evaluate the importance of other variables, such as biotic aspects, pond characteristics, and landscape aspects that may affect amphibian populations and may conceal management effects.

3) Materials and Methods

3.1) Study area

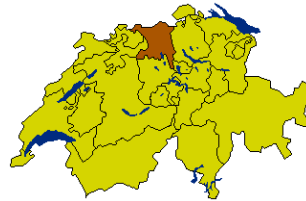


Fig. 1 Map of Switzerland, with canton Aargau highlighted in brown color.

(Source: <http://en.wikipedia.org/wiki/Aargau>)

The data used arise from the amphibian monitoring program of the canton Aargau in the north-central Switzerland (Meier & Schelbert 1999). The landscape is typical for the Swiss Plateau: a combination of farmland, forests, small to medium-sized villages and important traffic networks. The state comprises also the four major rivers and their floodplains, which represent suitable amphibian habitat. It is therefore a hotspot for amphibian diversity in Switzerland and, given the long-term data available of amphibian populations and management actions, an excellent opportunity to investigate conservation issues.

3.2) Study species

I decided to analyze eight of the thirteen species of amphibians that were detected during the monitoring program of the Canton Aargau. Out of these eight species analyzed, six were also focus species in the monitoring program (Tab.1).

Tab. 1: Common names of the study species with indication of whether they belong to the focus species of the monitoring program of the canton Aargau

Common name	Scientific name	Focus species
Midwife toad	<i>Alytes obstetricans</i>	√
Yellow bellied toad	<i>Bombina variegata</i>	√
Natterjack	<i>Bufo calamita</i>	√
Pool frog	<i>Rana lessonae</i>	√
Alpine newt	<i>Triturus alpestris</i>	-
Palmate newt	<i>Triturus helveticus</i>	-
Warty newt	<i>Triturus cristatus</i>	√
Smooth newt	<i>Triturus vulgaris</i>	√

General information about the natural history of the species is given by Brodmann-Kron & Grossenbacher (1994).

3.3) Data sources

3.3.1) Amphibian populations

The amphibian population data used for this study comes from field surveys, and is based on the amphibian monitoring program of the canton Aargau (Departement Bau, Verkehr und Umwelt; Sektion Natur und Landschaft; see Meier and Schelbert 1999). The main goal of the program is the continuous assessment of the status of eight amphibian focus species. It has been run since 1999. In 2007, more than 600 breeding sites were known to host at least one of the target species. Every year, approximately one third of these objects are surveyed.

The volunteer-based monitoring consists of three visits per object per year. The first two visits are done at night between April and May, the third one during the day in the months of June or July. The standardised survey protocol requires the volunteers to follow precise time rules for the visit to of each object according to its size. All counted (and not estimated numbers of) adults, juveniles and calls as well as tadpoles and spawn are reported (Tab.2). The counts are reported at the level of the object. One object is considered a place with one water body or more water bodies in close spatial proximity.

Tab. 2 Populations variables recorded by the volunteers

Population variables	Dimension
Population size	Number of counted individuals

For the analysis of site occupancy, extinction, and colonization probabilities, counts were dichotomized into detection/non detection data; other information regarding past population sizes were calculated (Tab. 3).

Tab. 3: Information about amphibian populations indirectly recorded by the volunteers

Variables	Dimension
Presence	Yes/No
Population size at last survey	Number of counted individuals
Time elapsed since last survey	Number of years

3.3.2) Pond Characteristics

Pond characteristics are noted for each object during the third survey of the monitoring on a percentage scale. The area of the water surface is estimated in the field. The point in time when the surveys were done is also recorded (Tab.4).

Tab. 4: Pond characteristics and phenology, both directly recorded by volunteers

Pond variables	Dimension
Pond surface	Square meters
Floating leave plants	Percentage (%)
Aquatic plants	Percentage (%)
Reeds	Percentage (%)
Access limitation	Yes/No
Survey variables	Dimension
Phenology	Day during the year (1 January = 1)

Several variables describing pond characteristics were correlated to each other. I used a principal component analysis to reduce the number of explanatory variables. The statistical program SPSS 16.0.1 delivered the results shown in Tables 5 and 6.

Tab. 5: Total variance explained by the PCA run with the pond vegetation variables floating leave plant, aquatic plants, reeds

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.078	69.278	69.278	2.078	69.278	69.278
2	0.525	17.494	86.772			
3	0.397	13.228	100			

Extraction Method: Principal Component Analysis.

Tab. 6: Component matrix for the first extracted component

Component Matrix ^a	
	Component
	1
Reeds	0.805
Floating leave plants	0.861
Aquatic plants	0.830
Extraction Method: Principal Component Analysis. 1 components extracted.	

The results show that the first component of the PCA explains 69.3% of the total variance. Table 6 illustrates that all three variables are highly correlated to the first principal component: a high score on this first principal component means a pond with high vegetation coverage. For the subsequent analyses, I used the scores of the first principal component to describe pond vegetation.

3.3.3) *Landscape*

I introduced in the analysis three variables describing the landscape in which the ponds are imbedded. Using the digital version of the official 1:25'000 map provided by the Swiss federal Office of Topography (Swisstopo 2003), a circular buffer of radius 1 km was drawn around each pond. The area within this buffer that was defined as settlement, forest, or wetland, was extracted and utilized in the analysis (Tab.7).

Tab. 7: Name and dimension of landscape variables

Variables	Dimension
Settlement	Square meters
Forest	Square meters
Wetland	Square meters

A principal component analysis showed that a reduction of the three landscape variables to a single principle component was not meaningful, i.e. the first principal component explained little of the total variance.

3.3.4) *Connectivity*

The next variable that I used in the analysis is a measure of connectivity. This is a numeric expression of the distance between the focus pond and all the ponds around it (Tab. 8) . Based on metapopulation theory (Hanski et al. 1994), I defined connectivity as the sum of the exponential negative distance between the ponds:

$$C = \sum_i e^{-d_i}$$

This way of calculating connectivity automatically includes a weighting of the terms of the sum: ponds that are further away from the focal pond get less weight.

Tab. 8: Name and dimension of the variable connectivity

Variables	Dimension
Connectivity	exp(- meters)

3.3.5) Management

The data concerning the management and conservation measures conducted in and around the amphibian breeding sites were kindly provided by the Canton Aargau. Management at and around amphibian breeding sites embraces a wide range of activities. Nevertheless, all management activities have the goal to “stop the loss of habitat and stabilize or increase the number of populations of endangered species” (Amphibienschutzkonzept Kanton Aargau, 1999).

The wide range of activities can not be analyzed in a meaningful way. It was therefore necessary to group different management activities into smaller set. The whole set of management activities was reduced to three classes (Tab. 9):

1) Construction of a new pond

The category ‘new habitat’ groups all the activities that created a new pond (e.g. „neues Gewässer“, „neue Gräben“, „neue Tümpel“).

2) Aquatic habitat management

The category ‘aquatic habitat management’ groups all the activities that were executed inside the perimeter of the water surface of each one pond (e.g. „Nachtiefen“, „Entschlammung“, „Ausbaggerung“).

3) Terrestrial habitat management

The category ‘terrestrial habitat management’ groups all activities that were executed around the water surface of each one pond (e.g. „Ausmähen“, „Umfeldgestaltung“, „Planierarbeiten“)

Tab. 99: Name and dimension of the three management classes included into the analysis

Variables	Focus	Dimension
Management class 1	New habitat	Yes/No
Management class 2	Aquatic habitat	Yes/No
Management class 3	Terrestrial habitat	Yes/No

The three categories were created this way because the records of the cantonal agency do not make a finer classification possible. The terms used by the cantonal agency for the activities are often context-dependent. Keeping the number of classes down to three permits to overcome the problem of imprecise definition of management activities and still allows to assess which part of the pond is the most responsive to conservation activities.

The list of conservation measures provided by the canton Aargau and their class assignment is shown in Appendix 2.

Management may have short-term or long-term effects. To keep track of the fact that some kind of management could have long-term effects, I defined three new classes of management, where a “lasting effect” is accounted for. That means, the supposed effect starts when the management is done and lasts for the remaining years (Tab. 10).

Tab. 10: Name and dimension of the three management classes which consider a long-term effect

Variables	Dimension
Management class 1 "lasting effects"	Yes/No
Management class 2 "lasting effects"	Yes/No
Management class 3 "lasting effects"	Yes/No

3.3.6) *Weather*

Weather data were provided by the Federal Office of Meteorology and Climatology MeteoSwiss which relies on a dense meteorological monitoring network. I utilized the data from the station in Buchs-Aarau (Swiss coordinates 648 400 / 248 380), which is approximately in the center of the study area. Even though some local variation in the weather variables (Tab. 11) could have been present during the sampling period, I assume that it would not affect the analysis, and therefore I took the measurements of this single station for all ponds tested.

Tab. 11: Name and dimension of the weather variables provided by MeteoSwiss

Variables	Dimension
Air temperature	Degree Celsius
Rainfall	Liter per square meter
Wind	Kilometer per hour

Given that these variables were correlated, I used a principle component analysis to reduce their number. The statistical program SPSS 16.0.1 delivered the results shown in Tables 12 and 13.

Tab. 12: Total variance explained by the PCA run with the weather variables air temperature, rainfall, wind

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.263	42.108	42.108	1.263	42.108	42.108
2	0.958	31.944	74.052			
3	0.778	25.948	100			

Extraction Method: Principal Component Analysis.

Tab. 13: Component matrix for the first extracted component

	Component
	1
Air temperature	-0.759
Wind	0.624
Rainfall	0.545

Extraction Method: Principal Component Analysis.
1 component extracted.

Table 12 shows that weather variables could be reduced to one principal component explaining 42,1 % of the total variance. High score on this first component depicts a situation where there are cold, windy and rainy weather conditions. For the subsequent analyses, I used the scores of the first principal component to describe weather variables.

3.4) Data analysis

A common difficulty of modeling approaches is the problem of missing values in the data set. As a matter of fact, the software used (PRESENCE 2) does not allow to model correctly the data if there are sites with missing site or sampling covariates (Jim Hines, personal communication). To overcome the problem of missing site covariates, I excluded from the analysis sites where pond characteristics were not recorded. I also excluded from the analysis sites where data on phenology and/or weather (sampling covariates) were not available. These measures restricted the number of sites suitable for the analysis from 720 to 589.

After this first step, I still had sites with missing site covariates for past population size. Therefore I pooled the amphibian data from the years 1999-2002. From this three-year period, I only considered the most recent population size data within this period. This data management step was necessary to get a sufficient number of sites with complete information. This measure restricted the number of sites suitable for the analysis from 589 to 388. Pooling the data, management was defined as “0” when it did not occur in any of the three years and as “1” if it was conducted at least once during the period 1999-2002. Time-independent variables for the years 1999-2001 were no more necessary and consequently dropped.

The analysis of the data was carried out with the statistical software PRESENCE 2.0, which allows to estimate the detection probability, and the site occupancy in relation to different factors (MacKenzie et al. 2002). This program has the advantage that the natural variability of field data and the problem of “false negatives” are statistically accounted for (MacKenzie et al. 2002). Furthermore, having access to long term data (1999-2007), PRESENCE allows the estimation of rates of colonization, local extinction, and persistence when the probability of detection is less than one (MacKenzie et al. 2003, MacKenzie & Nichols 2004). Explanatory variables for all parameters in the model (site occupancy, extinction, colonization, detectability) can be added to the basic model.

The data were analyzed in a four-step approach. I first modeled detection probability, and then the variables of biological interest. Of these variables, I started from modeling site occupancy, then extinction and colonization. In terms of explanatory variables, I first modeled site occupancy, colonization and extinction, using pond, landscape and metapopulation variables. Then, in the fourth step, I added management variables.

3.4.1) Step 1: Determining the factors best explaining detection probability

The goal of this step was to find a model that best explains detection probability. I did not test specific hypotheses, I rather searched exploratively for a best model. In this step, all other parameters were held fixed and constant.

I used the variables shown in Table 14. Each variable was first entered alone. I then built models with combinations of variables that had good AIC values (AIC is a measure of the goodness of fit of a statistical model). In addition to models with variables, I also built models with constant or simply time-dependent detection probabilities.

Tab. 14: Variables suspected to affect detection probability

Variables
Population size
Vegetation
Access limitation
Weather
Phenology
Pond surface

3.4.2) Step 2: Determining the factors best explaining occupancy

In this step, I used a similar approach to model occupancy ψ , as I did for the detection probability p . In this case, however, I tested a specific set of a priori hypotheses (Table 14). Colonization γ and extinction probability ϵ were kept constant. Detection probability p was fixed as determined in step 1.

The hypotheses were formulated according to the literature, discussing predominantly two different ways of understanding species distribution (e.g. Pellet et al. 2007). The first approach is the niche-based approach, which states that habitat characteristics determine distribution. I tested models with the covariates pond surface, pond vegetation, and landscape variable (and combinations thereof) (Tab. 15, top). The second approach refers to the concept of metapopulation, where population dynamic processes explain occupancy. For this case I selected population size, connectivity, and landscape (and combinations thereof) (Tab.15, bottom).

Tab. 15: Models assessed following two different conceptual approaches with the objective of determining the factors that best explain occupancy

Approach	Variables
Niche-based	Landscape
	Vegetation + Pond surface
	Landscape + Vegetation + Pond surface
Metapopulation	Population size
	Connectivity
	Landscape
	Population size + Connectivity
	Population size + Landscape
	Landscape + Connectivity

3.4.3) Step 3: Determining the factors best explaining colonization and extinction

While modeling extinction and colonization probabilities, occupancy ψ and detection probability p were fixed as determined in steps 1 and 2, respectively.

At this stage, I took into account three different levels of covariates reflecting the idea that amphibian occurrence can be explained through local abiotic, local biotic, and landscape covariates (Van Buskirk 2005, Richter-Boix et al. 2007). I used population size as measure for the local biotic covariate; pond surface, and pond vegetation as local abiotic covariates; connectivity, settlement, forest, and wetland Were used as landscape covariates (Tab 16).

Tab. 16: Variables utilized according to the approach adopted

Approach	Variables
Local biotic	Past population size
Local abiotic	Vegetation, pond size
Landscape	Connectivity, settlement, forest, wetland

I ran models for all the listed variables following the scheme in Table 17, where each set of variables on the right (extinction) was modeled in combination with all the sets of variables on the left (colonization):

Tab. 17: Combination of variables which form models to be tested as predictor of colonization and local extinction probability

Colonization probability	Extinction probability
Connectivity	Population size
Vegetation + Pond surface	Population size + connectivity
Landscape	Population size + landscape
Landscape + connectivity	Landscape
Landscape + Vegetation + Pond surface	Landscape + Vegetation + Pond surface
Constant model	Landscape + connectivity
	Vegetation + Pond surface
	Constant model

3.4.4) Step 4: Considering management

The variables regarding management were added to the best model from step 3, i.e. the model where detection probability p , occupancy ψ , colonization γ and extinction probability ε best explained the data.

I tested whether management affects colonization and local extinction probabilities. I used the seven possible combinations of the three types of management listed in Table 18. These variables and combinations thereof Were used to model both extinction and colonization probabilities. I tested both short-term and long-term effects of management, which gave a total of 14 models per parameter.

Tab. 18: List of combination of management classes tested

Management
Class 1
Class 2
Class 3
Class 1 + Class 2
Class 1 + Class 3
Class 2 + Class 3
Class 1 + Class 2 + Class 3

4) Results

During the period of the years 1999-2007, the monitoring program assessed at least once the presence of amphibian species in 720 locations distributed all over the Canton Aargau. Here, I analyzed the distribution of eight amphibian species in 386 sites during a period of six years.

4.1) Detection probability p

Table 19 summarizes the model selection results of the first step of the analysis, where the goal was to determine the factors that best explain the detection probability p . Detection probability is not a biological process. Rather, it describes the sampling process, where imperfect detection is typical. Estimation and modeling of the detection probability allows an unbiased analysis of the parameters of biological interest concerning the status of the populations under study.

Tab. 19: Summary of the model selection results for detection probability. Only models with an Akaike weight ≥ 0.099 are shown. Results are shown for all species.

The full set of candidate models is shown in Appendix 4.

Species	Model	delta AIC	AIC wgt	No.Par.	(-2*LogLike)
<i>A. obstetricans</i>	(psi(.),gamma(.),eps(.),p(day,night; PG ; s1))	0	0.3621	12	1256.016805
	(psi(.),gamma(.),eps(.),p(day,night; PG))	0.98	0.2218	11	1259.003359
	(psi(.),gamma(.),eps(.),p(day,night; PG ; s1 ; s2))	1.89	0.1407	13	1255.908139
	(psi(.),gamma(.),eps(.),p(night: s2; day: s2; PG))	2.38	0.1102	12	1258.396685
<i>B. variegata</i>	(psi(.),gamma(.),eps(.),p(night:s2; day:s2; PG))	0	0.3684	12	2069.210556
	(psi(.),gamma(.),eps(.),p(night:s2; day:s2; PG ; s1))	1.27	0.1952	13	2068.484441
	(psi(.),gamma(.),eps(.),p(night: s1, s2; day:s2; PG))	1.83	0.1476	13	2069.037937
	(psi(.),gamma(.),eps(.),p(nights2; day:s2; PG ; veg))	1.98	0.1369	13	2069.193773
<i>B. calamita</i>	(psi(.),gamma(.),eps(.),p(night: s1,s2; day:s2; PG))	0	0.4378	13	930.971407
	(psi(.),gamma(.),eps(.),p(night: s1, s2; day: veg, s2; PG))	0.53	0.3359	14	929.498801
	(psi(.),gamma(.),eps(.),p(night: s1,s2; day: s1, s2; PG))	1.91	0.1685	14	930.880326
<i>R. lessonae</i>	(psi(.),gamma(.),eps(.),p(night:s2; day:s2; PG))	0	0.5958	12	2430.918902
	(psi(.),gamma(.),eps(.),p(night:s2; veg ;day:s2; PG))	1.72	0.2521	13	2430.64163
	(psi(.),gamma(.),eps(.),p(night, day; PG))	2.73	0.1521	11	2435.650534
<i>T. alpestris</i>	(psi(.),gamma(.),eps(.),p(night: s2, day: s2; PG; wflae))	0	0.5369	14	2894.386163
	(psi(.),gamma(.),eps(.),p(night: s2, day: s2; PG; wflae; veg))	1.73	0.2261	15	2894.117423
	(psi(.),gamma(.),eps(.),p(night, day; PG; wflae))	3.06	0.1163	12	2901.448838
<i>T. cristatus</i>	(psi(.),gamma(.),eps(.),p(nigh,day; eingsch; s2))	0	0.6236	7	557.515605
	(psi(.),gamma(.),eps(.),p(nigh,day; eingsch))	3.63	0.1015	6	563.146007
<i>T. helveticus</i>	(psi(.),gamma(.),eps(.),p(night: s2; day:s2 ; PG; veg; wflae))	0	0.6529	15	1923.753012
	(psi(.),gamma(.),eps(.),p(night: s1,s2; day:s2 ; PG))	2.24	0.213	14	1927.993601
<i>T. vulgaris</i>	(psi(.),gamma(.),eps(.),p(night, day; eingsch))	0	0.255	6	203.618539
	(psi(.),gamma(.),eps(.),p(s2; eingsch))	0.29	0.2206	6	203.913752
	(psi(.),gamma(.),eps(.),p(night:s2, day; eingsch))	1.06	0.1501	7	202.681107

Abbreviations: day,night=differentiation between night-time and day-time surveys,
 pg=past population size, s1=weather, s2=phenology, veg=pond vegetation,
 wflae=pond surface, eingsch=pond accessibility, (.)=constant term
 (Abbreviations, full names, and description of the variables used, see Appendix 1)

For all species, detection probability p differed between day-time and night-time surveys. Detection probabilities were higher during the night-time surveys than during the day (Fig. 2).

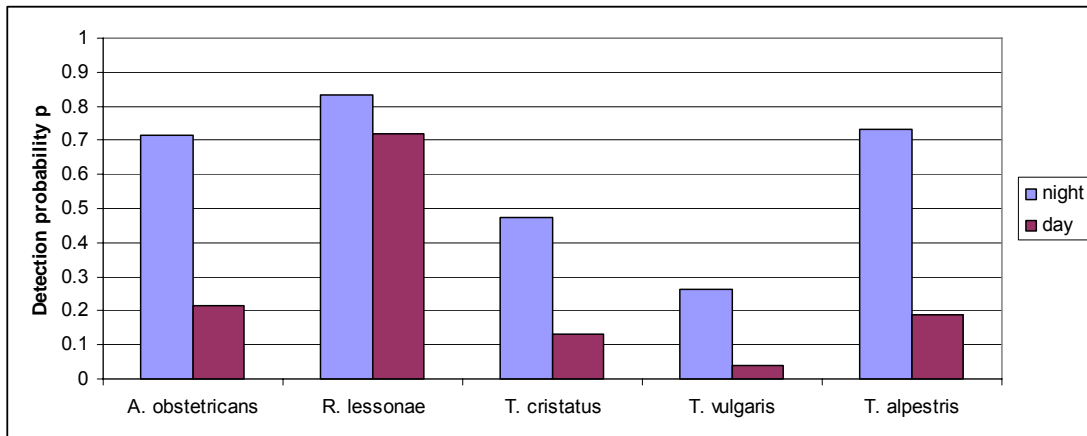


Fig. 2: Detection probability of five species during night-time and day-time surveys. Mean values were used when other explanatory variables than those represented graphically were included in the model. Shown are the predictions based on the models:

psi(.),gamma(.),eps(.),p(day,night; pg, s1) for *A. obstetricans*

psi(.),gamma(.),eps(.),p(night,day; pg) for *R. lessonae*

psi(.),gamma(.),eps(.),p(night,day; eingsch, s2) for *T. cristatus*

psi(.),gamma(.),eps(.),p(night,day; eingsch) for *T. vulgaris*

psi(.),gamma(.),eps(.),p(night,day; eingsch, s2) for *T. cristatus*

(Abbreviations are explained in Appendix 1)

There was also strong evidence that population size at the last time of survey effected the detection probability. For all species, except for *T. vulgaris* and *T. cristatus*, detection probability increased with past population size (for the two newts, past population size did not affect detectability), although the effect size varied among years (Fig. 3).

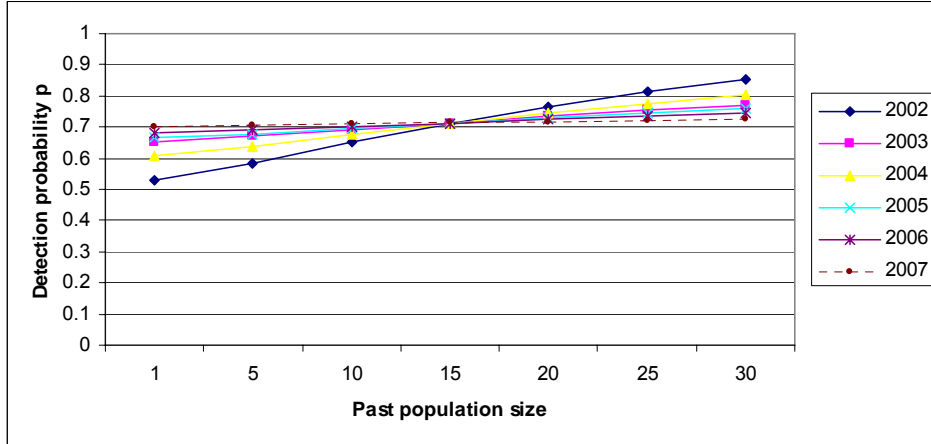


Fig. 3: Relationship between detection probability and past population size. All years are shown for the example *Alytes obstetricans* at night. Shown is the prediction based on the model $\text{psi}(\cdot)\text{gamma}(\cdot)\text{eps}(\cdot)\text{p}(\text{day},\text{night}; \text{pg}, \text{s1})$. (Abbreviations are explained in Appendix 1). Mean values were used when other explanatory variables than those represented graphically were included in the model. Dotted lines represent statistically not significant curves.

The following two survey-specific variables also played an important role: both weather conditions and phenology were present in the best models, regardless the species. All species had lower detection probabilities later in the season (Fig. 4). The warmer, the less windy, and the less rainy the weather conditions, the higher the detection probability tended to be.

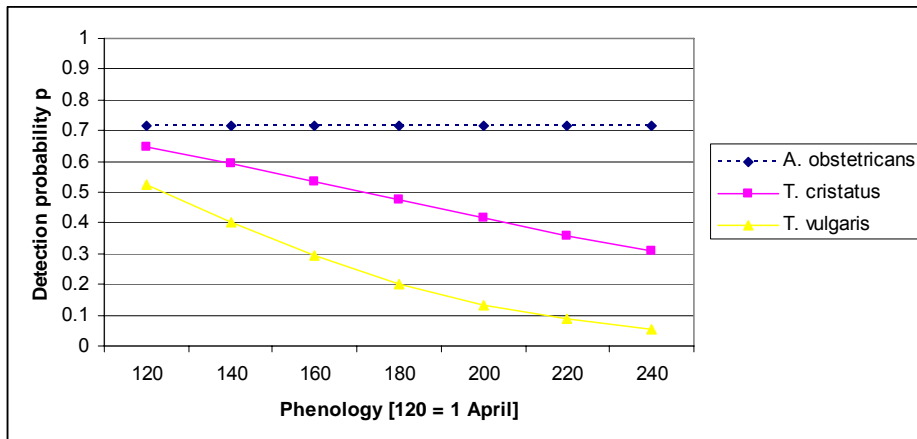


Fig. 4: The effect of phenology on detection probability for three species at night. Mean values were used when other explanatory variables than those represented graphically were included in the model. Dotted lines represent statistically not significant curves. Shown are the predictions based on the models: $\text{psi}(\cdot)\text{gamma}(\cdot)\text{eps}(\cdot)\text{p}(\text{day},\text{night}; \text{pg}, \text{s1}, \text{s2})$ for *A. obstetricans*, $\text{psi}(\cdot)\text{gamma}(\cdot)\text{eps}(\cdot)\text{p}(\text{night},\text{day}; \text{eingsch}, \text{s2})$ for *T. cristatus*, $\text{psi}(\cdot)\text{gamma}(\cdot)\text{eps}(\cdot)\text{p}(\text{s2}, \text{eingsch})$ for *T. vulgaris* (Abbreviations are explained in Appendix 1)

In contrast to frogs and toads, I also found evidence that the detection probability for the four newt species strongly depended on pond characteristics. Detection probabilities were lower in larger ponds (Fig. 5), and where access to the pond is limited. Newts had higher detection probabilities with higher vegetation cover.

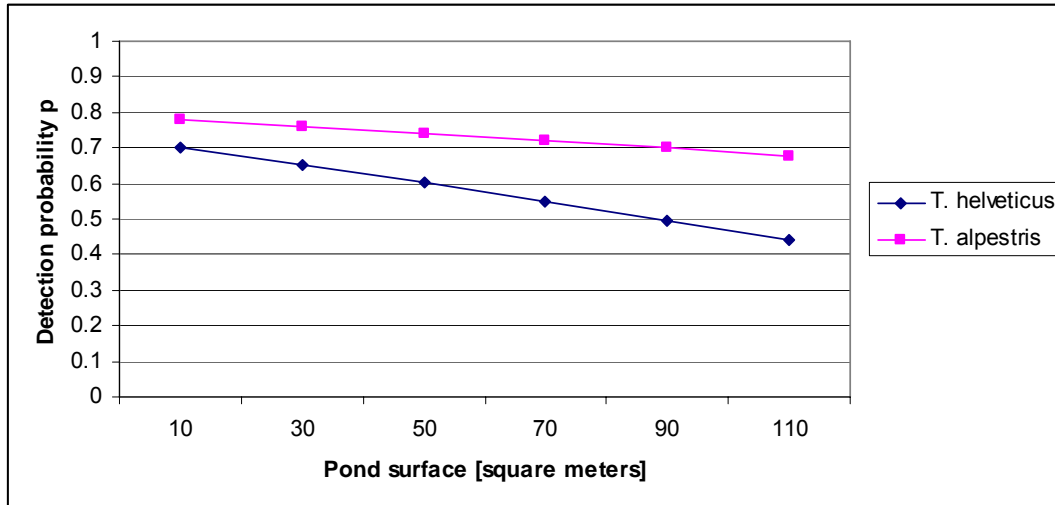


Fig. 5: Relationship between pond surface and detection probability for two newt species at night. Mean values were used when other explanatory variables than those represented graphically were included in the model. Shown are the predictions based on the models: $\psi(\cdot)\gamma(\cdot)\epsilon(\cdot)p(\text{night:s2,day:s2}; \text{pg, wflae})$ for *T. alpestris* $\psi(\cdot)\gamma(\cdot)\epsilon(\cdot)p(\text{night:s2,day:s2}; \text{pg, veg, wflae})$ for *T. helveticus* (Abbreviations are explained in Appendix 1)

4.2) Site occupancy

Table 20 summarizes the model selection results for the second step of the analysis, in which I determined the factors best explaining site occupancy ψ .

Tab. 20: Summary of the model selection results for site occupancy. Only models with an Akaike weight ≥ 0.099 are shown. Parameters not modeled in this step of the analysis were either held constant “(.)” or the best model from the previous step was used “(best)”. Results are shown for all species. The full set of candidate models is shown in Appendix 4.

Species	Model	delta AIC	AIC wgt	No.Par.	(-2*LogLike)
<i>A. obstetricans</i>	psi(PG ; kon),gamma(.),eps(.),p(best)	0	0.9454	14	1079.896032
<i>B. variegata</i>	psi(PG ; gis),gamma(.),eps(.),p(best)	0	0.475	16	1924.437863
	psi(PG),gamma(.),eps(.),p(best)	0.85	0.3105	13	1931.294389
	psi(PG ; kon),gamma(.),eps(.),p(best)	1.59	0.2145	14	1930.025471
<i>B. calamita</i>	(psi(PG),gamma(.),eps(.),p(best))	0	0.6074	14	867.118372
	(psi(PG ; kon),gamma(.),eps(.),p(best))	1.37	0.3062	15	866.490308
<i>R. lessonae</i>	(psi(PG ; kon),gamma(.),eps(.),p(best))	0	0.811	14	2232.85241
	(psi(PG ; gis),gamma(.),eps(.),p(best))	3.1	0.1721	16	2231.948417
<i>T. alpestris</i>	(psi(PG ; kon),gamma(.),eps(.),p(best))	0	0.8648	15	2893.833104
<i>T. cristatus</i>	psi(PG ; gis),gamma(.),eps(.),p(best)	0	0.7948	11	476.236589
	psi(PG ; kon),gamma(.),eps(.),p(best)	2.71	0.205	9	482.952742
<i>T. helveticus</i>	(psi(PG),gamma(.),eps(.),p(best))	0	0.5698	15	1887.803612
	(psi(PG ; kon),gamma(.),eps(.),p(best))	1.51	0.2678	16	1887.313487
	(psi(PG ; gis),gamma(.),eps(.),p(best))	2.51	0.1624	18	1884.308914
<i>T. vulgaris</i>	psi(gis ; veg ; wflae),gamma(.),eps(.),p(best)	0	0.9138	11	178.318271

Abbreviations: pg=past population size, kon=connectivity, gis=landscape variables (settlement, forest, wetland), veg=pond vegetation, wflae=pond surface, (.)=constant term, best=best model from previous step (Abbreviations, full names, and description of the variables used, see Appendix 1)

Past population size (i.e. the number of individuals counted during surveys in previous years) was present in the best models for all species, except for *Triturus vulgaris*. Past population size had a positive effect on occupancy, although the effect size varied among species (Fig. 6).

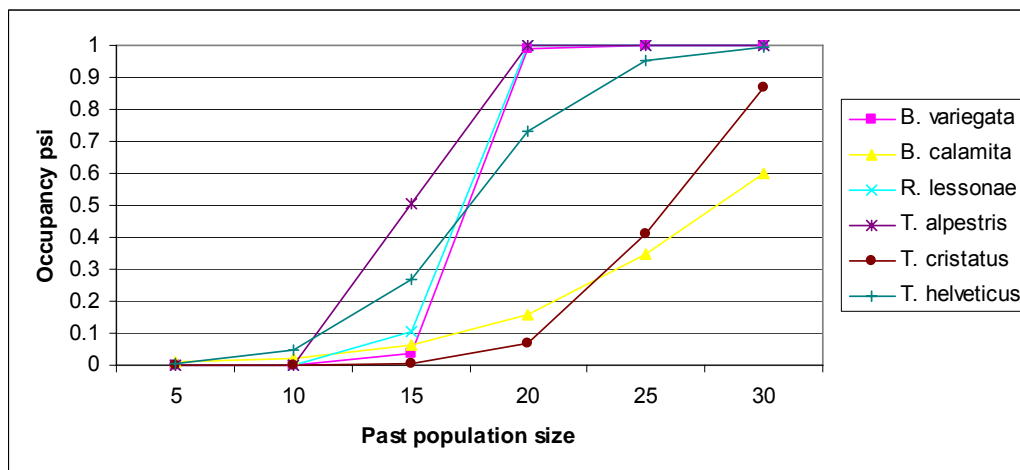


Fig. 6: Relationship between occupancy past population size. Mean values were used when other explanatory variables than those represented graphically were included in the model.

Shown are the predictions based on the models:
 psi(pg, gis)gamma(.),eps(.),p(best) for *B. variegata*
 psi(pg)gamma(.),eps(.),p(best) for *B. calamita*
 psi(pg, kon)gamma(.),eps(.),p(best) for *R. lessonae*
 psi(pg, kon)gamma(.),eps(.),p(best) for *T. alpestris*
 psi(pg, gis)gamma(.),eps(.),p(best) for *T. cristatus*
 psi(pg)gamma(.),eps(.),p(best) for *T. helveticus*
 (Abbreviations are explained in Appendix 1)

Connectivity also played an important role in explaining occupancy of all species. In general, connectivity was positively correlated with presence. Nevertheless, there were a few exceptions: *Alytes obstetricans* and *Triturus alpestris* showed a negative relationship (Fig. 7). *B. calamita* and *T. helveticus* also show a negative relationship, but the confidence interval of the estimate includes zero.

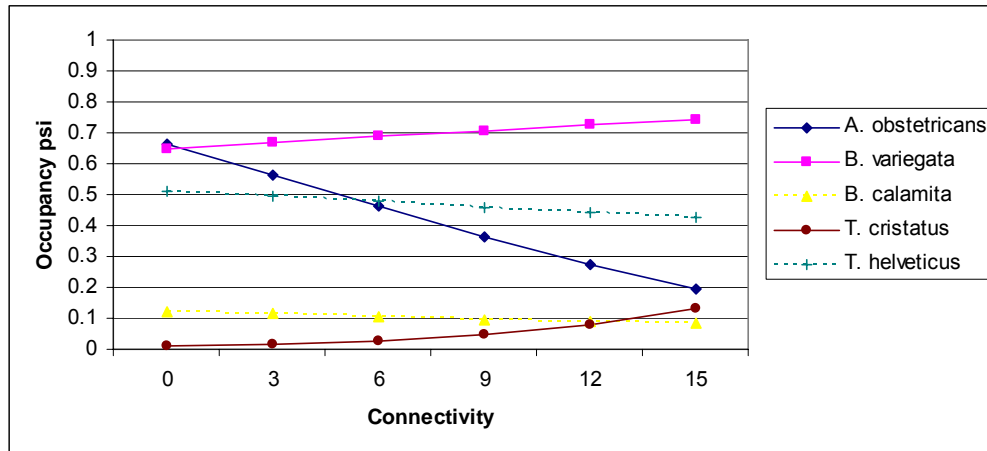


Fig. 7: Relationship between connectivity and occupancy. Mean values were used when other explanatory variables than those represented graphically were included in the model. Dotted lines represent statistically not significant curves. Shown are the predictions based on the models: $\text{psi}(\text{pg}, \text{kon})\text{gamma}(\cdot)\text{eps}(\cdot)\text{p}(\text{best})$ for all species (Abbreviations are explained in Appendix 1)

The landscape variables settlement, forest, and wetland also showed to be important for the majority of the species, and show up frequently among the top-ranking models (Tab. 20). Three species showed results where settlement, forest, and wetland all had the same sign of contribution. All landscape variables correlated negatively with occupancy for *Triturus cristatus*, but positively for *B. variegata* and *T. helveticus* (Fig. 8-1 to 8-3).

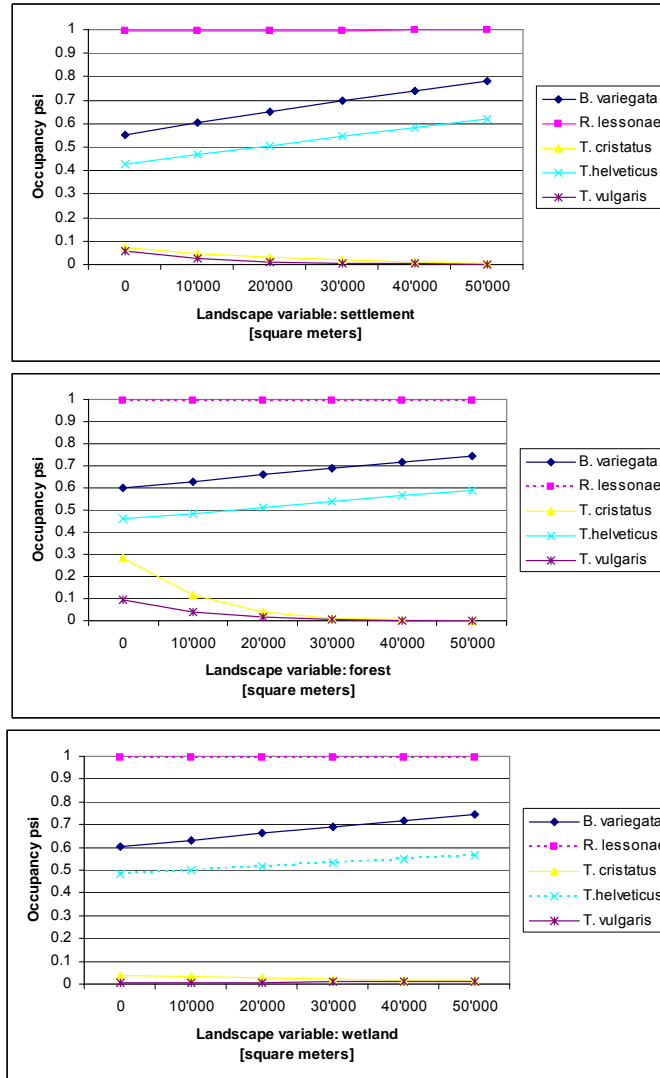


Fig. 8.1-8.3: Relationship between landscape variables (settlement, forest, wetland) (measured as surface in a circular buffer of radius 1 km around the focus pond) and occupancy. Mean values were used when other explanatory variables than those represented graphically were included in the model. Dotted lines represent statistically not significant curves. Shown are the predictions based on the model $\text{psi}(\text{pg, gis})\text{gamma}(\cdot)\text{eps}(\cdot)\text{p}(\text{best})$ for all species. (Abbreviations are explained in Appendix 1)

For the pool frog *Rana lessonae*, the variables settlement and wetland were increased occupancy, whereas forest decreased it. For the two latter results, the confidence interval of the estimate included zero.

Triturus vulgaris differed from all other species in the following: the best model included a completely different set of explanatory variables. Occupancy depended solely on landscape variables and pond characteristics, but not on past population size and connectivity, like for most other species. Pond vegetation, pond surface, and the landscape variable wetland all increased occupancy, whereas settlement and forest coverage decreased occupancy.

4.3) Colonization and extinction probability

Table 21 summarizes the model selection results for the third step of the analysis, in which I determined the factors best explaining colonization (gamma) and local extinction (epsilon) probability.

Tab. 21: Summary of the model selection results for colonization and local extinction probability. Only models with an Akaike weight ≥ 0.099 are shown. Parameters not modeled in this step of the analysis were either held constant “(.)” or the best model from the previous step was used “(best)”.

Results are shown for all species. The full set of candidate models is shown in Appendix 4.

Species	Model	delta AIC	AIC wgt	No.Par.	(-2*LogLike)
<i>A. obstetricans</i>	psi(best),gamma(.),eps(pg),p(best)	0	0.2588	19	1056.320138
	psi(best),gamma(kon),eps(pg),p(best)	0.31	0.2216	20	1054.626061
	psi(best),gamma(.),eps(pg,kon),p(best)	0.63	0.1889	24	1046.947031
	psi(best),gamma(kon),eps(pg,kon),p(best)	1.03	0.1546	25	1045.349393
<i>B. variegata</i>	psi(best),gamma(.),eps(pg,kon),p(best) time constant	0	0.3905	19	1889.778343
	psi(best),gamma(.),eps(pg,kon),p(best)	1.09	0.2265	23	1882.871441
	psi(best),gamma(.),eps(pg),p(best)	1.63	0.1729	22	1885.410565
	psi(best),gamma(kon),eps(pg,kon),p(best)	2.13	0.1346	24	1881.909287
<i>B. calamita</i>	psi(best),gamma(gis,kon),eps(pg),p(best)	0	0.2182	23	842.57339
	psi(best),gamma(gis,kon),eps(pg,kon),p(best)	1.24	0.1174	24	841.806276
<i>R. lessonae</i>	psi(best),gamma(kon),eps(veg,wflae),p(best)	0	0.3601	17	2194.048663
	psi(best),gamma(gis,kon),eps(veg,wflae),p(best)	1.07	0.2109	20	2189.121307
	psi(best),gamma(kon),eps(pg),p(best)	2.36	0.1106	20	2190.40937
<i>T. alpestris</i>	psi(best),gamma(.),eps(pg,kon),p(best)	0	0.4057	21	2860.411038
	psi(best),gamma(kon),eps(pg,kon),p(best)	1.12	0.2317	22	2859.530055
	psi(best),gamma(veg,wflae),eps(pg,kon),p(best)	2.14	0.1391	23	2858.546018
<i>T. cristatus</i>	psi(best),gamma(.),eps(gis,veg,wflae),p(best)	0	0.1494	16	466.119082
	psi(best),gamma(.),eps(.),p(best)	0.12	0.1407	11	476.236589
	psi(best),gamma(.),eps(veg,wflae),p(best)	0.36	0.1247	13	472.48491
	psi(best),gamma(kon),eps(.),p(best)	0.62	0.1095	12	474.738667
<i>T. helveticus</i>	psi(best),gamma(veg,wflae),eps(pg,kon),p(best)	0	0.2792	27	1855.014906
	psi(best),gamma(.),eps(pg,kon),p(best)	0.81	0.1862	25	1859.820016
	psi(best),gamma(kon),eps(pg,kon),p(best)	1.63	0.1236	26	1858.639486
<i>T. vulgaris</i>	psi(best),gamma(.),eps(veg,wflae),p(best)	0	0.39	13	172.931632
	psi(best),gamma(.),eps(.),p(best)	1.39	0.1947	11	178.318271
	psi(best),gamma(kon),eps(veg,wflae),p(best)	2	0.1435	14	172.931969

Abbreviations: pg=past population size, kon=connectivity,
gis=landscape variables (settlement, forest, wetland), veg=pond vegetation,
wflae=pond surface, (.)=constant term, best=best model from previous step
(Abbreviations, full names, and description of the variables used, see Appendix 1)

Notes: *= numerical convergence was not reached, **Numerical convergence was not reached and variance-covariance matrix was not computed successfully.

Affected models are no further considered.

Before modeling the combination of variable as planned (Table 15, Section Materials and Methods), I tested whether a model with a constant extinction or colonization probability for each year (every year is constant, but differences between years are allowed) ranked better than time constant extinction or colonization probabilities term for all years (the term is constant and equal for all years). The colonization probability for *B. variegata*, and the local extinction probability for *A. obstetricans* and *T. helveticus* were better modeled by a constant term for each year.

4.3.1) Colonization probability

Overall, I observed that models with a constant colonization probability were well supported by the data. The variables connectivity, landscape, pond vegetation, pond surface, and combinations thereof found also some support.

The model with constant colonization probabilities “(.)” was the most common one among the models shown in Table 21. Constant colonization probabilities were the best description for five species: three newt species (*T. alpestris*, *T. cristatus*, *T. vulgaris*), *Alytes obstetricans*, and *Bombina variegata*.

Connectivity was the second most important term, showing up in at least one top-ranking model for each species. The sign of its contribution differed among species, though. The effect of higher connectivity is negative for *Alytes obstetricans*, *Bufo calamita*, and *Triturus alpestris*, but is positive for all other species (Fig. 9). The estimate for *T. vulgaris* is not interpretable due to computational complications.

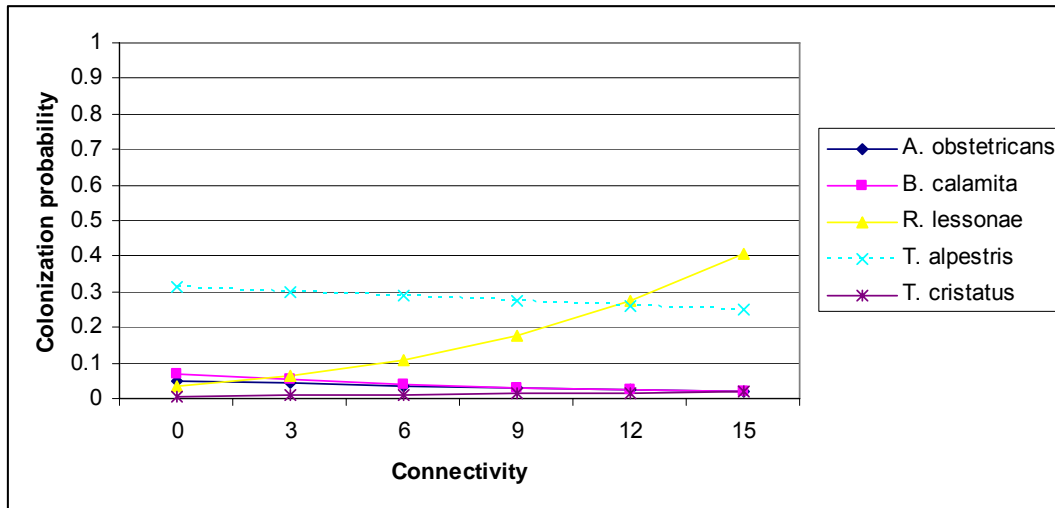


Fig. 9: Relationship between connectivity and colonization probability. Mean values were used when other explanatory variables than those represented graphically were included in the model. Dotted lines represent statistically not significant curves. Shown are the predictions based on the models:

$\text{psi}(\text{best})\gamma(\text{kon})\epsilon(\text{pg})\text{p}(\text{best})$ for *A. obstetricans*
 $\text{psi}(\text{best})\gamma(\text{gis}, \text{kon})\epsilon(\text{pg})\text{p}(\text{best})$ for *B. calamita*
 $\text{psi}(\text{best})\gamma(\text{kon})\epsilon(\text{veg}, \text{wflae})\text{p}(\text{best})$ for *R. lessonae*
 $\text{psi}(\text{best})\gamma(\text{kon})\epsilon(\text{pg}, \text{kon})\text{p}(\text{best})$ for *T. alpestris*
 $\text{psi}(\text{best})\gamma(\text{kon})\epsilon(\cdot)\text{p}(\text{best})$ for *T. cristatus*
 (Abbreviations are explained in Appendix 1)

The landscape approach (see Table 15, section Materials and Methods) was strongly supported for *Bufo calamita* and *Rana lessonae* (Fig. 10). For these two species, connectivity and the landscape variables settlement, forest, and wetland explained colonization probability well. The sign and importance of those variables vary among and within species.

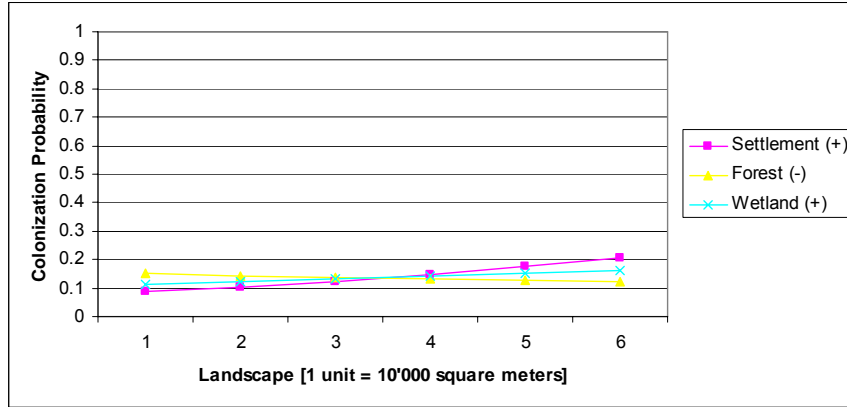


Fig. 10: Effect of landscape variables on colonization probability for *Rana lessonae*. The sign of effect for each variable is shown in the legend. Mean values were used when other explanatory variables than those represented graphically were included in the model. Shown is the prediction based on the model $\psi(\text{best})\gamma(\text{gis}, \text{kon})\epsilon(\text{veg}, \text{wflae})\rho(\text{best})$. (Abbreviations are explained in Appendix 1)

The data of the alpine newt *T. alpestris* and the palmate newt *T. helveticus* supported the model with local abiotic variables (see Table 15 in the Material and Methods section). For both species, pond vegetation and pond surface were important factors in modeling colonization. Colonization probabilities were higher in ponds with high vegetation coverage, but lower in larger ponds (Fig. 11).

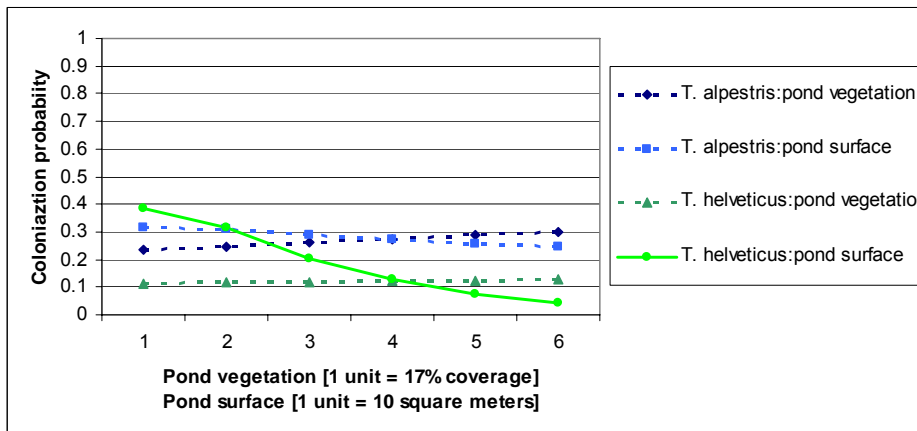


Fig. 11: Relationship between pond vegetation and pond surface and colonization probability for *T. alpestris* and *T. helveticus*. Mean values were used when other explanatory variables than those represented graphically were included in the model. Dotted lines represent statistically not significant curves. Shown are the predictions based on the model $\psi(\text{best})\gamma(\text{veg}, \text{wflae})\epsilon(\text{pg}, \text{kon})\rho(\text{best})$ for both species. (Abbreviations are explained in Appendix 1)

4.3.2) Local extinction probability

Depending on the species, local extinction probability was best modeled either as constant, as dependent on past population size, sometimes in combination with connectivity, or local pond characteristics, sometimes in combination with characteristics of the landscape surrounding the pond.

The model with constant extinction probabilities was best for the newts *T. cristatus* and *T. vulgaris*, but otherwise it did not appear in the top-ranking models for other species.

Past population size was the most common variable needed to describe extinction probabilities. There was strong evidence that it had an important effect on local extinction for *B. variegata*, *T. alpestris*, and *T. helveticus*. In general, extinction probabilities were lower at high population size, and higher at high connectivity (Fig. 12). For only three species, past population size was not important: *R. lessonae*, *T. cristatus*, *T. vulgaris*.

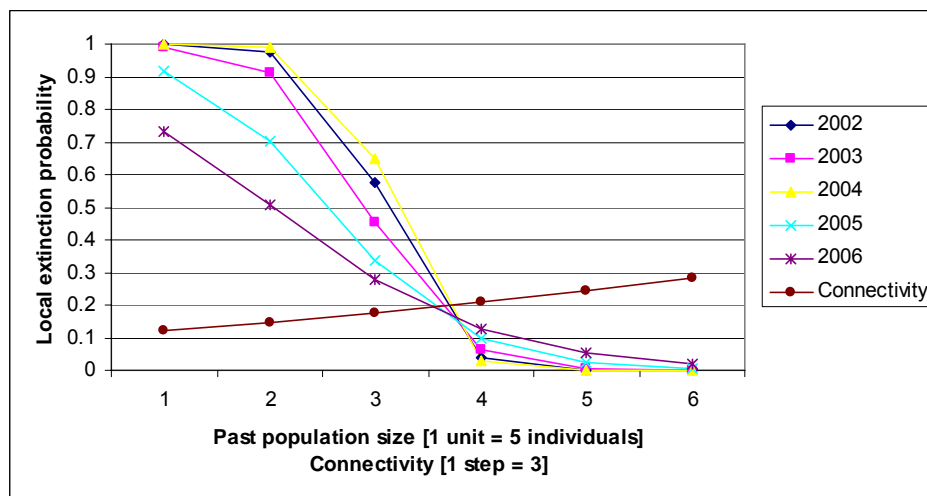


Fig. 12: Relationship between past population size and connectivity and the probability of local extinction for *Bombina variegata*. Shown is the prediction based on the model $\psi(\text{best})\gamma(\cdot)\epsilon(\text{pg}, \text{kon})\rho(\text{best})$ time constant. (Abbreviations are explained in Appendix 1) Mean values were used when other explanatory variables than those represented graphically were included in the model.

Except for the four newt species, past population size alone was also present in the best models. Otherwise, past population size showed up in combination with local abiotic and landscape variables.

Local abiotic variables (see Table 15 in the Material and Methods section) played an important role in explaining local extinction probability for *R. lessonae*, and the two newts *T. cristatus* and *T. vulgaris*. For the frog species, the contribution of these factors was negative, and for the newts species-specific (Fig. 13).

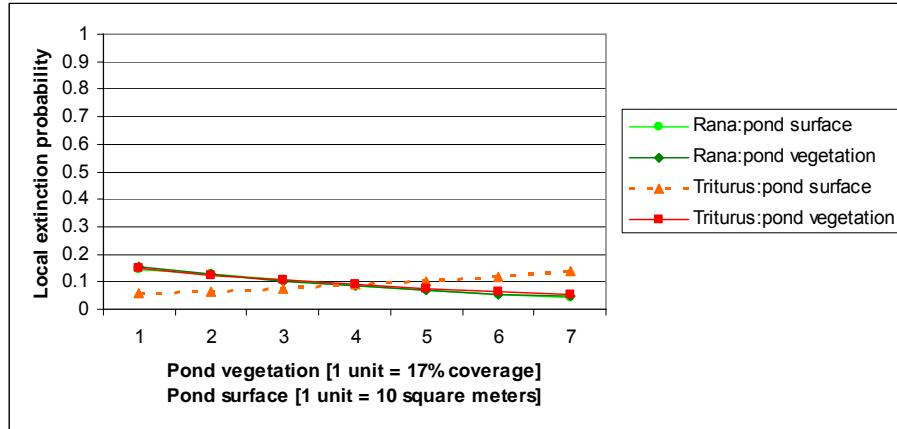


Fig. 13: Effect of pond vegetation and pond surface on local extinction probability for *Rana lessonae* and *Triturus cristatus*.

Mean values were used when other explanatory variables than those represented graphically were included in the model. Dotted lines represent statistically not significant curves.

Shown are the predictions based on the models:

$\text{psi}(\text{best})\text{gamma}(\text{kon})\text{eps}(\text{veg}, \text{wflae})\text{p}(\text{best})$ for *R. lessonae*

$\text{psi}(\text{best})\text{gamma}(\cdot)\text{eps}(\text{gis}, \text{veg}, \text{wflae})\text{p}(\text{best})$ for *T. cristatus*.

(Abbreviations are explained in Appendix 1)

4.4) Colonization and extinction probabilities with management

Table 22 summarizes the model selection results for the fourth step of the analysis, where I considered the effects of different classes of management on colonization and local extinction probabilities.

Tab. 22: Summary of the model selection results for management. Only models with an Akaike weight ≥ 0.099 are shown. Parameters not modeled in this step of the analysis were either held constant “(.)” or the best model from the previous step was used “(best)”. Results are shown for all species. The full set of candidate models is shown in Appendix 4.

Species	Model	delta AIC	AIC wgt	No.Par.	(-2*LogLike)	
A. obstetricans	psi(best),gamma(best),eps(best),p(best)	0	0.7545	19	1056.320138	*
B. variegata	psi(best),gamma(best),eps(best,k3),p(best)	0	0.3954	24	1874.892036	*
	psi(best),gamma(best),eps(best,k2,k3),p(best)	2	0.1455	29	1866.890501	**
	psi(best),gamma(best),eps(best,k3le),p(best)	2.37	0.1209	24	1877.264716	*
B. calamita	(psi(best),gamma(best),eps(best),p(best))	0	0.3602	23	842.57339	*
	(psi(best),gamma(best,k3le),eps(best),p(best))	1.22	0.1957	28	833.789624	*
	(psi(best),gamma(best,k2),eps(best),p(best))	1.96	0.1352	28	834.526386	*
	(psi(best),gamma(best,k2le),eps(best),p(best))	2.1	0.126	28	834.674015	*
R. lessonae	psi(best),gamma(best),eps(best,k3le),p(best)	0	0.3473	22	2183.75154	**
	psi(best),gamma(best),eps(best),p(best)	0.3	0.2989	17	2194.048663	*
	psi(best),gamma(best),eps(best,k2le),p(best)	2.13	0.1197	22	2185.879924	*
T. alpestris	psi(best),gamma(best),eps(best,k3),p(best)	0	0.5391	26	2844.395826	*
	psi(best),gamma(best),eps(best,k2,k3),p(best)	2.69	0.1405	31	2837.094758	*
T. cristatus	psi(best),gamma(best),eps(best),p(best)	0	0.8212	11	476.236589	
T. helveticus	psi(best),gamma(best),eps(best,k3),p(best)	0	0.42	28	1856.183321	*
	psi(best),gamma(best),eps(best),p(best)	1.8	0.1707	23	1867.980469	*
	psi(best),gamma(best),eps(best,k3le),p(best)	2.77	0.1051	28	1858.948218	**
T. vulgaris	psi(best),gamma(best),eps(best),p(best)	0	0.8404	11	178.318271	

Abbreviations: best=best model from previous step, k1=new habitat, k1le=new habitat “lasting effects”, k2=aquatic habitat management, k2le= aquatic habitat management “lasting effects”, k3=terrestrial habitat management, k3le= terrestrial habitat management “lasting effects”

(Abbreviations, full names, and description of the variables used, see Appendix 1)

Notes: *= numerical convergence was not reached, **Numerical convergence was not reached and variance-covariance matrix has not been computed successfully.

Questionable estimates are no further considered.

In general, we see that for three species (*A. obstetricans*, *T. cristatus*, *T. vulgaris*) the factor management was not present in the best models. For the five other species, instead, management played a role.

The most important type of management was the management of the area surrounding the ponds, i.e. management of the terrestrial habitat. This type of management had both short-term and long-term effects. In fact, either short-term, or long-term effects of management of the terrestrial habitat were present in the best models for every species where management was relevant. Where both types of terrestrial habitat management were present in the best models for one species, the short-term effects always performed better than “lasting effects”.

The second most important management type was management of the pond itself. Pond management had both short-term and long-term effects, and often showed up in combination with terrestrial habitat management in the top-ranking models.

The third class of management was the construction of new ponds, and was not present in top-ranking models.

Management usually affected local extinction probabilities. *B. calamita* is the only species where management affected the colonization probability, rather than local extinction.

Terrestrial habitat management had a positive effect on colonization (Fig. 14), and showed species-specific effects on the local extinction probability.

Local extinction was negatively correlated with terrestrial habitat management for *T. alpestris* and *T. helveticus* (Fig.15), but positively correlated for *B. variegata*. *Rana lessonae* also showed a positive relationship, but the confidence interval of the estimate included zero. *T. helveticus* was the only species where only the management of the terrestrial habitat played a role.

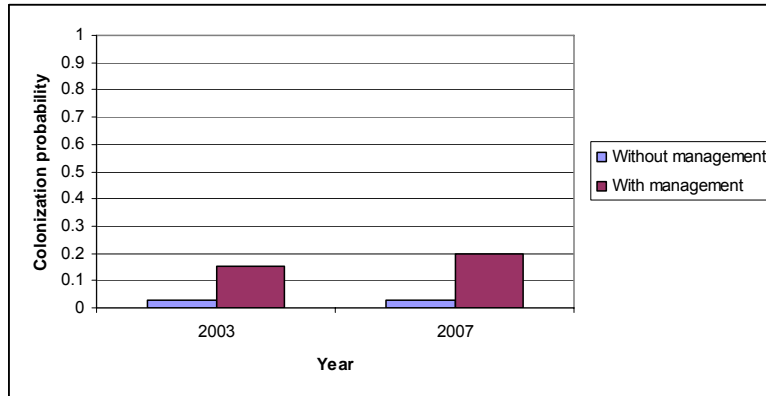


Fig. 14: Relationship between colonization probability and terrestrial area management with lasting effects for *Bufo calamita*. Only the years 2003 and 2007 provided reliable estimates. Shown is the prediction based on the model $\psi(\text{best})\gamma(\text{best}, k3l)\epsilon(\text{best})p(\text{best})$. (Abbreviations are explained in Appendix 1) Mean values were used when other explanatory variables than those represented graphically were included in the model.

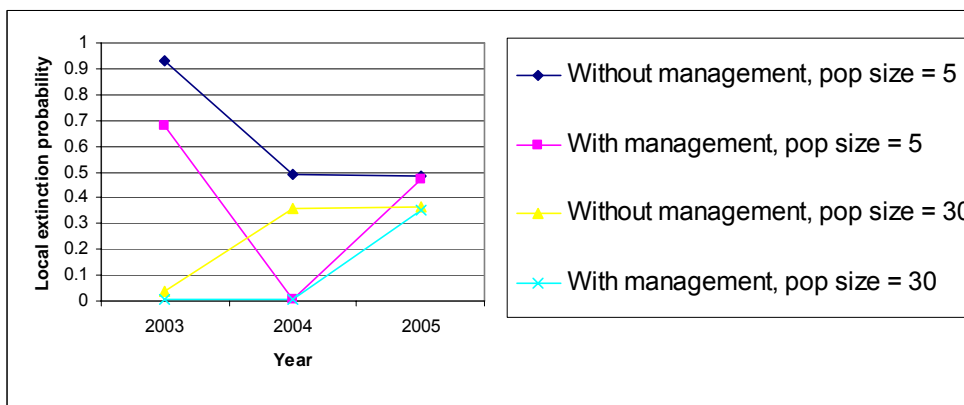


Fig. 15: Relationship between surrounding area management and local extinction probability at two different population sizes for *T. helveticus*. Shown is the prediction based on the model $\psi(\text{best})\gamma(\text{best})\epsilon(\text{best}, k3l)p(\text{best})$. (Abbreviations are explained in Appendix 1) Mean values were used when other explanatory variables than those represented graphically were included in the model.

Pond management increased colonization probability and increased local extinction. Pond management played an important role in modeling colonization for *B. calamita* (Fig. 16) and its long-term form the local extinction for *Rana lessonae*. Otherwise it was found only in combination with surroundings area management (*B. variegata*, *T. alpestris* (Fig. 17)).

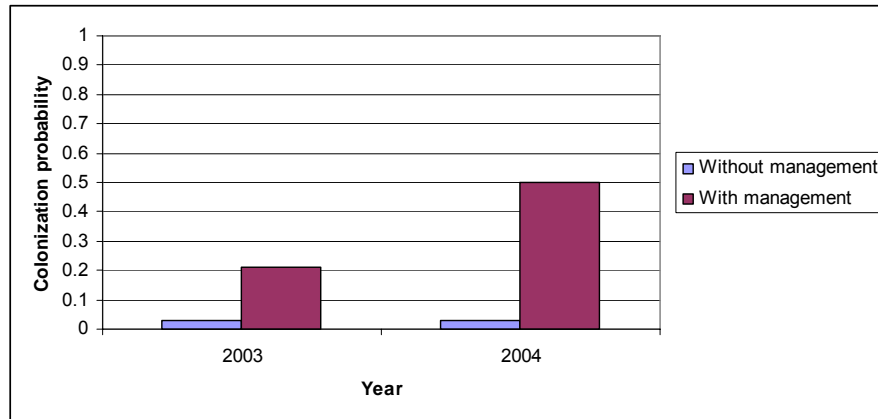


Fig. 16: The effect of aquatic habitat management on colonization probability for *B. calamita* in the years 2003 and 2004. Shown is the prediction based on the model $\psi(\text{best})\gamma(\text{best}, k_2)\epsilon(\text{best})p(\text{best})$. (Abbreviations are explained in Appendix 1). Mean values were used when other explanatory variables than those represented graphically were included in the model.

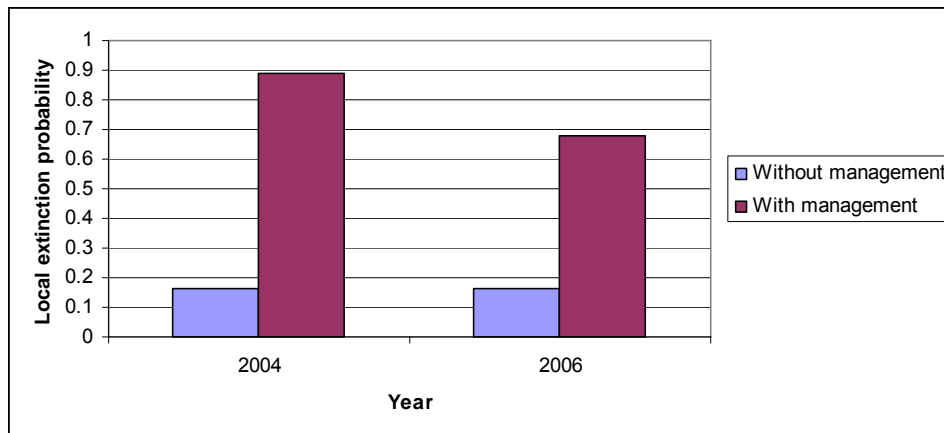


Fig. 17: Relationship between aquatic habitat management and local extinction probability for *B. variegata*. Shown is the prediction based on the model $\psi(\text{best})\gamma(\text{best})\epsilon(\text{best}, k_2, k_3)p(\text{best})$. Abbreviations are explained in Appendix ? Mean values were used when other explanatory variables than those represented graphically were included in the model.

5) Discussion

I used an information-theoretic approach to evaluate whether, how, and which types of habitat management affected amphibian populations at the landscape scale. To do so, I modeled site occupancy probability, detection probability, colonization and local extinction probability of amphibian species. Several combinations of variables (local to landscape, biotic to abiotic, and different types of habitat management) were considered.

5.1) Detection probability

Four variables played an important role in explaining detection probabilities: the difference between day-time and night-time surveys, past population size, weather, and phenology.

Detection probabilities differed between day and night. The variable night/day was included in nearly all high-ranking models. I assume that the difference between day and night is the result of two concurring situations. The first one is the fact that at night, amphibians are more active and call, which makes their detection easier. Second, the day-time survey is always done late in the season, and the probability that amphibians have already left the pond is high.

Past population size was also an important factor for almost all species. Unsurprisingly it was positively correlated with detection probability for all species, and all years. The positive correlation confirms the results of other studies (e.g. Royle & Nichols 2003).

The two survey-specific variables weather and phenology also played an important role in explaining detection probability. As already seen in other studies (Wells 1977, Tanadini & Schmidt, unpublished results), phenology is negatively correlated with detection probability. This correlation is easily explained by the biology of the amphibians and the mathematics behind the model. The amphibians show up relatively early in the season at the ponds. Since they are many and in the breeding season, they are easily found. Therefore, the detection probability is high. At the end of the season, the breeding season is over. Amphibians are less active and call less, and some may have already left the pond. At this point, it is difficult to find amphibians, and the detection probability decreases. The way I entered the variables “forced” the program PRESENCE to find a linear relationship between phenology and detection probability, which explains the results very well.

Weather situations in which air temperature is low, and wind and rain are present lead to higher detection probabilities for almost all species. Amphibians like wet conditions, but also mild temperatures and wind absence. Our explanation of this discrepancy is that weather variables actually reflect when the volunteers go out in the field, rather than

describing the ideal conditions for amphibians. If we assigned random dates for the surveys, we would expect our prediction to be true. In reality, volunteers freely chose the days when they do field work. In this way, a bias for good days emerges. Furthermore, the range of the values of weather variables indicates that temperature was never really cold (overall mean temperature =16.8 ° C, min= 2.7 °C, max= 26.2 °C), and the wind was, when present, moderate (overall mean wind speed= 4.7 Km/h, min=0.5 Km/h, max=15 Km/h).

For all newt species (*Triturus ssp.*), I found that pond vegetation increased, and pond surface decreased detection probability. The first aspect is supported by the newts' biology: they prefer relatively small and densely vegetated habitats (Pavignano et al 1990). Consequently, populations are larger in these ponds which makes the species easier to detect (Royle and Nichols 2003).

The negative effect of pond surface on detection probability is a consequence of the reduced operating range of the volunteers. The volunteers can only assess the presence of amphibians at the perimeter of the pond, and only a fraction of the total pond area is checked. The bigger the pond, the smaller this fraction is, compared to the pond's total surface. I believe that accessibility lowers detection primarily because of the impediment it represents for the field workers, rather than being a real abiotic constraint for the newts.

5.2) Occupancy, colonization and extinction probability

All best models for occupancy included past population size. The addition of landscape variables or connectivity led to equally good models. As the only exception, the occupancy of *Triturus vulgaris* was best explained by landscape and pond characteristics.

The same trend can be seen for the local extinction probability, where past population size was present in the majority of the top-ranking models. In addition to connectivity, past population size formed the most common combination of variables explaining local extinction. Pond vegetation and pond surface, sometimes together with landscape variables, also found some support in explaining extinction probability.

Colonization is best explained by the variable connectivity, either alone or in combination with landscape variables. The constant term is also present in many models. Characteristics of the ponds themselves, such as pond vegetation and pond surface, played a role for two newt species (*T. helveticus*, *T. alpestris*), but not for the anurans.

5.2.1) Past population size

Occupancy models that included past population size were superior to all others. The correlation was always positive, meaning high probability of occupancy in ponds that were occupied by large populations in the past. The same trend can be observed for local extinction. A large past population size means a present low extinction probability.

This evidence confirms the importance population processes in the distribution and abundance of amphibians (Schmidt & Pellet 2005). Two aspects are particularly important in this context. First, small populations show a much stronger variance in population size over years than bigger ones (Green 2003), and are therefore more likely to disappear because of demographic stochasticity. The second aspect to consider is the spatial aggregation tendency of individuals. Ray and Gilpin (1991) showed that dispersing individuals tend to be attracted to places where conspecifics are already present. Theoretically, attraction further increases the size of relatively big populations and further destabilizes small ones. Surveying the literature, Stamps (1987) suggested that territorial aggregation could be explained by the fact that conspecifics presence may give information about the quality of the habitat. This aspect is apparently in contradiction with our result showing that pond characteristics were bad predictors for presence. Other, in this analysis not considered factors could be better predictor.

5.2.2) *Connectivity*

Connectivity was a well-supported variable, and present in all three parameters modeled. The sign of the contribution was species-specific

The importance of maintaining the possibility for dispersal for amphibian populations has been emphasized several times in the literature (e.g. Semlitsch 2002, but for a critical essay see Harrison & Bruna 1999). Aware of the fact that amphibians have an important migratory range (Jehle & Sinsch 2007), I conclude that populations in well-connected ponds have a higher probability to persist over time, because they are adequately linked to source populations (the “rescue effect”, see Brown & Kodric-Brown 1977). This can explain cases where connectivity is positively correlated with occupancy and colonization, or negatively correlated with local extinction. Under other circumstances, higher connectivity may lead to the opposite result. Denoël and Lehmann (2006) reported the case of a newt species where high abundance is negatively associated with the number of surrounding ponds. For example, if high connectivity permits mobility at the landscape scale, than I expect that proportionately more individuals tend to migrate. The population size at the focus pond would decrease. For pioneer species, I expect them to leave ponds when climax-vegetation is reached (Skelly et al. 1999). High connectivity could accelerate this process. Another possibility is that individuals concentrate in the best habitats at a landscape scale, resulting thus in local extinction of less suitable habitats. The explanation for the negative relationship between connectivity and colonization probability is controversial. The literature furnishes mostly evidence for the contrary (e.g. Lehtinen & Galatowitsch 2001). I advance the hypothesis of the “anti-rescue effect”(Harding & McNamara 2002), where immigrants could carry e.g. diseases or pathogens. Conspecific attraction (Ray & Gilpin 1991) could also contribute to this trend. Even though connectivity is widely accepted as an important aspect in the context of metapopulation, Prugh et al (2008) showed that isolation was a poor predictor of species occupancy.

The variables past population size and connectivity show together that the persistence of a species is determined to a great extent by the population sizes in the focus pond, and in those around it.

5.2.3) *Landscape*

Still important, but less supported, are the variables settlement, forest, and wetland. They describe the landscape in which the ponds are embedded. The landscape is much more important for occupancy and colonization than it is for local extinction.

According to the overview by Hermann et al. (2005), I expected a negative effect of settlement, but a positive one for wetland and forest. This was not always the case. I speculate that a positive correlation of settlement with occupancy could be found for those species that have adapted and/or are forced to live in human-made habitats (Hamer & MacDonnell 2008). For the variable forest, I explain the results with the different biological preferences for the different species analyzed. If we consider the variable wetland as a surrogate for pond surface, I believe this would explain the different contribution for different species favoring different habitat types.

5.2.4) *Pond vegetation*

In general, as expected, all four newt species benefit from highly vegetated ponds. Pond surface played an important role in explaining site occupancy solely for *Triturus vulgaris*, where it showed a positive effect. Also for the modeling of colonization probability, pond vegetation was not a common influence, but important and positive for two newt species (*T. alpestris*, *T. helveticus*). Pond vegetation seemed to well explain local extinction for *Rana lessonae* and *T. vulgaris*. For both species, high vegetation coverage lowered the local extinction probability.

5.2.5) *Pond surface*

Pond surface is included in the best model explaining occupancy for *T. vulgaris*. It appears in well supported models explaining colonization for *T. alpestris* and *T. helveticus*, and the local extinction for *R. lessonae*, *T. cristatus*, and *T. vulgaris*.

The importance of pond surface in our study supports the idea that newts prefer small ponds (colonization of big ponds is low, extinction is high) but *Rana lessonae* does not (extinction probability for big ponds is low). I can only speculate about the high occupancy in big ponds for *T. vulgaris*.

5.2.6) *Triturus vulgaris* - Occupancy

The model best explaining occupancy for *T. vulgaris* was different from all others. Only landscape variables and pond characteristics were important in explaining occupancy. The importance of vegetation and landscape for these species are confirmed in many publications (e.g. Pavignano et al. 1990; Cirovic et al. 2008). Surprisingly, this is not true for the other three newt species.

5.2.7) Constant extinction and colonization probabilities

For many species, a model with constant colonization/extinction probabilities (without any explanatory variables) explained the data best. The constant term is present most notably in many top-ranking models explaining colonization probability. Before asserting too quickly that no single factor is important, we must consider the way in which models are ranked. All models were ranked following their score of the Akaike's Information Criterion. This criterion is the sum of two terms. The first takes into account the loss of information when one model is used to approximate full reality. The second is a penalty term accordant to the number of parameters estimated for each model. It could be that the loss of information (mathematically $-2 \cdot \text{LogLikelihood}$) of one model is smaller than the constant models, but the penalty term produces the inverted rank order (Anderson 2007, page 55). Table ? shows that often simpler models with fewer explanatory variables ranked better than more complex models; this comparison is somewhat confounded, though, because one might also expect to see constant extinction probabilities and colonization probabilities dependent on explanatory variables.

5.3) Occupancy, colonization and extinction probability with management

In general, management was found in the top-ranking models for five out of eight species (*B. variegata*, *B. calamita*, *R. lessonae*, *T. alpestris*, *T. helveticus*). For three species (*A. obstetricans*, *T. cristatus*, *T. vulgaris*) management effects were not included in the top-ranking models. For the species where management mattered, it was the management of the terrestrial or aquatic habitat that was important; the management action "creation of new ponds" was never included in the best models. Management more often affected local extinction probabilities than colonization probabilities.

It may be that management effects were not detectable because some species had very low occupancy rates (e.g. occupancy estimate (mean \pm SD, $n = 200$ objects) for the two newts: *T. cristatus* = 0.0155 ± 0.0291 , *T. vulgaris* = 0.021 ± 0.041). When occupancy is so low, it is inevitable that no explanatory variable plays a role. *A. obstetricans* showed a higher occupancy estimates. For these species it may simply be that no modeled variable had enough explanatory power.

Management affected local extinction probabilities of four species (*B. variegata*, *R. lessonae*, *T. alpestris*, *T. helveticus*), whereas it colonization in the fifth (*B. calamita*).

For the first four species, terrestrial habitat management showed up in the top-ranking models explaining local extinction probability. Terrestrial habitat management decreased extinction probability for *T. alpestris* and *T. helveticus*, but increased extinction probability for *B. variegata* and *R. lessonae* (but for the latter the confidence interval of the estimate included zero). For the newt species, terrestrial habitat management favored the persistence of the species in the occupied ponds. It seems that newt species prefer a vegetation-rich pond, and at the same time a vegetation free zone around the pond. This may be important to allow terrestrial movement and dispersal for this slow-moving species. On the other hand, the extinction probability of *B. variegata* was higher when terrestrial habitat was managed. Terrestrial habitat management with the goal to e.g. “clean” off possible hiding places in the surrounding area might lead *B. variegata* to leave the place.

Pond management increased colonization for *B. calamita*, and increased the extinction probability of *B. variegata*, *R. lessonae*, and *T. alpestris*. The fact that *B. calamita* prefers vegetation-free ponds explains the higher colonization rate for managed ponds. The very same explanation would apply to *R. lessonae* and *T. alpestris*, where pond management promoted local extinction. In fact, these species prefer vegetation-rich ponds, and management often has the goal to clear vegetation. The results for *B. variegata* are more difficult to interpret because this species prefers ponds with poor vegetation. However, pond management increased local extinction probability.

The construction of new ponds did not show up in the top-ranking models for any species. This may sound counterintuitive, but it is not so surprising because the construction of a new pond always took place close to an already existing site. (Remember: monitoring is done at object-scale (see 3.3.1) Amphibian population, Section Material and Methods)) The fact that the creation of additional ponds in an area with already existing ponds ranked so low has important management implications. In fact, it seems to be much better to invest time and resources in the management of the aquatic and terrestrial habitats. Another implication could be to keep creating new ponds, but those outside the geographical range of the object.

B. calamita was the only species where management increased the colonization probability, but had no effect on local extinction. Stevens et al. (2006) confirm the importance of colonization and recolonization in assuring persistence at a landscape scale for pioneer species like *B. calamita*. The effect on colonization was positive for both terrestrial habitat and pond management. I believe this is due to the fact that *B. calamita* is a pioneer species that rapidly colonizes suitable habitat after disturbance. In this context, I could see management actions as disturbance of the natural trajectory. Therefore, any modification of habitat conditions has an important effect on the population dynamics of *B. calamita*.

What is more, the results could be affected by the analysis mechanism that focuses on ponds as patches. I would expect *B. calamita* to “follow” habitat in early successional stages. With ongoing succession, populations move to other places. These displacements can be evaluated as extinctions and new colonization, even though the population at a landscape scale was stable (Marsh & Trenham 2001).

6) Conclusions

Management primarily affected local extinction probabilities. The most influential type of management was management of the terrestrial habitat in the vicinity of the ponds. The response to terrestrial habitat management was a decreased local extinction probability for newts, but local extinction probability increased for frogs and toads. The second-most influential management type was the management of the aquatic habitat, which increased local extinction for all species studied. In some cases, management of the terrestrial, or of the aquatic habitat increased colonization probabilities.

This statistical-based analysis of effectiveness of management activities showed that habitat management does indeed affect amphibian populations. However, it did not always affect these populations in the expected way. Management practice should take advantage of these new findings and adjust management practice orientating their practice toward more effective practices, such as terrestrial and aquatic habitat management.

7) Future research

In further occupancy studies, I suggest to consider fish presence. It can strongly influence biotic relationships and competition between co-occurring species (Van Buskirk 2005) and have a negative impact on native amphibians communities (Hartel et al 2007). Because big and stable ponds host more likely fishes, fish presence may play an important role in explaining the responses of different species to the variable pond surface.

In this project, I defined connectivity as the sum of the exponential negative distance between ponds. Barrier-based buffer approaches and/or landscape-based inter-patch distances may be more realistic ways of measuring distances between ponds (Zanini 2006).

The creation of new ponds poorly explained colonization and local extinction probability. It might be that the impact of new ponds is not to be searched in the explanatory variable coding their implementation. Other variables, like connectivity, may be a better way of taking account of the effect of new ponds in the landscape.

In general, the biggest difficulty regarding the modeling part was the lack of complete information regarding the sites and especially the time gaps between years of subsequent visit at the same site. I therefore suggest the governmental agency to accordingly improve the selection of sites to be visited during future years if the goal is to better link amphibian data with management data.

Further research is needed in several aspects of measuring the effectiveness of conservation actions. I suggest to start with a verification of the results obtained in this project in the field.

8) Acknowledgments

I owe a particular thank to my supervisor Dr. Beni Schmidt for his precious support during the whole duration of this project. Thanks also to his son Leon, who kept my project exciting until its very end.

Many thanks to the people running the amphibian monitoring program of the Canton Aargau who gave me the possibility to develop my thesis using their data. In this sense a special mention to dipl. biol. Bühler Christoph. Thanks also to André Seippel and Thomas Gerber for the friendly discussion and data about monitoring activities.

Many thanks to Fabien Fivat for providing the GIS data.

Furthemore, I would like to thank Prof. Dr. Heinz-Ulrich Reyer and the whole ecology lab for this eventful year together.

Special thanks go to my parents too, who supported me throughout my years at university.

9) Literature cited

- Allison S. K.** 2007. You can't not choose: embracing the role of choice in ecological restoration. *Restoration Ecology*, Vol. 15, No. 4, 601-605
- ANDERSON D. R. 2007. *Model based inference in the life science: a primer on evidence*. Pringer
- Barrows C. W., Allen M. F.** 2007. Biological monitoring and bridging the gap between land management and science. *Natural areas journal*, 27, 194-197
- Barrows C.W. et al.** 2005. A framework for monitoring multiple-species conservation plans. *Journal of wildlife management*, 69 (4), 1333-1345
- BEEBEE T.J.C. 1996: *Ecology and conservation of amphibians*. Springer Edition
- Brodman R. et al.** 2006. Amphibian biodiversity recovery in a large-scale ecosystem restoration. *Herpetological Conservation and Biology*, 1(2), 101-108
- Brown J. H., Kodric-Brown A.** 1977. Rates in insular biogeography: effects of immigration on extinction. *Ecology*, Vol. 58, No. 2, 445-449
- Clewell A., Rieger J.P.** 1997. What practitioners need from restoration ecologists. *Restoration Ecology*, Vol. 5, No. 4, 350-354
- Corovic R. et al.** 2008. Breeding site traits of European newts (*Triturus macedonicus*, *Lissotriton vulgaris*, and *Mesotriton alpestris*: Salamandridae) in the Montenegrin Karst region. *Arch. Biol. Sci.*, 60(3), 459-468
- Daily G. C.** 2001. Ecological forecast. *Nature*, 411, 245
- Denoël M., Lehmann A.** 2006. Multi-scale effect of landscape processes and habitat quality on newt abundance: implication for conservation. *Biological conservation*, 130, 495-504
- Edgar P. W. et al.** 2004. Evaluation of translocation as a tool for mitigating development threats to great crested newts (*Triturus cristatus*) in England, 1990-2001. *Biological Conservation*, 122, 45-52
- Green D. M.** 2003. The ecology of extinction: population fluctuation and decline in amphibians. *Biological Conservation*, 111, 331-343
- Hamer a. J., McDonnell M. J.** 2008. Amphibian ecology and conservation in the urbanizing world: a review. *Biological Conservation*, 2432-2449

- Hanski, Kuussaari, Nieminen** 1994. Metapopulation structure and migration in the butterfly *melitaea cinxia*. *Ecology* 75: 747-762
- Harding K. C., McNamara J. M.** 2002. A unifying framework for metapopulation dynamics. *The American Naturalist*, Vol. 160, No. 2, 173-185
- Harrison S., Bruna E.** 1999. Habitat fragmentation and large-scale conservation: what do we know for sure? *Ecography*, 22, 225-232
- Herrmann H.L. et al.** 2005. Effects of landscape characteristics on amphibian distribution in a forest-dominated landscape. *Biological Conservation*, 123, 139-149
- Houlahan J. E. et al.** 2000. Quantitative evidence for global amphibian population declines. *Nature*, 404, 752-755
- Houlahan J. E. et al.** 2001. Global amphibian population declines. *Nature*, 412, 499
- Jehle R., Sinsch U.** 2007. Wanderleistung und Orientierung von Amphibien: eine Übersicht. *Zeitschrift für Feldherpetologie*, 14, 137-152
- Lee Y. et al.** 2006. Composition, diversity, and spatial relationships of Anurans following wetland restoration in a managed tropical forest. *Zoological Science*, 23, 883-891
- Lehtinen R. M., Galatowitsch S. M.** 2000. Colonization of restored wetlands by amphibians in Minnesota. *The American Midland Naturalist*, 145, 388-396
- MACKENZIE D. I., NICHOLS J. D., ROYLE J. A., POLLOCK K. H., BAILEY L. L., HINES J. E. 2006: *Occupancy estimation and modeling*. Elsevier Press, London
- Marsh D. M., Trenham P.C.** 2001. Metapopulation dynamics and amphibian conservation. *Conservation biology*, Vol. 15, No.1, 40-49
- McCoy E. D., Mushinsky H. R.** 2002. Measuring the success of wildlife community restoration. *Ecological Application*, 12(6), 1861-1871
- Meier C., Schelbert B.** 1999. Amphibienschutzkonzept Kanton Aargau. *Aargauische Naturforschende Gesellschaft, Mitteilungen* 35:41-69
- Miller J. R., Hobbs R. J.** 2007. Habitat restoration – Do we know what we're doing? *Restoration Ecology*, Vol. 15, No.3, 382-390
- Pavignano I. et al.** 1990. A multivariate analysis of amphibian habitat determinants in north western Italy. *Amphibia-Reptilia*, 11, 311-324

Petranka J. W., Holbrook C. T. 2006. Wetland restoration for amphibians: Should local site be designed to support metapopulations or patchy populations? *Restoration Ecology*, Vol. 14, No. 3, 404-411

Prugh L. R. et al. 2008. Effect of habitat area and isolation on fragmented animal populations. *PNAS*, Vol. 105, No. 52, 20770-20775

Pullin A. S., Knight T. M. 2001. Effectiveness in conservation practice: pointers from medicine and public health. *Conservation Biology*, Vol. 15, No. 1, 50-54

Ray C., Gilpin M. 1991. The effect of conspecific attraction on metapopulation dynamics. *Biological Journal of the Linnean Society*, 42, 123-134

Royle J. A., Nichols J. D. 2003. Estimating abundance from repeated presence-absence data or point counts. *Ecology*, 84(3), 777-790

Semlitsch R. D. 2002. Critical elements for biologically based recovery plans of aquatic-breeding amphibians. *Conservation Biology*, Vol. 16, No. 3, 619-629

SEMLITSCH R. D. 2003: *Amphibian conservation*. Smithsonian books

SCHOLZ R.W.2001 : *Erfolgskontrolle von Umweltmassnahmen. Perspektiven für ein integratives Umweltmanagement*. Springer Verlag, Berlin Heidelberg

Schmidt B. R., Pellet J. 2005. Monitoring distributions using call surveys: estimating site occupancy, detection probabilities and inferring absence. *Biological Conservation*, 123, 27-35

Schmidt B. R., Pellet J. 2005. Relative importance of population processes and habitat characteristics in determining site occupancy of two anurans. *Journal of wildlife management*, 69(3), 884-893

Skelly D. K. et al. 1999. Long-term distributional dynamics of a Michigan amphibian assemblage. *Ecology*, 80(7), 2326-2337

Stamps J. A. 1987. Conspecific attraction and aggregation in territorial species. *The American naturalist*, Vol. 1, 329-347

Stevens V. M. et al. 2006. Quantifying functional connectivity: experimental assessment of boundary permeability for the natterjack toad (*Bufo calamita*). *Oecologia*, 150, 161-171

Stewart G. B. et al. 2005. Applying evidence-based practice in conservation management : lessons from the first systematic review and dissemination projects. *Biological Conservation*, 126, 270-278

- Stuart S. N. et al.** 2004. Status and trends of amphibians declines and extinctions worldwide. *Science*, 306, 1783-1786
- Stumpel A. H. P., van der Voet H.** 1998. Characterizing the suitability of new ponds for amphibians. *Amphibia-Reptilia*, 19, 125-142
- Van Buskirk J.** 2005. Local and landscape influence on amphibian occurrence and abundance. *Ecology*, Vol. 86, No. 7, 1936-1947
- Wells.** 1977. Social-behavior of anuran amphibians. *Animal Behaviour*, 25, 666-693
- Zanini F., Klingemann A., Schlaepfer R.** 2008. The effects of landscape structure on the occurrence of two anura species: a barriers-based buffer approach. Submitted to Conservation biology
- Zanini F. et al. 2008.** How does the landscape effect patch occupancy in metapopulation models ? Comparing Euclidean vs. landscape-based inter-patch distance. Submitted to Landscape ecology

Appendix 1 : Abbreviations, full names, and description of the variables used.

Abbreviation	Full name	Description	Unit
PG or pg	Past population size	Number of individuals counted during surveys in previous years	#
night/day	Night-time, day-time surveys	Differentiation between night-time and day-time surveys	-
wflae	Pond surface	Estimated surface of the pond estimated in the field	m ²
eingsch	Access limitation	Description of the accessibility of the pond	1/0
veg	Pond vegetation	First component of PCA run with reeds, floating leave plants, aquatic plants	-
s1	Weather Variables	First component of PCA run with air temperature, rainfall, wind	%
s2	Phenology	Day during the year (1 January = 1)	-
gis	Settlement	Area within a buffer of 1 Km around the pond	m ²
gis	Forest	Area within a buffer of 1 Km around the pond	m ²
gis	Wetland	Area within a buffer of 1 Km around the pond	m ²
kon	Connectivity	Expression of the distance between the focus pond and all the them around	exp(- m)
k1	Management class 1	New habitat	1/0
k2	Management class 2	Aquatic habitat management	1/0
k3	Management class 3	Terrestrial habitat management	1/0
k1le	Management 1 lasting effects	Class 1, the supposed effect starts when it is done and lasts for the remaining years	1/0
k2le	Management 2 lasting effects	Class 2, the supposed effect starts when it is done and lasts for the remaining years	1/0
k3le	Management 3 lasting effects	Class 3, the supposed effect starts when it is done and lasts for the remaining years	1/0
(.)	Constant Model	A constant term is modeled	-
(best)	Best model	Best model from the previous step is used	-

Notes: Night-time/Day-time defferentiation: "night:s2, day:s2" → Surveys depend on s2, differently for day and night
The three landscape variable are always modelled together.

Appendix 2: Alphabetic list of management activity subdivided in the corresponding classes.

Construction of a new habitat	Aquatic habitat management	Terrestrial habitat management
Neue Folientümpel	Abdichten	Abtrag Uferschwalbenwand
Neue Gräben	Abtiefen	Abziehen Böschung
Neue Kleingewässer	Aufwertung	Abziehen Weiher
Neue Laichgewässer	Ausbaggerung	Abziehen Weiherumfeld
Neue Tümpel	Auspackern	Aufreißen Rohbodenflächen
Neue Wasserstellen	Dammsanierung	Ausbaggern Schilfrhizome
Neue Weiher	Entschlammung	Aushubarbeiten Steinbruch
Neuerstellung	Erneuerung	Böschungsplanie
Neues Gewässer	Erneuerung Gräben	Entbuschung
Neues Kleinstgewässer	Erweiterung Gewässer	Entfernung Rohrkolbenbewuchs
Neues sporadische Gewässer	Gestaltung Flusslauf	Entkrautung
Neues Unkengewässer	Gewässer austossen	Erstellung von Kleinstrukturen
	Graben öffnen	Extensive Beweidung
	Lehmdichtung	Flaches Abziehen Weiher
	Nachdichtung	Goldruten- und Schilfeindämmung
	Nachtiefung	Heckenpflege
	Neugestaltung	Holzen
	Regeneration	Jährliche Ausmähen
	Sanierung	Kiesfläche umbrechen
	Sanierung Amphibienzugstelle	Mahd Disteln
	Sanierung Bachaue	Mahd Riedfläche, Schilf, Hochstauden- u.
	Sanierung Wasserzufluss	Neophytenbekämpfung
	Stau erneuern	Planiearbeiten
	Wasserfüllung	Rohrriech teilweise geschnitten
	Zustandverbesserung	Schnittgutentsorgung
		Stockausschläge
		Uferabflachung
		Umfeldgestaltung
		Umgebung abstossen
		Unterschlupfstruktur
		Waldrandbehandlung
		Waldrandstufung
		Wallschüttung

Appendix 3: Design matrix of the best model for each species.

Alytes obstetricans

psi(pg, konn), gamma(.), eps(pg), p(day, night; pg, s1)

psi1	1	PG_02	Kon						
gam1	1								
gam2	1								
gam3	1								
gam4	1								
gam5	1								
eps1	1	PG_03	0	0	0	0			
eps2	1	0	PG_04	0	0	0			
eps3	1	0	0	PG_05	0	0			
eps4	1	0	0	0	PG_06	0			
eps5	1	0	0	0	0	PG_07			
P[1-1]	1	0	PG_02	0	0	0	0	0	Weather
P[1-2]	1	0	PG_02	0	0	0	0	0	Weather
P[1-3]	1	1	PG_02	0	0	0	0	0	Weather
P[2-1]	1	0	0	PG_03	0	0	0	0	Weather
P[2-2]	1	0	0	PG_03	0	0	0	0	Weather
P[2-3]	1	1	0	PG_03	0	0	0	0	Weather
P[3-1]	1	0	0	0	PG_04	0	0	0	Weather
P[3-2]	1	0	0	0	PG_04	0	0	0	Weather
P[3-3]	1	1	0	0	PG_04	0	0	0	Weather
P[4-1]	1	0	0	0	0	PG_05	0	0	Weather
P[4-2]	1	0	0	0	0	PG_05	0	0	Weather
P[4-3]	1	1	0	0	0	PG_05	0	0	Weather
P[5-1]	1	0	0	0	0	0	PG_06	0	Weather
P[5-2]	1	0	0	0	0	0	PG_06	0	Weather
P[5-3]	1	1	0	0	0	0	PG_06	0	Weather
P[6-1]	1	0	0	0	0	0	0	PG_07	Weather
P[6-2]	1	0	0	0	0	0	0	PG_07	Weather
P[6-3]	1	1	0	0	0	0	0	PG_07	Weather

Bombina variegata

psi(pg, gis), gamma(.), eps(pg, kon, k3), p(night:s2, day:s2, pg)

psi1	1	PG_02											
gam1	1												
gam2	1												
gam3	1												
gam4	1												
gam5	1												
eps1	1	PG_03	0	0	0	0	Kon	K3_02	0	0	0	0	0
eps2	1	0	PG_04	0	0	0	Kon	0	K3_03	0	0	0	0
eps3	1	0	0	PG_05	0	0	Kon	0	0	K3_04	0	0	0
eps4	1	0	0	0	PG_06	0	Kon	0	0	0	K3_05	0	0
eps5	1	0	0	0	0	PG_07	Kon	0	0	0	0	K3_06	0
P[1-1]	1	SampCov2	0	PG_02	0	0	0	0	0	0	0	0	0
P[1-2]	1	SampCov2	0	PG_02	0	0	0	0	0	0	0	0	0
P[1-3]	1	0	SampCov2	PG_02	0	0	0	0	0	0	0	0	0
P[2-1]	1	SampCov2	0	0	PG_03	0	0	0	0	0	0	0	0
P[2-2]	1	SampCov2	0	0	PG_03	0	0	0	0	0	0	0	0
P[2-3]	1	0	SampCov2	0	PG_03	0	0	0	0	0	0	0	0
P[3-1]	1	SampCov2	0	0	0	PG_04	0	0	0	0	0	0	0
P[3-2]	1	SampCov2	0	0	0	PG_04	0	0	0	0	0	0	0
P[3-3]	1	0	SampCov2	0	0	PG_04	0	0	0	0	0	0	0
P[4-1]	1	SampCov2	0	0	0	0	PG_05	0	0	0	0	0	0
P[4-2]	1	SampCov2	0	0	0	0	PG_05	0	0	0	0	0	0
P[4-3]	1	0	SampCov2	0	0	0	PG_05	0	0	0	0	0	0
P[5-1]	1	SampCov2	0	0	0	0	0	PG_06	0	0	0	0	0
P[5-2]	1	SampCov2	0	0	0	0	0	PG_06	0	0	0	0	0
P[5-3]	1	0	SampCov2	0	0	0	0	PG_06	0	0	0	0	0
P[6-1]	1	SampCov2	0	0	0	0	0	0	PG_07	0	0	0	0
P[6-2]	1	SampCov2	0	0	0	0	0	0	PG_07	0	0	0	0
P[6-3]	1	0	SampCov2	0	0	0	0	0	PG_07	0	0	0	0

Bufo clamita

psi(pg), gamma(gis, kon), eps(pg), p(night:s1,s2 ; day:s2; pg)

psi1	1	PG_02								
gam1	1	Sied	Wald	Fgeb	Kon					
gam2	1	Sied	Wald	Fgeb	Kon					
gam3	1	Sied	Wald	Fgeb	Kon					
gam4	1	Sied	Wald	Fgeb	Kon					
gam5	1	Sied	Wald	Fgeb	Kon					
eps1	1	PG_03	0	0	0	0				
eps2	1	0	PG_04	0	0	0				
eps3	1	0	0	PG_05	0	0				
eps4	1	0	0	0	PG_06	0				
eps5	1	0	0	0	0	PG_07				
P[1-1]	1	Weather	Phenology	0	PG_02	0	0	0	0	0
P[1-2]	1	Weather	Phenology	0	PG_02	0	0	0	0	0
P[1-3]	1	0	0	Phenology	PG_02	0	0	0	0	0
P[2-1]	1	Weather	Phenology	0	0	PG_03	0	0	0	0
P[2-2]	1	Weather	Phenology	0	0	PG_03	0	0	0	0
P[2-3]	1	0	0	Phenology	0	PG_03	0	0	0	0
P[3-1]	1	Weather	Phenology	0	0	0	PG_04	0	0	0
P[3-2]	1	Weather	Phenology	0	0	0	PG_04	0	0	0
P[3-3]	1	0	0	Phenology	0	0	PG_04	0	0	0
P[4-1]	1	Weather	Phenology	0	0	0	0	PG_05	0	0
P[4-2]	1	Weather	Phenology	0	0	0	0	PG_05	0	0
P[4-3]	1	0	0	Phenology	0	0	0	PG_05	0	0
P[5-1]	1	Weather	Phenology	0	0	0	0	0	PG_06	0
P[5-2]	1	Weather	Phenology	0	0	0	0	0	PG_06	0
P[5-3]	1	0	0	Phenology	0	0	0	0	PG_06	0
P[6-1]	1	Weather	Phenology	0	0	0	0	0	0	PG_07
P[6-2]	1	Weather	Phenology	0	0	0	0	0	0	PG_07
P[6-3]	1	0	0	Phenology	0	0	0	0	0	PG_07

Rana lessonae

psi(pg, kon), gamma(kon), eps(veg, wflae, k3le), p(night:s2;day:s2; pg)

psi1	1	PG_02	Kon						
gam1	1	Kon							
gam2	1	Kon							
gam3	1	Kon							
gam4	1	Kon							
gam5	1	Kon							
eps1	1	Veg	Wflae	K3LE_02	0	0	0	0	
eps2	1	Veg	Wflae	0	K3LE_03	0	0	0	
eps3	1	Veg	Wflae	0	0	K3LE_04	0	0	
eps4	1	Veg	Wflae	0	0	0	K3LE_05	0	
eps5	1	Veg	Wflae	0	0	0	0	K3LE_06	
P[1-1]	1	Phenology	0	PG_02	0	0	0	0	0
P[1-2]	1	Phenology	0	PG_02	0	0	0	0	0
P[1-3]	1	0	Phenology	PG_02	0	0	0	0	0
P[2-1]	1	Phenology	0	0	PG_03	0	0	0	0
P[2-2]	1	Phenology	0	0	PG_03	0	0	0	0
P[2-3]	1	0	Phenology	0	PG_03	0	0	0	0
P[3-1]	1	Phenology	0	0	0	PG_04	0	0	0
P[3-2]	1	Phenology	0	0	0	PG_04	0	0	0
P[3-3]	1	0	Phenology	0	0	PG_04	0	0	0
P[4-1]	1	Phenology	0	0	0	0	PG_05	0	0
P[4-2]	1	Phenology	0	0	0	0	PG_05	0	0
P[4-3]	1	0	Phenology	0	0	0	PG_05	0	0
P[5-1]	1	Phenology	0	0	0	0	0	PG_06	0
P[5-2]	1	Phenology	0	0	0	0	0	PG_06	0
P[5-3]	1	0	Phenology	0	0	0	0	PG_06	0
P[6-1]	1	Phenology	0	0	0	0	0	0	PG_07
P[6-2]	1	Phenology	0	0	0	0	0	0	PG_07
P[6-3]	1	0	Phenology	0	0	0	0	0	PG_07

Triturus alpestris

psi(pg, kon), gamma(.), eps(pg, kon, k3), p(night:s2; day:s2; pg, wflae)

psi1	1	PG_02	Kon										
gam1	1												
gam2	1												
gam3	1												
gam4	1												
gam5	1												
eps1	1	PG_03	0	0	0	0	Kon	K3_02	0	0	0	0	
eps2	1	0	PG_04	0	0	0	Kon	0	K3_03	0	0	0	
eps3	1	0	0	PG_05	0	0	Kon	0	0	K3_04	0	0	
eps4	1	0	0	0	PG_06	0	Kon	0	0	0	K3_05	0	
eps5	1	0	0	0	0	PG_07	Kon	0	0	0	0	K3_06	
P[1-1]	1	Phenology	0	PG_02	0	0	0	0	0	Wflae			
P[1-2]	1	Phenology	0	PG_02	0	0	0	0	0	Wflae			
P[1-3]	1	0	Phenology	PG_02	0	0	0	0	0	Wflae			
P[2-1]	1	Phenology	0	0	PG_03	0	0	0	0	Wflae			
P[2-2]	1	Phenology	0	0	PG_03	0	0	0	0	Wflae			
P[2-3]	1	0	Phenology	0	PG_03	0	0	0	0	Wflae			
P[3-1]	1	Phenology	0	0	0	PG_04	0	0	0	Wflae			
P[3-2]	1	Phenology	0	0	0	PG_04	0	0	0	Wflae			
P[3-3]	1	0	Phenology	0	0	PG_04	0	0	0	Wflae			
P[4-1]	1	Phenology	0	0	0	0	PG_05	0	0	Wflae			
P[4-2]	1	Phenology	0	0	0	0	PG_05	0	0	Wflae			
P[4-3]	1	0	Phenology	0	0	0	PG_05	0	0	Wflae			
P[5-1]	1	Phenology	0	0	0	0	0	PG_06	0	Wflae			
P[5-2]	1	Phenology	0	0	0	0	0	PG_06	0	Wflae			
P[5-3]	1	0	Phenology	0	0	0	0	PG_06	0	Wflae			
P[6-1]	1	Phenology	0	0	0	0	0	0	PG_07	Wflae			
P[6-2]	1	Phenology	0	0	0	0	0	0	PG_07	Wflae			
P[6-3]	1	0	Phenology	0	0	0	0	0	PG_07	Wflae			

Triturus cristatus

psi(pg, gis), gamma(.), eps(.), p(night,day; eingsch;s2)

psi1	1	PG_02	Sied	Wald	Fgeb
gam1	1				
gam2	1				
gam3	1				
gam4	1				
gam5	1				
eps1	1				
eps2	1				
eps3	1				
eps4	1				
eps5	1				
P[1-1]	1	0	Eingsch	Phenology	
P[1-2]	1	0	Eingsch	Phenology	
P[1-3]	1	1	Eingsch	Phenology	
P[2-1]	1	0	Eingsch	Phenology	
P[2-2]	1	0	Eingsch	Phenology	
P[2-3]	1	1	Eingsch	Phenology	
P[3-1]	1	0	Eingsch	Phenology	
P[3-2]	1	0	Eingsch	Phenology	
P[3-3]	1	1	Eingsch	Phenology	
P[4-1]	1	0	Eingsch	Phenology	
P[4-2]	1	0	Eingsch	Phenology	
P[4-3]	1	1	Eingsch	Phenology	
P[5-1]	1	0	Eingsch	Phenology	
P[5-2]	1	0	Eingsch	Phenology	
P[5-3]	1	1	Eingsch	Phenology	
P[6-1]	1	0	Eingsch	Phenology	
P[6-2]	1	0	Eingsch	Phenology	
P[6-3]	1	1	Eingsch	Phenology	

Triturus helveticus

psi(pg), gamma(veg, wflae), eps(pg, kon, k3), p(night:s2;day:s2, pg neg, wflae)

psi1	1	PG_02											
gam1	1	Veg	Wflae										
gam2	1	Veg	Wflae										
gam3	1	Veg	Wflae										
gam4	1	Veg	Wflae										
gam5	1	Veg	Wflae										
eps1	1	PG_03	0	0	0	0	Kon	K3_02	0	0	0	0	
eps2	1	0	PG_04	0	0	0	Kon	0	K3_03	0	0	0	
eps3	1	0	0	PG_05	0	0	Kon	0	0	K3_04	0	0	
eps4	1	0	0	0	PG_06	0	Kon	0	0	0	K3_05	0	
eps5	1	0	0	0	0	PG_07	Kon	0	0	0	0	K3_06	
P[1-1]	1	Phenology	0	PG_02	0	0	0	0	0	Veg	Wflae		
P[1-2]	1	Phenology	0	PG_02	0	0	0	0	0	Veg	Wflae		
P[1-3]	1	0	Phenology	PG_02	0	0	0	0	0	Veg	Wflae		
P[2-1]	1	Phenology	0	0	PG_03	0	0	0	0	Veg	Wflae		
P[2-2]	1	Phenology	0	0	PG_03	0	0	0	0	Veg	Wflae		
P[2-3]	1	0	Phenology	0	PG_03	0	0	0	0	Veg	Wflae		
P[3-1]	1	Phenology	0	0	0	PG_04	0	0	0	Veg	Wflae		
P[3-2]	1	Phenology	0	0	0	PG_04	0	0	0	Veg	Wflae		
P[3-3]	1	0	Phenology	0	0	PG_04	0	0	0	Veg	Wflae		
P[4-1]	1	Phenology	0	0	0	0	PG_05	0	0	Veg	Wflae		
P[4-2]	1	Phenology	0	0	0	0	PG_05	0	0	Veg	Wflae		
P[4-3]	1	0	Phenology	0	0	0	PG_05	0	0	Veg	Wflae		
P[5-1]	1	Phenology	0	0	0	0	0	PG_06	0	Veg	Wflae		
P[5-2]	1	Phenology	0	0	0	0	0	PG_06	0	Veg	Wflae		
P[5-3]	1	0	Phenology	0	0	0	0	PG_06	0	Veg	Wflae		
P[6-1]	1	Phenology	0	0	0	0	0	0	PG_07	Veg	Wflae		
P[6-2]	1	Phenology	0	0	0	0	0	0	PG_07	Veg	Wflae		
P[6-3]	1	0	Phenology	0	0	0	0	0	PG_07	Veg	Wflae		

Triturus vulgaris

psi(gis, veg, wflae), gamma(.), eps(.), p(night, day; eingsch)

psi1	1	Sied	Wald	Fgeb	Veg	Wflae
gam1	1					
gam2	1					
gam3	1					
gam4	1					
gam5	1					
eps1	1					
eps2	1					
eps3	1					
eps4	1					
eps5	1					
P[1-1]	1	0	Eingsch			
P[1-2]	1	0	Eingsch			
P[1-3]	1	1	Eingsch			
P[2-1]	1	0	Eingsch			
P[2-2]	1	0	Eingsch			
P[2-3]	1	1	Eingsch			
P[3-1]	1	0	Eingsch			
P[3-2]	1	0	Eingsch			
P[3-3]	1	1	Eingsch			
P[4-1]	1	0	Eingsch			
P[4-2]	1	0	Eingsch			
P[4-3]	1	1	Eingsch			
P[5-1]	1	0	Eingsch			
P[5-2]	1	0	Eingsch			
P[5-3]	1	1	Eingsch			
P[6-1]	1	0	Eingsch			
P[6-2]	1	0	Eingsch			
P[6-3]	1	1	Eingsch			

Appendix 4: All models for all steps and species

Alytes obstetricans

Detection probability

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
(psi,gamma(),eps(),p(day,night; PG ; s1))	1280.02	0	0.3621	1	12	1256.016805
(psi,gamma(),eps(),p(day,night; PG))	1281.00	0.98	0.2218	0.6126	11	1259.003359
(psi,gamma(),eps(),p(day,night; PG ; s1 ; s2))	1281.91	1.89	0.1407	0.3887	13	1255.908139
(psi,gamma(),eps(),p(night: s2; day: s2; PG))	1282.40	2.38	0.1102	0.3042	12	1258.396685
(psi,gamma(),eps(),p(day,night; PG ; s2))	1282.86	2.84	0.0875	0.2417	12	1258.863402
(psi,gamma(),eps(),p(night: s1, s2; day: s2; PG))	1284.22	4.2	0.0443	0.1225	13	1258.224366
(psi,gamma(),eps(),p(night: s1, s2; day:k; PG))	1284.82	4.8	0.0329	0.0907	13	1258.823807
(psi,gamma(),eps(),p(day,night))	1293.81	13.79	0.0004	0.001	5	1283.811595
(psi,gamma(),eps(),p(night: s1, s2; day:k))	1297.70	17.68	0.0001	0.0001	7	1283.702674
(psi,gamma(),eps(),p(survey))	1310.83	30.81	0	0	21	1268.832648
(psi,gamma(),eps(),p(s2))	1326.28	46.26	0	0	5	1316.282123
(psi,gamma(),eps(),p(PG))	1421.39	141.37	0	0	10	1401.385789
(psi,gamma(),eps(),p(night:s1,day0 ; PG ; s1))	1423.38	143.36	0	0	11	1401.380532
(psi,gamma(),eps(),p(.))	1434.65	154.63	0	0	4	1426.654623
(psi,gamma(),eps(),p(veg))	1435.19	155.17	0	0	5	1425.186101
(psi,gamma(),eps(),p(Wflae))	1435.50	155.48	0	0	5	1425.49693
(psi,gamma(),eps(),p(s1))	1435.71	155.69	0	0	5	1425.710153
(psi,gamma(),eps(),p(eingesch))	1436.39	156.37	0	0	5	1426.39475
(psi,gamma(),eps(),p(year))	1443.47	163.45	0	0	9	1425.472584

Occupancy

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
psi(PG ; kon),gamma(),eps(),p(best)	1107.90	0	0.9454	1	14	1079.896032
psi(PG),gamma(),eps(),p(best)	1113.74	5.84	0.051	0.0539	13	1087.740209
psi(PG ; gis),gamma(),eps(),p(best)	1119.03	11.13	0.0036	0.0038	16	1087.027758
psi(gis ; kon),gamma(),eps(),p(best)	1257.84	149.94	0	0	16	1225.835969
psi,gamma(),eps(),p(night:0,day:1 ; PG ; s1)	1280.02	172.12	0	0	12	1256.016805
psi(gis),gamma(),eps(),p(best)	1280.11	172.21	0	0	15	1250.106447
psi(veg ; wflae),gamma(),eps(),p(best)	1281.84	173.94	0	0	14	1253.835775
psi(gis ; veg ; wflae),gamma(),eps(),p(best)	1282.10	174.2	0	0	17	1248.101936

Colonization and extinction probability

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
psi(best),gamma(.),eps(pg),p(best)	1094.32	0	0.2588	1	19	1056.320138
psi(best),gamma(kon),eps(pg),p(best)	1094.63	0.31	0.2216	0.8564	20	1054.626061
psi(best),gamma(.),eps(pg,kon),p(best)	1094.95	0.63	0.1889	0.7298	24	1046.947031
psi(best),gamma(kon),eps(pg,kon),p(best)	1095.35	1.03	0.1546	0.5975	25	1045.349393
psi(best),gamma(veg,wflae),eps(pg),p(best)	1097.33	3.01	0.0575	0.222	21	1055.333132
psi(best),gamma(veg,wflae),eps(pg,kon),p(best)	1097.79	3.47	0.0457	0.1764	26	1045.794831
psi(best),gamma(gis),eps(pg),p(best)	1099.91	5.59	0.0158	0.0611	22	1055.913174
psi(best),gamma(gis,kon),eps(pg),p(best)	1100.43	6.11	0.0122	0.0471	23	1054.434138
psi(best),gamma(gis),eps(pg,kon),p(best)	1100.55	6.23	0.0115	0.0444	27	1046.554254
psi(best),gamma(gis,kon),eps(pg,kon),p(best)	1101.17	6.85	0.0084	0.0325	28	1045.174146
psi(best),gamma(.),eps(pg,gis),p(best)	1101.21	6.89	0.0083	0.0319	34	1033.210767
psi(best),gamma(kon),eps(pg,gis),p(best)	1101.73	7.41	0.0064	0.0246	35	1031.730901
psi(best),gamma(gis,veg,wflae),eps(pg),p(best)	1103.06	8.74	0.0033	0.0127	24	1055.060889
psi(best),gamma(gis,veg,wflae),eps(pg,kon),p(best)	1103.55	9.23	0.0026	0.0099	29	1045.553284
psi(best),gamma(veg,wflae),eps(pg,gis),p(best)	1104.31	9.99	0.0018	0.0068	36	1032.3082
psi(best),gamma(.),eps(fi),p(best)	1105.44	11.12	0.001	0.0038	18	1069.444133
psi(best),gamma(gis),eps(pg,gis),p(best)	1106.82	12.5	0.0005	0.0019	37	1032.821304
psi(best),gamma(kon),eps(.),p(best)	1107.24	12.92	0.0004	0.0016	15	1077.243921
psi(best),gamma(gis,kon),eps(pg,gis),p(best)	1107.52	13.2	0.0004	0.0014	38	1031.516745
psi(pg ; kon),gamma(.),eps(.),p(night0,day1 ; pg ; s1)	1107.90	13.58	0.0003	0.0011	14	1079.896032
psi(best),gamma(gis,veg,wflae),eps(pg,gis),p(best)	1110.05	15.73	0.0001	0.0004	39	1032.045005
psi(best),gamma(veg,wflae),eps(.),p(best)	1110.93	16.61	0.0001	0.0002	16	1078.929034
psi(best),gamma(fi),eps(.),p(best)	1111.67	17.35	0	0.0002	18	1075.671817
psi(best),gamma(gis,kon),eps(.),p(best)	1113.05	18.73	0	0.0001	18	1077.045885
psi(best),gamma(fi),eps(fi),p(best)	1113.07	18.75	0	0.0001	22	1069.069988
psi(best),gamma(gis),eps(.),p(best)	1113.52	19.2	0	0.0001	17	1079.52398
psi(best),gamma(.),eps(veg,wflae),p(best)	1115.51	21.19	0	0	24	1067.512695
psi(best),gamma(gis,veg,wflae),eps(.),p(best)	1116.65	22.33	0	0	19	1078.653637
psi(best),gamma(veg,wflae),eps(veg,wflae),p(best)	1118.56	24.24	0	0	26	1066.563986
psi(best),gamma(gis),eps(veg,wflae),p(best)	1121.12	26.8	0	0	27	1067.119322
psi(best),gamma(gis,kon),eps(veg,wflae),p(best)	1121.98	27.66	0	0	28	1065.981145
psi(best),gamma(kon),eps(gis,kon),p(best)	1122.85	28.53	0	0	35	1052.847023
psi(best),gamma(gis,veg,wflae),eps(veg,wflae),p(best)	1124.26	29.94	0	0	29	1066.262855
psi(best),gamma(.),eps(gis,kon),p(best)	1124.57	30.25	0	0	34	1056.566115

Colonization and extinction probability - continued

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
psi(best),gamma(kon),eps(gis),p(best)	1124.98	30.66	0	0	30	1064.981231
psi(best),gamma(.),eps(gis),p(best)	1126.42	32.1	0	0	29	1068.418287
psi(best),gamma(veg,wflae),eps(gis,kon),p(best)	1127.47	33.15	0	0	36	1055.474135
psi(best),gamma(gis,kon),eps(gis,kon),p(best)	1128.70	34.38	0	0	38	1052.70409
psi(best),gamma(veg,wflae),eps(gis),p(best)	1129.34	35.02	0	0	31	1067.339712
psi(best),gamma(gis),eps(gis,kon),p(best)	1130.02	35.7	0	0	37	1056.019089
psi(best),gamma(gis,kon),eps(gis),p(best)	1130.72	36.4	0	0	33	1064.723204
psi(best),gamma(gis),eps(gis),p(best)	1131.81	37.49	0	0	32	1067.807822
psi(best),gamma(gis,veg,wflae),eps(gis,kon),p(best)	1133.04	38.72	0	0	39	1055.036352
psi(best),gamma(.),eps(gis,veg,wflae),p(best)	1133.23	38.91	0	0	39	1055.229846
psi(best),gamma(kon),eps(gis,veg,wflae),p(best)	1134.02	39.7	0	0	40	1054.022235
psi(best),gamma(gis,veg,wflae),eps(gis),p(best)	1134.86	40.54	0	0	34	1066.864237
psi(best),gamma(veg,wflae),eps(gis,veg,wflae),p(best)	1136.23	41.91	0	0	41	1054.23273
psi(best),gamma(gis),eps(gis,veg,wflae),p(best)	1138.70	44.38	0	0	42	1054.695453
psi(best),gamma(gis,kon),eps(gis,veg,wflae),p(best)	1139.63	45.31	0	0	43	1053.634442
psi(best),gamma(gis,veg,wflae),eps(gis,veg,wflae),p(best)	1141.82	47.5	0	0	44	1053.823507
psi(best),gamma(kon),eps(veg,wflae),p(best)	1418.21	323.89	0	0	25	1368.209863

Colonization and extinction probability with management

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
psi(best),gamma(best),eps(best),p(best)	1094.32	0	0.7545	1	19	1056.320138
psi(best),gamma(best),eps(best,k3),p(best)	1099.91	5.59	0.0461	0.0611	24	1051.911328
psi(best),gamma(best,k2le),eps(best),p(best)	1100.00	5.68	0.0441	0.0584	24	1052.001625
psi(best),gamma(best,k3),eps(best),p(best)	1100.88	6.56	0.0284	0.0376	24	1052.880199
psi(best),gamma(best),eps(best,k3le),p(best)	1101.52	7.2	0.0206	0.0273	24	1053.524025
psi(best),gamma(best,k3le),eps(best),p(best)	1101.99	7.67	0.0163	0.0216	24	1053.992162
psi(best),gamma(best,k2),eps(best),p(best)	1102.20	7.88	0.0147	0.0194	24	1054.199094
psi(best),gamma(best),eps(best,k2),p(best)	1102.52	8.2	0.0125	0.0166	24	1054.524818
psi(best),gamma(best),eps(best,k2le),p(best)	1102.57	8.25	0.0122	0.0162	24	1054.566015
psi(best),gamma(best,k1le),eps(best),p(best)	1102.74	8.42	0.0112	0.0148	24	1054.74046
psi(best),gamma(best),eps(best,k1le),p(best)	1102.92	8.6	0.0102	0.0136	24	1054.920501
psi(best),gamma(best),eps(best,k2,k3),p(best)	1103.10	8.78	0.0094	0.0124	29	1045.103133
psi(best),gamma(best,k1),eps(best),p(best)	1103.40	9.08	0.0081	0.0107	24	1055.398329
psi(best),gamma(best),eps(best,k1),p(best)	1103.99	9.67	0.006	0.0079	24	1055.98787
psi(best),gamma(best,k1le,k2le),eps(best),p(best)	1105.95	11.63	0.0023	0.003	29	1047.950532
psi(best),gamma(best,k2le,k3le),eps(best),p(best)	1107.48	13.16	0.001	0.0014	29	1049.482693
psi(best),gamma(best,k2,k3),eps(best),p(best)	1108.95	14.63	0.0005	0.0007	29	1050.946746
psi(best),gamma(best),eps(best,k2le,k3le),p(best)	1109.67	15.35	0.0004	0.0005	29	1051.670018
psi(best),gamma(best),eps(best,k1,k3),p(best)	1109.80	15.48	0.0003	0.0004	29	1051.799707
psi(best),gamma(best,k1,k3),eps(best),p(best)	1110.10	15.78	0.0003	0.0004	29	1052.104949
psi(best),gamma(best,k1,k2),eps(best),p(best)	1110.20	15.88	0.0003	0.0004	29	1052.197016
psi(best),gamma(best,k1le,k3le),eps(best),p(best)	1110.83	16.51	0.0002	0.0003	29	1052.827517
psi(best),gamma(best),eps(best,k1le,k3le),p(best)	1110.83	16.51	0.0002	0.0003	29	1052.832317
psi(best),gamma(best),eps(best,k1le,k2le),p(best)	1111.01	16.69	0.0002	0.0002	29	1053.012417
psi(best),gamma(best),eps(best,k1,k2),p(best)	1112.19	17.87	0.0001	0.0001	29	1054.185171
psi(best),gamma(best),eps(best,k1,k2,k3),p(best)	1113.00	18.68	0.0001	0.0001	34	1044.995713
psi(best),gamma(best,k1le,k2le,k3le),eps(best),p(best)	1113.23	18.91	0.0001	0.0001	34	1045.230418
psi(best),gamma(best,k1,k2,k3),eps(best),p(best)	1116.97	22.65	0	0	34	1048.97062
psi(best),gamma(best),eps(best,k1le,k2le,k3le),p(best)	1119.04	24.72	0	0	34	1051.039043

Bombina variegata

Detection probability

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
(psi,gamma(),eps(),p(night:s2; day:s2; PG))	2093.21	0	0.3684	1	12	2069.210556
(psi,gamma(),eps(),p(night:s2; day:s2; PG ; s1))	2094.48	1.27	0.1952	0.5299	13	2068.484441
(psi,gamma(),eps(),p(night: s1, s2; day:s2; PG))	2095.04	1.83	0.1476	0.4005	13	2069.037937
(psi,gamma(),eps(),p(night:s2; day:s2; PG ; veg))	2095.19	1.98	0.1369	0.3716	13	2069.193773
(psi,gamma(),eps(),p(night: s1, s2, veg; day:k; PG))	2096.22	3.01	0.0818	0.222	14	2068.216905
(psi,gamma(),eps(),p(night: s1, s2; day:s2; PG; veg))	2097.01	3.8	0.0551	0.1496	14	2069.012472
(psi,gamma(),eps(),p(night: s1, s2; day:k; PG))	2099.62	6.41	0.0149	0.0406	13	2073.619152
(psi,gamma(),eps(),p(s2 ; PG))	2119.62	26.41	0	0	11	2097.618944
(psi,gamma(),eps(),p(s1, s2; PG))	2121.18	27.97	0	0	12	2097.182968
(psi,gamma(),eps(),p(survey))	2159.72	66.51	0	0	21	2117.717315
(psi,gamma(),eps(),p(night, day))	2159.90	66.69	0	0	5	2149.895732
(psi,gamma(),eps(),p(night: s1, s2; day:k))	2162.84	69.63	0	0	7	2148.838007
(psi,gamma(),eps(),p(PG))	2178.33	85.12	0	0	10	2158.325952
(psi,gamma(),eps(),p(s2))	2181.89	88.68	0	0	5	2171.888714
(psi,gamma(),eps(),p(s1, s2))	2183.78	90.57	0	0	6	2171.784584
(psi,gamma(),eps(),p(.))	2241.82	148.61	0	0	4	2233.820864
(psi,gamma(),eps(),p(veg))	2243.00	149.79	0	0	5	2233.004787
(psi,gamma(),eps(),p(s1))	2243.46	150.25	0	0	5	2233.455276
(psi,gamma(),eps(),p(eingesch))	2243.58	150.37	0	0	5	2233.57667
(psi,gamma(),eps(),p(Wflae))	2243.80	150.59	0	0	5	2233.802121

Occupancy

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
psi(PG ; gis),gamma(),eps(),p(best)	1956.44	0	0.475	1	16	1924.437863
psi(PG),gamma(),eps(),p(best)	1957.29	0.85	0.3105	0.6538	13	1931.294389
psi(PG ; kon),gamma(),eps(),p(best)	1958.03	1.59	0.2145	0.4516	14	1930.025471
psi(gis ; veg ; wflae),gamma(),eps(),p(best)	2093.72	137.28	0	0	17	2059.718115
psi(gis),gamma(),eps(),p(best)	2095.37	138.93	0	0	15	2065.371567
psi(gis ; kon),gamma(),eps(),p(best)	2095.54	139.1	0	0	16	2063.535602
psi(veg ; wflae),gamma(),eps(),p(best)	2102.02	145.58	0	0	14	2074.023556
psi,gamma(),eps(),p(night:s2,day:s2 ; PG)	2103.32	146.88	0	0	12	2079.324558

Colonization and extinction probability

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
psi(best),gamma(.),eps(pg,kon),p(best) time constant	1927.78	0	0.3905	1	19	1889.778343
psi(best),gamma(.),eps(pg,kon),p(best)	1928.87	1.09	0.2265	0.5798	23	1882.871441
psi(best),gamma(.),eps(pg),p(best)	1929.41	1.63	0.1729	0.4426	22	1885.410565
psi(best),gamma(kon),eps(pg,kon),p(best)	1929.91	2.13	0.1346	0.3447	24	1881.909287
psi(best),gamma(kon),eps(pg),p(best)	1932.47	4.69	0.0374	0.0958	23	1886.471864
psi(best),gamma(.),eps(pg,gis),p(best)	1933.82	6.04	0.0191	0.0488	25	1883.819205
psi(best),gamma(veg,wflae),eps(pg,kon),p(best)	1934.21	6.43	0.0157	0.0402	29	1876.20939
psi(best),gamma(kon),eps(pg,gis),p(best)	1938.41	10.63	0.0019	0.0049	26	1886.410249
psi(best),gamma(veg,wflae),eps(pg),p(best)	1939.31	11.53	0.0012	0.0031	28	1883.314756
psi(best),gamma(veg,wflae),eps(pg,gis),p(best)	1944.48	16.7	0.0001	0.0002	31	1882.482901
psi(best),gamma(fi),eps(.),p(best)	1947.04	19.26	0	0.0001	17	1913.035965
psi(best),gamma(.),eps(.),p(best)	1947.20	19.42	0	0.0001	13	1921.19609
psi(best),gamma(veg,wflae),eps(.),p(best)	1950.34	22.56	0	0	23	1904.343903
psi(best),gamma(kon),eps(.),p(best)	1950.56	22.78	0	0	18	1914.564703
psi(best),gamma(.),eps(veg,wflae),p(best)	1950.68	22.9	0	0	19	1912.680185
psi(best),gamma(.),eps(gis,kon),p(best)	1951.60	23.82	0	0	21	1909.603325
psi(best),gamma(.),eps(gis),p(best)	1951.99	24.21	0	0	20	1911.988166
psi(best),gamma(gis,kon),eps(pg,kon),p(best)	1952.41	24.63	0	0	39	1874.412817
psi(best),gamma(.),eps(fi),p(best)	1952.55	24.77	0	0	21	1910.552527
psi(best),gamma(fi),eps(fi),p(best)	1952.55	24.77	0	0	21	1910.552527
psi(best),gamma(gis),eps(pg,kon),p(best)	1952.87	25.09	0	0	34	1884.872291
psi(best),gamma(gis),eps(pg),p(best)	1953.62	25.84	0	0	33	1887.622829
psi(best),gamma(gis,kon),eps(pg),p(best)	1954.16	26.38	0	0	38	1878.164079
psi(best),gamma(kon),eps(veg,wflae),p(best)	1954.25	26.47	0	0	20	1914.251814
psi(best),gamma(kon),eps(gis,kon),p(best)	1954.71	26.93	0	0	22	1910.712491
psi(best),gamma(.),eps(gis,veg,wflae),p(best)	1955.69	27.91	0	0	22	1911.685279
psi(best),gamma(kon),eps(gis),p(best)	1955.70	27.92	0	0	21	1913.703979
psi(best),gamma(gis),eps(pg,gis),p(best)	1957.70	29.92	0	0	36	1885.704127
psi(best),gamma(veg,wflae),eps(gis,veg,wflae),p(best)	1959.39	31.61	0	0	28	1903.392273
psi(best),gamma(gis,kon),eps(pg,gis),p(best)	1959.39	31.61	0	0	41	1877.393512
psi(best),gamma(kon),eps(gis,veg,wflae),p(best)	1959.40	31.62	0	0	23	1913.404876
psi(best),gamma(veg,wflae),eps(veg,wflae),p(best)	1959.57	31.79	0	0	25	1909.572454
psi(best),gamma(veg,wflae),eps(gis,kon),p(best)	1960.57	32.79	0	0	27	1906.569801
psi(best),gamma(veg,wflae),eps(gis),p(best)	1961.28	33.5	0	0	26	1909.283417
psi(best),gamma(gis,veg,wflae),eps(pg,kon),p(best)	1962.28	34.5	0	0	44	1874.27848

Colonization and extinction probability - continued

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
psi(best),gamma(gis,veg,wflae),eps(pg),p(best)	1963.62	35.84	0	0	43	1877.621916
psi(best),gamma(gis,veg,wflae),eps(pg,gis),p(best)	1968.82	41.04	0	0	46	1876.816778
psi(best),gamma(gis,kon),eps(.),p(best)	1968.98	41.2	0	0	33	1902.983884
psi(best),gamma(gis),eps(.),p(best)	1970.05	42.27	0	0	28	1914.04741
psi(best),gamma(gis),eps(veg,wflae),p(best)	1973.60	45.82	0	0	30	1913.602895
psi(best),gamma(gis,kon),eps(gis,kon),p(best)	1974.28	46.5	0	0	37	1900.278765
psi(best),gamma(gis,kon),eps(gis),p(best)	1974.47	46.69	0	0	36	1902.472857
psi(best),gamma(gis),eps(gis,kon),p(best)	1974.69	46.91	0	0	32	1910.688335
psi(best),gamma(gis),eps(gis),p(best)	1975.17	47.39	0	0	31	1913.174032
psi(best),gamma(gis,kon),eps(gis,veg,wflae),p(best)	1978.00	50.22	0	0	38	1901.999297
psi(best),gamma(gis,kon),eps(veg,wflae),p(best)	1978.83	51.05	0	0	38	1902.832647
psi(best),gamma(gis,veg,wflae),eps(.),p(best)	1978.86	51.08	0	0	38	1902.862146
psi(best),gamma(gis),eps(gis,veg,wflae),p(best)	1979.38	51.6	0	0	33	1913.37716
psi(best),gamma(gis,veg,wflae),eps(veg,wflae),p(best)	1982.46	54.68	0	0	40	1902.45851
psi(best),gamma(gis,veg,wflae),eps(gis),p(best)	1984.38	56.6	0	0	41	1902.375014
psi(best),gamma(gis,veg,wflae),eps(gis,kon),p(best)	1984.45	56.67	0	0	42	1900.4463
psi(best),gamma(gis,veg,wflae),eps(gis,veg,wflae),p(best)	1987.80	60.02	0	0	43	1901.799029

Colonization and extinction probability with management

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
psi(best),gamma(best),eps(best,k3),p(best)	1922.89	0	0.3954	1	24	1874.892036
psi(best),gamma(best),eps(best,k2,k3),p(best)	1924.89	2	0.1455	0.3679	29	1866.890501
psi(best),gamma(best),eps(best,k3le),p(best)	1925.26	2.37	0.1209	0.3057	24	1877.264716
psi(best),gamma(best,k3),eps(best),p(best)	1926.17	3.28	0.0767	0.194	24	1878.170184
psi(best),gamma(best,k3le),eps(best),p(best)	1926.57	3.68	0.0628	0.1588	24	1878.57473
psi(best),gamma(best),eps(best,k2le,k3le),p(best)	1927.13	4.24	0.0475	0.12	29	1869.12603
psi(best),gamma(best),eps(best,k2le),p(best)	1927.22	4.33	0.0454	0.1147	24	1879.215169
psi(best),gamma(best),eps(best,k1,k3),p(best)	1927.44	4.55	0.0406	0.1028	29	1869.435457
psi(best),gamma(best),eps(best),p(best)	1927.78	4.89	0.0343	0.0867	19	1889.778343
psi(best),gamma(best),eps(best,k1le,k3le),p(best)	1931.50	8.61	0.0053	0.0135	29	1873.495943
psi(best),gamma(best),eps(best,k2),p(best)	1931.64	8.75	0.005	0.0126	24	1883.64389
psi(best),gamma(best,k1),eps(best),p(best)	1932.87	9.98	0.0027	0.0068	24	1884.874986
psi(best),gamma(best),eps(best,k1le),p(best)	1932.87	9.98	0.0027	0.0068	24	1884.8691
psi(best),gamma(best,k1le),eps(best),p(best)	1932.91	10.02	0.0026	0.0067	24	1884.913294
psi(best),gamma(best,k1le,k3le),eps(best),p(best)	1933.32	10.43	0.0021	0.0054	29	1875.322546
psi(best),gamma(best,k2le,k3le),eps(best),p(best)	1933.92	11.03	0.0016	0.004	29	1875.915958
psi(best),gamma(best),eps(best,k1),p(best)	1933.95	11.06	0.0016	0.004	24	1885.946421
psi(best),gamma(best,k2le),eps(best),p(best)	1934.02	11.13	0.0015	0.0038	24	1886.018649
psi(best),gamma(best),eps(best,k1,k2,k3),p(best)	1934.03	11.14	0.0015	0.0038	34	1866.032416
psi(best),gamma(best,k1,k3),eps(best),p(best)	1934.22	11.33	0.0014	0.0035	29	1876.224538
psi(best),gamma(best,k2),eps(best),p(best)	1934.78	11.89	0.001	0.0026	24	1886.776201
psi(best),gamma(best,k2,k3),eps(best),p(best)	1934.87	11.98	0.001	0.0025	29	1876.866405
psi(best),gamma(best),eps(best,k1le,k2le,k3le),p(best)	1937.06	14.17	0.0003	0.0008	34	1869.055489
psi(best),gamma(best),eps(best,k1le,k2le),p(best)	1937.32	14.43	0.0003	0.0007	29	1879.319362
psi(best),gamma(best,k1le,k2le,k3le),eps(best),p(best)	1939.50	16.61	0.0001	0.0002	34	1871.50383
psi(best),gamma(best,k1le,k2le),eps(best),p(best)	1940.00	17.11	0.0001	0.0002	29	1882.00235
psi(best),gamma(best),eps(best,k1,k2),p(best)	1941.74	18.85	0	0.0001	29	1883.741722
psi(best),gamma(best,k1,k2),eps(best),p(best)	1941.94	19.05	0	0.0001	29	1883.943089
psi(best),gamma(best,k1,k2,k3),eps(best),p(best)	1943.04	20.15	0	0	34	1875.039722

Bufo calamita

Detection probability

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
(psi,gamma(),eps(),p(night: s1,s2; day:s2; PG))	956.97	0	0.4378	1	13	930.971407
(psi,gamma(),eps(),p(night: s1, s2; day: veg, s2; PG))	957.50	0.53	0.3359	0.7672	14	929.498801
(psi,gamma(),eps(),p(night: s1,s2; day: s1, s2; PG))	958.88	1.91	0.1685	0.3848	14	930.880326
(psi,gamma(),eps(),p(night: s1,s2; day:k; PG))	961.02	4.05	0.0578	0.132	13	935.024591
(psi,gamma(),eps(),p(night: s1,s2; day:k))	993.71	36.74	0	0	7	979.712662
(psi,gamma(),eps(),p(night: s2, day))	994.77	37.8	0	0	6	982.76556
(psi,gamma(),eps(),p(night, day))	995.58	38.61	0	0	5	985.576964
(psi,gamma(),eps(),p(survey))	1021.00	64.03	0	0	21	978.99969
(psi,gamma(),eps(),p(PG))	1030.64	73.67	0	0	10	1010.642774
(psi,gamma(),eps(),p(.))	1062.31	105.34	0	0	4	1054.312542
(psi,gamma(),eps(),p(wflaeche))	1062.58	105.61	0	0	5	1052.581935
(psi,gamma(),eps(),p(s2))	1063.07	106.1	0	0	5	1053.070799
(psi,gamma(),eps(),p(s2; wflae))	1063.38	106.41	0	0	6	1051.380507
(psi,gamma(),eps(),p(s1))	1063.77	106.8	0	0	5	1053.765804
(psi,gamma(),eps(),p(eingesch))	1064.10	107.13	0	0	5	1054.10332
(psi,gamma(),eps(),p(veg))	1064.19	107.22	0	0	5	1054.190994

Occupancy

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
(psi(PG),gamma(),eps(),p(best))	895.12	0	0.6074	1	14	867.118372
(psi(PG ; kon),gamma(),eps(),p(best))	896.49	1.37	0.3062	0.5041	15	866.490308
(psi(PG ; gis),gamma(),eps(),p(best))	899.02	3.9	0.0864	0.1423	17	865.019506
(psi(gis , kon),gamma(),eps(),p(best))	953.77	58.65	0	0	17	919.774242
(psi(gis),gamma(),eps(),p(best))	956.50	61.38	0	0	16	924.496957
(psi(.),gamma(),eps(),p(BEST night:s1,s2 ; day:s2 ; PG))	956.97	61.85	0	0	13	930.971407
(psi(gis ; veg ; wflae),gamma(),eps(),p(best))	958.07	62.95	0	0	18	922.065282
(psi(veg ; wflae),gamma(),eps(),p(best))	958.75	63.63	0	0	15	928.753568
(psi(.),gamma(.),eps(.),p(.))	1062.31	167.19	0	0	4	1054.312542

Colonization and extinction probability

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
psi(best),gamma(gis,kon),eps(pg),p(best)	888.57	0	0.2182	1	23	842.57339
psi(best),gamma(gis,kon),eps(pg,kon),p(best)	889.81	1.24	0.1174	0.5379	24	841.806276
psi(best),gamma(.),eps(pg),p(best)	890.19	1.62	0.0971	0.4449	19	852.193379
psi(best),gamma(kon),eps(pg),p(best)	890.25	1.68	0.0942	0.4317	20	850.250776
psi(best),gamma(gis),eps(pg),p(best)	890.80	2.23	0.0715	0.3279	22	846.799912
psi(best),gamma(.),eps(pg,kon),p(best)	890.81	2.24	0.0712	0.3263	20	850.810763
psi(best),gamma(kon),eps(pg,kon),p(best)	891.30	2.73	0.0557	0.2554	21	849.303641
psi(best),gamma(gis),eps(pg,kon),p(best)	891.49	2.92	0.0507	0.2322	23	845.492855
psi(best),gamma(veg,wflae),eps(pg),p(best)	892.30	3.73	0.0338	0.1549	21	850.298493
psi(best),gamma(veg,wflae),eps(pg,kon),p(best)	892.58	4.01	0.0294	0.1347	22	848.575411
psi(best),gamma(gis,veg,wflae),eps(pg),p(best)	893.19	4.62	0.0217	0.0993	24	845.186337
psi(best),gamma(gis,kon),eps(pg,gis),p(best)	893.25	4.68	0.021	0.0963	26	841.24999
psi(best),gamma(gis,veg,wflae),eps(pg,kon),p(best)	893.57	5	0.0179	0.0821	25	843.571668
psi(best),gamma(gis,kon),eps(.),p(best)	894.00	5.43	0.0144	0.0662	18	857.996052
psi(best),gamma(.),eps(pg,gis),p(best)	894.58	6.01	0.0108	0.0495	22	850.582968
psi(best),gamma(kon),eps(pg,gis),p(best)	894.77	6.2	0.0098	0.045	23	848.771336
psi(best),gamma(.),eps(.),p(best)	895.12	6.55	0.0083	0.0378	14	867.118372
psi(best),gamma(kon),eps(.),p(best)	895.40	6.83	0.0072	0.0329	15	865.398002
psi(best),gamma(gis),eps(pg,gis),p(best)	895.49	6.92	0.0069	0.0314	25	845.490111
psi(best),gamma(gis),eps(.),p(best)	896.00	7.43	0.0053	0.0244	17	861.996489
psi(best),gamma(gis,kon),eps(veg,wflae),p(best)	896.12	7.55	0.005	0.0229	20	856.12103
psi(best),gamma(veg,wflae),eps(pg,gis),p(best)	896.41	7.84	0.0043	0.0198	24	848.408824
psi(best),gamma(.),eps(veg,wflae),p(best)	897.02	8.45	0.0032	0.0146	16	865.022763
psi(best),gamma(kon),eps(veg,wflae),p(best)	897.24	8.67	0.0029	0.0131	17	863.235682
psi(best),gamma(veg,wflae),eps(.),p(best)	897.28	8.71	0.0028	0.0128	16	865.27626
psi(best),gamma(gis,veg,wflae),eps(pg,gis),p(best)	897.57	9	0.0024	0.0111	27	843.571196
psi(best),gamma(gis),eps(veg,wflae),p(best)	898.14	9.57	0.0018	0.0084	19	860.137477
psi(best),gamma(gis,kon),eps(gis,kon),p(best)	898.38	9.81	0.0016	0.0074	22	854.378948
psi(best),gamma(gis,veg,wflae),eps(.),p(best)	898.53	9.96	0.0015	0.0069	19	860.525219
psi(best),gamma(gis,kon),eps(gis),p(best)	898.61	10.04	0.0014	0.0066	21	856.606184
psi(best),gamma(.),eps(gis,kon),p(best)	899.01	10.44	0.0012	0.0054	18	863.007981
psi(best),gamma(veg,wflae),eps(veg,wflae),p(best)	899.02	10.45	0.0012	0.0054	18	863.02282
psi(best),gamma(.),eps(gis),p(best)	899.41	10.84	0.001	0.0044	17	865.405781
psi(best),gamma(kon),eps(gis,kon),p(best)	899.56	10.99	0.0009	0.0041	19	861.562842
psi(best),gamma(kon),eps(gis),p(best)	899.68	11.11	0.0008	0.0039	18	863.678916

Colonization and extinction probability - continued

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
psi(best),gamma(gis),eps(gis,kon),p(best)	899.99	11.42	0.0007	0.0033	21	857.990591
psi(best),gamma(fi),eps(.),p(best)	900.24	11.67	0.0006	0.0029	18	864.240262
psi(best),gamma(gis,kon),eps(gis,veg,wflae),p(best)	900.29	11.72	0.0006	0.0029	23	854.292955
psi(best),gamma(gis,veg,wflae),eps(veg,wflae),p(best)	900.52	11.95	0.0006	0.0025	21	858.524525
psi(best),gamma(gis),eps(gis),p(best)	900.62	12.05	0.0005	0.0024	20	860.618071
psi(best),gamma(veg,wflae),eps(gis,kon),p(best)	901.05	12.48	0.0004	0.0019	20	861.051636
psi(best),gamma(.),eps(gis,veg,wflae),p(best)	901.14	12.57	0.0004	0.0019	19	863.141268
psi(best),gamma(kon),eps(gis,veg,wflae),p(best)	901.24	12.67	0.0004	0.0018	20	861.242656
psi(best),gamma(veg,wflae),eps(gis),p(best)	901.47	12.9	0.0003	0.0016	19	863.469538
psi(best),gamma(gis,veg,wflae),eps(gis,kon),p(best)	902.38	13.81	0.0002	0.001	23	856.381735
psi(best),gamma(gis),eps(gis,veg,wflae),p(best)	902.44	13.87	0.0002	0.001	22	858.440161
psi(best),gamma(.),eps(fi),p(best)	902.52	13.95	0.0002	0.0009	18	866.520256
psi(best),gamma(veg,wflae),eps(gis,veg,wflae),p(best)	903.00	14.43	0.0002	0.0007	21	860.997602
psi(best),gamma(gis,veg,wflae),eps(gis),p(best)	903.02	14.45	0.0002	0.0007	22	859.019166
psi(best),gamma(gis,veg,wflae),eps(gis,veg,wflae),p(best)	904.66	16.09	0.0001	0.0003	24	856.660284
psi(best),gamma(fi),eps(fi),p(best)	906.60	18.03	0	0.0001	22	862.599189

Colonization and extinction probability with management

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
(psi(best),gamma(best),eps(best),p(best))	888.57	0	0.3602	1	23	842.57339
(psi(best),gamma(best,k3le),eps(best),p(best))	889.79	1.22	0.1957	0.5434	28	833.789624
(psi(best),gamma(best,k2),eps(best),p(best))	890.53	1.96	0.1352	0.3753	28	834.526386
(psi(best),gamma(best,k2le),eps(best),p(best))	890.67	2.1	0.126	0.3499	28	834.674015
(psi(best),gamma(best),eps(best,k3),p(best))	893.52	4.95	0.0303	0.0842	28	837.52212
(psi(best),gamma(best,k3),eps(best),p(best))	893.81	5.24	0.0262	0.0728	28	837.806118
(psi(best),gamma(best,k2le,k3le),eps(best),p(best))	894.36	5.79	0.0199	0.0553	33	828.362308
(psi(best),gamma(best),eps(best,k3le),p(best))	894.48	5.91	0.0188	0.0521	28	838.478557
(psi(best),gamma(best,k2,k3),eps(best),p(best))	894.81	6.24	0.0159	0.0442	33	828.805948
(psi(best),gamma(best),eps(best,k1le),p(best))	894.90	6.33	0.0152	0.0422	28	838.902074
(psi(best),gamma(best),eps(best,k2),p(best))	895.65	7.08	0.0104	0.029	28	839.648216
(psi(best),gamma(best,k1),eps(best),p(best))	895.92	7.35	0.0091	0.0253	28	839.920223
(psi(best),gamma(best),eps(best,k2le),p(best))	896.76	8.19	0.006	0.0167	28	840.758117
(psi(best),gamma(best,k1le,k3le),eps(best),p(best))	896.81	8.24	0.0059	0.0162	33	830.806569
(psi(best),gamma(best,k1,k2),eps(best),p(best))	896.90	8.33	0.0056	0.0155	33	830.902117
(psi(best),gamma(best),eps(best,k1),p(best))	896.93	8.36	0.0055	0.0153	28	840.932199
(psi(best),gamma(best,k1le),eps(best),p(best))	896.97	8.4	0.0054	0.015	28	840.96867
(psi(best),gamma(best,k1le,k2le),eps(best),p(best))	898.10	9.53	0.0031	0.0085	33	832.098308
(psi(best),gamma(best,k1le,k2le,k3le),eps(best),p(best))	899.68	11.11	0.0014	0.0039	38	823.682187
(psi(best),gamma(best),eps(best,k2,k3),p(best))	900.38	11.81	0.001	0.0027	33	834.38175
(psi(best),gamma(best),eps(best,k1le,k2le),p(best))	900.66	12.09	0.0009	0.0024	33	834.65706
(psi(best),gamma(best),eps(best,k1le,k3le),p(best))	901.27	12.7	0.0006	0.0017	33	835.271005
(psi(best),gamma(best,k1,k3),eps(best),p(best))	901.75	13.18	0.0005	0.0014	33	835.751536
(psi(best),gamma(best),eps(best,k1,k3),p(best))	901.91	13.34	0.0005	0.0013	33	835.907679
(psi(best),gamma(best),eps(best,k2le,k3le),p(best))	902.64	14.07	0.0003	0.0009	33	836.637301
(psi(best),gamma(best,k1,k2,k3),eps(best),p(best))	902.85	14.28	0.0003	0.0008	38	826.847879
(psi(best),gamma(best),eps(best,k1,k2),p(best))	903.92	15.35	0.0002	0.0005	33	837.920579
(psi(best),gamma(best),eps(best,k1le,k2le,k3le),p(best))	906.94	18.37	0	0.0001	38	830.936297
(psi(best),gamma(best),eps(best,k1,k2,k3),p(best))	908.55	19.98	0	0	38	832.549594

Rana lessonae

Detection probability

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
(psi,gamma(),eps(),p(night:s2;day:s2; PG))	2454.92	0	0.5958	1	12	2430.918902
(psi,gamma(),eps(),p(night:s2,veg ;day:s2; PG))	2456.64	1.72	0.2521	0.4232	13	2430.64163
(psi,gamma(),eps(),p(night, day; PG))	2457.65	2.73	0.1521	0.2554	11	2435.650534
(psi,gamma(),eps(),p(night:s1,s2; day:k; PG))	2479.20	24.28	0	0	12	2455.20061
(psi,gamma(),eps(),p(night:s2, day:k; PG))	2481.15	26.23	0	0	11	2459.153994
(psi,gamma(),eps(),p(PG))	2481.34	26.42	0	0	10	2461.34348
(psi,gamma(),eps(),p(PG; eingsch))	2481.65	26.73	0	0	11	2459.652499
(psi,gamma(),eps(),p(night, day))	2537.26	82.34	0	0	5	2527.256552
(psi,gamma(),eps(),p(survey))	2538.73	83.81	0	0	21	2496.726724
(psi,gamma(),eps(),p(s2))	2552.27	97.35	0	0	5	2542.268449
(psi,gamma(),eps(),p(s1))	2554.80	99.88	0	0	5	2544.803218
(psi,gamma(),eps(),p(eingesch))	2560.22	105.3	0	0	5	2550.220821
(psi,gamma(),eps(),p(.))	2560.85	105.93	0	0	4	2552.845646
(psi,gamma(),eps(),p(veg))	2562.01	107.09	0	0	5	2552.006481
(psi,gamma(),eps(),p(wflae))	2562.26	107.34	0	0	5	2552.262097

Occupancy

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
(psi(PG ; kon),gamma(),eps(),p(best))	2260.85	0	0.811	1	14	2232.85241
(psi(PG ; gis),gamma(),eps(),p(best))	2263.95	3.1	0.1721	0.2122	16	2231.948417
(psi(PG),gamma(),eps(),p(best))	2268.59	7.74	0.0169	0.0209	13	2242.585404
(psi(gis ; kon),gamma(),eps(),p(best))	2399.28	138.43	0	0	16	2367.278468
(psi(gis ; veg ; wflae),gamma(),eps(),p(best))	2416.01	155.16	0	0	17	2382.006875
(psi(gis),gamma(),eps(),p(best))	2434.34	173.49	0	0	15	2404.342808
(psi(veg ; flae),gamma(),eps(),p(best))	2435.96	175.11	0	0	14	2407.963212
(psi(.),gamma(),eps(),p(BEST night:s2 ; day:s2; PG))	2454.92	194.07	0	0	12	2430.918902
(psi(.),gamma(),eps(),p(.))	2560.85	300	0	0	4	2552.845646

Colonization and extinction probability

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
psi(best),gamma(kon),eps(veg,wflae),p(best)	2228.05	0	0.3601	1	17	2194.048663
psi(best),gamma(gis,kon),eps(veg,wflae),p(best)	2229.12	1.07	0.2109	0.5857	20	2189.121307
psi(best),gamma(kon),eps(pg),p(best)	2230.41	2.36	0.1106	0.3073	20	2190.40937
psi(best),gamma(gis,kon),eps(pg),p(best)	2231.50	3.45	0.0642	0.1782	23	2185.497253
psi(best),gamma(kon),eps(.),p(best)	2231.75	3.7	0.0566	0.1572	15	2201.753142
psi(best),gamma(kon),eps(pg,kon),p(best)	2231.89	3.84	0.0528	0.1466	21	2189.891062
psi(best),gamma(kon),eps(gis,veg,wflae),p(best)	2232.53	4.48	0.0383	0.1065	20	2192.532268
psi(best),gamma(gis,kon),eps(pg,kon),p(best)	2232.95	4.9	0.0311	0.0863	24	2184.947985
psi(best),gamma(gis,kon),eps(.),p(best)	2233.01	4.96	0.0302	0.0837	18	2197.014414
psi(best),gamma(gis,kon),eps(gis,veg,wflae),p(best)	2233.32	5.27	0.0258	0.0717	23	2187.320762
psi(best),gamma(kon),eps(pg,gis),p(best)	2236.20	8.15	0.0061	0.017	23	2190.198748
psi(best),gamma(gis,kon),eps(pg,gis),p(best)	2237.17	9.12	0.0038	0.0105	26	2185.168235
psi(best),gamma(kon),eps(gis),p(best)	2237.52	9.47	0.0032	0.0088	18	2201.51633
psi(best),gamma(fi),eps(fi),p(best)	2238.45	10.4	0.002	0.0055	22	2194.449006
psi(best),gamma(gis,kon),eps(gis),p(best)	2238.67	10.62	0.0018	0.0049	21	2196.665965
psi(best),gamma(kon),eps(gis,kon),p(best)	2238.89	10.84	0.0016	0.0044	19	2200.891351
psi(best),gamma(gis,kon),eps(gis,kon),p(best)	2240.07	12.02	0.0009	0.0025	22	2196.067007
psi(best),gamma(fi),eps(.),p(best)	2242.89	14.84	0.0002	0.0006	18	2206.894826
psi(best),gamma(gis),eps(veg,wflae),p(best)	2251.01	22.96	0	0	19	2213.007958
psi(best),gamma(gis,veg,wflae),eps(veg,wflae),p(best)	2253.34	25.29	0	0	21	2211.341361
psi(best),gamma(gis),eps(gis,veg,wflae),p(best)	2254.64	26.59	0	0	22	2210.643112
psi(best),gamma(gis,veg,wflae),eps(pg),p(best)	2254.91	26.86	0	0	24	2206.905746
psi(best),gamma(gis),eps(pg),p(best)	2255.15	27.1	0	0	22	2211.147712
psi(best),gamma(gis),eps(pg,kon),p(best)	2255.56	27.51	0	0	23	2209.562264
psi(best),gamma(gis,veg,wflae),eps(pg,kon),p(best)	2255.60	27.55	0	0	25	2205.602087
psi(best),gamma(.),eps(veg,wflae),p(best)	2255.70	27.65	0	0	16	2223.703709
psi(best),gamma(gis),eps(.),p(best)	2255.96	27.91	0	0	17	2221.956998
psi(best),gamma(gis,veg,wflae),eps(.),p(best)	2256.24	28.19	0	0	19	2218.239894
psi(best),gamma(gis,veg,wflae),eps(gis,veg,wflae),p(best)	2257.29	29.24	0	0	24	2209.289993
psi(best),gamma(veg,wflae),eps(veg,wflae),p(best)	2257.80	29.75	0	0	18	2221.801271
psi(best),gamma(.),eps(gis,veg,wflae),p(best)	2258.87	30.82	0	0	19	2220.872473
psi(best),gamma(.),eps(fi),p(best)	2259.28	31.23	0	0	18	2223.279876
psi(best),gamma(.),eps(pg),p(best)	2260.47	32.42	0	0	19	2222.465685
psi(best),gamma(veg,wflae),eps(pg),p(best)	2260.50	32.45	0	0	21	2218.497806
psi(best),gamma(gis,veg,wflae),eps(pg,gis),p(best)	2260.59	32.54	0	0	27	2206.591819

Colonization and extinction probability - continued

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
psi(best),gamma(.),eps(pg,kon),p(best)	2260.67	32.62	0	0	20	2220.665357
psi(best),gamma(gis),eps(pg,gis),p(best)	2260.70	32.65	0	0	25	2210.703624
psi(pg,kon),gamma(.),eps(.),p(n:s2,d:s2, pg)	2260.85	32.8	0	0	14	2232.85241
psi(best),gamma(veg,wflae),eps(pg,kon),p(best)	2260.98	32.93	0	0	22	2216.981601
psi(best),gamma(veg,wflae),eps(.),p(best)	2261.22	33.17	0	0	16	2229.223889
psi(best),gamma(veg,wflae),eps(gis,veg,wflae),p(best)	2261.23	33.18	0	0	21	2219.2343
psi(best),gamma(gis),eps(gis),p(best)	2261.59	33.54	0	0	20	2221.593189
psi(best),gamma(gis),eps(gis,kon),p(best)	2261.83	33.78	0	0	21	2219.829897
psi(best),gamma(gis,veg,wflae),eps(gis),p(best)	2261.89	33.84	0	0	22	2217.888308
psi(best),gamma(gis,veg,wflae),eps(gis,kon),p(best)	2262.52	34.47	0	0	23	2216.518878
psi(best),gamma(.),eps(pg,gis),p(best)	2266.00	37.95	0	0	22	2221.999417
psi(best),gamma(veg,wflae),eps(pg,gis),p(best)	2266.06	38.01	0	0	24	2218.0605
psi(best),gamma(.),eps(gis),p(best)	2266.40	38.35	0	0	17	2232.401703
psi(best),gamma(.),eps(gis,kon),p(best)	2266.70	38.65	0	0	18	2230.70057
psi(best),gamma(veg,wflae),eps(gis),p(best)	2266.71	38.66	0	0	19	2228.710889
psi(best),gamma(veg,wflae),eps(gis,kon),p(best)	2267.42	39.37	0	0	20	2227.419627

Colonization and extinction probability with management

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
psi(best),gamma(best),eps(best,k3le),p(best)	2227.75	0	0.3473	1	22	2183.75154
psi(best),gamma(best),eps(best),p(best)	2228.05	0.3	0.2989	0.8607	17	2194.048663
psi(best),gamma(best),eps(best,k2le),p(best)	2229.88	2.13	0.1197	0.3447	22	2185.879924
psi(best),gamma(best),eps(best,k2le,k3le),p(best)	2231.69	3.94	0.0484	0.1395	27	2177.689221
psi(best),gamma(best),eps(best,k1le,k3le),p(best)	2232.12	4.37	0.0391	0.1125	27	2178.119759
psi(best),gamma(best),eps(best,k3),p(best)	2232.16	4.41	0.0383	0.1103	22	2188.161454
psi(best),gamma(best),eps(best,k1le),p(best)	2233.00	5.25	0.0252	0.0724	22	2188.99678
psi(best),gamma(best),eps(best,k2),p(best)	2233.19	5.44	0.0229	0.0659	22	2189.187209
psi(best),gamma(best),eps(best,k1),p(best)	2233.67	5.92	0.018	0.0518	22	2189.666587
psi(best),gamma(best,k1le),eps(best),p(best)	2235.01	7.26	0.0092	0.0265	22	2191.012598
psi(best),gamma(best,k3),eps(best),p(best)	2235.69	7.94	0.0066	0.0189	22	2191.691873
psi(best),gamma(best,k3le),eps(best),p(best)	2236.01	8.26	0.0056	0.0161	22	2192.005205
psi(best),gamma(best,k1),eps(best),p(best)	2236.50	8.75	0.0044	0.0126	22	2192.498239
psi(best),gamma(best,k2),eps(best),p(best)	2236.74	8.99	0.0039	0.0112	22	2192.744533
psi(best),gamma(best,k2le),eps(best),p(best)	2237.07	9.32	0.0033	0.0095	22	2193.072452
psi(best),gamma(best),eps(best,k2,k3),p(best)	2237.72	9.97	0.0024	0.0068	27	2183.715479
psi(best),gamma(best),eps(best,k1,k3),p(best)	2237.73	9.98	0.0024	0.0068	27	2183.732417
psi(best),gamma(best),eps(best,k1le,k2le,k3le),p(best)	2238.28	10.53	0.0018	0.0052	32	2174.282558
psi(best),gamma(best),eps(best,k1le,k2le),p(best)	2238.55	10.8	0.0016	0.0045	27	2184.548409
psi(best),gamma(best,k1le,k3le),eps(best),p(best)	2241.32	13.57	0.0004	0.0011	27	2187.322731
psi(best),gamma(best),eps(best,k1,k2),p(best)	2241.39	13.64	0.0004	0.0011	27	2187.393969
psi(best),gamma(best,k1le,k2le),eps(best),p(best)	2243.04	15.29	0.0002	0.0005	27	2189.038396
psi(best),gamma(best,k1,k3),eps(best),p(best)	2244.25	16.5	0.0001	0.0003	27	2190.252438
psi(best),gamma(best,k2,k3),eps(best),p(best)	2244.94	17.19	0.0001	0.0002	27	2190.935625
psi(best),gamma(best,k1,k2),eps(best),p(best)	2245.10	17.35	0.0001	0.0002	27	2191.096503
psi(best),gamma(best,k2le,k3le),eps(best),p(best)	2245.20	17.45	0.0001	0.0002	27	2191.2012
psi(best),gamma(best),eps(best,k1,k2,k3),p(best)	2246.29	18.54	0	0.0001	32	2182.291761
psi(best),gamma(best,k1le,k2le,k3le),eps(best),p(best)	2250.30	22.55	0	0	32	2186.297183
psi(best),gamma(best,k1,k2,k3),eps(best),p(best)	2253.44	25.69	0	0	32	2189.441226

Triturus alpestris

Detection probability

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
(psi,gamma(),eps(),p(night: s2, day: s2; PG; wflae))	2922.39	0	0.5369	1	14	2894.386163
(psi,gamma(),eps(),p(night: s2, day: s2; PG; wflae; veg))	2924.12	1.73	0.2261	0.4211	15	2894.117423
(psi,gamma(),eps(),p(night, day; PG; wflae))	2925.45	3.06	0.1163	0.2165	12	2901.448838
(psi,gamma(),eps(),p(night: s2, day: s2; PG))	2926.46	4.07	0.0702	0.1307	13	2900.461913
(psi,gamma(),eps(),p(night: s2, veg; day: s2; PG))	2928.17	5.78	0.0298	0.0556	14	2900.170228
(psi,gamma(),eps(),p(night, day; PG))	2929.97	7.58	0.0121	0.0226	11	2907.97242
(psi,gamma(),eps(),p(night: s2, day; PG))	2931.69	9.3	0.0051	0.0096	12	2907.688485
(psi,gamma(),eps(),p(night: s1,s2; day:k; PG))	2932.51	10.12	0.0034	0.0063	13	2906.514208
(psi,gamma(),eps(),p(night, day))	2939.42	17.03	0.0001	0.0002	5	2929.416174
(psi,gamma(),eps(),p(survey))	2943.24	20.85	0	0	21	2901.236218
(psi,gamma(),eps(),p(PG))	3404.04	481.65	0	0	10	3384.035146
(psi,gamma(),eps(),p(s2,wflae))	3407.63	485.24	0	0	6	3395.629961
(psi,gamma(),eps(),p(wflae))	3409.27	486.88	0	0	5	3399.272801
(psi,gamma(),eps(),p(s1))	3411.32	488.93	0	0	5	3401.322996
(psi,gamma(),eps(),p(s2))	3412.11	489.72	0	0	5	3402.108027
(psi,gamma(),eps(),p(eingsch))	3412.32	489.93	0	0	5	3402.324843
(psi,gamma(),eps(),p(.))	3413.75	491.36	0	0	4	3405.751348
(psi,gamma(),eps(),p(veg))	3415.05	492.66	0	0	5	3405.054226

Occupancy

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
(psi(PG ; kon),gamma(),eps(),p(best))	2923.83	0	0.8648	1	15	2893.833104
(psi(PG),gamma(),eps(),p(best))	2928.52	4.69	0.0829	0.0958	14	2900.520319
(psi(PG ; gis),gamma(),eps(),p(best))	2929.44	5.61	0.0523	0.0605	17	2895.440077
(psi(gis ; veg ; wflae),gamma(),eps(),p(best))	2974.26	50.43	0	0	18	2938.264099
(psi(gis ; kon),gamma(),eps(),p(best))	2974.95	51.12	0	0	17	2940.952048
(psi(wflae ; veg),gamma(),eps(),p(best))	2975.74	51.91	0	0	15	2945.742397
(psi(gis),gamma(),eps(),p(best))	2980.85	57.02	0	0	16	2948.853158
(psi(.),gamma(),eps(),p(BEST night:s2 ; day:s2 ; PG ; Wflae))	2984.97	61.14	0	0	13	2958.966865
(psi(.),gamma(),eps(),p(.))	3413.75	489.92	0	0	4	3405.751348

Colonization and extinction probability

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
psi(best),gamma(.),eps(pg,kon),p(best)	2902.41	0	0.4057	1	21	2860.411038
psi(best),gamma(kon),eps(pg,kon),p(best)	2903.53	1.12	0.2317	0.5712	22	2859.530055
psi(best),gamma(veg,wflae),eps(pg,kon),p(best)	2904.55	2.14	0.1391	0.343	23	2858.546018
psi(best),gamma(gis),eps(pg,kon),p(best)	2905.27	2.86	0.0971	0.2393	24	2857.268057
psi(best),gamma(gis,kon),eps(pg,kon),p(best)	2905.69	3.28	0.0787	0.194	25	2855.68546
psi(best),gamma(gis,veg,wflae),eps(pg,kon),p(best)	2906.90	4.49	0.043	0.1059	26	2854.901673
psi(best),gamma(.),eps(gis,kon),p(best)	2914.18	11.77	0.0011	0.0028	19	2876.182736
psi(best),gamma(kon),eps(gis,kon),p(best)	2914.87	12.46	0.0008	0.002	20	2874.874992
psi(best),gamma(veg,wflae),eps(gis,kon),p(best)	2915.26	12.85	0.0007	0.0016	21	2873.255836
psi(best),gamma(.),eps(pg),p(best)	2916.28	13.87	0.0004	0.001	20	2876.275122
psi(best),gamma(kon),eps(pg),p(best)	2916.29	13.88	0.0004	0.001	21	2874.292994
psi(best),gamma(gis),eps(gis,kon),p(best)	2917.66	15.25	0.0002	0.0005	22	2873.663745
psi(best),gamma(.),eps(pg,gis),p(best)	2917.73	15.32	0.0002	0.0005	23	2871.73454
psi(best),gamma(kon),eps(pg,gis),p(best)	2917.93	15.52	0.0002	0.0004	24	2869.925022
psi(best),gamma(gis,kon),eps(gis,kon),p(best)	2918.38	15.97	0.0001	0.0003	23	2872.381614
psi(best),gamma(veg,wflae),eps(pg),p(best)	2918.66	16.25	0.0001	0.0003	22	2874.655915
psi(best),gamma(gis,kon),eps(pg),p(best)	2918.73	16.32	0.0001	0.0003	24	2870.729717
psi(best),gamma(gis,veg,wflae),eps(gis,kon),p(best)	2918.77	16.36	0.0001	0.0003	24	2870.770396
psi(best),gamma(gis,kon),eps(pg,gis),p(best)	2919.46	17.05	0.0001	0.0002	27	2865.457149
psi(best),gamma(gis),eps(pg,gis),p(best)	2919.76	17.35	0.0001	0.0002	26	2867.761403
psi(best),gamma(veg,wflae),eps(pg,gis),p(best)	2920.20	17.79	0.0001	0.0001	25	2870.195404
psi(best),gamma(gis,veg,wflae),eps(pg),p(best)	2921.23	18.82	0	0.0001	25	2871.229476
psi(best),gamma(gis,veg,wflae),eps(pg,gis),p(best)	2921.94	19.53	0	0.0001	28	2865.937611
psi(best),gamma(kon),eps(.),p(best)	2923.34	20.93	0	0	16	2891.342005
psi(best),gamma(.),eps(.),p(best)	2923.83	21.42	0	0	15	2893.833104
psi(best),gamma(gis),eps(pg),p(best)	2924.61	22.2	0	0	23	2878.608788
psi(best),gamma(veg,wflae),eps(.),p(best)	2925.16	22.75	0	0	17	2891.155406
psi(best),gamma(kon),eps(veg,wflae),p(best)	2926.20	23.79	0	0	18	2890.202811
psi(best),gamma(gis,kon),eps(.),p(best)	2926.54	24.13	0	0	19	2888.54495
psi(best),gamma(.),eps(veg,wflae),p(best)	2926.59	24.18	0	0	17	2892.593725
psi(best),gamma(kon),eps(gis),p(best)	2926.74	24.33	0	0	19	2888.739515
psi(best),gamma(gis),eps(.),p(best)	2926.97	24.56	0	0	18	2890.972556
psi(best),gamma(.),eps(gis),p(best)	2927.10	24.69	0	0	18	2891.097822
psi(best),gamma(fi),eps(.),p(best)	2927.83	25.42	0	0	19	2889.83042
psi(best),gamma(.),eps(fi),p(best)	2928.06	25.65	0	0	19	2890.062109

Colonization and extinction probability - continued

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
psi(best),gamma(gis,veg,wflae),eps(.),p(best)	2928.31	25.9	0	0	20	2888.313371
psi(best),gamma(veg,wflae),eps(veg,wflae),p(best)	2928.41	26	0	0	19	2890.414595
psi(best),gamma(veg,wflae),eps(gis),p(best)	2928.72	26.31	0	0	20	2888.721762
psi(best),gamma(gis,kon),eps(gis),p(best)	2929.09	26.68	0	0	22	2885.091676
psi(best),gamma(gis,kon),eps(veg,wflae),p(best)	2929.24	26.83	0	0	21	2887.236652
psi(best),gamma(kon),eps(gis,veg,wflae),p(best)	2929.54	27.13	0	0	21	2887.544163
psi(best),gamma(gis),eps(veg,wflae),p(best)	2929.62	27.21	0	0	20	2889.621934
psi(best),gamma(gis),eps(gis),p(best)	2929.64	27.23	0	0	21	2887.63955
psi(best),gamma(.),eps(gis,veg,wflae),p(best)	2929.76	27.35	0	0	20	2889.757365
psi(best),gamma(gis,veg,wflae),eps(gis),p(best)	2931.08	28.67	0	0	23	2885.082231
psi(best),gamma(gis,veg,wflae),eps(veg,wflae),p(best)	2931.44	29.03	0	0	22	2887.444933
psi(best),gamma(veg,wflae),eps(gis,veg,wflae),p(best)	2931.81	29.4	0	0	22	2887.813172
psi(best),gamma(gis,kon),eps(gis,veg,wflae),p(best)	2931.85	29.44	0	0	24	2883.84945
psi(best),gamma(gis),eps(gis,vrg,wflae),p(best)	2932.29	29.88	0	0	23	2886.287138
psi(best),gamma(fi),eps(fi),p(best)	2932.86	30.45	0	0	23	2886.863575
psi(best),gamma(gis,veg,wflae),eps(gis,veg,wflae),p(best)	2934.11	31.7	0	0	25	2884.107071

Colonization and extinction probability with management

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
psi(best),gamma(best),eps(best,k3),p(best)	2896.40	0	0.5391	1	26	2844.395826
psi(best),gamma(best),eps(best,k2,k3),p(best)	2899.09	2.69	0.1405	0.2605	31	2837.094758
psi(best),gamma(best),eps(best,k2le),p(best)	2899.96	3.56	0.0909	0.1686	26	2847.960232
psi(best),gamma(best),eps(best,k1,k3),p(best)	2900.50	4.1	0.0694	0.1287	31	2838.500036
psi(best),gamma(best),eps(best,k1le,k2le),p(best)	2900.91	4.51	0.0565	0.1049	31	2838.910909
psi(best),gamma(best),eps(best),p(best)	2902.41	6.01	0.0267	0.0495	21	2860.411038
psi(best),gamma(best),eps(best,k1,k2,k3),p(best)	2903.09	6.69	0.019	0.0353	36	2831.092398
psi(best),gamma(best),eps(best,k1le,k2le,k3le),p(best)	2903.78	7.38	0.0135	0.025	36	2831.778464
psi(best),gamma(best),eps(best,k2),p(best)	2904.42	8.02	0.0098	0.0181	26	2852.421387
psi(best),gamma(best,k2),eps(best),p(best)	2905.11	8.71	0.0069	0.0128	26	2853.111415
psi(best),gamma(best,k1le),eps(best),p(best)	2905.54	9.14	0.0056	0.0104	26	2853.54145
psi(best),gamma(best),eps(best,k2le,k3le),p(best)	2906.07	9.67	0.0043	0.0079	31	2844.068149
psi(best),gamma(best),eps(best,k3le),p(best)	2906.47	10.07	0.0035	0.0065	26	2854.467359
psi(best),gamma(best,k1),eps(best),p(best)	2906.70	10.3	0.0031	0.0058	26	2854.699448
psi(best),gamma(best,k3),eps(best),p(best)	2907.05	10.65	0.0026	0.0049	26	2855.0525
psi(best),gamma(best,k3le),eps(best),p(best)	2907.33	10.93	0.0023	0.0042	26	2855.33207
psi(best),gamma(best,k2le),eps(best),p(best)	2907.87	11.47	0.0017	0.0032	26	2855.866659
psi(best),gamma(best),eps(best,k1le),p(best)	2908.63	12.23	0.0012	0.0022	26	2856.626777
psi(best),gamma(best),eps(best,k1le,k3le),p(best)	2909.56	13.16	0.0007	0.0014	31	2847.556786
psi(best),gamma(best,k1le,k3le),eps(best),p(best)	2909.85	13.45	0.0006	0.0012	31	2847.846647
psi(best),gamma(best),eps(best,k1),p(best)	2910.07	13.67	0.0006	0.0011	26	2858.067386
psi(best),gamma(best,k2,k3),eps(best),p(best)	2911.04	14.64	0.0004	0.0007	31	2849.037065
psi(best),gamma(best,k1,k3),eps(best),p(best)	2911.38	14.98	0.0003	0.0006	31	2849.384164
psi(best),gamma(best),eps(best,k1,k2),p(best)	2911.43	15.03	0.0003	0.0005	31	2849.425865
psi(best),gamma(best,k1,k2),eps(best),p(best)	2912.50	16.1	0.0002	0.0003	31	2850.495387
psi(best),gamma(best,k1le,k2le),eps(best),p(best)	2912.94	16.54	0.0001	0.0003	31	2850.944279
psi(best),gamma(best,k2le,k3le),eps(best),p(best)	2913.01	16.61	0.0001	0.0002	31	2851.012692
psi(best),gamma(best,k1le,k2le,k3le),eps(best),p(best)	2916.74	20.34	0	0	36	2844.735661
psi(best),gamma(best,k1,k2,k3),eps(best),p(best)	2918.14	21.74	0	0	36	2846.142514

Triturus cristatus

Detection probability

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
(psi,gamma(),eps(),p(nigth,day; eingsch; s2))	571.52	0	0.6236	1	7	557.515605
(psi,gamma(),eps(),p(nigth,day; eingsch))	575.15	3.63	0.1015	0.1628	6	563.146007
(psi,gamma(),eps(),p(nigth: s2; day:k; PG; eingsch))	575.90	4.38	0.0698	0.1119	13	549.898125
(psi,gamma(),eps(),p(eingsch; s2))	576.05	4.53	0.0647	0.1038	6	564.054008
(psi,gamma(),eps(),p(nigth,day))	577.76	6.24	0.0275	0.0442	5	567.763558
(psi,gamma(),eps(),p(eingsch; s2 ; veg))	577.91	6.39	0.0255	0.041	7	563.906438
(psi,gamma(),eps(),p(nigth: s2; day:k; PG))	578.01	6.49	0.0243	0.039	12	554.005298
(psi,gamma(),eps(),p(s2))	578.70	7.18	0.0172	0.0276	5	568.700598
(psi,gamma(),eps(),p(nigth,day; PG; eingsch))	579.10	7.58	0.0141	0.0226	12	555.096984
(psi,gamma(),eps(),p(nigth: s1,s2; day:k; PG))	579.92	8.4	0.0094	0.015	13	553.916501
(psi,gamma(),eps(),p(nigth:0,day:s2; eingsch))	580.40	8.88	0.0074	0.0118	6	568.402228
(psi,gamma(),eps(),p(s2 ; PG ; eingsch))	580.59	9.07	0.0067	0.0107	12	556.593778
(psi,gamma(),eps(),p(nigth,day; PG))	581.56	10.04	0.0041	0.0066	11	559.558293
(psi,gamma(),eps(),p(nigth,day; PG))	581.56	10.04	0.0041	0.0066	11	559.558293
(psi,gamma(),eps(),p(survey))	591.83	20.31	0	0	21	549.825347
(psi,gamma(),eps(),p(nigth:s2; day:0; PG; eingsch))	606.57	35.05	0	0	12	582.56903
(psi,gamma(),eps(),p(eingsch))	637.51	65.99	0	0	5	627.507042
(psi,gamma(),eps(),p(.))	639.45	67.93	0	0	4	631.44532
(psi,gamma(),eps(),p(wflae))	640.55	69.03	0	0	5	630.552118
(psi,gamma(),eps(),p(s1))	641.42	69.9	0	0	5	631.420523
(psi,gamma(),eps(),p(veg))	641.44	69.92	0	0	5	631.441356
(psi,gamma(),eps(),p(PG))	644.42	72.9	0	0	10	624.419578

Occupancy

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
psi(PG ; gis),gamma(),eps(),p(best)	498.24	0	0.7948	1	11	476.236589
psi(PG ; kon),gamma(),eps(),p(best)	500.95	2.71	0.205	0.2579	9	482.952742
psi(PG),gamma(),eps(),p(best)	515.55	17.31	0.0001	0.0002	8	499.545064
psi(gis ; kon),gamma(),eps(),p(best)	548.02	49.78	0	0	11	526.017431
psi(gis),gamma(),eps(),p(best)	564.61	66.37	0	0	10	544.60791
psi(gis ; veg ; wflae),gamma(),eps(),p(best)	565.56	67.32	0	0	12	541.556498
psi(veg ; wflae),gamma(),eps(),p(best)	571.25	73.01	0	0	9	553.253063
psi,gamma(),eps(),p(night:0,day:1; eingesch ; s2)	571.52	73.28	0	0	7	557.515605

Colonization and extinction probability

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
psi(best),gamma(.),eps(gis,veg,wflae),p(best)	498.12	0	0.1494	1	16	466.119082
psi(best),gamma(.),eps(.),p(best)	498.24	0.12	0.1407	0.9418	11	476.236589
psi(best),gamma(.),eps(veg,wflae),p(best)	498.48	0.36	0.1247	0.8353	13	472.48491
psi(best),gamma(kon),eps(.),p(best)	498.74	0.62	0.1095	0.7334	12	474.738667
psi(best),gamma(kon),eps(veg,wflae),p(best)	499.11	0.99	0.091	0.6096	14	471.111156
psi(best),gamma(.),eps(gis,kon),p(best)	500.42	2.3	0.0473	0.3166	15	470.424353
psi(best),gamma(gis,kon),eps(.),p(best)	501.29	3.17	0.0306	0.2049	15	471.294297
psi(best),gamma(kon),eps(gis,kon),p(best)	501.43	3.31	0.0285	0.1911	16	469.425478
psi(best),gamma(veg,wflae),eps(gis,veg,wflae),p(best)	501.57	3.45	0.0266	0.1782	18	465.570083
psi(best),gamma(kon),eps(gis,veg,wflae),p(best)	501.61	3.49	0.0261	0.1746	17	467.610105
psi(best),gamma(gis,kon),eps(veg,wflae),p(best)	501.76	3.64	0.0242	0.162	17	467.756619
psi(best),gamma(veg,wflae),eps(.),p(best)	501.82	3.7	0.0235	0.1572	13	475.822983
psi(best),gamma(gis),eps(.),p(best)	501.97	3.85	0.0218	0.1459	14	473.968955
psi(best),gamma(veg,wflae),eps(veg,wflae),p(best)	502.08	3.96	0.0206	0.1381	15	472.08307
psi(best),gamma(gis),eps(veg,wflae),p(best)	502.29	4.17	0.0186	0.1243	16	470.292581
psi(best),gamma(.),eps(gis),p(best)	502.65	4.53	0.0155	0.1038	14	474.646988
psi(best),gamma(kon),eps(gis),p(best)	502.97	4.85	0.0132	0.0885	15	472.973822
psi(best),gamma(.),eps(fi),p(best)	503.49	5.37	0.0102	0.0682	15	473.494502
psi(best),gamma(veg,wflae),eps(gis,kon),p(best)	503.94	5.82	0.0081	0.0545	17	469.943551
psi(best),gamma(gis),eps(gis,kon),p(best)	504.00	5.88	0.0079	0.0529	18	467.995996
psi(best),gamma(gis,kon),eps(gis,kon),p(best)	504.05	5.93	0.0077	0.0516	19	466.050308
psi(best),gamma(gis,kon),eps(gis,veg,wflae),p(best)	504.08	5.96	0.0076	0.0508	20	464.080612
psi(best),gamma(gis),eps(gis,veg,wflae),p(best)	504.18	6.06	0.0072	0.0483	19	466.175526
psi(best),gamma(.),eps(pg,kon),p(best)	504.27	6.15	0.0069	0.0462	17	470.267281
psi(best),gamma(gis,kon),eps(gis),p(best)	505.14	7.02	0.0045	0.0299	18	469.143702
psi(best),gamma(kon),eps(pg,kon),p(best)	505.27	7.15	0.0042	0.028	18	469.270951
psi(best),gamma(gis,veg,wflae),eps(.),p(best)	505.78	7.66	0.0032	0.0217	16	473.780518
psi(best),gamma(gis),eps(gis),p(best)	505.86	7.74	0.0031	0.0209	17	471.855546
psi(best),gamma(veg,wflae),eps(gis),p(best)	506.03	7.91	0.0029	0.0192	16	474.034171
psi(best),gamma(gis,veg,wflae),eps(veg,wflae),p(best)	506.13	8.01	0.0027	0.0182	18	470.127695
psi(best),gamma(.),eps(pg),p(best)	506.29	8.17	0.0025	0.0168	16	474.293994
psi(best),gamma(kon),eps(pg),p(best)	506.83	8.71	0.0019	0.0128	17	472.829224
psi(best),gamma(gis,veg,wflae),eps(gis,kon),p(best)	507.77	9.65	0.0012	0.008	20	467.771812
psi(best),gamma(gis,veg,wflae),eps(gis,veg,wflae),p(best)	507.98	9.86	0.0011	0.0072	21	465.980808
psi(best),gamma(gis,kon),eps(pg,kon),p(best)	508.10	9.98	0.001	0.0068	21	466.096866

Colonization and extinction probability - continued

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
psi(best),gamma(gis),eps(pg,kon),p(best)	508.10	9.98	0.001	0.0068	20	468.100894
psi(best),gamma(.),eps(pg,gis),p(best)	509.08	10.96	0.0006	0.0042	19	471.079266
psi(best),gamma(gis,kon),eps(pg),p(best)	509.39	11.27	0.0005	0.0036	20	469.393498
psi(best),gamma(veg,wflae),eps(pg),p(best)	509.86	11.74	0.0004	0.0028	18	473.864054
psi(best),gamma(gis),eps(pg),p(best)	510.02	11.9	0.0004	0.0026	19	472.022336
psi(best),gamma(kon),eps(pg,gis),p(best)	510.09	11.97	0.0004	0.0025	20	470.092769
psi(best),gamma(veg,wflae),eps(pg,kon),p(best)	510.50	12.38	0.0003	0.002	19	472.500333
psi(best),gamma(gis,veg,wflae),eps(pg,kon),p(best)	511.88	13.76	0.0002	0.001	22	467.883273
psi(best),gamma(veg,wflae),eps(pg,gis),p(best)	512.55	14.43	0.0001	0.0007	21	470.553788
psi(best),gamma(gis,kon),eps(pg,gis),p(best)	512.64	14.52	0.0001	0.0007	23	466.635751
psi(best),gamma(gis),eps(pg,gis),p(best)	512.71	14.59	0.0001	0.0007	22	468.713128
psi(best),gamma(gis,veg,wflae),eps(pg),p(best)	513.82	15.7	0.0001	0.0004	21	471.824382
psi(best),gamma(gis,veg,wflae),eps(pg,gis),p(best)	516.50	18.38	0	0.0001	24	468.49714
psi(best),gamma(gis,veg,wflae),eps(gis),p(best)	522.10	23.98	0	0	19	484.098416
psi(best),gamma(fi),eps(fi),p(best)	606.75	108.63	0	0	19	568.750182
psi(best),gamma(fi),eps(.),p(best)	620.00	121.88	0	0	15	589.996055

Colonization and extinction probability with management

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
psi(best),gamma(best),eps(best),p(best)	498.24	0	0.8212	1	11	476.236589
psi(best),gamma(best),eps(best,k3le),p(best)	503.79	5.55	0.0512	0.0623	16	471.794273
psi(best),gamma(best),eps(best,k3),p(best)	503.90	5.66	0.0485	0.059	16	471.902188
psi(best),gamma(best, k3le),eps(best),p(best)	507.16	8.92	0.0095	0.0116	16	475.161451
psi(best),gamma(best, k2le),eps(best),p(best)	507.21	8.97	0.0093	0.0113	16	475.212301
psi(best),gamma(best, k1le),eps(best),p(best)	507.29	9.05	0.0089	0.0108	16	475.294322
psi(best),gamma(best, k3),eps(best),p(best)	507.37	9.13	0.0085	0.0104	16	475.366544
psi(best),gamma(best, k2),eps(best),p(best)	507.53	9.29	0.0079	0.0096	16	475.530085
psi(best),gamma(best, k1),eps(best),p(best)	507.76	9.52	0.007	0.0086	16	475.755525
psi(best),gamma(best),eps(best,k2le),p(best)	507.86	9.62	0.0067	0.0081	16	475.859677
psi(best),gamma(best),eps(best,k1le),p(best)	507.89	9.65	0.0066	0.008	16	475.890885
psi(best),gamma(best),eps(best,k1),p(best)	507.99	9.75	0.0063	0.0076	16	475.991512
psi(best),gamma(best),eps(best,k2),p(best)	508.01	9.77	0.0062	0.0076	16	476.01034
psi(best),gamma(best),eps(best,k2le,k3le),p(best)	513.51	15.27	0.0004	0.0005	21	471.511662
psi(best),gamma(best),eps(best,k1le,k3le),p(best)	513.57	15.33	0.0004	0.0005	21	471.568134
psi(best),gamma(best),eps(best,k1,k3),p(best)	513.65	15.41	0.0004	0.0005	21	471.648274
psi(best),gamma(best),eps(best,k2,k3),p(best)	513.68	15.44	0.0004	0.0004	21	471.681083
psi(best),gamma(best,k2le,k3le),eps(best),p(best)	515.46	17.22	0.0001	0.0002	21	473.463523
psi(best),gamma(best, k1le,k3le),eps(best),p(best)	515.98	17.74	0.0001	0.0001	21	473.97915
psi(best),gamma(best,k2,k3),eps(best),p(best)	516.22	17.98	0.0001	0.0001	21	474.222673
psi(best),gamma(best, k1le,k2le),eps(best),p(best)	516.23	17.99	0.0001	0.0001	21	474.231061
psi(best),gamma(best, k1,k3),eps(best),p(best)	516.67	18.43	0.0001	0.0001	21	474.668566
psi(best),gamma(best, k1,k2),eps(best),p(best)	517.22	18.98	0.0001	0.0001	21	475.223081
psi(best),gamma(best),eps(best,k1le,k2le),p(best)	517.60	19.36	0.0001	0.0001	21	475.602034
psi(best),gamma(best),eps(best,k1,k2),p(best)	517.82	19.58	0	0.0001	21	475.824854
psi(best),gamma(best),eps(best,k1le,k2le,k3le),p(best)	523.27	25.03	0	0	26	471.270551
psi(best),gamma(best),eps(best,k1,k2,k3),p(best)	523.49	25.25	0	0	26	471.488964
psi(best),gamma(best, k1le,k2le,k3le),eps(best),p(best)	524.38	26.14	0	0	26	472.378779
psi(best),gamma(best, k1,k2,k3),eps(best),p(best)	525.70	27.46	0	0	26	473.703912

Triturus helveticus

Detection probability

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
(psi,gamma(),eps(),p(night: s2; day:s2 ; PG; veg; wflae))	1953.75	0	0.6529	1	15	1923.753012
(psi,gamma(),eps(),p(night: s1,s2; day:s2 ; PG))	1955.99	2.24	0.213	0.3263	14	1927.993601
(psi,gamma(),eps(),p(night: s2; day:s2 ; PG; veg))	1958.96	5.21	0.0483	0.0739	14	1930.964697
(psi,gamma(),eps(),p(night: s2; day:s2 ; PG; wflae))	1959.06	5.31	0.0459	0.0703	14	1931.058776
(psi,gamma(),eps(),p(night, day; PG; veg))	1960.92	7.17	0.0181	0.0277	12	1936.922336
(psi,gamma(),eps(),p(night, day; PG; wflae))	1961.17	7.42	0.016	0.0245	12	1937.171402
(psi,gamma(),eps(),p(night: s2; day:s2 ; PG))	1964.18	10.43	0.0035	0.0054	13	1938.178468
(psi,gamma(),eps(),p(night: s2; day:k ; PG))	1966.25	12.5	0.0013	0.0019	12	1942.249867
(psi,gamma(),eps(),p(night, day; PG))	1966.65	12.9	0.001	0.0016	11	1944.647822
(psi,gamma(),eps(),p(night, day))	1978.09	24.34	0	0	5	1968.093756
(psi,gamma(),eps(),p(survey))	1988.07	34.32	0	0	21	1946.074279
(psi,gamma(),eps(),p(s1))	2241.06	287.31	0	0	5	2231.06013
(psi,gamma(),eps(),p(PG))	2244.52	290.77	0	0	10	2224.520752
(psi,gamma(),eps(),p(veg))	2250.00	296.25	0	0	5	2240.002657
(psi,gamma(),eps(),p(wflae))	2251.14	297.39	0	0	5	2241.143909
(psi,gamma(),eps(),p(s2; wflae))	2252.72	298.97	0	0	6	2240.715575
(psi,gamma(),eps(),p(.))	2256.83	303.08	0	0	4	2248.826153
(psi,gamma(),eps(),p(s2))	2258.34	304.59	0	0	5	2248.337897
(psi,gamma(),eps(),p(eingsch))	2258.70	304.95	0	0	5	2248.703164

Occupancy

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
(psi(PG),gamma(),eps(),p(best))	1917.80	0	0.5698	1	15	1887.803612
(psi(PG ; kon),gamma(),eps(),p(best))	1919.31	1.51	0.2678	0.47	16	1887.313487
(psi(PG ; gis),gamma(),eps(),p(best))	1920.31	2.51	0.1624	0.2851	18	1884.308914
(psi(veg ; wflae),gamma(),eps(),p(best))	1986.45	68.65	0	0	16	1954.449977
(psi(.),gamma(),eps(),p(BEST night:s2, day:s2 ; PG ; veg ; wflae))	1987.51	69.71	0	0	14	1959.511021
(psi(gis ; veg ; wflae),gamma(),eps(),p(best))	1990.06	72.26	0	0	19	1952.06166
(psi(gis),gamma(),eps(),p(best))	1990.29	72.49	0	0	17	1956.286549
(psi(gis ; kon),gamma(),eps(),p(best))	1992.10	74.3	0	0	18	1956.097011
(psi(.),gamma(),eps(),p(.))	2256.83	339.03	0	0	4	2248.826153

Colonization and extinction probability

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
psi(best),gamma(veg,wflae),eps(pg,kon),p(best)	1909.01	0	0.2792	1	27	1855.014906
psi(best),gamma(.),eps(pg,kon),p(best)	1909.82	0.81	0.1862	0.667	25	1859.820016
psi(best),gamma(kon),eps(pg,kon),p(best)	1910.64	1.63	0.1236	0.4426	26	1858.639486
psi(best),gamma(veg,wflae),eps(pg),p(best)	1912.16	3.15	0.0578	0.207	22	1868.162336
psi(best),gamma(.),eps(pg,gis),p(best)	1912.35	3.34	0.0526	0.1882	35	1842.348488
psi(best),gamma(veg,wflae),eps(pg,gis),p(best)	1912.42	3.41	0.0507	0.1818	37	1838.417148
psi(best),gamma(.),eps(pg),p(best)	1912.85	3.84	0.0409	0.1466	20	1872.854247
psi(best),gamma(gis,veg,wflae),eps(pg,kon),p(best)	1912.93	3.92	0.0393	0.1409	30	1852.925288
psi(best),gamma(kon),eps(pg),p(best)	1913.55	4.54	0.0288	0.1033	21	1871.547406
psi(best),gamma(kon),eps(pg,gis),p(best)	1913.67	4.66	0.0272	0.0973	36	1841.667929
psi(best),gamma(gis),eps(pg,kon),p(best)	1914.03	5.02	0.0227	0.0813	28	1858.026824
psi(best),gamma(gis,kon),eps(pg,kon),p(best)	1914.18	5.17	0.021	0.0754	29	1856.181331
psi(best),gamma(gis,veg,wflae),eps(pg,gis),p(best)	1915.61	6.6	0.0103	0.0369	40	1835.608666
psi(best),gamma(gis),eps(pg,gis),p(best)	1915.91	6.9	0.0089	0.0317	38	1839.913054
psi(best),gamma(gis,veg,wflae),eps(pg),p(best)	1916.37	7.36	0.007	0.0252	25	1866.366873
psi(best),gamma(gis,kon),eps(pg,gis),p(best)	1916.82	7.81	0.0056	0.0201	39	1838.820608
psi(best),gamma(gis),eps(pg),p(best)	1917.34	8.33	0.0043	0.0155	23	1871.336221
psi(best),gamma(veg,wflae),eps(.),p(best)	1917.53	8.52	0.0039	0.0141	17	1883.527367
psi(best),gamma(gis,kon),eps(pg),p(best)	1917.59	8.58	0.0038	0.0137	24	1869.587214
psi(best),gamma(.),eps(fi),p(best)	1917.65	8.64	0.0037	0.0133	19	1879.651244
psi(best),gamma(.),eps(.),p(best)	1917.80	8.79	0.0034	0.0123	15	1887.803612
psi(best),gamma(veg,wflae),eps(veg,wflae),p(best)	1918.55	9.54	0.0024	0.0085	27	1864.551946
psi(best),gamma(fi),eps(fi),p(best)	1918.73	9.72	0.0022	0.0078	23	1872.72924
psi(best),gamma(.),eps(veg,wflae),p(best)	1918.90	9.89	0.002	0.0071	25	1868.895812
psi(best),gamma(.),eps(gis,veg,wflae),p(best)	1918.97	9.96	0.0019	0.0069	40	1838.967444
psi(best),gamma(veg,wflae),eps(gis,veg,wflae),p(best)	1918.99	9.98	0.0019	0.0068	42	1834.993484
psi(best),gamma(kon),eps(.),p(best)	1919.01	10	0.0019	0.0067	16	1887.010733
psi(best),gamma(fi),eps(.),p(best)	1919.38	10.37	0.0016	0.0056	19	1881.382067
psi(best),gamma(kon),eps(veg,wflae),p(best)	1920.13	11.12	0.0011	0.0038	26	1868.126389
psi(best),gamma(kon),eps(gis,veg,wflae),p(best)	1920.47	11.46	0.0009	0.0032	41	1838.467057
psi(best),gamma(gis,veg,wflae),eps(.),p(best)	1921.43	12.42	0.0006	0.002	20	1881.432937
psi(best),gamma(gis),eps(.),p(best)	1922.04	13.03	0.0004	0.0015	18	1886.043113
psi(best),gamma(gis,veg,wflae),eps(gis,veg,wflae),p(best)	1922.07	13.06	0.0004	0.0015	45	1832.072171
psi(best),gamma(gis,veg,wflae),eps(veg,wflae),p(best)	1922.39	13.38	0.0003	0.0012	30	1862.389013
psi(best),gamma(gis),eps(gis,veg,wflae),p(best)	1922.62	13.61	0.0003	0.0011	43	1836.619183

Colonization and extinction probability - continued

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
psi(best),gamma(gis,kon),eps(.),p(best)	1922.75	13.74	0.0003	0.001	19	1884.748814
psi(best),gamma(gis),eps(veg,wflae),p(best)	1923.16	14.15	0.0002	0.0008	28	1867.163662
psi(best),gamma(gis,kon),eps(gis,veg,wflae),p(best)	1923.74	14.73	0.0002	0.0006	44	1835.742605
psi(best),gamma(gis,kon),eps(veg,wflae),p(best)	1923.85	14.84	0.0002	0.0006	29	1865.85336
psi(best),gamma(veg,wflae),eps(gis),p(best)	1925.25	16.24	0.0001	0.0003	32	1861.246776
psi(best),gamma(.),eps(gis),p(best)	1925.29	16.28	0.0001	0.0003	30	1865.291347
psi(best),gamma(kon),eps(gis),p(best)	1926.59	17.58	0	0.0002	31	1864.589394
psi(best),gamma(gis,veg,wflae),eps(gis),p(best)	1928.25	19.24	0	0.0001	35	1858.254195
psi(best),gamma(gis),eps(gis),p(best)	1928.74	19.73	0	0.0001	33	1862.741824
psi(best),gamma(veg,wflae),eps(gis,kon),p(best)	1929.29	20.28	0	0	37	1855.286284
psi(best),gamma(gis,kon),eps(gis),p(best)	1929.62	20.61	0	0	34	1861.615979
psi(best),gamma(.),eps(gis,kon),p(best)	1929.90	20.89	0	0	35	1859.903234
psi(best),gamma(kon),eps(gis,kon),p(best)	1931.19	22.18	0	0	36	1859.18721
psi(best),gamma(gis,veg,wflae),eps(gis,kon),p(best)	1932.36	23.35	0	0	40	1852.360142
psi(best),gamma(gis),eps(gis,kon),p(best)	1933.36	24.35	0	0	38	1857.355834
psi(best),gamma(gis,kon),eps(gis,kon),p(best)	1933.91	24.9	0	0	39	1855.911843

Colonization and extinction probability with management

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
psi(best),gamma(best),eps(best,k3),p(best)	1912.18	0	0.42	1	28	1856.183321
psi(best),gamma(best),eps(best),p(best)	1913.98	1.8	0.1707	0.4066	23	1867.980469
psi(best),gamma(best),eps(best,k3le),p(best)	1914.95	2.77	0.1051	0.2503	28	1858.948218
psi(best),gamma(best),eps(best,k1le,k3le),p(best)	1915.83	3.65	0.0677	0.1612	33	1849.829235
psi(best),gamma(best),eps(best,k1le),p(best)	1915.99	3.81	0.0625	0.1488	28	1859.988875
psi(best),gamma(best,k3),eps(best),p(best)	1916.96	4.78	0.0385	0.0916	28	1860.963342
psi(best),gamma(best,k2le),eps(best),p(best)	1917.34	5.16	0.0318	0.0758	28	1861.337115
psi(best),gamma(best,k3le),eps(best),p(best)	1917.47	5.29	0.0298	0.071	28	1861.465894
psi(best),gamma(best),eps(best,k2),p(best)	1918.12	5.94	0.0215	0.0513	28	1862.116709
psi(best),gamma(best,k2),eps(best),p(best)	1919.79	7.61	0.0093	0.0223	28	1863.786066
psi(best),gamma(best),eps(best,k2,k3),p(best)	1919.86	7.68	0.009	0.0215	33	1853.856055
psi(best),gamma(best),eps(best,k2le),p(best)	1919.92	7.74	0.0088	0.0209	28	1863.919762
psi(best),gamma(best),eps(best,k1le,k2le),p(best)	1921.23	9.05	0.0046	0.0108	33	1855.228114
psi(best),gamma(best),eps(best,k1,k3),p(best)	1921.54	9.36	0.0039	0.0093	33	1855.544901
psi(best),gamma(best,k1),eps(best),p(best)	1921.85	9.67	0.0033	0.0079	28	1865.845626
psi(best),gamma(best,k1le),eps(best),p(best)	1921.92	9.74	0.0032	0.0077	28	1865.921093
psi(best),gamma(best),eps(best,k2le,k3le),p(best)	1922.74	10.56	0.0021	0.0051	33	1856.742828
psi(best),gamma(best,k2,k3),eps(best),p(best)	1923.03	10.85	0.0019	0.0044	33	1857.032911
psi(best),gamma(best),eps(best,k1),p(best)	1923.26	11.08	0.0016	0.0039	28	1867.262524
psi(best),gamma(best),eps(best,k1le,k2le,k3le),p(best)	1923.50	11.32	0.0015	0.0035	38	1847.504101
psi(best),gamma(best,k2le,k3le),eps(best),p(best)	1924.25	12.07	0.001	0.0024	33	1858.246777
psi(best),gamma(best,k1le,k2le),eps(best),p(best)	1925.90	13.72	0.0004	0.001	33	1859.898823
psi(best),gamma(best,k1,k2),eps(best),p(best)	1926.00	13.82	0.0004	0.001	33	1859.995776
psi(best),gamma(best,k1,k3),eps(best),p(best)	1926.01	13.83	0.0004	0.001	33	1860.013843
psi(best),gamma(best,k1le,k3le),eps(best),p(best)	1926.32	14.14	0.0004	0.0009	33	1860.320247
psi(best),gamma(best),eps(best,k1,k2),p(best)	1927.38	15.2	0.0002	0.0005	33	1861.381108
psi(best),gamma(best),eps(best,k1,k2,k3),p(best)	1928.84	16.66	0.0001	0.0002	38	1852.83879
psi(best),gamma(best,k1,k2,k3),eps(best),p(best)	1929.98	17.8	0.0001	0.0001	38	1853.976371
psi(best),gamma(best,k1le,k2le,k3le),eps(best),p(best)	1932.99	20.81	0	0	38	1856.991162

Triturus vulgaris

Detection probability

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
(psi,gamma(),eps(),p(night, day; eingsch))	215.62	0	0.255	1	6	203.618539
(psi,gamma(),eps(),p(s2; eingsch))	215.91	0.29	0.2206	0.865	6	203.913752
(psi,gamma(),eps(),p(night:s2, day; eingsch))	216.68	1.06	0.1501	0.5886	7	202.681107
(psi,gamma(),eps(),p(night, day; eingsch ; s2))	217.56	1.94	0.0967	0.3791	7	203.563071
(psi,gamma(),eps(),p(s1 ; s2; eingsch))	217.71	2.09	0.0897	0.3517	7	203.708653
(psi,gamma(),eps(),p(s1,s2))	218.79	3.17	0.0523	0.2049	6	206.790857
(psi,gamma(),eps(),p(night:s2, day ; eingsch))	219.81	4.19	0.0314	0.1231	6	207.813881
(psi,gamma(),eps(),p(s1 ; s2 ; wflae))	220.25	4.63	0.0252	0.0988	7	206.246192
(psi,gamma(),eps(),p(night, day))	220.51	4.89	0.0221	0.0867	5	210.507336
(psi,gamma(),eps(),p(night:s2, day:k))	220.65	5.03	0.0206	0.0809	6	208.650095
(psi,gamma(),eps(),p(s2, PG))	221.53	5.91	0.0133	0.0521	11	199.52719
(psi,gamma(),eps(),p(night:s1, s2; day: s1, s2))	221.56	5.94	0.0131	0.0513	8	205.556155
(psi,gamma(),eps(),p(night, day; PG))	223.85	8.23	0.0042	0.0163	11	201.851857
(psi,gamma(),eps(),p(eingsch))	224.92	9.3	0.0024	0.0096	5	214.923723
(psi,gamma(),eps(),p(PG ; s1 ; s2))	225.72	10.1	0.0016	0.0064	12	201.723655
(psi,gamma(),eps(),p(survey))	227.95	12.33	0.0005	0.0021	21	185.946157
(psi,gamma(),eps(),p(veg))	228.41	12.79	0.0004	0.0017	5	218.413635
(psi,gamma(),eps(),p(.))	229.25	13.63	0.0003	0.0011	4	221.250283
(psi,gamma(),eps(),p(s1))	229.82	14.2	0.0002	0.0008	5	219.823307
(psi,gamma(),eps(),p(wflae))	230.61	14.99	0.0001	0.0006	5	220.607145
(psi,gamma(),eps(),p(s2))	230.91	15.29	0.0001	0.0005	5	220.913624
(psi,gamma(),eps(),p(PG))	233.22	17.6	0	0.0002	10	213.216761

Occupancy

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
psi(gis ; veg ; wflae),gamma(),eps(),p(best)	200.32	0	0.9138	1	11	178.318271
psi(gis),gamma(),eps(),p(best)	206.83	6.51	0.0353	0.0386	9	188.832027
psi(PG ; gis),gamma(),eps(),p(best)	207.61	7.29	0.0239	0.0261	10	187.607113
psi(gis , kon),gamma(),eps(),p(best)	208.38	8.06	0.0162	0.0178	10	188.376135
psi(veg ; wflae),gamma(),eps(),p(best)	210.22	9.9	0.0065	0.0071	8	194.218229
psi(PG ; kon),gamma(),eps(),p(best)	211.49	11.17	0.0034	0.0038	8	195.4938
psi(PG),gamma(),eps(),p(best)	215.23	14.91	0.0005	0.0006	7	201.231602
psi,gamma(),eps(),p(night:o,day:1 ; eingesch)	215.62	15.3	0.0004	0.0005	6	203.618539

Colonization and extinction probability

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
psi(best),gamma(.),eps(veg,wflae),p(best)	198.93	0	0.39	1	13	172.931632
psi(best),gamma(.),eps(.),p(best)	200.32	1.39	0.1947	0.4991	11	178.318271
psi(best),gamma(kon),eps(veg,wflae),p(best)	200.93	2	0.1435	0.3679	14	172.931969
psi(best),gamma(veg,wflae),eps(veg,wflae),p(best)	202.84	3.91	0.0552	0.1416	15	172.844982
psi(best),gamma(.),eps(gis,veg,wflae),p(best)	203.27	4.34	0.0445	0.1142	16	171.266398
psi(best),gamma(kon),eps(.),p(best)	204.42	5.49	0.0251	0.0642	12	180.423686
psi(best),gamma(veg,wflae),eps(.),p(best)	204.44	5.51	0.0248	0.0636	13	178.442972
psi(best),gamma(gis),eps(veg,wflae),p(best)	204.99	6.06	0.0188	0.0483	16	172.988354
psi(best),gamma(gis),eps(.),p(best)	205.01	6.08	0.0187	0.0478	14	177.005613
psi(best),gamma(kon),eps(gis,veg,wflae),p(best)	205.64	6.71	0.0136	0.0349	17	171.637232
psi(best),gamma(fi),eps(.),p(best)	206.08	7.15	0.0109	0.028	15	176.079685
psi(best),gamma(.),eps(gis),p(best)	206.31	7.38	0.0097	0.025	14	178.313087
psi(best),gamma(gis,kon),eps(veg,wflae),p(best)	206.93	8	0.0071	0.0183	17	172.931969
psi(best),gamma(veg,wflae),eps(gis,veg,wflae),p(best)	207.37	8.44	0.0057	0.0147	18	171.371766
psi(best),gamma(.),eps(gis,kon),p(best)	207.93	9	0.0043	0.0111	15	177.928487
psi(best),gamma(.),eps(pg),p(best)	207.97	9.04	0.0042	0.0109	16	175.965058
psi(best),gamma(kon),eps(gis),p(best)	208.22	9.29	0.0037	0.0096	15	178.222888
psi(best),gamma(gis,veg,wflae),eps(veg,wflae),p(best)	208.90	9.97	0.0027	0.0068	18	172.902231
psi(best),gamma(.),eps(pg,gis),p(best)	208.91	9.98	0.0027	0.0068	19	170.914785
psi(best),gamma(gis),eps(gis,veg,wflae),p(best)	208.93	10	0.0026	0.0067	19	170.929401
psi(best),gamma(gis,veg,wflae),eps(.),p(best)	208.98	10.05	0.0026	0.0066	16	176.983162
psi(best),gamma(.),eps(fi),p(best)	209.82	10.89	0.0017	0.0043	15	179.824799
psi(best),gamma(kon),eps(gis,kon),p(best)	209.86	10.93	0.0017	0.0042	16	177.861836
psi(best),gamma(kon),eps(pg),p(best)	209.97	11.04	0.0016	0.004	17	175.965058
psi(best),gamma(veg,wflae),eps(gis),p(best)	210.26	11.33	0.0014	0.0035	16	178.256706
psi(best),gamma(gis,kon),eps(.),p(best)	210.42	11.49	0.0012	0.0032	15	180.423686
psi(best),gamma(kon),eps(pg,gis),p(best)	211.19	12.26	0.0008	0.0022	20	171.18729
psi(best),gamma(gis,kon),eps(gis,veg,wflae),p(best)	211.30	12.37	0.0008	0.0021	20	171.301791
psi(best),gamma(veg,wflae),eps(pg,kon),p(best)	211.55	12.62	0.0007	0.0018	19	173.549938
psi(best),gamma(veg,wflae),eps(gis,kon),p(best)	211.83	12.9	0.0006	0.0016	17	177.826169
psi(best),gamma(veg,wflae),eps(pg),p(best)	211.97	13.04	0.0006	0.0015	18	175.965058
psi(best),gamma(fi),eps(fi),p(best)	212.32	13.39	0.0005	0.0012	19	174.323698
psi(best),gamma(gis),eps(gis),p(best)	212.32	13.39	0.0005	0.0012	17	178.317395
psi(best),gamma(.),eps(pg,kon),p(best)	212.75	13.82	0.0004	0.001	17	178.752462
psi(best),gamma(gis,veg,wflae),eps(gis,veg,wflae),p(best)	212.86	13.93	0.0004	0.0009	21	170.859296

Colonization and extinction probability - continued

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
psi(best),gamma(veg,wflae),eps(pg,gis),p(best)	212.93	14	0.0004	0.0009	21	170.928438
psi(best),gamma(kon),eps(pg,kon),p(best)	213.29	14.36	0.0003	0.0008	18	177.292267
psi(best),gamma(gis),eps(gis,kon),p(best)	213.92	14.99	0.0002	0.0006	18	177.923495
psi(best),gamma(gis),eps(pg),p(best)	213.97	15.04	0.0002	0.0005	19	175.965058
psi(best),gamma(gis),eps(pg,gis),p(best)	214.06	15.13	0.0002	0.0005	22	170.058168
psi(best),gamma(gis,kon),eps(gis),p(best)	214.31	15.38	0.0002	0.0005	18	178.312753
psi(best),gamma(gis,kon),eps(pg,gis),p(best)	215.89	16.96	0.0001	0.0002	23	169.892621
psi(best),gamma(gis,kon),eps(gis,kon),p(best)	215.92	16.99	0.0001	0.0002	19	177.92347
psi(best),gamma(gis,kon),eps(pg),p(best)	215.97	17.04	0.0001	0.0002	20	175.965058
psi(best),gamma(gis,veg,wflae),eps(gis),p(best)	216.22	17.29	0.0001	0.0002	19	178.222865
psi(best),gamma(gis),eps(pg,kon),p(best)	217.29	18.36	0	0.0001	20	177.291411
psi(best),gamma(gis,veg,wflae),eps(pg,gis),p(best)	217.49	18.56	0	0.0001	24	169.490975
psi(best),gamma(gis,veg,wflae),eps(gis,kon),p(best)	217.97	19.04	0	0.0001	20	177.968524
psi(best),gamma(gis,veg,wflae),eps(pg),p(best)	217.97	19.04	0	0.0001	21	175.965058
psi(best),gamma(gis,kon),eps(pg,kon),p(best)	219.29	20.36	0	0	21	177.292267
psi(best),gamma(gis,veg,wflae),eps(pg,kon),p(best)	221.29	22.36	0	0	22	177.287865

Colonization and extinction probability with management

Model	AIC	delta AIC	AIC wgt	Model Likelihood	No.Par.	(-2*LogLike)
psi(best),gamma(best),eps(best),p(best)	200.32	0	0.8404	1	11	178.318271
psi(best),gamma(best,k3),eps(best),p(best)	205.84	5.52	0.0532	0.0633	16	173.844818
psi(best),gamma(best,k3le),eps(best),p(best)	206.01	5.69	0.0489	0.0581	16	174.013148
psi(best),gamma(best,k2le),eps(best),p(best)	209.96	9.64	0.0068	0.0081	16	177.956381
psi(best),gamma(best),eps(best,k1le),p(best)	210.04	9.72	0.0065	0.0078	16	178.038849
psi(best),gamma(best),eps(best,k1),p(best)	210.09	9.77	0.0064	0.0076	16	178.090323
psi(best),gamma(best),eps(best,k2),p(best)	210.10	9.78	0.0063	0.0075	16	178.096168
psi(best),gamma(best),eps(best,k2le),p(best)	210.10	9.78	0.0063	0.0075	16	178.096168
psi(best),gamma(best,k2),eps(best),p(best)	210.12	9.8	0.0063	0.0074	16	178.117031
psi(best),gamma(best,k1),eps(best),p(best)	210.19	9.87	0.006	0.0072	16	178.186219
psi(best),gamma(best),eps(best,k3le),p(best)	210.70	10.38	0.0047	0.0056	16	178.697301
psi(best),gamma(best),eps(best,k3),p(best)	211.29	10.97	0.0035	0.0041	16	179.286778
psi(best),gamma(best,k1le),eps(best),p(best)	212.42	12.1	0.002	0.0024	16	180.423686
psi(best),gamma(best,k2,k3),eps(best),p(best)	214.21	13.89	0.0008	0.001	21	172.208317
psi(best),gamma(best,k1,k3),eps(best),p(best)	214.64	14.32	0.0007	0.0008	21	172.643494
psi(best),gamma(best,k2le,k3le),eps(best),p(best)	214.92	14.6	0.0006	0.0007	21	172.924245
psi(best),gamma(best,k1le,k3le),eps(best),p(best)	215.40	15.08	0.0004	0.0005	21	173.401741
psi(best),gamma(best),eps(best,k1le,k2le),p(best)	219.81	19.49	0	0.0001	21	177.805168
psi(best),gamma(best),eps(best,k1,k2),p(best)	219.89	19.57	0	0.0001	21	177.893706
psi(best),gamma(best,k1,k2),eps(best),p(best)	220.04	19.72	0	0.0001	21	178.038156
psi(best),gamma(best),eps(best,k2le,k3le),p(best)	220.54	20.22	0	0	21	178.536625
psi(best),gamma(best),eps(best,k1le,k3le),p(best)	220.56	20.24	0	0	21	178.556298
psi(best),gamma(best),eps(best,k2,k3),p(best)	221.11	20.79	0	0	21	179.110384
psi(best),gamma(best),eps(best,k1,k3),p(best)	221.16	20.84	0	0	21	179.160544
psi(best),gamma(best,k1le,k2le),eps(best),p(best)	222.42	22.1	0	0	21	180.423686
psi(best),gamma(best,k1,k2,k3),eps(best),p(best)	224.07	23.75	0	0	26	172.074049
psi(best),gamma(best,k1le,k2le,k3le),eps(best),p(best)	224.66	24.34	0	0	26	172.65772
psi(best),gamma(best),eps(best,k1le,k2le,k3le),p(best)	230.35	30.03	0	0	26	178.348005
psi(best),gamma(best),eps(best,k1,k2,k3),p(best)	230.98	30.66	0	0	26	178.980393