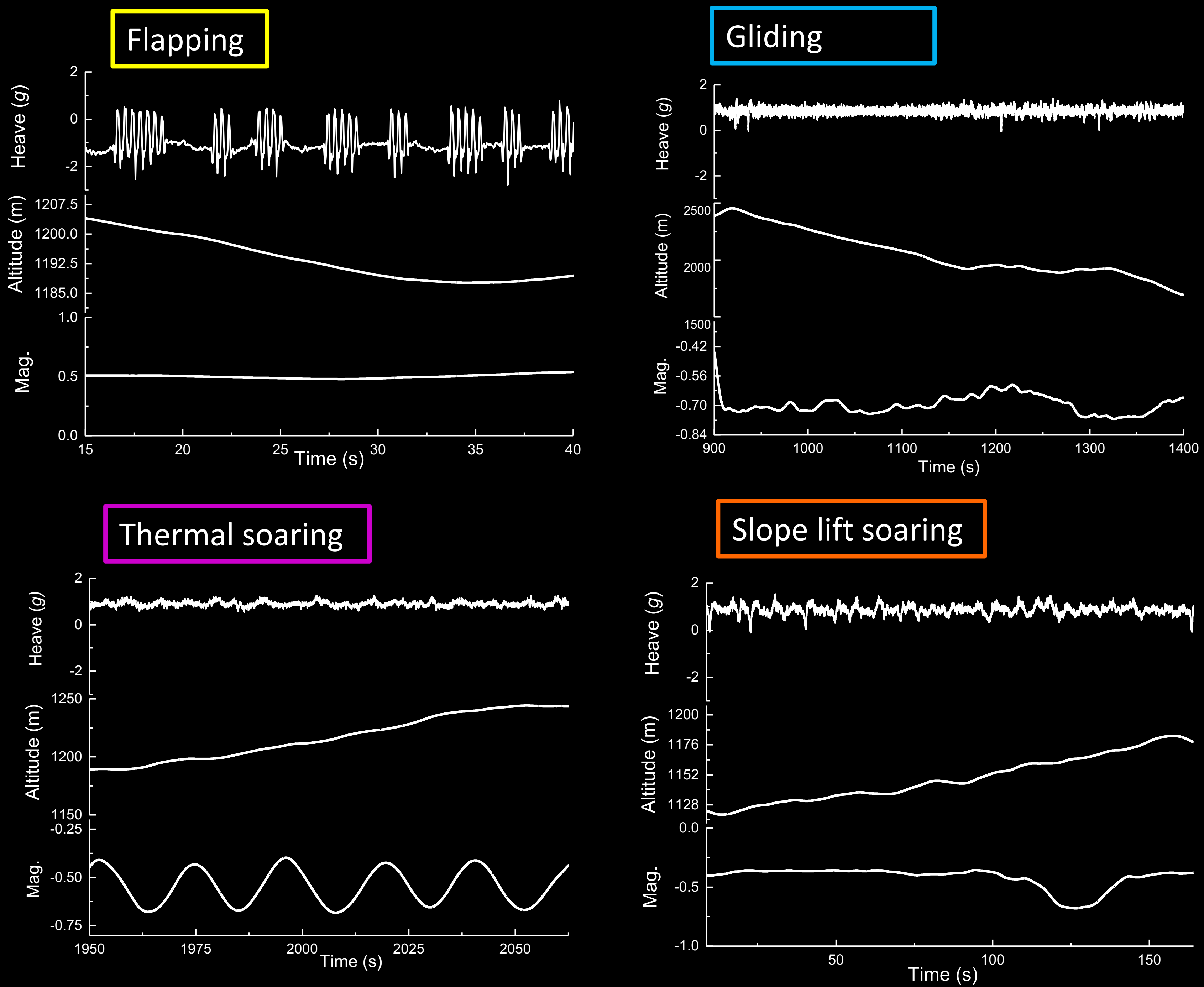
osture, Activity, Behaviour from IMU

- detailed metadata on the attachment type and position on the animal of the loggers, as otherwise, establishing a close relationship between the output from sensor data (such as tri-axial accelerometer) and the heading and posture of the animal will be near impossible.
- Partition the static and dynamic components
- then converted to DBA (ideally correlated with energy or oxygen in lab)
- Magnetometry corrections
- Pre-processing should be per-formed before subsampling (in the case of autocorrelation)
- visualize and display quantitative information
- **Behavioural classificiation**
- **Dead-reckoning**



Flapping
Heave (g)
Altitude (m)
Mag.
2
0
-2
1207.5
1200.0
1192.5
1185.0
1.0
0.5
0.0
15
20
25
30
35
40
Time (s)
Gliding
Heave (g)
Altitude (m)
Mag.
2
0
-2
2500
2000
1500
-0.42
-0.56
-0.70
-0.84
900
1000
1100
1200
1300
1400
Time (s)
Thermal soaring
Heave (g)
Altitude (m)
Mag.
2
0
-2
1250
1200
1150
-0.25
-0.50
-0.75
1950
1975
2000
2025
2050
Time (s)
Slope lift soaring
Heave (g)
Altitude (m)
Mag.
2
0
-2
1200
1176
1152
1128
0.0
-0.5
-1.0
50
100
150
Time (s)

ehavioural Classification

behaviour-linked thresholds, such as an increase in pressure to indicate diving, but more commonly will involve consideration of multiple data streams

machine-learning algorithms:
- K-nearest neighbour [KNN]
- support vector machines [SVMs]
- classification and regression trees [CART]
- artificial neural networks [ANNs])

- hidden Markov models (HMMs) to infer hidden behavioural states

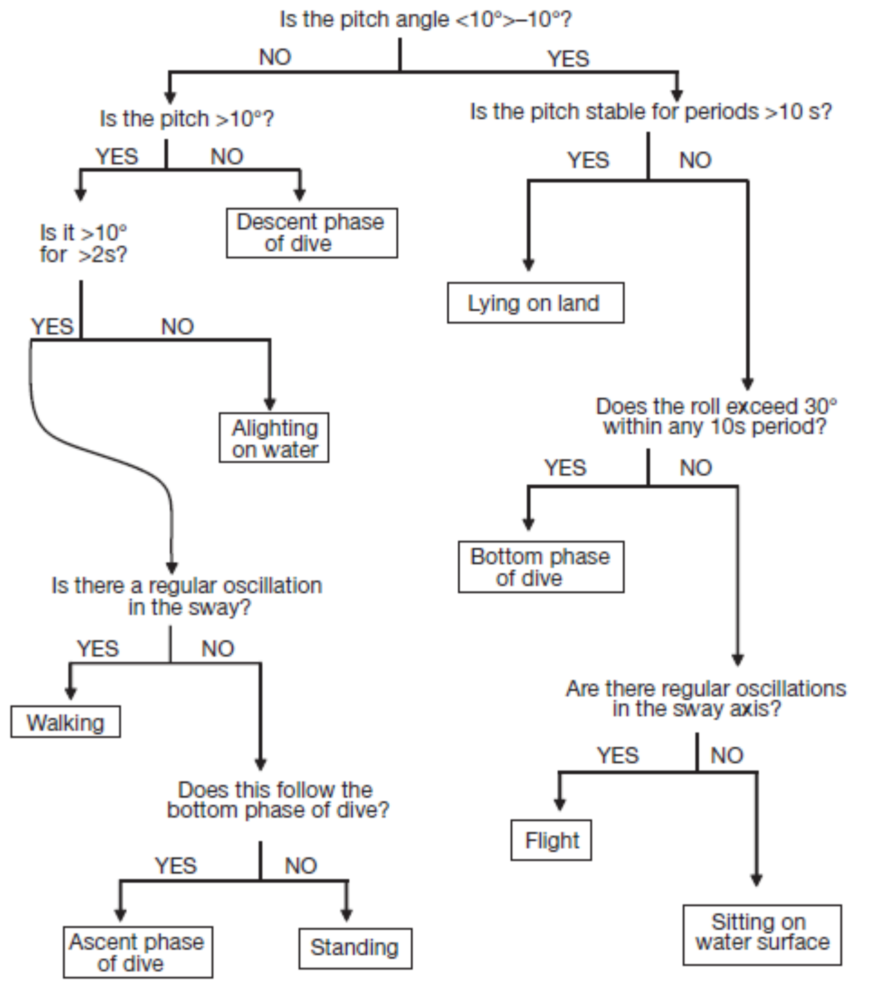


Fig. 6. *Phalacrocorax atriceps*. Simplistic diagram to show how behaviour of an imperial cormorant (cf. Fig. 5) can be resolved using data from a tri-axial accelerometer

Wilson et al (2020) JAE

ehavioural Classification

behaviour-linked thresholds, such as an increase in pressure to indicate diving (Kooyman, 1964), but more commonly will involve consideration of multiple data streams

machine-learning algorithms:

- K-nearest neighbour [KNN]
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- classification and regression trees [CART]
- artificial neural networks [ANNs])

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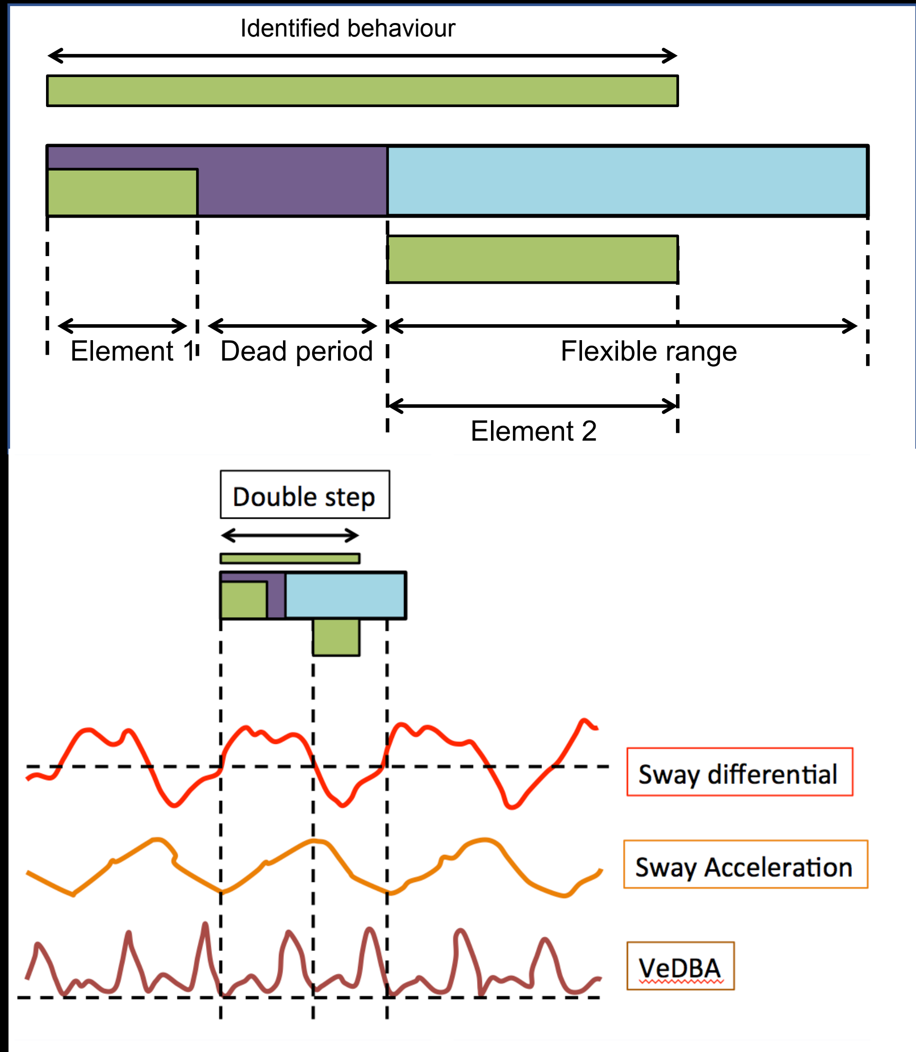
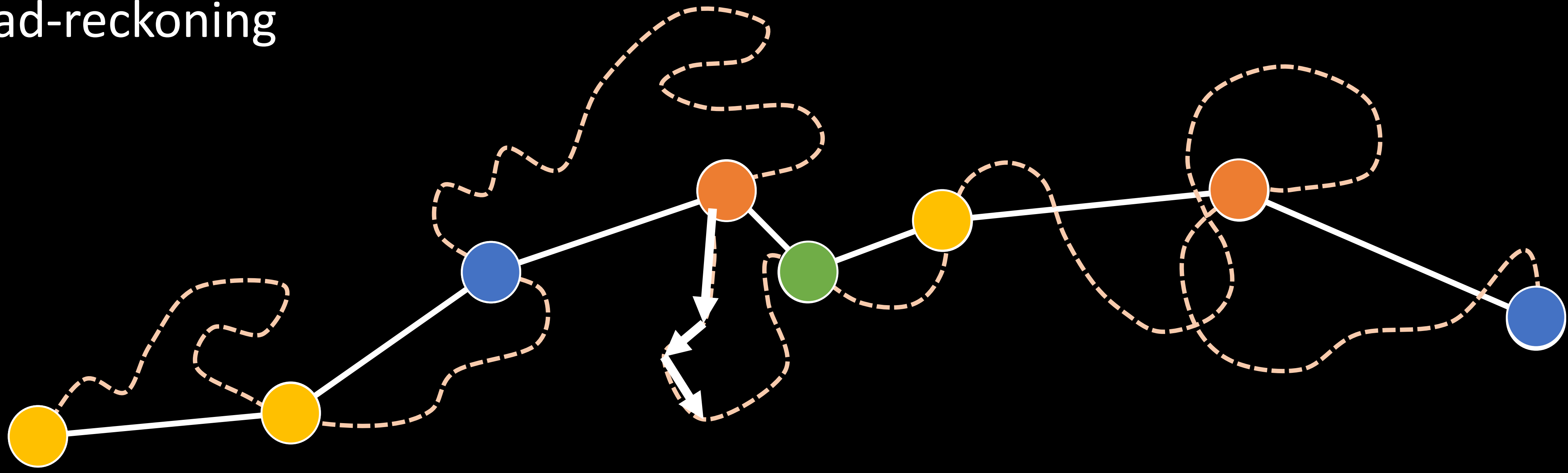
Boolean framework and requires that the researchers have enough specialist knowledge to be able to pick out a sequence of features in behaviours

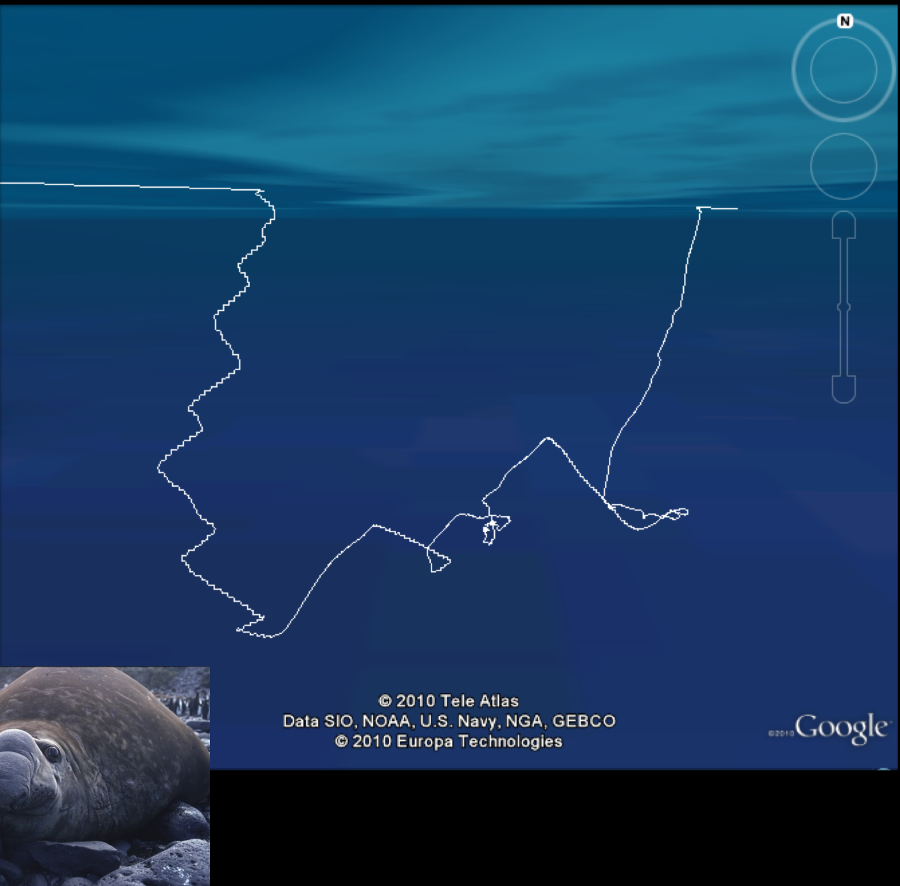


Wilson et al (2020) JAE

ead-reckoning

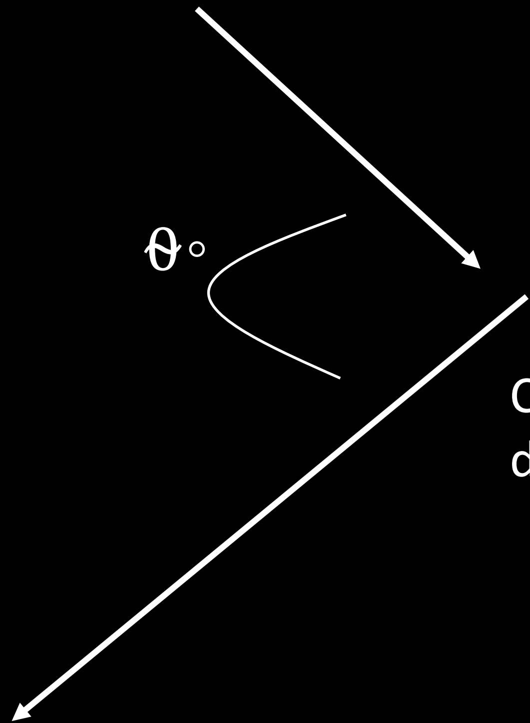


- Limitations of telemetry devices
- Properly identify true turn-points in the data
- Connect behaviour to landscape ecology and population dynamics with increased confidence
- embrace optimality approach - incorporate the energetic costs and benefits derived from detailed biologging data
- the bio-energetic reasons behind ani-mal movement choices, rather than simply describing landscape aspects that covary with animal movement



Compute acceleration compone

Resolve heading



Calculated speed from
dynamic acceleration

dead-reckon!

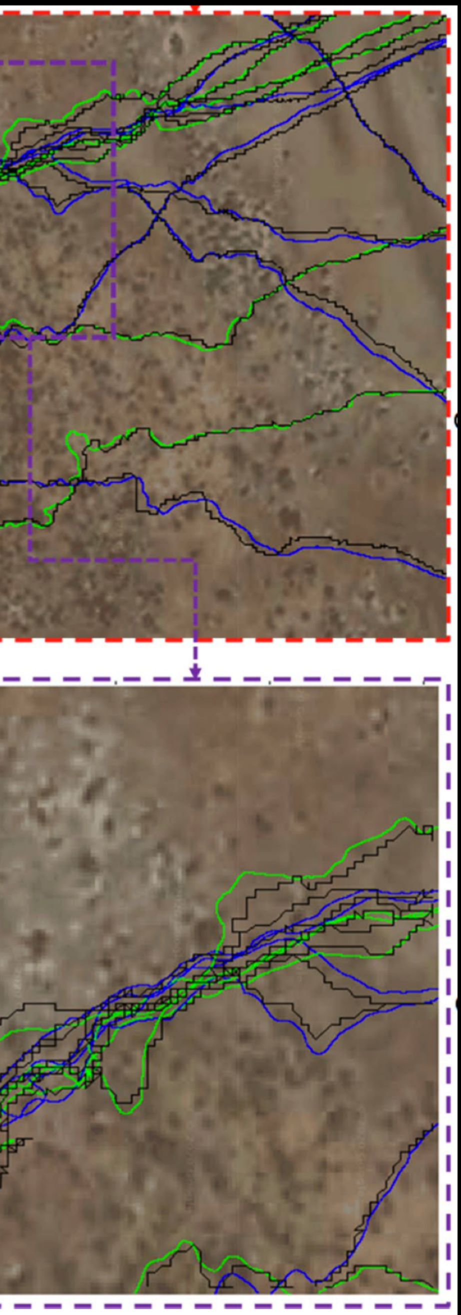
https://github.com/Richard6195/Dead-reckoning-animal-movements-in-R

- More recently, dynamic body acceleration has been validated as a linear proxy of speed for terrestrial animal (such as from treadmill tests or using GPS- derived speed)
- peak periodicity (and amplitude) may be used as a proxy of distance moved by providing a distance per step estimate
- Ground-truthing dead-reckoned tracks typically involves the linear drift correction method to provide a correction vector that is applied linearly between time point one and time point two
- correction coefficients for both heading and distance are calculated

  - uncorrected errors in speed estimations
  - heading inaccuracies
  - infrequent VPC rate

https://github.com/Richard6195/Dead-reckoning-animal-movements-in-R

Dead-Reckoning procedure



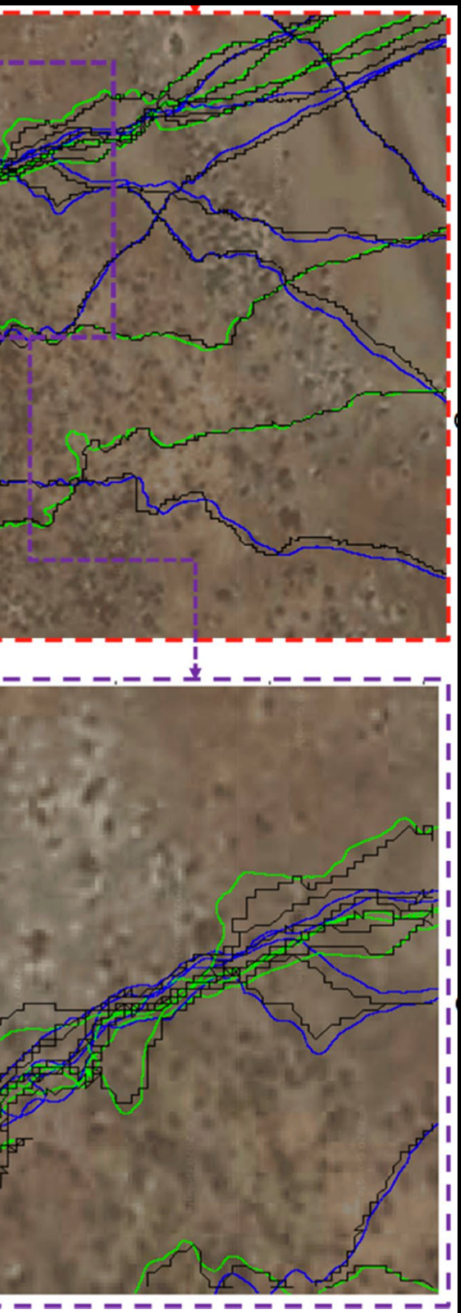
Gunner et al 2021

1. Device orientation is expressed in terms of a sequence of Euler angle [roll (Φ), pitc (ϑ), yaw (Ψ)] rotations about the *x*-, *y*- and *z*-axes, respectively, relative to the (inertial) Earths fixed frame of reference

For the correct computation of heading, these two channels need to be aligned parall to To the Earth's surface

Taken together then, in R, pitch and roll are computed according to, ($R_{24:25}$) with outpu within the range of − 90° to + 90° for pitch and − 180° to + 180° for roll, and this is the formula we use in the tilt-compensated method outlined below

```
R24)  Pitch = atan2(-NGbx, sqrt(NGby^2 + NGbz^2)) * 180/pi
R25)  Roll = atan2(NGby, sign * sqrt(NGbz^2 + mu * NGbx^2)) * 180/pi
```



Gunner et al 2021

Dead-Reckoning procedure

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2. Magnetometer calibration, rotation correction and deriving of yaw

3. The magnetic vector of the device is then de-rotated to the Earth frame (tilt-corrected) by pre-multiplying by the product of the inverse roll multiplied by inver pitch rotation matrix

4. Speed estimate e.g. VedBA, DBA, step frequency - distance per step

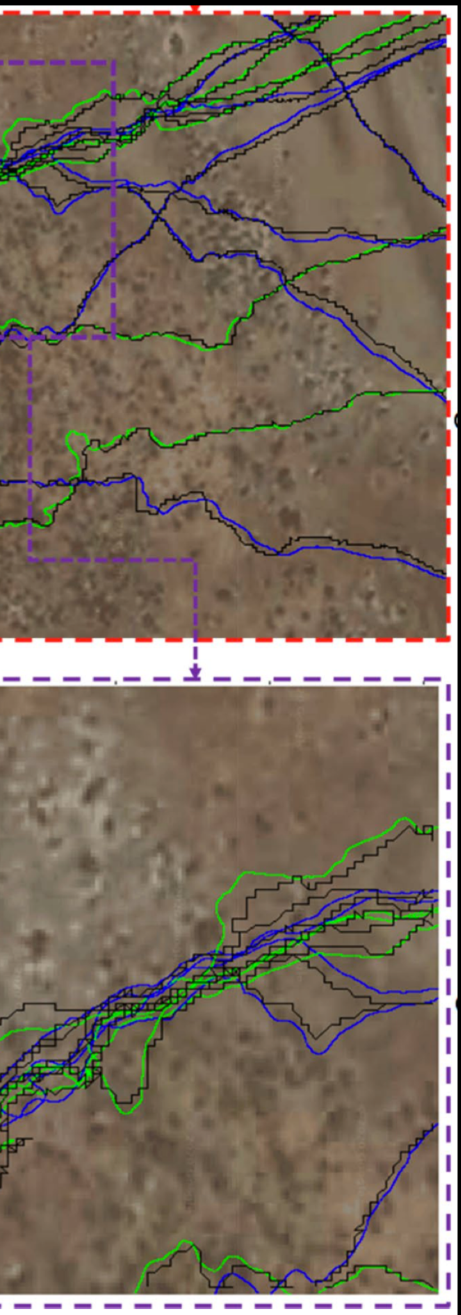
5. Convert speed to distance

6. Compute coordinates

7. Integrate current vectors

Verified Position Correction (VPC) dead-reckoning in R using the tilt-compensated compass method

- ✓ Reconstruct continuous, fine-scale 2-/3-D movement paths, irrespective of the environment and at higher resolution than any VP system
- ✓ Reduces the recording frequency of GPS locations, extending battery life and/or reducing deployment bulk/weight.
- ✓ Limits positional noise ('jitter') of 'high-res' (e.g., ≥ 1 Hz) GPS datasets, which is most apparent during non-moving behaviours such as rest and in highly heterogenous environments where radio signal can be easily obstructed

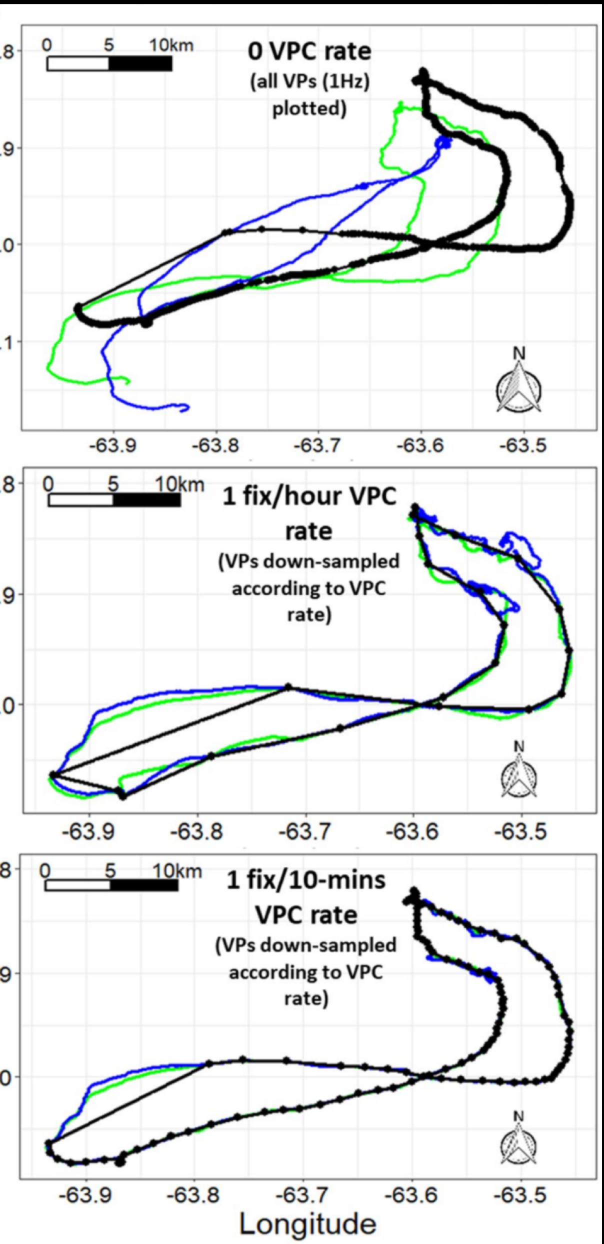


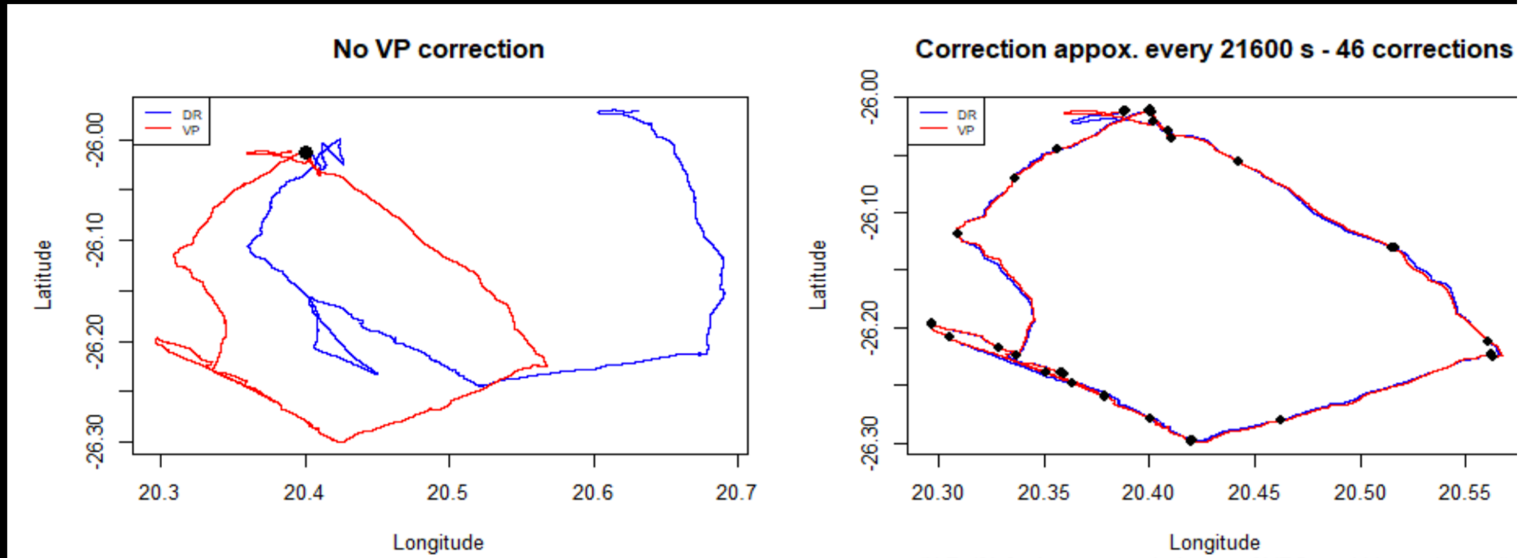
Gunner et al 2021

Verified Position Correction (VPC) procedure

Haversine distance (net error; great-circle distance) and bearing (from true No great circular bearing) between consecutive VPs and the corresponding time-matched dead-reckoned track positions.

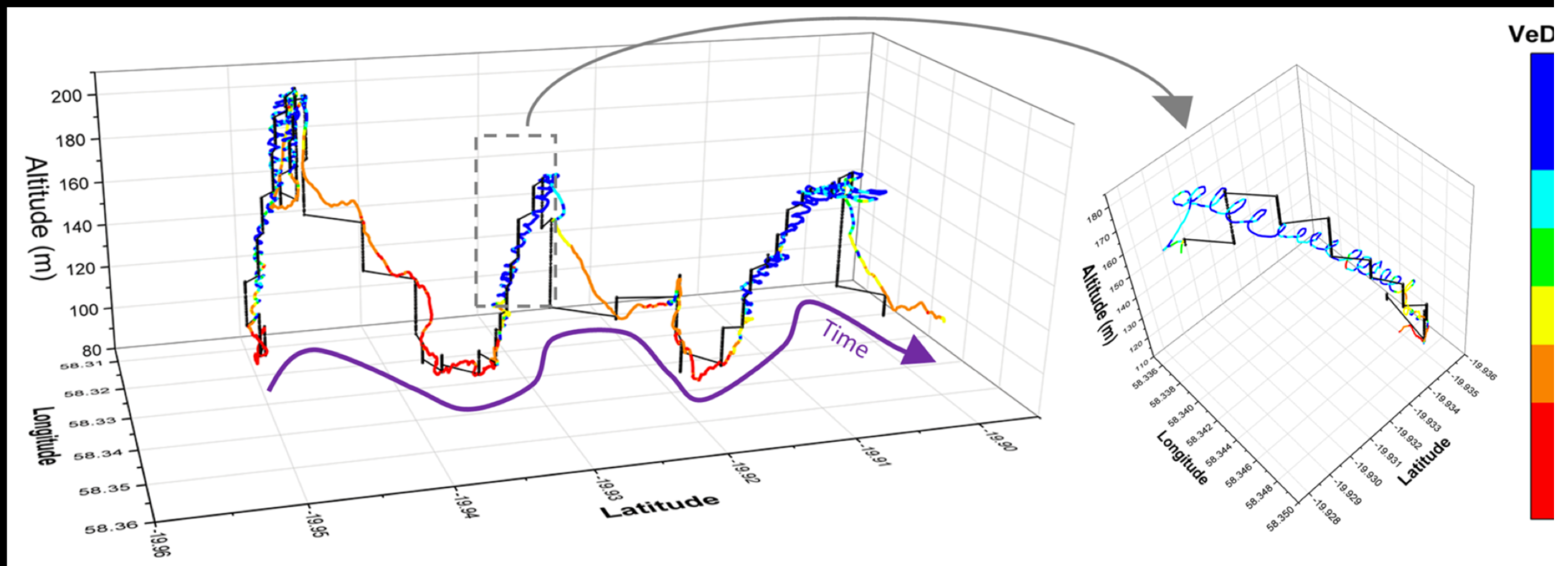
1. Index row number with NA for non-VPs
2. Under sampled data frame time-matched DR tracks
3. Distance correction factor = VP distance / DR distance
4. Heading correction factor = VP head - DR head
5. Merged back to the main data frame
6. Updated coefficients are substituted into DR formular and process repeate iteratively





Lion

Gunner et al (2021a) Animal Biotelemet

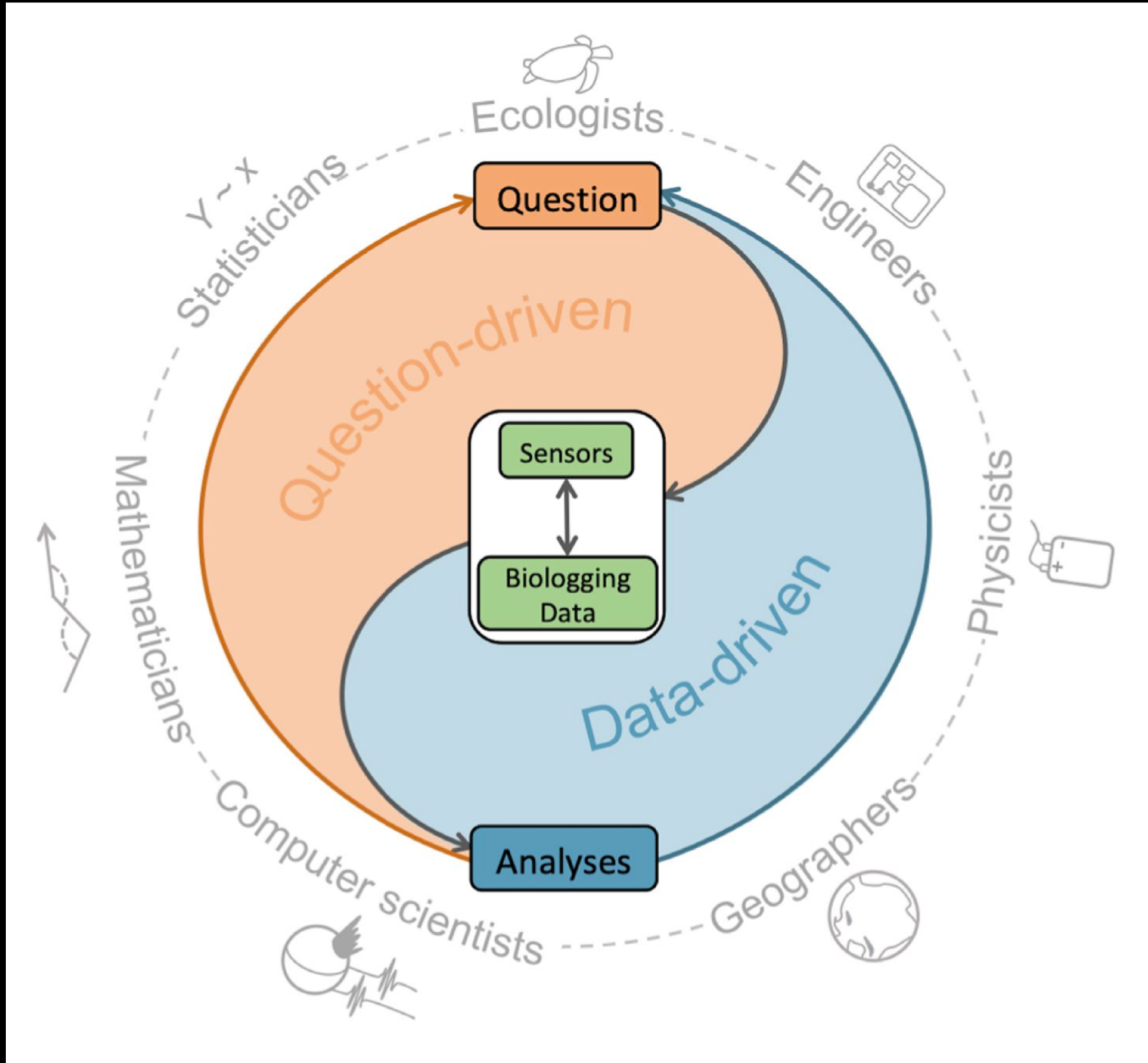


Tropic bird

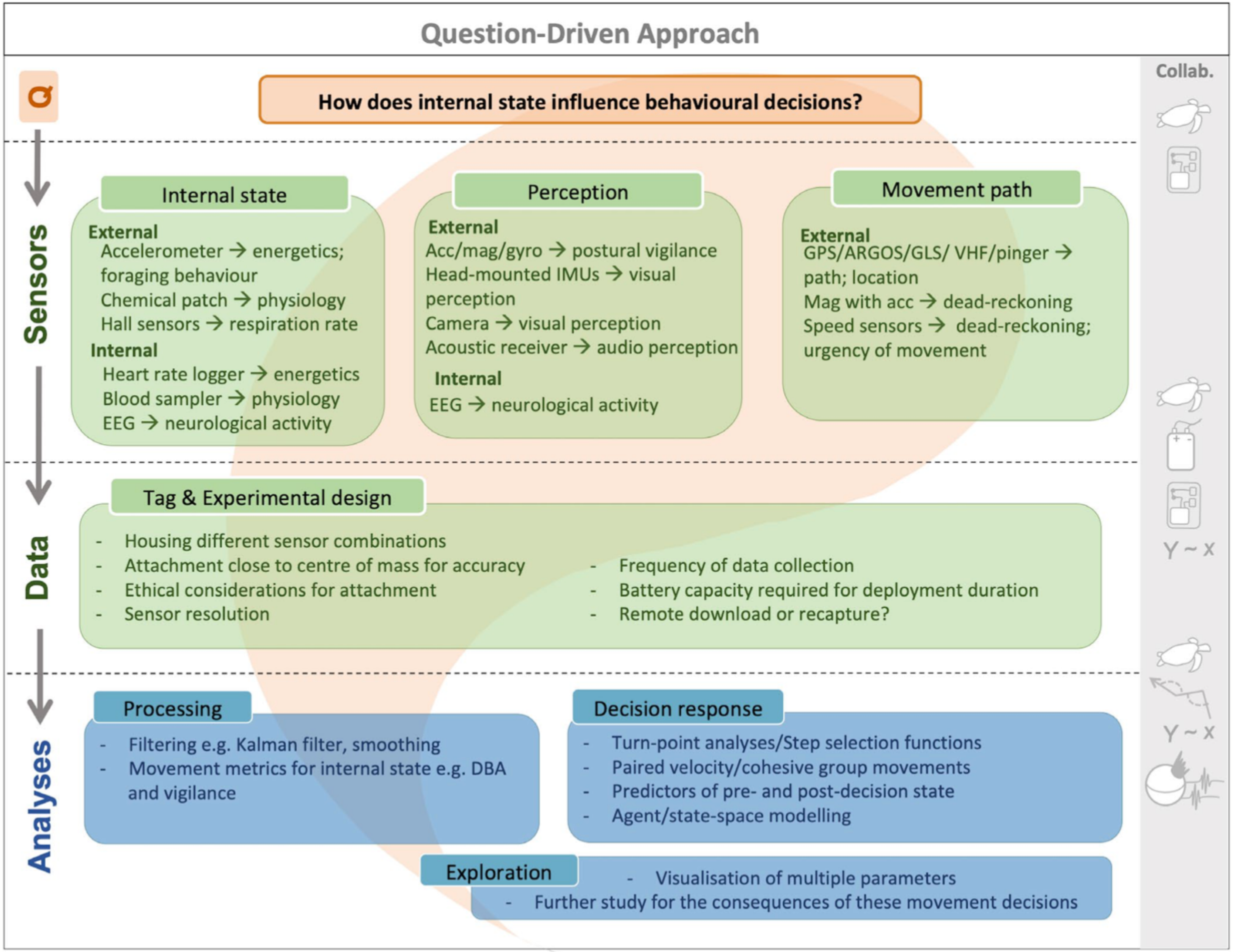
Gunner et al (2021b) Animal Biotelemet

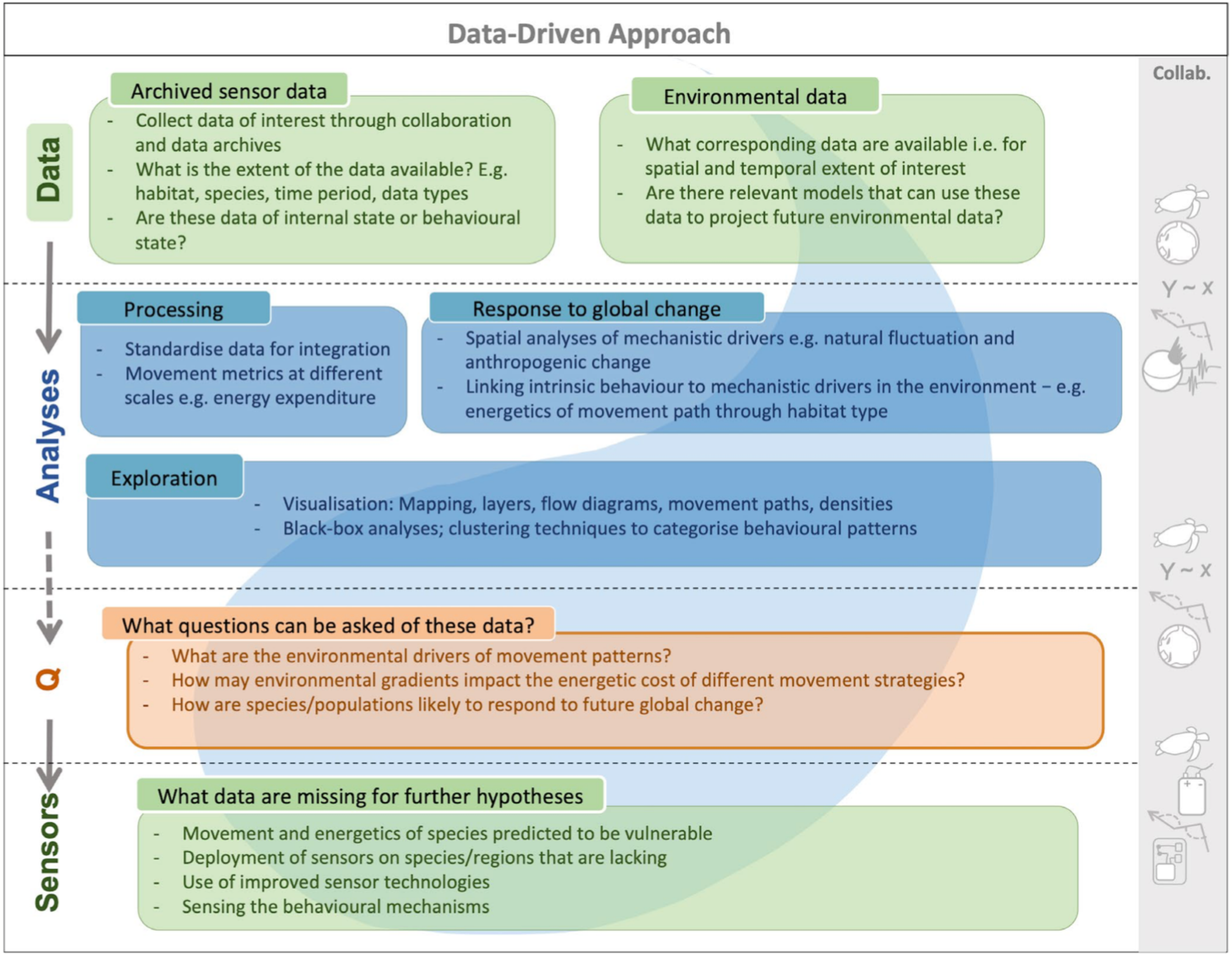
guin

timising use of biologging and IMUs

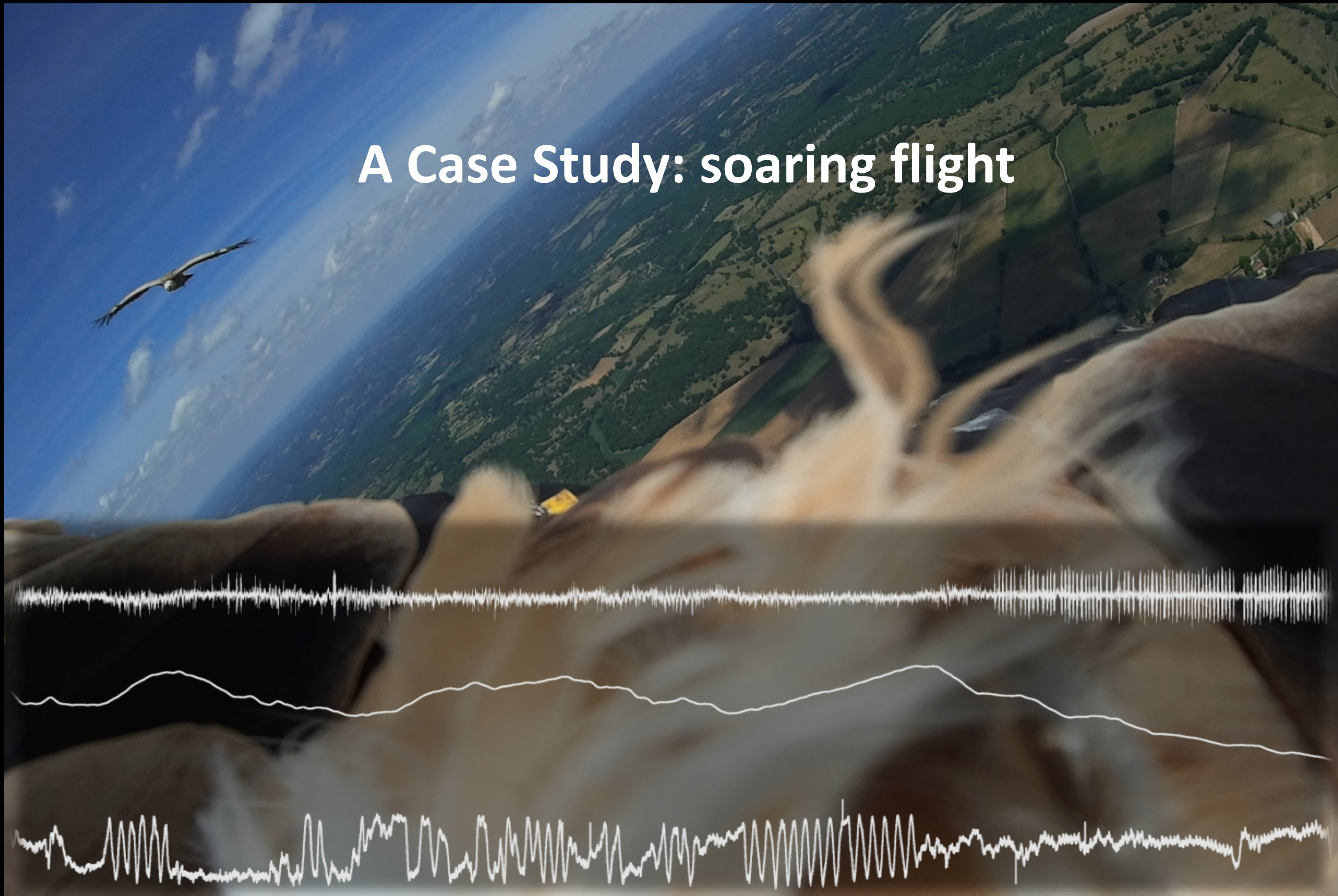


Williams et al (2020) JAE


Question-Driven Approach
Q
How does internal state influence behavioural decisions?
Collab.
Sensors
Internal state
External
Accelerometer → energetics; foraging behaviour
Chemical patch → physiology
Hall sensors → respiration rate
Internal
Heart rate logger → energetics
Blood sampler → physiology
EEG → neurological activity
Perception
External
Acc/mag/gyro → postural vigilance
Head-mounted IMUs → visual perception
Camera → visual perception
Acoustic receiver → audio perception
Internal
EEG → neurological activity
Movement path
External
GPS/ARGOS/GLS/ VHF/pinger → path; location
Mag with acc → dead-reckoning
Speed sensors → dead-reckoning; urgency of movement
Data
Tag & Experimental design
- Housing different sensor combinations
- Attachment close to centre of mass for accuracy
- Ethical considerations for attachment
- Sensor resolution
- Frequency of data collection
- Battery capacity required for deployment duration
- Remote download or recapture?
Y ~ X
Analyses
Processing
- Filtering e.g. Kalman filter, smoothing
- Movement metrics for internal state e.g. DBA and vigilance
Decision response
- Turn-point analyses/Step selection functions
- Paired velocity/cohesive group movements
- Predictors of pre- and post-decision state
- Agent/state-space modelling
Y ~ X
Exploration
- Visualisation of multiple parameters
- Further study for the consequences of these movement decisions


Data-Driven Approach
Collab.
Data
Archived sensor data
- Collect data of interest through collaboration and data archives
- What is the extent of the data available? E.g. habitat, species, time period, data types
- Are these data of internal state or behavioural state?
Environmental data
- What corresponding data are available i.e. for spatial and temporal extent of interest
- Are there relevant models that can use these data to project future environmental data?
Analyses
Processing
- Standardise data for integration
- Movement metrics at different scales e.g. energy expenditure
Response to global change
- Spatial analyses of mechanistic drivers e.g. natural fluctuation and anthropogenic change
- Linking intrinsic behaviour to mechanistic drivers in the environment – e.g. energetics of movement path through habitat type
Exploration
- Visualisation: Mapping, layers, flow diagrams, movement paths, densities
- Black-box analyses; clustering techniques to categorise behavioural patterns
Q
What questions can be asked of these data?
- What are the environmental drivers of movement patterns?
- How may environmental gradients impact the energetic cost of different movement strategies?
- How are species/populations likely to respond to future global change?
Sensors
What data are missing for further hypotheses
- Movement and energetics of species predicted to be vulnerable
- Deployment of sensors on species/regions that are lacking
- Use of improved sensor technologies
- Sensing the behavioural mechanisms
Y ~ X
Y ~ X

A Case Study: soaring flight



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Move inFormation

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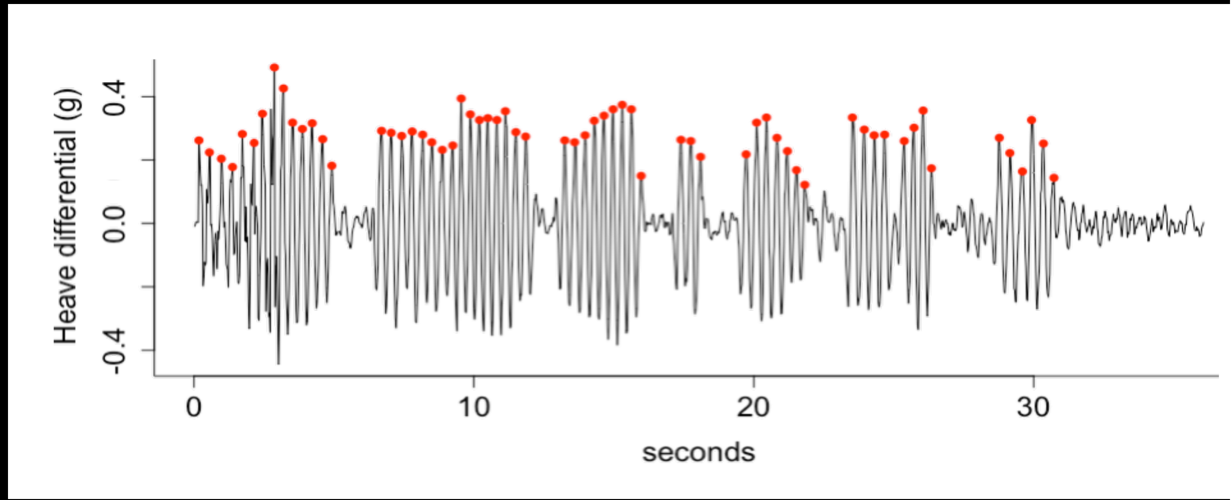
For Animal Movement

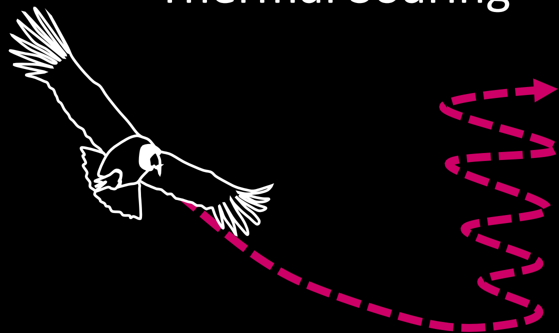
GRINBIC

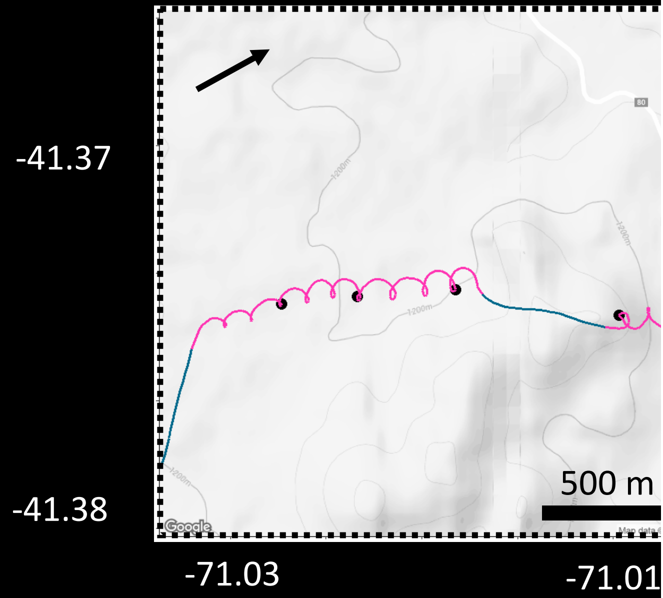
Animal-Environment Interactions

AniMove



Thermal Soaring





Andean Condors (*Vultur gryphus*)

Bariloche, Argentina, 2013-2018

8 Juveniles

9.5-13.9 kg

freely flying for 8 days of data collection

DD 40 Hz, GPS 0.1 Hz

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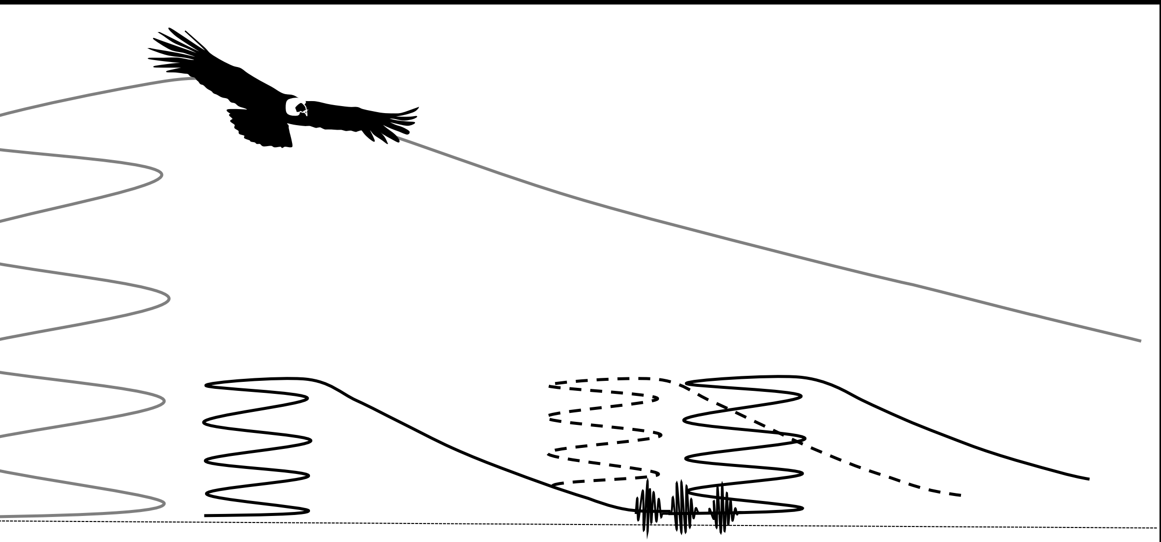
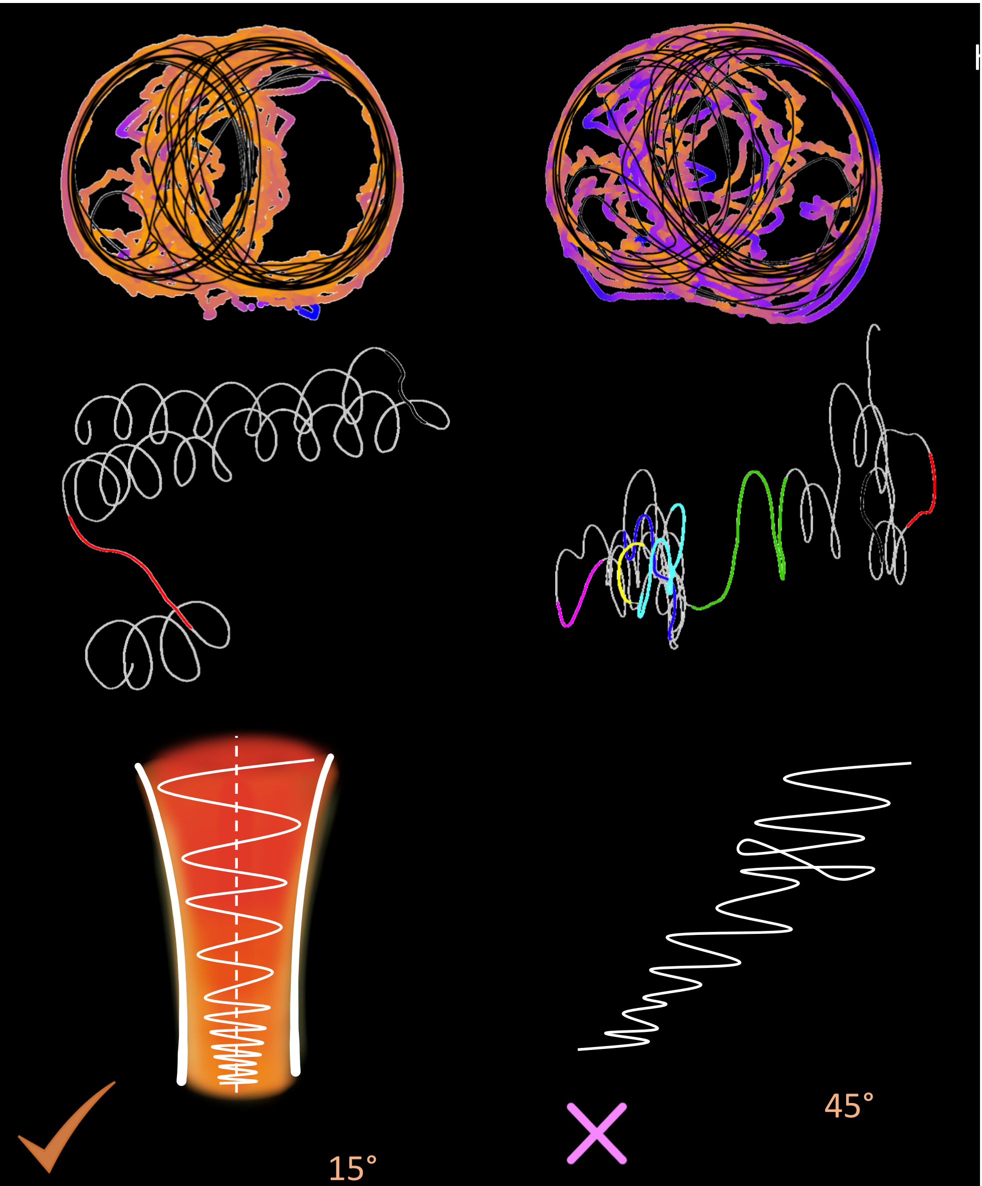
miting conditions

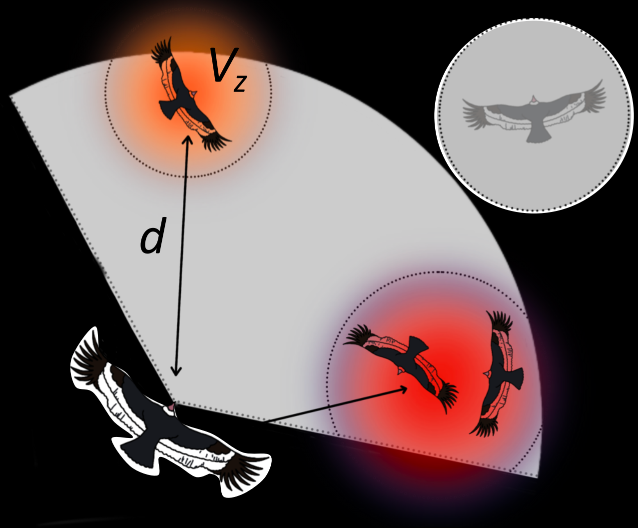


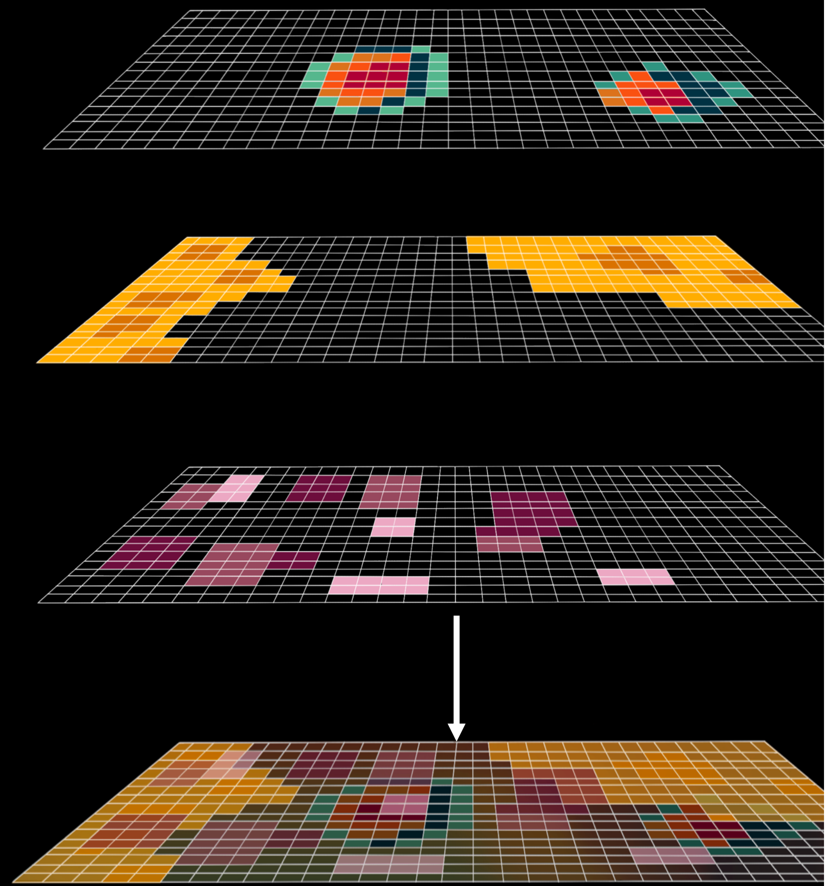
x. 1% flapping flight,
= 20% daily energy expenditure



timal Movement Theory

gration and certainty of resource landscapes in movement decisions





Decision landscape

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Animal-
Environment
Interactions

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rtial Measurement Units

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Move inFormation

MAX PLANCK INSTITUTE
OF ANIMAL BEHAVIOR

Animal-
Environment
Interactions

AniMove