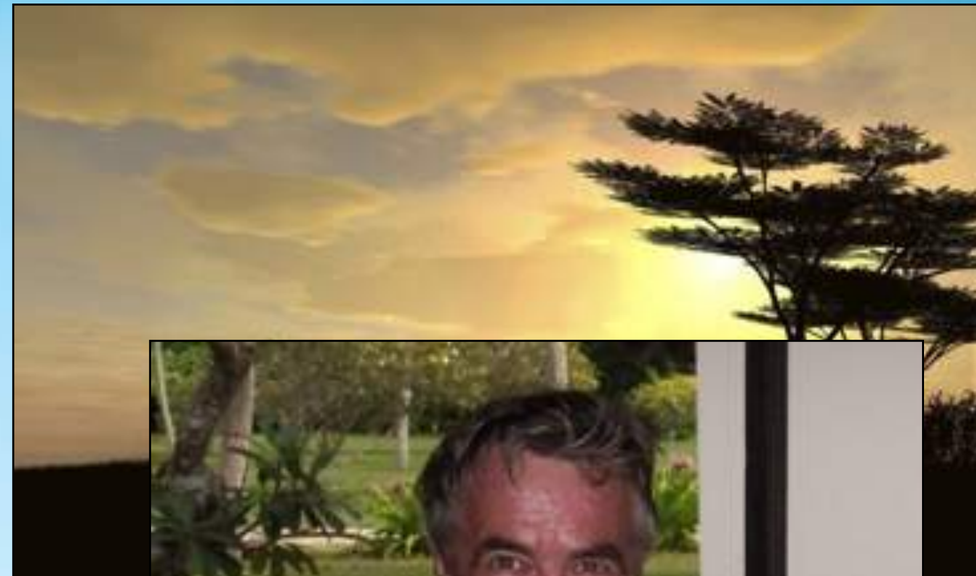
Segmentation and characterization of movement-based behavioural patterns of white sharks, *Carcharodon carcharias*, inferred from active acoustic telemetry data

Enrico Gennari[1,2,3], Paul Cowley [2], Dylan Irion [1]



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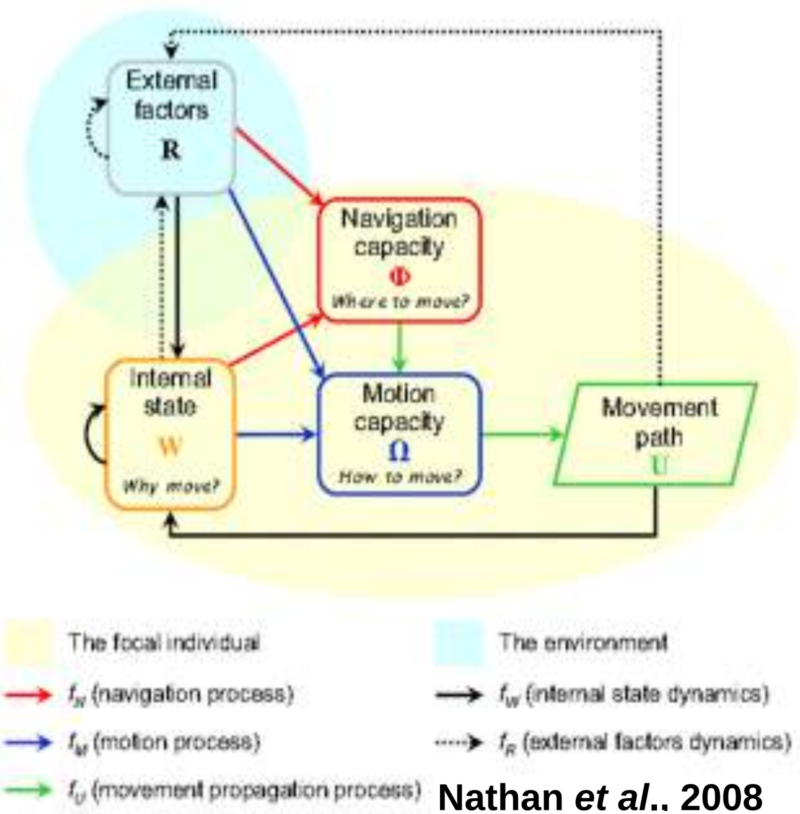
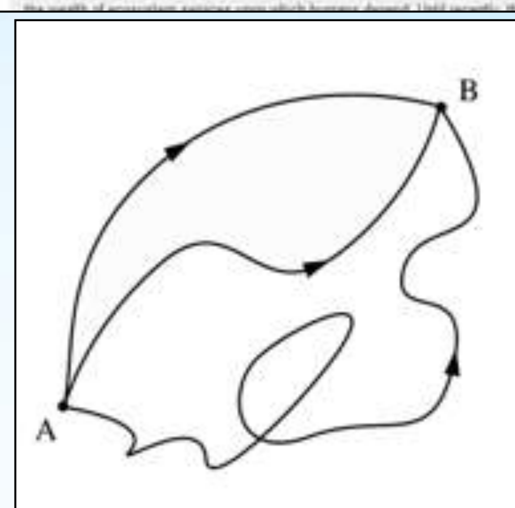


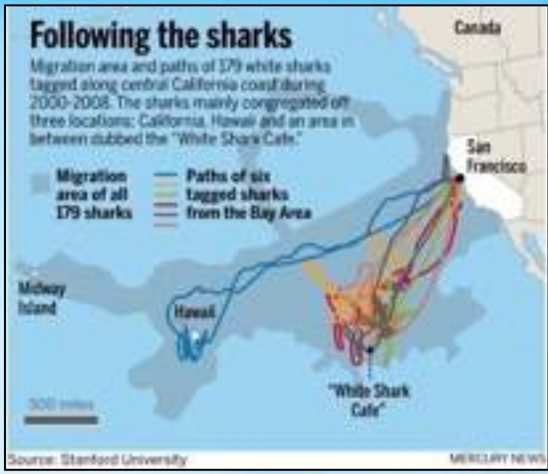
Nathan *et al*.. 2008

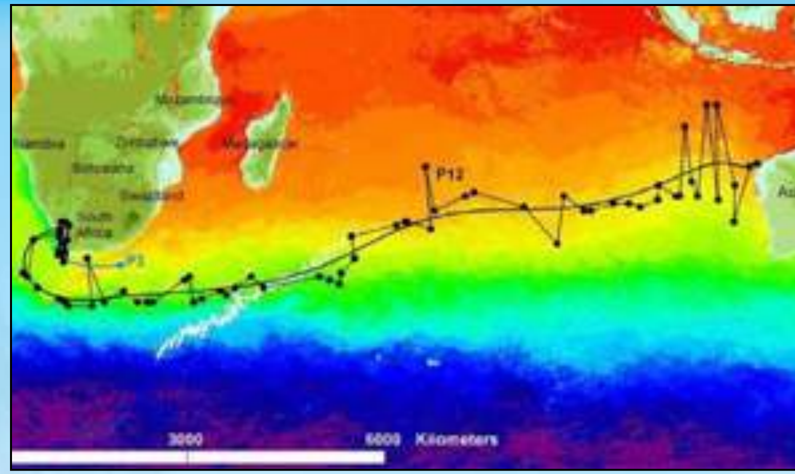


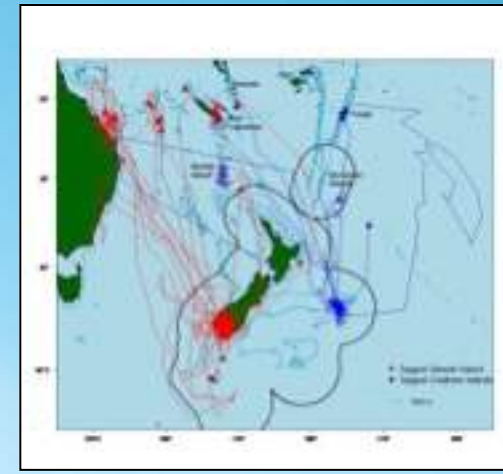
Marine movement data are:

- multidimensional
- non-independent (autocorrelated)
- gappy (variable sampling intervals)

Gurarie (2008): "Temporal and/or spatial correlation are intrinsic properties of an animal's movement process and is a fundamental feature that distinguishes tracking data from a random sequence of positional data".


Following the sharks
Migration area and paths of 179 white sharks tagged along central California coast during 2000-2008. The sharks mainly congregated off three locations: California, Hawaii and an area in between dubbed the "White Shark Cafe."
Migration area of all 179 sharks
Paths of six tagged sharks from the Bay Area
Canada
San Francisco
Midway Island
Hawaii
"White Shark Cafe"
Source: Stanford University
MERCURY NEWS


P12
3000
6000 Kilometers



OR

AIMS AND OBJECTIVES

HIGH RES ACOUSTIC DATA → **LOW RES SAT DATA**

From high-res active acoustic tracking data of GWS in Mossel Ba (ZA):

- To identify and characterize movement patterns:
  - creating **trajectories**
  - **segmenting** trajectories
  - **clustering** segments into **movement phases**

- To model movement phases with some driving covariates to help defining the **behaviour** behind each movement phase.

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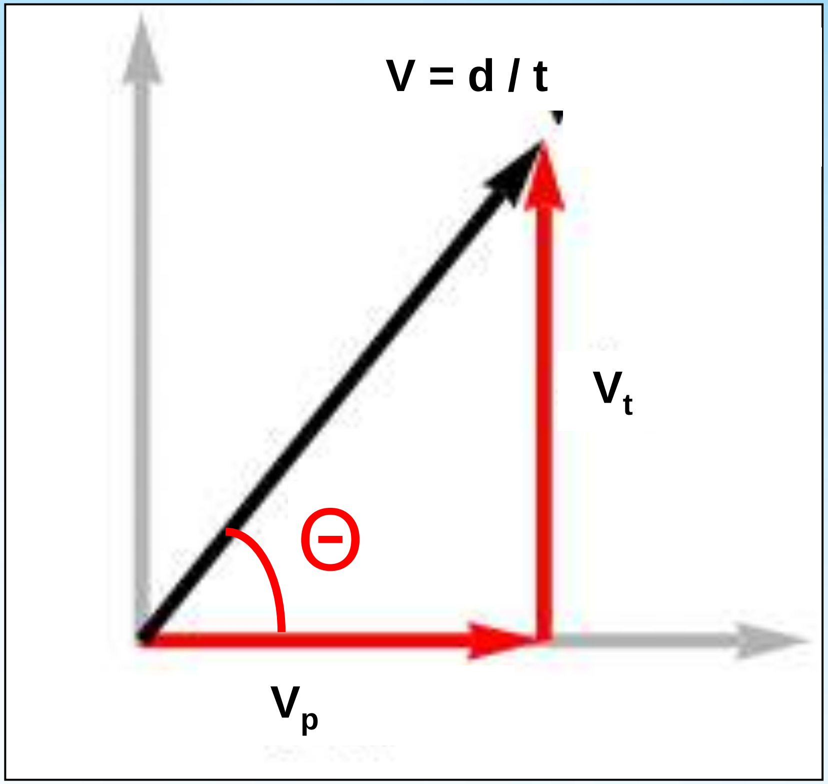
Segmentation of movement data (1)

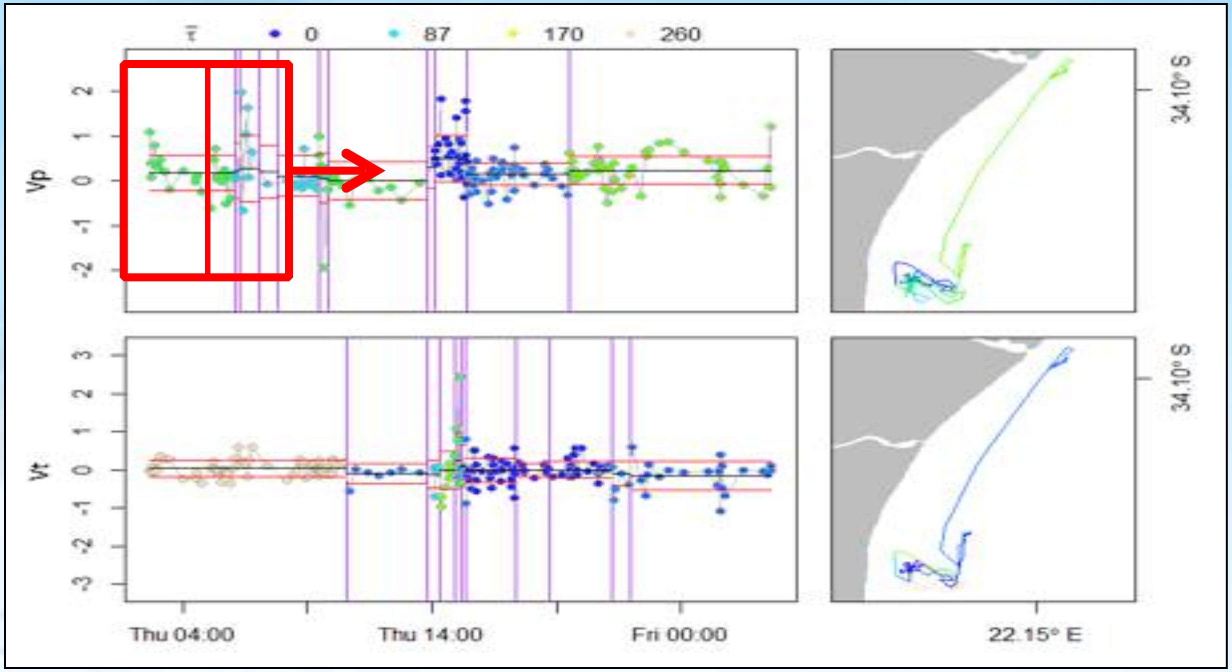
1. Movement = time series of variations in position : X(i) and Θ (i)
2. WGS 84 into UTM 34S : trajectories
3. In gappy data, distributions influences by sampling rates
4. For each segment: V (t) and Θ (t)
5. V_p (t) = V (t) cos (Θ(t))

   V_t (t) = V (t) sin (Θ(t))



Segmentation of movement data (2)

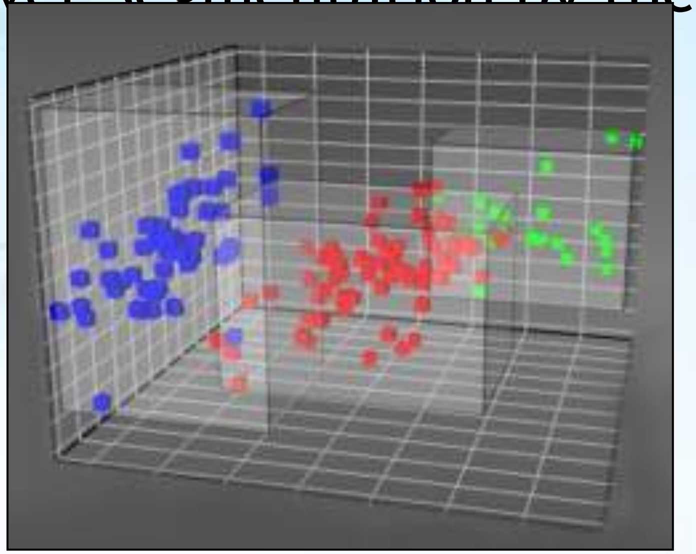
5. R: BCPA package (Gurarie, 2008)
   - Define segments μ_i , σ_i , τ_i for each orthogonal component of V(i)
   - Sweeping (moving) window (30 steps) + MLE to identify times of MLCP



   - BIC to identify combination of significant parameters
   - Merging the BCPA results for Vp and Vt

Characterization of movement phases

- R: Bayesclust package (Gopal *et al.*, 2012)
- Without *a priori* assumptions on n. clusters and threshold distances
- Empirical Posterior Probabilities
- Combines similar segments
- Reduce possible over-segmentation by the BCPA



Characterization of behavioural phases

- GAMMs in R: MGCV package (Wood, 2011)
- Influence of explanatory variables on movement phases:
  - Wind strength and direction
  - Tidal phase
  - Time of Day (TOD)
  - Location
- Binomial distributions with logit transformation
- Individual sharks included as a random term
- Suitable temporal correlation structure (obtained from the maximum value of τ from the BCPA)
- AIC; cyclic cubic regression splines (cc) used for TOD-models (as the variable is circular); low rank isotropic smoothers (tp) for all the other models
- 2 size classes based on Estrada et al (2006): <3.4 m TL and ≥ 3.4 m TL modelled separately for TOD and location

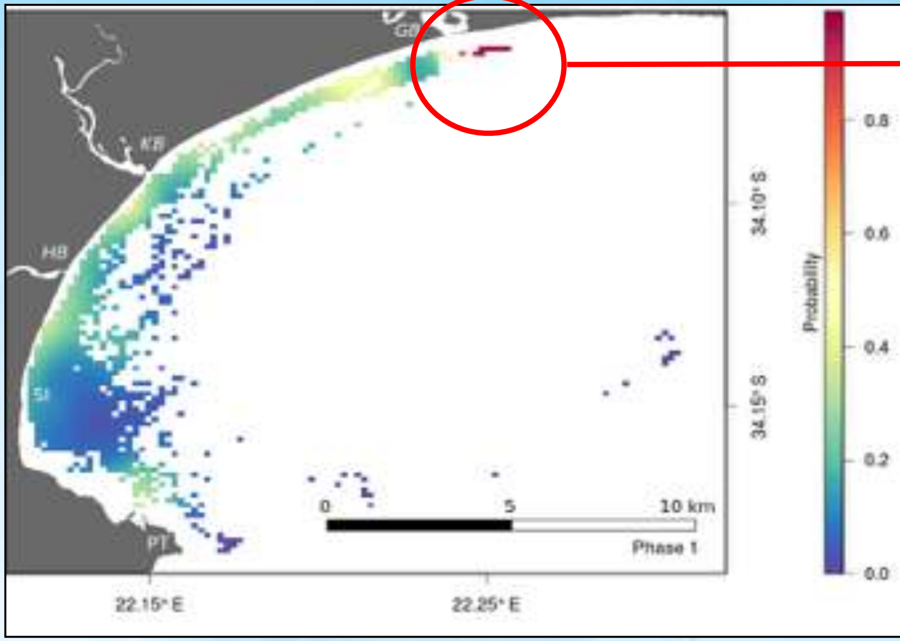
Results

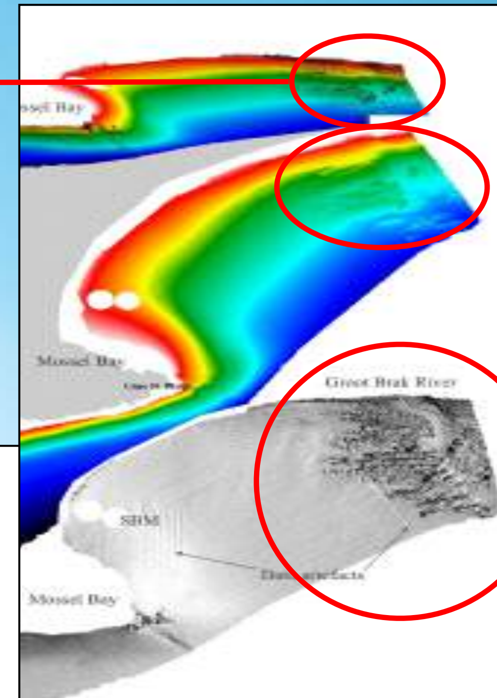
- 6 white sharks tracked in Mossel Bay, South Africa
- From 1.7 m TL to 4.2 m TL (0.5 m increment)
- 26 tracking sessions
- Combined tracking effort : 700 hrs over 1,446 Km

- 7 movement-based behavioural clusters
  with posterior probability of 97%

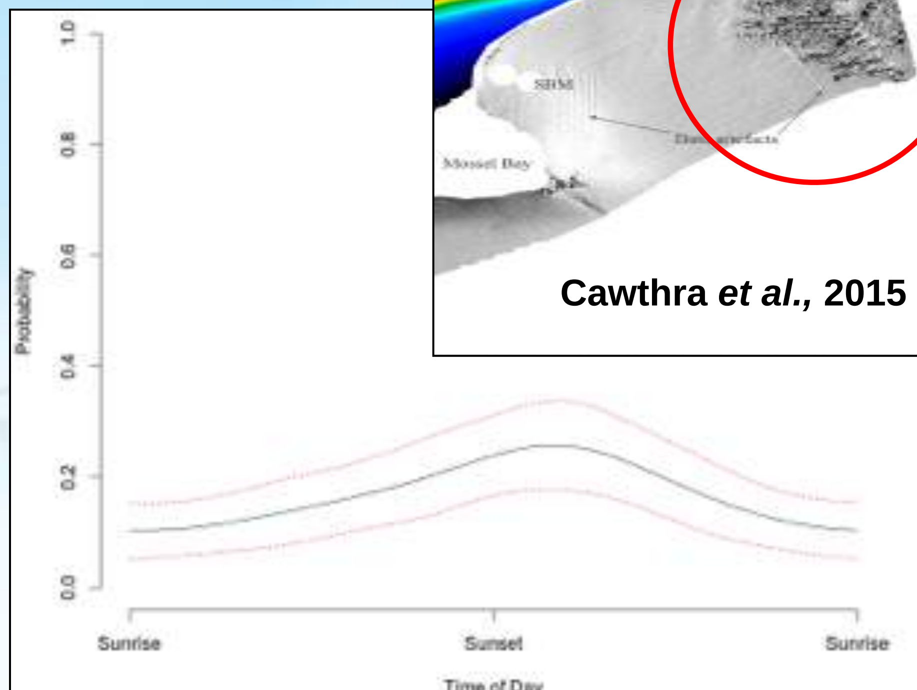
Foraging on fish

Phase 1





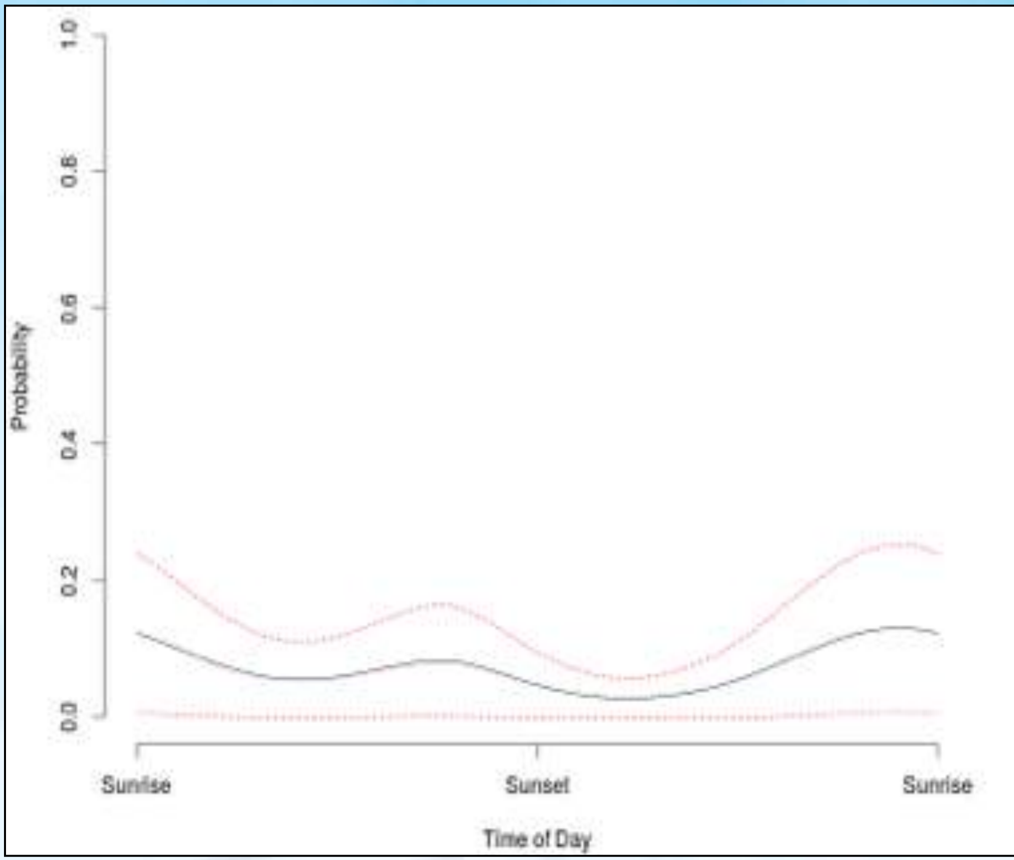
Cawthra *et al.*, 2015



BCPA parameters	
Occurrence	*17.4 %*
Mean ROM	*0.6 m/s*

Area Restricted Search (ARS)

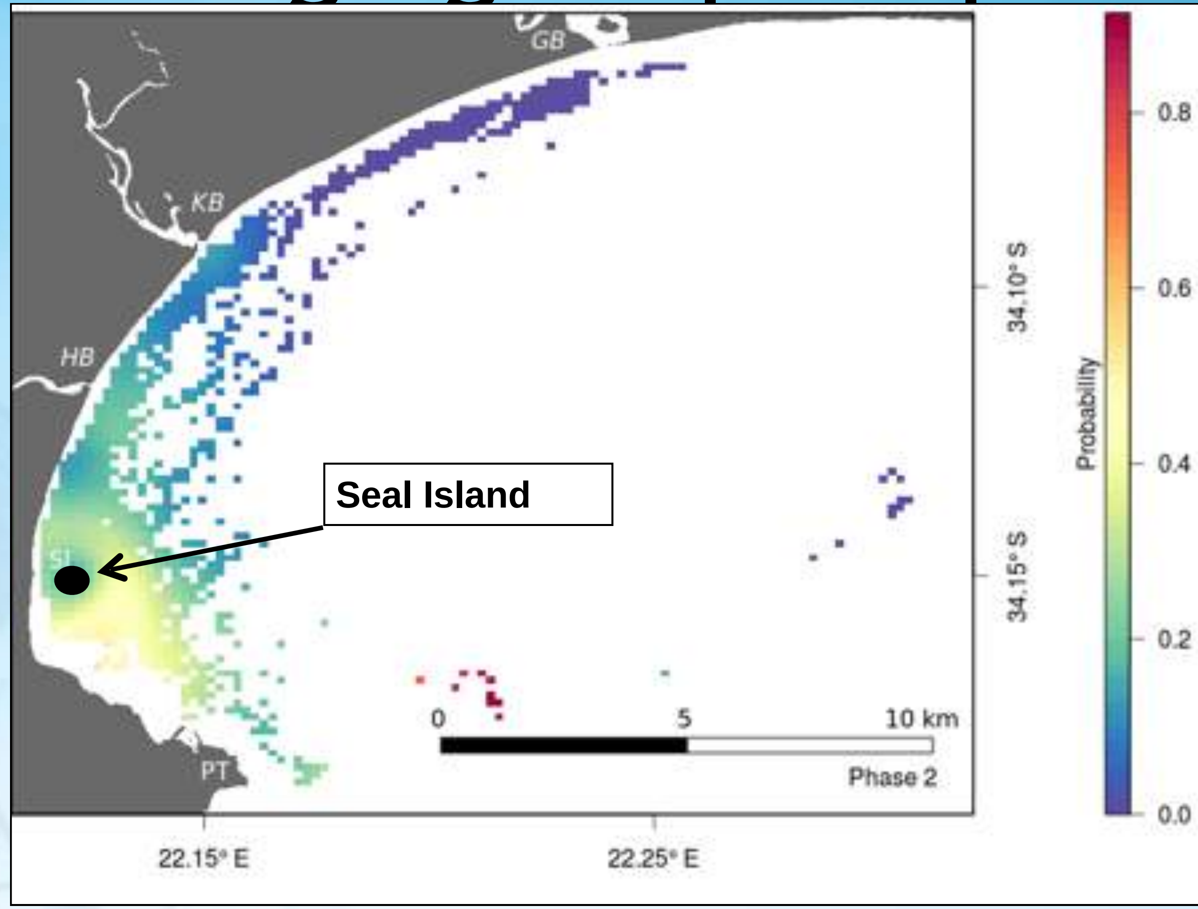
Phase 7
Patrolling for pinnipeds



BCPA parameters	
Occurrence	*12.3 %*
Mean ROM	*0.8 m/s*

Phase 2
Foraging on pinnipeds

BCPA parameters	
Occurrence	*17.9 %*
Mean ROM	*0.9 m/s*



- Larger white sharks spent less time in this phase
- No size threshold but a continuum self-learnt behaviour
- Not best candidate for calculation on RMR (Semmens *et al.*, 2013)

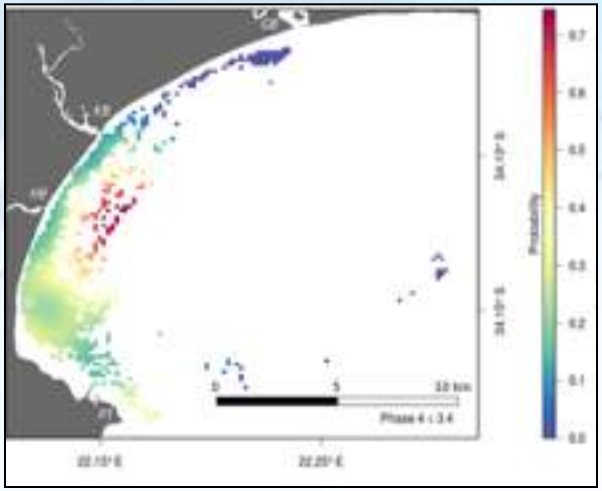
Phase 3, 4, 5
Travelling

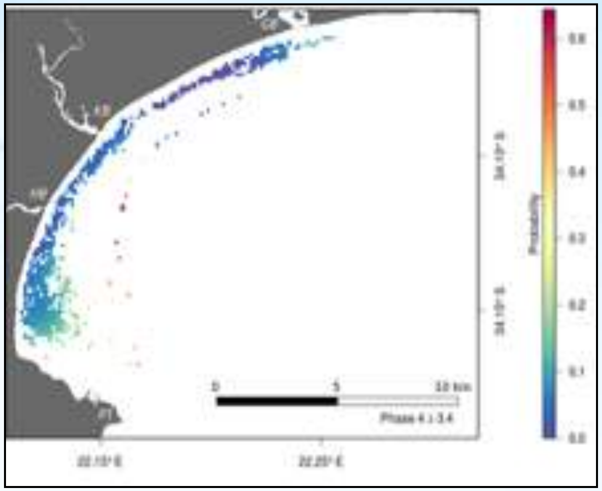
Occurrence	*42 %*
Average Mean	*2-3 km/h*

Low-location related probabilities (not ARS)

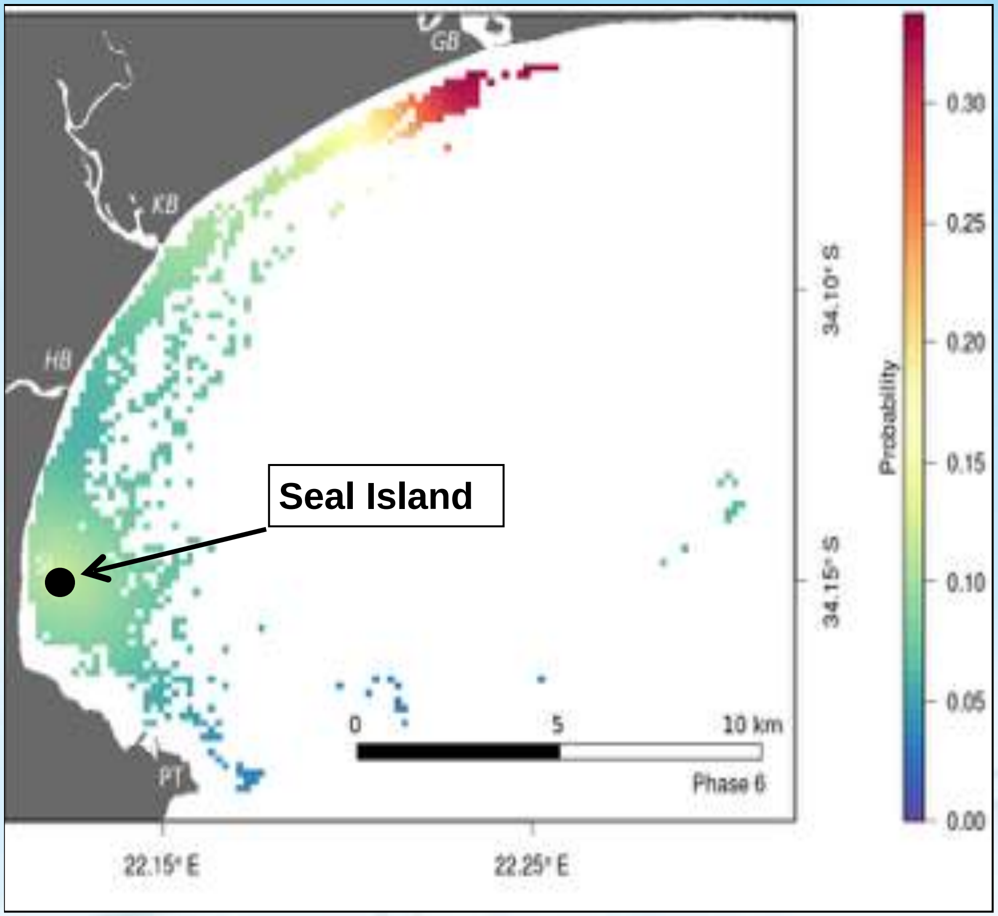
Related to movement *per se*

Phase 3: medium speed highly directional (intersite, large jumps in Lévy flights)
Phase 4: faster offshore (highest $V_p(\tau)$) (individual learning + hearing threshold)
Phase 5: slower inshore with correlated turns ($Vt(\tau)$): energy saving roaming (random walk component of in Lévy flights)

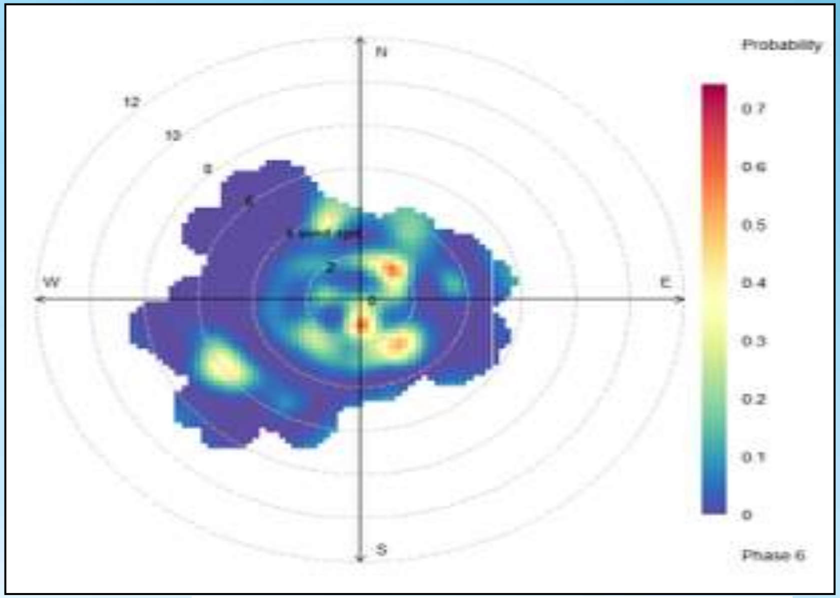


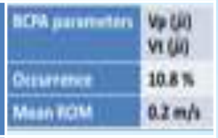


Phase 6
Scavenging around chumming boats



R: Openair package (Carslaw and Ropkins, 2012)



BCPA parameters	
Occurrence	*10.8 %*
Mean ROM	*0.2 m/s*

- Only converging significant wind-related model
- Around chumming vessels: wind limit vessels not sharks
- Slowest ROM : scavenging

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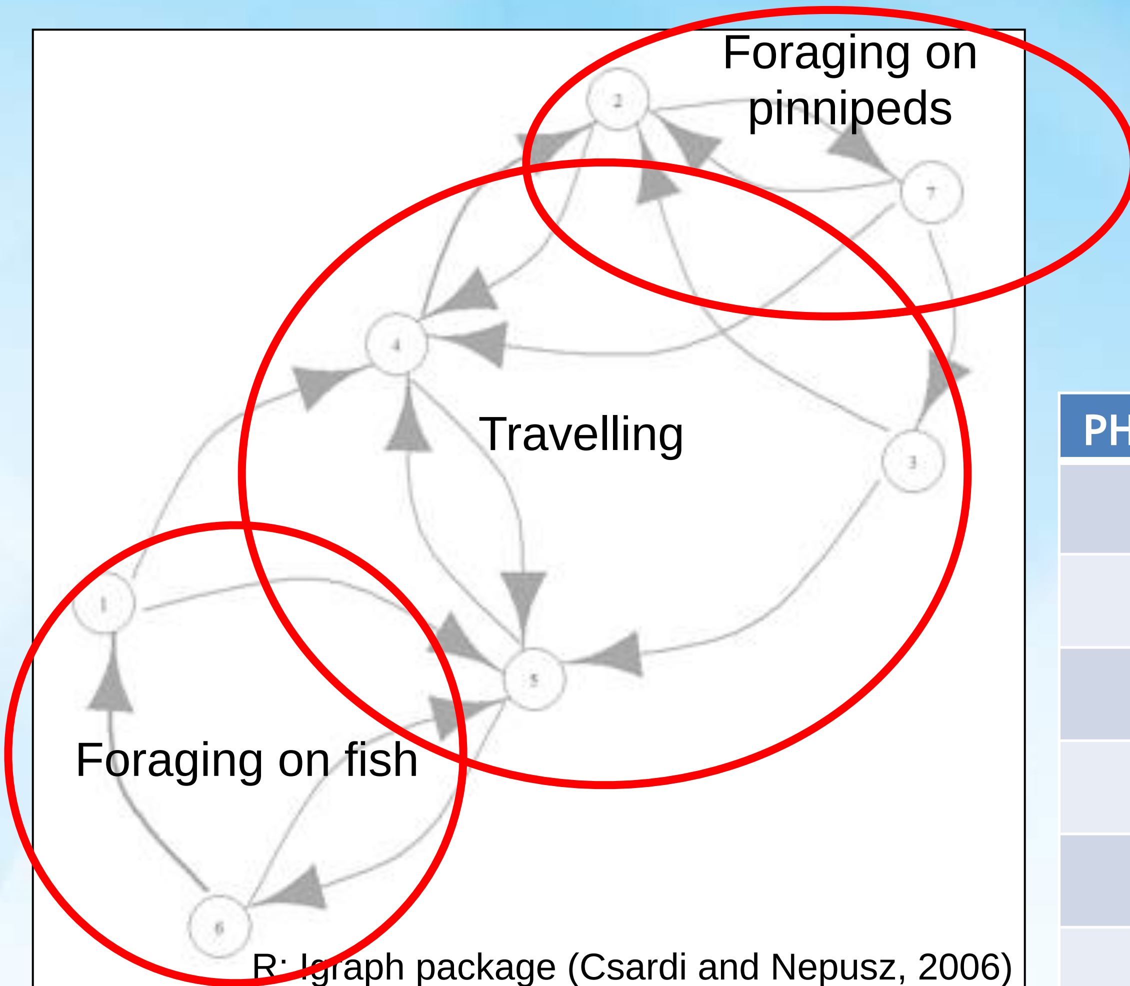
Weighted Behavioural Transition Matrix



R: Igraph package (Csardi and Nepusz, 2006)

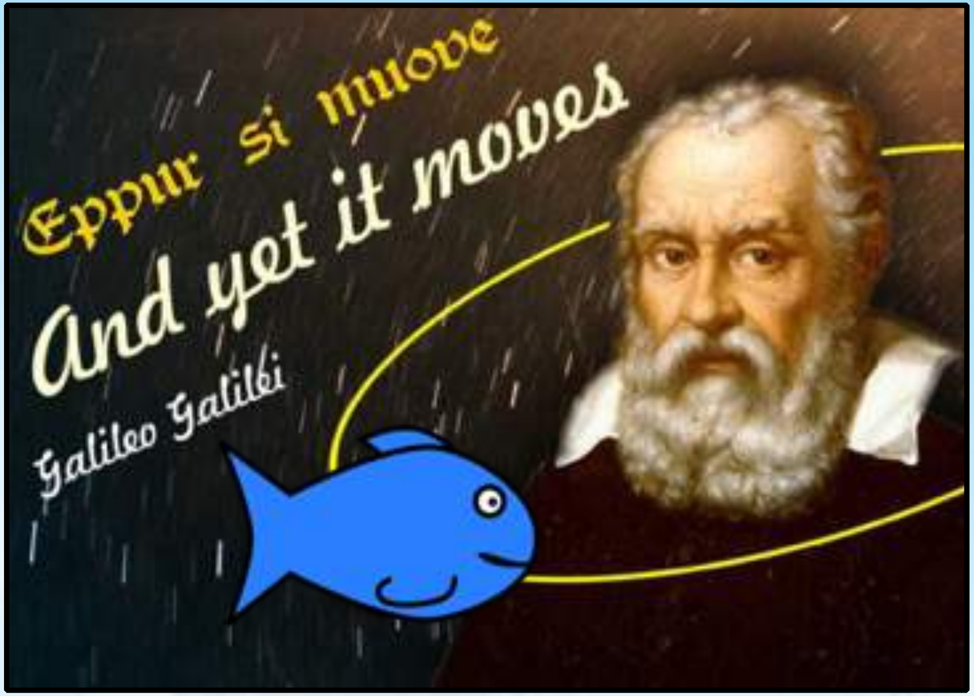
PHASES	BEHAVIOUR
1	*Foraging on fish*
2	*Foraging for pinnipeds*
3	*Intersite (Lévy)*
4	*Offshore fast (shortcuts)*
5	*Intrasite roaming (random)*
6	*Scavenging on chumming*
7	*Patrolling on pinnipeds*

CONCLUSIONS

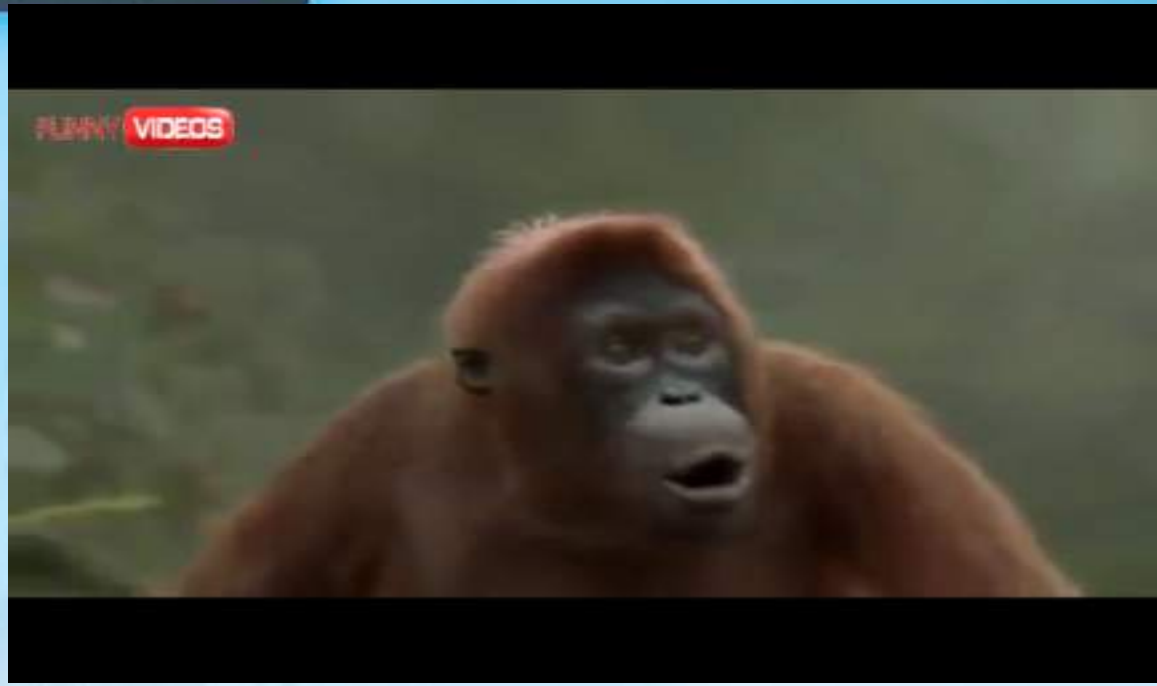
The use of a semi-unsupervised routine
(BCPA + Bayesian framework + mixed modelling)
allowed to characterize movement-based behavioural patterns without *a priori* definitions of movement parameters based on the vicinity of the animal to geographic landmarks

Future applications

- 3-dimensional BCPA on white sharks
- Applicable to all of you using VPS on other species
- Sat data of geographic positions + state space models + using behavioural classes parameters = run simulations to match the sat data and extrapolate behaviours
- Predicting behaviours in problematic areas (Cape Town, Western Australia)
- Identify not recognised behaviours (mating, birthing etc…)



South African famous proverb:
"We need to learn more why animals move as we all know that animals…



THANK YOU !

QUESTIONS ?

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NRF National Research Foundation

SAIAB South African Institute for Aquatic Biodiversity

RHODES UNIVERSITY
Where leaders learn

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