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REPORT

Power analysis for a potential white-backed woodpecker monitoring design in Switzerland

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IMPRESSUM
*Power analysis for a potential
white-backed woodpecker
monitoring design in Switzerland*

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*A white-backed woodpecker in his
natural habitat
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Introduction

The white-backed woodpecker (*Dendrocops leucotos*) is the rarest and most endangered woodpecker species in Switzerland and Europe (Aangelstam & Mikusinski, 1994; Frank, 2002). Its global range spans the Palearctic region from the Baltic states to the southeastern-most part of Russia, Kamchatka, and Japan. However, in central and western Europe, the distribution becomes very fragmented with patchy populations in southern Scandinavia, the Alps, the Balkans, Italy, and the Pyrenees. Within the Alpine range, the species is found from Austria to Liechtenstein and very locally in the easternmost parts of Switzerland.

This woodpecker is a food specialist, and its presence is strongly conditioned by high abundance of xylobiont insects, and more particularly the larvae of longhorn beetles and jewel beetles (*Cerambycidae*, *Buprestidae*), which feed on dead wood (Bauer et al., 2005). In the Alps, this woodpecker primarily inhabits mixed spruce-beech forests at altitudes between 500 and 1500 meters above sea level. Intensive forestry for centuries resulted in the loss of such mature habitats. Effectively, this led to the displacement of the species from Switzerland and a large part of the Alps back to remote and inaccessible areas (Carlson, 2000; Czeszczewik & Walankiewicz, 2006). At present, in most of Europe, the species finds adequate habitat in protected areas exempt from timber harvesting. In recent decades, in the Alpine region, the species has been gradually expanding its range westwards by colonizing sustainably managed commercial forests (Mollet et al., 2009). The species was rediscovered in the Principality of Liechtenstein in 1981, and has been recorded in easternmost Switzerland since 1996, with 526 records in 236 different 1x1 squares according to the *ornitho* database (Knaus, 1997; Figure 1).

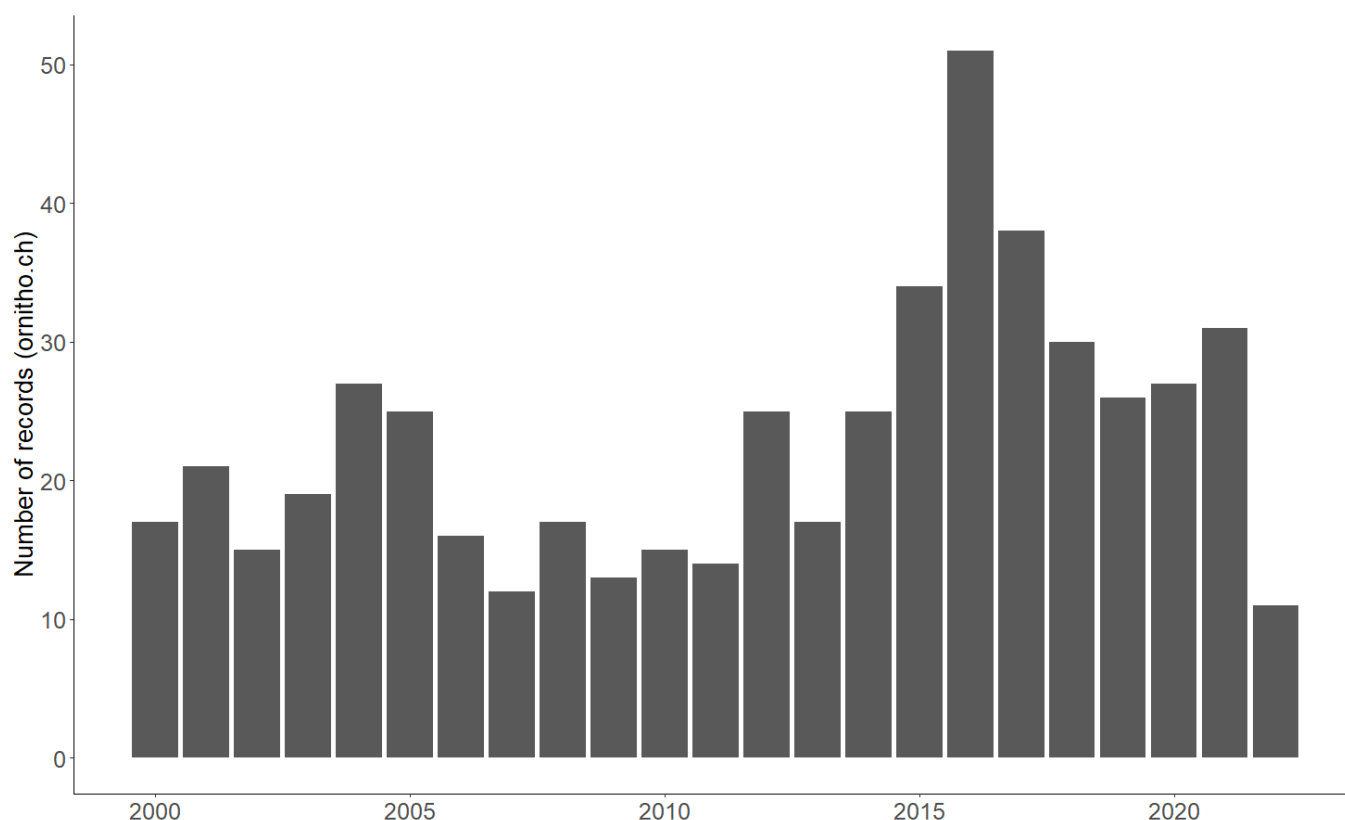


Fig. 1 Number of white-backed woodpecker records between 2020 and 2022 in Switzerland in the citizen-science data platform *ornitho.ch*

Due to its rarity, specialized ecological needs and low population density, the white-backed woodpecker is highly sensitive to disturbance and eventually extinction, which justifies the monitoring of the population trends in this species. However, its rarity presents challenges in gathering sufficient monitoring data. Statistical models based on limited or low-quality data may produce inaccurate population estimates, thus limiting the ability to reliably assess population trends or spatial dynamics (Wisiz et al., 2008). Therefore, selecting effective monitoring strategies that ensure the collection of large enough, high-quality datasets is essential for the conservation of this species. In this respect, simulation-based approaches are valuable tools for planning and optimizing monitoring designs, as they allow the evaluation of different scenarios without

the need for their implementation in real life, thus avoiding expending large amounts of economic and human resources for years without any guarantee of success (Nielsen et al., 2009).

Here, we analyzed the potential effectiveness of a proposed structured monitoring design for the white-backed woodpecker in Switzerland in capturing the trends of the study population through time and across space. To do so, we simulated site occupancy (or presence/absence) data of the species at a 1 km x 1 km resolution and modelled an observation process comprising non-detection errors under the proposed monitoring design. Then, we analyzed the resulting detection/nondetection data using logistic regression models to evaluate how powerful the analytical methods and the proposed monitoring design are at retrieving the trends of the Swiss population over time and space. The main aim of the study is to provide evidence to support or refine the proposed monitoring design. In addition, we provide specific advice on data formatting and analysis settings.

1 The monitoring design

The monitoring design envisioned for the Swiss white-backed woodpecker population is based on the selective monitoring of 1x1 squares (hereafter “sites”) defined in the Swiss Breeding Bird Atlas using yearly transects to ascertain the presence or absence of the species. To select which sites are to be monitored and to distribute the sampling effort across space, the design is based on a nested hierarchy that considers two additional spatial resolutions: 20x20 and 5x5 km grids. Every 20x20 square is composed of 16 5x5 squares, and every 5x5 square is composed of 25 1x1 km² sites. The selection of the monitored sites is done as follows.

In a first step, the 5x5 squares where monitoring is going to be conducted are chosen. A 5x5 square is selected if there have been at least two records of the species in two different years during the last 20 years, regardless of whether the records were in the same site or in different ones within the square. Once a 5x5 square is selected, it will be permanently included into the sampling scheme in future years. Importantly, there is a limit of two monitored sites per year in each 5x5 square. If more than two sites contain historic records of the species, we select two at random. If all historic records belonged to one site, we select a second site with favorable habitat for the species, that is, a large forest cover and an altitude between 500 and 1500 m above sea level. The selected sites are also monitored permanently for all study years. As a last important rule, in every 20x20 square, no more than four 5x5 squares can be monitored. If more than four 5x5 squares satisfy the criteria to be monitored, the four selected squares are determined at random. The selected 5x5 squares are surveyed permanently during the study period. Following this criterion, 30 1x1 squares within 15 5x5 squares from seven 20x20 squares respectively would be initially sampled in 2024 (Figure 2).

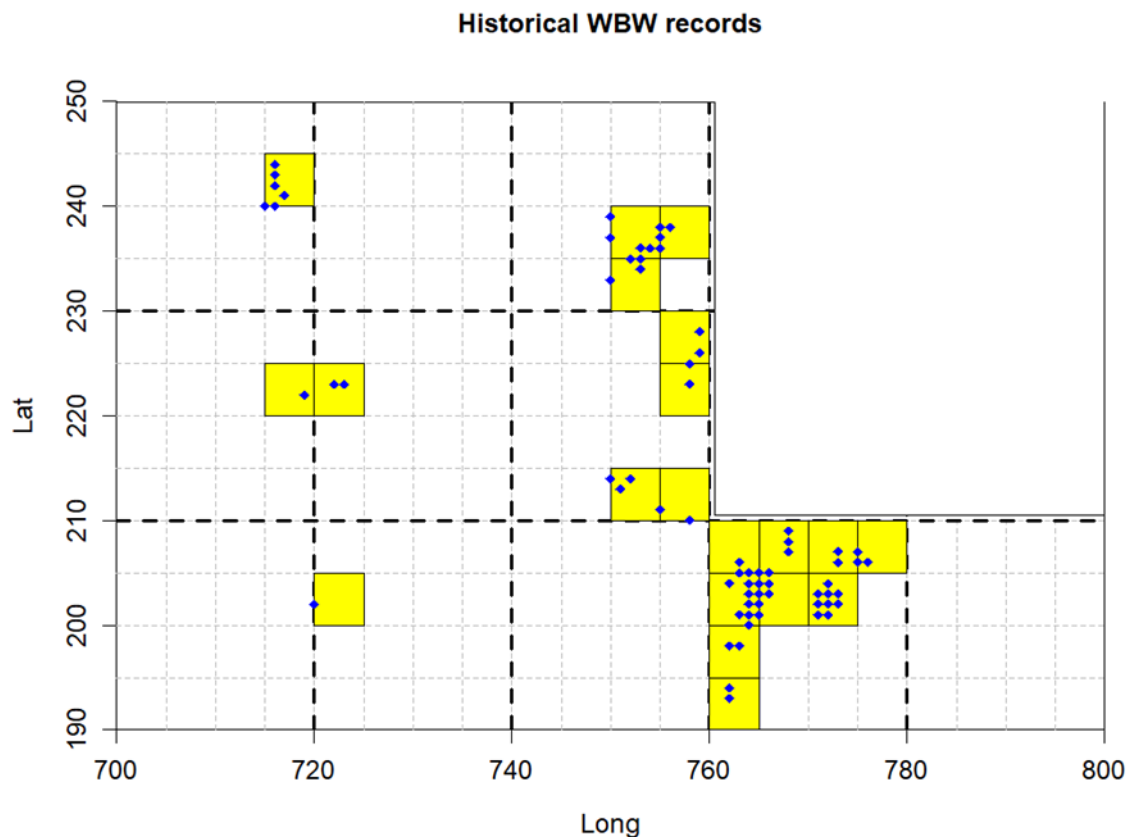


Fig. 2 Eastern Switzerland divided into 20x20 squares (black dashed lines) and nested 5x5 squares (grey dashed lines). The white area in the upper right corner corresponds to a region outside Switzerland (Liechtenstein and Austria). Blue points correspond to the 1x1 square locations of the historic records of the species during 1996-2023. 5x5 squares filled in yellow indicate that the squares satisfy the conditions to be sampled (at least 2 historic records in the same or different 1x1 square). In total, 20 5x5 squares could be selected, but because only four can be sampled in each 20x20 square, this adds up to 15 chosen 5x5 squares.

The proposed scheme also defines the incorporation of new squares to be monitored every year. In particular, any new 5x5 square in Switzerland that eventually accumulates two historical ornitho records must be included into the sampling scheme. The selection of the monitored sites follows the same rules as described before, and again respecting the 20x20 square limit.

2 Simulation of observed detection/nondetection data under the proposed monitoring design

To assess the power to detect a distributional trend under variants of such a monitoring design, we developed simulations that emulated the generation of detection/nondetection data by the observers under the monitoring design described above. As is commonly done in many simulation studies, we first modelled the state process, followed by the observation process. The state process stands for the true presence/absence patterns of the species in the study area. We simulated it in the 1x1 square grids defined in the Swiss Bird Atlas using autologistic dynamic occupancy models (Bled et al., 2011). The observation process stands for the generation of detection/nondetection data under the monitoring design described above and under the effect of imperfect detection (that is, assuming that even if the species is present at a given location, there is a non-zero probability of missing it).

2.1 The state process (simulation of true occupancy patterns)

We simulated the true distribution dynamics of the white-backed woodpecker in Switzerland at the 1 km x 1 km spatial resolution using an autologistic dynamic occupancy model. Autologistic models describe animal movement, as it relates to colonization / persistence dynamics in dynamic occupancy models, locally, that is, in some defined neighborhood around each target cell (Kéry & Royle, 2021). The dynamic rates are expressed as a function of an autocovariate which we define as the proportion of cells occupied in that neighborhood. The size of such neighborhood usually relates to the dispersal ability of the species and the size of the defined cells, so that it adequately represents the ability of the study species to expand to neighboring locations from year to year.

The true presence/absence state z at each 1x1 square i and year t was modelled as a draw of a Bernoulli distribution, where occupied sites at year t had a persistence probability φ of remaining occupied at $t+1$, and empty sites at t had a probability of colonization γ of becoming occupied at $t+1$.

$$z_{i,t+1} \sim \text{Bernoulli}(z_{i,t} * \varphi_{i,t} + (1 - z_{i,t}) * \gamma_{i,t})$$

The probability of colonization γ of a given site i and year t was expressed as follows.

$$\text{logit}(\gamma_{i,t}) = \alpha + \beta_1 * \text{forest}_i + \beta_2 * \text{altitude}_i + \beta_3 * \text{altitude}_i^2 + \beta_4 * \text{Autocov}_{i,t}$$

Here, α is defined as the average colonization probability of every cell. Parameter β describes the relationship between colonization probabilities and different covariates. In the present study, we defined two environmental covariates that could affect colonization rates: forest cover and elevation. We established their relationships with colonization rates based on the features of the actual occupied sites in Switzerland (Figure 3). In the case of elevation, there is a visible strong preference for areas between 500 and 1500 meters a.s.l.. In the case of forest cover, sites with more than 40 % forest cover appear more likely to be occupied. We set the β values accordingly to recreate these relationships.

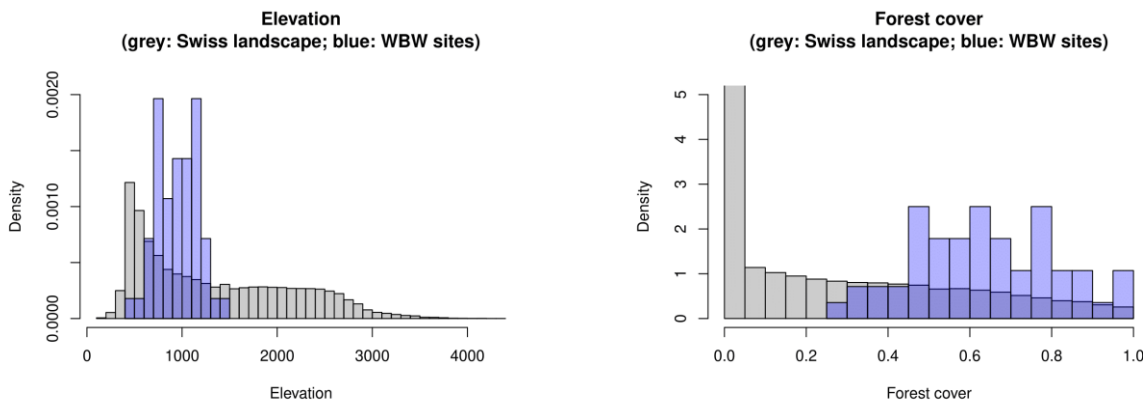


Fig. 3. Elevation (left) and forest cover (right) profile of 1x1 squares all over Switzerland (grey) and in 1x1 squares ever occupied by the white-backed woodpecker since 1996 (blue).

As for persistence probability φ , we defined the same type of relationship with covariates. Again, we defined the β values to establish larger persistence probabilities at specific forest cover and elevation values as in the modelling of colonization.

$$\text{logit}(\varphi_{i,t}) = \alpha + \beta_1 * \text{forest}_i + \beta_2 * \text{altitude}_i + \beta_3 * \text{altitude}_i^2 + \beta_4 * \text{Autocov}_{i,t}$$

We initialized the model setting as occupied at year one all sites where the species has been recorded at least twice from 1996, that is, 70 different sites (Figure 4). We ran the simulations for ten years (Figure 5). We selected intercept average persistence and colonization probabilities such that the resulting range expansion patterns looked realistic to us and some of our colleagues (e.g., Pierre Mollet).

We ran simulations based on these parameters and selected datasets with true rates of increase between 0 and 300 % in the number of occupied sites for the next ten years. We selected this range of increasing rates as it encompasses mostly realistic values according to the biology and demographic traits of the species.

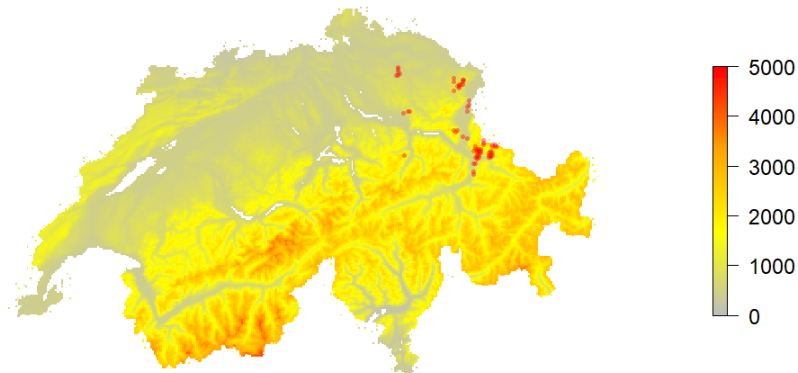


Fig. 2 Points in red indicate the location of sites set as occupied at the beginning of simulations, which corresponds to the 70 locations with historical records in Switzerland. Map background colors indicate altitude.

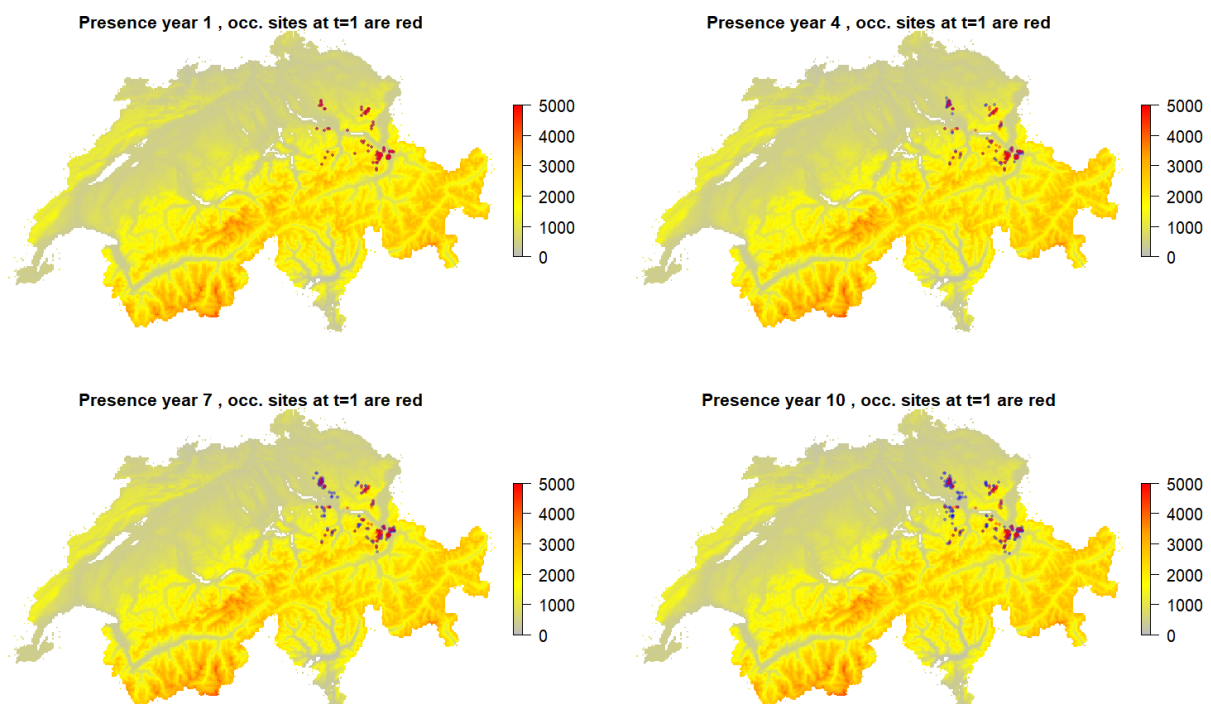


Fig. 3. Example of maps of the simulated presence/absence patterns of the white-backed woodpecker during year 1, 4, 7, and 10 of in one of the simulated datasets, with a 10-year increase rate in the number of occupied sites of 121% (close to the average increase rate of all datasets, 106%). Red points indicate initially occupied sites at year 1, blue points indicate sites occupied in subsequent years. Map background colors indicate altitude.

2.2 The observation process

To simulate the generation of observation data, we designed a simulation model that emulated the monitoring scheme designed for the Swiss population. To select which 1x1, 5x5, and 20x20 squares would be monitored, the same exact rules described in the structured monitoring design were followed.

We simulated a second scenario with an increased initial sample size, with 25 5x5 squares monitored instead of 15. We did so for two reasons. First, owing to the elusive nature of the woodpecker, it is reasonable to think that the distribution of the white-backed woodpecker encompasses a larger number of sites than those recorded at ornitho.ch. Second, testing larger initial monitoring sizes would provide information about whether increased initial sampling efforts would improve the effectiveness of our analytical methods to reliably assess population trends. To select the new monitored sites in this scenario, we followed all rules defined in the monitoring scheme. Hence, we selected ten additional 5x5 squares with at least one historical record in the last 20 years, always considering that a 20x20 square can never have more than four 5x5 monitored squares. In every 5x5 square, we selected the site where the species was historically detected along with a second site with favorable habitat (closest forest cover to 100 %, as close as possible to 1000 m a.s.l.). The species was assumed to be present at those sites at the start of the simulations.

For simplicity, the scenario with a starting population size of 15 5x5 square and that with 25 squares will be called Scenario 15 and Scenario 25 respectively from now on.

We modelled the detection process of the species by the participants of the monitoring scheme considering imperfect detection. To do so, if the species was present in a monitored site, we modelled detection using Bernoulli draws with a 25 % probability of success, following the estimates of occupancy models of the species in Switzerland (Kéry, 2014).

To simulate the addition of new sampled squares into the monitoring scheme every year, we modelled an opportunistic observation scheme. With this scheme, we modelled reports to citizen-science birding platforms by casual observers not belonging to any professional monitoring scheme. We modelled this process by providing every occupied site with a 15 % probability of being detected every year using Bernoulli draws. We selected this 15 % probability as expert detection probabilities for the species are estimated at around 25-30 % (Kéry, 2014), and hence, a decline by almost half in case of non-specialists appeared reasonable. Whenever two casual observations were accumulated in a 5x5 square in two different years, the location was included in the professional sampling scheme from that year onwards, but in all times following the rules of the monitoring scheme (max. four 5x5 squares in a 20x20 square, always two sites in a 5x5 square).

2.3 Simulation settings

We generated 1'700 true presence/absence datasets and their corresponding observed detection/nondetection datasets for both Scenario 15 and Scenario 25. As a spatial resolution within Switzerland, we simulated the data in an area containing 18'000 1x1 squares of the Swiss national grid in the center and east of Switzerland, which corresponded to 37.5 % of the total extension of the country.

2.4 Data analysis

We evaluated the power of the monitoring and analytical designs to retrieve a trend in the number of occupied sites over time. To do so, we performed two analyses sequentially. First, for each observation dataset, we estimated the trend in the number of occupied sites over time. Second, we evaluated the power of the first analyses to detect a significant trend at different true rates of increase of the population.

For analytical purposes, a critical assumption was whether to treat the non-sampled sites every year in the observation dataset as missing values or NAs (i.e., no occupancy information available), or as 0's (assumed as non-occupied by the species). Every assumption has its advantages and disadvantages. By specifying all non-sampled squares as NAs, one is acknowledging that nothing is known about the occupancy status of the squares, even though it appears quite likely, according to the data available at present, that the white-backed woodpecker is only present at a minuscule fraction of them. By specifying all squares as 0s, one assumes that the species is absent at all nonsampled squares. This is of course not true, as we are evidently just sampling a fraction of the whole distribution of the species in Switzerland due to our own monitoring rules and imperfect detection. However, most 0s are likely to be true given the rare nature of the species. Using 0s may lead to overconfidence in model estimates, and using NAs may lead to underconfidence.

We performed our analyses using both 0s and NAs in unsampled squares in the observation datasets. Hence, we performed analyses for four combinations: Scenario 15 + NAs, Scenario 15 + Zeros, Scenario 25 + NAs, and Scenario 25 + Zeros.

2.4.1 Analyses of observed datasets

We fitted a logistic regression using the observed detection/nondetection data as a response variable, time as an explanatory variable, and site random effects for all 1x1 squares. Variable *Detected* takes value 1 if a site has been

ascertained as occupied in a given year (i.e., the woodpecker was detected), and 0 otherwise. α is the intercept and the β coefficient fits a logit-linear relationship between the probability that a site is occupied and time (year). Because all datasets are built with positive population growth, a significant positive estimate of β corresponds to a correct assessment of the population's trend.

$$Detection_{site,year} \sim \text{Bernoulli}(\alpha + \beta * year + \varepsilon_{site})$$

2.4.2 Power analysis

We evaluated how effective our monitoring scheme is at detecting an increasing trend in the number of occupied squares at different true rates of increase over ten years (0-250 %). To do so, we performed a logistic regression where the response variable was the detection of a significant increasing trend in the first analysis (*Sig*, takes value 1 if a significant increasing trend is estimated, 0 otherwise). The explanatory variable was the true rate of increase in the population according to the simulated true occupancy data. α is the intercept and the β coefficient fits a linear relationship between the true population increase rate and the probability of detecting a significant increasing trend in the analyses.

$$Sig_i \sim \text{Bernoulli}(\alpha + \beta * TrueRate_i)$$

This analysis tells us what the power of the design is as a function of the actual magnitude of the increase in the number of occupied sites.

3 Results and discussion

3.1 Overview of the simulated datasets

The generated true state process datasets encompassed a large range of true rates of increase, from 0 % to 300 % mainly ($n = 3'400$ datasets, 1'700 for each Scenario; Figure 6).

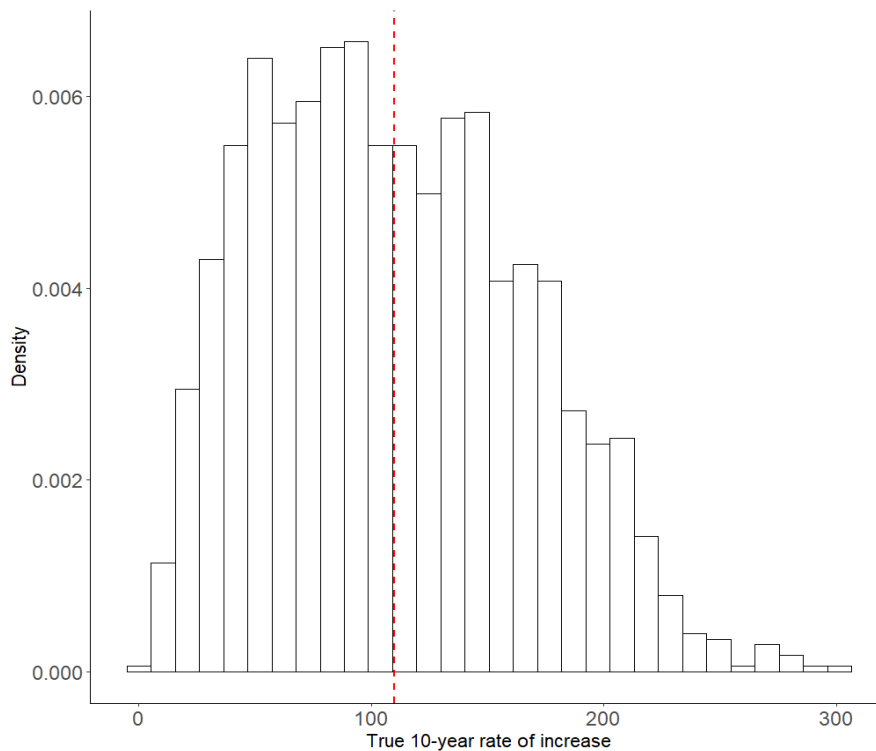


Fig. 4 Relative frequencies of the ten-year rates of increase in the number of occupied 1x1 squares in all simulated occupancy datasets. The mean rate is shown by the red dashed vertical line.

3.2 Analyses of the observed datasets

Overall, for all models and scenarios, the analyses showed a poor ability to detect an increase in the number of occupied sites over time, especially at the most likely rates of ten-year increase, between 0 and 150 %). The power of the models was remarkably improved when applied to data generated under Scenario 25, and also considerably higher in models filled with zeros instead of NAs (Figure 7).

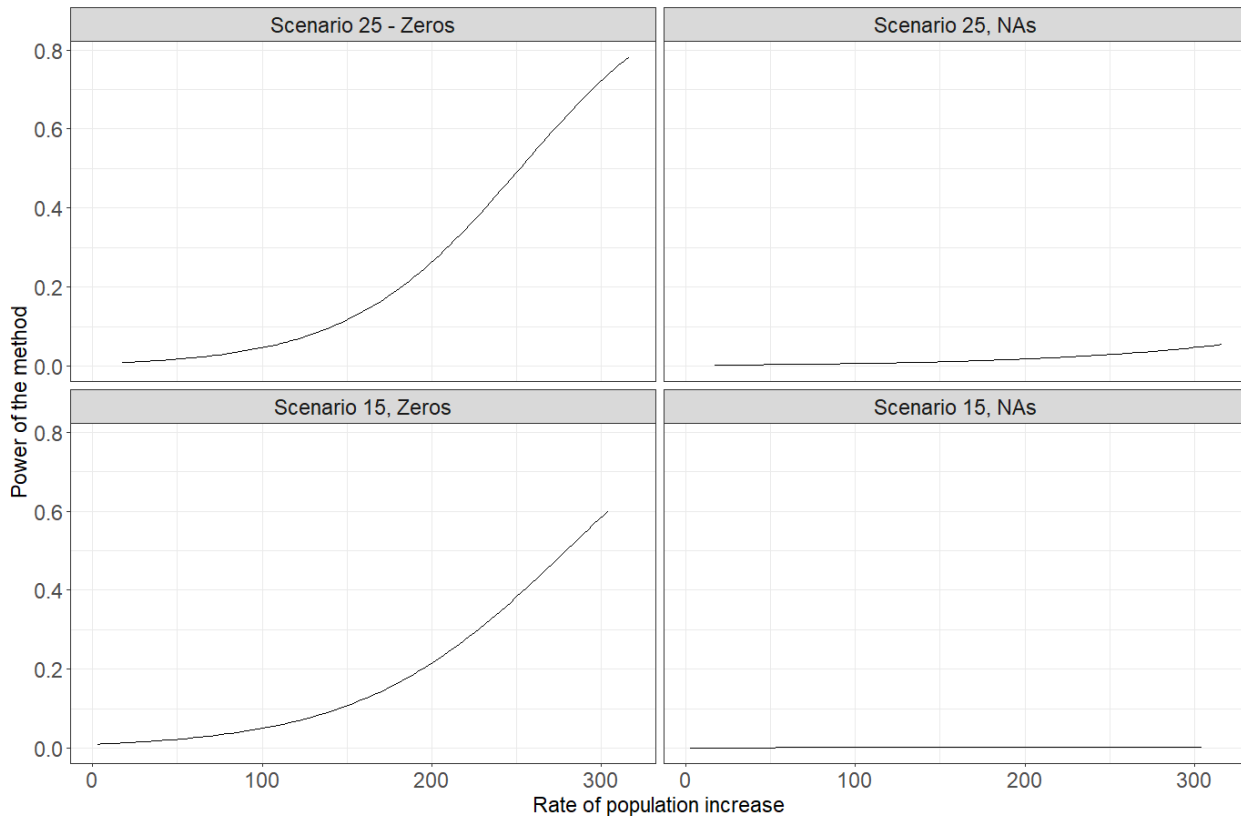


Fig. 5 Probabilities of estimating a significant increase in the number of occupied sites over the years using detection datasets ("Power of the method" on the y axis) at different true rates of population increase (on the x axis) in different combinations of scenarios of initially sampled 5x5 squares (15 and 25), NA-, and zero-filled observation datasets.

When the observation datasets were filled with NAs in nonsampled sites, the power of our methods was basically null. When these were filled by zeros, increased power was clearly visible. However, at growth rates below 200 %, power always remained below 20 % regardless of the scenario. Only at large true rates of population growth, which may be unlikely given the rare nature of the species, power goes over 50 % in the Scenario 25 models. That is, only in those specific circumstances it is more likely that our sampling design and analyses correctly detect an increasing trend than to miss it. The reason for such lack of power may be related to 1) low sample sizes, which limit statistical power, and/or 2) ineffectiveness of the proposed monitoring design. In addition, the low detection probability of the species will also play a role. As for sample size issues, our linear models fitted to the observation datasets failed to detect significant population growth trends in most of the datasets. In this respect, only 8 % of all analyses found a significant positive slope in Scenario 15 with zeros, which declined to 0.2 % when NAs were used. In scenario 25, values slightly increased to 12.9 % with zeros and 1.1 % with NAs. This fact also reveals that using zeros to fill unsampled sites in specific years provides our method with considerably stronger power to detect significant population trends. However, it does so at the cost of invoking a stronger assumption: that all sites not surveyed were unoccupied by the species.

As for the adequacy of the monitoring design, there are two considerations that may show an inability of the methods to capture the true trends of the population. First, the numbers of positive detections per year in the observation datasets show no clear increase over time (Figure 8). On average, in both scenarios an initial decrease can be observed, followed by a slight recovery, although with large variation across datasets. As a second reason for the monitoring design's inadequacy, the linear models fitted to the observed datasets estimated mainly population declines. In Scenarios 15 and 25 with NAs, 82 % and 69 % of all population growth estimates were negative. In scenarios using zeros, the situation was

better, but still far from optimal, with 49 and 41 % of all models predicting a negative growth in Scenarios 15 and 25 respectively. Both findings may be related to the permanent definition of the sampled sites in the monitoring design, which may contrast with the relatively dynamic spatial patterns of the species. In fact, average persistence probabilities were set at around 75% per site and year based on former occupancy models (Kéry, 2014). Hence, extinction is still likely to happen at some of the sampled squares. Even with extinctions, sites are continuously sampled, and contiguous sites are most probably missed as the number of sampled squares per 5x5 square is relatively low (2 out of 25, 8 %). This could be a reasonable explanation for the non-increasing trends found in the observed datasets and in most of the analyses.

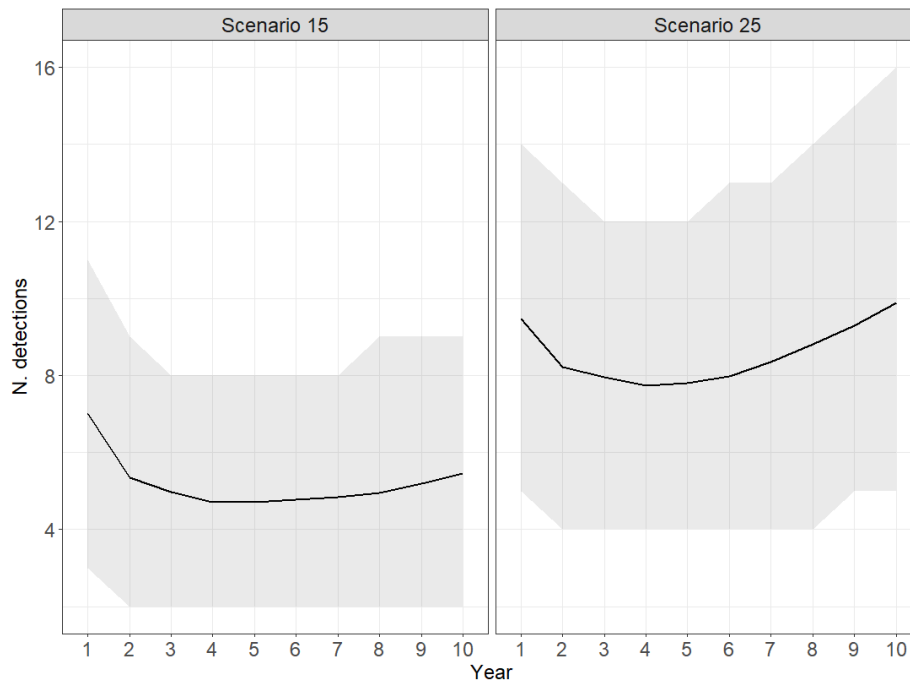


Fig. 6 Average (bold line) and 95% confidence intervals (shaded areas) of the number of times the species is detected every year in the simulated detection datasets in scenarios with an initial number of 15 sampled 5x5 squares (left) and 25 (right).

The monitoring scheme permitted the introduction of new sites to be sampled if certain conditions were satisfied. In the simulated observed datasets, an average of twelve new sites were added over the years, although most of them were added in the last years of the study (Figure 9). However, with a detection probability of ca. 25 % this should add up to an average of three more positive detections in the best of cases, that is, if the species does not go extinct in any of the sites. Such a small value may be too low statistically to detect a population increase.

The results of the models could also be strongly influenced by a mismatch between the dispersal ability of the species and the monitoring design. According to the reported observation patterns from the late 1990s onwards, the spread of the species in Switzerland is rather slow, meaning that the species has slowly expanded westwards, but the distribution is still very localized in the easternmost part of the country. Consequently, the spread has probably occurred mainly within the 5x5 or 20x20 squares defined in the study. Hence, the spatial distribution of the monitoring effort that is restricted to the defined 5x5 and 20x20 squares could have been too spread out for an effective detection of a population increase.

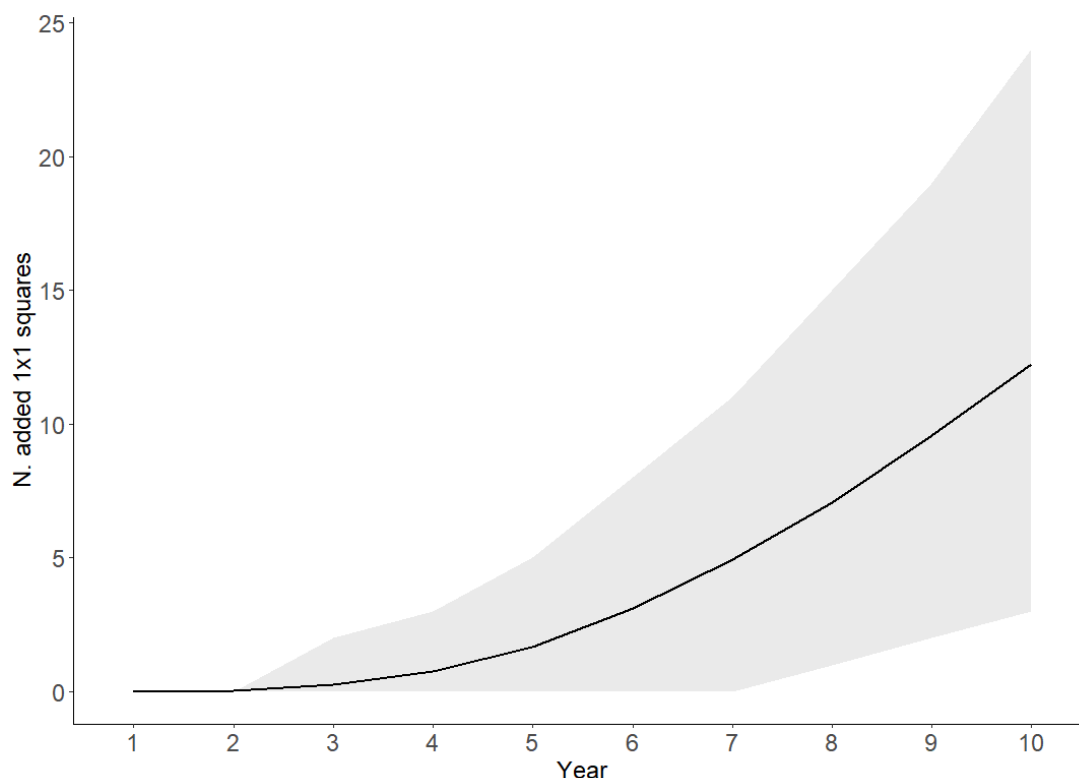


Fig. 7 Average number (bold black line) and 95% confidence intervals (grey shaded area) of added 1x1 squares ("sites") in the monitoring scheme over the years in the simulated observation datasets.

4 Management recommendations

Given the present results, it is highly unlikely that the proposed monitoring design can successfully capture the true dynamics of the population. Our results suggest that only in the scenario of 25 5x5 squares initially sampled and in cases of very large and most probably unrealistic rates of increase (more than 225% in 10 years), the power of our design to capture a population increase will be larger than 50% - still far away from 100%. The results also suggest that filling observation datasets with zeros instead of NAs for unsampled areas may provide the method with a stronger power for this particular study case. While this implies the strong assumption that nonsampled areas have no presence of the species, given the rarity of the species and the large number of modelled 1x1 sites (more than 10,000), most in-filled 0s are likely to be true. Thus, the use of zeros is probably better than that of NAs in our case.

Alternative monitoring designs have not been tested. Opting for monitoring schemes that do not sample the initially selected squares permanently, but try to alternate squares across the years, might not be a guarantee of success given, first, potential technical difficulties associated with the changes in the sampling locations from year to year; and second, the very specific habitat requirements the species has. Any changes in the sampled sites should consider the presence of adequate habitat for the species. More intensive monitoring approaches that select more 1x1 squares within 5x5 squares, or more 5x5 squares within 20x20 squares, could provide larger statistical power as the amount of data and probably also of positive records would increase. However, this would also imply larger amounts of human and economic resources, and probably additional technical challenges too.

Potentially, other alternative monitoring designs based on adaptive sampling, which first identify potential habitat for the species and then specifically monitor a subset of such areas, could be a feasible approach for the species given its high degree of specialization (Pacifi et al., 2012). However, the economic and human resources needed for such exploratory sampling and future implementation of the project have not been discussed.

5 Acknowledgements

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