Wildlife monitoring by camera traps

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ERAIFT
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Overview

1. **History & concepts**

2. **Implementation in the field**

3. **Management, analysis & data interpretation**

4. **Perspectives**


1. History & general concepts
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1. History & general concepts

19th century — **1890** — **1927** — **1950-1980**

19th century: Development of animal photography

1890: George Shiras: 1st 'automatic' triggering devices ➔ "flashlight trapping"

1927: Frank M. Chapman: 1st scientific use ("Census of the living", Panama)

1950-1980: **Continuous improvement of the material:**

- Powder ➔ Light flash powder
- Metal wire ➔ electric current & light beam (Pearson, 1959)
- Series of photos taken consecutively
- Development of time-lapse photos
- Resistance to extreme conditions (-35°C)



Flash photography with a magnesium powder light explosion triggered by the movement of a metal cable

1. History & general concepts

1980 **1984** First rigorous scientific studies

Seydack:

Identification of individuals & density estimates

- 6 survey blocks (100 ha)
- 6 cameras per block triggered with a plate and left for 1 month in the field
- 6 repetitions per block over 3 years

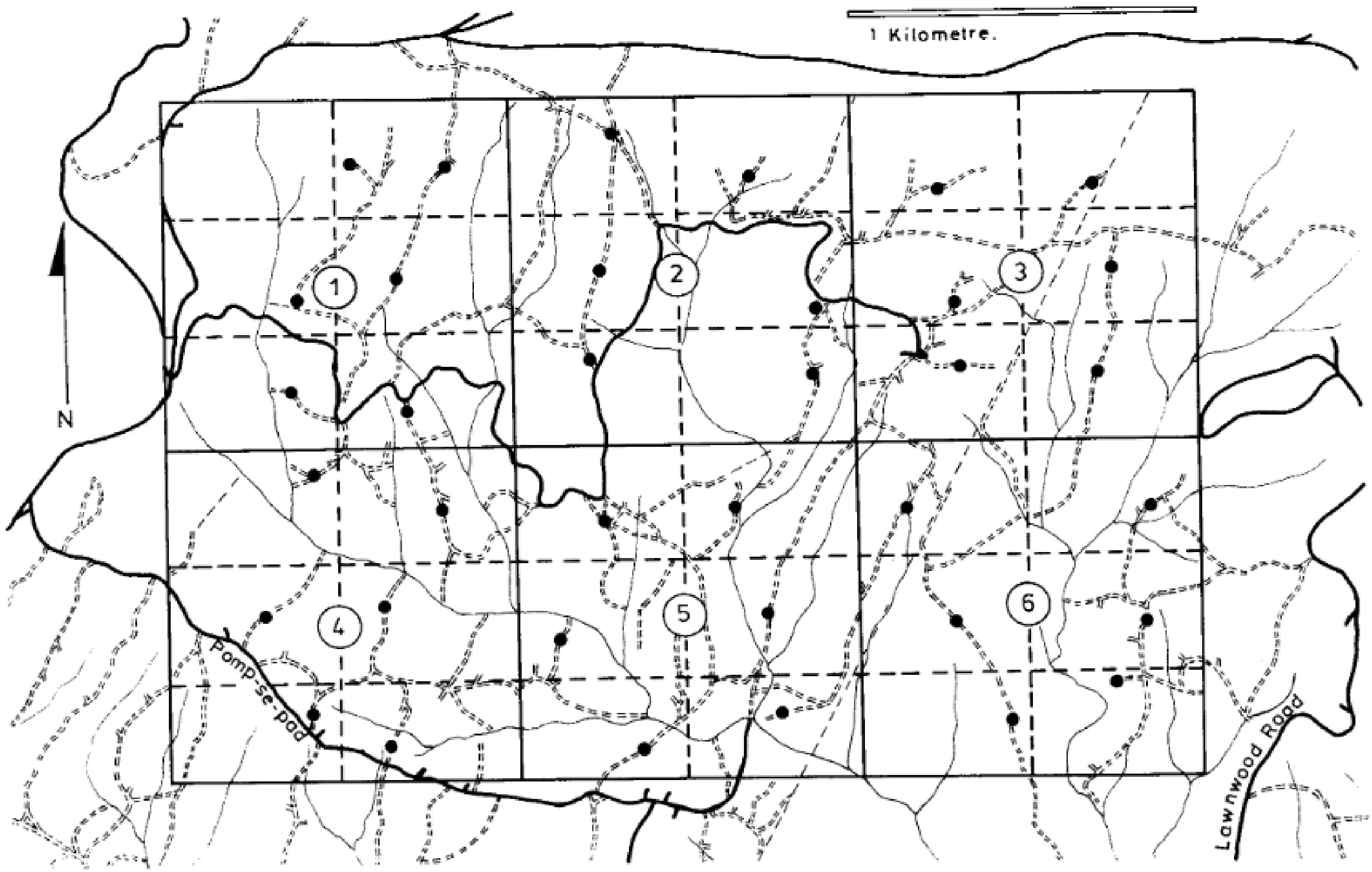


Figure 1 The census layout of the study area in the Sourflats Forest, Knysna. (1)–(6) census block numbers; ● survey points; — roads; = = = slip-paths; rivers.

1. History & general concepts

1991 **1993** **1994** **1995** **>1995** First rigorous scientific studies

Extension to other individually recognizable carnivores (jaguar, leopard, ocelots,...)

Karanth: Estimation of tiger densities in a National Park in southern India through individual identification based on fur coloration

Mace et al.: Use of a passive infrared thermal sensor and a displacement sensor

Griffiths & Van Schaik: *"Camera trapping: a new tool for the study of elusive rain forest animals"*

Carthew & Slater:

- Models with an infrared beam
- Automatic camera triggering when beam is disturbed
- Automatic date and time recording

Use of camera traps in studies with **various objectives**:

- Bird nest predation
- Activity rhythms
- Use of infrastructure by wildlife
- Predation and seed dispersal
- Distribution of rare species

1. History & general concepts

Monitoring animal populations over **time** and **space** is crucial to any wildlife conservation strategy

Survey methods will be chosen according to the context:

- Environment
- Species
- Human resources and skills
- Financial resources

Traditional methods: **line transects**, ***Recce*** (direct or indirect counting), etc.

➔ Bias due to species ecology and environmental factors

Camera trap inventories have proven to be more effective than traditional inventory methods (Silveira et al., 2003; Srbek-Araujo & Chiarello, 2005) and against newer methods (Gogarten et al., 2020)

However, specific biases and challenges persist...

Benefits of camera traps:

+ Non-invasive method
+ Sampling of large areas for long periods of time
+ Relatively low personnel demands
+ Operates day and night
+ Capture of rare species
+ Public awareness tools (images speak louder than complex statistical calculations)

Possible outcomes:

- Presence/absence data
- Species activity patterns and behavior
- Spatial patterns of occurrence and occupancy (Wildlife Picture Index)
- Species detection probability
- Density index (#detections/unit of time): Relative Abundance Index (RAI)
- Absolute density:
    - Recognizable individuals: capture-recapture
    - Unrecognizable individuals: Random Encounter Model, Distance Sampling…

… but what’s a camera trap?

Many different models and brands for a common basic principle

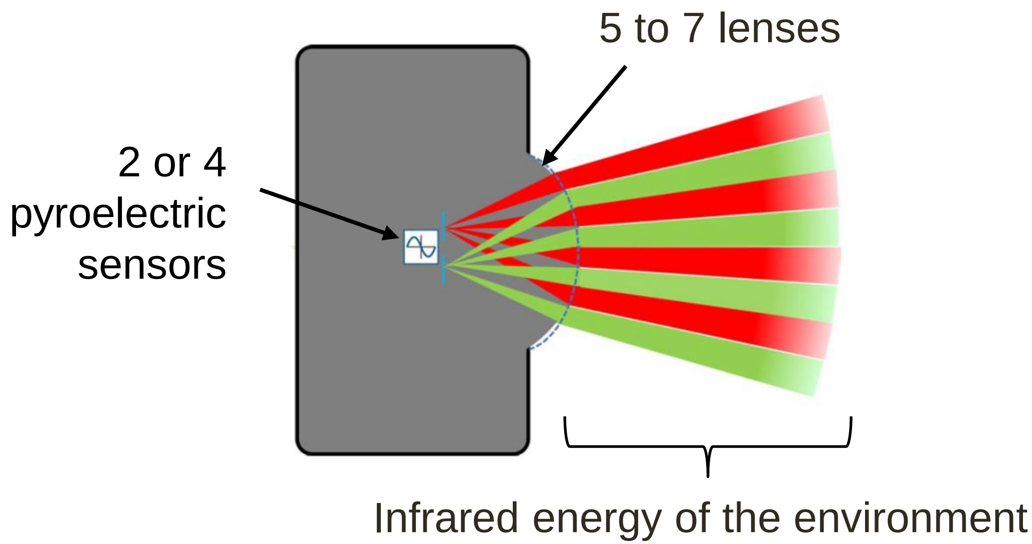
Camera trap =

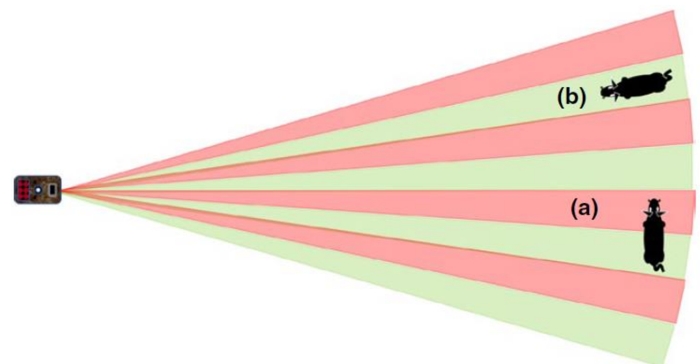
A photo/video camera contained in a protective case that is triggered by the passage of an animal in a defined detection zone

1. History & general concepts

Triggering with a motion **and** heat sensor

➔ Usually a **passive infrared motion sensor** (PIR motion detectors)





Apps & McNutt (2008)

- The sensor is triggered when an object/animal with a different surface temperature than the background environment moves into the detection area

  ↘ detection of small species far away from the detection area

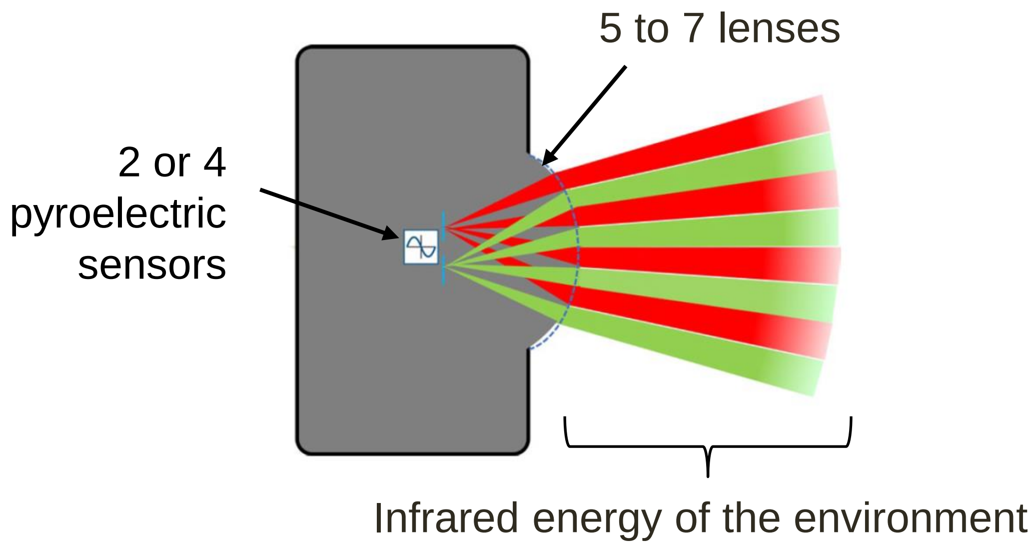
- The lens focuses infrared rays to pyroelectric sensors that generate a voltage as their temperature changes

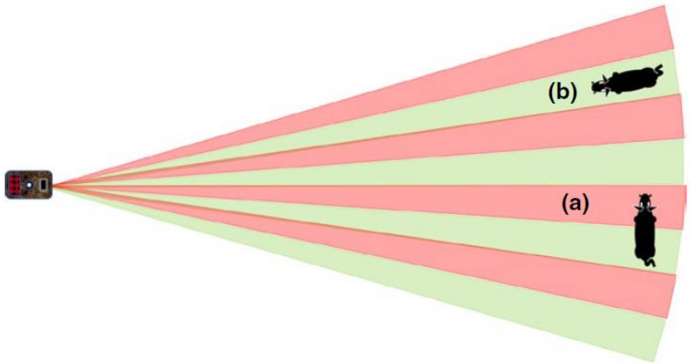
- Rapid changes in T° (and voltage) indicate movement

1. History & general concepts

Triggering with a motion **and** heat sensor

➔ Usually a **passive infrared motion sensor** (PIR motion detectors)





Apps & McNutt (2008)

- More sensitivity to tangential displacement (a) than to diagonal displacement (b) towards the lens
- The sensitivity is lower at the edges of the detection area because only one IR beam is disturbed
- Bigger animals are detected at longer ranges than smaller ones
- Cameras need to be in the shade: if the camera itself gets hot enough because of the sun, the PIR sensor is blinded by being hotter than both the animals and the background, and it will not trigger at all

Trigger time and recovery speed

- **Trigger time**
  = Time from detection to photo/video capture
  = +- 0.5s for photos
  = 0.4-1.7s for videos

- **Recovery speed**
  = 0.5-3.4s for photos
  = 0.7-5s for videos

- **The minimum time between two consecutive triggers**
  = Trigger time + recovery speed
  = 1-3.5s for photos
  = 1.1-6.7s for videos

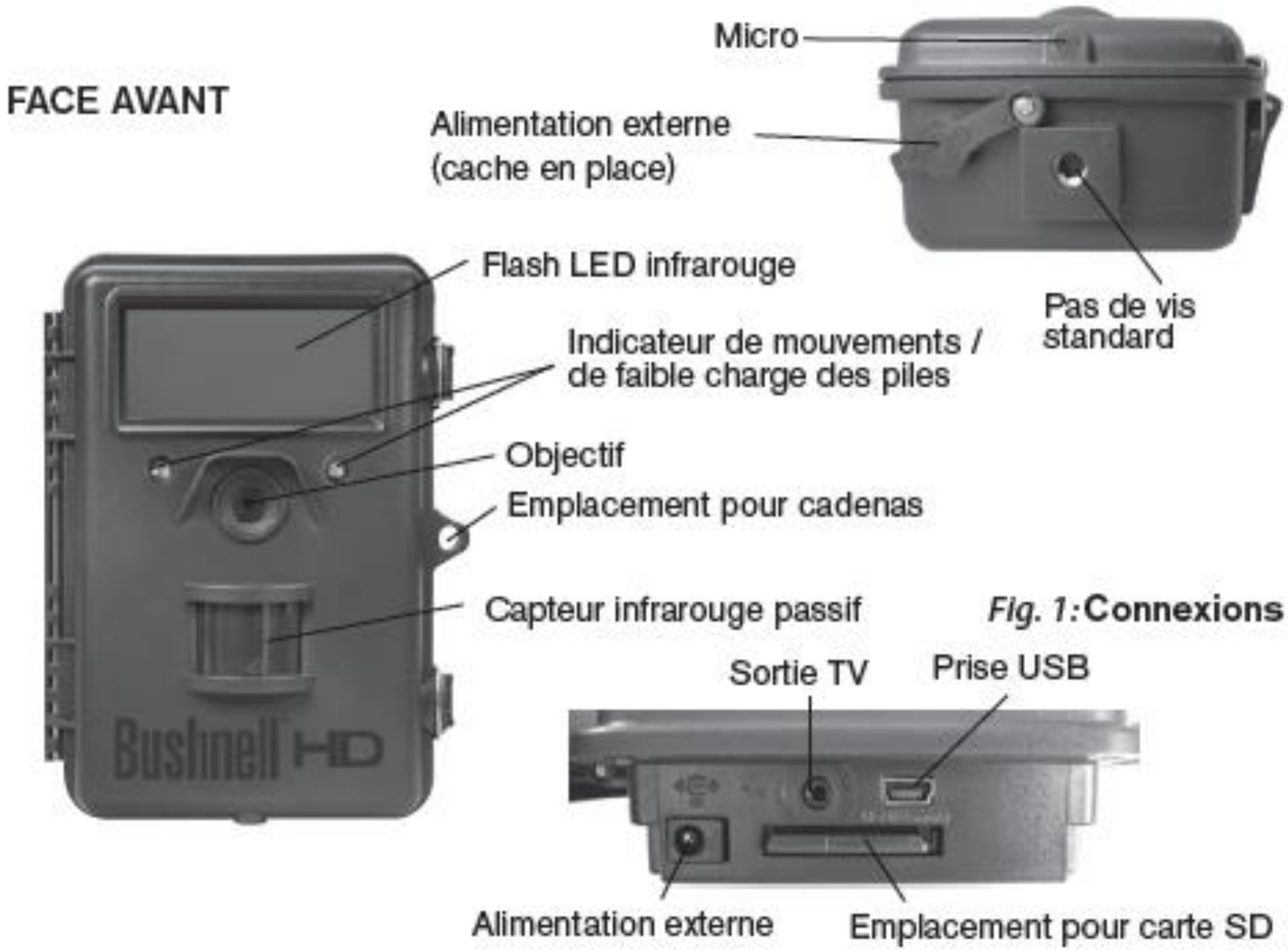


Fig. 1: **Connexions**

1. History & general concepts

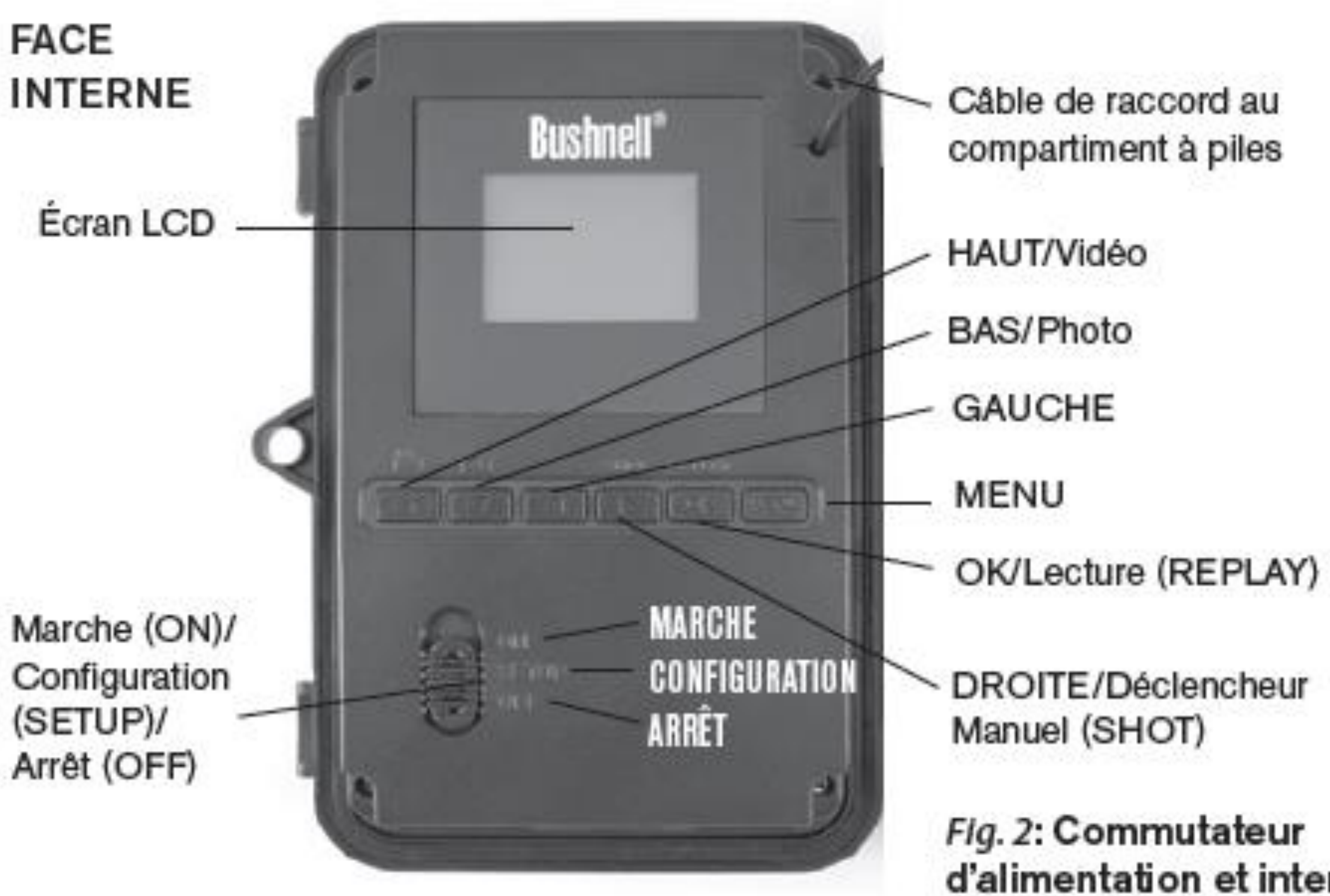


***Fig. 2*: Commutateur d'alimentation et interface de contrôle à six touches**

2. Implementation in the field

2. Implementation in the field

From office preparation to field setup

2. Implementation in the field

- Camera trap studies have multiple objectives, for studying wildlife:
  - Distribution
  - Abundance
  - Behavior
  - Community structure
  - ...

- These multiple applications lead to various methodologies and field installation protocols

2. Implementation in the field

- TEAM (Tropical Ecology Assessment and Monitoring) network
- Standard protocol for camera trap surveys in 17 tropical sites
- Early warning system based on annual monitoring data

Wildlife Insights

https://www.wildlifeinsights.org/

TEAM NETWORK

TROPICAL ECOLOGY ASSESSMENT AND MONITORING

2. Implementation in the field

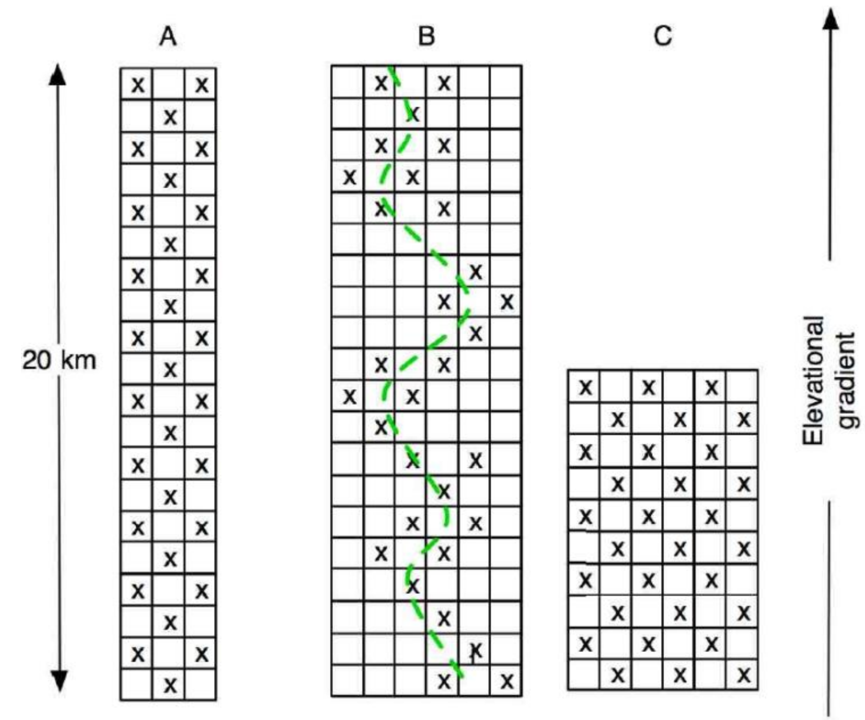
TEAM NETWORK
TROPICAL ECOLOGY ASSESSMENT AND MONITORING

Objective: monitor changes in the community of ground-dwelling, terrestrial vertebrates

TEAM protocol = **compromise** at the pantropical scale between the level of effort required to detect species with large home ranges and those with smaller home ranges

In practice...

- The whole set-up includes **60 to 90** sampling points
- Annual survey of **30 days** per point during a similar season and without bait
- Simultaneous sampling recommended but possibility of splitting into 2 or 3 consecutive grids
- Density of installation of one sampling point **per 2 km²**



2. Implementation in the field

TEAM NETWORK
TROPICAL ECOLOGY ASSESSMENT AND MONITORING

In the field...

- Go to the **theoretical installation point** established on a GIS tool

- As you approach the predetermined position (stored in the GPS), be aware of the **surrounding environment** (ridge lines, streams)

- Determine an **installation buffer zone** (depending on the study)

- Once arrived at the theoretical position, look for the **wildlife-friendly site** that will give the highest probability of obtaining photos/videos of the greatest number of species

➔ Wildlife-friendly site = animal tracks, presence of animal tracks (droppings, footprints), stream banks, etc.

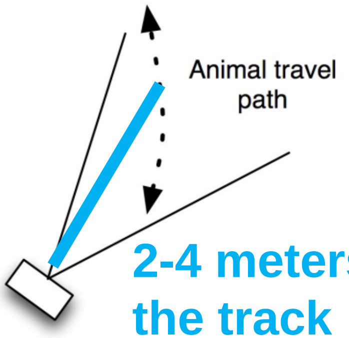
2. Implementation in the field

In the field…

- Orientation of the trap towards the chosen site

Recommended

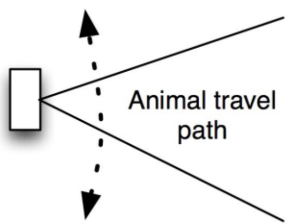
A. Camera diagonal to animal travel path; requires less disturbance



2-4 meters from the track

Not Recommended

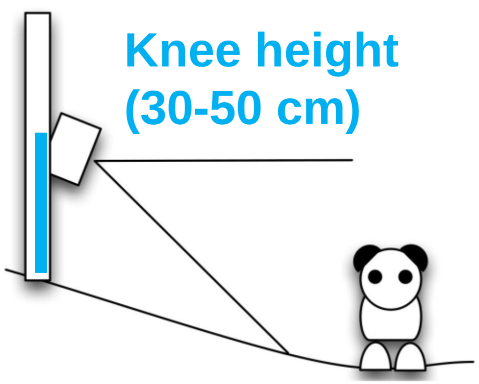
B. Camera perpendicular to animal travel path but too close to it



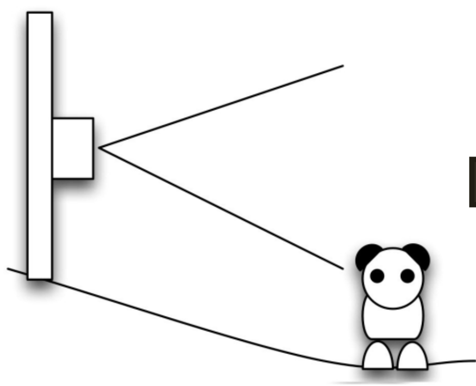
A large portion of the passage area is included in the detection zone to avoid false negatives

C. In sloped terrain, camera should be angled and parallel to the ground to ensure detection

Knee height (30-50 cm)



D. In sloped terrain, not adjusting the camera angle will result in incomplete detection



Tilt of the camera parallel to the ground

TEAM NETWORK
TROPICAL ECOLOGY ASSESSMENT AND MONITORING

2. Implementation in the field

In the field...

- Choice of a stable tree

- Clearance of grassy and liana vegetation that can lead to false triggers, without altering the site!

Strong reaction of some animals to too disturbed sites

TEAM NETWORK
TROPICAL ECOLOGY ASSESSMENT AND MONITORING

2. Implementation in the field

In the field...

- Avoid exposure to the sun: image in backlight, reduces sensitivity to heat (N/S orientation preferred to E/W)

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2. Implementation in the field

In the field...

- Quickly check the configuration

- Take some pictures to test the framing

In the field...

- Use a reader to validate the framing

2. Implementation in the field

In the field…

- Take a picture of the site in front of the camera trap: visibility estimation

➔ More robust protocols for estimating visibility exist

2. Implementation in the field

In the field...

- Watch out for humidity!

  - Sachet of silica gel + silicone grease
  - Umbrella and towel
  - Leaf on the ground to reduce splashing of mud on the lens or flash!

In the field...

- Have the camera trap take a picture before leaving: record the beginning of the sampling period with ideally a sign indicating the trap name, date, latitude-longitude, camera settings, GPS point name

- Record GPS location (GPS/carnet): to find the site back!

In the field...

Information to be recorded for each site on a **field sheet**:

- Name(s) of observer(s)
- Site name
- Coordinates Latitude/Longitude
- Settings (time interval, sensor sensitivity...)
- Date and time of start/end of recording
- Vegetation type, fruiting trees
- Visibility index in the camera field?
- Other variables?
- ...

In the field...

Don’t forget to put the camera ON when leaving... ☺

3. Management, analysis & data interpretation

Photo management & species identification

e.g., **1.2 million images** in Tanzania (Swanson et al., 2015),
2.6 million images in the eastern US (McShea et al., 2015)

Photo management & species identification

- **Camera Base** (Tobler, 2007) ➔ **Microsoft Access**
- **Timelapse** (Greenberg, 2019) ➔ **Software**
- **CamtrapR** (Niedballa et al., 2016) ➔ **R**
- **CPW Photo Warehouse** (Ivan and Newkirk, 2016) ➔ **Microsoft Access**
- **Aardwolf** (Krishnappa and Turner, 2014) ➔ **Software**
- **DeskTEAM ➔ Wild.ID** (TEAM network, 2015) ➔ **Software**
- Etc.

Remote Sensing in Ecology and Conservation
Open Access
ZSL LET'S WORK FOR WILDLIFE

REVIEW

Best practices and software for the management and sharing of camera trap data for small and large scales studies

Photo management & species identification

Camera Base

http://www.atrium-biodiversity.org/tools/camerabase/

- Created in 2007 by Mathias Tobler, San Diego Zoo Global Institute for Conservation Research

- Processes photos and videos

- Allows export of summary results:
  - ✓ List of captured species
  - ✓ Number of cameras.days per site
  - ✓ Detection events by species
  - ✓ Detection events by site
  - ✓ Capture frequencies (N captures / 1000 camera.days) for each species

- Displays the graphs of activity rates of species

- Exports data to MARK, PRESENCE, DENSITY, EstimateS and other statistical or GIS software

Photo management & species identification

Camera Base

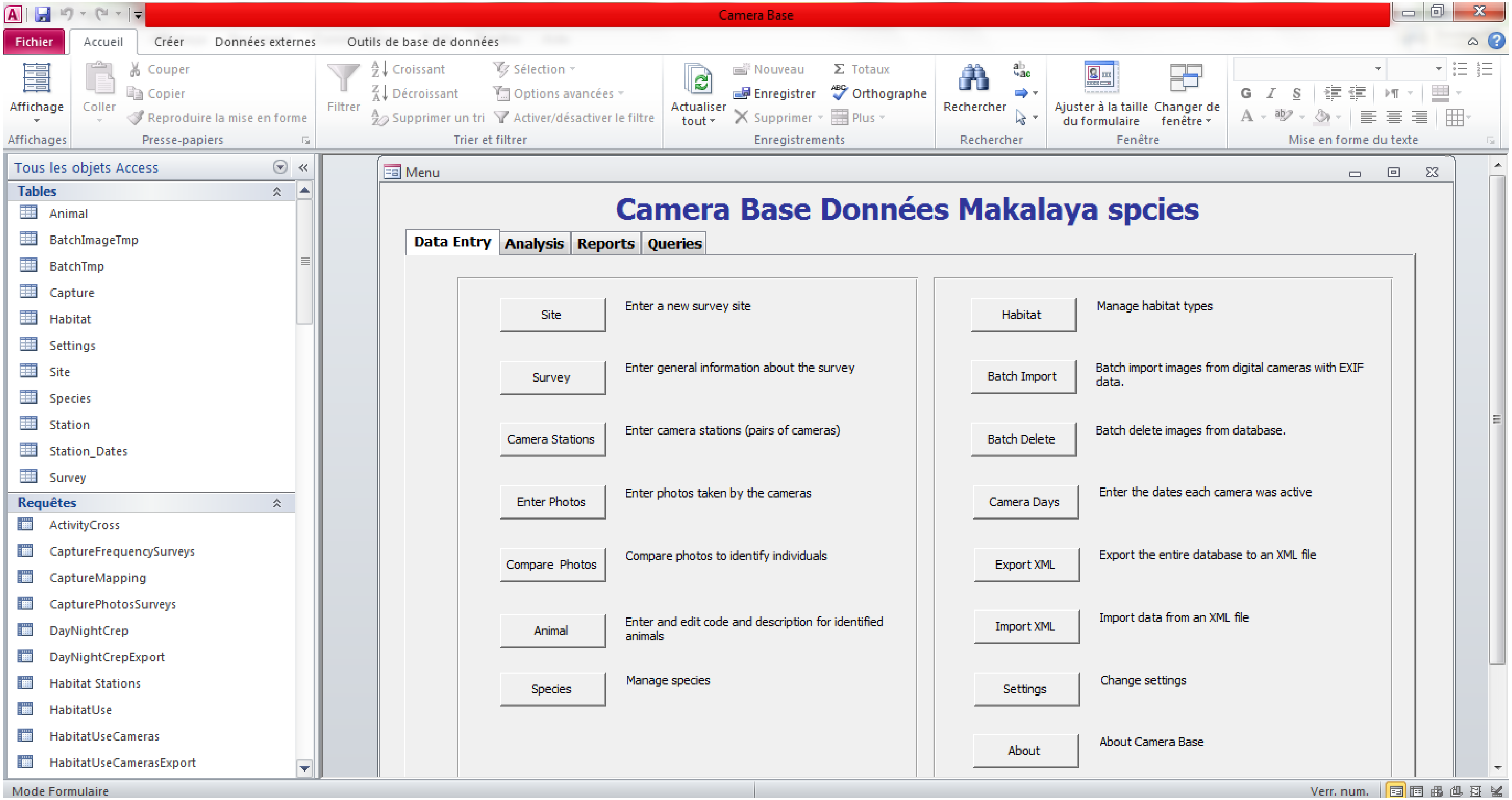


Photo management & species identification

Camera Base

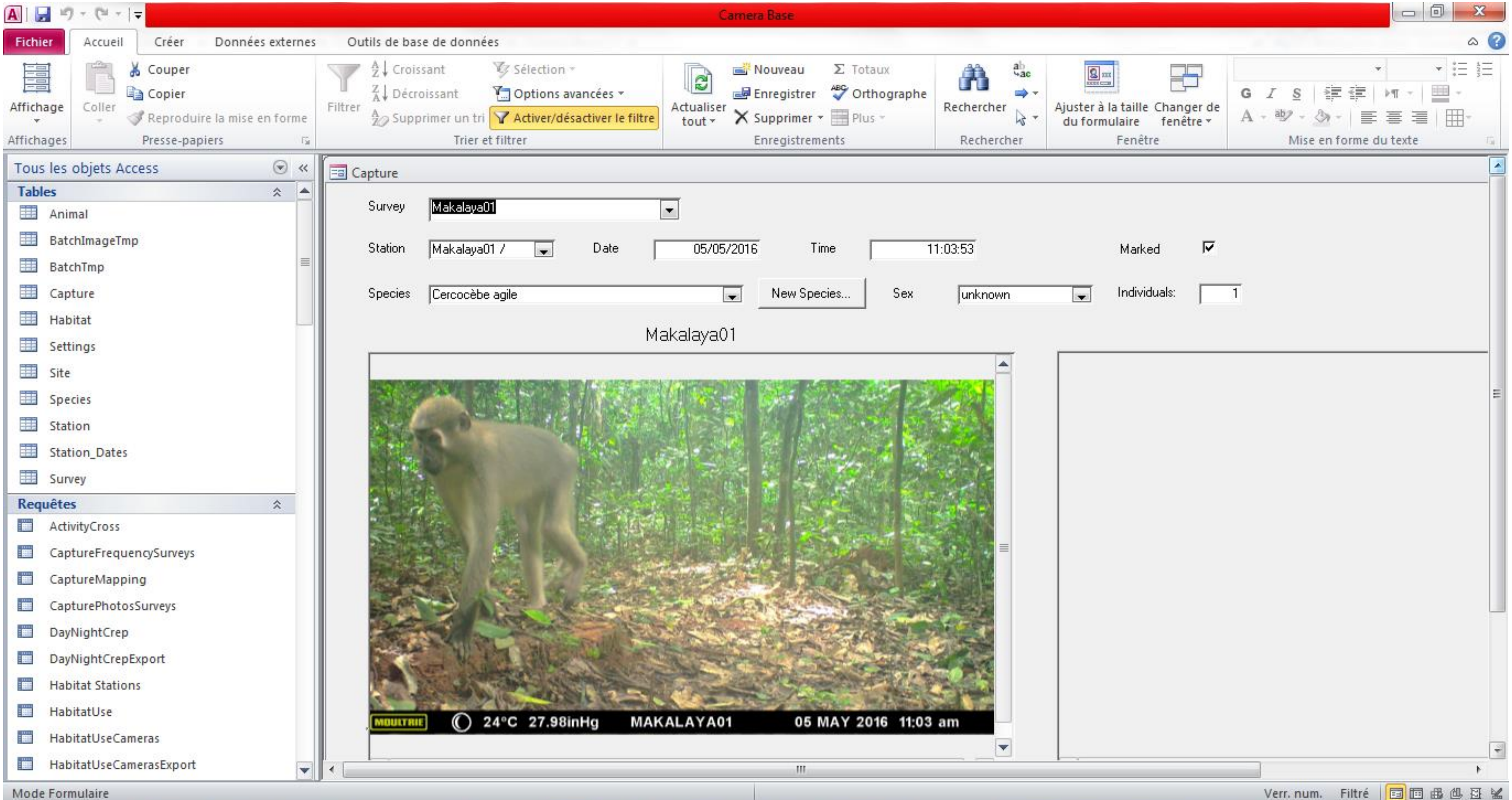


Photo management & species identification

Timelapse

http://saul.cpsc.ucalgary.ca/timelapse/

- Created by Saul Greenberg of the University of Calgary
- Processes photos and videos
- Allows to create adaptable encoding interfaces
- Does not require duplication of data unlike Camera Base

Photo management & species identification

Timelapse

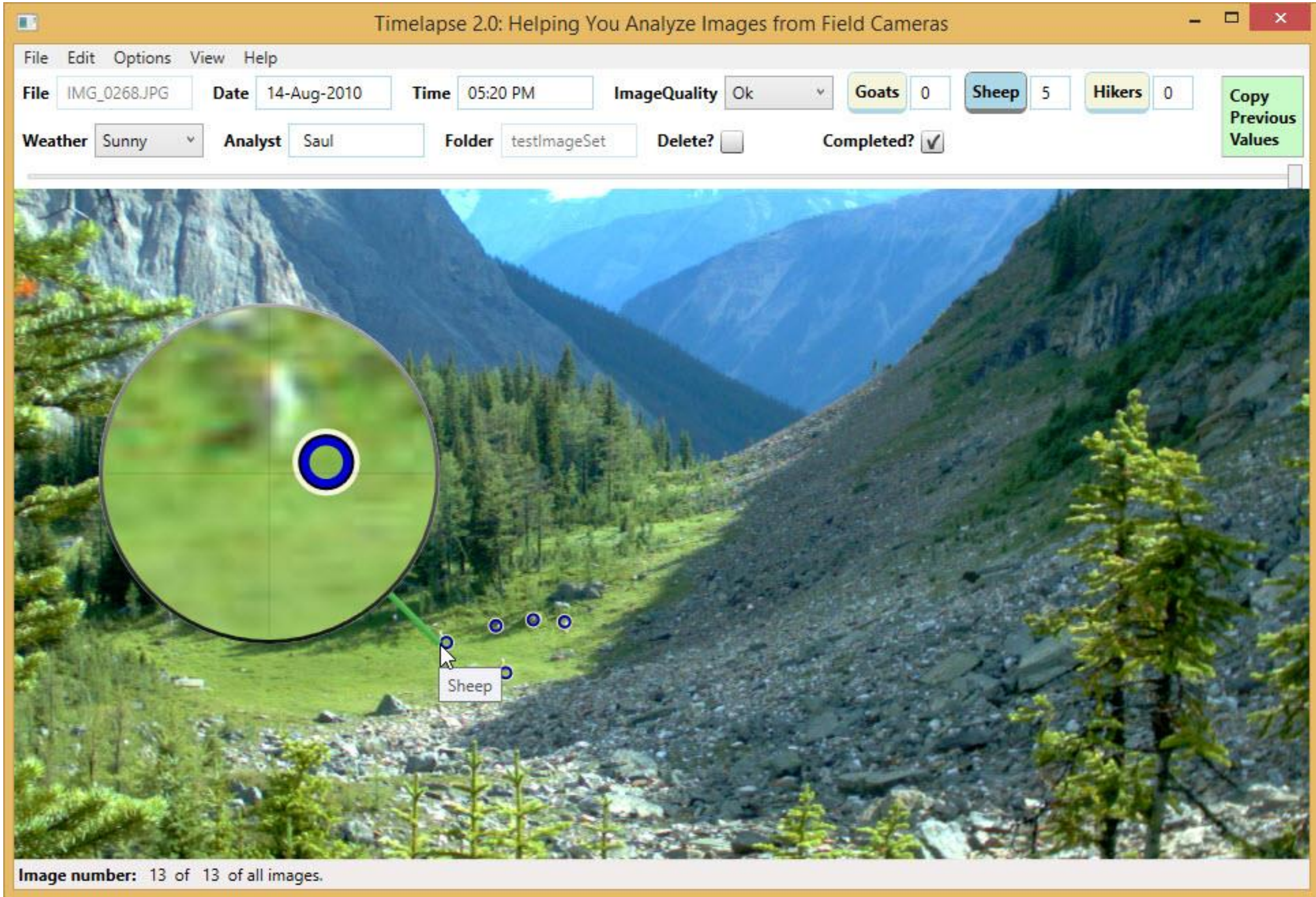


Photo management & species identification

CamtrapR

https://cran.r-project.org/web/packages/camtrapR/camtrapR.pdf

- Created in 2016 by Juergen Niedballa
- Package for analysis and preparation of photographic data for further analysis (occupancy modeling and spatial capture-recapture model)
- Processes only photos
- Different functions for :
  - ✓ Management and organization of images
  - ✓ Identification of species and individuals
  - ✓ Date extraction
  - ✓ Data visualization (richness maps, daily activity graph)
  - ✓ Export of data for further analysis

Photo management & species identification

Currently species identification is still done manually in most cases...

... but tools based on automatic species detection and artificial intelligence for specific identification are being developed

➔ Machine learning and Deep Learning

Automatically identifying, counting, and describing wild animals in camera-trap images with deep learning

Mohammed Sadegh Norouzzadeh[1], Anh Nguyen[2], Margaret Kosmala[3], Ali Swanson[4], Meredith Palmer[5], Craig Packer[5], and Jeff Clune[1,6]

nature

Review Article | Published: 27 May 2015

Deep learning

Yann LeCun, Yoshua Bengio & Geoffrey Hinton

DEEP CONVOLUTIONAL NEURAL NETWORK BASED SPECIES RECOGNITION FOR WILD ANIMAL MONITORING

*Guobin Chen, Tony X. Han, Zhihai He**　　*Roland Kays, and Tavis Forrester*

Photo management & species identification

Currently species identification is still done manually in most cases...

... but tools based on automatic species detection and artificial intelligence for specific identification are being developed

➔ Machine learning and Deep Learning

High performance machine learning models can fully automate labeling of camera trap images for ecological analyses

bioRxiv
THE PREPRINT SERVER FOR BIOLOGY

Robin Whytock, Jędrzej Świeżewski, Joeri A. Zwerts, Tadeusz Bara-Słupski, Aurélie Flore Koumba Pambo, Marek Rogala, Laila Bahaa-el-din, Kelly Boekee, Stephanie Brittain, Anabelle W. Cardoso, Philipp Henschel, David Lehmann, Brice Momboua, Cisquet Kiebou Opepa, Christopher Orbell, Ross T. Pitman, Hugh S. Robinson, Katharine A. Abernethy

“The model was trained on a relatively small dataset (**c.300,000 images**) but generalizes to fully independent data and outperforms humans in several respects (e.g. detecting ‘invisible’ animals). We show how the model’s precision and accuracy can be evaluated in an ecological modeling context by comparing species richness, activity patterns and occupancy derived from machine learning labels with the same estimates derived from expert labels. **Results show that fully automated labels can be equivalent to expert labels when calculating these widely-used ecological metrics**.”

Photo management & species identification

➔ Machine learning and Deep Learning

- Field of study of **artificial intelligence**
- Gives the computer the "ability to learn" from data (training phase + production phase)
- Learning algorithms can be classified according to the learning mode (supervised or unsupervised...)
- Among the algorithms used, we find the deep learning corresponding to the class of machine learning algorithms. The Convolutional Neural Networks (CNN) method is based on this deep learning. It is an artificial neural network based on the visual cortex of animals.

Standard architecture of a convolution network

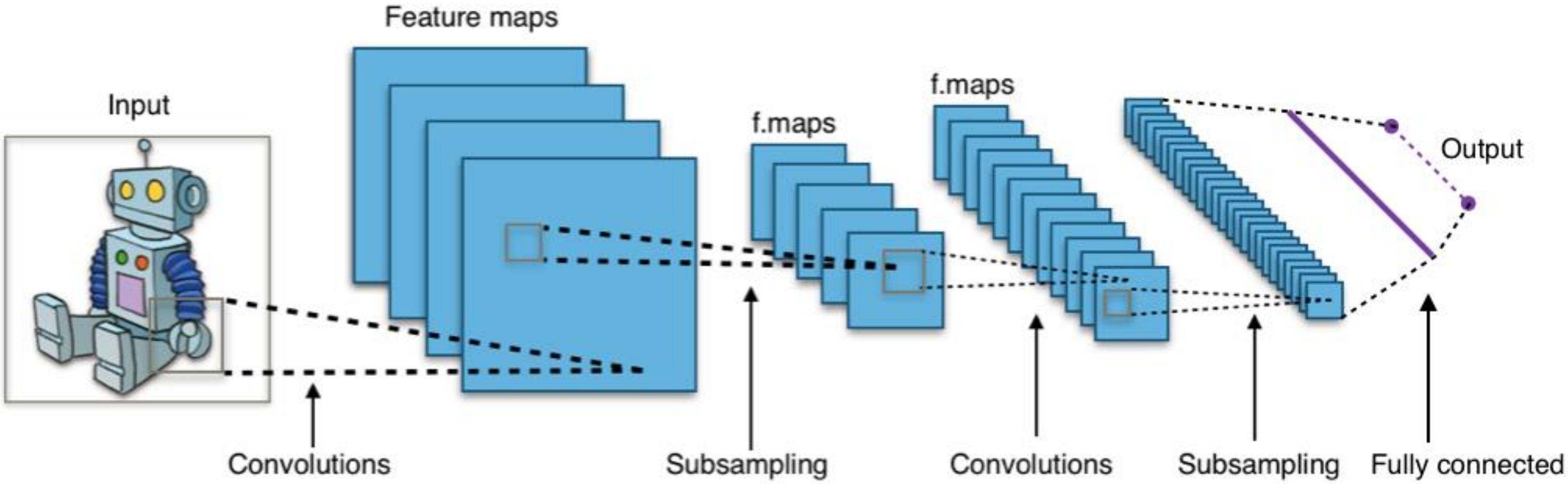


Photo management & species identification

➔ Machine learning and Deep Learning

Wildlife Insights

TEAM NETWORK
TROPICAL ECOLOGY ASSESSMENT AND MONITORING

The **Wildlife Insight** platform offers its machine learning technology on the dataset collected through the TEAM network and other partners' data including 614 species worldwide

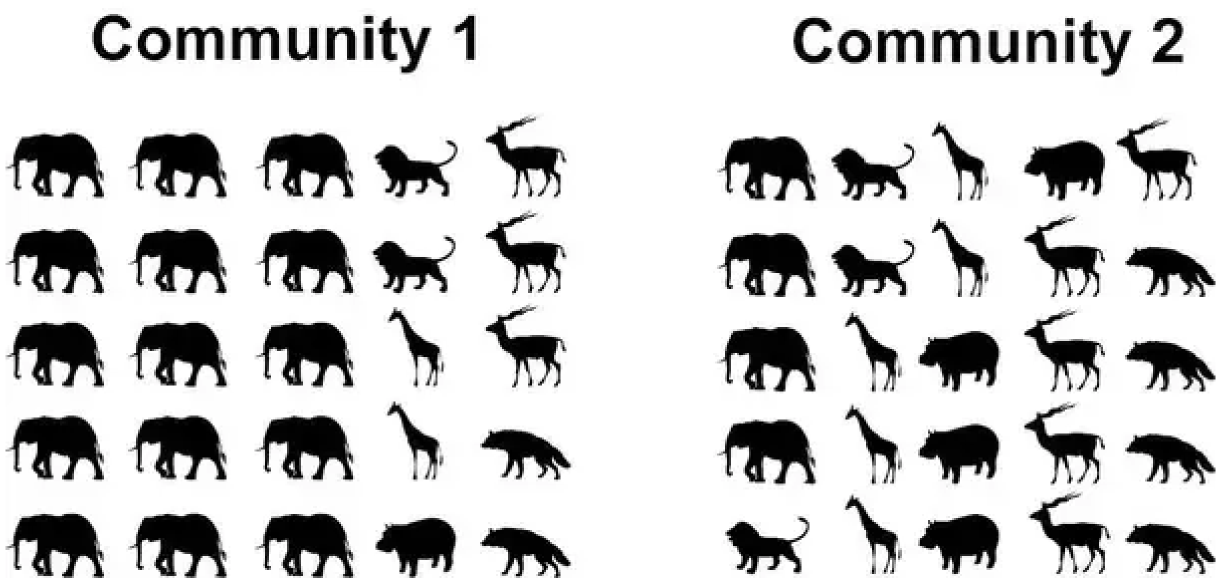
➔ **80-95% accuracy**

Data analysis & interpretation

➔ "*Biodiversity analysis methods*" class

Animal communities can be characterized by:

- **Richness** and **diversity**
- **Abundance**
- **Composition**



Data analysis & interpretation

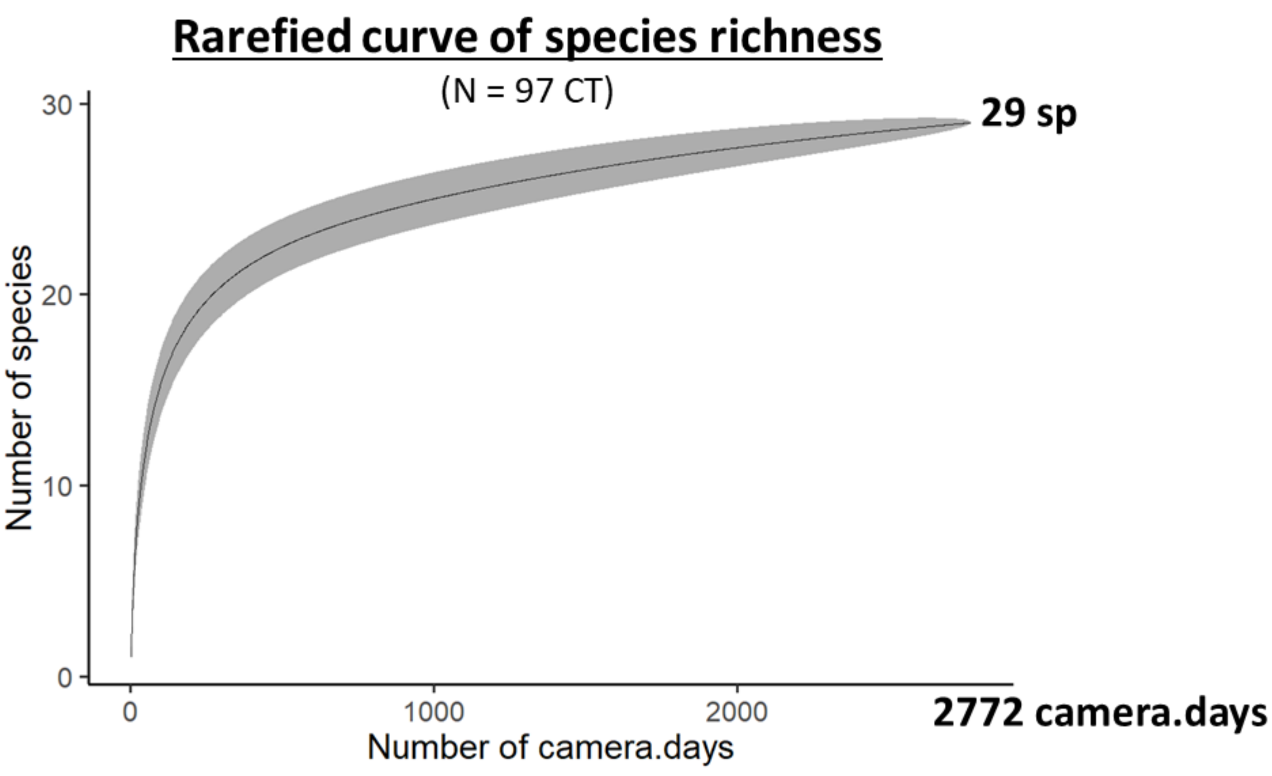
Species richness

Sampling effort

- Number of days of cumulative survey (unit: camera.day) = Sum of the duration of presence of all cameras

- A threshold of 1000 camera.days per grid is generally considered sufficient to detect rare (but not the rarest) species (O'Brien et al., 2010; Tobler et al., 2008)

- Species accumulation/ rarefaction curve over time: having a plateau is an indicator of satisfactory sampling effort

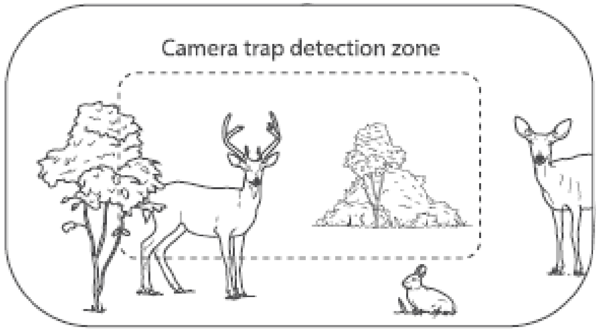


Data analysis & interpretation

Sources of error related to sampling

Imperfect detection of species at 2 spatial scales:

1. **Camera-scale:**
   ➔ Individuals passing through the detection zone but not photographed
   ➔ Detection probability = fct (model sensitivity, installation site, presence of natural or artificial baits, ambient and animal temperature, sampling time, density and behavior of species...)



Camera-scale considerations
- Camera specifications
- Animal body size and temperature
- Movement speed, behaviour, group size
- Ambient temperature and light
- Vegetation and other obstructions

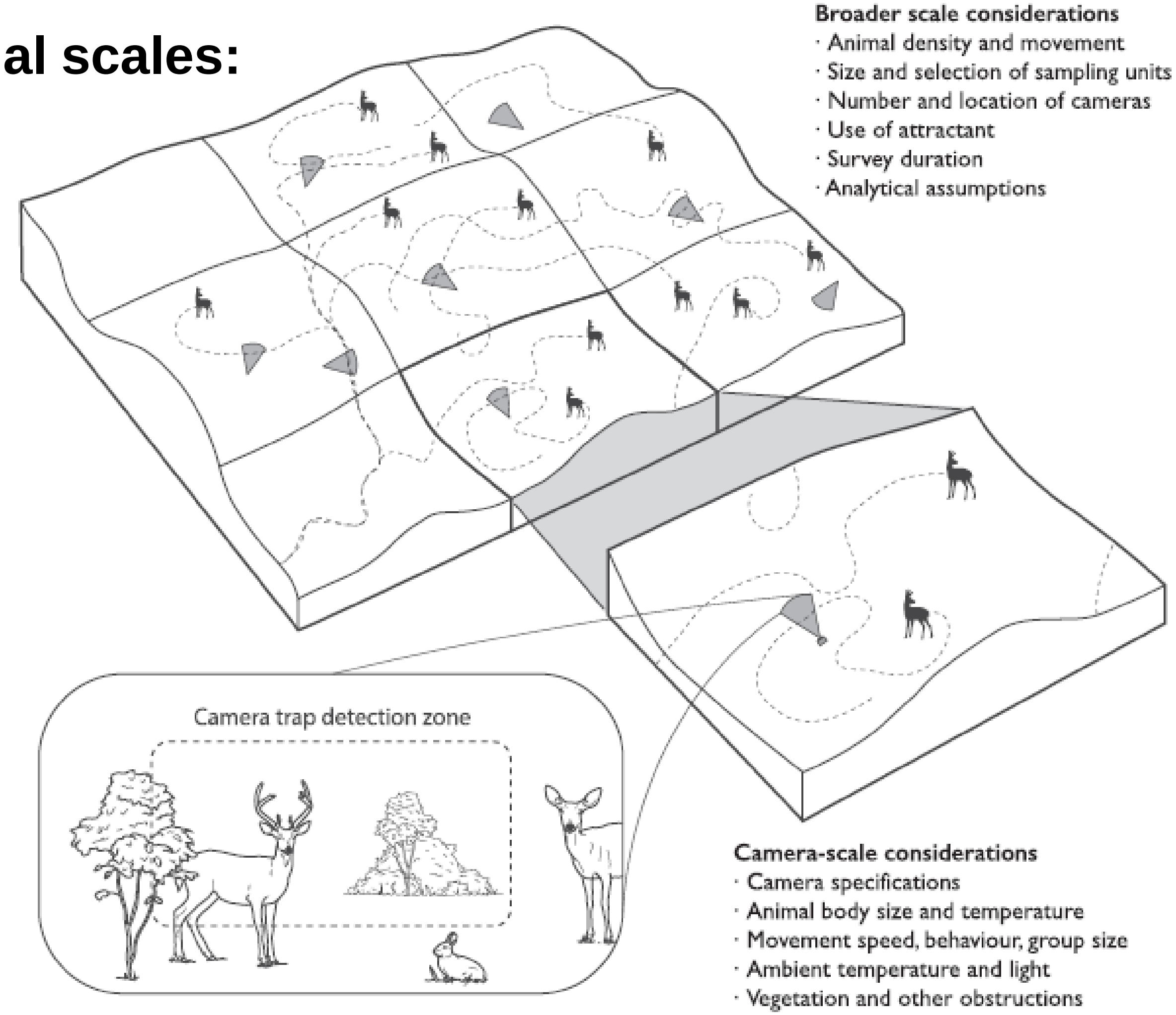
Burton et al.(2015)

Data analysis & interpretation

Sources of error related to sampling

Imperfect detection of species at 2 spatial scales:

2. **Broader-scale:**
   ➔ Individuals with a home range > theoretical area covered by the camera, that do not enter the detection zone
   ➔ Spatial variability allowing inference to the entire study area



Burton et al.(2015)

Adapted sampling design
&
Analytical approaches integrating imperfect species detection

Data analysis & interpretation

Species abundance

Is individual identification possible?

Yes

No

Capture-Recapture models

1. **Index approach – Relative Abundance Index**
2. **Density estimation**
3. **Occupancy modeling**

Data analysis & interpretation

Species abundance

Capture-Recapture (CR) models

Principle

- For species whose individuals can be distinguished (individually recognizable coat or mark: tiger, leopard, jaguar, etc.)
- Capture at least 5 to 10 individuals (Otis et al., 1978; Karanth and Nichols, 1998)

Advantages

- Most accurate method for measuring species abundance
- Considers individuals that may be present in the study area but never actually detected

Limitations

- Needs a strong knowledge of the area sampled

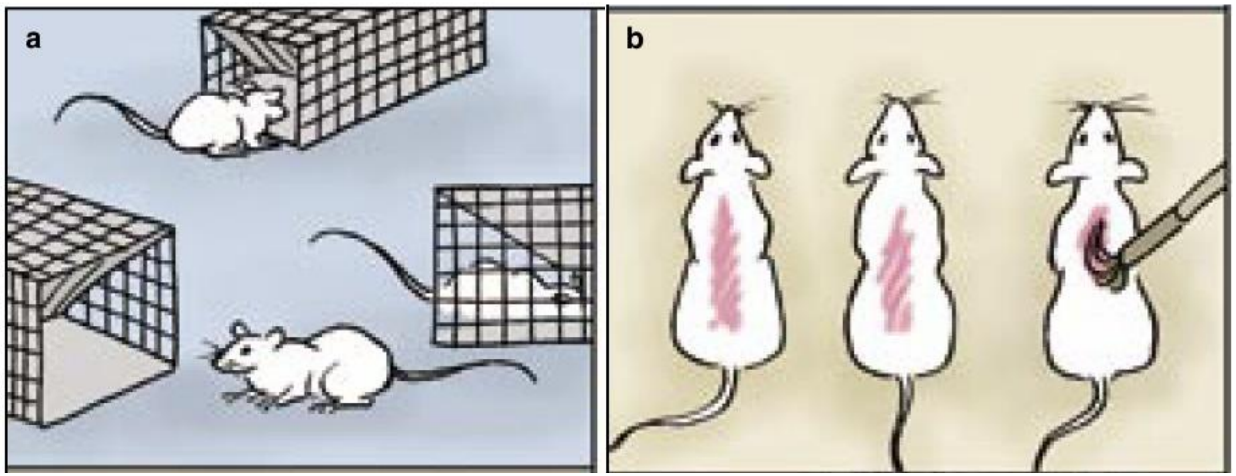
Spatial Capture-Recapture models: incorporating spatial movements of species within and outside the sampling grid in density estimation (Efford, 2004; Royle and Young, 2008)
➔ e.g., Srivathsa et al. (2015) "Estimating population sizes of leopard cats in the Western Ghats using camera surveys"

Data analysis & interpretation

Species abundance

Capture-Recapture (CR) models

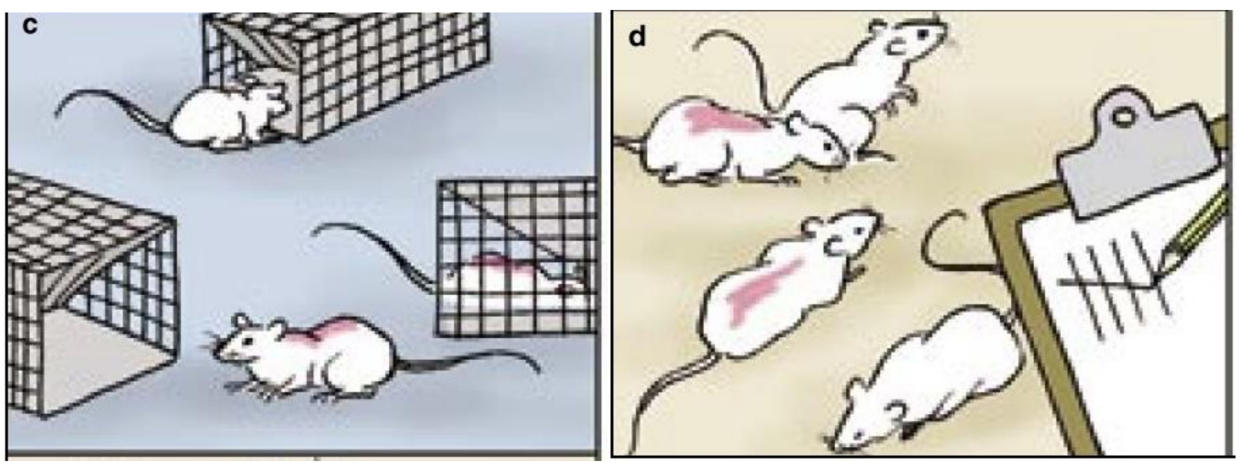
Day 1



n_1 captured

Marking of n_1

Day 2



n_2 captured

m_2 marked

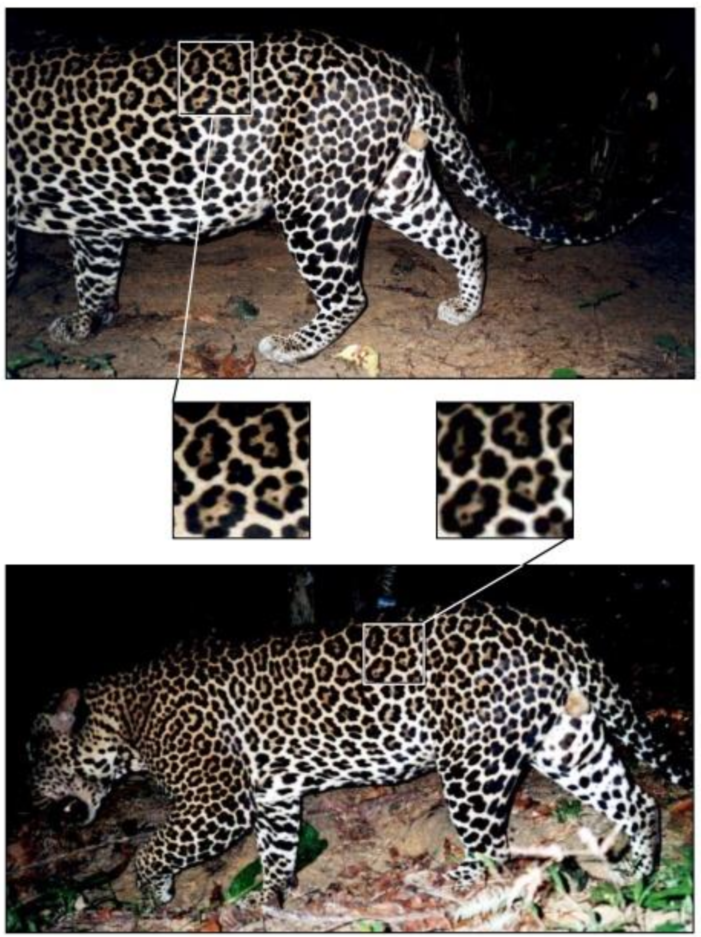
$$n_t = n_2 n_1 / m_2$$

https://www.americanscientist.org/sites/americanscientist.org/files/200521710336_306.pdf

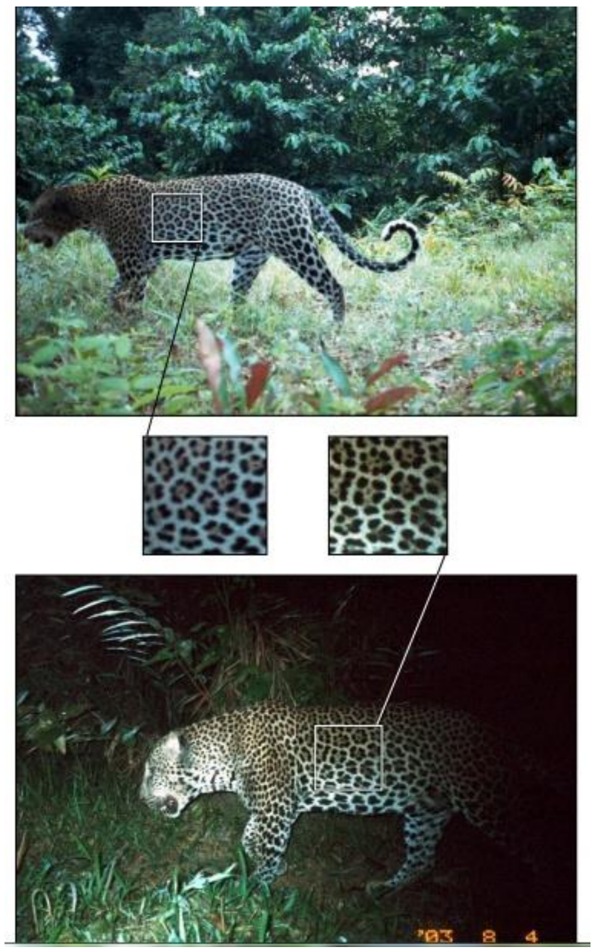
Data analysis & interpretation

Species abundance

Capture-Recapture (CR) models



Unambiguous identification of the same individual



Unambiguous identification of different individuals

https://canada.wcs.org/portals/42/media/file/fr-leopard-med2.pdf

Data analysis & interpretation

Species abundance

Is individual identification possible?

Yes

No

Capture-Recapture models

1. Index approach – Relative Abundance Index
2. Density estimation
3. Occupancy modeling

Data analysis & interpretation

Species abundance

1. Index approach – Relative Abundance Index (RAI)

Principle

- An index can correspond to any type of animal or sign count whose variation over time and space is supposed to follow directly the variation of the population size

- The actual index-abundance relationship is very rarely tested leading to many limitations in extrapolations: linear, exponential relationship?

- The most used index for camera trap studies is an **average detection rate per species**

Advantages

- Easy to calculate

$$\text{RAI} = \frac{\#\, independent\ events}{number\ of\ camera.days\ of\ the\ CT}$$

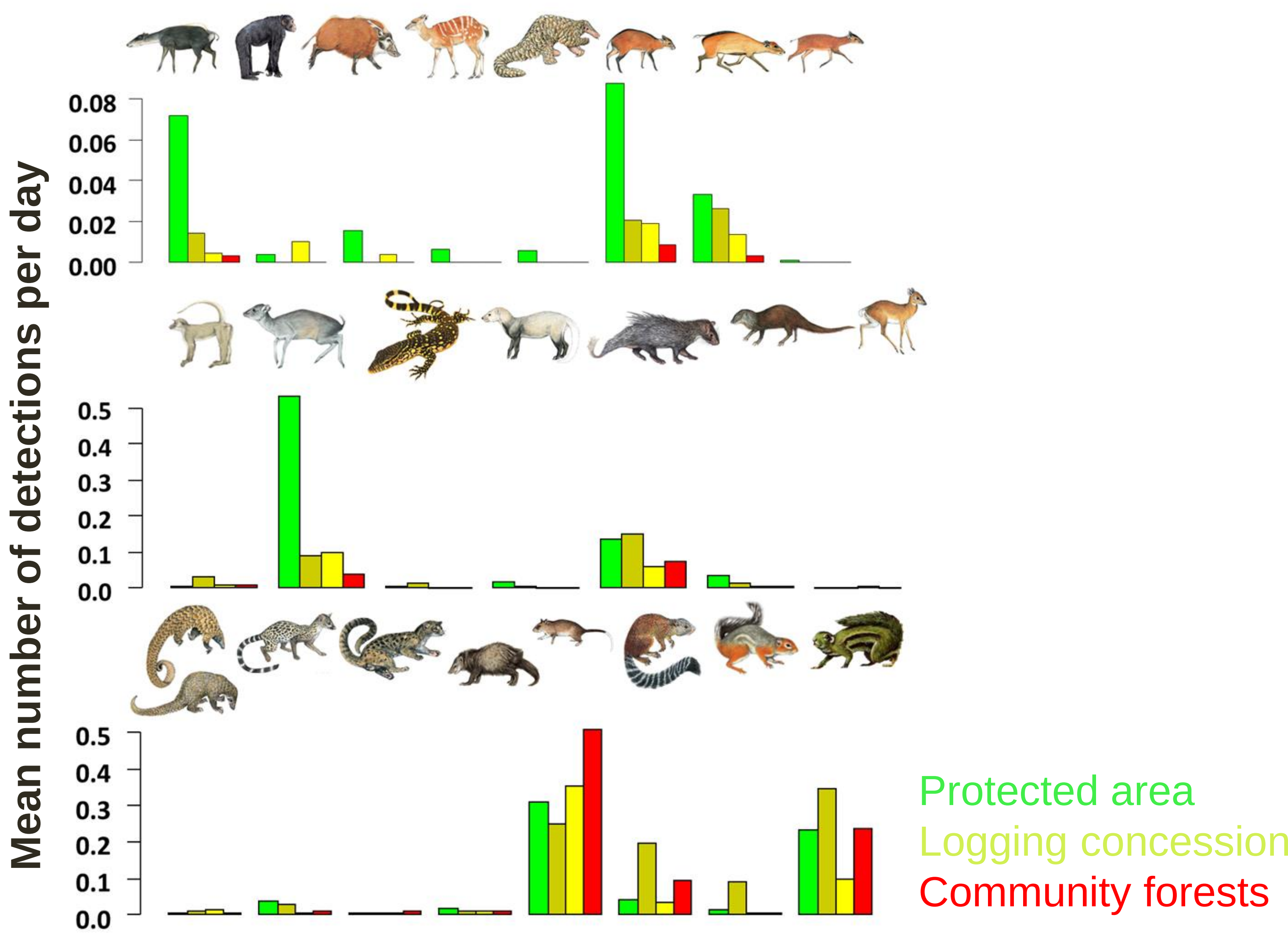
Limitations

- Implicit assumption that the probability of detection is constant across space, time and species ➔ Detection rate mixes abundance and detectability

Data analysis & interpretation

Species abundance

1. Index approach – Relative Abundance Index (RAI)



Fonteyn (2017) in Cameroon forests

Data analysis & interpretation

Species abundance

2. Density estimation: several recent approaches!

Random Encounter Model (2008)

- Density estimation based on detection rate, detection area size and animal movement
- Eliminates the need for individual recognition
- Random sampling allows extrapolation to larger scales
- No bias if spatial correlation exists (Cusack et al., 2015)
- Minimum of 50 captures per species to obtain reasonable results (Rovero et al., 2013)

Journal of Applied Ecology
British Ecological Society
Journal of Applied Ecology 2008, **45**, 1228–1236 doi: 10.1111/j.1365-2664.2008.01473.x

Estimating animal density using camera traps without the need for individual recognition

J. Marcus Rowcliffe[1]*, Juliet Field[2], Samuel T. Turvey[1] and Chris Carbone[1]

Data analysis & interpretation

Species abundance

2. Density estimation: several recent approaches!

Random Encounter Model (2008)

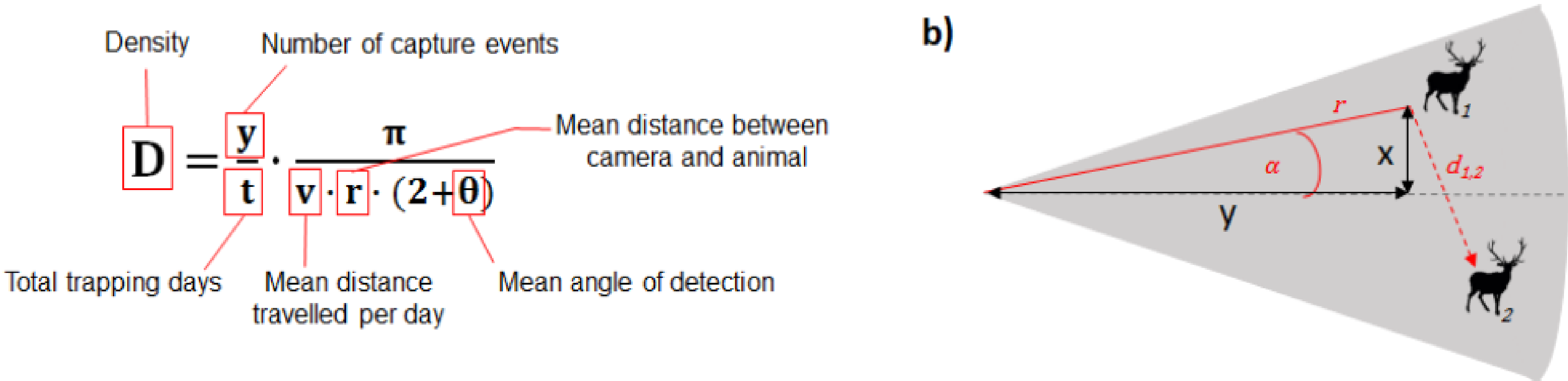


Figure 5: **a)** Random Encounter Model (REM). **b)** Camera detection zone. *r* represents distance between camera and animal (red line), *α* the angle of first detection (red angle) referring to the middle field of view (black dashed line), $d_{1,2}$ the distance an individual is walking between two pictures (red dashed line), and *x* and *y* the horizontal and vertical distance of the detected animal to the camera (black arrows).

Unknown 1: Detection area parameters **r** and **θ**

Unknown 2: Animal-related parameter **v**

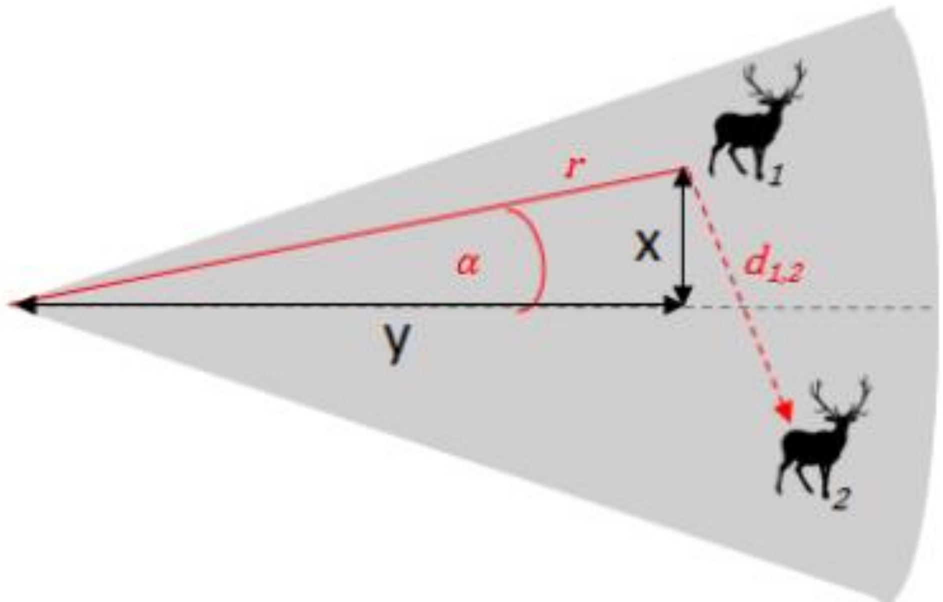
Data analysis & interpretation

Species abundance

2. Density estimation: several recent approaches!

Random Encounter Model (2008)

Determine **r**, **θ**, and **v** from the photos of each detection event



$$r = \frac{\sqrt{{x_1}^2 + {y_1}^2} + \sqrt{{x_2}^2 + {y_2}^2} + \cdots \sqrt{{x_i}^2 + {y_i}^2})}{i}$$

$$\theta = \frac{2\alpha_1 + 2\alpha_2 + \cdots + 2\alpha_i}{i}$$

$$v = s \cdot p$$

i: total number of detection events
s: average speed of movement
p: proportion of active time

Data analysis & interpretation

Species abundance

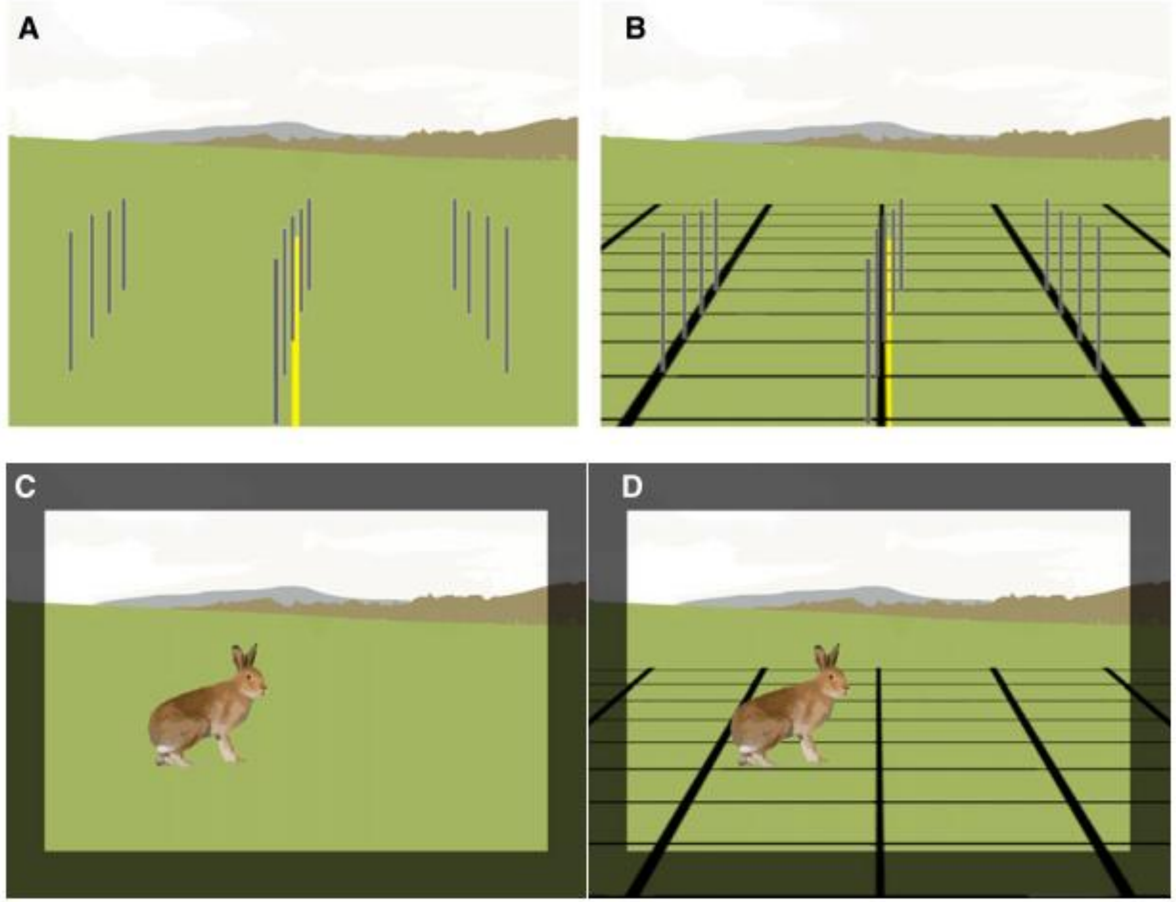
2. Density estimation: several recent approaches!

Random Encounter Model (2008)

Determine **r**, **θ**, and **v** in the field

To determine **v**: direct tracking of the animal (Cusack et al., 2015)

Example of a field device to automate the calculation of distances



Caravaggi et al. (2016)

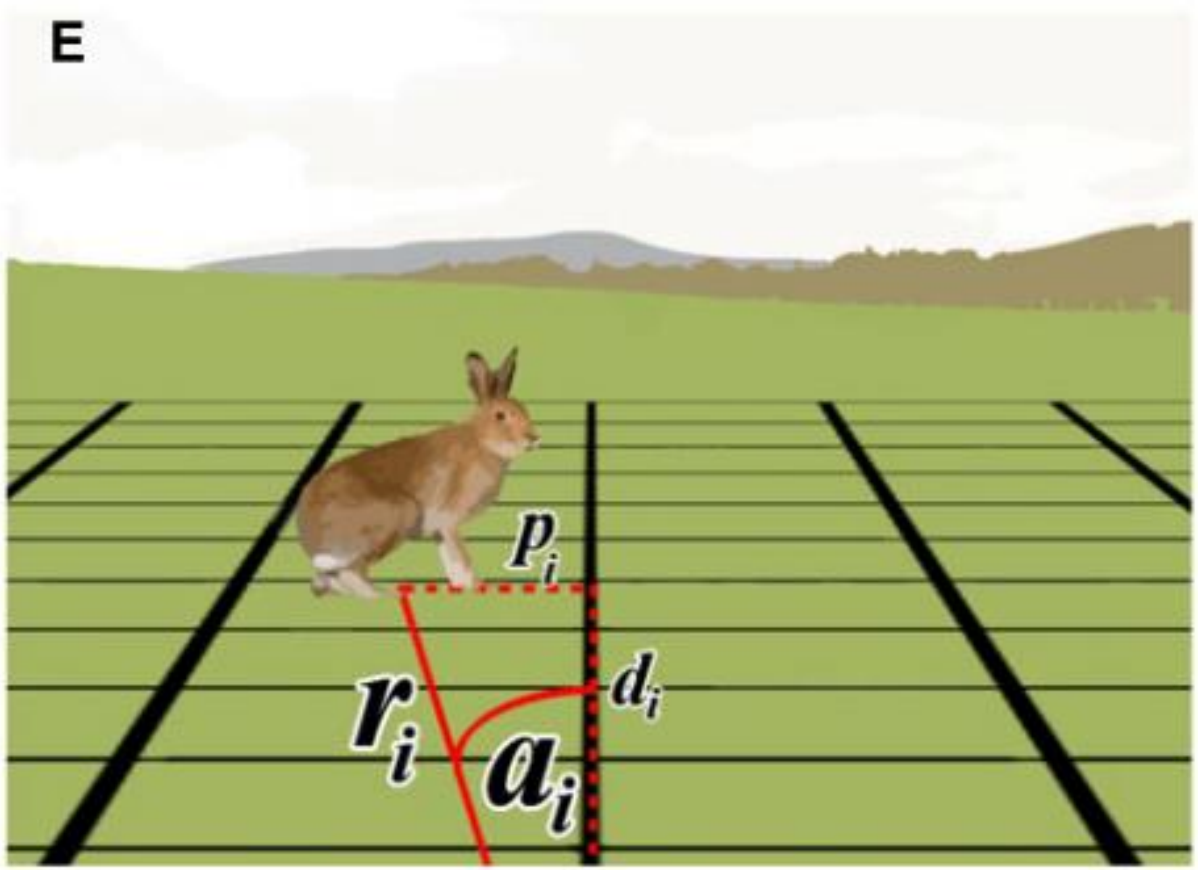
Data analysis & interpretation

Species abundance

2. Density estimation: several recent approaches!

Random Encounter Model (2008)

Determine **r**, **θ**, and **v** in the field



Caravaggi et al. (2016)

Data analysis & interpretation

Species abundance

2. Density estimation: several recent approaches!

Random Encounter Model (2008)

Figure 1. Camera trap photograph with a transect of markers at 2.5 m, 5 m, 7.5 m and 10 m, and a passing red fox (*Vulpes vulpes*).

Hofmeester et al. (2017)

Data analysis & interpretation

Species abundance

2. Density estimation: several recent approaches!

Random Encounter Model (2008)

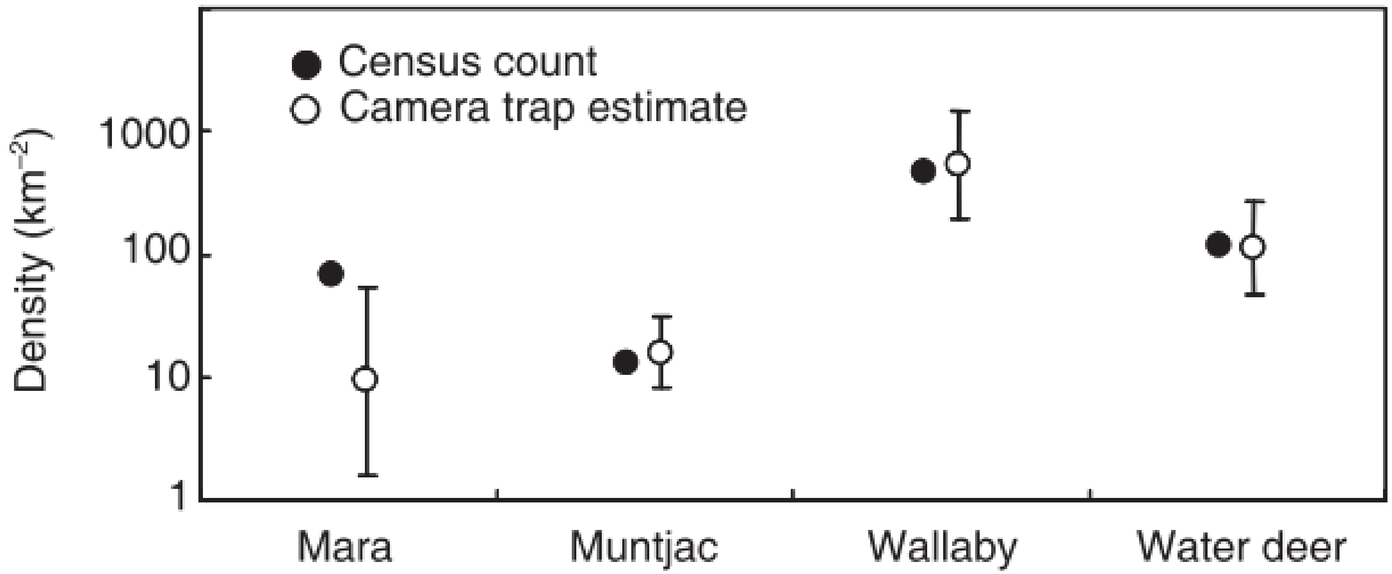


Fig. 3. Overall densities for the four focal species, compared between census densities and camera trap estimates stratified by region (±95% bootstrap confidence intervals).

Rowcliffe et al. (2008)

Data analysis & interpretation

Species abundance

2. Density estimation: several recent approaches!

Random Encounter and Staying Time (REST) model (2017)

- Describes the relationship between the time of presence, capture rate and density
- Extension of the REM model
- Time of presence = amount of time an animal remains in a specific area within the camera's field of view

RESEARCH ARTICLE

Journal of Applied Ecology BRITISH ECOLOGICAL SOCIETY

Estimating animal density without individual recognition using information derivable exclusively from camera traps

Yoshihiro Nakashima[1] | Keita Fukasawa[2] | Hiromitsu Samejima[3]

Data analysis & interpretation

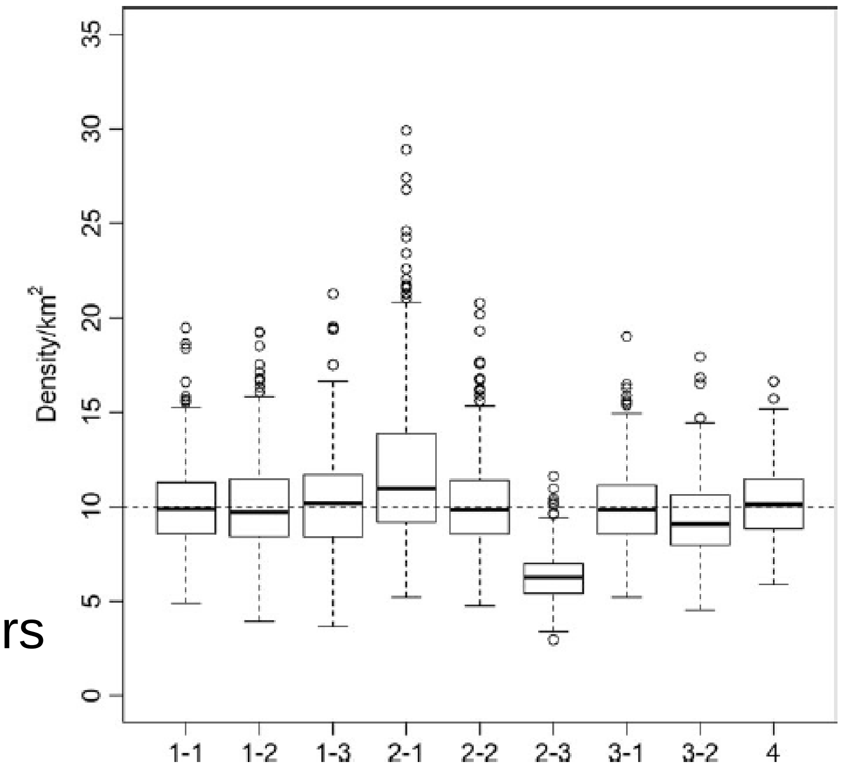
Species abundance

2. Density estimation: several recent approaches!

Random Encounter and Staying Time (REST) model (2017)

Provides **unbiased estimates of densities** with several modalities tested:

- 1-1: Individuals move constantly without rest 12h/day
- 1-2: Average distance traveled per individual varies
- 1-3: Two individuals move in pairs
- 2-1 & 2-2: Animals are not always active, and the proportion of active time was estimated
- 2-3: No synchronization of activity among individuals
- 3-1 & 3-2: Effects of different camera trap's parameters
- 4: Animals move every 2 seconds



Data analysis & interpretation

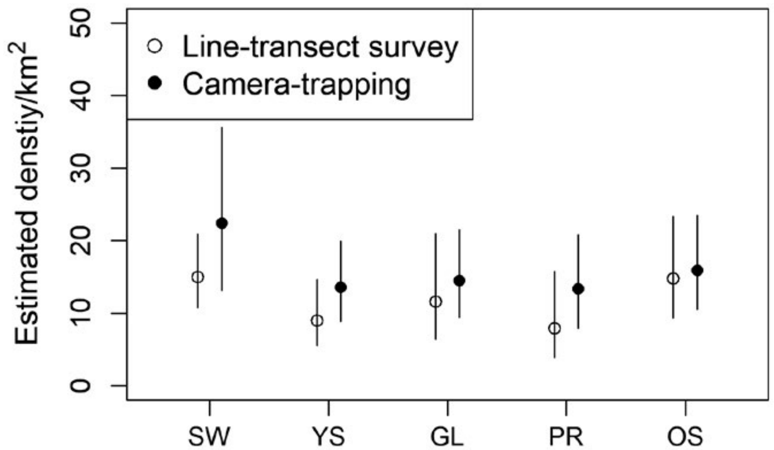
Species abundance

2. Density estimation: several recent approaches!

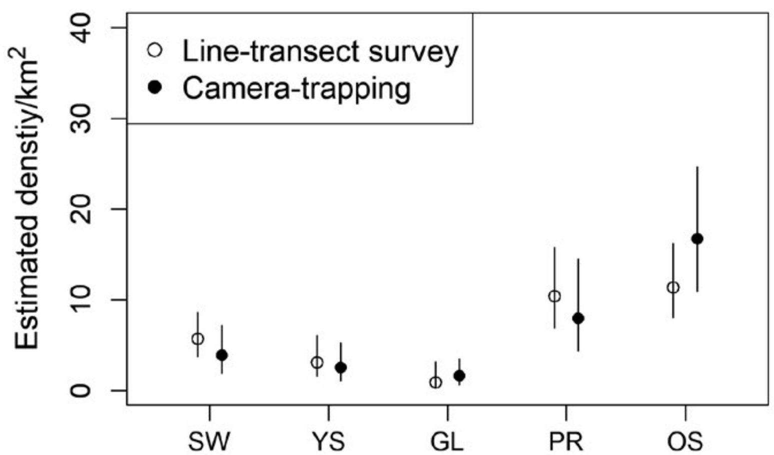
Random Encounter and Staying Time (REST) model (2017)

Effects of sampling effort:
Better to ↗ the number of CT rather than ↗ the time spent on a reduced number of CT

Estimated densities in agreement with those from line transects →



Limitations:
- Distribution of activity patterns must be representative of the species
- Need of biological information on the species to have a good estimate of active time and average presence time during active time



Data analysis & interpretation

Species abundance

2. Density estimation: several recent approaches!

Distance Sampling (2017)

- Method based on the traditional approach of Distance Sampling
- Application for the density estimation of *Philantomba maxwellii* in Taï National Park, Ivory Coast

Methods in Ecology and Evolution
BRITISH ECOLOGICAL SOCIETY
Methods in Ecology and Evolution 2017
doi: 10.1111/2041-210X.12790

Distance sampling with camera traps

Eric J. Howe*[,1], Stephen T. Buckland[1], Marie-Lyne Després-Einspenner[2] and Hjalmar S. Kühl[2,3]

Drawn out of the shadows: Surveying secretive forest species with camera trap distance sampling

Mattia Bessone[1,2] | Hjalmar S. Kühl[3,4] | Gottfried Hohmann[3] | Ilka Herbinger[5] | Kouame Paul N'Goran[6] | Papy Asanzi[2] | Pedro B. Da Costa[2] | Violette Dérozier[2] | Ernest D. B. Fotsing[2] | Bernard Ikembelo Beka[2] | Mpongo D. Iyomi[2] | Iyomi B. Iyatshi[7] | Pierre Kafando[8] | Mbangi A. Kambere[2] | Dissondet B. Moundzoho[2] | Musubaho L. K. Wanzalire[2] | Barbara Fruth[1,2,9]

Data analysis & interpretation

Species abundance

2. Density estimation: several recent approaches!

Distance Sampling (2017)

Density estimate =

$$\widehat{D} = \frac{\sum_{k=1}^{K} n_k}{\pi w^2 \sum_{k=1}^{K} e_k \widehat{P}_k}$$

Overall sampling effort at point *k* =

$$e_k = \frac{\theta T_k}{2\pi t}$$

$$\widehat{D} = \frac{2t \sum_{k=1}^{K} n_k}{\theta w^2 \sum_{k=1}^{K} T_k \widehat{P}_k}$$

Measurement of the horizontal radial distance r_i between the midpoint of each animal and the camera at snapshot moment ***t***, to model the detection function and to estimate P_k

T_k = time survey period at camera trap *k*

t = unit of time for each snapshot moment

$\frac{T_k}{t}$ = temporal effort at the point

$\frac{\theta}{2\pi}$ = fraction of a circle covered by the camera

w = truncation distance beyond which observations are discarded

n_k = nbr of observations of animals in the population at point *k*

$\widehat{P}_k$ = estimated probability of obtaining an image of an animal that is within θ and w in front of the camera at a snapshot moment

Data analysis & interpretation

Species abundance

2. Density estimation: several recent approaches!

Time To Event (TTE) model (2018)

- "The time until the target species is detected is a function of **abundance**, **movement rate**, and **detectability** (Jennelle et al., 2002; Parsons et al., 2017)"

- Based on the first detection of the species

- Need to integrate species movement
  ➔ Sampling period = average time for an animal to cross the camera's field of view

esa ECOSPHERE

Three novel methods to estimate abundance of unmarked animals using remote cameras

Anna K. Moeller,[1,†] Paul M. Lukacs,[1] and Jon S. Horne[2]

Data analysis & interpretation

Species abundance

2. Density estimation: several recent approaches!

Time To Event (TTE) model (2018)

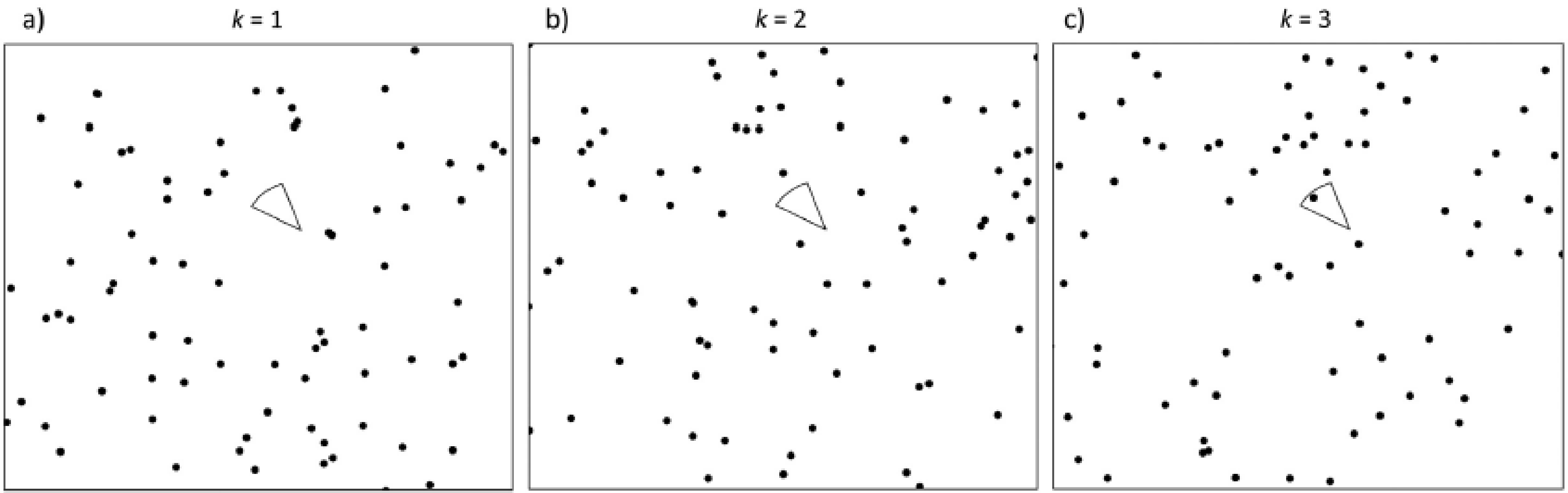


Fig. 2. Conceptual diagram of the time to event (TTE) model. The circular sector is the viewshed of a single camera i on a single occasion j divided into three successive sampling periods (a–c). The black dots represent randomly placed animals. The observed TTE T_{ij} is equal to the period k in which the camera first contains an animal. There are no animals in the camera in (a) $k = 1$ or (b) $k = 2$, but there is an animal in the camera in (c) $k = 3$, so for this camera and sampling occasion, $T_{ij} = 3$.

Data analysis & interpretation

Species abundance

2. Density estimation: several recent approaches!

Space To Event (STE) model (2018)

- The '*time-lapse*' function of camera traps allows to get rid of the variability of the sensor and thus of the variable detection

  ➔ No need of information on the movement of the species

- Based on the total area sampled before the first detection of the species

Data analysis & interpretation

Species abundance

2. Density estimation: several recent approaches!

Space To Event (STE) model (2018)

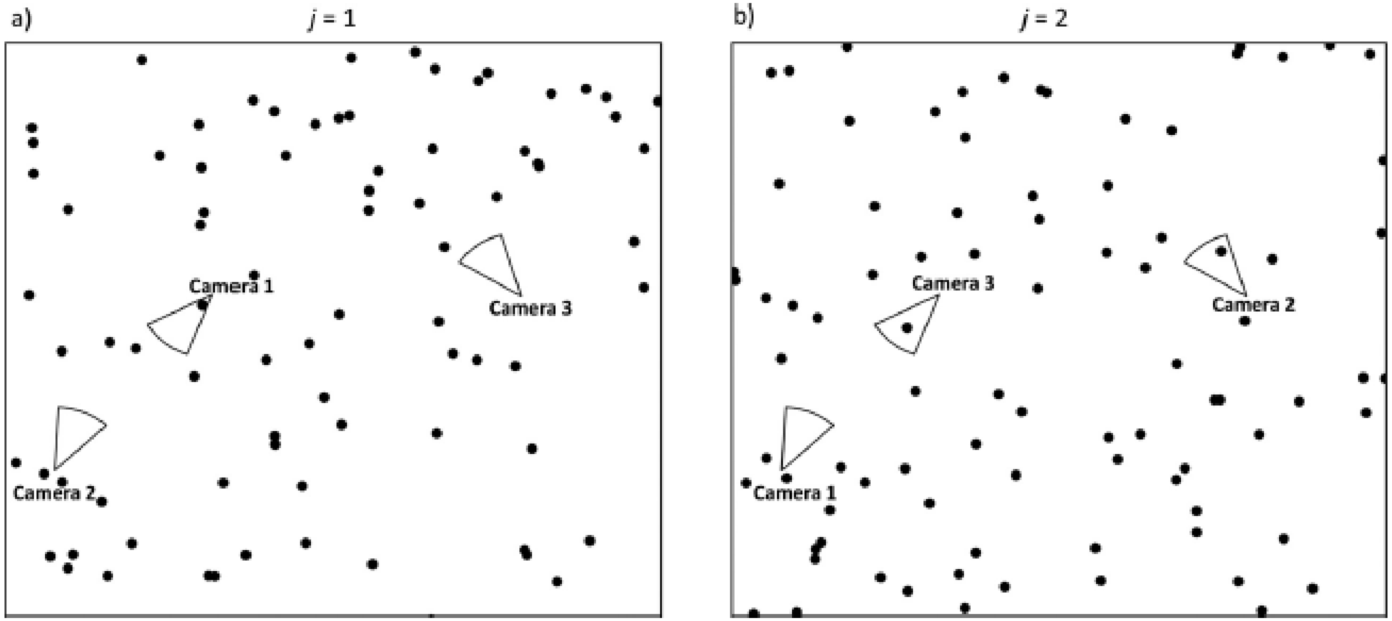


Fig. 3. Conceptual diagram of the space to event (STE) model. The circular sectors represent three different cameras on two different occasions (a–b). On each occasion $j = 1, 2, \ldots, J$, we randomly order the cameras $i = 1, 2, \ldots, M$. If the first animal detection is in the nth camera, the observed STE S_j is the sum of the areas of cameras $1, 2, \ldots n$. (a) On occasion $j = 1$, camera 1 contains at least one animal, so we record the space to first event $S_{j=1} = a_1$. (b) On occasion $j = 2$, cameras 2 and 3 both contain animals, but we use the first camera in the series. Therefore, we record the space to first event $S_{j=1} = a_1 + a_2$.

Data analysis & interpretation

Species abundance

2. Density estimation: several recent approaches!

Space To Event (STE) model (2018)

Case study: Elk abundance in Idaho

- 80 CT in February 2016
- Calculation of the camera's field of view
- Estimated speed based on GPS tracking (*N* = 53) ➔ 30 m/h
- Sampling period
  = 1 h for the TTE model
  = 1 min for the STE model

Conclusions:
- TTE model sensitive to different displacement speeds
- Based on snapshots, the STE model is free from :
  - Problems related to displacement
  - The variation in detection probabilities

Data analysis & interpretation

Species abundance

3. Occupancy modeling

- Modeling occupancy, considering imperfect species detection, can be considered as a proxy for abundance (MacKenzie et al., 2006)

- Reduction of photo count data to a **binary format (0/1)**
  - 0: species not detected, but not necessarily absent!
  - 1: species detected at least 1 time

- Estimation of **PAO (Proportion of area occupied)**, **probabilities of occupancy** and **detection** of species at the site (need for **detection history**)

- Occupancy models are based on repeated visits, in a short time interval, to multiple sampled sites (camera traps)

Data analysis & interpretation

Species abundance

3. Occupancy modeling

Detection history (e.g., obtained from Camera Base / Timelapse)

	Season
Sites	**A**	
1	111	Site occupied and species often detected
2	010	Site occupied and often missed species
3	000	Site occupied and species not detected OR site unoccupied
…	…	

- Sampling undertaken over a sufficiently short period of time to ensure that sites are closed to changes in occupancy
- Sampled sites that are far apart so that the occupancy of a given site is independent of the occupancy of all other sites

Data analysis & interpretation

Species abundance

3. Occupancy modeling

Naive occupation

$$\text{PAO} = \frac{\#\ \text{sites where species detected}}{\text{total}\ \#\ \text{sites surveyed}}$$

- Useful to know in a practical way the probable distribution of the species
- But no consideration of species present but not detected

Data analysis & interpretation

Species abundance

3. Occupancy modeling

Probability of individual presence at each site L_i

111

$$L_i = \underset{\text{Species present}}{\psi_i}\underbrace{p_{1i}\,p_{2i}\,p_{3i}}_{\text{Species detected on each occasion}}$$

101

$$L_i = \underset{\text{Species present}}{\psi_i}\underbrace{p_{1i}(1-p_{2i})\,p_{3i}}_{\text{Species detected on occasions 1 and 3 but not detected on occasion 2}}$$

000

$$L_i = \underbrace{\psi_i(1-p_{1i})(1-p_{2i})(1-p_{3i})}_{\text{The species may be present but never detected}} + \underbrace{(1-\psi_i)}_{\text{Or absent species}}$$

ψ_i: probability that the species is present on the *i*

p_{oi}: probability of detection of the species at site *i* on occasion *o*, if present at site *i*

Data analysis & interpretation

Species abundance

3. Occupancy modeling

Probability of the whole dataset at the *S* sampled sites

$$L_{data} = \prod_{i=1}^{S} L_i$$

Multiple sampling seasons

	Seasons		
Sites	**A**	**B**	**C**
1	111	010	000
2	010	0 . .	100
3	000	101	111
–			
–			
s	0.1	101	110

➔ Possibility to get an idea of the population dynamics (colonization, extinction)

Data analysis & interpretation

Species abundance

3. Occupancy modeling

Conditions of application ⚠

- Closed site: closed to occupancy changes during the sampling period
- No false detection: a species is never falsely detected but may be undetected at a site where it is present (no false positive, acceptance of false negative)
- Detection at one site is independent of detection at all other sites
- Detection probabilities are homogeneous from one site to another, or any heterogeneity is considered in the occupation model

Data analysis & interpretation

Species abundance

3. Occupancy modeling

- Possibility to run the model by suggesting a variation of p_{oi} and ψ_i

- Possibility to run the model with covariates:
  - Site-related (habitat types, elevation, etc.)
  - Reflecting human activities (cartridges and other hunting signs, logging activities, distance to roads, distance to villages…)
  - Etc.

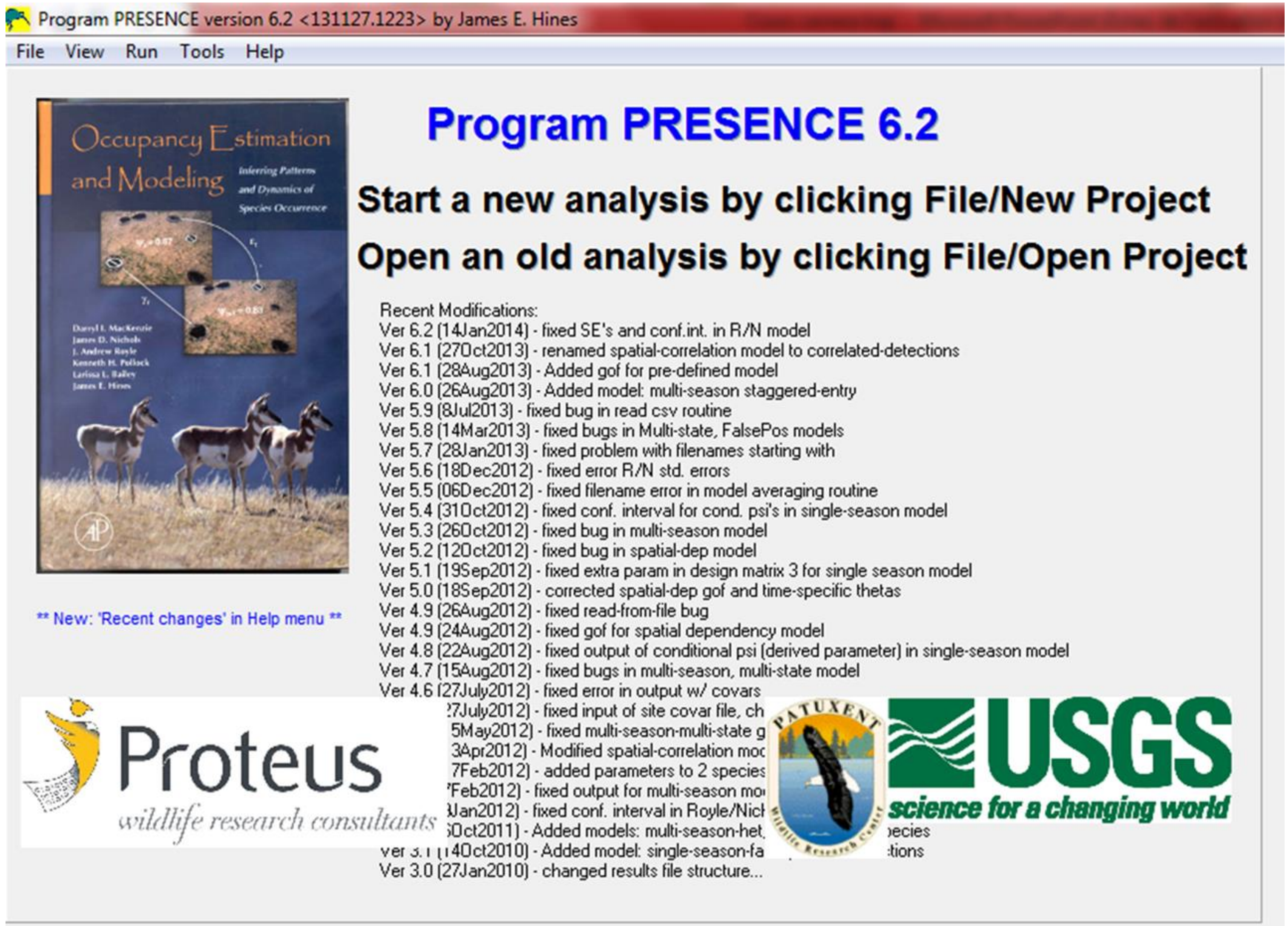
- **Choose the appropriate model according to the AIC**

Data analysis & interpretation

Species abundance

3. Occupancy modeling

Rpresence **package allows to make the occupancy models initially developed in the *Presence* software**

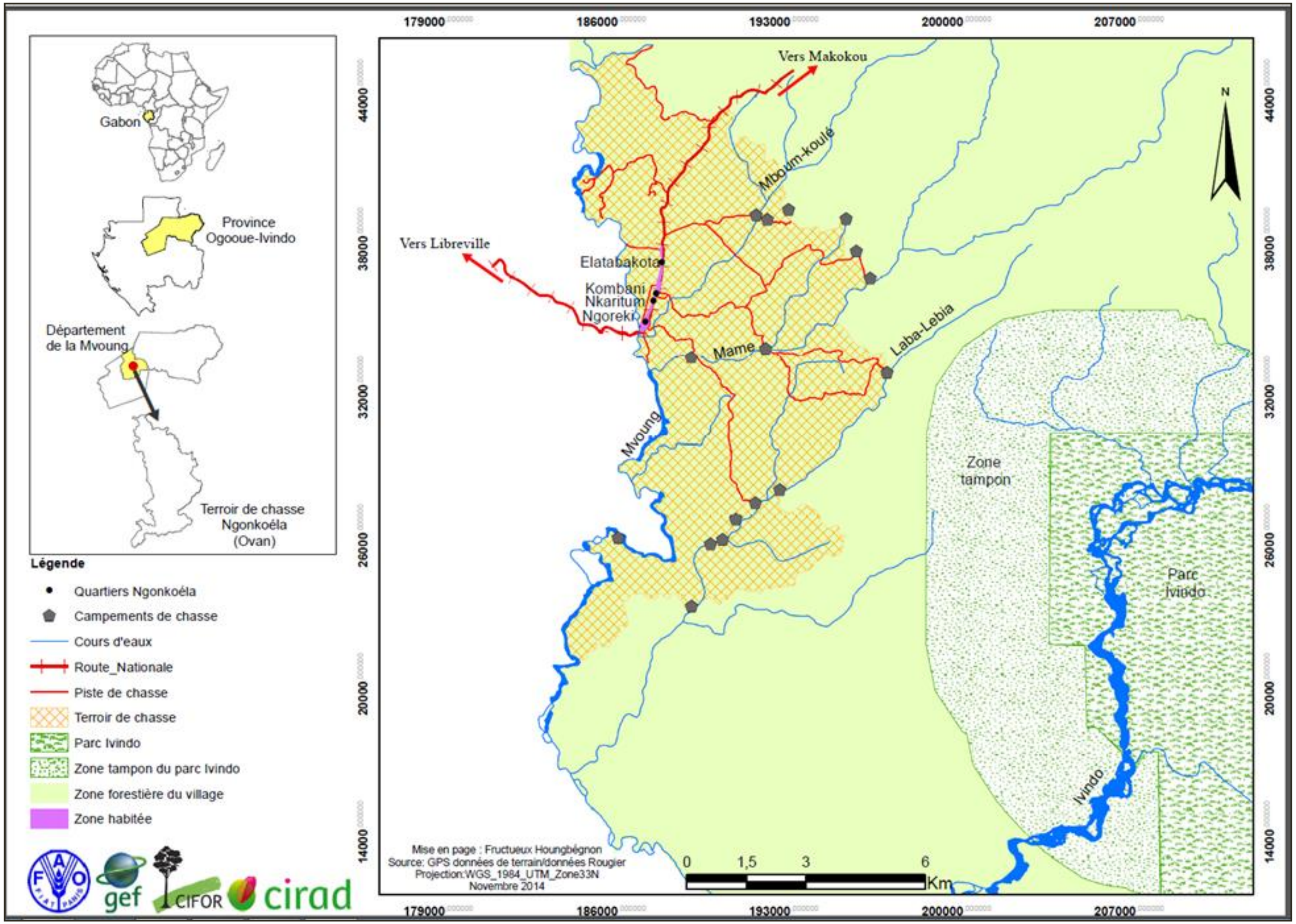


Data analysis & interpretation

Species abundance

3. Occupancy modeling

Case study

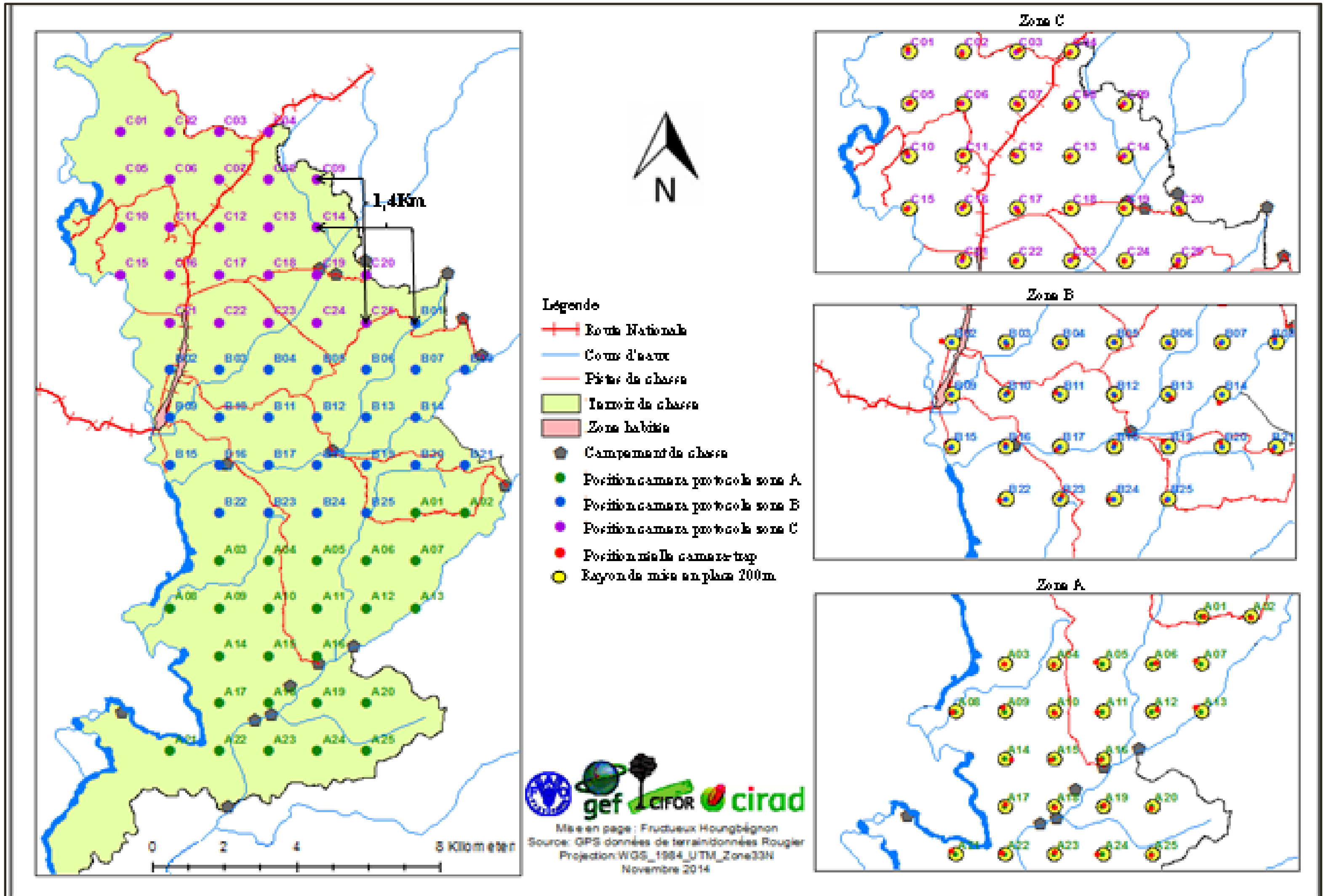


Data analysis & interpretation

Species abundance

3. Occupancy modeling

Case study



Data analysis & interpretation

Species abundance

3. Occupancy modeling

Case study

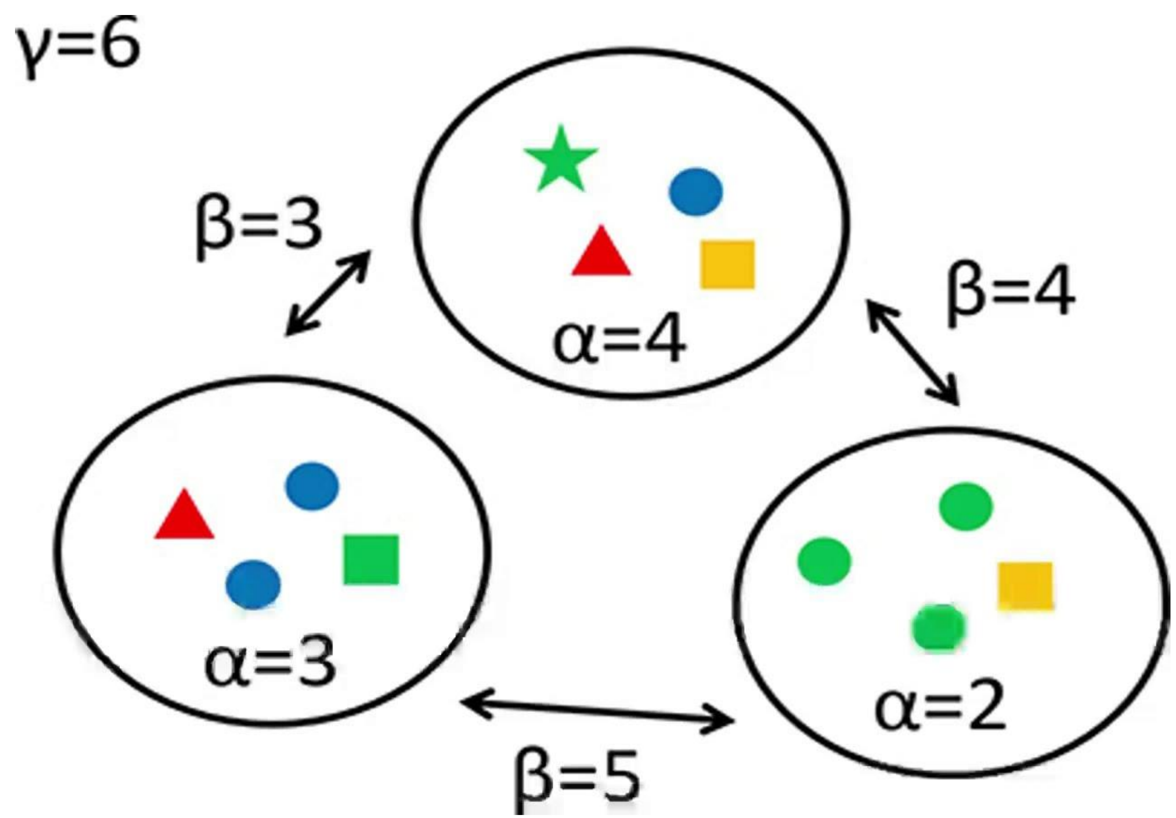
- Sites considered as closed, and homogeneous detection probability
- 1 season of 30 days composed of 5 primary seasons of 6 days

Species	AIC	Naive occupation	Occupation probability	Standard error	Detection probability	Standard error
Blue duiker	292.16	**0.7347**	0.7385	0.0634	**0.6522**	0.0363
Other duikers	275.62	0.6327	0.6392	0.0697	0.6003	0.0408
Brush-tailed porcupine	237.52	0.5102	0.5631	0.0822	0.3769	0.0498
Bushpig	81.92	**0.1429**	**0.2275**	0.1068	0.1794	0.0866
Mandrill	190.07	0.4898	**0.9859**	0.2842	**0.1283**	0.0428

Data analysis & interpretation

Species composition

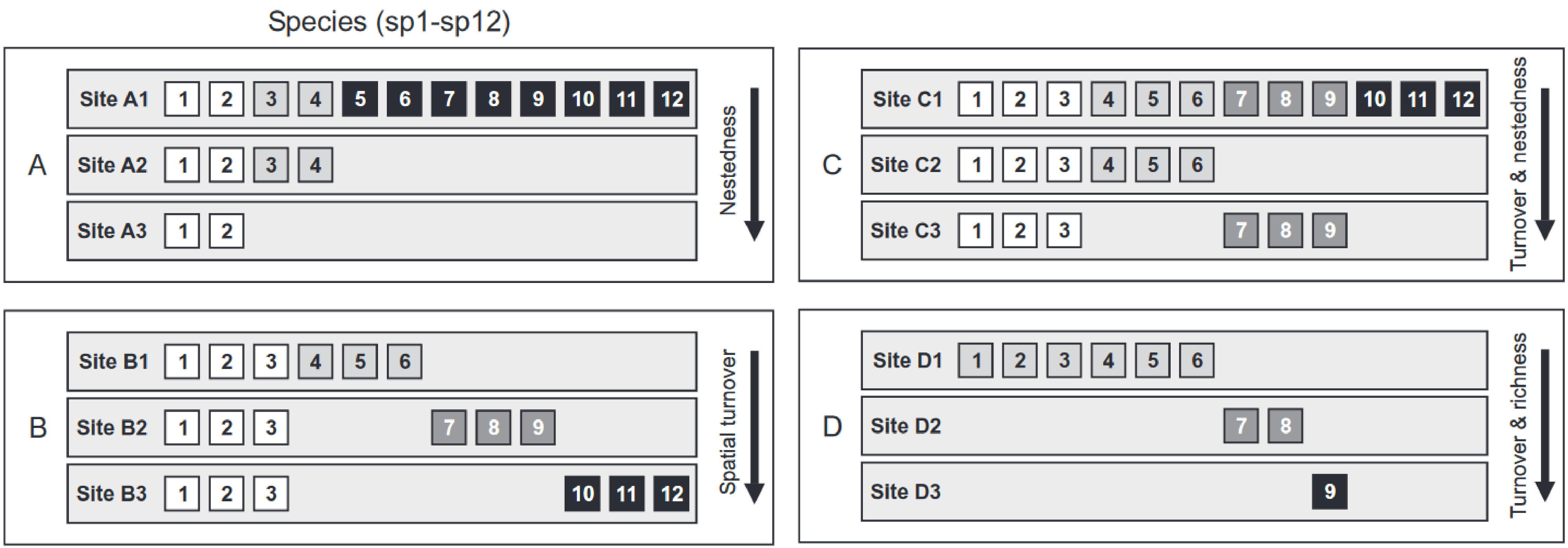
Reminder: α, β, and γ-diversity



Data analysis & interpretation

Species composition

β-diversity partitioning = turnover + nestedness



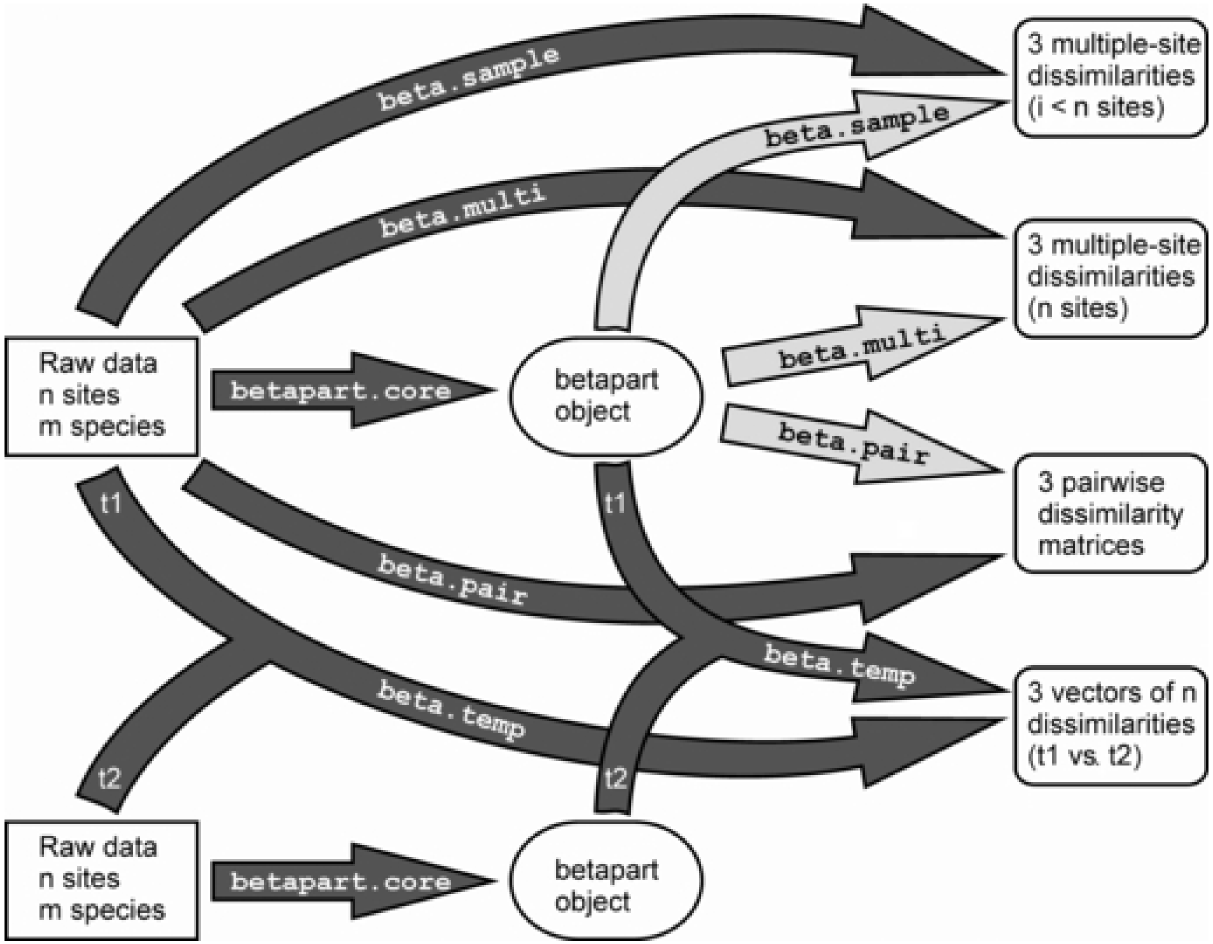
Baselga (2009)

Data analysis & interpretation

Species composition

β-diversity partitioning = turnover + nestedness

R package ***betapart***

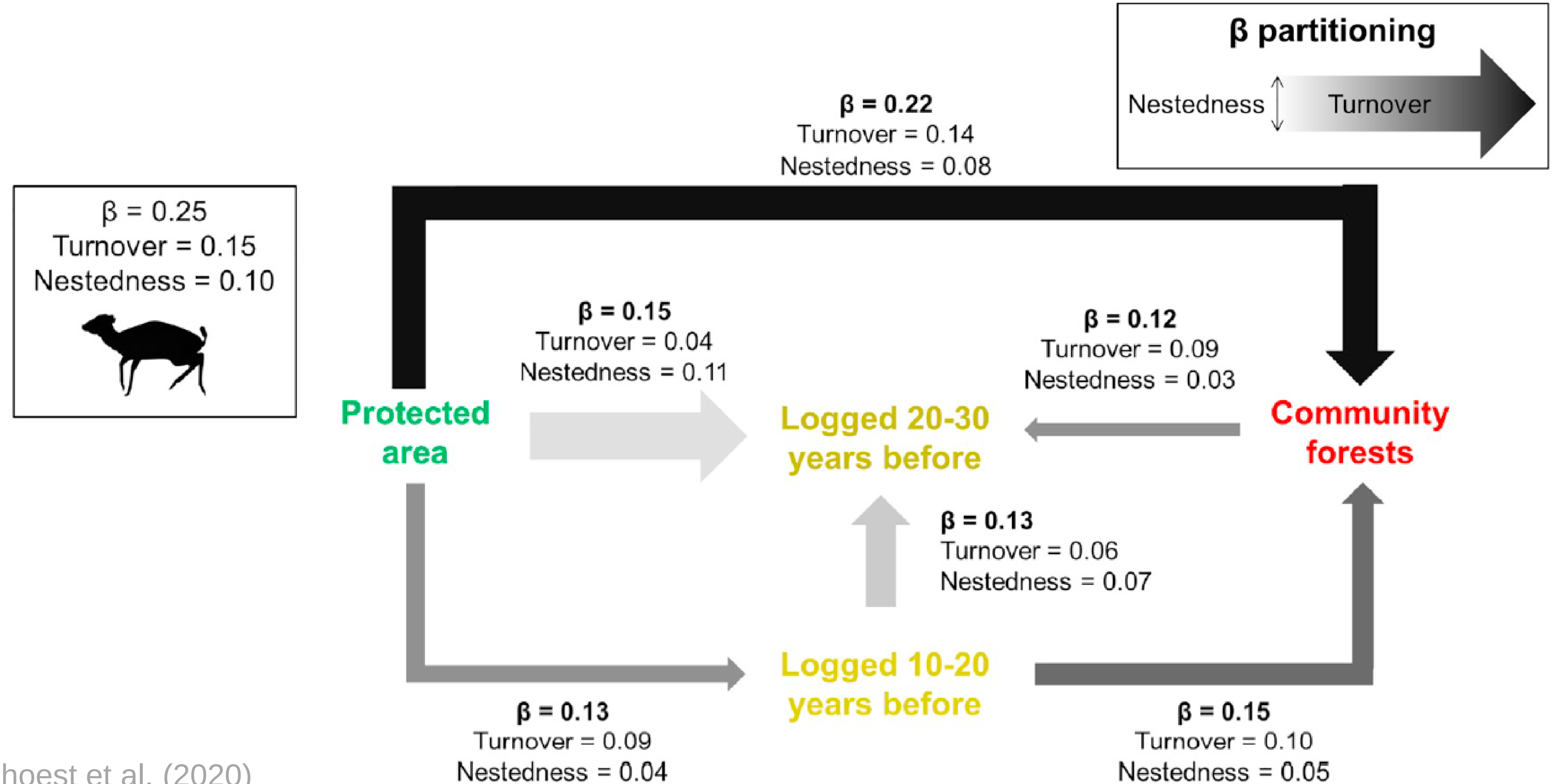


Baselga & Orme (2012)

Data analysis & interpretation

Species composition

β-diversity partitioning = turnover + nestedness



Lhoest et al. (2020)

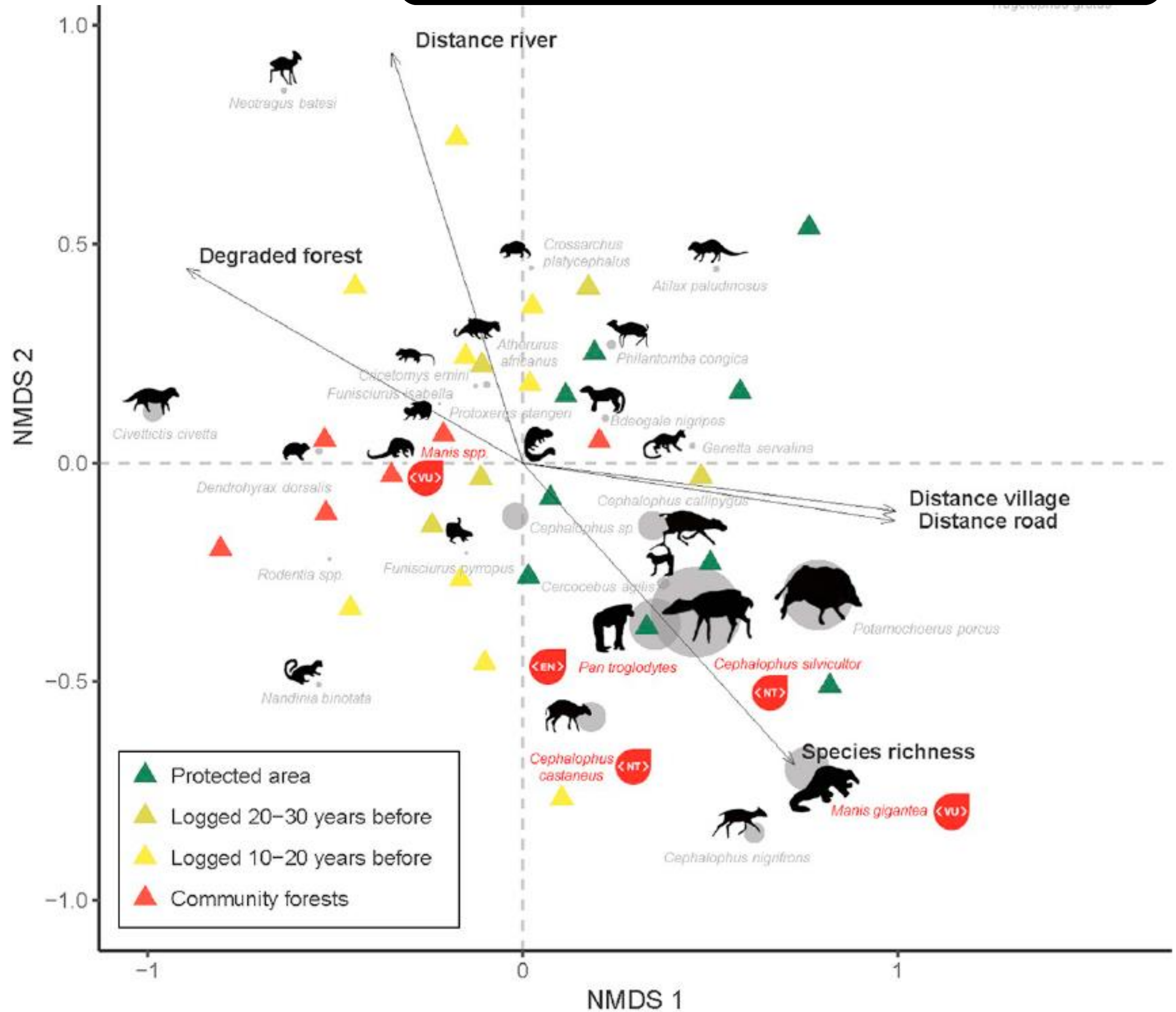
Data analysis & interpretation

Species composition

Nonmetric Multidimensional Scaling

Based on the abundance matrix of animal species:
cameras X species

- Triangles: sampling sites (camera traps)
- Gray points: species (+ IUCN status), point size proportional to the mean adult body mass
- Arrows: projection of supplementary variables



Lhoest et al. (2020)

4. Perspectives

Combining environmental DNA (eDNA) analysis with camera trap studies

- Automatic identification of a panel of species from a sample
  ➔ **Metabarcoding**

- eDNA has been used extensively to characterize aquatic communities...

- Invertebrate-derived DNA (iDNA) obtained from leeches or flies found on carrion (family Calliphoridae and Sarcophagidae) has already shown high potential as a rapid tool for the detection of many species

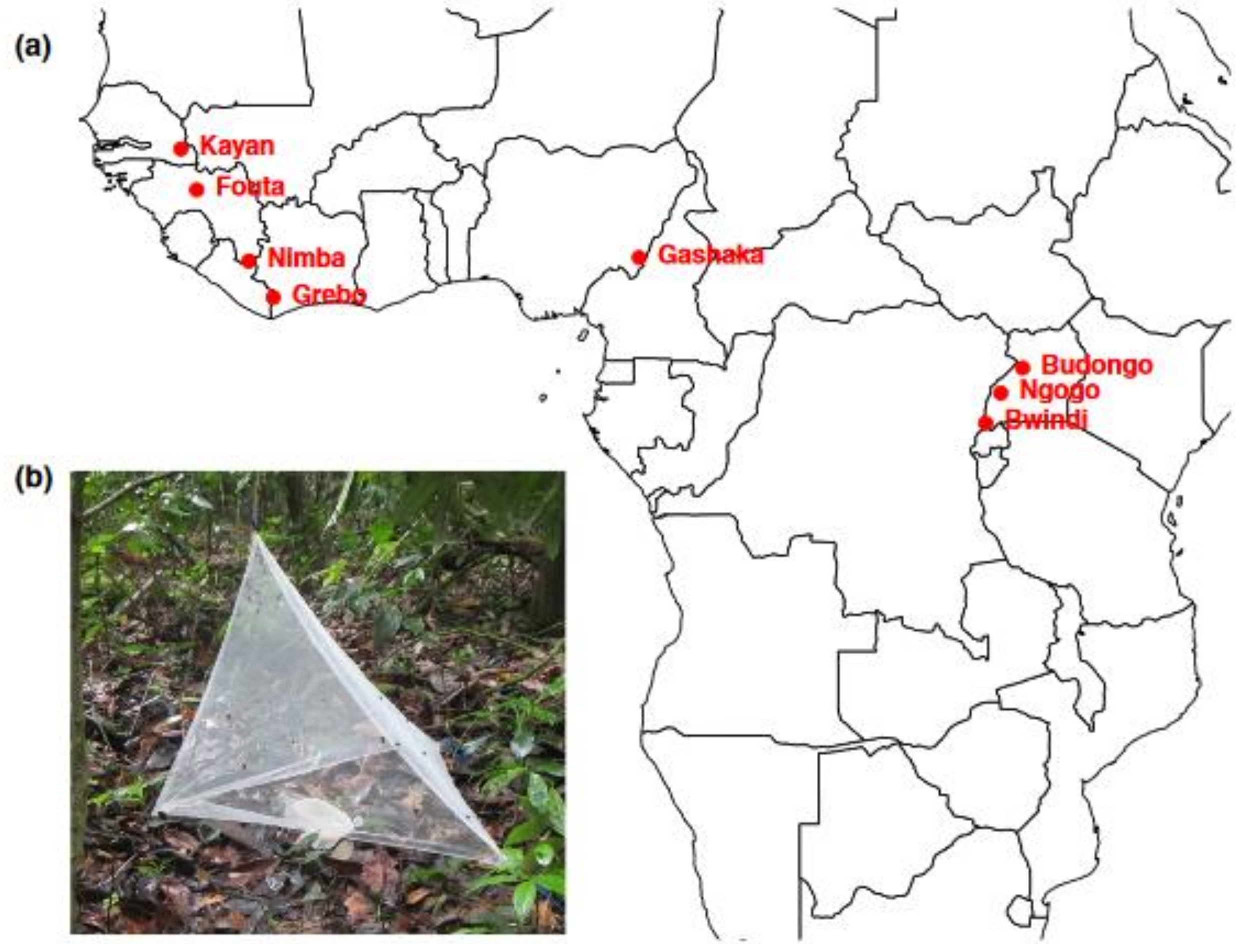
ORIGINAL ARTICLE

Environmental DNA
Open Access
Dedicated to the study and use of environmental DNA for basic and applied sciences
WILEY

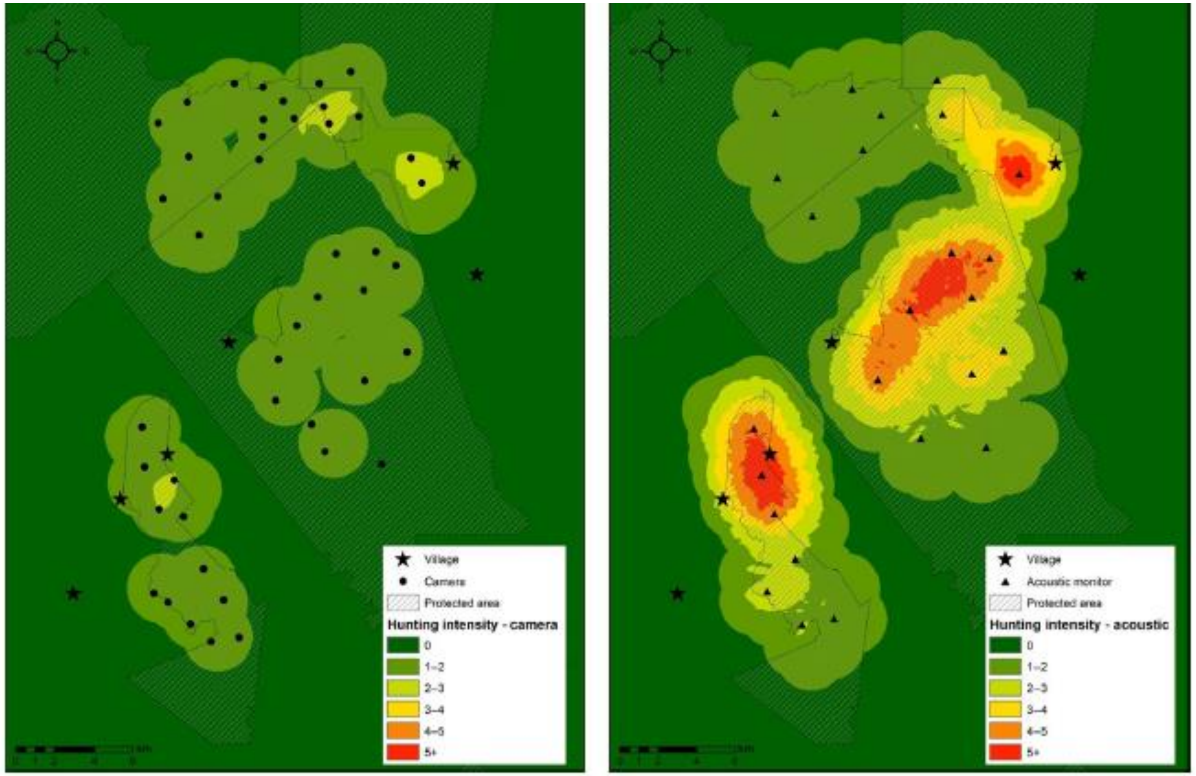
Fly-derived DNA and camera traps are complementary tools for assessing mammalian biodiversity

Combining environmental DNA (eDNA) analysis with camera trap studies

- The two approaches are complementary and do not detect the same taxa (Lee et al., 2016; Rodgers et al., 2017)
- Field data collection is relatively easy and can be done in parallel with camera trap inventories
- Logistical difficulties in analyzing these iDNA but less costly than camera traps
- Many mammal species are not known yet from a genetic point of view



Couple camera trap inventories with acoustic sensor inventories



RESEARCH ARTICLE

Journal of Applied Ecology BRITISH ECOLOGICAL SOCIETY

An integrated approach to measure hunting intensity and assess its impacts on mammal populations

Michael Dobbins[1,2] | Rahel Sollmann[1] | Scot Menke[2] | Angelica Almeyda Zambrano[2] | Eben Broadbent[2]

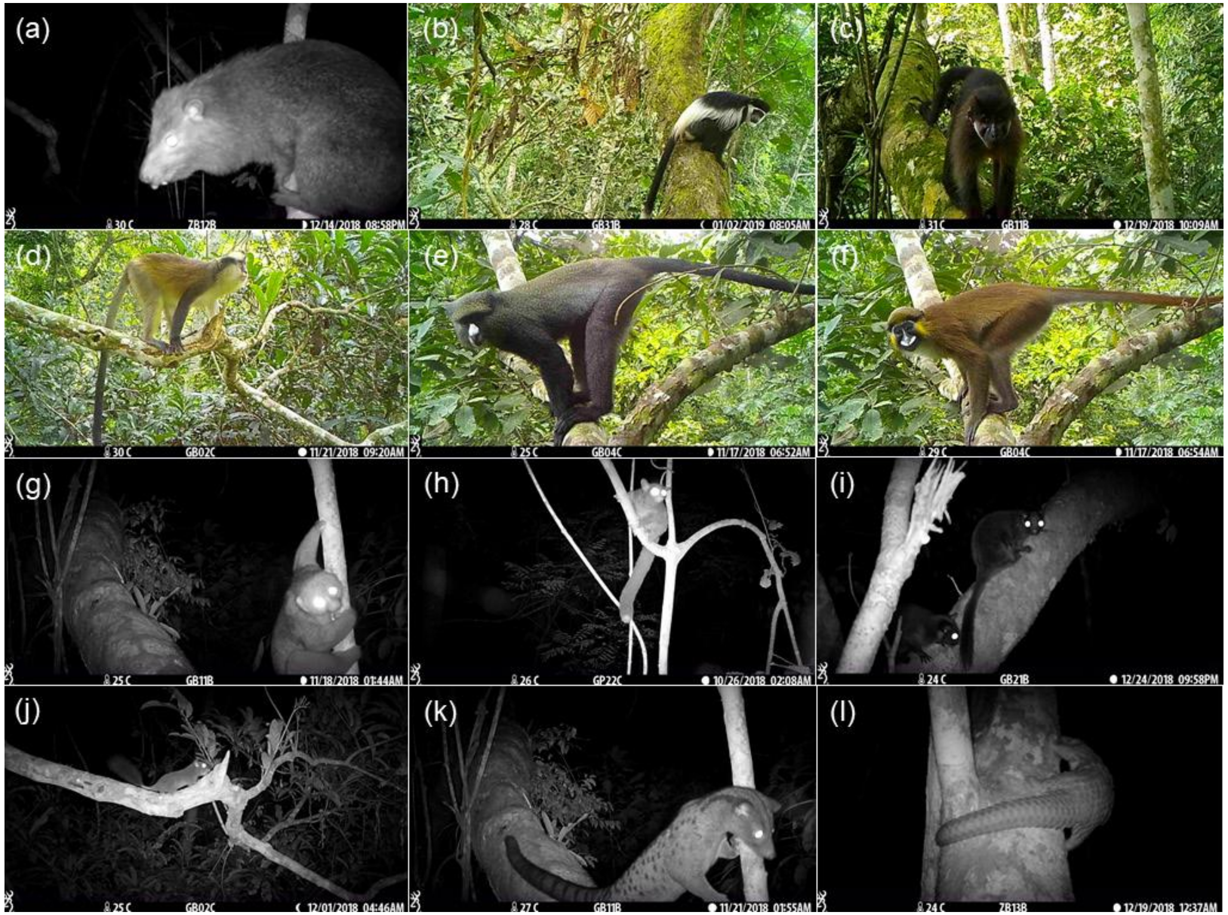
REVIEW

Conservation Science and Practice
A Journal of the Society for Conservation Biology
WILEY

Methods for wildlife monitoring in tropical forests: Comparing human observations, camera traps, and passive acoustic sensors

Joeri A. Zwerts[1,2] | P. J. Stephenson[3] | Fiona Maisels[4,5] | Marcus Rowcliffe[6] | Christos Astaras[7] | Patrick A. Jansen[8,9] | Jaap van der Waarde[10] | Liesbeth E. H. M. Sterck[2] | Pita A. Verweij[11] | Tom Bruce[12,13] | Stephanie Brittain[14] | Marijke van Kuijk[1]

Survey of arboreal species by camera traps

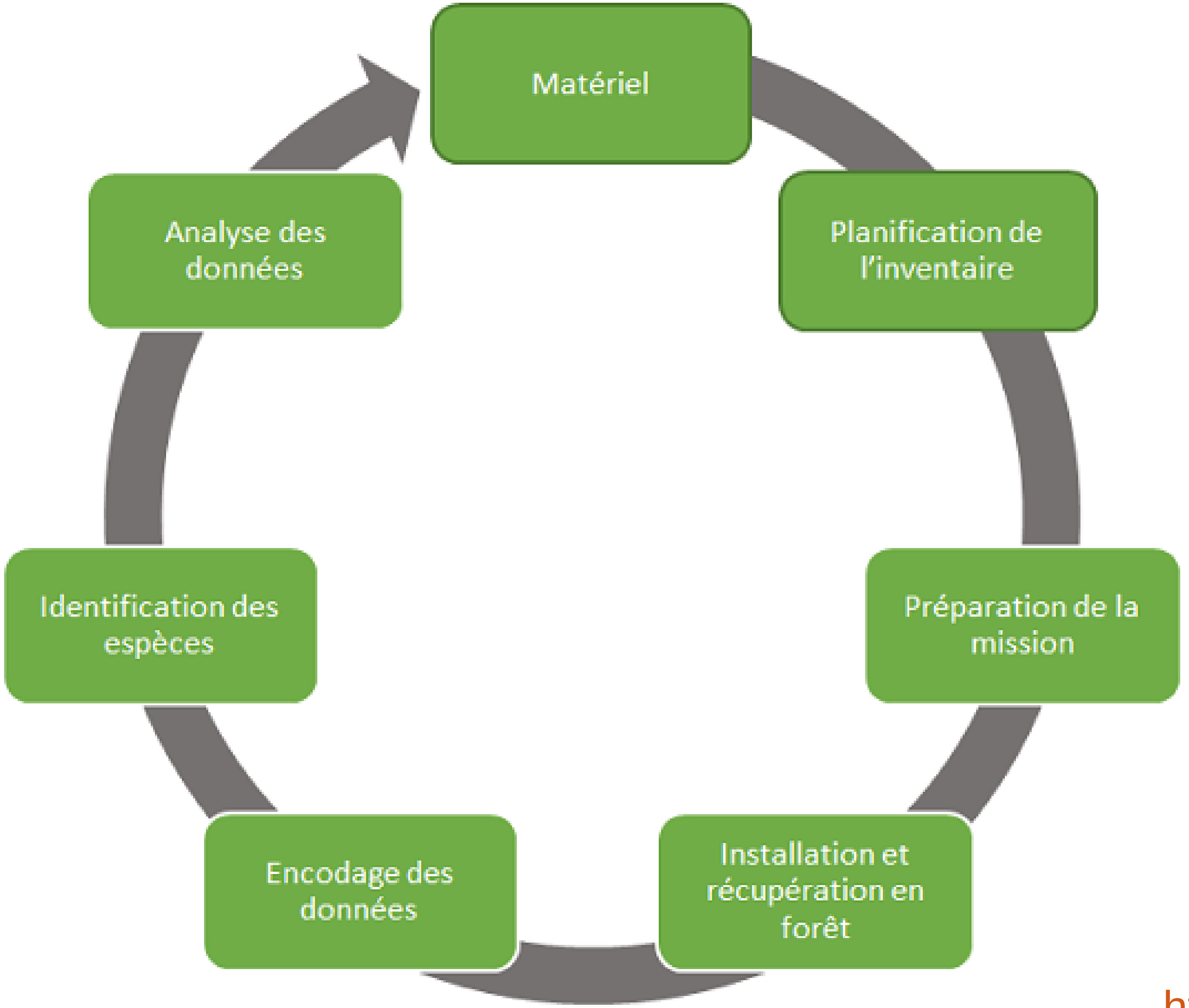


African Study Monographs, Suppl. 60: 21–37, March 2020

USE OF MULTI-LAYER CAMERA TRAPPING TO INVENTORY MAMMALS IN RAINFORESTS IN SOUTHEAST CAMEROON

'FauneFAC' platform

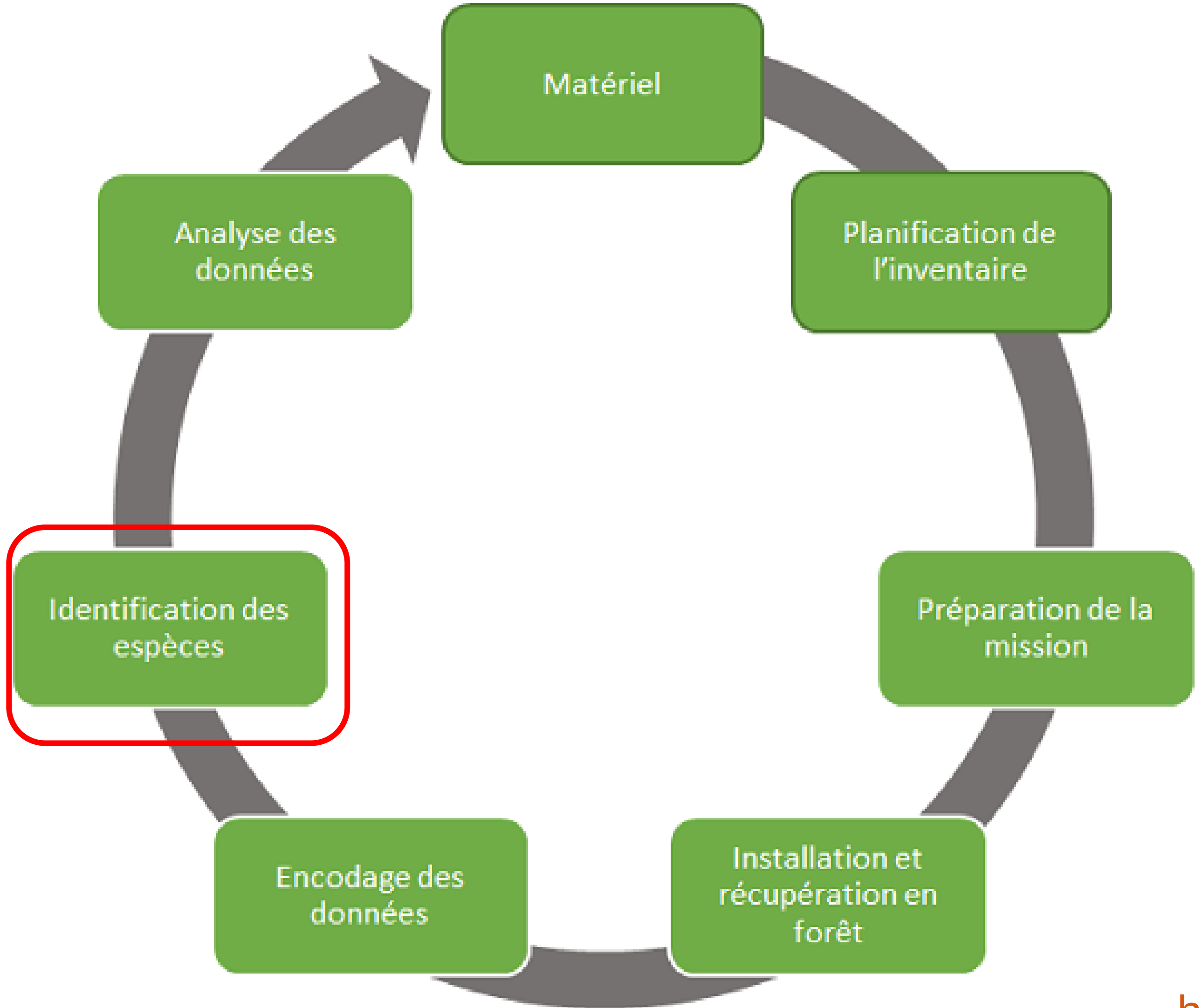
Methodological toolbox for the implementation of photographic trap inventories



https://www.gembloux.ulg.ac.be/faunefac/

'FauneFAC' platform

Methodological toolbox for the implementation of photographic trap inventories



Découvrez les espèces d'Afrique centrale !

Mammifères

- **Artiodactyles**
  - Bovidae
    - Antilope de Bates – *Neotragus batesi*
    - Bongo – *Tragelaphus eurycerus*
    - Buffle – *Syncerus caffer*
    - Céphalophe à bande dorsale noire – *Cephalophus dorsalis*
    - Céphalophe bleu – *Philantomba monticola*
    - Céphalophe à dos jaune – *Cephalophus silvicultor*
    - Céphalophe à front noir – *Cephalophus nigrifrons*
    - Céphalophe à pattes blanches – *Cephalophus ogilbyi*
    - Céphalophe à ventre blanc – *Cephalophus leucogaster*
    - Céphalophe de Peters – *Cephalophus callipygus*
    - Chevrotain aquatique – *Hyemoschus aquaticus*
    - Guib harnaché – *Tragelaphus scriptus*
    - Sitatunga – *Traglepahus spekii*
  - Suidae
    - Hylochère – *Hylocherus meinertzhageni*
    - Potamochère roux – *Potamochoerus porcus*
- **Carnivores**
  - Herpestidae
    - Autres mangoustes – *Atilax paludinosus / Herpestes naso*
    - Cusimanse – *Crossarchus platycephalus*
    - Mangouste à pattes noires – *Bdeogale nigripes*
  - Felidae
    - Chat doré africain – *Caracal aurata*
    - Léopard – *Panthera pardus*
    - Serval – *Leptailurus serval*
  - Mustelidae
    - Ratel – *Mellivora capensis*

https://www.gembloux.ulg.ac.be/faunefac/

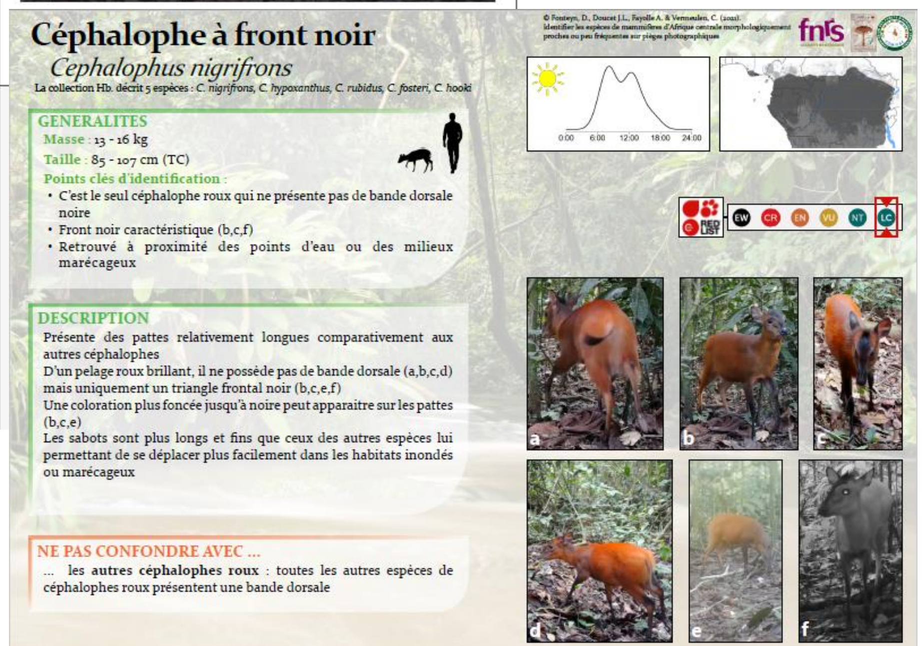
‘FauneFAC’ platform

Methodological toolbox for the implementation of photographic trap inventories

Céphalophe à front noir

Parc National de l'Ivindo 12/05/2018
© Davy Fonteyn

Parc National de l'Ivindo 12/05/2018
© Davy Fonteyn



Céphalophe à front noir

Cephalophus nigrifrons

La collection Hb. décrit 5 espèces : *C. nigrifrons, C. hypoxanthus, C. rubidus, C. fosteri, C. hooki*

© Fonteyn, D., Doucet J.L., Fayolle A. & Vermeulen, C. (2021). Identifier les espèces de mammifères d'Afrique centrale morphologiquement proches ou peu fréquentes sur pièges photographiques

GENERALITES

Masse : 13 - 16 kg

Taille : 85 - 107 cm (TC)

Points clés d'identification :
- C'est le seul céphalophe roux qui ne présente pas de bande dorsale noire
- Front noir caractéristique (b,c,f)
- Retrouvé à proximité des points d'eau ou des milieux marécageux

0:00 6:00 12:00 18:00 24:00

RED LIST EW CR EN VU NT LC

DESCRIPTION

Présente des pattes relativement longues comparativement aux autres céphalophes
D'un pelage roux brillant, il ne possède pas de bande dorsale (a,b,c,d) mais uniquement un triangle frontal noir (b,c,e,f)
Une coloration plus foncée jusqu'à noire peut apparaitre sur les pattes (b,c,e)
Les sabots sont plus longs et fins que ceux des autres espèces lui permettant de se déplacer plus facilement dans les habitats inondés ou marécageux

NE PAS CONFONDRE AVEC ...

... les autres céphalophes roux : toutes les autres espèces de céphalophes roux présentent une bande dorsale

a b c d e f

Découvrez les espèces d'Afrique centrale !

Mammifères

- **Artiodactyles**
  - Bovidae
    - Antilope de Bates – *Neotragus batesi*
    - Bongo – *Tragelaphus eurycerus*
    - Buffle – *Syncerus caffer*
    - Céphalophe à bande dorsale noire – *Cephalophus dorsalis*
    - Céphalophe bleu – *Philantomba monticola*
    - Céphalophe à dos jaune – *Cephalophus silvicultor*
    - Céphalophe à front noir – *Cephalophus nigrifrons*
    - Céphalophe à pattes blanches – *Cephalophus ogilbyi*
    - Céphalophe à ventre blanc – *Cephalophus leucogaster*
    - Céphalophe de Peters – *Cephalophus callipygus*
    - Chevrotain aquatique – *Hyemoschus aquaticus*
    - Guib harnaché – *Tragelaphus scriptus*
    - Sitatunga – *Traglepahus spekii*
  - Suidae
    - Hylochère – *Hylocherus meinertzhageni*
    - Potamochère roux – *Potamochoerus porcus*
- **Carnivores**
  - Herpestidae
    - Autres mangoustes – *Atilax paludinosus / Herpestes naso*
    - Cusimanse – *Crossarchus platycephalus*
    - Mangouste à pattes noires – *Bdeogale nigripes*
  - Felidae
    - Chat doré africain – *Caracal aurata*
    - Léopard – *Panthera pardus*
    - Serval – *Leptailurus serval*
  - Mustelidae
    - Ratel – *Mellivora capensis*

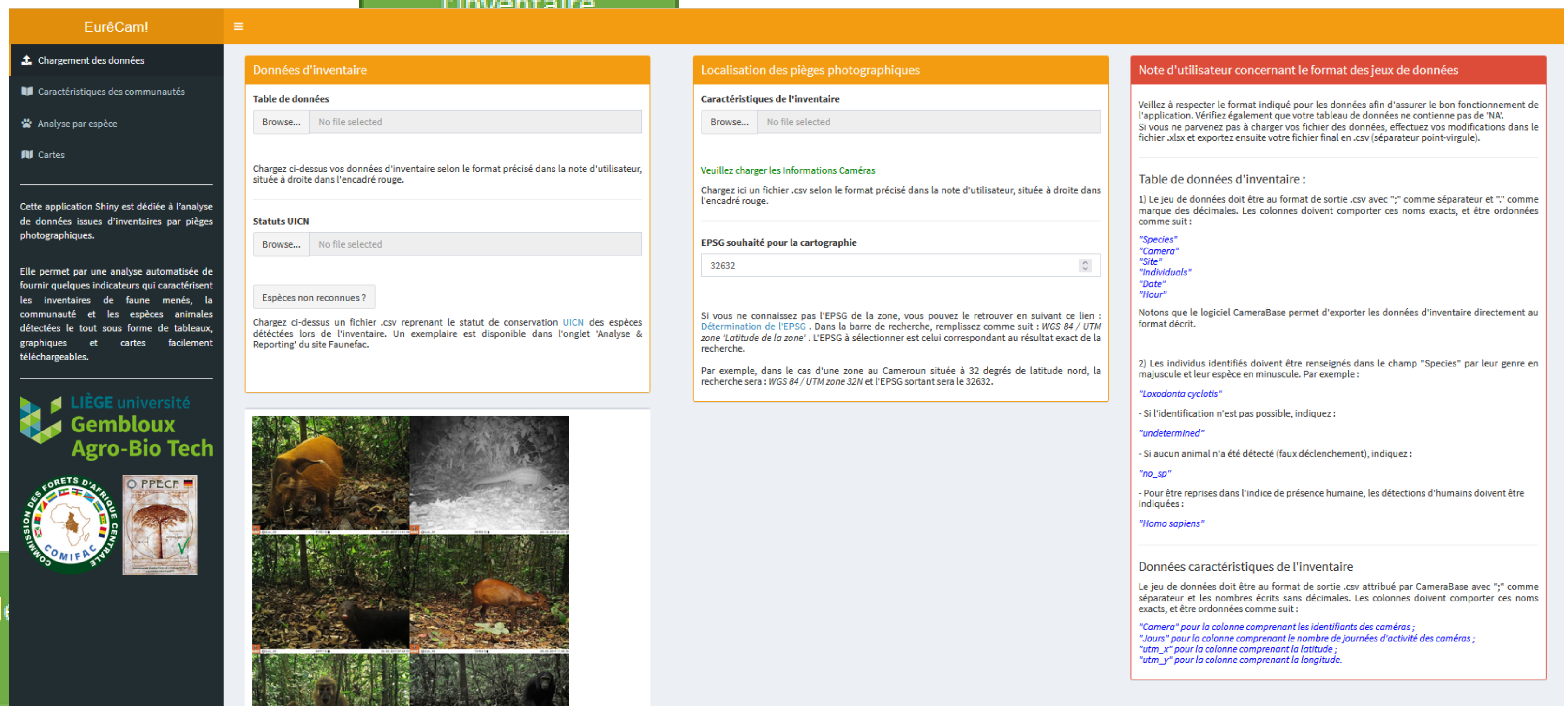
https://www.gembloux.ulg.ac.be/faunefac/

‘FauneFAC’ platform

Methodological toolbox for the implementation of photographic trap inventories

Demonstration

EurêCam! application



http://shiny.gxabt.ulg.ac.be/FauneFac/?fbclid=IwAR10dGHtuH-vvD81Ql8zNagF0VClA3e7YpkdbRZabdtrWQO3x85N5RiEeOE

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