Seasonal Sea Otters, Foraging Fur Seals and Whimsical Wolves

Analysis of individual animal movement on all kinds of scales

Eli Gurarie

Metapopulation Research Group
Department of Biological and Environmental Sciences University of Helsinki - Finland

October 11, 2009

Importance of Movement

Importance of Movement

- Fundamental characteristic of all animals.

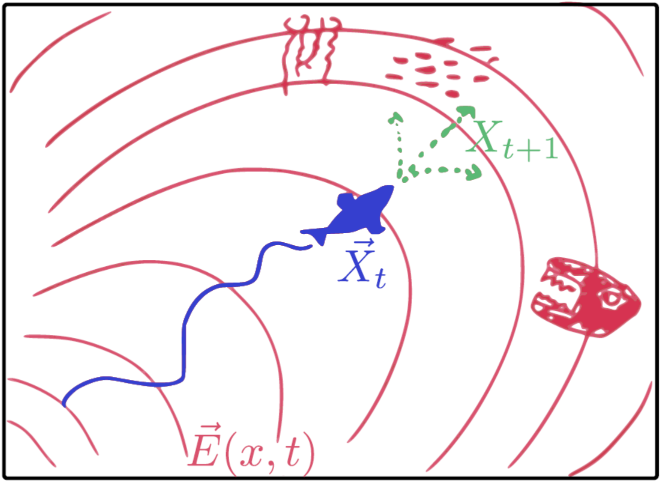
Importance of Movement

- Fundamental characteristic of all animals.
- Ecological processes
  - Foraging
  - Survival
  - Reproduction
  - Migration
  - Invasion
  - Dispersal
  - Aggregation

Importance of Movement

- Fundamental characteristic of all animals.
- Ecological processes
  - Foraging
  - Survival
  - Reproduction
  - Migration
  - Invasion
  - Dispersal
  - Aggregation
- Measurable behavioral output

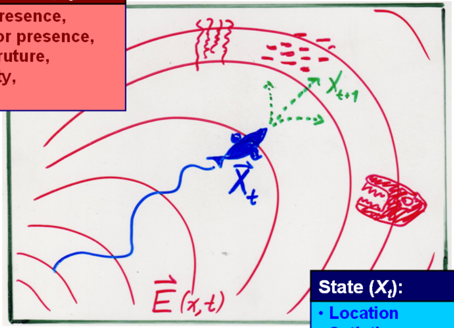
Conceptual model of Behavior



Conceptual model of Behavior

Environment (E_t):

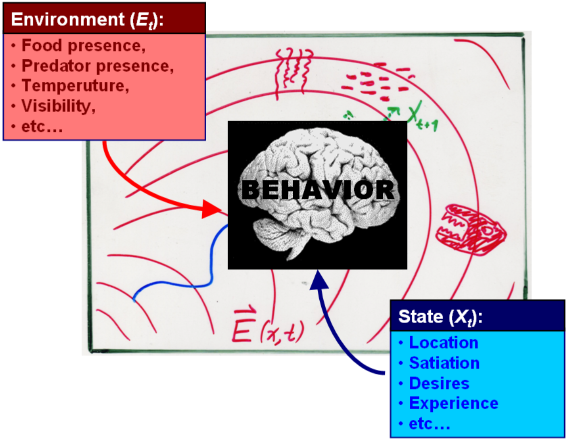
- Food presence,
- Predator presence,
- Temperuture,
- Visibility,
- etc…



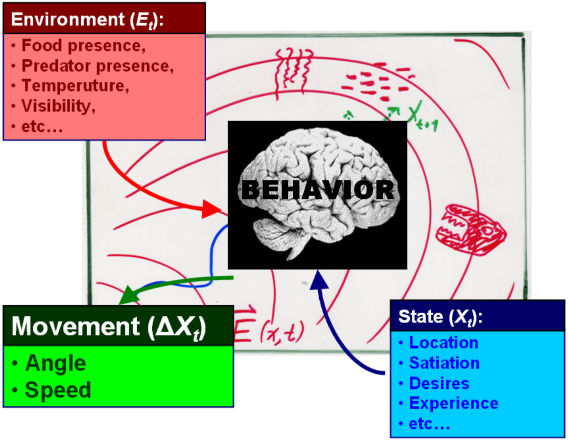
State (X_t):

- Location
- Satiation
- Desires
- Experience
- etc…

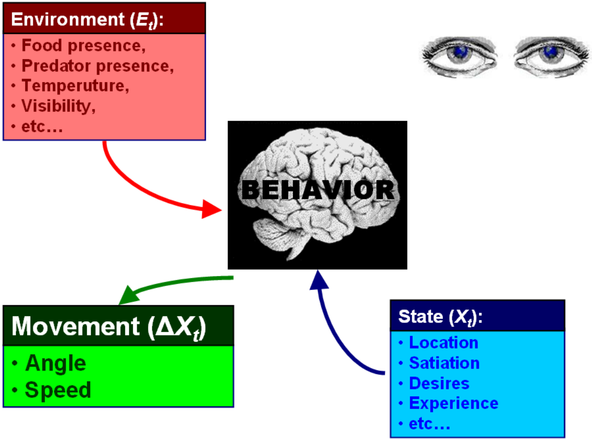
Conceptual model of Behavior



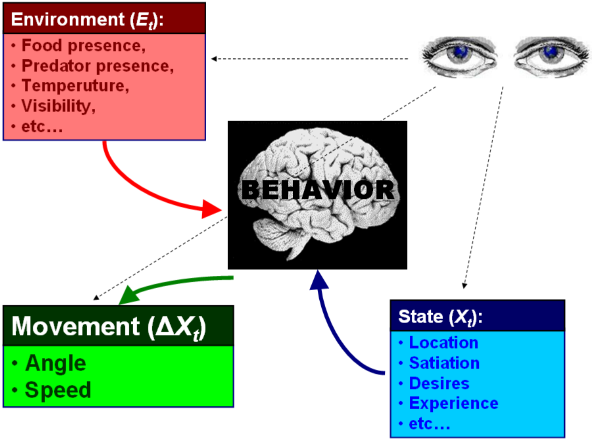
Conceptual model of Behavior



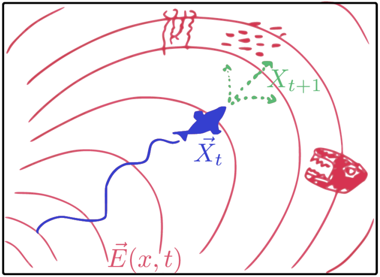
Conceptual model of Behavior



Conceptual model of Behavior



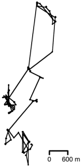
Conceptual model of Behavior



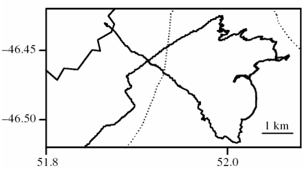
In Math: $\Delta X_t = f(\mathbf{X}_t, \mathbf{E}_t)$

In English: *Behavior* (f) is a process which transforms the state of an organism (X_t) and the the local environment (E_t) into Movement (ΔX_t).

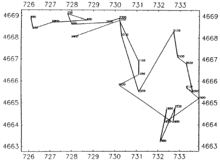
Track Data



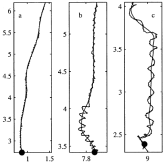
Treecreeper (Doerr 2004)



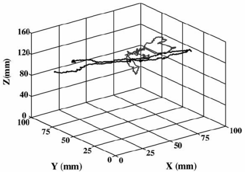
Albatross (Fritz 2002)



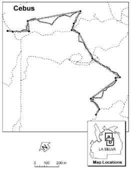
Iberian wolf (Bascompte 1997)



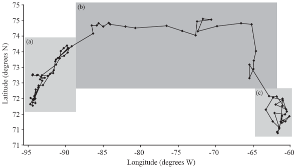
Heterosigma (Bearon 2003)



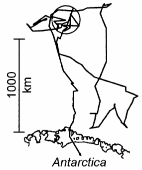
Daphnia Pulex (Uttieri 2005)



Cebus monkey (Wentz 2003)



Narwhal (Laidre 2004)



Petrel (Fouchauld 2003)

Common, Inconvenient Features of Movement Data: (CIF's)

Common, Inconvenient Features of Movement Data: (CIF's)

- Multi-dimensional (X,Y,Time)

Common, Inconvenient Features of Movement Data: (CIF's)

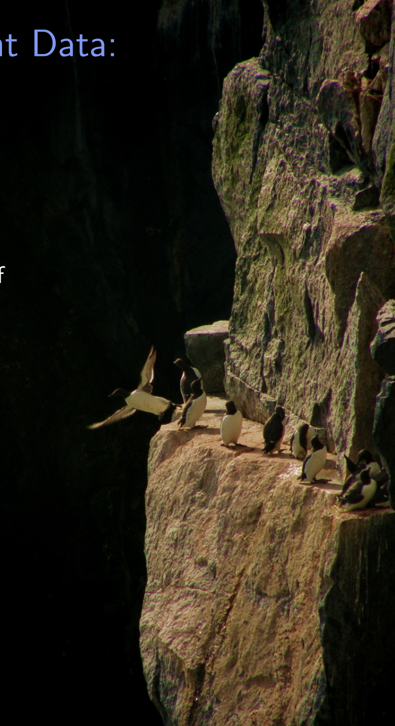
- Multi-dimensional (X,Y,Time)
- Not independent!
  (Auto- and Cross-correlated)

Common, Inconvenient Features of Movement Data: (CIF's)

- Multi-dimensional (X,Y,Time)
- Not independent!
  (Auto- and Cross-correlated)
- Bonus Feature: Measurement error / irregular sampling.

Extra Special Features of Movement Data: (ESF's)

- Heterogeneous!
  • Population • Individual • Habitat • Time of Day/Year • etc.



Extra Special Features of Movement Data: (ESF's)

- Heterogeneous!
  • Population • Individual • Habitat • Time of Day/Year • etc.

  But that's OK! Because often this is what we want to learn!

Extra Special Features of Movement Data: (ESF's)

- Heterogeneous!
  • Population • Individual • Habitat • Time of Day/Year • etc.

  But that's OK! Because often this is what we want to learn!

- No Consensus On Analysis In The Literature.

Extra Special Features of Movement Data: (ESF's)

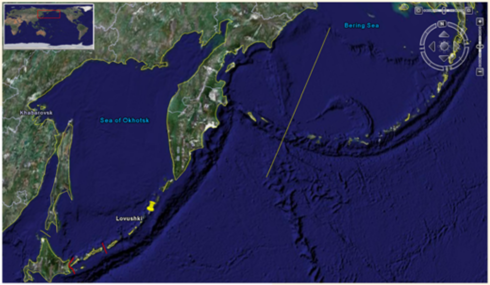
- Heterogeneous!
  • Population • Individual • Habitat • Time of Day/Year • etc.

  But that's OK! Because often this is what we want to learn!

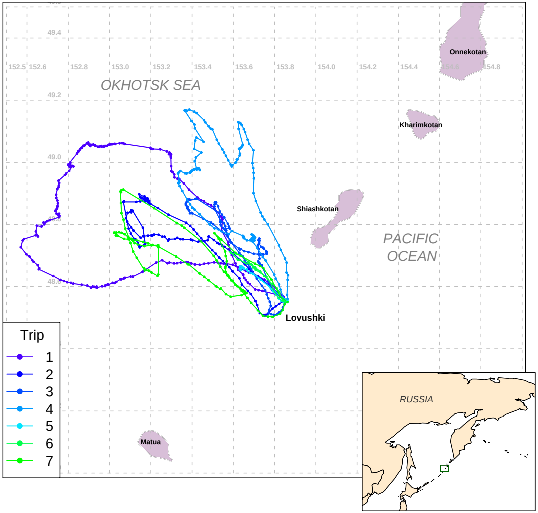
- No Consensus On Analysis In The Literature.

  But that's OK, too! Because every analysis is special!

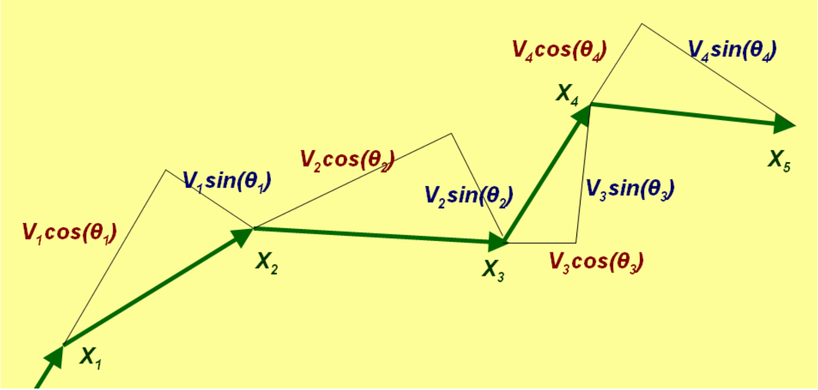
Northern Fur Seal (*Callorhinus ursinus*) and BCPA



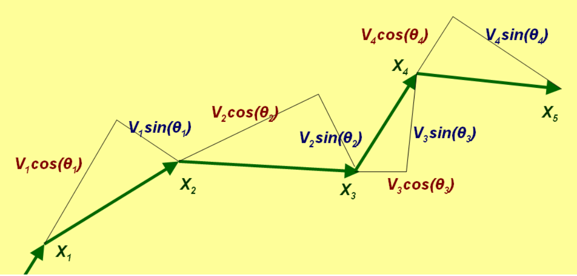
Map of all foraging trips for F01



Orthogonal decomposition



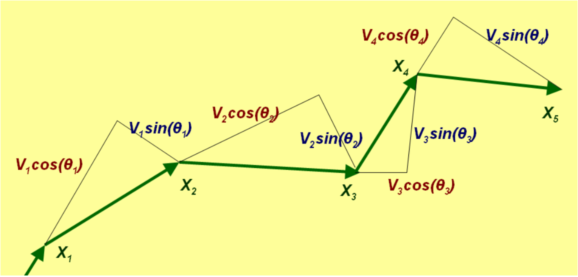
Orthogonal decomposition



Persistence Velocity Component: $V_p = V\cos(\theta)$

- **mean** = speed + consistency of orientation
- **variance** = variability of behavior
- **auto-correlation** = movement changes with respect to sampling interval

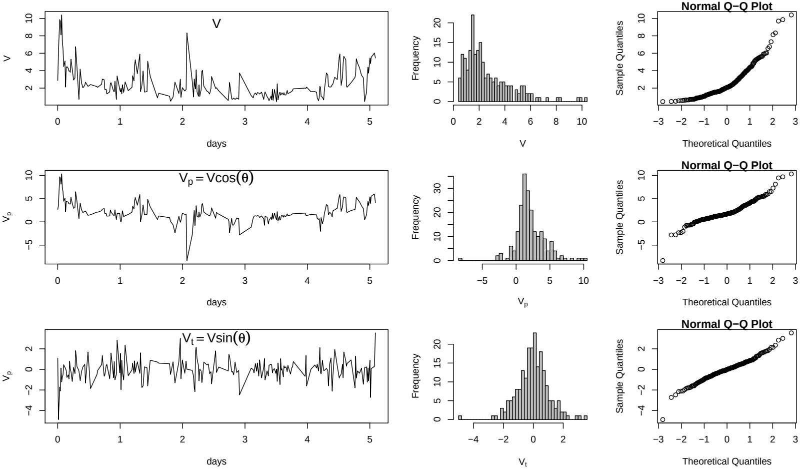
Orthogonal decomposition

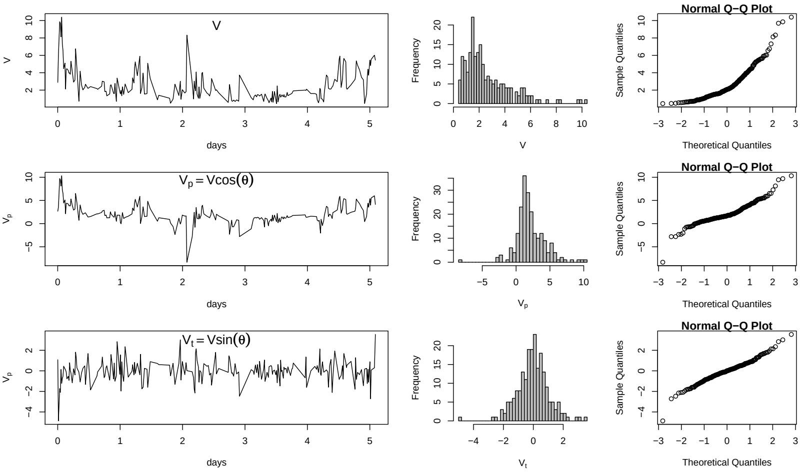


Orthogonal Component of Velocity: $V_t = V\sin(\theta)$

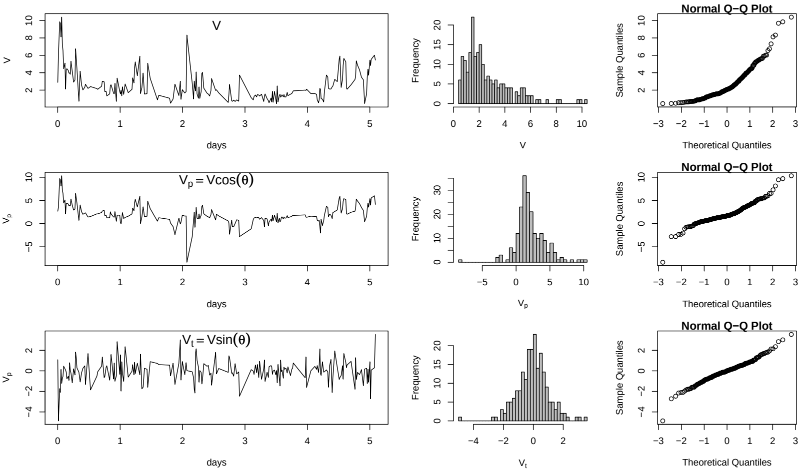
- **mean** $= 0$.
- **variance** $=$ speed and sharpness of turns
- **auto-correlation** $=$ turning radius.

Actual Data Decomposed (northern fur seal)

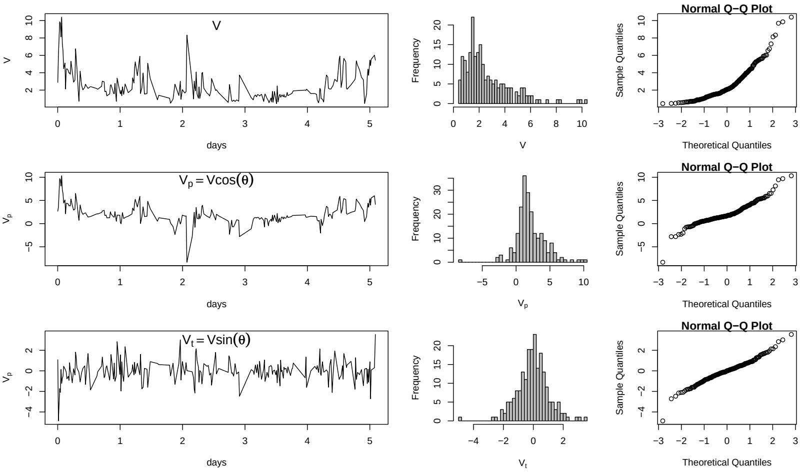




- Stationary
- Gaussian
- Modelable using standard time-series techniques



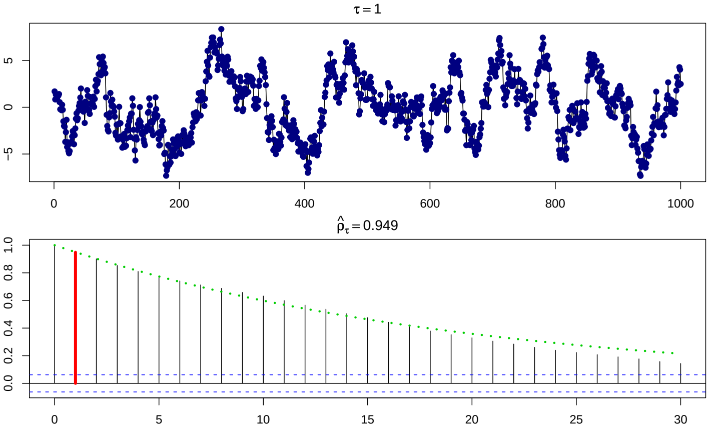
- Stationary
- Gaussian
- Modelable using standard time-series techniques



- Stationary
- Gaussian
- Modelable using standard time-series techniques

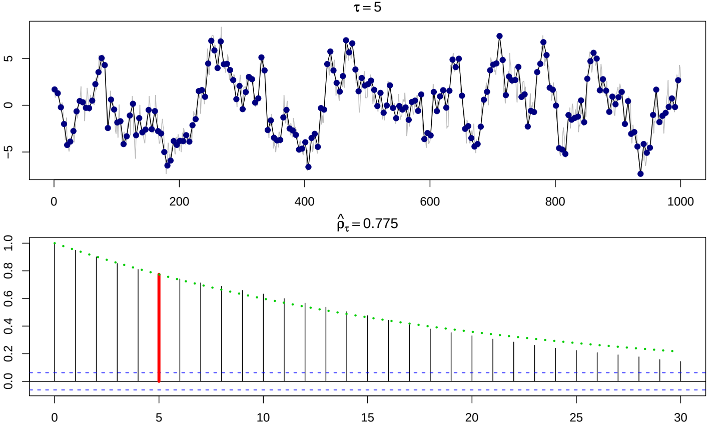
Properties of AR(1)

$$X_t = \rho\left(X_{t-1} - \mu\right) + \mu + \epsilon$$
$$\epsilon \sim \mathrm{N}(0, \sigma^2)$$



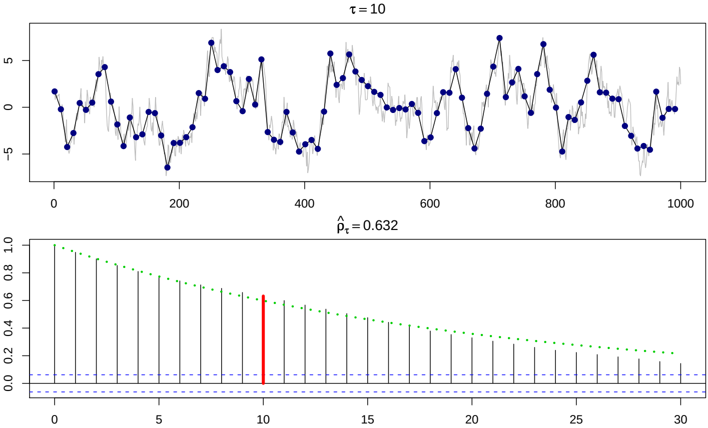
Properties of AR(1)

$$
\begin{aligned}
X_t &= \rho\left(X_{t-1} - \mu\right) + \mu + \epsilon \\
\epsilon &\sim \mathrm{N}(0, \sigma^2)
\end{aligned}
$$



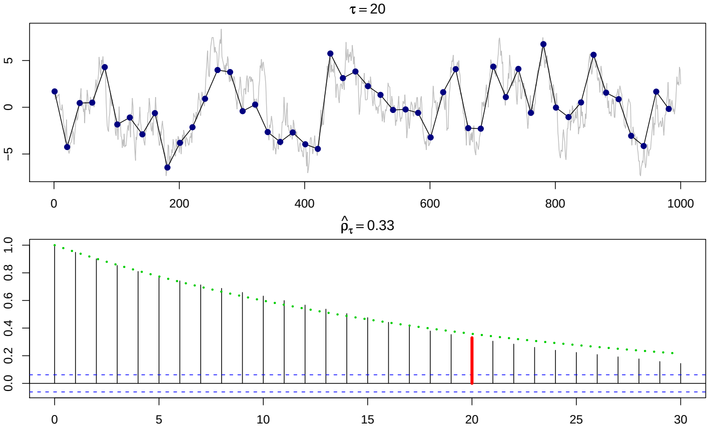
Properties of AR(1)

$$X_t = \rho\,(X_{t-1} - \mu) + \mu + \epsilon$$
$$\epsilon \sim \mathrm{N}(0, \sigma^2)$$



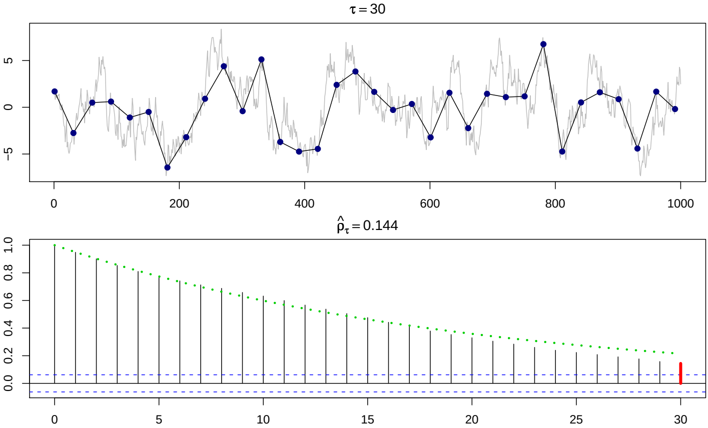
Properties of AR(1)

$$X_t = \rho\,(X_{t-1} - \mu) + \mu + \epsilon$$
$$\epsilon \sim \mathrm{N}(0, \sigma^2)$$

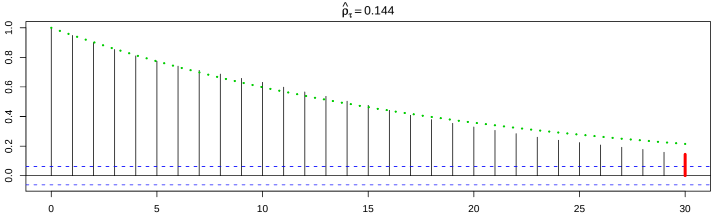


Properties of AR(1)

$$
\begin{aligned}
X_t &= \rho\,(X_{t-1} - \mu) + \mu + \epsilon \\
\epsilon &\sim \mathrm{N}(0, \sigma^2)
\end{aligned}
$$

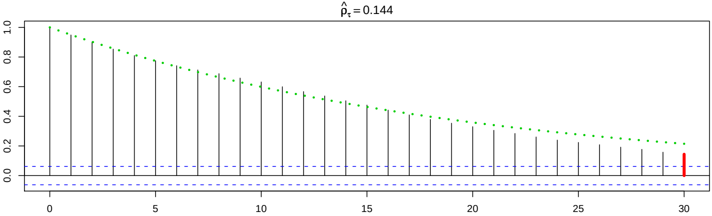


AR(1): Arbitrary Interval



$$
\begin{aligned}
\mathsf{E}\left[X(t)\right] &= \mu \\
\mathsf{Var}\left[X(t)\right] &= \sigma^2 \\
\mathsf{Corr}[X(t), X(t-\tau)] &= \rho^\tau
\end{aligned}
$$

AR(1): Arbitrary Interval



$$f(X(t)|X(t-\tau)) \sim$$
$$\text{Gaussian}\left[\rho^{\tau}X(t-\tau), \sigma^2(1-\rho^{2\tau})\right]$$

Estimating ρ

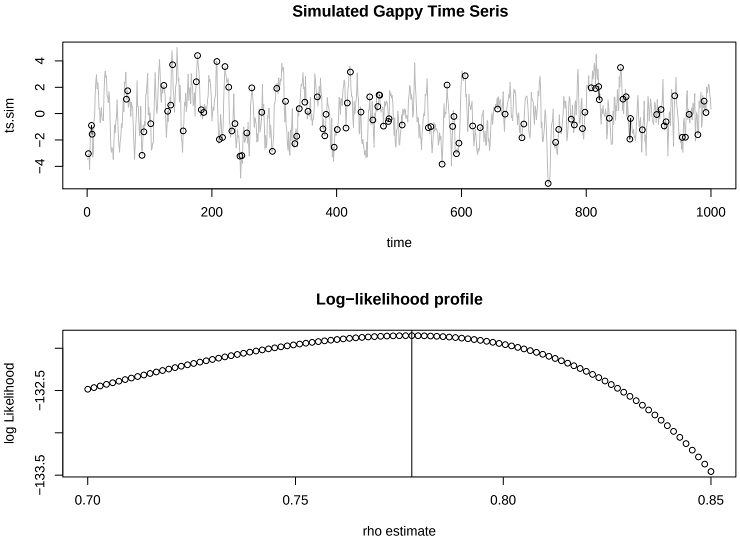
Conditional Likelihood:

$$L(\rho|\mathbf{X}, \mathbf{T}) = \prod_{i=1}^{n} f(X_i|X_{i-1}, \tau_i, \rho),$$

then:

$$\widehat{\rho} = \underset{\rho}{\operatorname{argmax}}\ L(\rho|\mathbf{X}, \mathbf{T})$$

Estimating ρ

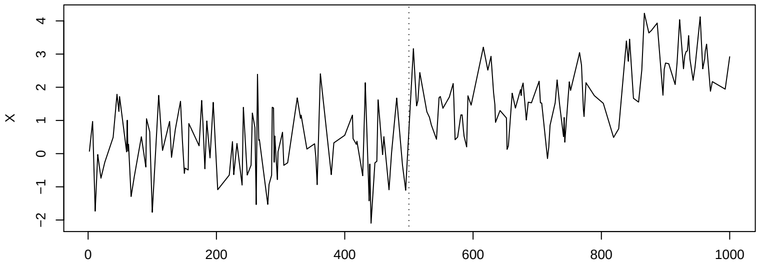


Structural shifts

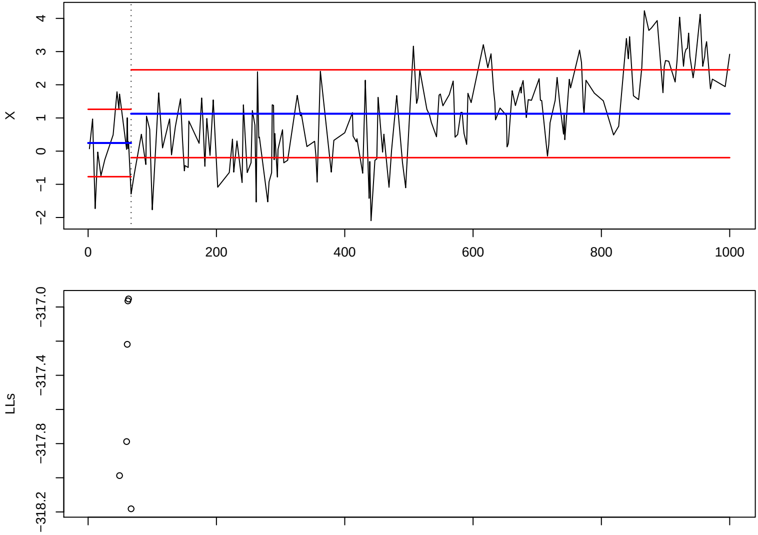
$$\Theta(t) = \left\{ \begin{array}{lll} \Theta_1 & \text{if} & 0 < t \leq t_1 \\ \Theta_2 & \text{if} & t_1 < t \leq T \end{array} \right\}$$

$$L(\Theta|\mathbf{X}, \mathbf{T}) = \prod_{i=1}^{n} f(X_i|X_{i-1}, \Theta_1) \prod_{j=n+1}^{N} f(X_j|X_{j-1}, \Theta_2)$$

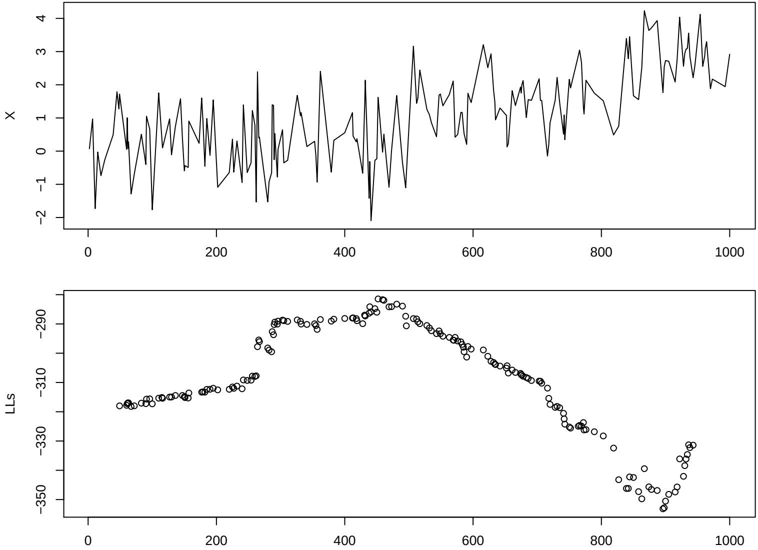
Identifying Change Point



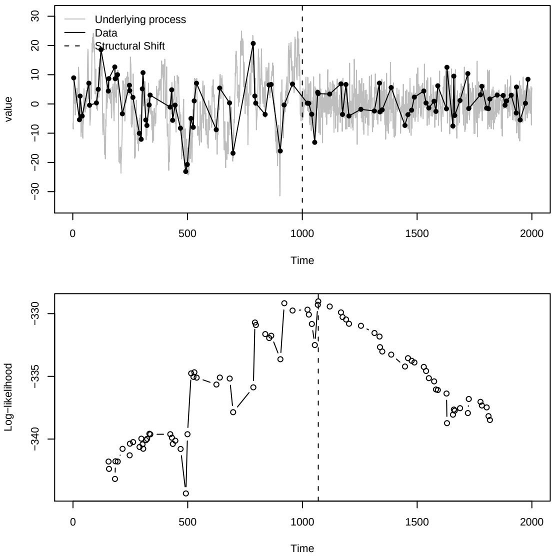
Identifying Change Point



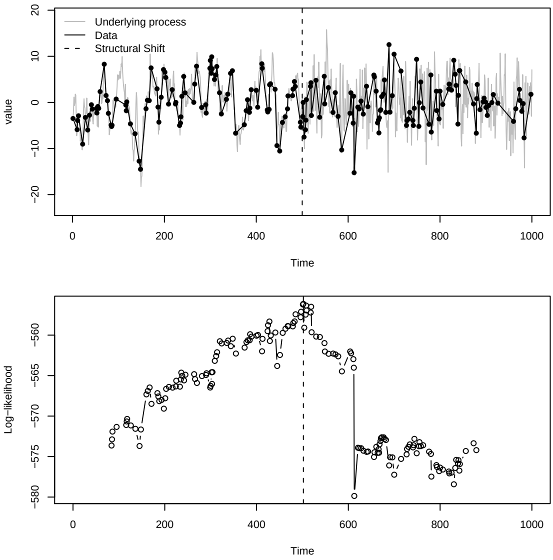
Identifying Change Point



Identifying Change Point, sparce data



Identifying Change Point, different ρ's



Identifying Models

Model 0	$\mu_1 = \mu_2$	$\sigma_1 = \sigma_2$	$\rho_1 = \rho_2$
Model 1	$\mu_1 \neq \mu_2$	$\sigma_1 = \sigma_2$	$\rho_1 = \rho_2$
Model 2	$\mu_1 = \mu_2$	$\sigma_1 \neq \sigma_2$	$\rho_1 = \rho_2$
Model 3	$\mu_1 = \mu_2$	$\sigma_1 = \sigma_2$	$\rho_1 \neq \rho_2$
Model 4	$\mu_1 \neq \mu_2$	$\sigma_1 \neq \sigma_2$	$\rho_1 = \rho_2$
Model 5	$\mu_1 \neq \mu_2$	$\sigma_1 = \sigma_2$	$\rho_1 \neq \rho_2$
Model 6	$\mu_1 = \mu_2$	$\sigma_1 \neq \sigma_2$	$\rho_1 \neq \rho_2$
Model 7	$\mu_1 \neq \mu_2$	$\sigma_1 \neq \sigma_2$	$\rho_1 \neq \rho_2$

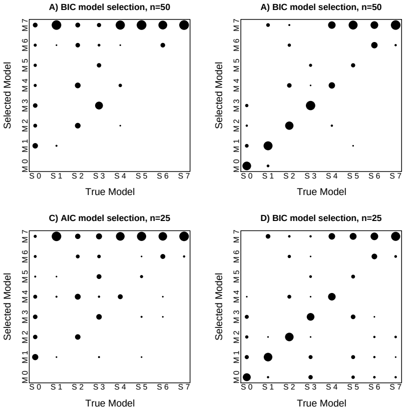
Identifying Models

Model 0	$\mu_1 = \mu_2$	$\sigma_1 = \sigma_2$	$\rho_1 = \rho_2$
Model 1	$\mu_1 \neq \mu_2$	$\sigma_1 = \sigma_2$	$\rho_1 = \rho_2$
Model 2	$\mu_1 = \mu_2$	$\sigma_1 \neq \sigma_2$	$\rho_1 = \rho_2$
Model 3	$\mu_1 = \mu_2$	$\sigma_1 = \sigma_2$	$\rho_1 \neq \rho_2$
Model 4	$\mu_1 \neq \mu_2$	$\sigma_1 \neq \sigma_2$	$\rho_1 = \rho_2$
Model 5	$\mu_1 \neq \mu_2$	$\sigma_1 = \sigma_2$	$\rho_1 \neq \rho_2$
Model 6	$\mu_1 = \mu_2$	$\sigma_1 \neq \sigma_2$	$\rho_1 \neq \rho_2$
Model 7	$\mu_1 \neq \mu_2$	$\sigma_1 \neq \sigma_2$	$\rho_1 \neq \rho_2$

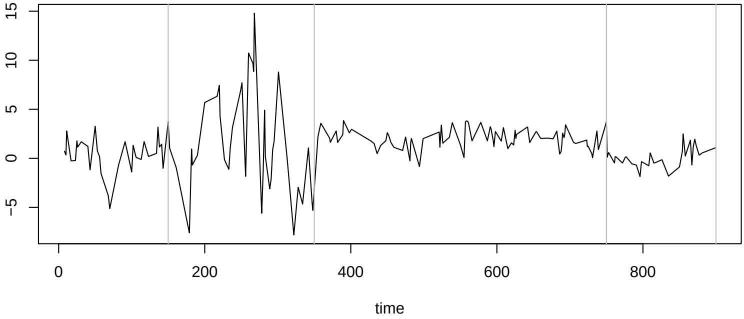
How to choose?

$$
\begin{aligned}
\text{AIC} : I_A(\mathbf{X}, \mathbf{T}) &= -2n \log\left(L(\hat{\theta}|\mathbf{X}, \mathbf{T})\right) + 2d \\
\text{BIC} : I_B(\mathbf{X}, \mathbf{T}) &= -2n \log\left(L(\hat{\theta}|\mathbf{X}, \mathbf{T})\right) + d \log(n)
\end{aligned}
$$

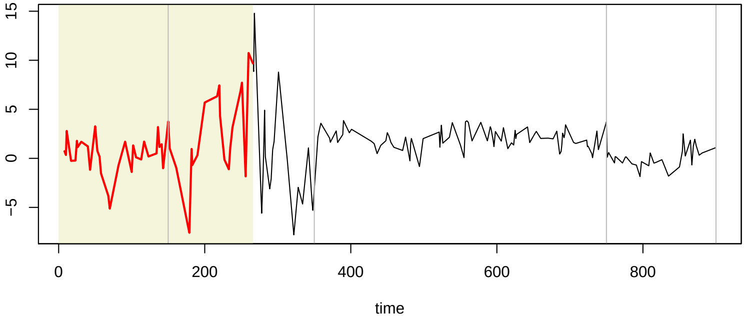
Identifying Models



	μ_1	μ_2	σ_1	σ_2	ρ_1	ρ_2
S0	0	0	1	1	0.5	0.5
S1	**-1**	**1**	1	1	0.5	0.5
S2	0	0	**0.5**	**2**	0.5	0.5
S3	0	0	1	1	**0.2**	**0.9**
S4	**-1**	**1**	**0.5**	**2**	0.5	0.5
S5	**-1**	**1**	1	1	**0.2**	**0.9**
S6	0	0	**0.5**	**2**	**0.2**	**0.9**
S7	**-1**	**1**	**0.5**	**2**	**0.2**	**0.9**

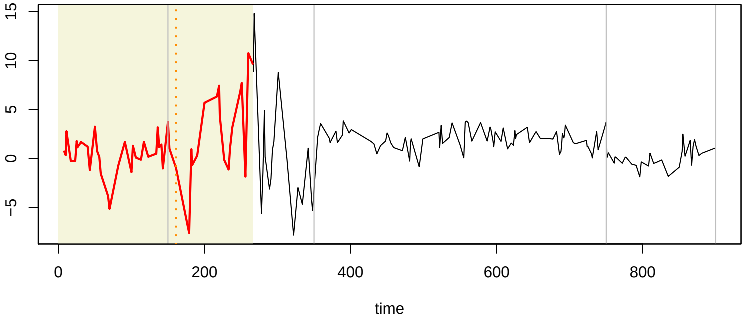


15
10
5
0
−5
0
200
400
600
800
time



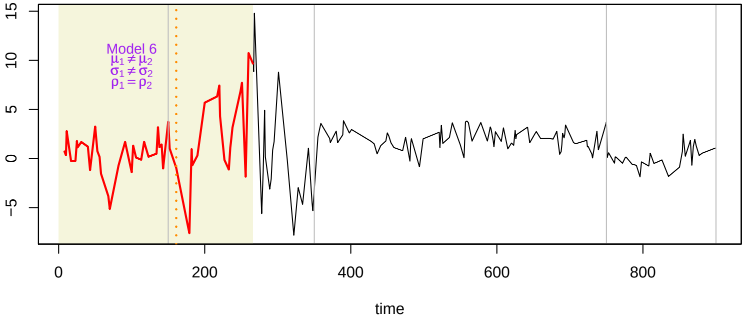
Algorithm for Identifying Multiple Changepoints

- Select Window
- Find MLBP
- Identify Model
- Record estimates based on model selected.
- Move window forward and repeat



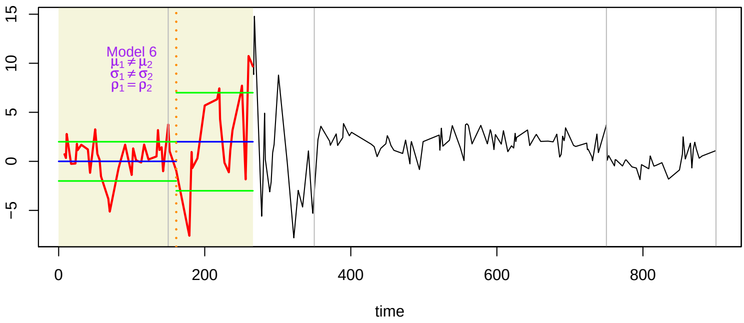
Algorithm for Identifying Multiple Changepoints

- Select Window
- Find MLBP
- Identify Model
- Record estimates based on model selected.
- Move window forward and repeat



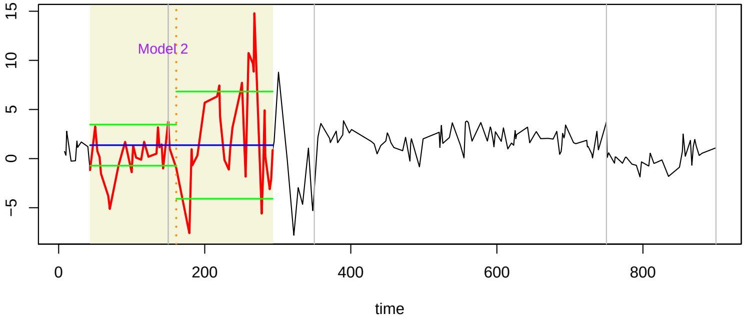
Algorithm for Identifying Multiple Changepoints

- Select Window
- Find MLBP
- Identify Model
- Record estimates based on model selected.
- Move window forward and repeat



Algorithm for Identifying Multiple Changepoints

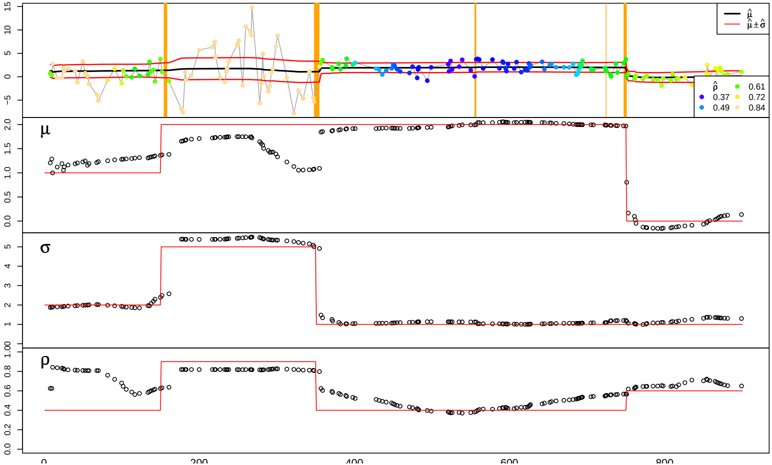
- Select Window
- Find MLBP
- Identify Model
- Record estimates based on model selected.
- Move window forward and repeat



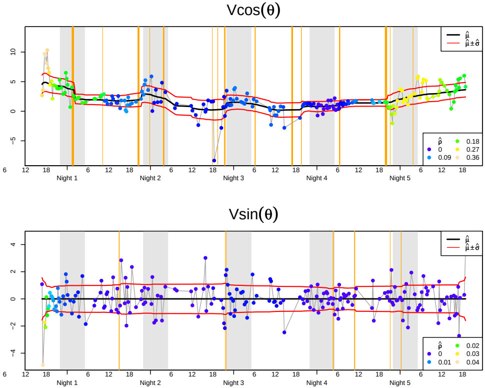
Algorithm for Identifying Multiple Changepoints

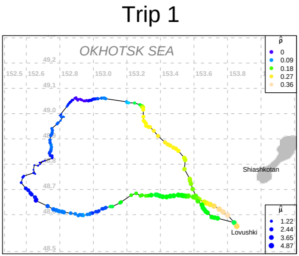
- Select Window
- Find MLBP
- Identify Model
- Record estimates based on model selected.
- Move window forward and repeat

BCPA analysis output

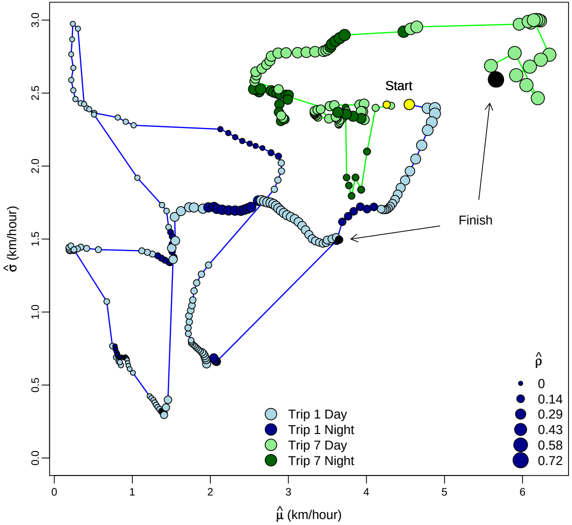


BCPA Track Analysis





Behavioral Phaseplot



Summary points

Summary points

- Behavior can be very complex!
- But patterns *can* be robustly picked out of messy data.
- Method suggests the possibility of asking more sophisticated questions.

Gurarie, E., R.D. Andrews, and K.L. Laidre. 2009. A novel method for identifying behavioural changes in animal movement data. *Ecology Letters* **12**: 395–408.

Summary points

- Behavior can be very complex!
- But patterns *can* be robustly picked out of messy data.
- Method suggests the possibility of asking more sophisticated questions.

Gurarie, E., R.D. Andrews, and K.L. Laidre. 2009. A novel method for identifying behavioural changes in animal movement data. *Ecology Letters* **12**: 395–408.

Summary points

- Behavior can be very complex!
- But patterns *can* be robustly picked out of messy data.
- Method suggests the possibility of asking more sophisticated questions.

Gurarie, E., R.D. Andrews, and K.L. Laidre. 2009. A novel method for identifying behavioural changes in animal movement data. *Ecology Letters* **12**: 395–408.

Summary points

- Behavior can be very complex!
- But patterns *can* be robustly picked out of messy data.
- Method suggests the possibility of asking more sophisticated questions.

Gurarie, E., R.D. Andrews, and K.L. Laidre. 2009. A novel method for identifying behavioural changes in animal movement data. *Ecology Letters* **12**: 395–408.

So how'd we do on the CIF's and ESF's?

So how'd we do on the CIF's and ESF's?

1. Multi-dimensionality:
   Component decomposition (and continuous time)

So how'd we do on the CIF's and ESF's?

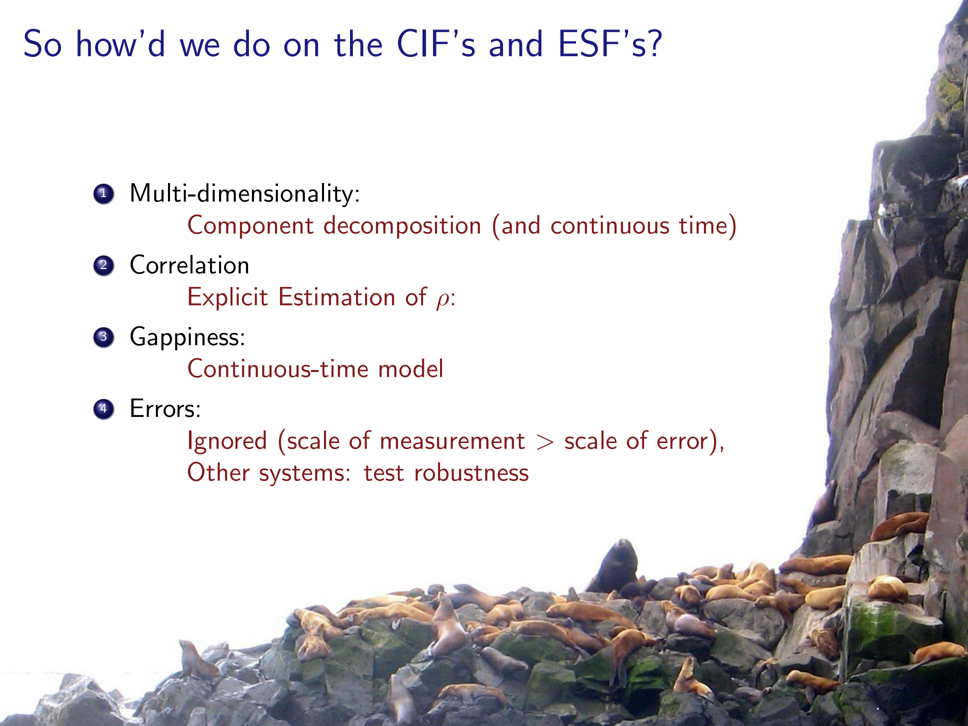
1. Multi-dimensionality:
   Component decomposition (and continuous time)
2. Correlation
   Explicit Estimation of ρ:

So how'd we do on the CIF's and ESF's?

1. Multi-dimensionality:
   Component decomposition (and continuous time)
2. Correlation
   Explicit Estimation of ρ:
3. Gappiness:
   Continuous-time model

So how'd we do on the CIF's and ESF's?

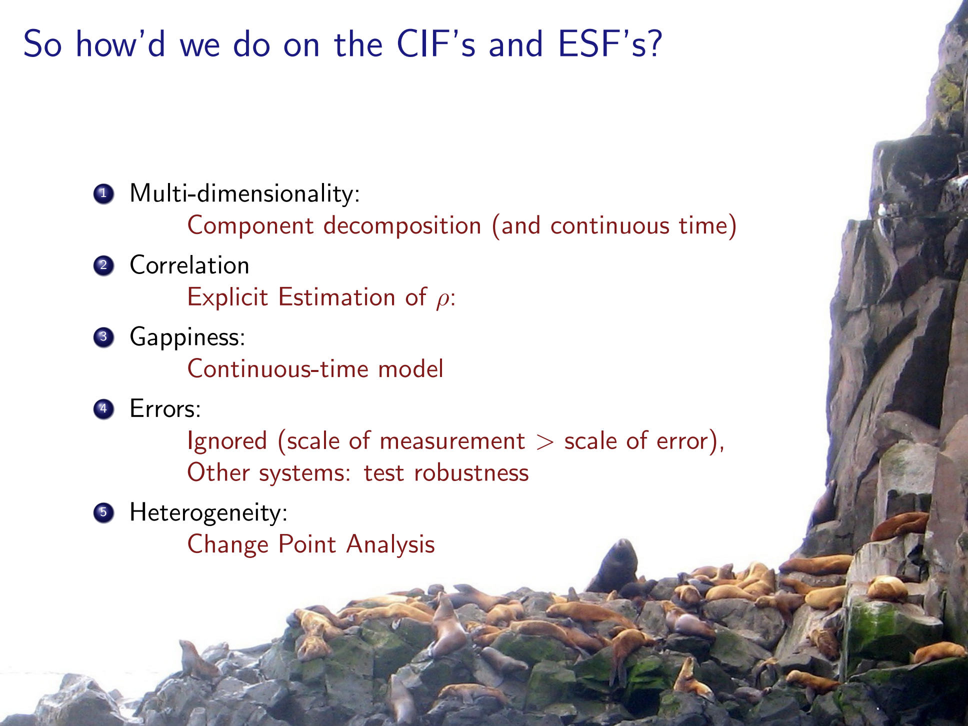
1. Multi-dimensionality:
   Component decomposition (and continuous time)
2. Correlation
   Explicit Estimation of ρ:
3. Gappiness:
   Continuous-time model
4. Errors:
   Ignored (scale of measurement $>$ scale of error),
   Other systems: test robustness



So how'd we do on the CIF's and ESF's?

1. Multi-dimensionality:
   Component decomposition (and continuous time)
2. Correlation
   Explicit Estimation of ρ:
3. Gappiness:
   Continuous-time model
4. Errors:
   Ignored (scale of measurement $>$ scale of error),
   Other systems: test robustness
5. Heterogeneity:
   Change Point Analysis

So how'd we do on the CIF's and ESF's?



1. Multi-dimensionality:
   Component decomposition (and continuous time)
2. Correlation
   Explicit Estimation of ρ:
3. Gappiness:
   Continuous-time model
4. Errors:
   Ignored (scale of measurement $>$ scale of error),
   Other systems: test robustness
5. Heterogeneity:
   Change Point Analysis

Washington sea otters (*Enhydra lutris kenyoni*)

- Extirpated by fur-trade hunting in the early 20^{th} century
- Re-established by translocations of 59 sea otters from Alaska in 1969-70
- Population index counts annually conducted since late 80's

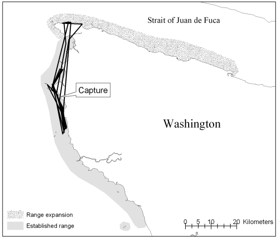
Movement Data: VHF Radio Telemetry Studies 1992-1999

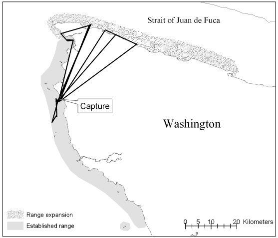
- 75 individuals captured using Wilson traps and instrumented (43 AF, 14 AM, 9 SF, and 9 SM)

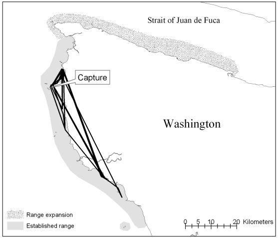
Individuals tracked on average for 684 days (SD 515, range 7 days to 5.9 years).

Average of 34 radio locations per individual (SD 29).

Mean number of resightings per sea otter per month ranged from 1.6 (December) to 5.8 (August) - mean of 2.9.


Strait of Juan de Fuca
Capture
Washington
Range expansion
Established range
0 5 10 20 Kilometers


Strait of Juan de Fuca
Capture
Washington
Range expansion
Established range
0 5 10 20 Kilometers


Strait of Juan de Fuca
Capture
Washington
Range expansion
Established range
0 5 10 20 Kilometers

Linearizing Otter movements

Linearizing Otter movements

Discretize coastline
(~600 m)

Linearizing Otter movements

Discretize coastline (~600 m)

Perpendicularly project sea otter location to “coast”.

Linearizing Otter movements

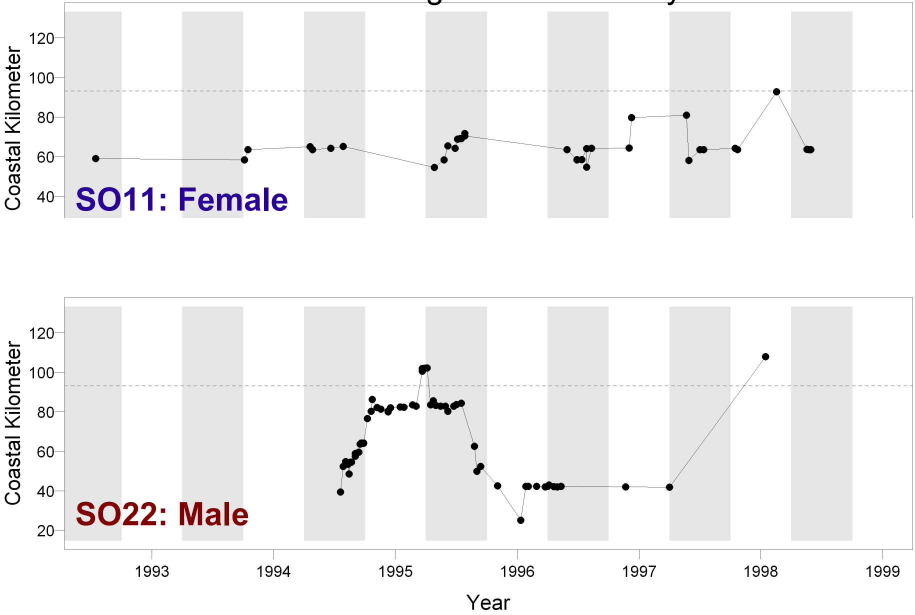
Discretize coastline (~600 m)

Perpendicularly project sea otter location to "coast".

Estimate "coastal kilometer value".

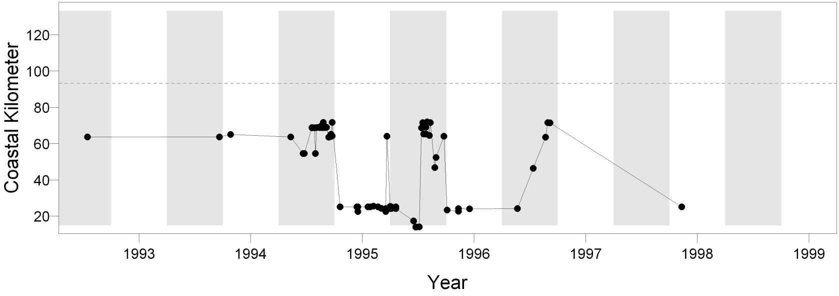
Analysis challenge: Quantify space use

● Home ranges ● Seasonality

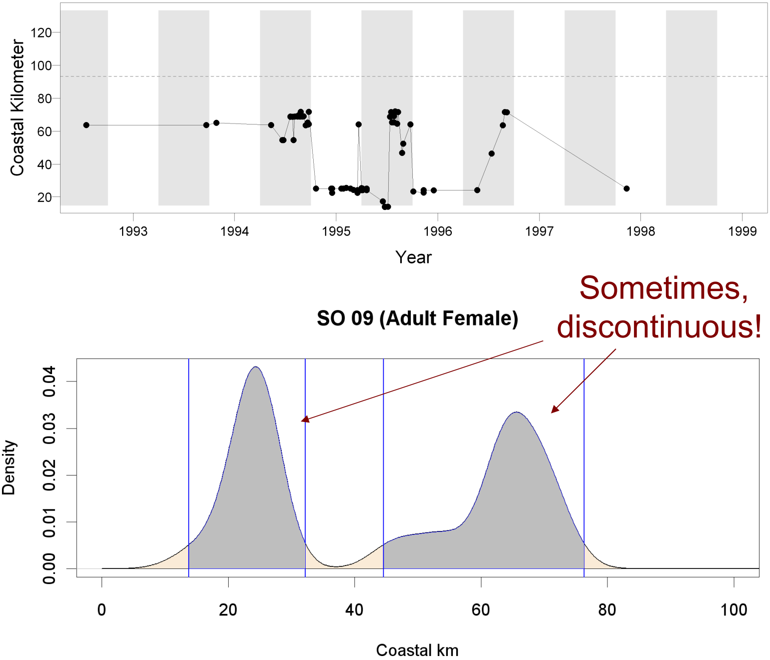


One-dimensional kernelized distributions

- Minimum of 20 observations (46 out of 75 individuals: 34 F, 12 M)
- Weighted according to number of days to neighboring observations, max 1 month
  - 4 obs/month = weight 7 day
  - 1 obs/year = weight 30 day

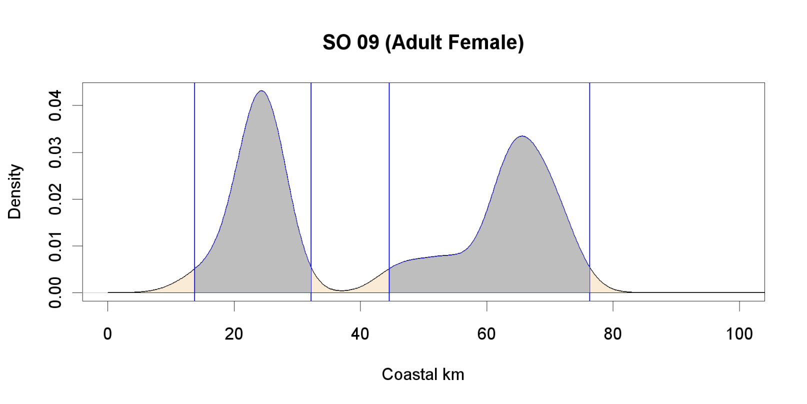


Home Range: 95% of time spent



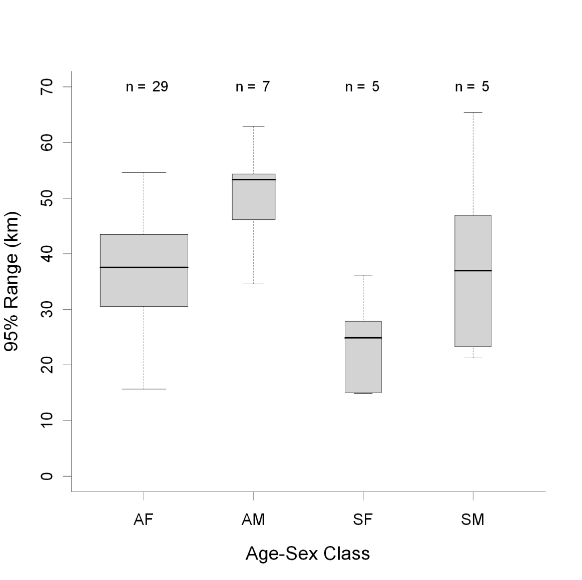
Continous otter

Discontinous otter

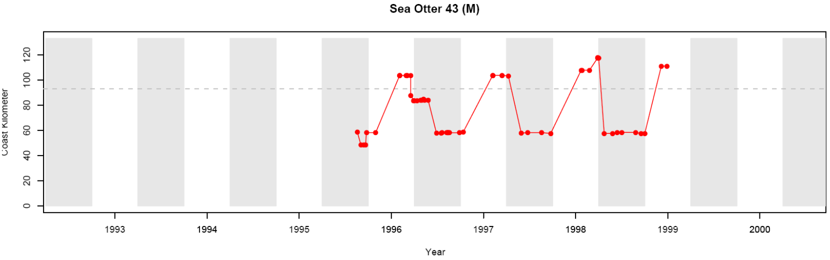


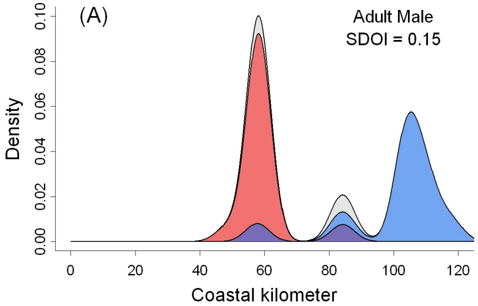
95% kernel home range by age class and sex.

Both significant ($p<0.01$)



How to **quantify** "seasonality"?

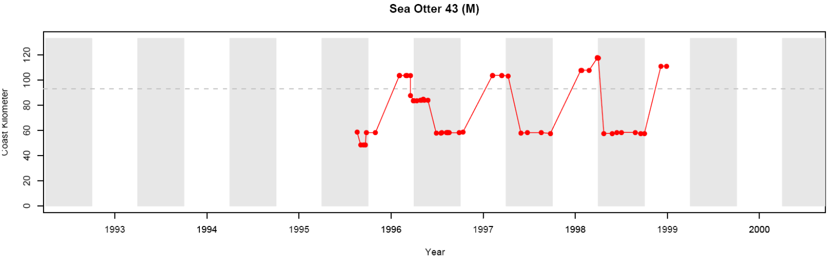


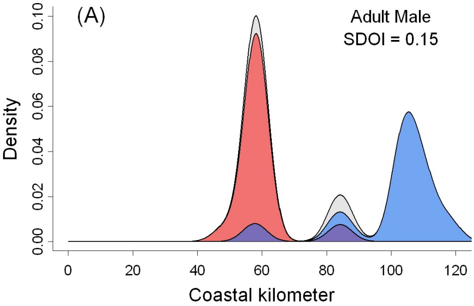


Summer (May-October)
and
Winter (November – April)**:**

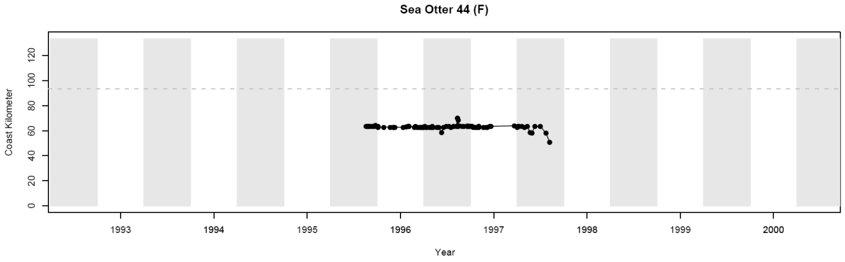
Seasonal **D**istribution **O**verlap **I**ndex

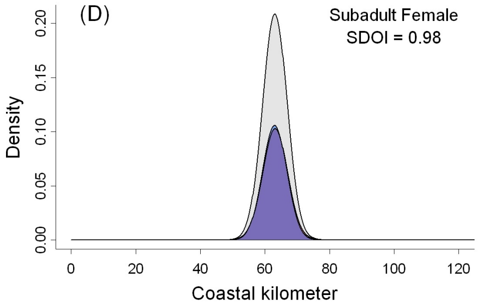
How to **quantify** "seasonality"?



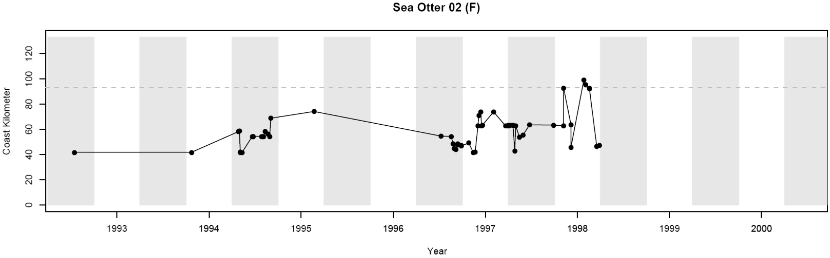


SDOI = 0.15

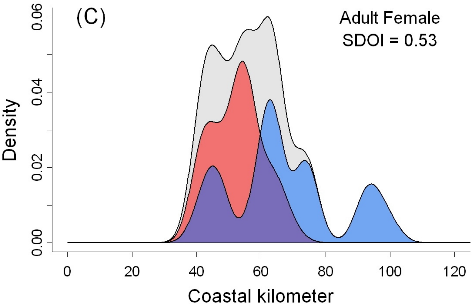

Sea Otter 44 (F)
Coast Kilometer
0
20
40
60
80
100
120
1993
1994
1995
1996
1997
1998
1999
2000
Year


(D)
Subadult Female
SDOI = 0.98
Density
0.00
0.05
0.10
0.15
0.20
0
20
40
60
80
100
120
Coastal kilometer

SDOI = 0.98



Sea Otter 02 (F)
Coast Kilometer
0
20
40
60
80
100
120
1993
1994
1995
1996
1997
1998
1999
2000
Year



(C)
Adult Female
SDOI = 0.53
Density
0.00
0.02
0.04
0.06
0
20
40
60
80
100
120
Coastal kilometer

SDOI = 0.53

SDOI by age class and sex

Sex significant but not age.

Age-Sex	Number of individuals	Mean seasonal distribution overlap (SD)
AF	29	0.63 (0.2)
AM	7	0.50 (0.24)
SF	5	0.70 (0.26)
SM	5	0.46 (0.22)

Some Sea Otter Conclusions

Some Sea Otter Conclusions

- Movements between 1992-1999 best described as semi-seasonal shifts within the range.
- The range expanded both North and South over the study period - driven primarily by males.
- High seasonal periodicity in range use in summer and winter, distributions were generally bimodal for adult males with adult females more variable more likely to have high year round site fidelity.

Some Sea Otter Conclusions

- Movements between 1992-1999 best described as semi-seasonal shifts within the range.
- The range expanded both North and South over the study period - driven primarily by males.
- High seasonal periodicity in range use in summer and winter, distributions were generally bimodal for adult males with adult females more variable more likely to have high year round site fidelity.

K.L. Laidre, R.J. Jameson, E. Gurarie, S.J. Jeffries and H. Allen. Spatial habitat use of sea otters in coastal Washington. *Journal of Mammalogy*, 90(4): 906–917, 2009.

Some Sea Otter Conclusions

- Movements between 1992-1999 best described as semi-seasonal shifts within the range.
- The range expanded both North and South over the study period - driven primarily by males.
- High seasonal periodicity in range use in summer and winter, distributions were generally bimodal for adult males with adult females more variable more likely to have high year round site fidelity.

K.L. Laidre, R.J. Jameson, E. Gurarie, S.J. Jeffries and H. Allen. Spatial habitat use of sea otters in coastal Washington. *Journal of Mammalogy*, 90(4): 906–917, 2009.

Some Sea Otter Conclusions

- Movements between 1992-1999 best described as semi-seasonal shifts within the range.
- The range expanded both North and South over the study period - driven primarily by males.
- High seasonal periodicity in range use in summer and winter, distributions were generally bimodal for adult males with adult females more variable more likely to have high year round site fidelity.

K.L. Laidre, R.J. Jameson, E. Gurarie, S.J. Jeffries and H. Allen. Spatial habitat use of sea otters in coastal Washington. *Journal of Mammalogy*, 90(4): 906–917, 2009.

So how'd we do on the CIF's and ESF's?

1. **Multi-dimensionality:**
   1D-projection

So how'd we do on the CIF's and ESF's?

1. **Multi-dimensionality:**
   1D-projection
2. **Correlation:**
   Choose time scale (1 month) and distance kernel (15km) that makes data independent

So how'd we do on the CIF's and ESF's?

1. **Multi-dimensionality:**
   1D-projection
2. **Correlation:**
   Choose time scale (1 month) and distance kernel (15km) that makes data independent
3. **Errors:**
   Ignored (scale of measurement > scale of error).

So how'd we do on the CIF's and ESF's?

1. **Multi-dimensionality:**
   1D-projection
2. **Correlation:**
   Choose time scale (1 month) and distance kernel (15km) that makes data independent
3. **Errors:**
   Ignored (scale of measurement $>$ scale of error),
4. **Heterogeneity:**
   Analysis according Sex/Age, Seasonality

So how'd we do on the CIF's and ESF's?

1. **Multi-dimensionality:**
   1D-projection
2. **Correlation:**
   Choose time scale (1 month) and distance kernel (15km) that makes data independent
3. **Errors:**
   Ignored (scale of measurement > scale of error),
4. **Heterogeneity:**
   Analysis according Sex/Age, Seasonality

Wolf (*Canis lupus*) in Finland

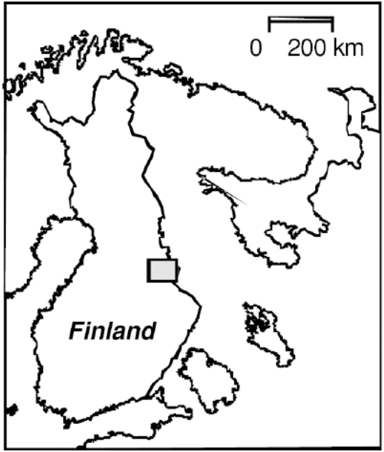
- Extirpated by hunting by early 20th century.
- Since 1980's influx from Western Russia.
- Currently, roughly 200 individuals. Hunter vs. Conservation tensions.

Movement Data

Eastern Finland, two wolves:
- Viki: female 2006
- Niki: male 2008

GPS and radio collared, 1/2 hour transmission interval

2-months of intensive ground tracking of every location away from den.



Movement Data

Eastern Finland, two wolves:
  Viki: female 2006
  Niki: male 2008

GPS and radio collared, 1/2 hour transmission interval

2-months of intensive ground tracking of every location away from den.

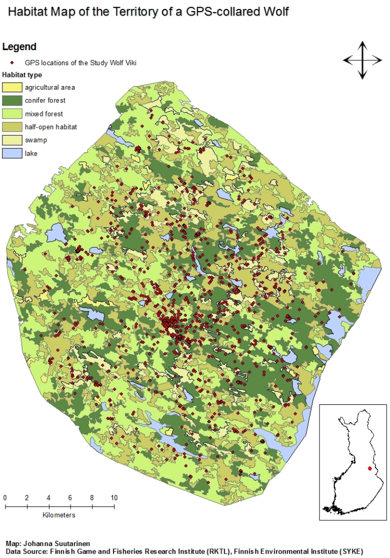
Movement Data

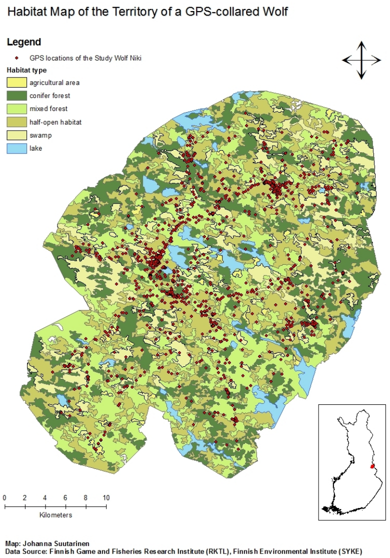
Eastern Finland, two wolves:
 Viki: female 2006
 Niki: male 2008

GPS and radio collared, 1/2 hour transmission interval

2-months of intensive ground tracking of every location away from den.

Habitat Data

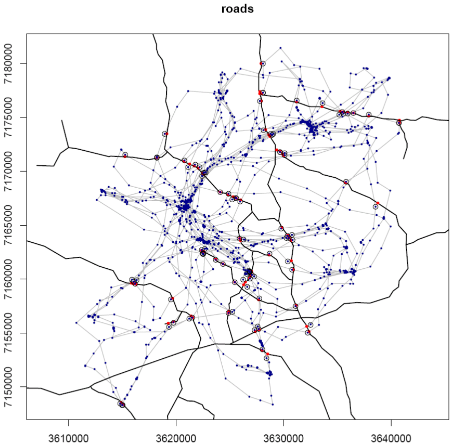


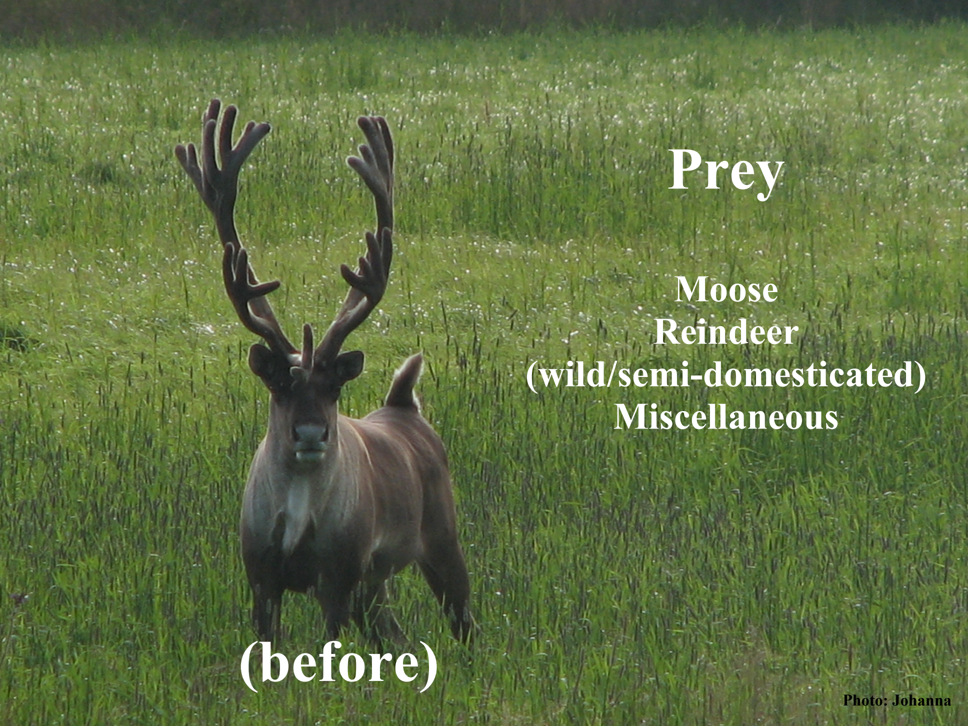



Mixed/Open
Forest Edge

Linear Elements

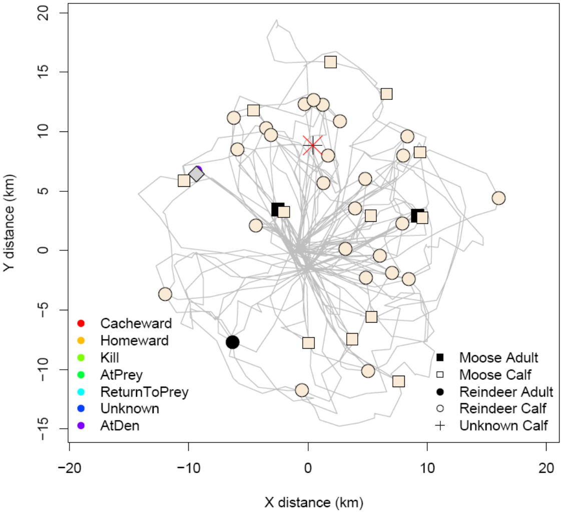
Primary Roads
Forest Roads
Rivers
Power Lines
Railways
Reindeer Fence




Prey
Moose
Reindeer
(wild/semi-domesticated)
Miscellaneous
(before)
Photo: Johanna


(after)
Photo: Johanna

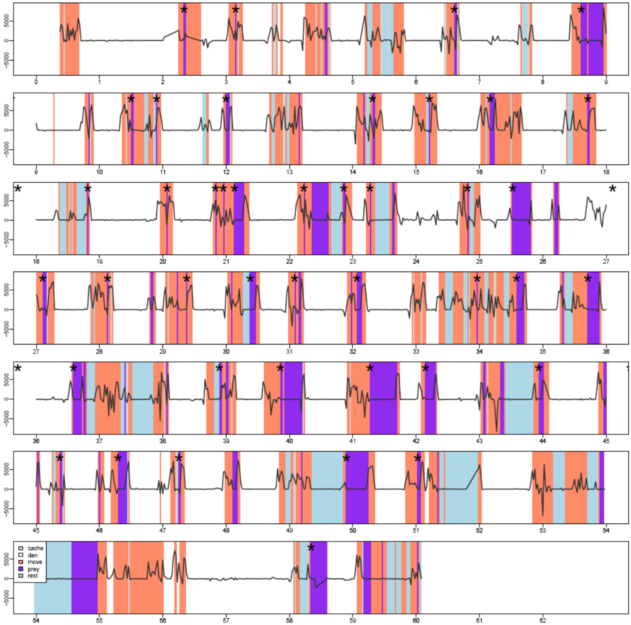
Prey


Y distance (km)
X distance (km)
−20
−10
0
10
20
−15
−10
−5
0
5
10
15
20
Cacheward
Homeward
Kill
AtPrey
ReturnToPrey
Unknown
AtDen
Moose Adult
Moose Calf
Reindeer Adult
Reindeer Calf
Unknown Calf

Behavior

(show some images from file)

Behavior: time series



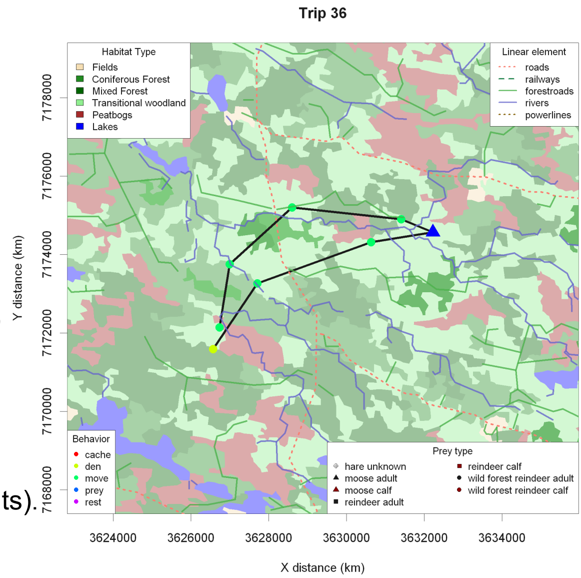
Goal

To model*:*

BEHAVIOR,
(movement and predation)

with respect to

HABITAT
(landscape and linear elements).



Behavior Vectors

Z_i – position

B_i – behavior

P_i – purpose

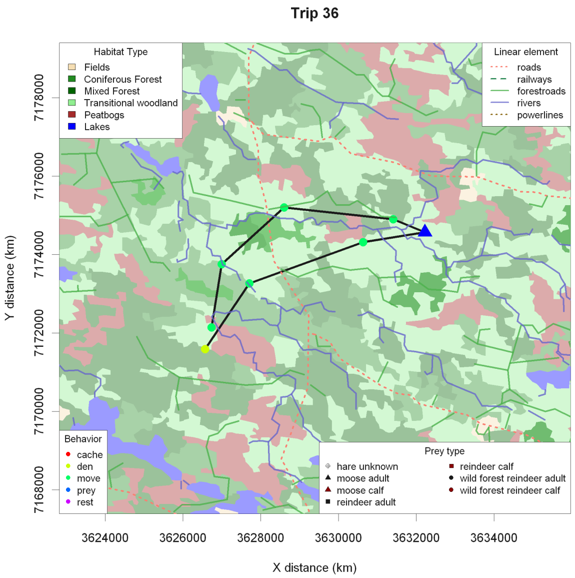
K_i – kill

Habitat Vectors

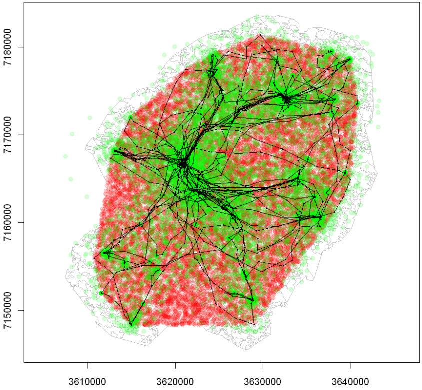
H_i – habitat land class

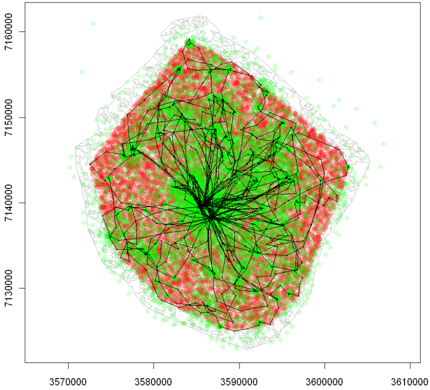
N_i – nearest neighbor habitat

L_i – linear element



Testing Hypotheses: Null Sets

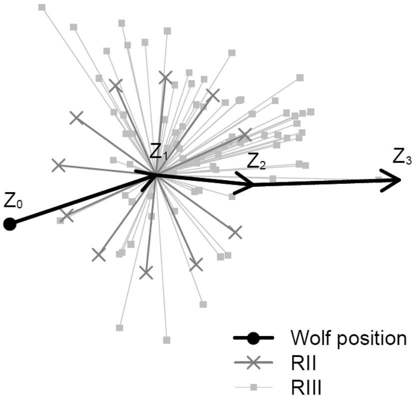




RI: All Possible Points in Home Range

RII/RIII: Points Localized Around Each Location

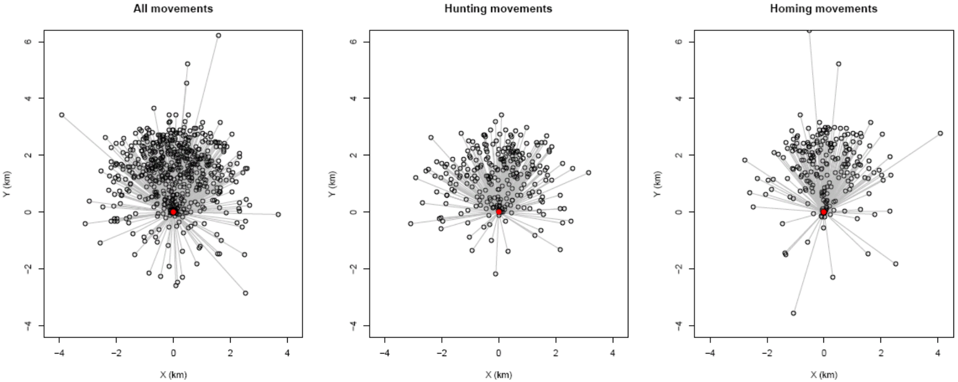
Localized Null Set



RII: Points Localized Around Each Location

RIII: Points reflecting "actual movements"

Localized Null Set



RIII: Points Localized Around Each Location

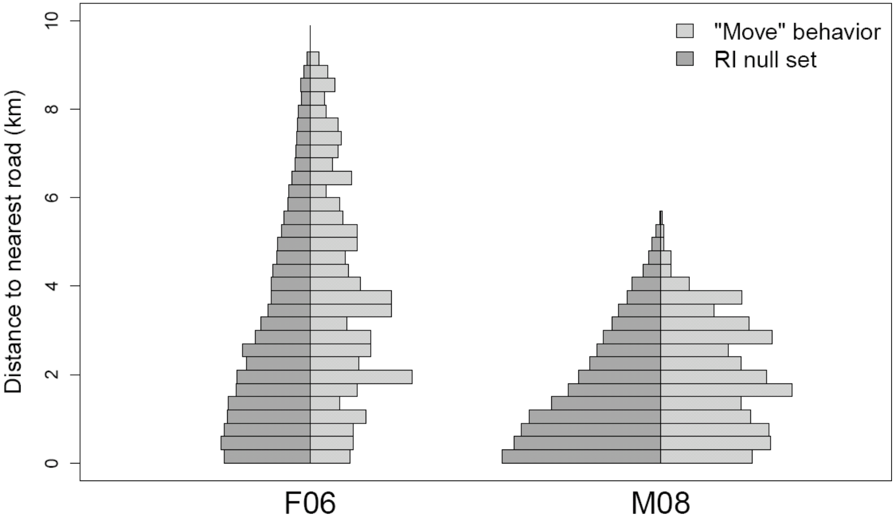
Results: Habitat Use

Viki	*movement*	RI	RII	*homing*	*hunting*	*kill*
n	717	10^5	5512	227	317	40
Habitat types						
Fields	0.007	0.009	0.01	0.004	0.000	0.000
Coniferous forest	0.283	0.269	0.291	0.256	0.284	0.225
Mixed forest	0.233	***0.315***	0.247	0.264	**0.177**	0.225
Open woodland	0.347	**0.314**	0.336	0.392	0.372	0.475
Peatbogs	0.130	***0.093***	0.122	**0.084**	0.167	0.075
Niki						
n	878	10^5	3540	307	187	50
Habitat types						
Fields	0.008	0.012	0.006	0.006	0.007	0.000
Coniferous forest	0.167	**0.194**	0.180	0.129	0.182	0.180
Mixed forest	0.284	0.302	0.310	0.246	***0.195***	0.200
Open woodland	0.435	***0.333***	***0.351***	***0.544***	**0.492**	0.460
Peatbogs	0.106	***0.159***	***0.154***	0.075	0.124	0.160
χ^2 test against:		*movement*	*movement*	*movement*	*movement*	*hunting*

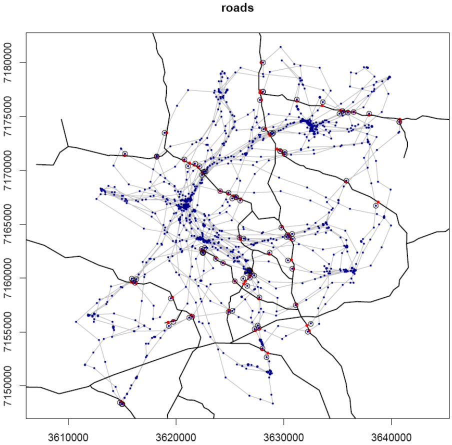
Results: Linear Element Use

Viki	*movement*	RI	RII	*homing*	*hunting*	*kill*
n	717	10^5	5512	227	317	40
Forest roads	0.117	***0.068***	***0.077***	0.075	0.097	0.050
Rivers	0.041	0.034	0.036	***0.097***	**0.075**	0.075
Roads	0.006	0.011	0.004	0.004	0.009	0.000
Railways	0.012	***0.003***	***0.003***	0.000	0.016	0.000
Forest edge	0.297	**0.266**	0.280	0.335	0.328	0.450
Bog edge	0.106	***0.063***	0.093	0.075	**0.147**	0.125
Niki						
Forest roads	0.129	***0.054***	***0.052***	**0.176**	0.091	0.060
Rivers	0.071	**0.046**	***0.046***	0.075	***0.267***	0.140
Roads	0.021	0.020	0.016	0.029	0.000	0.000
Railways	0.017	***0.004***	***0.004***	0.003	0.000	0.000
Forest edge	0.298	0.279	0.286	0.257	***0.406***	0.340
Bog edge	0.110	**0.092**	0.098	0.114	0.123	0.100
χ^2 test against:		*movement*	*movement*	*movement*	*movement*	*hunting*

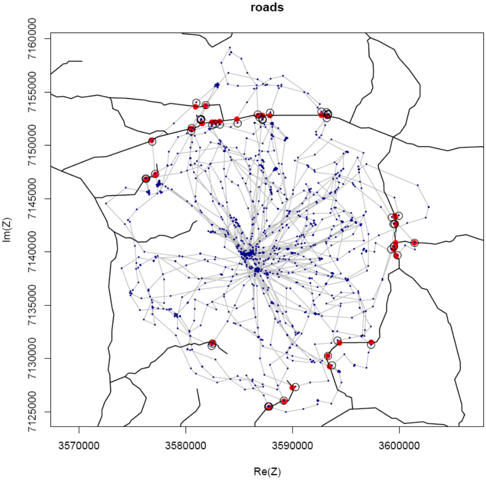
Results: Large Road Avoidance



Road Network

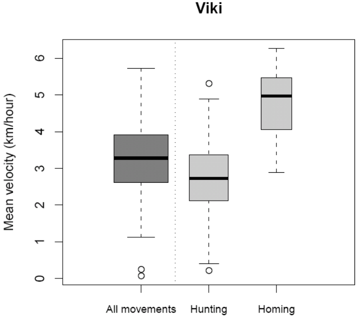


Niki

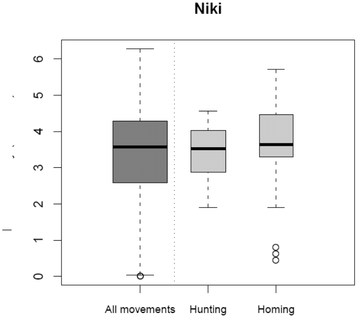


Viki

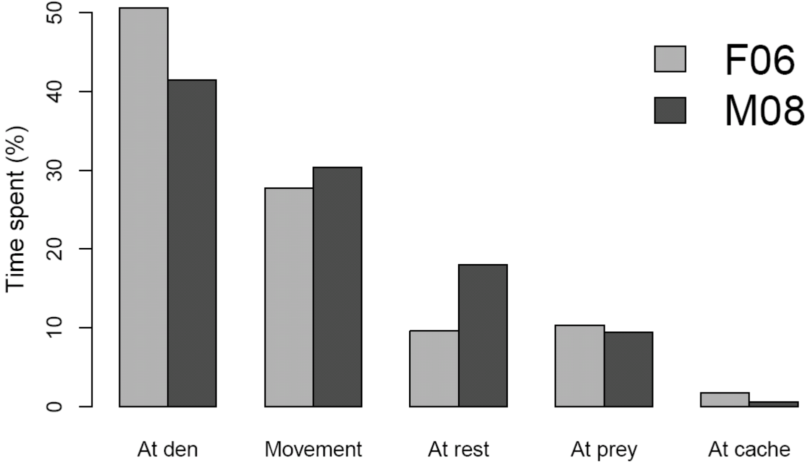
Movement Parameters



	$\overline{\cos(\theta)}$	$\widehat{V}$ (km/hour)	IQR (25%-75%)
F06			
All movements	0.52	3.21	2.88 - 9.96
Hunting	0.42	2.42	1.1 - 8.2
Homing	0.74	5.45	6.14 - 12.66
M08			
All movements	0.61	3.59	3.68 - 9.42
Hunting	0.58	3.56	4.44 - 8.96
Homing	0.59	3.39	0.4 - 9.56



Behavior


F06
M08
Time spent (%)
0
10
20
30
40
50
At den
Movement
At rest
At prey
At cache

Some Tentative Wolf Conclusions

- Wolves like using natural and manmade corridors for movement,
- but they avoid large roads!
- Higher road density disrupts freedom of movement, efficiency of habitat use, with possible consequences for pup-rearing success, etc.

E. Gurarie, I. Kohola, J. Suutarinen, O. Ovaskainen. Wolf (*Canis lupus*) movement and kill behavior with respect to human-influenced habitat features in Finland. *in prep*.

Some Tentative Wolf Conclusions

- Wolves like using natural and manmade corridors for movement,
- but they avoid large roads!
- Higher road density disrupts freedom of movement, efficiency of habitat use, with possible consequences for pup-rearing success, etc.

E. Gurarie, I. Kohola, J. Suutarinen, O. Ovaskainen. Wolf (*Canis lupus*) movement and kill behavior with respect to human-influenced habitat features in Finland. *in prep*.

Some Tentative Wolf Conclusions

- Wolves like using natural and manmade corridors for movement,
- but they avoid large roads!
- Higher road density disrupts freedom of movement, efficiency of habitat use, with possible consequences for pup-rearing success, etc.

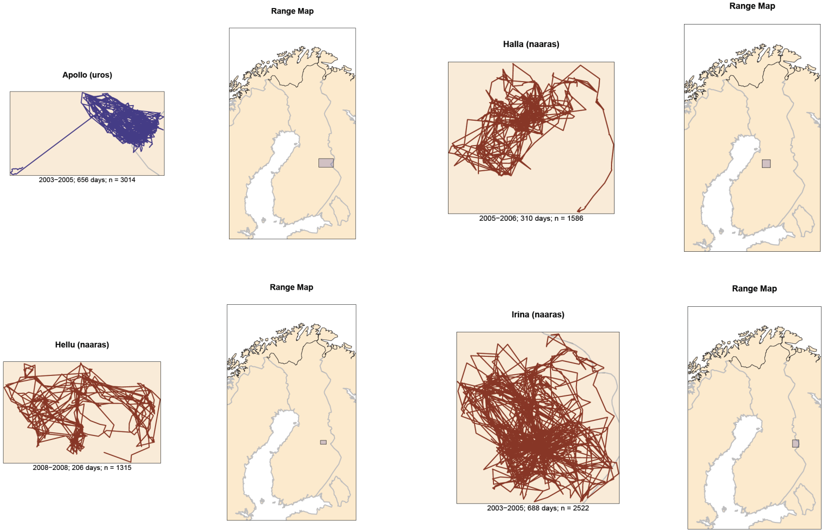
E. Gurarie, I. Kohola, J. Suutarinen, O. Ovaskainen. Wolf (*Canis lupus*) movement and kill behavior with respect to human-influenced habitat features in Finland. *in prep*.

A Big Problem With Conclusions

Only 2 data points!

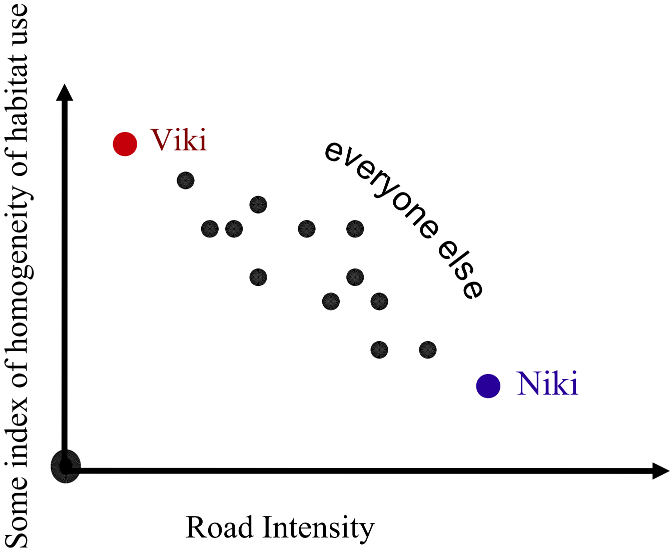
(Different years, different sexes, etc.)

But we have More Wolves ...

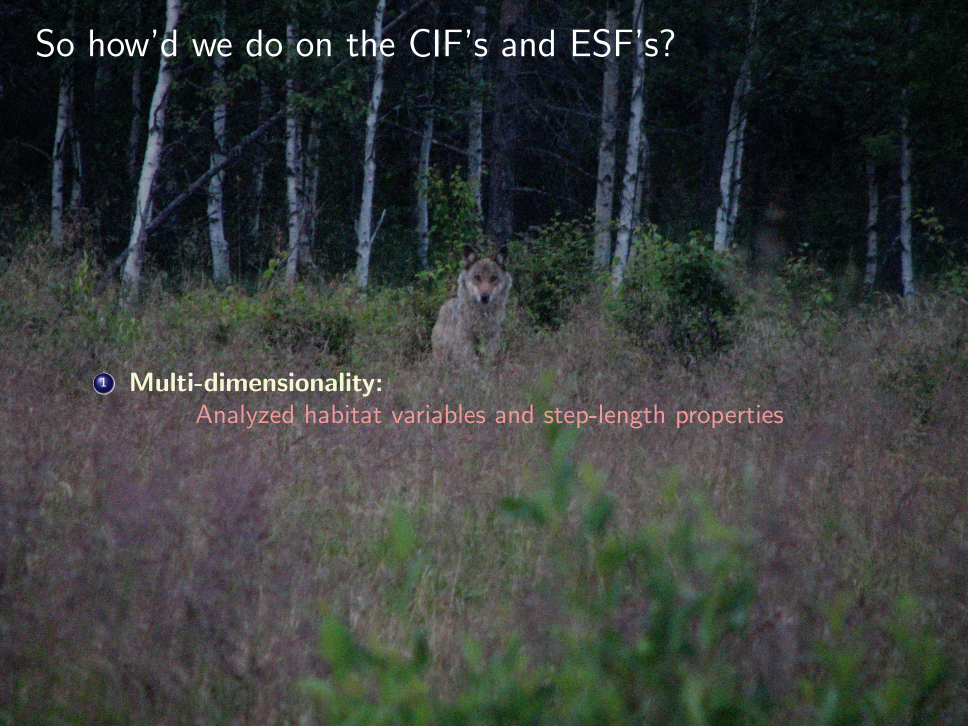


(More coarsely sampled and without behaviors, but still...)

Possible Hypothesis ...

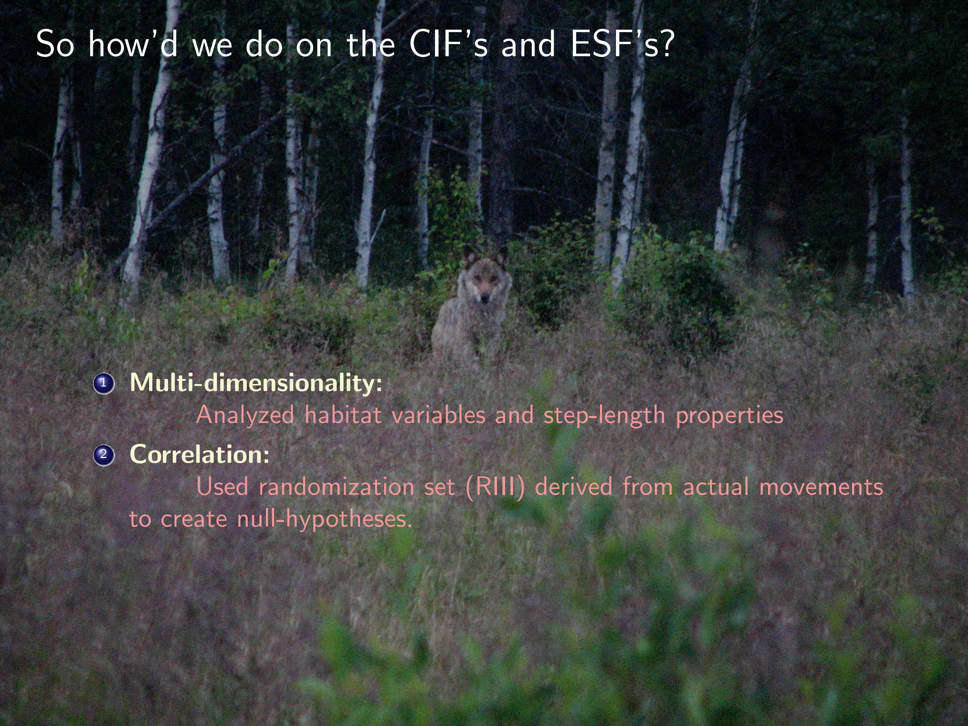


So how'd we do on the CIF's and ESF's?



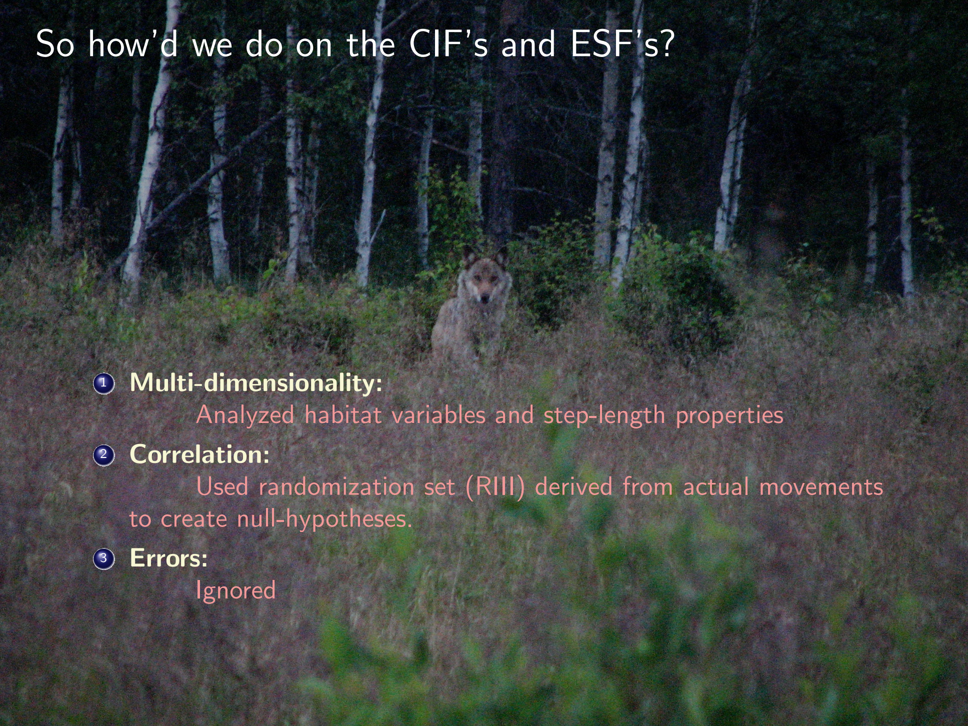
1. **Multi-dimensionality:**
   Analyzed habitat variables and step-length properties

So how'd we do on the CIF's and ESF's?

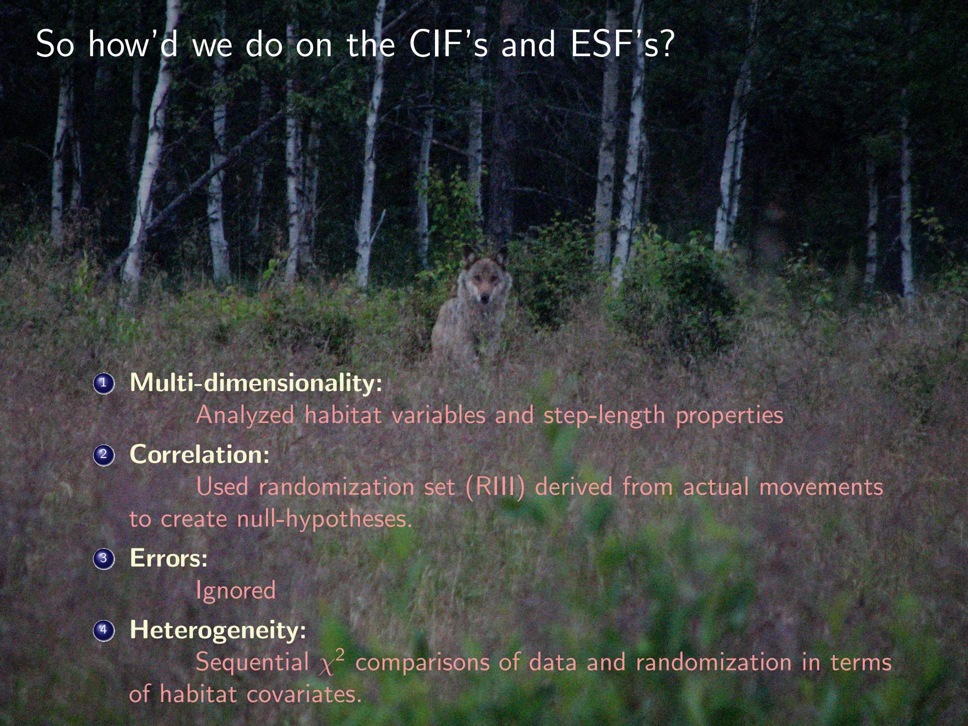


1. **Multi-dimensionality:**
   Analyzed habitat variables and step-length properties
2. **Correlation:**
   Used randomization set (RIII) derived from actual movements to create null-hypotheses.

So how'd we do on the CIF's and ESF's?



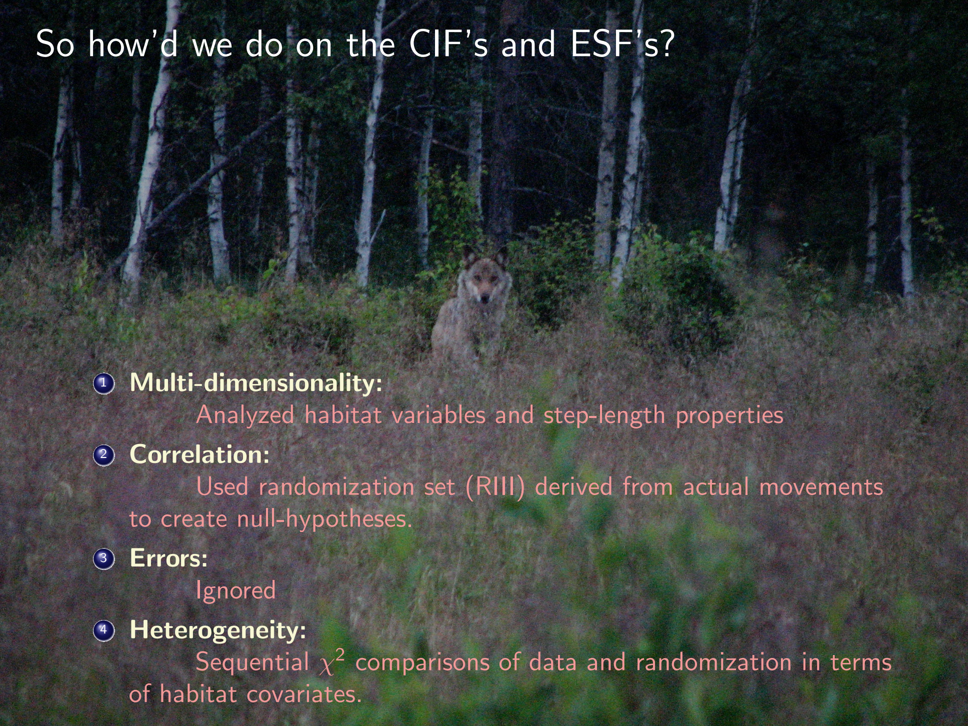
1. **Multi-dimensionality:**
   Analyzed habitat variables and step-length properties
2. **Correlation:**
   Used randomization set (RIII) derived from actual movements to create null-hypotheses.
3. **Errors:**
   Ignored



So how'd we do on the CIF's and ESF's?

1. **Multi-dimensionality:**
   Analyzed habitat variables and step-length properties
2. **Correlation:**
   Used randomization set (RIII) derived from actual movements to create null-hypotheses.
3. **Errors:**
   Ignored
4. **Heterogeneity:**
   Sequential χ^2 comparisons of data and randomization in terms of habitat covariates.

So how'd we do on the CIF's and ESF's?



1. **Multi-dimensionality:**
   Analyzed habitat variables and step-length properties
2. **Correlation:**
   Used randomization set (RIII) derived from actual movements to create null-hypotheses.
3. **Errors:**
   Ignored
4. **Heterogeneity:**
   Sequential χ^2 comparisons of data and randomization in terms of habitat covariates.

General Principles of Movement Analysis:

If you keep track of your:

Correlations! Dimensions! Gaps! Errors!

General Principles of Movement Analysis:

If you keep track of your:
Correlations! Dimensions! Gaps! Errors!

Match your questions to your data,

General Principles of Movement Analysis:

If you keep track of your:
Correlations! Dimensions! Gaps! Errors!

Match your questions to your data,
Explore all the heterogeneities ...

General Principles of Movement Analysis:

If you keep track of your:
Correlations! Dimensions! Gaps! Errors!

Match your questions to your data,
Explore all the heterogeneities ...

(and maybe make up some acronyms on the way)

General Principles of Movement Analysis:

If you keep track of your:
Correlations! Dimensions! Gaps! Errors!

Match your questions to your data,
Explore all the heterogeneities ...

(and maybe make up some acronyms on the way)

Then you're bound to learn *SOMETHING*

Acknowledements

Fur Seals and BCPA

- Co-authors: R. Andrews and K. Laidre.
- V. Burkanov and all colleagues/friends in the field in Russia
- Discussions: T. Gneiting, M. Kot, V. Minin, H. Nesse

Sea Otters

- Co-authors: K. Laidre, R. Jameson, S. Jeffries
- Trackers: M. Stafford, B. Krause
- Capture, tagging and tracking of sea otters was funded by USGS, Fish and Wildlife and WDFW and Olympic Coast National Marine Sanctuary (OCNMS).

Wolves

- Co-authors: Ilpo Kojala, Johanna Suutarinen, Otso Ovaskainen
- Support: Metapopulation Research Group, University of Helsinki

Thank you!