



Local abundance and observer's identity affect visual detectability of Sardinian mountain newts

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Visual counts gathered within citizen science programs are increasingly used to determine distribution and abundance of species of conservation concern. However, to obtain reliable patterns from counts, imperfect detection should always be considered, with particular reference to rare and elusive species. By analysing data from a citizen science monitoring program based on multiple simultaneous observers, we studied detection probability of the Sardinian mountain newt, *Euproctus platycephalus*. Detectability of individual newts widely varied among observers, and was positively affected by the number of newts exposed to during sampling. Training, although appearing to improve detectability, did not accommodate for differences among trained observers. No effect of sampling hour, tree shade, cloud cover, water flow, turbidity, and temperature was found, possibly due to standardisation of sampling conditions. Depending on observer's skills and the population exposed to during sampling, detection probability of newt populations can widely vary. Most of the sampling units (pools) had few newts exposed to during sampling, with a high probability of recording false absences. Herpetological surveys could be more extensively based on multiple simultaneous observers to reduce observer heterogeneity bias in the detection process, and obtain more reliable patterns of species abundance and distribution for conservation purposes.

Key words: detection probability; *Euproctus platycephalus*, multiple observers, observer heterogeneity; visual counts, citizen science

INTRODUCTION

Citizen science is an important source of information to assess distribution, abundance, and conservation status of animals (Anadón et al., 2009; Conrad & Hilchey, 2010; Griffiths et al., 2015; McKinley et al., 2016; Vignoli et al., 2016). For practical and economic reasons, visual counts are often used to determine species distribution and abundance of animal populations (Williams, Nichols & Conroy, 2002). Simple counts are also widely used in herpetological surveys, which often involve non-professionals for visual or acoustic observations (Griffiths et al., 2015).

To provide reliable inference about distribution and abundance, simple counts need to address variation in detectability through space and time (Royle & Nichols 2003; Royle, 2004; Schmidt & Pellet, 2009; Tanadini & Schmidt, 2011). However, species availability and conditional detection probability (i.e. probability of detection, given an animal is exposed to sampling) need to be partitioned to understand the detection process (Pollock et al., 2004; O'Donnell, Thompson & Semlitsch, 2015). Conditional detection probability can be studied by applying capture-recapture models to count data

coming from multiple simultaneous observers (Nichols, Tomlinson & Waggerman, 1986; Williams, Nichols & Conroy, 2002; Grant et al., 2005; Schmidt & Pellet, 2009; O'Donnell, Thompson & Semlitsch, 2015). With the available statistical software (White & Burnham, 1999; Nichols et al., 2000; Fiske & Chandler, 2011), multiple observer data can be analysed if individual detection histories of animals are recorded. Nevertheless, recording detection histories in monitoring programs that involve non-professionals can be difficult, as people that do monitoring for fun or within a non-research position (Griffiths et al., 2015) could perceive it as unnecessary.

The Sardinian mountain newt, *Euproctus platycephalus* (Urodela, Amphibia), is an endemic species (Carranza & Amat, 2005) restricted to Sardinia, Italy, where it inhabits creeks and small lakes (Lecis & Norris, 2003a; b). Given its reduced distribution and continuing decline, the species was classified as Endangered by the IUCN Red List (IUCN, 2009). The species has been consequently monitored by the regional governmental agency Forestas, in cooperation with other public bodies, research institutions and non-professionals (Casula et al., 2010). A recent assessment based on data from this community-based monitoring effort (Conrad & Hilchey, 2010) showed that the distribution of the Sardinian

mountain newt was underestimated (Vignoli et al., 2016), possibly as a consequence of low detectability of this well camouflaged and elusive species. It is therefore important to understand the detection process involved during monitoring programs for better monitoring and conservation (Nichols & Williams, 2006; Tanadini & Schmidt, 2011).

Here, using data coming from multiple observers that did not record individual detection histories of newts, we apply capture-recapture models to study the conditional detection process involved in the monitoring effort mentioned above. We evaluate whether detection probability of newts varies among observers, and depends on factors potentially affecting the observation process (Henke, 1998; Schmidt & Pellet, 2009; Tanadini & Schmidt, 2011; Lardner et al., 2015). Specifically, we hypothesise that visual detection of individual newts varies with observer's skills (identity and training), and is affected by light conditions (tree shade and presence of clouds), speed of water flow, turbidity, water temperature, time of the day, and newt abundance.

METHODS

Sampling design

The Sardinian mountain newt is the only aquatic newt inhabiting Sardinian streams (Lecis & Norris, 2003b; Grill et al., 2007), and its identification is therefore straightforward. Surveys could thus involve trained and untrained personnel of the regional government agency Forestatas, who are non-professional researchers. Nine technicians with previous experience in newt visual sampling were considered as trained, whereas eight forestry workers that participated for the first time to sampling were considered as untrained. The 17 observers conducting visual surveys contributed unevenly to the data set, and the proportion of trained and untrained observers was unbalanced (see Table 1).

Due to logistic, economic, and safety constraints, surveys were diurnal. Even if Sardinian mountain newt activity (i.e. availability for sampling) could be higher at night, diurnal surveys proved to be a valid tool to study the species distribution (Lecis & Norris, 2003a; b; Vignoli et al., 2016). Local populations of the Sardinian mountain newt are often associated with steep creeks that are difficult to hike, due to waterfalls, rugged landscape, or vegetation barriers. The sampling process was thus as quick as possible, to allow more extensive survey of the creek within the available time and personnel.

In an attempt to standardise sampling conditions and maximise newt conditional detectability and availability for sampling (O'Donnell et al., 2015), surveys were planned for warm, sunny days between March and October, according to the local climate and creek water regime. We avoided cold and rainy months (November – February), conducting surveys when water tended to be slower and at optimal temperatures (Lecis & Norris, 2003b) to increase visibility and newt availability for sampling.

Creeks known to be inhabited by Sardinian newts were surveyed by no less than two observers (2-4) by

hiking upstream for variable transect lengths (Table 1). Newts were searched in the upper parts of creeks where pools are small (1-5 m wide). Different pools were clearly separated by creek narrowing, rocks, or dry parts (Lecis & Norris, 2003b; Bovero et al., 2005).

The observation process was driven by a leading observer. When slow moving waters allowed observation (pools), observers were asked to stop for simultaneous visual inspection. The observation lasted up to 5 minutes, with searching effort increasing with the size of the inspected pool. During this time, observers were allowed to freely move around the pool to change visual angle. Each observer inspected the whole pool and counted newts silently, carefully avoiding any sign of successful observation. In this way observers attempted to be independent (Nichols, Tomlinson & Waggenerman, 1986) despite simultaneous search. To reduce bias in detectability due to newt disturbance, observers approached the pool simultaneously, so that hiding or moving of disturbed newts could similarly affect observer's detection probability. However, in most of the cases newts did not respond to approaching observers with a sudden escape, as they tend to stand still or move slowly towards a refuge.

At the end of the independent observation, observers were asked to share their visual captures by saying in which positions single newts were seen, and where they eventually moved. As pools were small and Sardinian newts tend to be sedentary, discriminating "visual recaptures" (animals seen by more than one observer) vs. single captures (animal seen by only one observer) was possible (a mental map of newt locations could be immediately shared among crew members). In this way, it was possible to exclude multiple counts in recording the total number of different animals jointly seen by the crew in each pool inspected (C_i). The number of newts seen by each observer (j) was also recorded (C_{ij}). Despite the fact that such observations could be translated into individual detection histories of newts, only simple counts were recorded to speed up the survey (e.g., using observer's initials, records were as follows $C_{IPC} = 5$; $C_{IEC} = 7$; $C_{ISM} = 4$; $C_i = 12$). As discussed in the statistical analysis section, this simplification of data gathering can be handled by simple extensions of capture-recapture models applied to multiple independent observers (Nichols, Tomlinson & Waggenerman, 1986; Williams, Nichols & Conroy, 2002; Schmidt & Pellet, 2009).

All suitable pools found within transects were inspected during surveys. However, only data relating to pools where at least one newt was seen were recorded (pools with no or unknown exposed newts cannot be used to estimate conditional detection probability). During 2010 and 2014, 23 transects (different creek/day) were surveyed, and 152 independent pools with newts were recorded. The number of pools with at least one newt differed widely among creeks (1-25 pools).

Factors affecting newt conditional detectability

Among the factors thought to affect newt conditional detectability, observer's identity (*Identity*) is a potentially important source of variation that need to be addressed

Table 1. Summary of Sardinian newt counts gathered with multiple simultaneous independent observers.

Tr	Creek name	Day	Hour	Observers	Length (m)	Pools	Newts
1	Su Cunventu	March 15, 2010	12,00-13,00	PC, SM, X	180	1	1
2	Su Gattu	March 19, 2010	11,15-15,15	PC, SM, X	980	2	8
3	Maidopis	April 7, 2010	09,50-11,20	AM, SM	150	2	2
4	Lardai	April 9, 2010	11,00-12,30	PC, SM, X	360	5	6
5	Codula Orbisi	April 14, 2010	14.30-16,40	PC, SM	800	1	1
6	Cedrino	April 21, 2010	16,00-17,00	PC, SM	400	1	2
7	Donna Pruna	May 5, 2010	12,30-15,15	PC, EC, SM	240	1	1
8	Maidopis	May 10, 2010	09,20-11,20	AM, EC	150	2	3
9	Serra e scova	May 21, 2010	12,00-13,00	PC, SM, X	210	9	27
10	Su Gattu	June 3, 2010	10,30-14,00	AM, SM, X	1030	6	27
11	Serra e scova	June 6, 2010	17,00-19,00	PC, EC, SF, X	320	25	89
12	Donna Pruna	June 14, 2010	11,00-13,00	PC, EC	400	3	4
13	Cedrino	June 25, 2010	11,50-13,00	PC, EC, SF	1020	1	1
14	Codula Orbisi	June 30, 2010	14,00-16,00	PC, X	400	1	5
15	Su Cunventu	April 15, 2014	10,00-14,00	PC, SF	330	3	3
16	Badde gattiu	June 6, 2014	10,30-12,30	PC, DL	240	13	52
17	Bacu Orrodas	June 6, 2014	14,00-14,45	PC, DL	200	2	3
18	Lardai	June 17, 2014	10,00-12,00	PC, X	260	2	2
19	Paolino	August 7, 2014	12,20-16,20	PC, MM	1060	1	1
20	Pisciaroni	August 12, 2014	13,00-16,00	PC, RS, CA	450	20	70
21	Bacu non bie boe	August 27, 2014	12,00-15,00	PC, MM, DL, X	420	21	102
22	Serra e scova	October 1, 2014	11,00-13,00	PC, DL, X	210	22	102
23	Isadalu	October 1, 2014	14,00-16,00	PC, DL, X	290	8	18

Notes. Tr: transect progressive number; Observers: trained technicians are identified with initials; X = untrained personnel; Length: transect length; Pools: number of pools found per transect with at least 1 newt; Newts: total number of newts counted during the transect (multiple counts excluded).

in monitoring programs (Lardner et al., 2015). Indeed, observers might have different skills and level of attention, and might therefore greatly differ in visual detection capabilities despite training (e.g. Henke, 1998; Lardner et al., 2015).

Environmental factors thought to affect the visual detection process were measured by the leading observer as follows.

Light conditions (*Shade*) were measured as 0, 10, ..., 100% of water surface covered by trees, visually estimated at the sub-transect level (i.e., portions of transects with homogeneous vegetation cover). Shade should negatively affect conditional detectability (no artificial light was used during surveys).

Speed of water flow (*Flow*) was visually estimated as 1= null, 2 = low, 3 = medium, and 4 = strong (data ranging from null to medium). Water turbidity (*Turb*) was visually estimated using the same four categories, with data ranging from null to low. Higher flows or turbidity should lower the visibility below water, with consequent lower detectability of newts.

Water temperature (*Temp*) was measured several times at the transect level, and generally did not change among adjacent pools. Depending on transect, data ranged from 7 to 25 °C. Optimal water temperature (Lecis

& Norris, 2003b) could positively affect newt mobility and response to disturbance, with possible increased visibility of exposed newts (it is more likely to see newts when they move as the observers approach the pool).

Cloud cover (*Clouds*) was measured by assigning value 0 = clouds < 50% sky, and 1 = clouds > 50% sky. Time of the day (*Hour*) was measured as morning or afternoon ($Hour < 13 = 1$; $> 13 = 0$). *Clouds* and *Hour* could capture variation of light conditions or daily patterns of observer's activity.

Local abundance positively affects the probability of detecting amphibian populations (Tanadini & Schmidt, 2011) as well as single animals (Henke, 1998). Here the focus will be on detection probability of individual newts available for sampling at the pool level (sampling unit), which could increase with a higher number of "searched items" present (Henke, 1998). The number of newts available for sampling was approximated by total number of different newts jointly seen by the crew in a given pool (C_i).

Statistical models

Simple counts can be analysed using N-mixtures, which account for detectability by using spatially and temporally replicated counts (Royle, 2004). However, temporally

Table 2. Model selection results.

#	Model description	log L	AIC _c	ΔAIC _c	w _i	K
1	$p_j(\text{Identity}, C_i)$	-597.142	1216.860	0.000	0.577	11
2	$p_j(\text{Identity}, \text{Hour}, C_i)$	-596.851	1218.383	1.523	0.269	12
3	$p_j(\text{Identity}, \text{Cloud}, \text{Hour}, C_i)$	-596.843	1220.482	3.623	0.094	13
4	$p_j(\text{Identity}, \text{Temp}, \text{Cloud}, \text{Hour}, C_i)$	-596.801	1222.523	5.663	0.034	14
5	$p_j(\text{Identity}, \text{Turb}, \text{Temp}, \text{Cloud}, \text{Hour}, C_i)$	-596.800	1224.655	7.796	0.012	15
6	$p_j(\text{Identity})$	-602.618	1225.715	8.855	0.007	10
7	$p_j(\text{Identity}, \text{Flow}, \text{Turb}, \text{Temp}, \text{Cloud}, \text{Hour}, C_i)$	-596.504	1226.206	9.346	0.005	16
8	$p_j(\text{Identity}, \text{Shade}, \text{Flow}, \text{Turb}, \text{Temp}, \text{Cloud}, \text{Hour}, C_i)$	-596.423	1228.196	11.336	0.002	17
9	$p_j(\text{trained and untrained}, C_i)$	-618.279	1242.609	25.749	0.000	3
10	$p_j(1 \text{ group}, C_i)$	-629.968	1263.962	47.102	0.000	2

Notes: log L = log-likelihood of the model; w_i = Akaike’s weight; K = number of parameters.

replicated counts could result in variation of the number of animals exposed to sampling due to temporary emigration, potentially confounding availability of animals for sampling with conditional detection probability (O’Donnell, Thompson & Semlitsch, 2015). To study conditional detection probability, multiple simultaneous observers can be involved, either independent (Nichols, Tomlinson & Waggerman, 1986) or dependent (Nichols et al. 2000; Williams, Nichols & Conroy, 2002).

Available statistical software (White & Burnham, 1999; Nichols et al., 2000; Fiske & Chandler, 2011) allows to estimate detectability from count data coming from multiple observers if individual detection histories of animals are recorded. However, counts coming from multiple independent observers (Nichols, Tomlinson & Waggerman, 1986) can provide estimates of detection probability even when no detection histories are recorded, as follows.

By applying capture – recapture models to simultaneous counts (Nichols, Tomlinson & Waggerman, 1986), the expected count of observer j , sampling on newt population N_i exposed to sampling in pool i , can be written as:

$$1) C_{ij} = N_i p_j,$$

The parameter p_j is the observer-specific conditional detection probability of individual newts, given their exposure to sampling. This parameter is equivalent to capture probability of individuals given their presence in the sampled area (see Schmidt & Pellet, 2009 for a nice review).

The total number of different newts jointly seen by the crew in pool i can be written as:

$$2) C_i = N_i p_c,$$

where p_c is the cumulative detection probability (Schmidt & Pellet, 2009) that, with $j=1,2, \dots, z$ independent observers, can be written as:

$$3) p_c = 1-(1-p_1)(1-p_2)\dots(1-p_z).$$

By combining model 2 and 3, and solving for N_i , the model can be written as:

$$4) N_i = C_i / (1 - \prod (1 - p_j)).$$

By combining models 1 and 4, expectations for observer- and pool-specific counts can be derived:

$$5) C_{ij} = p_j C_i / (1 - \prod (1 - p_j)).$$

Therefore, we obtained a model that allows estimating observer-specific detection probability of individual newts (p_j) by using observer- and pool-specific counts (C_{ij}), and total number of different newts jointly seen by the crew in a given pool (C_i). Individual detection histories of newts are not necessary for detection probability estimation, which is done by comparing expected with observed C_{ij} .

The main limit of this application, as well as of original multiple observers approaches (Nichols, Tomlinson & Waggerman, 1986; Nichols et al., 2000), is that the proportion of animals not exposed to sampling cannot be estimated (Schmidt & Pellet, 2009; O’Donnell, Thompson & Semlitsch, 2015). However, this approach allows exploring the variation of conditional detection probability of exposed individuals depending on observer’s identity and factors thought to affect the sighting process.

The variation of conditional detection probability with such factors was modelled with a logistic function (Neter et al., 1996; Royle & Nichols, 2003; Grant et al., 2005), where the probability of individual newts to be detected by observer j in a given pool i was:

$$6) p_{ij} = \frac{e^{(a_j+b * \text{Shade}+c * \text{Flow}+d * \text{Turb}+e * \text{Temp}+f * \text{Cloud}+g * \text{Hour}+h * C_i)}}{1+e^{(a_j+b * \text{Shade}+c * \text{Flow}+d * \text{Turb}+e * \text{Temp}+f * \text{Cloud}+g * \text{Hour}+h * C_i)}}$$

The parameter a_j is an intercept that determines the intrinsic conditional detection probability of observer j . Such intrinsic probability can vary according to the estimated parameters ($b, c, d, e, f, g,$ and h), and the value of the factors.

Finally, for a give observer j , the probability of recording false absence on a sampling unit with exposed population N_i can be estimated using the following model:

$$7) p_{\text{false absence}} = (1-p_j)^{N_i}$$

Model selection

Model selection was based on AIC_c (Burnham & Anderson, 2002). Considering that comparison was performed between expected and observed counts, maximum likelihood estimation was based on a Poisson likelihood function (Neter et al., 1996). The log-likelihood of the model was given by the sum of the log-likelihood of all pool- and observer-specific counts ($n=471$), as follows:

$$\log_e L = \sum C_{ij} \log_e (C_{ij(e)}) - \sum (C_{ij(e)}) - \sum \log_e (C_{ij}!),$$

Where C_{ij} are pool- and observer-specific counts, and $C_{ij(e)}$ are expected pool- and observer-specific counts derived from model 5 combined with model 6.

Model selection started from the general model p_{ji} (*Identity, Shade, Flow, Turb, Temp, Cloud, Hour, C_i*), where observer- and pool-specific conditional detection probabilities are estimated using the full model 6. In the general model, the intercepts a_j (*Identity*) were estimated for each trained observer, whereas for untrained observers data were merged and 1 intercept estimated (see Models.xlsx, supplementary material).

To evaluate strength of evidence for each hypothesised effect on detection probability, the general model was progressively simplified starting from the factor *Shade* up to *Count*, and eliminating one factor at a time. To evaluate training effects, intercepts of the trained technicians were merged, resulting in two groups (*trained* and *untrained*). The presence of identity effects was evaluated assuming one common intercept for all observers (*1 group*).

RESULTS

Overall, 529 different newts in 152 independent pools were seen, with an average cumulative count of 3.48 ± 3.74 (SD) per pool. The distribution of pool specific total counts (C_i) is shown in Figure 1. The majority of pools (68%) host few newts (counts ranging from 1 to 3).

Table 2 shows that the best model selected was $p_{ji}(\text{Identity}, C_i)$, with an Akaike weight (w_i) of 0.577, and Pearson’s chi-square of 603.55 ($n= 471$, $K= 11$; overdispersion, $c = 1.31$). The model states that detection probability of newts changes with the total number of newts counted per pool (C_i) and among observers (*Identity*).

Strength of evidence relative to the effect of the number of newt counted on detection probability is shown by comparing the best model with model ranked 6th, $p_{ji}(\text{Identity})$, which, starting from the best, assumes no effect of C_i on detectability (h set to 0). This simplification step provides a model with no support: $w_i = 0.007$ and $\Delta AIC_c = 8.855$.

The evidence in support of the heterogeneity of detection probability among observers is even stronger. This is shown by the comparison of the best model with model ranked 10th, $p_{ji}(1 \text{ group}, C_i)$, which assumes no identity effects by using a single constant detection probability for all observers and has no support ($\Delta AIC_c = 47.102$; $w_i = 0.000$). Additionally, *a posteriori* grouping of similar intercepts showed that at least four groups of observers (i.e. four different a_j) are necessary to explain the data (lowest AIC_c). However, such arbitrary grouping of observers without functional, *a priori*, means of

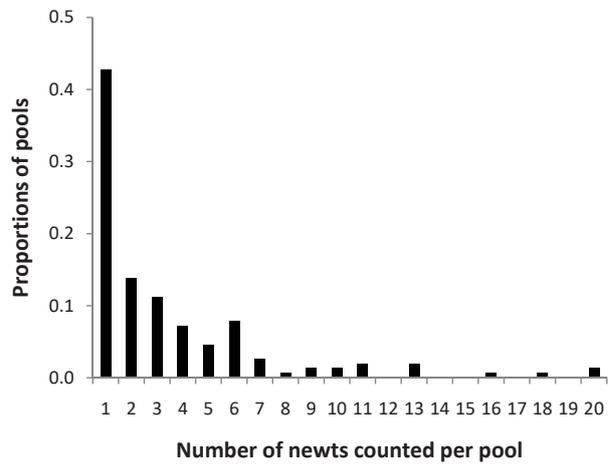


Figure 1. Proportion of pools with increasing number of newts exposed to sampling.

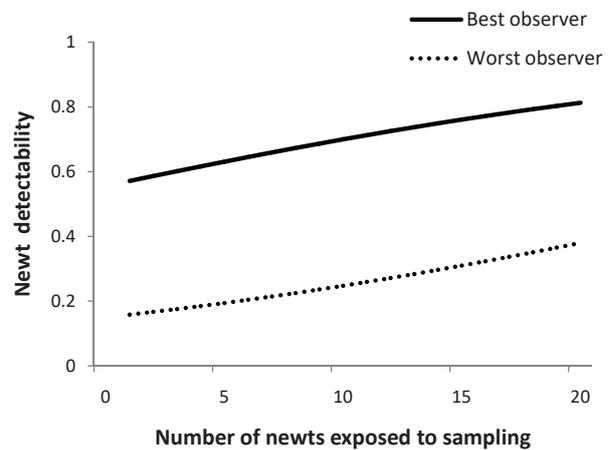


Figure 2. Newt detection probability variation among observers (best and worst), and with increasing number of newts exposed to sampling.

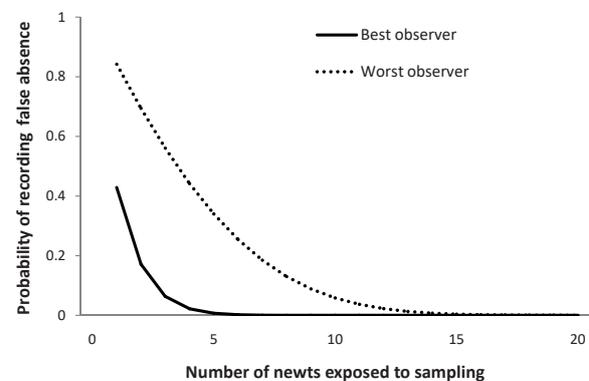


Figure 3. Probability of recording false absence, depending on the number of newts exposed to sampling, and observer’s skills (best and worst).

identifying relevant groups does not provide meaningful information and is not presented in Table 2. Considering the much lower ΔAIC_c of model ranked 9th, $p_{ji}(\text{trained} - \text{untrained}, C_i)$, $\Delta AIC_c = 25.749$, compared to the 10th (which assumes one group with no difference between trained and untrained), observer heterogeneity appears to be partially explained with training.

Ten intercepts (starting from the best observer: $a_{EC} = 0.225$, $a_{PC} = -0.378$, $a_{MM} = -0.491$, $a_{CA} = -0.549$, $a_{DL} = -0.996$, $a_{RS} = -0.999$, $a_{AM} = -1.169$, $a_{SM} = -1.248$, $a_X = -1.398$, $a_{SF} = 1.734$), and one slope parameter relating detectability to the total number of newts counted ($h = 0.062$) were estimated from the best model. The positive sign of the parameter h suggests higher detectability with increasing number of newts observed. The intercepts above result in a wide variation of detection probability among observers, depending on the number of newts exposed to sampling, as shown in Figure 2. Figure 3 shows the corresponding probability of recording false absences. Depending on observer's skills, more than four (best) or 12 (worst) newts must be available for sampling in the pool to be certain not to miss the population ($p_{\text{False absence}} \approx 0.02$).

No evidence was found about the effect on detectability of shade, water flow, turbidity, water temperature, cloud cover and time of day. Table 2 shows that relative simplification steps from the general model resulted in a reduction of the AIC_c values, with the unsupported factors eliminated progressively from the model selected.

DISCUSSION

By applying capture-recapture models (Nichols, Tomlinson & Waggerman, 1986; Williams, Nichols & Conroy, 2002; Schmidt & Pellet, 2009) to multiple observers data coming from a community-based monitoring program involving non-professionals, we showed that detectability of Sardinian mountain newts varies among observers and with the number of newts counted.

As in other herpetological studies (Lardner et al., 2015), visual detectability of Sardinian mountain newts widely varies among observers and, depending on the number of newts available for sampling, can range from less than 0.2 to more than 0.8. If one observer is involved in monitoring, false absences are very unlikely only when four to 12 newts are available for sampling at the pool level (sampling unit), assuming respectively a good or poor observer. In other words, only aggregations of these animals are very likely to be observed. Considering that in the majority of pools total counts ranged from one to three newts (Figure 1), the risk of recording false absence appears generally high. Additionally, the population exposed to sampling is likely smaller than the population actually present in the pool and overall in the area, due to hiding of individuals or temporary emigration (Bailey, Simons & Pollock, 2004; Pollock et al., 2004; O'Donnell, Thompson & Semlitsch, 2015). However, when two simultaneous observers are involved, the probability of recording false absences approaches zero

(0.03) when there are two to seven newts available for sampling, assuming good or poor observers respectively. Therefore, selecting the best observers and establishing an optimum number depending on their skills could be a practical way to reduce the likelihood of recording false absences.

The low value of a_X (intercept of untrained observers) compared with the majority of trained observers suggests that training positively affect observer's performance. However, training does not eliminate difference among trained observers, and observer's identity remains an important factor requiring to be accommodated in monitoring (Lardner et al., 2015). Therefore, with particular reference to citizen science programs (Griffiths et al., 2015), an initial stage of training could be performed by means of multiple observers, so that individual detectability can be improved and directly compared with the best skilled observers. Comparing multiple observers would be an effective way to preliminarily evaluate the quality of the data gathered by observers involved in citizen science programs (Burgess et al., 2016), and to generate prior estimates of individual-level detection probabilities that might enhance analysis of subsequent surveys.

The positive effect of the number of observed newts on their detectability suggests that observer's visual effectiveness could be positively affected by the repeated observation of the searched items, as hypothesised in other herpetological studies (Henke, 1998). The observation of newts in a pool will inevitably alert the observer, increasing attention. Despite the positive effect of animal density on detectability of populations is intuitive and well-known (Royle & Nichols, 2003; Tanadini & Schmidt, 2011), to our knowledge the effect on single newt detectability has not been further investigated after Henke's experimental findings. In practice, there is an additional effect related to the human dimension (e.g. Bart & Schoultz, 1984; Farmer, Leonard & Horn, 2012; Lardner et al., 2015) that would result in missing small and sparse populations. Such effect should be further investigated, with particular reference to citizen scientists, because non-professionals could be less motivated to survey areas where they "already know" the species is absent, or believe the habitat is unsuitable (Griffiths et al., 2015), thus possibly reducing their levels of attention in low populated areas.

Finally, our study showed no evidence of effects of environmental factors such as light conditions (tree shade and cloud cover), speed of water flow, turbidity, water temperature, and hour of the observation on detection probability. Similar to other studies (Tanadini & Schmidt, 2011), the attempt to standardise weather and environmental conditions by selecting suitable days for surveys could have resulted in little variations of the factors. Additionally, the coarse measurement of environmental factors used here might have masked any existing association with detectability. Therefore, further studies relating detectability to environmental factors measured across larger ranges and at the pool level could provide more insights about patterns of visual conditional detectability of the Sardinia mountain newt.

In conclusion, data taken from multiple observers can be used to study detectability even when detection histories are not recorded. This is not to encourage missing to record detection histories, which would allow better inference, but to show that data gathered with expeditious and simple methods developed within a citizen science program (Conrad & Hilchey, 2010; Griffiths et al., 2015; McKinley et al., 2016) can be nevertheless informative to explore variation of detectability among observers and other factor thought to affect the observation process involved in monitoring. Considering that ignoring the detectability issue translates in underestimated distributions (MacKenzie et al., 2005) and overstatement of conservation status of species (Vignoli et al., 2016), we would encourage designing herpetological surveys by using multiple simultaneous observers whenever possible. This appears even more necessary when variable observers skills markedly affect the observation process (Lardner et al., 2015), and given logistic and safety issues related to field surveys. Extensive surveys to assess species distribution (Vignoli et al., 2016), where unknown and sparse populations are sampled, seriously risk false absences. To reduce this risk two or three simultaneous observers could be involved, as they would have a high likelihood to record newt presence if the species is available for sampling. However, to maximise effectiveness of survey efforts, temporal patterns of species availability with changing environmental conditions and seasonal activity needs to be investigated (O'Donnell, Thompson & Semlitsch, 2015). To do that, simultaneous multiple observer counts could be repeated at appropriated temporal scales, following a range of variables thought to affect activity, aggregation, and exposure of animals to sampling.

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