A Lattice and Random Intermediate Point (LARI) Sampling Design for Animal Movement

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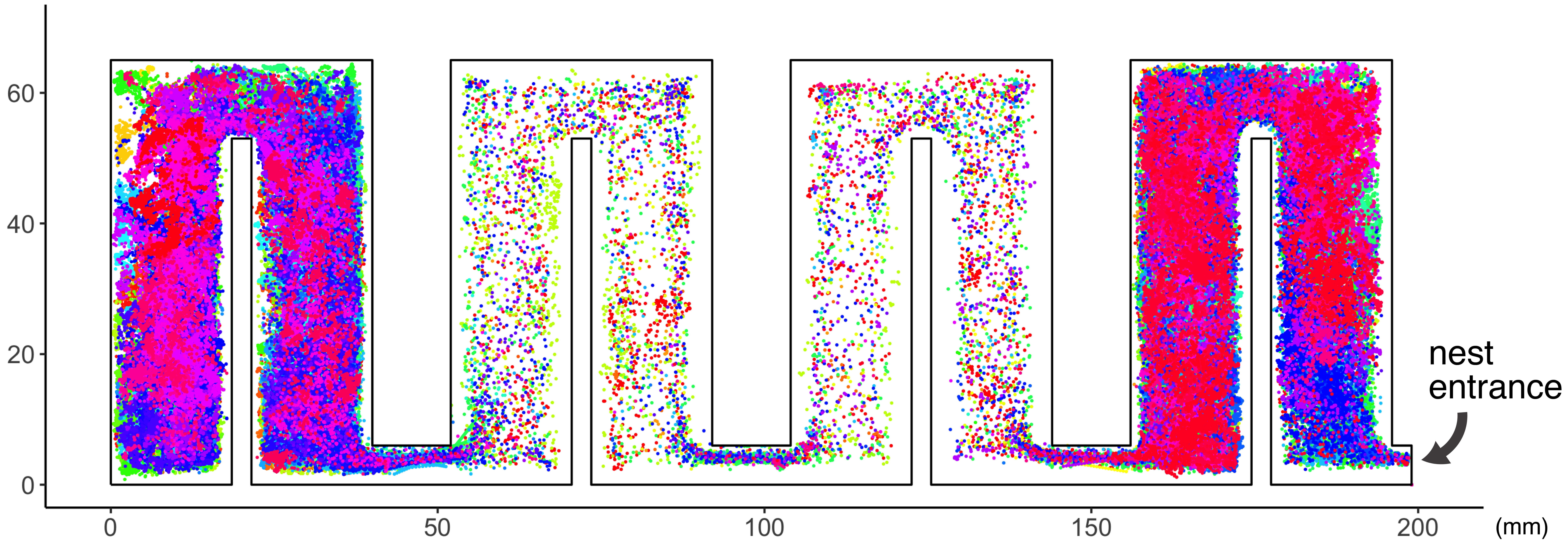
Hughes lab at Penn State collected **high resolution ant data,** but data collection was **time-consuming** (1000s of student-hours).

The resulting dataset consists of **4 hours** of movement data for **78 ants** at 1 second intervals (14,401 observations per ant).



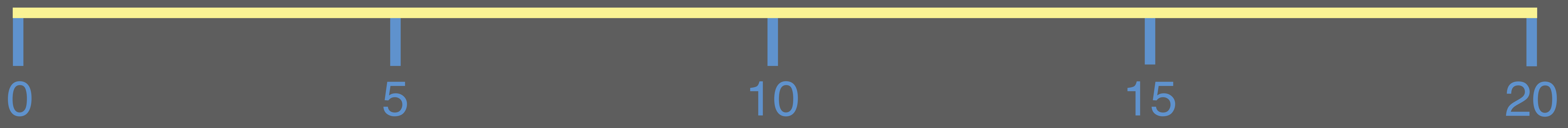
We were approached by the researchers with the **scenario**:

- Next time, we will collect **lower resolution** data.
- How should we do this to **minimize the loss of information** about movement behavior?

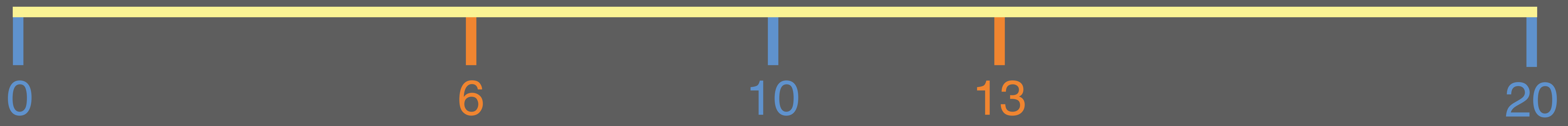
This question is **relevant to many researchers** collecting animal movement data.

2 sampling designs:

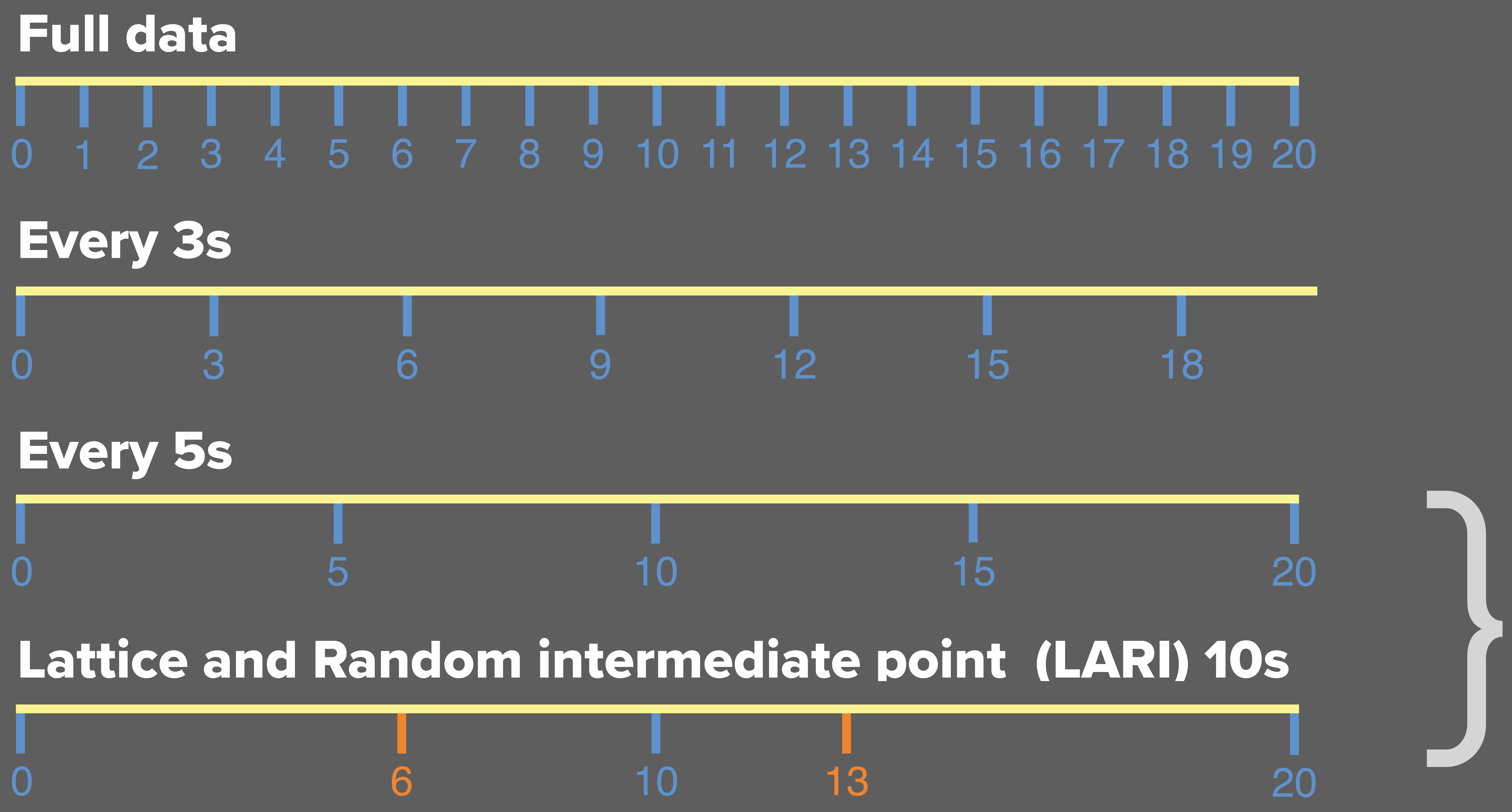
REGULAR



LATTICE AND RANDOM INTERMEDIATE POINT (LARI)



To compare regular and LARI sampling designs, we look at **4 subsamples** of the ant data.



Every 5s and LARI 10s have the same number of data points

Stochastic differential equation (SDE) model for animal movement

Data: $\mathbf{x}_t,\ t = 1, 2, \ldots, 14401$ for each ant

SDE model framework:

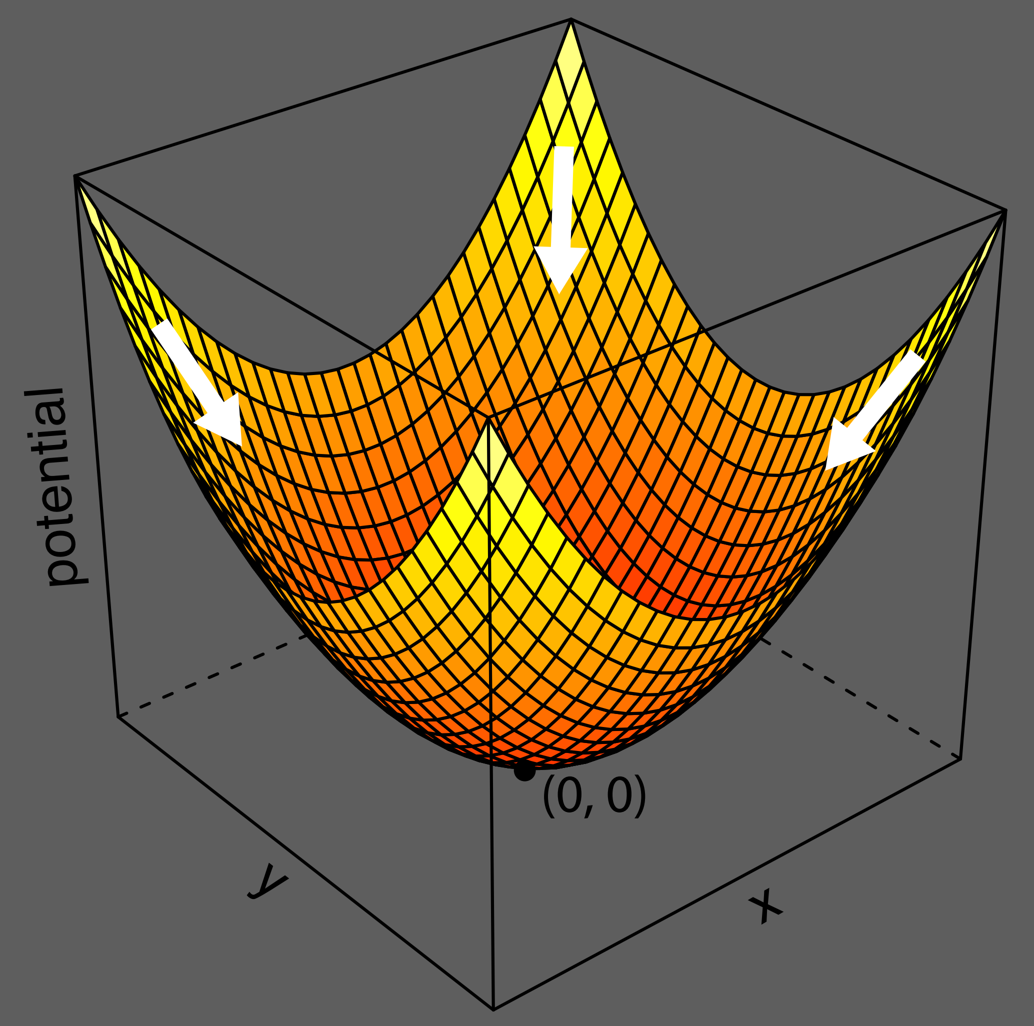
$$d\mathbf{x}_t = \mathbf{v}_t\, dt$$
$$d\mathbf{v}_t = -\beta\,(\mathbf{v}_t - \boldsymbol{\mu}(\mathbf{x}_t))\, dt + c(\mathbf{x}_t)\, \mathbf{I} d\mathbf{w}_t$$

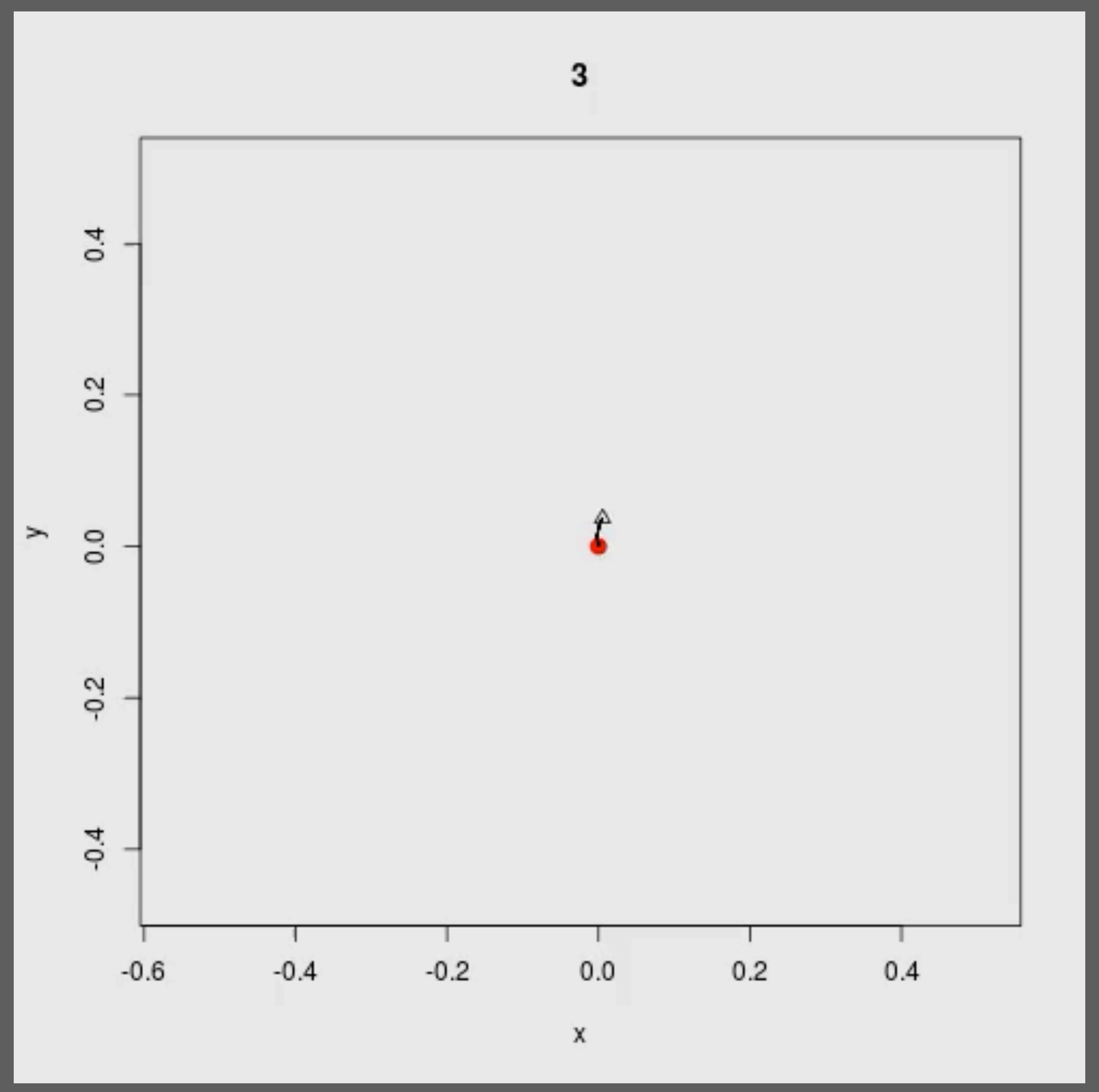
Utilizing motility and potential surfaces, define:

$$\boldsymbol{\mu}(\mathbf{x}_t) = m(\mathbf{x}_t)\,[-\nabla p(\mathbf{x}_t)] \qquad \text{(mean drift)}$$
$$c(\mathbf{x}_t) = \sigma\, m(\mathbf{x}_t) \qquad \text{(magnitude of stochasticity)}$$

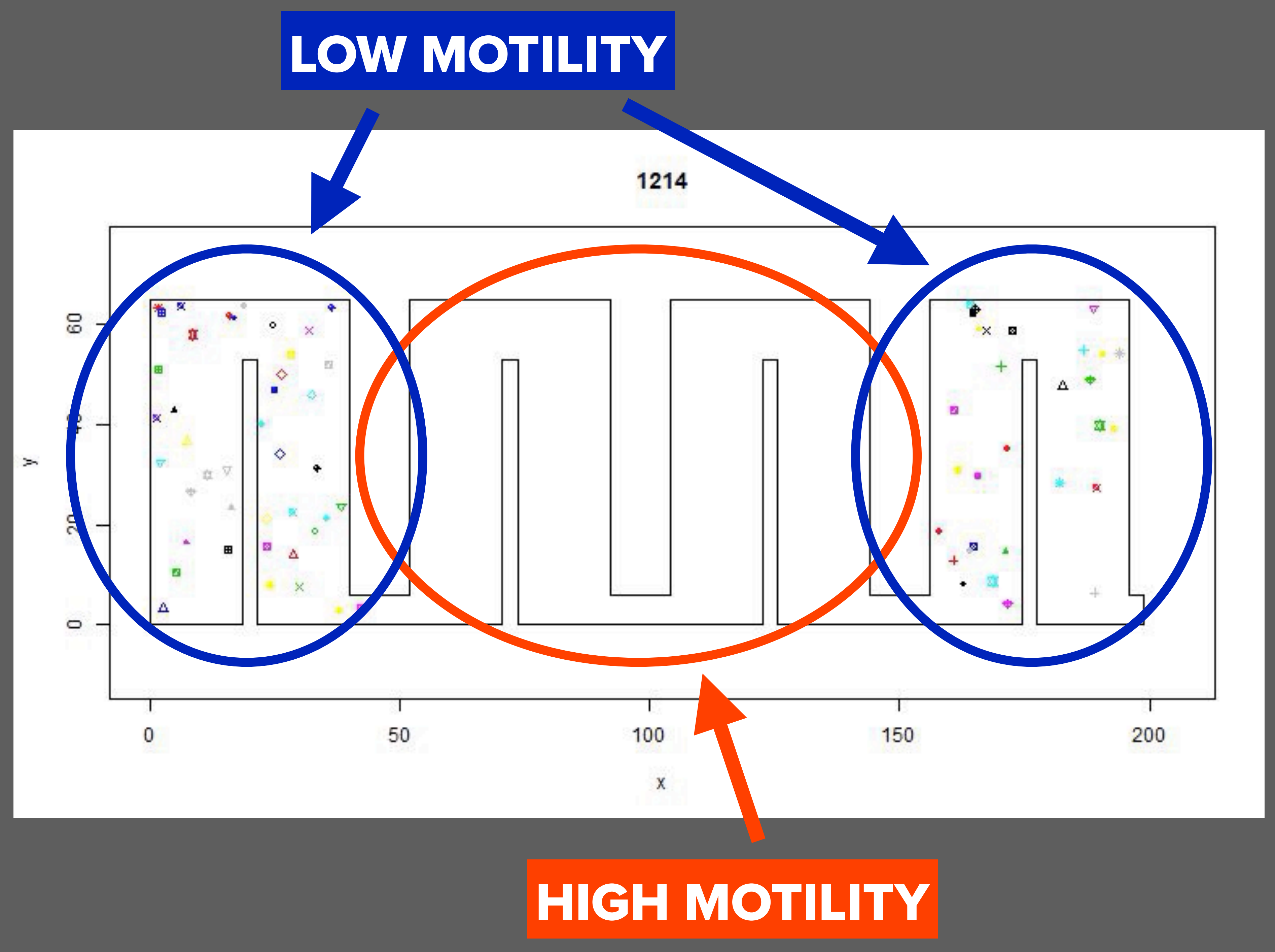
We describe animal movement using a stochastic differential equation model with 2 parameters:

POTENTIAL SURFACE





MOTILITY SURFACE



Since we don't observe animal movement in continuous time, we **numerically approximate derivatives.**

$$\left.\begin{aligned}\frac{d\mathbf{x}_\tau}{dt} &\approx \frac{\mathbf{x}_{\tau+1} - \mathbf{x}_\tau}{h_\tau} \\ \frac{d\mathbf{v}_\tau}{dt} &\approx \frac{\mathbf{v}_{\tau+1} - \mathbf{v}_\tau}{h_\tau} \approx \frac{\mathbf{x}_{\tau+2} - \mathbf{x}_{\tau+1}}{h_\tau h_{\tau+1}} - \frac{\mathbf{x}_{\tau+1} - \mathbf{x}_\tau}{h_\tau^2}\end{aligned}\right\}$$

Note that this works for data that is irregular in time.

where

- $\mathbf{x}_\tau$ is the position of ordered observation τ
- $\mathbf{v}_\tau$ is the (unobserved) velocity of observation τ
- h_τ is the change in time from observation τ to $\tau + 1$

Resulting in the **model equation**

$$\mathbf{x}_{\tau+2} = \left(1 + \frac{h_{\tau+1}}{h_\tau} - \beta h_{\tau+1}\right)\mathbf{x}_{\tau+1} + \left(\beta h_{\tau+1} - \frac{h_{\tau+1}}{h_\tau}\right)\mathbf{x}_\tau + \beta\ h_\tau h_{\tau+1}\ m(\mathbf{x}_\tau)\ [-\triangledown\, p(\mathbf{x}_\tau)] + \sigma\ m(\mathbf{x}_\tau)\ h_{\tau+1} h_\tau^2\ N(\mathbf{0}, I)$$

Spline expansion (degree 0, piecewise constant) of the motility and potential surfaces

$$m(\mathbf{x}_t) = \sum_{j=1}^{J} m_j s_j(\mathbf{x}_\tau)$$

$$p(\mathbf{x}_t) = \sum_{j=1}^{J} p_j s_j(\mathbf{x}_\tau)$$

$$s_j(\mathbf{x}_\tau) \equiv \begin{cases} 1, & \mathbf{x}_\tau \textbf{ in } j^{th} \textbf{ grid cell} \\ 0, & \textbf{otherwise} \end{cases}$$

Estimate motility surface (***m***) and potential surface (***p***)

Penalize the roughness of ***m*** and ***p***

- Maximize $\{[\mathbf{x}_\tau \,|\, \mathbf{x}_{\tau-1}, \mathbf{x}_\tau] - \lambda_1 \mathbf{m}' Q \mathbf{m} - \lambda_2 \mathbf{p}' Q \mathbf{p}\}$

REML-style approximation

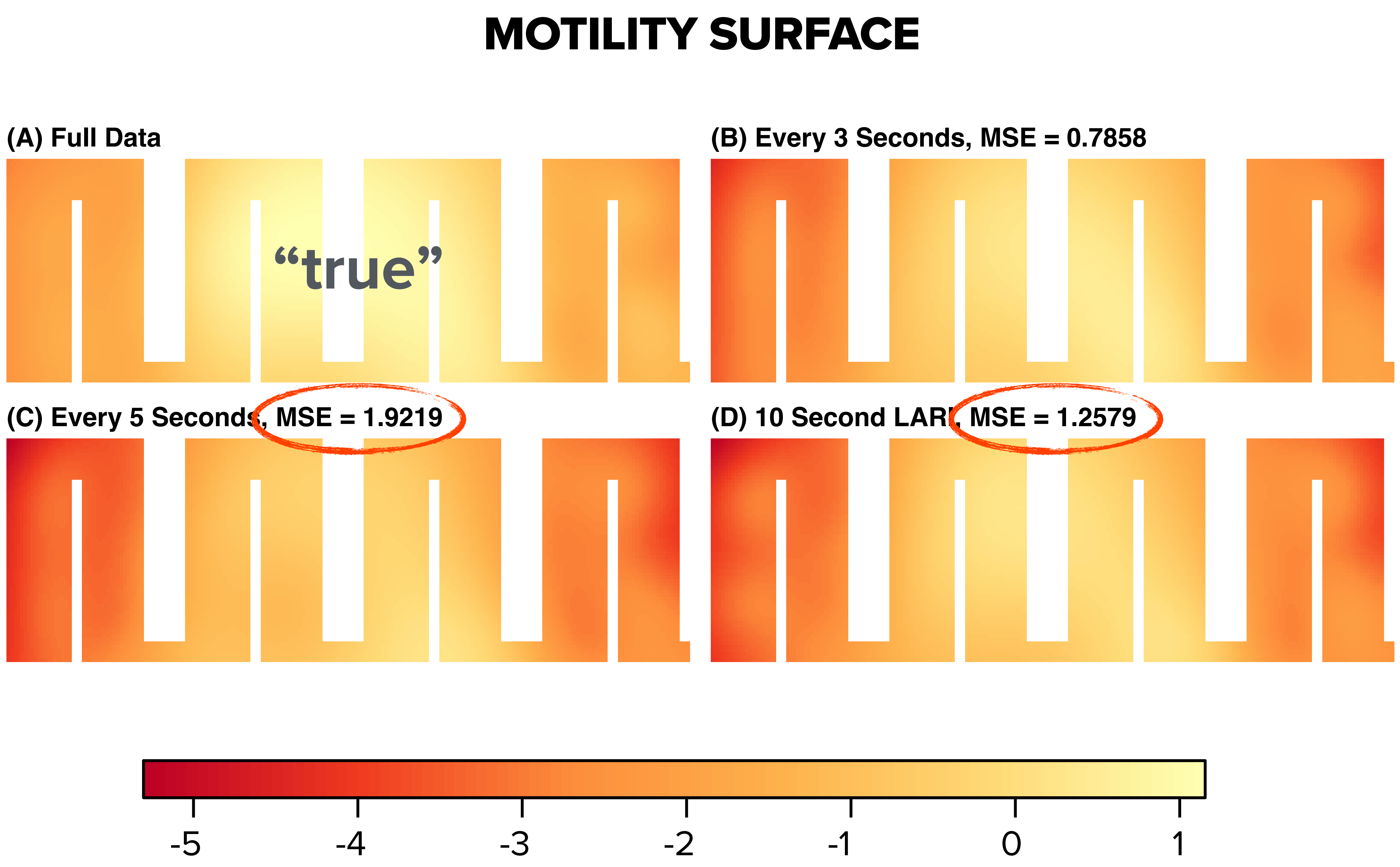
- First **estimate variance terms** to get ***m***
- Then **estimate mean** drift to get ***p***

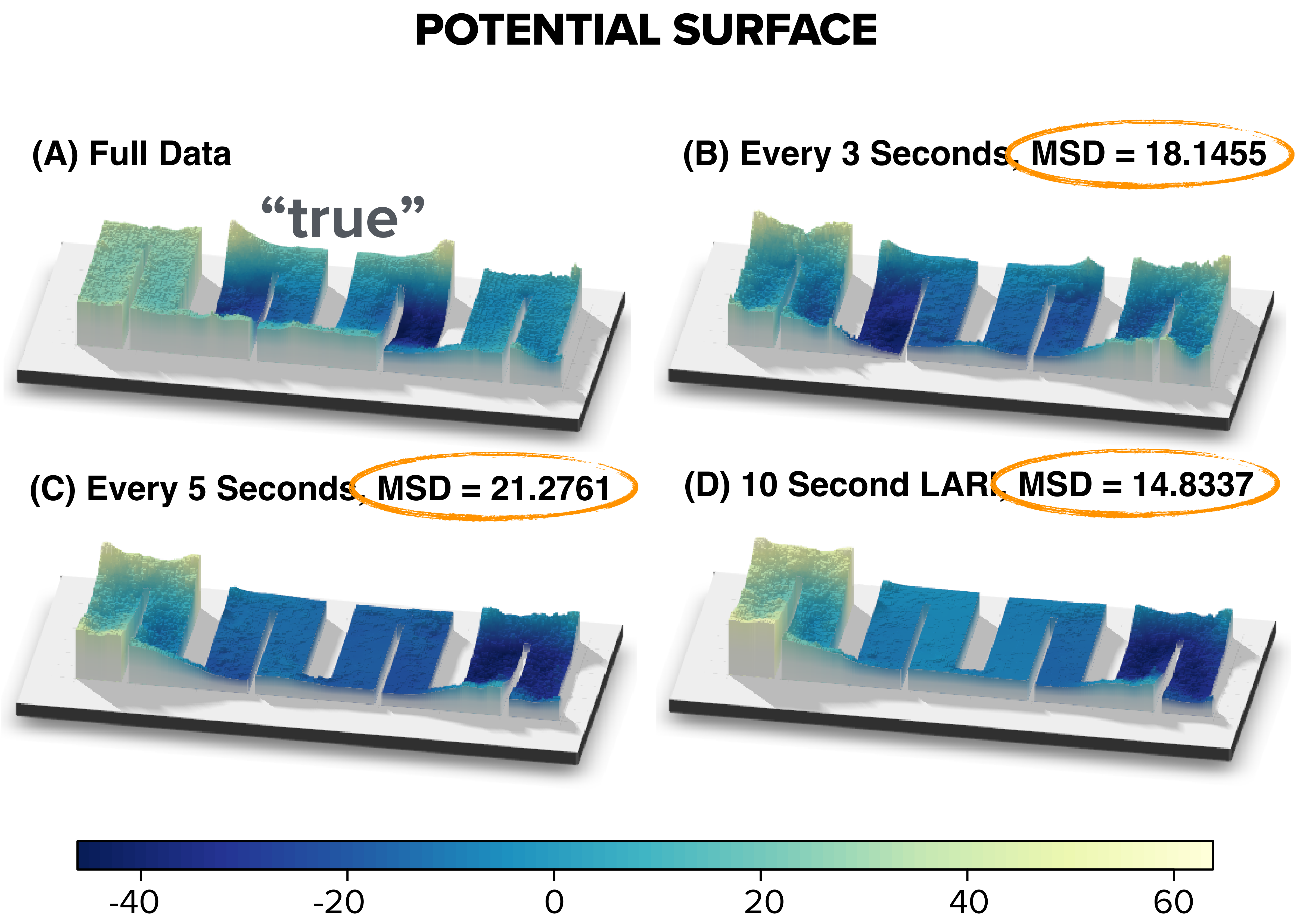
Smoothness parameters are chosen with a holdout set

Computing time **~20 minutes** (single core)

- 14,401 x 78 data points

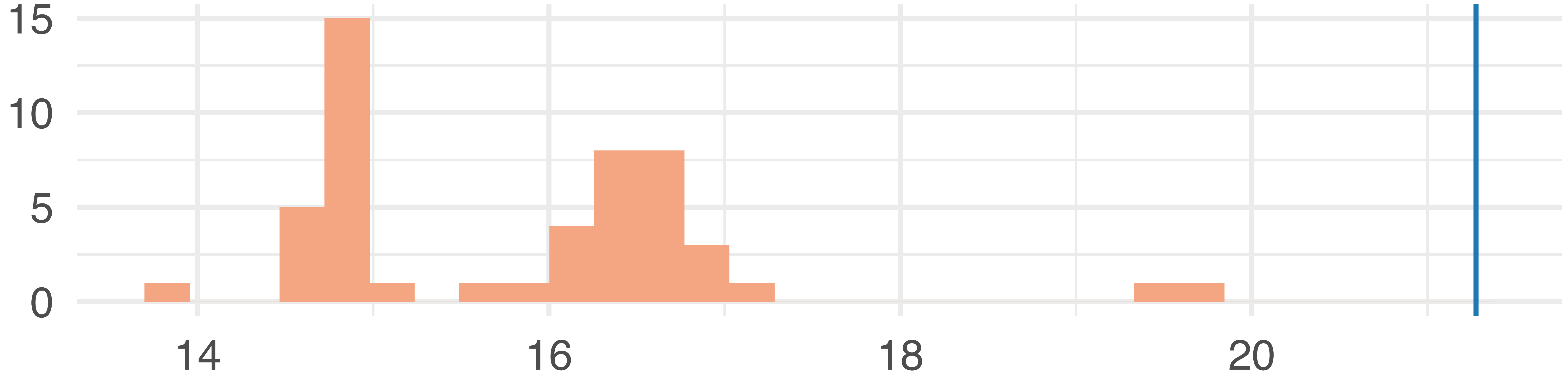
We **compare motility and potential** surfaces estimated with the 4 subsamples using multiple metrics.



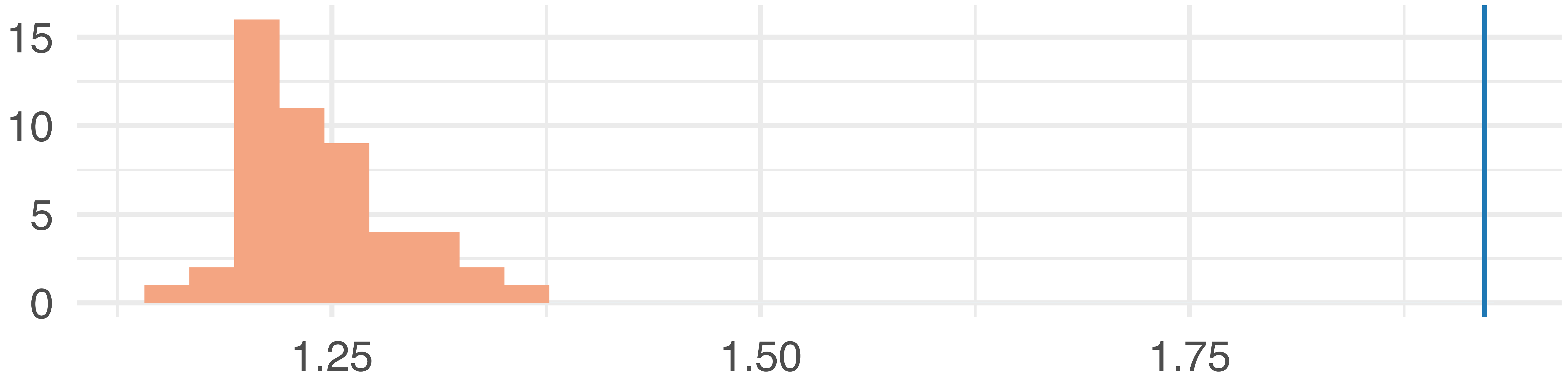


We fit 50 different LARI subsamples to understand random variation.

(A) Potential Surface MSD



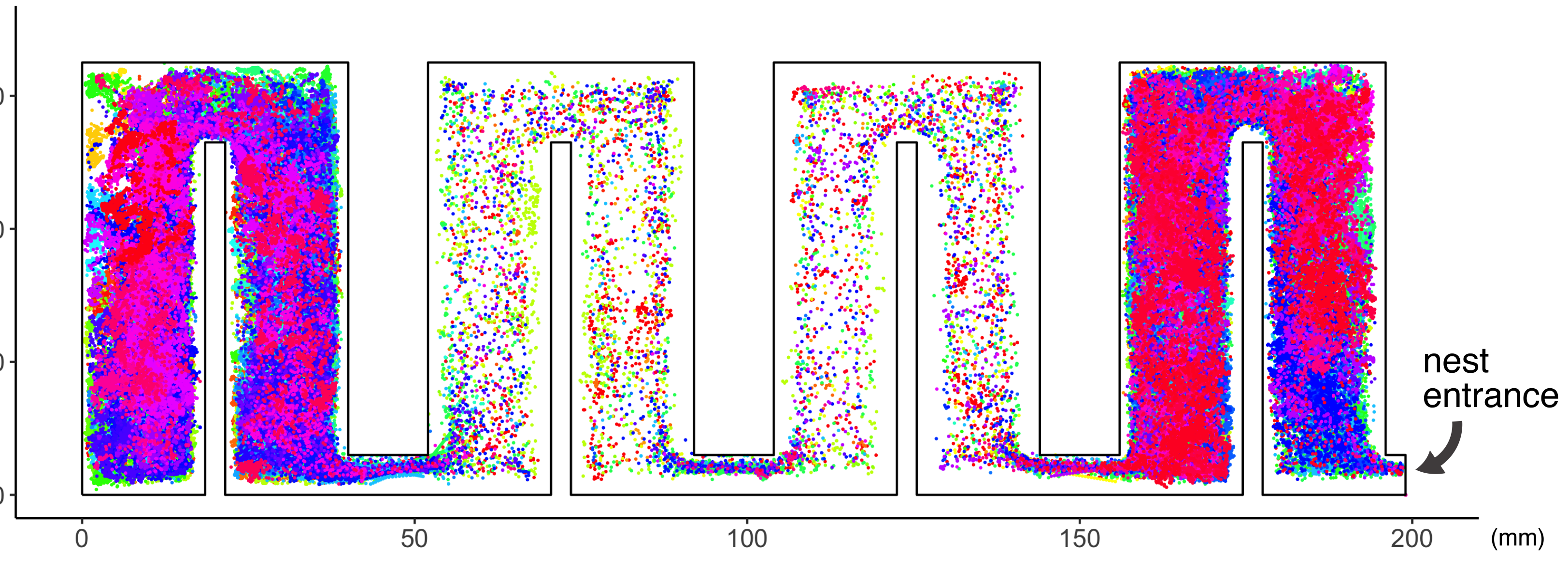
(B) Log Motility Surface MSE



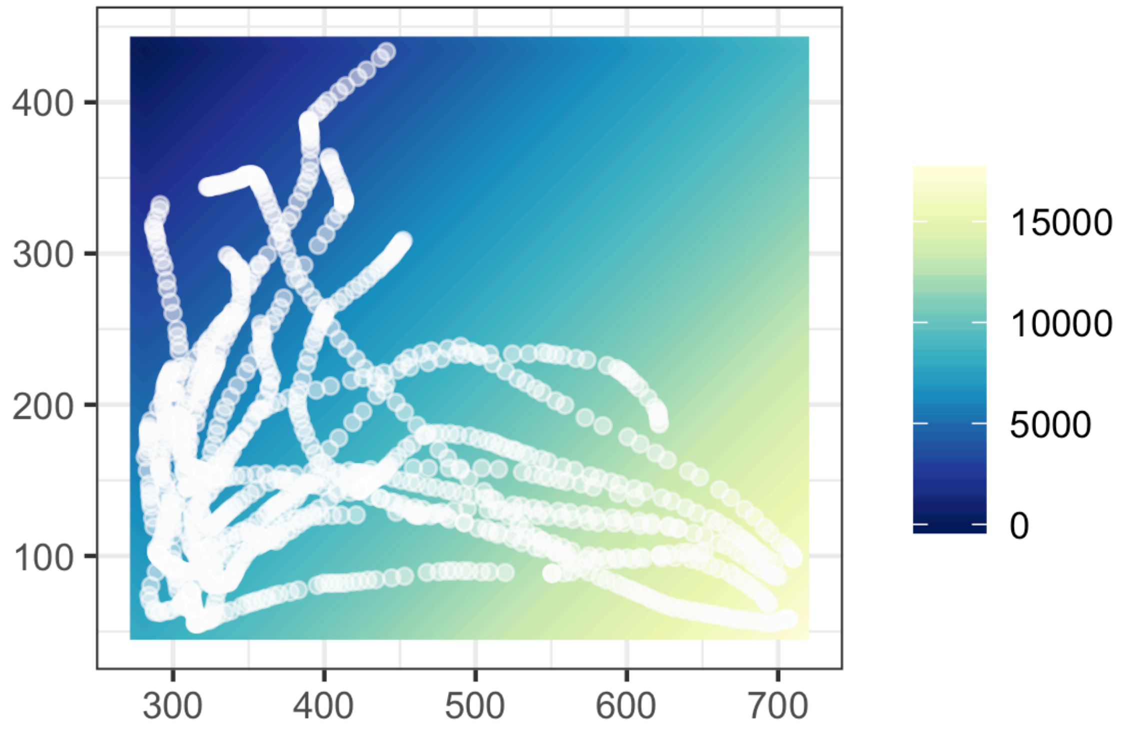
We compared the estimates of motility and potential surfaces using several different metrics.

Result: **LARI sampling was better** than regular sampling overall for understanding movement behavior. A simulation study and additional data example support this conclusion.

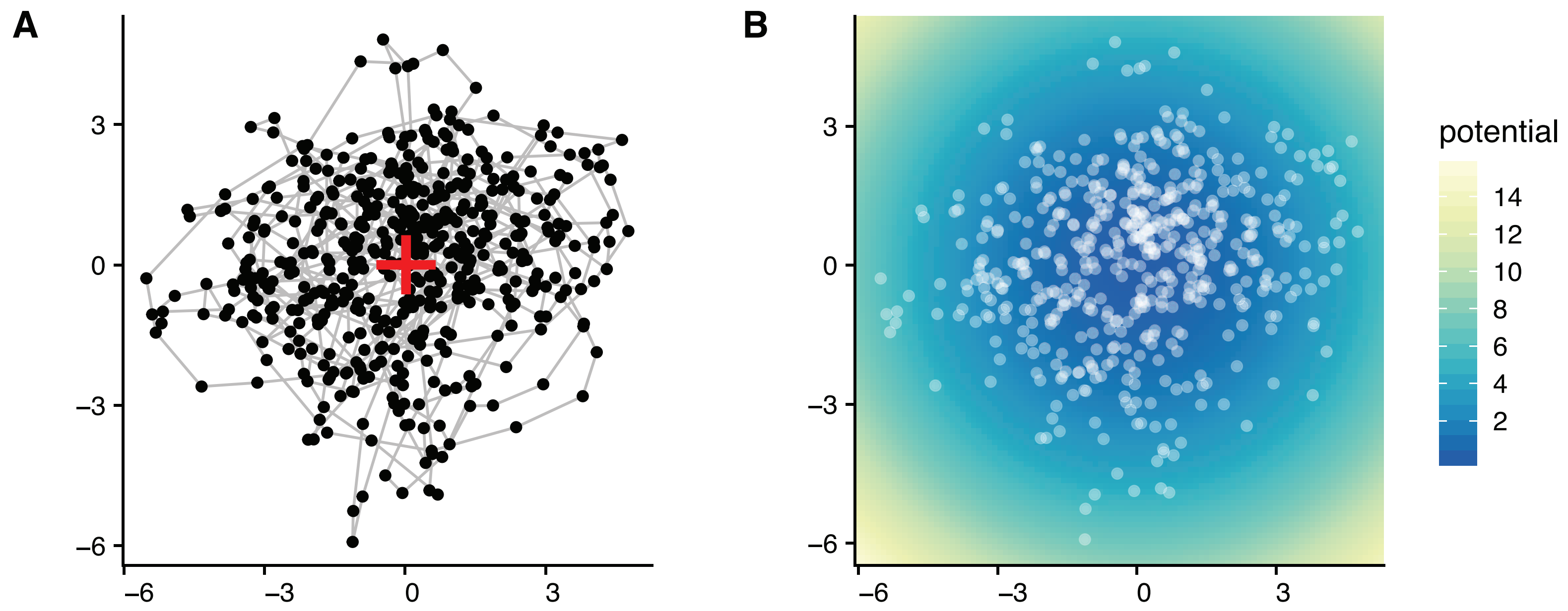
Ant data



Guppy data



Simulated data



Eisenhauer, Elizabeth, and Ephraim **Hanks**. "A lattice and random intermediate point sampling design for animal movement." *Environmetrics* (2020): e2618.