

Linking Caribou Movement and Mortality: A Dynamic Hazard Approach to Survival Modeling

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Introduction

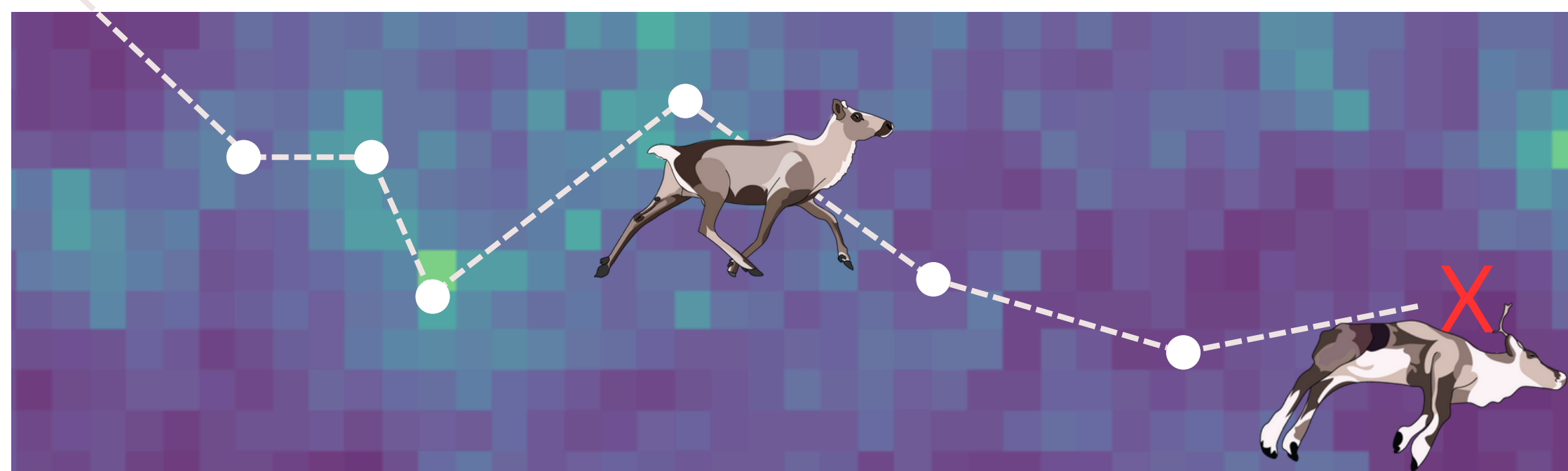
Survival varies across space and time, yet traditional survival models use time-averaged covariates which overlooks the temporal dynamics of how animals experience changing environmental conditions as they move.

Objective

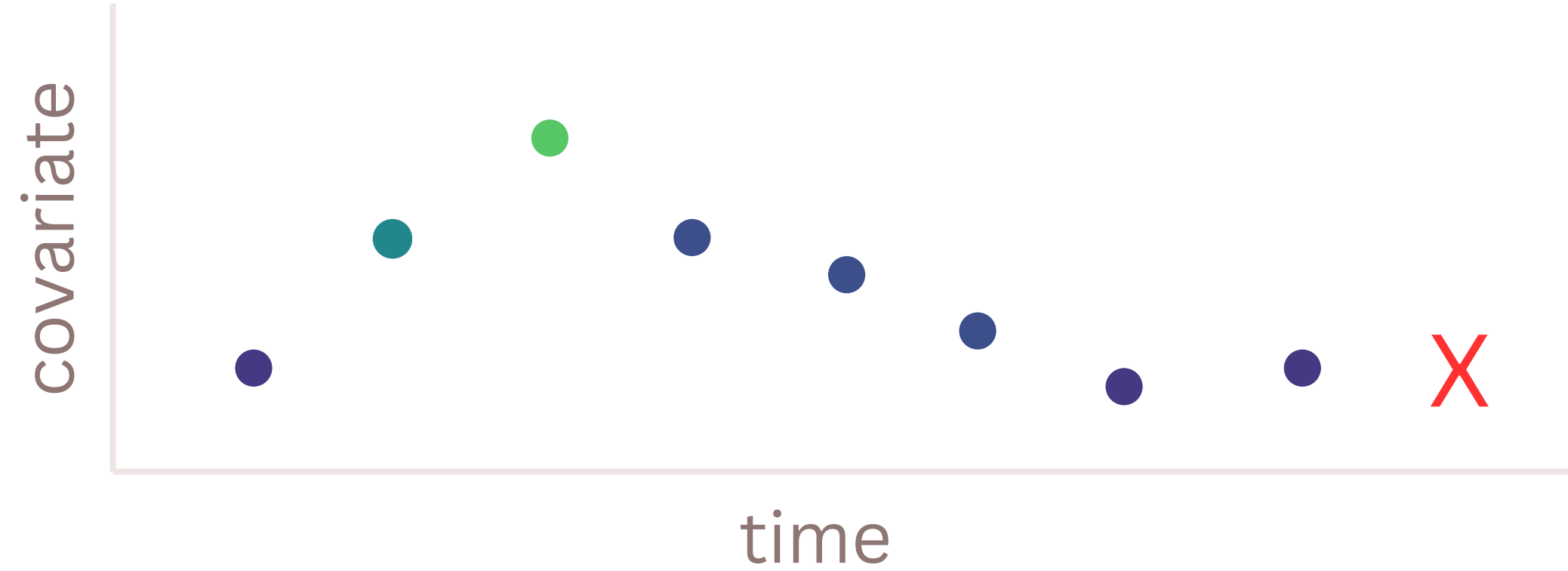
Develop a dynamic hazard model linking **time-varying environmental covariates** from animal telemetry data to **individual mortality risk**.

Methods

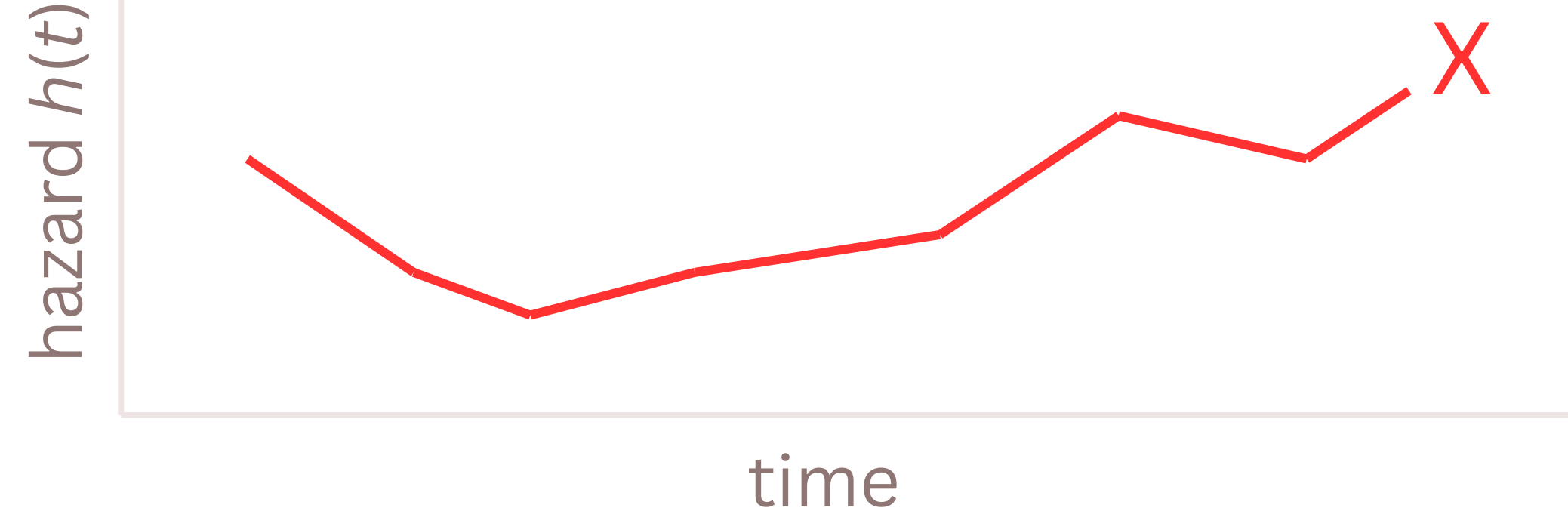
Extract (time-varying) covariates to individual movement trajectories



$\mathbf{X}(t)$ = environmental conditions at time t



Instantaneous hazard $h(t) = \exp(\mathbf{X}(t)\beta)$ varies inversely with covariate when $\beta < 0$



Estimate covariate effects using individual-specific risk profiles and Maximum Likelihood Estimation

Mathematical framework

Hazard:

$$h(t|\beta) = \exp(\mathbf{X}(t)\beta)$$

Survival:

$$S(t|\beta) = \exp\left(-\int_0^t h(u|\beta)du\right) = \exp\left(-\int_0^t \exp(\mathbf{X}(u)\beta)du\right)$$

Log-likelihood:

$$\ell(\beta) = \sum_{i=1}^{n_t} \mathbf{X}(T_i)\beta - \sum_{i=1}^{n_t} \int_0^{T_i} \exp(\mathbf{X}(u)\beta)du - \sum_{j=1}^{n_y} \int_0^{Y_j} \exp(\mathbf{X}(u)\beta)du$$

Simulation validation

Simulation design:

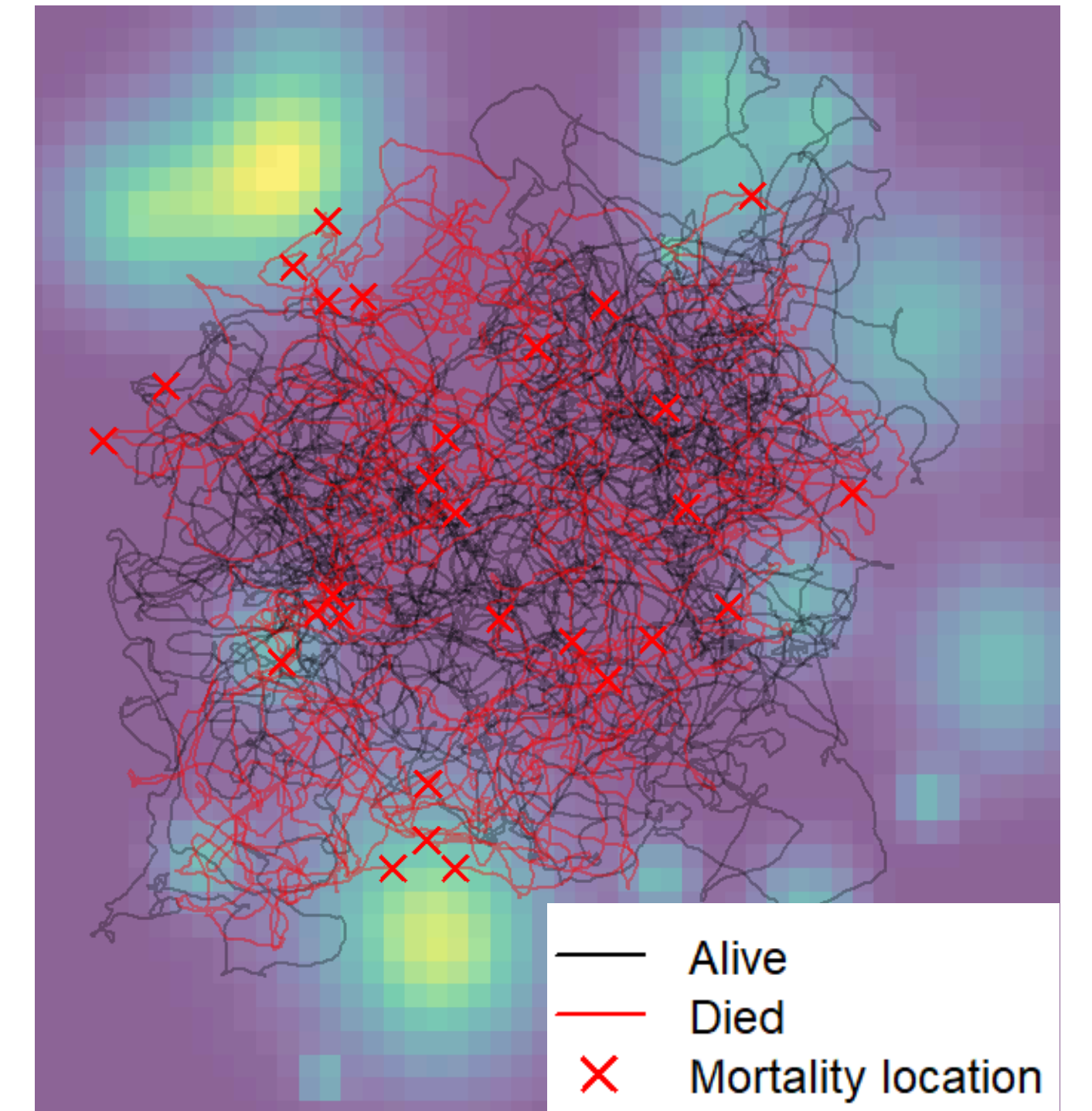
Movement: simulated 50 individuals from random starting locations with Ornstein-Uhlenbeck process

Environmental layer (R2): 'Predator density' surface generated as sum of 20 Gaussian hotspots representing predator territories

Mortality process: Immediate hazard response to predator density:

$$h(t) = \exp(\beta_0 + \beta_{R2} \times R2(t))$$

True Parameters: $\beta_0 = -5$, $\beta_{R2} = 3$



Parameter recovery and signal detection:

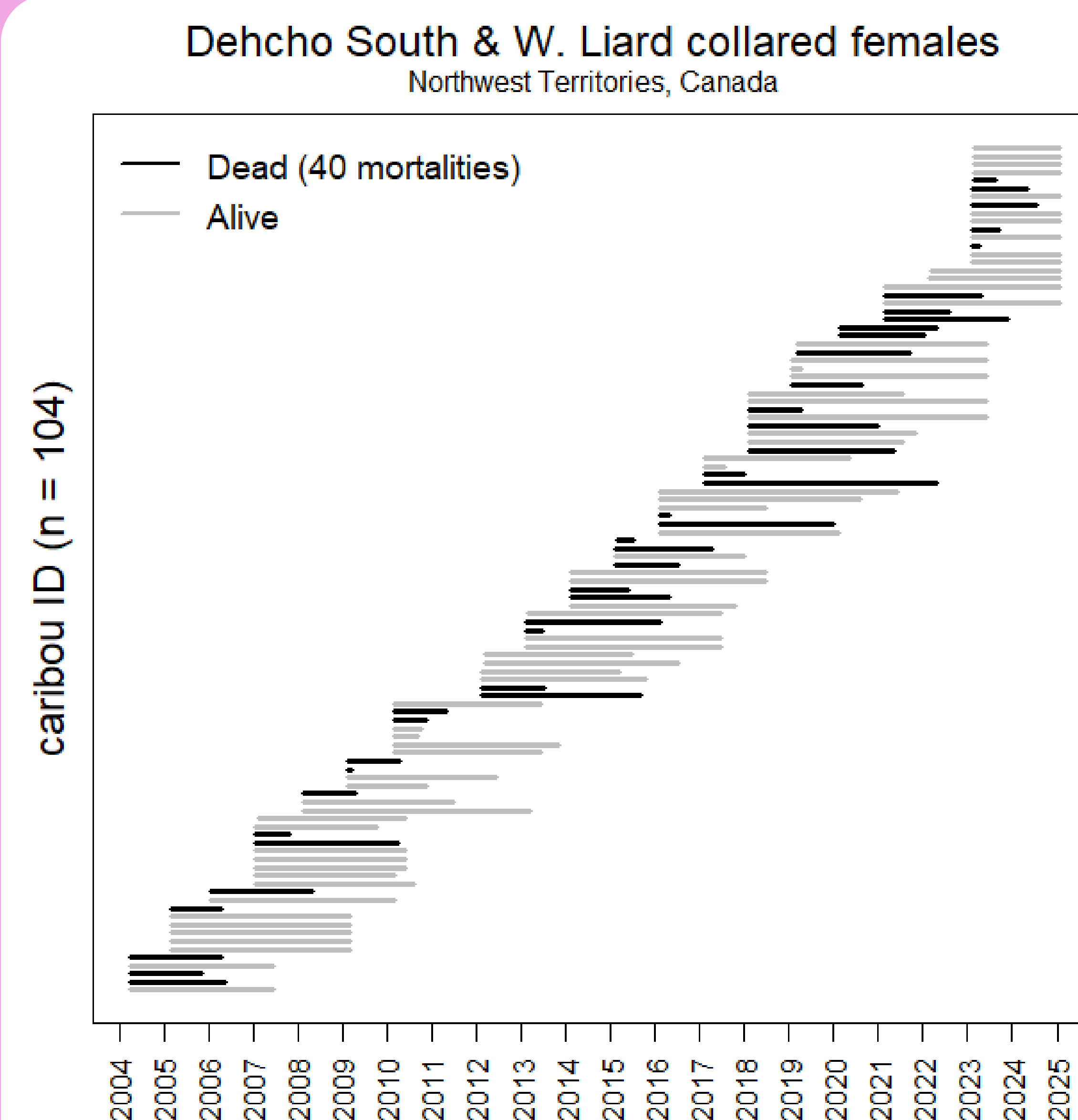
Covariate	True Effect	Dynamic Hazard Model	Cox Proportional Hazards	Performance
R2 (Predator Density)	$\beta = 3$	$\beta = 4.62$ $p < 0.001$	$\beta = 3.66$ $p = 0.16$	✓ Dynamic ✗ Cox PH
R1 (Null Covariate)	$\beta = 0$	$\beta = 1.53$ $p = 0.3$	$\beta = 3.8$ $p = 0.17$	✓ Both correct (no false positives)

Method successfully validates

Dynamic hazard model: (1) Recovers parameters ($\beta_0 = -5.3$, $\beta_{R2} = 4.6$), (2) Correctly identifies null effects (3) Best model fit via AIC

Cox Proportional Hazards model: Fails to detect the true effect ($p = 0.16$). Time-averaging obscures the signal.

Boreal Caribou Temperature Effects



Does temperature affect caribou survival?

Cox Proportional Hazards

Temperature Effect

$$\beta = -0.038$$

$$p = 0.583$$

“Temperature has no significant effect on caribou survival”

Method: uses mean temperature per individual

Dynamic Hazard Model

Temperature Effect

$$\beta = +0.143$$

$$p < 0.001$$

“Higher temperature raises mortality hazard”

Method: uses time-varying temperature as animals move through environments

Static covariates obscure biological signals

Cox PH with time-averaged temperature shows “no effect” ($p = 0.58$). The dynamic hazard model, using the same data but modeling time-varying temperature exposure, reveals that warmer temperatures increase caribou mortality risk ($p < 0.001$)

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Next steps

- model non-linear covariate relationships (thresholds, quadratic terms)
- estimate lagged effects with weighted covariate histories
- incorporate seasonal variation in covariate effects using time-varying splines