# 01\_question-info-box POST-DEMO

## (#i\_sp\_behav\_seasonal)=

# Behaviour – seasonal

**notes**

Include info pop-up for importance of considering seasonal behaviour

## (#i\_sp\_3identifying\_traits)=

# Target Species; Identifying traits

identifying traits

**Question:** Are there 3+ categories of traits that can be be used to identify individuals? (i.e., information used to identify individuals that can be divided into distinct groups, e.g, sex class, age class, coat colour, markings and antler point count; Clarke et al., 2023)

**notes**

## (#i\_sp\_markings)=

# Target Species; Natural or artificial markings

Marked, Partially marked, and Unmarked - definitions and explanation; can mention modelling approaches, but meant to be more conceptual

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| **Question:** Do individuals have natural or artificial marks such that they can be uniquely identified? (i.e. are the individuals, population, or species "marked," "unmarked," or "partially marked") | | | | |
| **Overview** | | | | |
| **Advanced**   * **Marked individuals / populations / species:** Individuals, populations, or species (varies with modelling approach and context) that can be identified using natural or artificial markings (e.g., coat patterns, scars, tags, collars). * **Unmarked individuals / populations / species:** Individuals, populations, or species (varies with modelling approach and context) that cannot be identified using natural or artificial markings (e.g., coat patterns, scars, tags, collars). Unmarked population models rely on supplementary data (e.g., animal movement speed) and/or assumptions as a surrogate for individual identification; that is, to distinguish between multiple detections of the same individual from detections of multiple individuals when individuals do not have unique features (Gilbert et al., 2020; Morin et al., 2022). * **Partially marked individuals / populations / species:** Individuals, populations, or species (varies with modelling approach and context) that have a suite of partially identifying traits (e.g., antler points, sex class, age class). For populations/species, those in which a proportion of individuals carry marks or in which individuals themselves are partially marked. | | | | |
| **Figures & Videos** | | | | |
| A collage of a giraffe and a goat  Description automatically generated  ```{figure} ./images/clarke\_et\_al\_2023/Clarke-et-al\_2023\_Fig1\_clipped.jpg  :align: center  ```  **Figure 1.** Examples of naturally (A) and artificially (B) marked animals. A) This jaguar’s unique pattern of spots can be used to distinguish it from other individuals in its population. © Chris Beirne, Wildlife Coexistence Lab and Osa Conservation. B) This mountain goat was collared and marked prior to camera trapping. Its numbered tag clearly identifies which individual it is. © Mitchell Fennell, Wildlife Coexistence Lab.  (Clarke et al., 2023) | |  | | |
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| **Analytical tools & resources** | | | | |
| **Name** | **Link** | | **Reference** | **Additional\_info** |
|  |  | |  |  |
|  |  | |  |  |
| **References**  (Clarke et al., 2023) | | | | |

**notes**

## (#i\_sp\_type)=

**Question:** Is the Target Species a carnivore or ungulate?

In this case, we define “carnivore” based on (diet....taxonomy).

carnivore taxa vs diet, ensure it is clear

check Rowcliffe et al., 2008

**notes**

* carnivores are known to cover a larger distance than species of other feeding guilds (Garland 1983)
* “For example, for a low-density highly mobile species such as a large carnivore, or a species with relatively large home ranges compared with the size of the sampling units, the proportion of area ‘used’ over a longer timeframe may be close to 100% even though population size is very small.” ([Mackenzie and Royle, 2005, p. 1108](about:blank)) ([pdf](about:blank))
* “carnivores were detected more frequently compared to the herbivores.” (Chatterhee et al., 2021)

## (#i\_focal\_binned\_distance)=

# Focal area measured or detections binned by distance?

provide more info on what this means

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| --- | --- | --- | --- | --- |
| **Question:** Focal area measured or detections binned by distance? | | | | |
| **Overview** | | | | |
| **Advanced** | | | | |
| **Figures & Videos** | | | | |
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| **Analytical tools & resources** | | | | |
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| **References** | | | | |

**notes**

## (#i\_mod\_zi\_overdispersion)=

# Overdispersion + Zero-inflation

explain zi + overdispersion and how to evaluate + info for glmmTMB R package (can be used for count data with ZI and random effects) + Dharma package for simulating overdispersion

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| --- | --- | --- | --- | --- |
| Question: | | | | |
| **Overview**  **Zero-inflation:** An excess of zeros that is "so large that those expected in standard distributions (e.g., normal, Poisson, binomial, negative binomial and beta)" (Heilbron, 1994) violate the assumptions of such distributions (Martin et al., 2005). Excess zeroes can be a result of ecological effects ("true" zeros) or due to sampling or observer error ("false zeros") (Martin et al., 2005). Excess zeroes contribute to overdispersion, but they don't necessarily account for all excess variability (Blasco-Moreno et al., 2019).  **Overdispersion**: A variance significantly larger than the mean (Bliss & Fisher, 1953); greater variability in a set of data than predicted by the error structure of the model (Harrison et al., 2018); excess variability can be caused by zero inflation, non-independence of counts, or both (Zuur et al., 2009).  Four ways zeros arise in ecological data (Martin et al., 2005): | | | | |
| **Advanced** | | | | |
| **Figures & Videos** | | | | |
| * **Video:** [Statistical Methods Series: Zero-Inflated GLM and GLMM](about:blank) (<https://www.youtube.com/watch?v=ISN9SE__QOU> | | |  | |
|  | | |  | |
| **Analytical tools & resources** | | | | |
| * Model types that can accommodate zero-inflation include combined models of occurrence and relative abundance (N-mixture models), such as Zero-inflated Poisson (ZIP) (Lambert, 1992) or Zero-inflated negative binomial (NB) regression models, Hurdle models (Mullahy, 1986), Royle–Nichols model (Royle & Nichols, 2003, e.g., Dénes et al., 2015), among others. * Wenger and Freeman (2008) also proposed a three-part model that can be used to simultaneously model detection probability, occupancy, and relative abundance. * Observation-level random effects may also be useful to address extra-Poisson variation (useful when overdispersion is present) (Harrison et al., 2014). * ZIP mixed models can be used to model predictors of detectability and minimize other confounding variation when species are relatively common, and sampling sites over extended periods reduces the variation in detection probability (O’Brien 2011). * In ZI mixed models, detection probability is modelling through the zero-inflation model-part...... does not assume that detection probability is independent of abundance (Johnson 2008; Etterson, Niemi, and Danz 2009). * Highly suggested to.... since failure to account for detection probability may result in an inability to differentiate preference from detectability (Jennelle, Runge, and MacKenzie 2002), which is a limitation of camera studies (Burton et al. 2015; Dénes et al. 2015; Kays et al. 2021), and/or cause large errors in estimates of both occurrence and abundance (Burton et al. 2015; Dénes et al. 2015; Kays et al. 2021). * Note that variability in sampling effort between cameras can be accounted for count data as an "offset" that is used to convert the count to a rate per unit time while still abiding by the assumptions of count-distributed data). | | | | |
| **Name** | **Link** | **Reference** | | **Additional\_info** |
|  | <https://www.youtube.com/watch?v=ISN9SE__QOU> |  | |  |
|  |  |  | |  |
| **References**  (Harrison et al., 2018)  (Harrison et al., 2014)  (Heilbron, 1994)  (Martin et al., 2005)  (Blasco-Moreno et al., 2019)  (Bliss & Fisher, 1953)  (Zuur et al., 2009) | | | | |

**notes: Choosing a model – count data**

* “They should only be used when it is not possible to conduct a proper population estimation study or a study that includes estimation of the detection probability. This issue is especially acute for sampling cryptic or rare species, typical target species in camera trap surveys (Carbone et al. 2001, 2002; Jennelle et al. 2002). An index can be any count of animals or sign that is expected to vary directly with population size (Caughley 1977).” {O’Brien, 2011 #409}
* **Data and R code VOLUME I (**<https://www.highstat.com/index.php/books2?view=article&id=10&catid=18>)
* Feng, C. X. (2021). A comparison of zero-inflated and hurdle models for modeling zero-inflated count data. J Stat Distrib Appl, 8(1), 8. <https://doi.org/10.1186/s40488-021-00121-4>

## (#i\_mod\_mixed)=

**Question:** Are you using / Do you plan to use mixed models?

provide more details for naive user + Explain random effects for site to account for repeated counts from the same location + Provide info for glmmTMB R package which can be used for count data with ZI and random effects + Dharma package for simulating overdispersion

## 

## (#i\_mod\_zi\_hurdle\_process)=

# Hurdle model vs. ZI model (zero-inflation secondary process)

INFO POP-UP ZI vs hurdle models + explanaton of "another process contributing"

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| --- | --- | --- | --- | --- |
| **Question:** Do you believe that another process may be contributing to excess zeros? [need to rephrase] | | | | |
| **Overview**  Zero-inflated Poisson (ZIP) and hurdle models are both generally used in the setting of excess zeros.  “Hurdle models suggest a two-part process. The first part induces an event, and once the hurdle to the first event has been cleared, the second part determines the number of subsequent events.” | | | | |
| **Advanced** | | | | |
| **Figures & Videos** | | | | |
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| **Analytical tools & resources** | | | | |
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| **References** | | | | |

**notes**

## (#i\_bait\_lure)=

# Influence of bait/lure

Include definitions for types of bait and lure types (Bait, Scent lure, Audible lure, Visual lure) + how bait/lure can affect detections of non-target species

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Question:** Do you plan to use bait or lure? If so, will you use the same type of bait or lure, or multiple types? | | | | |
| **Overview** | | | | |
| **Advanced** | | | | |
| **Figures & Videos** | | | | |
| ```{figure} ./images/Iannarilli-et-al\_2021\_Fig3.png  :align: center  ``` | | |  | |
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| **Analytical tools & resources** | | | | |
| **Name** | **Link** | **Reference** | | **Additional\_info** |
| Effects of lure - [lure\_project](https://github.com/mfidino/lure_project) (mfidino) | <https://github.com/mfidino/lure_project> |  | |  |
| Adjusting for Lure Effects | https://mabecker89.github.io/abmi.camera.extras/articles/lure.html |  | | Correction factors for: Gray Wolf, Black Bear, Coyote, Woodland Caribou, Canada Lynx, Pronghorn, Mule deer, Moose, Elk (wapiti), Snowshoe Hare, White-tailed Deer |
| **References**  (Fidino et al., 2020)  (Becker ....)  (Iannarilli et al., 2021)  (Ferreira-Rodríguez et al., 2019)  (Gerber et al., 2011)  (Holinda et al., 2020)  (Parsons et al., 2018)  (Webster et al., 2019)  (Rendall et al., 2021)  (Suárez-Tangil et al., 2017) | |  | | |

**notes**

* “Our analysis shows that lures can increase detections of carnivores, but species-specific responses and study objectives must be considered when choosing a lure. Attractants change the local movements of animals, but do not draw them from outside the study area (Gerber et al. 2012, Stewart et al. 2019) meaning attractants do not bias density estimates, maximum distances moved, or temporal activity (Gerber et al. 2012). Beyond increasing detections, attractants can increase the time an animal spends in front of the camera trap which leads to better picture quality and more visible body angles (Rocha et al. 2016, Ferreira-Rodrı guez and Pombal 2019, Mills et al. 2019). This can improve the accuracy of identification of species and individuals and ultimately improve the accuracy of abundance and occupancy estimates. Recaptures may also increase with attractants, which improves the precision of estimates (Gerber et al. 2012, Heinlein et al. 2020). Utilizing attractants at camera traps is a promising solution for increasing the accuracy of abundance and occupancy estimates through increased detections (Cove et al. 2014); however, more information is needed on efficacy and retention of attractants for many carnivore species” ([Avrin et al., 2021, p. 2](about:blank)) ([pdf](about:blank))

## (#i\_target\_feature)=

# Targeting specific features

FOV Target Feature VS Camera Location Characteristic(s)

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| **Question:** Do you plan to target specific feature(s)? (e.g., facing the camera towards a game trail or mineral lick) | | | | |
| **Overview** | | | | |
| **Advanced**  Remote cameras may be deployed to capture detections on specific man-made or natural features (i.e., “FOV Target Feature“) to maximize the detection of wildlife species or to measure the use of that feature. FOV Target Features may include, for example, game trails, human trails, watering holes, mineral licks, rub trees, nest sites, etc.  FOV Target Features differ from Camera Location Characteristics (see below) in that FOV Target Features are features the camera is aimed towards (e.g., a seismic line). In contrast, a Camera Location Characteristics may include features outside of the camera’s FOV (e.g., meadow habitat).  The decision of where exactly to place the camera will be influenced by the feature to target, the Survey Objectives and the number of Target Species, and, importantly, the sampling design, intended analysis and associated statistical assumptions.  Deploying cameras on or near FOV Target Features can provide meaningful information for some objectives, but often introduces detection biases (Wearn & Glover-Kapfer, 2017). These biases make it difficult to extrapolate findings to areas without these features or to collect data on multiple Target Species that vary in their use of these features (Wearn & Glover-Kapfer, 2017). To reduce potential biases, cameras should ideally be deployed using a paired design, with cameras on- and off-FOV Target Features (e.g., on- and off-trails).  In general, cameras should be placed approximately **3–5 m** from the FOV Target Feature (Figure 6; the “FOV Target Feature Distance (m)“ [Figure 7]). If cameras are placed too close to the FOV Target Feature, some species may not be detected since the camera may be too high to capture smaller species or the movement speed of certain species. In contrast, if cameras are placed too far from the FOV Target Feature (e.g., > 5 m), animals detected at night may not be visible in the images because they are less likely to be illuminated by the infrared flash.  This recommendation can be relaxed if users plan to estimate the detection distance (i.e., “the maximum distance that a sensor can detect a target” [Wearn and Glover-Kapfer, 2017]) and account for variability in detection probability. | | | | |
| **Figures & Videos** | | | | |
| ```{figure} ./images/Tanwar\_et.al\_2021\_Fig5.png  :align: center  ```  **Figure 6.** Illustration of a remote camera showing (A) the FOV Target Feature (a trail), (B) the camera’s detection zone (everything inside the red outline), and (C) the distance of the camera to the FOV Target Feature. Note that the detection zone will vary according to Camera Make and Camera Model. Camera users will need to identify a suitable attachment point (e.g., tree, fence post/ stake) near the target area. The most suitable attachment point will depend on the Camera Height, angle, and direction since these choices will impact the FOV (see section 7.4). Figure from WildCAM Network (2019). | | | A graph of a deer and a hedgehog  Description automatically generated  ```{figure} ./images/Tanwar\_et.al\_2021\_Fig5.png  :align: center  ``` | |
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| **Analytical tools & resources** | | | | |
| **Name** | **Link** | **Reference** | | **Additional\_info** |
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|  |  |  | |  |
| **References**  (Alberta Remote Camera Steering Committee (RCSC) et al., 2023) | | | | |

# 99\_other-concepts

* Scale
* FOV; Detection Zone [pull from survey guidelines]
* Walktests (Walktest Distance (m) + Walktest Height (m))) [pull from survey guidelines]

## (#i\_mod\_c\_autocorr)=

# Pseudoreplication + Spatial autocorrelation

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| Question: | | | | |
| **Overview** | | | | |
| **Advanced**  Spatial autocorrelation (i.e., the tendency for sites that are close together to be more similar) may occur when multiple cameras are placed nearby (such as in clustered, paired or array sampling). Spatial autocorrelation is a form of pseudoreplication (Hurlbert, 1984; when observations are not statistically independent but are treated as if they are) and can be problematic because it can artificially inflate or diminish ecological effects. The degree to which this is a problem will depend on the Target Species (i.e., how far they can travel may dictate the distance at which another camera is too near) and the modelling approach. In these cases, users should consider an analytical framework that accommodates autocorrelation to avoid issues of spatial pseudoreplication (Hurlbert, 1984) and false conclusions (Ramage et al., 2013) (e.g., using random effects [Wearn & Glover-Kapfer, 2017] or spatial autoregressive models [Kelejian & Prucha, 1998]).  Note that pseudoreplication (Hurlbert, 1984) can also occur over time (e.g., if camera locations are sampled repeatedly to obtain detection rates as repeated counts, or if the inter-detection interval is too short for a subsequent detection to be truly independent of the first detection). | | | | |
| **Figures & Videos** | | | | |
| A diagram of a diagram  Description automatically generated with medium confidence  ```{figure} ./images/Zuckerberg-et-al\_2020\_Fig1.png  :align: center  `````` | | | A screenshot of a computer screen  Description automatically generated ```{figure} ./images/zuckerberg-et-al\_2020\_fig3.png  :align: center  ``` | |
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| **Analytical tools & resources** | | | | |
| **Name** | **Link** | **Reference** | | **Additional\_info** |
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|  |  |  | |  |
| **References**  (Van Dooren 2016)  Ramage et al., 2013  (Zuckerberg et al., 2020)  (Wearn & Glover-Kapfer, 2017) | | | | |

**notes**

## (#i\_mod\_approach\_assumpt)=

# Analysis overview - Modelling approach + Model assumption

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| --- | --- | --- | --- |
| **Overview**  **Model assumption:** Explicitly stated (or implicitly premised) conventions, choices and other specifications (e.g., about the data, wildlife ecology/behaviour, the relationships between variables, etc.) on which a particular modelling approach is based that allows the model to provide valid inference.  **Modelling approach:** The method used to analyze the camera data, which should depend on the state variable, e.g., occupancy models [MacKenzie et al., 2002], spatially explicit capture recapture (SECR) for density estimation [Chandler and Royle, 2013], etc. and the target species. | | | |
| **Advanced** | | | |
| **Figures & Videos** | | | |
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| **Analytical tools & resources** | | | |
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