

## WILDPOP: AN INTERACTIVE TOOL FOR ESTIMATING OCCUPANCY AND ABUNDANCE OF WILDLIFE POPULATIONS

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**Abstract:** Species abundance or population size is an ecological parameter of critical importance for wildlife management and conservation decisions. Widely used data collection methods, such as sign surveys and remote cameras, often count non-identifiable individuals or individuals prone to misidentification. In ecological modeling, these individuals are considered unmarked, and a state-of-the-art modeling approach for such data is occupancy-type modeling for unmarked individuals, which explicitly incorporates imperfect detection. Hierarchical modeling of this kind requires advanced statistical analyses, typically conducted using the R software platform and the “unmarked” package. However, these models can be explored only by researchers with programming skills and a thorough understanding of hierarchical analysis of wildlife population data. To help researchers and practitioners implement these models, we have developed a Shiny web-based interactive tool for wildlife population assessment, which works with data collected by scientists and wildlife managers. This app facilitates the use of occupancy-type modeling for unmarked individuals (single-season single species occupancy and N-mixture models) for non-coder users. The app performs simulations for single-season single species occupancy and N-mixture models with or without covariates, and estimates occupancy and abundance employing users provided data. The results are displayed as text, tables, and graphs, helping users understand hierarchical modeling and answering real-life wildlife management questions.

**Keywords:** hierarchical modeling, single-season single species occupancy, N-mixture abundance, Shiny, unmarked, Romania

### 1. INTRODUCTION

Population size is an ecological parameter of critical importance when making wildlife management and conservation decisions. Mammalian species, such as ungulates and carnivores, are primarily managed based on the concept of optimum densities (i.e., carrying capacity) (Hunter et al., 2021). The effectiveness of wildlife management decisions (e.g., stricter protection, relocation of individuals, hunting permits) rely on robust wildlife abundance data (Darimont et al., 2018). In Romania, animal sign surveys are the main method for wildlife monitoring and have been used by wildlife managers for decades

(Cazacu et al., 2014). However, they lack appropriate sampling approaches (Popescu et al., 2019). The outcome of this process, which does not fully account for other sources of bias (e.g., unbalanced sampling, observer error, other sources of mortality), can propagate errors and produce inaccurate abundance estimates (Popescu et al., 2016).

Advances in digital technology used in animal ecological studies and emerging cost-effective tools, such as artificial intelligence (AI), provide an unprecedented opportunity for wildlife managers and conservationists to apply advanced monitoring methods worldwide, e.g., camera-trapping methods (Vélez et al., 2022). In Romania, recent studies using

camera traps to monitor terrestrial wildlife have produced numerous images/videos of animals (Băncilă et al., 2024). Still, these studies are rarely done methodically or with sufficient replication to allow robust statistical modeling (Rozyłowicz et al., 2024). Many studies focus on addressing wildlife manager queries (e.g., quantifying how many deer or bears congregate at a feeding station) rather than understanding which factors and processes drive the occurrence or distribution of species of interest. Consequently, much of the data collected has limited value for assessing patterns of species distribution across landscapes, and is often proprietary. Two of the most commonly used methods currently in Romania, including sign surveys and remote cameras, rely on counts of individuals that are not individually recognizable (i.e., unmarked) or can be misidentified by experts (Long et al., 2012). A state-of-the-art modeling approach known as occupancy-type modeling for unmarked individuals that explicitly accounts for imperfect detection has become widely used for such data (Fiske & Chandler 2011; MacKenzie et al., 2017; MacKenzie et al., 2002; Royle 2004; Tyre et al., 2003).

Camera traps, while easily deployable, require following a rigorous sampling design (i.e., spatial arrangement, number of sampling points, and sampling duration). Additionally, the analysis of camera trap data requires advanced statistical techniques, e.g., available via the R software platform and employing the “unmarked” R package (Fiske & Chandler 2011; Kellner et al., 2023). The R language platform is widely used for ecological modeling (R Core Team 2024), but complex methods such as those included in “unmarked” package can be explored only by users with good programming skills and a knowledge of hierarchical analysis of wildlife population data (Kery & Royle 2016; Royle & Dorazio 2008).

To estimate site occupancy, MacKenzie et al., (2002) developed a single-season occupancy model that accounts for imperfect detection during multiple surveys across multiple sites. The model uses detection/nondetection observations, from  $M$  sites and  $J$  surveys at site  $i$  during survey  $j$ , yielding  $y_{ij}$  data. These values are 1 when a species is detected at site  $i$  on survey  $j$  and values and 0 when the species is not detected. The occupancy model is a hierarchical model that couples an ecological process determining site occupancy, with an observation process determining species presence. In the ecological process part, the latent (unobserved) state, represented by the true occurrence  $z_i$  ( $z_i = 1$ , if the site  $i$  is occupied;  $z_i = 0$  if the site  $i$  is not occupied) is modeled as a Bernoulli random variable governed by the parameter occupancy probability  $\psi$  [ $z_i \sim \text{Bernoulli}(\psi)$ ]. In the observation process part the observations,  $y_{ij}$ , are

also modeled as a Bernoulli random variable with a success rate that depends on the actual occurrence at site  $i$ ,  $z_i$ , and the detection probability ( $p$ ) at site  $i$  during survey  $j$ : [ $y_{ij} | z_i \sim \text{Bernoulli}(z_i p)$ ]. In the single-season occupancy model, both occupancy ( $\psi$ ) and detection ( $p$ ) are constant across all sites. Both the ecological and the observation process are represented as logistic regressions making it natural to include covariates via a logit link function. For the observation process, we can distinguish between site covariates and survey covariates. The site covariates vary only by site and are constant across repeated surveys. Survey covariates vary across sites and surveys (MacKenzie et al., 2017; MacKenzie et al., 2002).

The N-mixture (binomial) model (Royle 2004) follows a repeated measures design similar to the occupancy model, where site  $i = 1$  to  $M$ , are sampled for occasions  $j = 1$  to  $J$ , and the number of individuals of a species is counted. The observations are counts,  $y_{ij}$  of independent individuals within a period of closure. The ecological and the observational process can be represented as  $N_i \sim \text{Poisson}(\lambda_i)$  (initial ecological process  $i$ ) and  $y_{ij} | N_i \sim \text{Binomial}(N_i p)$  (observation process), where  $p$  is individual-level detection probability. The spatial variation in local abundance at site  $i$ ,  $N_i$  is described by a Poisson distribution with a mean  $\lambda$ . The observation submodel assumes a binomial distribution condition on the true population size  $N_i$  at site  $i$ . We can specify covariates for both abundance and detection probability.

To date, there is no sampling-to-results application of these models available in Romania for wildlife managers or conservationists lacking advanced modeling skills. The absence of a structured framework for planning and implementing field monitoring, collecting and, analyzing data, and interpreting results impedes the widespread application of this modeling framework, particularly in countries like Romania with limited funding for applied research (Rozyłowicz et al., 2024). To bridge this gap, we facilitate the uptake of occupancy-type modeling for unmarked individuals (single-season single species occupancy and N-mixture models) for wildlife managers without advanced skills in modeling by deploying a Shiny web-based interactive tool (Chang et al., 2024; R Core Team 2024) (WildPop, available at <https://wildpop.ccmesi.ro/>). The WildPop app will perform the necessary computations outlined above in a user-friendly graphical interface while maintaining statistical rigor.

## 2. WORKFLOW AND METHODS

WildPop is designed to fit two types of hierarchical models for unmarked individuals

integrated into *R* package “unmarked” (Fiske & Chandler 2011), i.e., single-season single species occupancy model (MacKenzie et al., 2002) via function *occu*, and the N-mixture abundance model (Royle 2004) via function *pcount*. These models use detection/nondetection and count data (number of occurrences) recorded at multiple survey sites to concomitantly estimate the occurrence or abundance probability (state process) and detection probability (observation process) (Royle & Dorazio 2008).

WildPop offers users the opportunity to explore the results of the two hierarchical models using simulation data based on different occurrence and detection probabilities (for the single-season single species occupancy model), or abundance and detection probabilities (for the N-mixture model). The simulation module integrated into the app also enables users to investigate the effects of environmental covariates on these parameters and replicates examples provided by Kery & Royle (2016). In the single season occupancy and N-mixture modules, users can fit either the occupancy or N-mixture model and extract the results using their own data. For illustrative purposes, the models can be fitted with demo datasets. We provided Mink frogs (*Rana septentrionalis*) occurrence dataset, included in Popescu & Gibbs (2009) for the occupancy model, and *Plagionotus detritus* (long-horned beetle) abundance dataset included in Brodie et al., (2019) for the N-mixture abundance model.

In the simulation of the single-season single species occupancy model by MacKenzie et al., (2002), as included in Kery and Royle (2016), users are required to input of a random seed number (to facilitate obtaining the same outputs when using similar parameters), the number of sites to be surveyed, the number of visits to record the species of interest, the estimated probability of occupancy, and the estimated detection probability. The app fits the null model using function *occu* (i.e., no covariates included in model) and allows users to visualize the results as raw summaries (model summary generated by “unmarked”), and occupancy and detection probabilities back transformed to the probability scale using the function *backTransform*. The model can be extended to investigate further whether explanatory (covariates) influence occupancy or detection probability. Covariates that are known to influence detection alongside covariates that influence occurrence are randomly generated as scaled variables, i.e., lying within the range [-1,1]; scaling removes the units and makes numerical covariates comparable. Users can explore the model by

adjusting the intercept and slope of each covariate to understand how these variables affect detection and occupancy probabilities. Modeling results are visualized as occupancy and detection probabilities and through graphs that show the relationship between occurrence/detection probabilities and covariates.

The simulation of Royle’s (2004) N-mixture abundance model is also based on the code provided by Kery & Royle (2016) and requires parameters similar to those used in the occupancy model: a random seed number, the number of sites to be surveyed, the number of visits to record the species of interest, estimated abundance (instead of probability of occupancy), and estimated detection probability (at individuals level). Similar to the single-season single species occupancy model, the results of the N-mixture null model are shown as abundance (on log and natural scale) and detection probabilities (on logit scale and natural scale). In this null model version, the latent abundance distribution (mixture) is set as a Poisson-distributed random variable, but other types of count-based distributions (negative binomial and zero-inflated Poisson) can be specified. Extending the model with covariates for abundance and detection requires the input of the intercept and slope of each covariate. The app first fits a null N-mixture model for each latent abundance distribution (Poisson, negative binomial, or zero-inflated Poisson), ranks the three mixture-specific models by Akaike Information Criterion corrected for small sample sizes – AICc (Burnham & Anderson 2002; Mazerolle 2024). Then, the app displays the raw model results on the log and natural scale and uses the best model (lowest AICc) to plot the relationship between covariates and abundance and detection. This includes (1) the relationship between site covariates and true abundance, (2) estimated abundance as resulted from the N-mixture model, and (3) estimated abundance from a Poisson regression without accounting for imperfect detection.

Users can fit the single-season single species occupancy model (MacKenzie et al., 2002) on their own data (Figure 1). The model can include or exclude covariates for occupancy and detection. Input data can be selected from pre-populated datasets (for demonstration purposes) or uploaded by the user. The uploaded data must be in a single comma-separated values (.csv) file, following “unmarked” package format specifications (Fiske & Chandler 2011). Each row corresponds to a unique site (1 to  $M = 5$  sites). Columns correspond to visits (1 to  $J = 4$  surveys) and site-level covariates (i.e. distance to road (m) and land

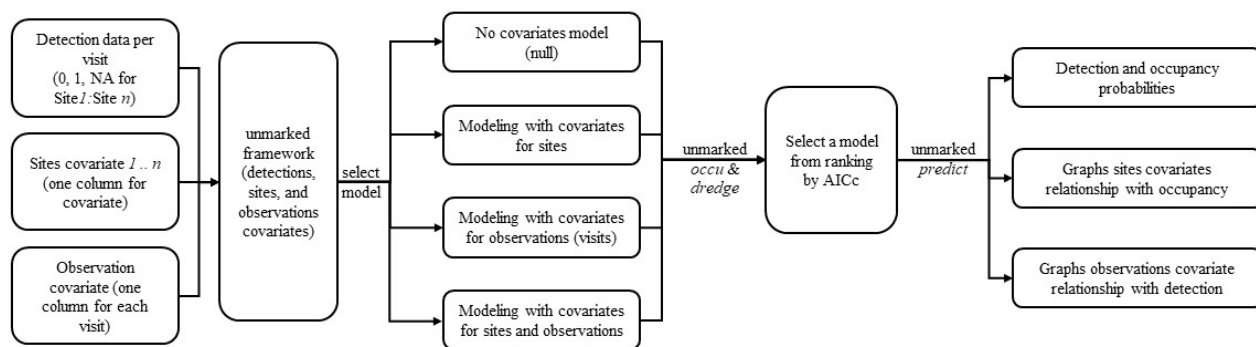


Figure 1 Workflow of single-season single species occupancy model included in WildPop. The model is based on *occu* function of “unmarked” R package.

Table 1 Example of dataset structure for single-season single species occupancy model: occurrence data, (binary data, 1 for detection, 0 for nondetection) from each site (e.g., Site 1 to Site 5) during multiple visits (e.g., Visit 1 to Visit 4), site-level covariates (e.g., distance to road and landuse) and survey covariates (e.g., wind speed recorded at each visit, Wind1 to Wind4). For the N-mixture abundance model, data includes counts (integer, from 0 to  $n$ ) from each site during multiple visits. NAs or blank are allowed only for visits.

Site name	Visit1	Visit2	Visit3	Visit4	Distance to roads	Landuse	Wind1	Wind2	Wind3	Wind4
Site1	0	1	0	1	1.2	forest	2.5	0	1	2.2
Site2	NA	0	0	0	0.1	grassland	12	2	0	4
Site3	1	0	0	1	5.5	forest	4	3	0	20
Site4	0	0	NA	0	4.5	grassland	5	4	0	2
Site5	0	0	1	1	2	forest	0	1	0	2

use type), and survey covariates (i.e. wind speed (m/s) (Table 1). Observations or detection/nondetection data ( $y_{1,1}, \dots, y_{J,M}$ ) and values/levels of covariates are represented as entries in the table. Observations can take a value of 0 (indicating the species of interest was not detected), 1 (indicating the species of interest was detected), or left blank or labeled NA (indicating no survey was conducted, for example, due to the loss of a camera at a specific site). Occupancy covariates are measurements taken at each site once and are represented by a single individual column in the dataset. We recommend fitting the model with no more than three covariates for site occupancy. Detection covariates are measured at each visit, i.e., if the detection/nondetection data is collected during four visits, detection covariates must be four columns wide (one measurement for each visit at each site). Other examples of detection covariates are: number of days the camera was active during the particular survey conducted (e.g., per week, month), weather conditions, such as precipitation, snow, temperature during the survey conducted once a month or specific season.

After selecting the columns covering the observation data (detection/nondetection data is mandatory while covariates are optional), users must select one of four types of models from a dropdown menu: (1) the Null model (the model with only detection/nondetection data), (2) the model with covariates for sites, (3) the model with covariates for

visits, and (4) the model with covariates for sites and visits. Then users run the model using *occu* function in “unmarked”. The model selected should match the data; for example, if no covariates for visits were selected, the options are the Null model or the model with covariates for sites. The results are presented as model summaries of the fitted models, and a model selection table listing all possible simpler models of the global model, i.e., the most complex model the user considers. The model selection is done using the function *dredge* from the R “MuMIn” package (Bartoń 2024), that partially automates the model generation. Models are ranked by AICc the model with the lowest AICc being the best model. Users should select a model from the list, and the WildPop will return (i) the model summary, including coefficient estimates of occupancy and detection on logit-scale, (ii) graphs that show the relationship between the predicted values of occupancy and detection probabilities (on the probability scale) and covariates, if any selected, and (iii) graphs that show the variation in species detection and occupancy probabilities across sites or among surveys.

For abundance, WildPop fits the N-mixture model of Royle (2004) with or without covariates using function *pcount* (Figure 2). Similarly to single-season single species occupancy models, WildPop can fit the model using demo or user provided data. Data structure follows the same specifications as for

the occupancy model (see Table 1), except the species records are counts instead of 0/1 (e.g., number of individuals photographed at a remote camera between visits, number of times an animal frequented the area).

After uploading the data and selecting the columns for counts, site-level covariates (optional) and surveys covariates (optional), the user can fit a null N-mixture model with any of three variants of distribution (Poisson, negative binomial, or zero-inflated Poisson), and identify the best supported model (lowest AICc). After this step, the user selects the best distribution (or mixture) that fits the data from a dropdown menu (P = Poisson, NB = negative binomial and ZIP = zero-inflated Poisson), and runs one of four types of N-mixture models: count data only (Null model), with covariates for sites, with covariates for visits, and with covariates for sites and visits. The selection should be based on entry data (i.e., if there are no survey covariates selected, then only the Null model and the model with covariates for sites can be fitted). After selecting the correct model type and fitting the N-mixture model with function *pcount*, the results are presented as in the single-season single species occupancy model.

The app, available in Romanian at <https://wildpop.ccmesi.ro/>, was built in R 4.3.3 (R Core Team 2024) via RStudio Desktop IDE (Posit Software) with the following packages: “Shiny” (Chang et al., 2024), “unmarked” (Fiske & Chandler 2011), “bslib” (Sievert et al., 2024), “AICcmoavg” (Mazerolle 2024), “MuMIn” (Bartoń 2024), “DT” (Xie et al. 2024), “tidyverse” (Wickham et al., 2019) and “shiny.busy” (Meyer & Perrier 2024).

### 3. DISCUSSION

Reliable estimates of population abundance and species distribution are paramount for informed wildlife management, especially for species in decline or species at the core of human-wildlife conflict. Yet, state-of-the-art modeling approaches, such as hierarchical analysis, are seldom applied by researchers and wildlife

management practitioners outside of developed countries (Rozyłowicz et al., 2024).

To fill this gap, we deployed a user-friendly Shiny app to integrate two commonly used hierarchical modeling methods of detection/nondetection and count data, i.e., static (single season) single species occupancy and N-mixture models implemented in “unmarked” R package (Fiske & Chandler 2011). Shiny is a promising tool for allowing non-coders to use R or Python complex modeling approaches (Chang et al., 2024) via a friendly user interface. Examples of its applications include (e.g., species distribution modeling (Kass et al., 2023), hierarchical modeling and environmental capacity (Tang et al., 2023), occupancy studies using camera trap data (Tabak et al., 2020), hierarchical Bayesian occupancy using environmental DNA data (Diana et al., 2021) or tutorials for occupancy modeling using RPresence (Donovan et al., 2024).

The static single species occupancy model (MacKenzie et al., 2002) was the first occupancy model developed (Kellner et al., 2023) and remains the most widely used in occupancy studies (Rozyłowicz et al., 2024). This popularity is due to low data requirements (i.e., detection/nondetection of unmarked individuals at multiple sites replicated over time) and the relative simplicity of the model (Kellner et al., 2023; Kery & Royle 2016). This model allows the researchers to estimate the probability of occurrence and detection of species within the study area, while exploring hypotheses about the influence of environmental and sampling covariates (MacKenzie et al., 2017).

A recent review of occupancy-types models (Rozyłowicz et al., 2024) showed that out of 697 studies selected for inclusion in the review, 31% employ single-season occupancy modeling, highlighting its widespread use. Common data collection methods for these studies include visual surveys (e.g., Schmidt et al., 2015), camera traps (e.g., Parren et al., 2022), and acoustic surveys (e.g., Tingley et al., 2020) (Rozyłowicz et al., 2024), which fits well our Shiny app. Mammals are the most

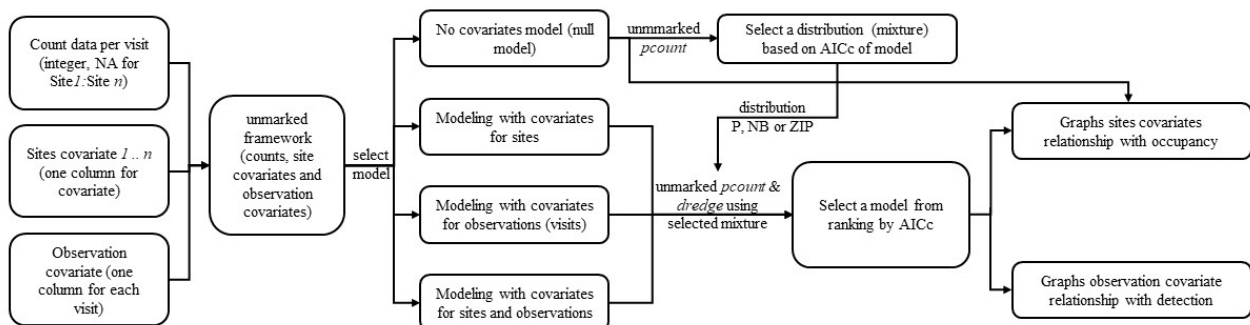


Figure 2 Workflow of N-mixture model included in WildPop. The model is based on *pcount* function of “unmarked” R package

modeled taxonomic groups, followed by birds and amphibians (Rozyłowicz et al., 2024). Research questions were diverse, ranging from understanding the local probability of occupancy of a species (e.g., Williams et al., 2020) to documenting the impact of climate change on species presence at the continental level (e.g., Soroye et al., 2020).

The static N-mixture method, first introduced by Royle (2004), is the second most used model in occupancy-types studies accounting for 15% out of 697 studies reviewed by Rozyłowicz et al., (2024). This model also has straightforward data requirements, relying on counts of unmarked individuals (Kellner et al., 2023). This model estimates the abundance and detection probability while examining the importance of environmental and detection covariates (MacKenzie et al., 2017; Royle 2004; Royle & Dorazio 2008). Researchers frequently use visual surveys (e.g., Harris & Betts 2021), followed by acoustic surveys (e.g., Fogarty et al., 2022) and camera traps (e.g., Farr et al., 2022), to model primarily abundance and detection of birds followed by amphibians and mammals (Rozyłowicz et al., 2024). The limited use of the static N-mixture approach for data obtained from camera traps, as well as the underrepresentation of mammals in these studies, are likely because count data obtained from camera traps can be easily integrated into more complex studies.

Despite the high biodiversity of Romania (Rozyłowicz et al., 2019, Stanciu et al., 2023) and stringent policy requirements for monitoring protected species (Pindaru et al., 2023), we found only four occupancy studies focused on Romania (Rozyłowicz et al., 2024). Two studies used the N-mixture static model to estimate the abundance of beetles and beetle community composition in Iron Gates Natural Park (Băncilă et al., 2019) and brown bears in Eastern Romanian Carpathians (Popescu et al., 2017). The other two studies used slightly more complex methods, i.e., a multi-state occupancy method for modeling occurrence and breeding probability of *Rana temporaria* in Retezat National Park (Băncilă et al., 2017) and a multispecies occupancy model of two or more interacting carnivore species in the Southern Carpathians (Dyck et al. 2022).

The lack of studies in Romania reaffirms the utility of an interactive app for non-coders. The app, together with the accompanying webpage (<https://wildpop.ccmesi.ro>) and the guideline for occupancy and abundance estimation of wildlife (Băncilă et al., 2024), will be maintained by the University of Bucharest and updated regularly to allow researchers and managers to explore the

hierarchical modeling of occupancy-types data. WildPop suite will unlock the development of wildlife monitoring services in Romania by improving the capacity of interested parties to analyze occupancy-type data that are currently accumulating in national and international repositories.

### Acknowledgments

The research was supported by a grant from the Executive Unit for Financing Higher Education Research Development and Innovation ([www.uefiscdi.ro](http://www.uefiscdi.ro)), PN-III-P2-2.1-PED-2021-1965, Interactive tool for estimating abundance of wildlife populations (WildPop).

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Received at: 02. 06. 2024

Revised at: 03. 07. 2024

Accepted for publication at: 06. 07. 2024

Published online at: 08. 07. 2024