Appendix 1: supplementary tables & figures

Table S1: Estimates of environmental covariate effects on golden eagle behavior and movements during migrations. Parameter estimates are from the correlated random walk model with full behavioral process, including and intercept (β_0) orographic uplift (β_{ou}), thermal uplift (β_{tu}), and wind support (β_{tw}) as predictors. Top model is the best fitting candidate of the behavioral process resulting from an approximate leave-one-out cross-validation model selection procedure. $\overline{\text{elpd}}$ is the mean across pointwise estimates of the expected log pointwise predictive density estimated with approximate leave-one-out cross-validation model for the full model; larger $\overline{\text{elpd}}$ indicates better fit.

ID[a]	**Season**	**Parameter**[b]				**Top Model**[c]	$\overline{\textbf{elpd}}$[e] (SE)
		β_0	β_{ou}	β_{tu}	β_{tw}		
117394	spring	-2.68	-1.52	0.98	0.67	oro	0.68 (0.21)
117396	spring	-2.70	-0.49	3.07	-0.46	-	0.62 (0.12)
	fall	-0.53	-3.11	0.08	0.49	full[d] / oro + twind	3.26 (0.62)
117397	spring	-4.80	1.43	3.06	0.25	therm + twind / therm	0.64 (0.13)
117398	spring	-2.21	-0.09	0.81	-0.45	oro / therm	0.39 (0.22)
135411	spring	-2.55	-2.62	1.84	-0.98	oro + therm / full / oro + twind	0.54 (0.19)
135413	spring	-2.98	0.12	1.13	0.06	oro	0.96 (0.22)
135414	spring	-0.74	-1.11	-0.38	1.94	oro + twind	1.69 (0.81)
135417	spring	-2.53	-1.36	2.28	-0.20	oro + therm	0.51 (0.13)
	fall	-2.90	-0.53	0.85	2.30	therm	1.75 (0.36)
135421	fall	-2.78	-1.09	2.91	0.69	twind	1.12 (0.16)
135423	spring	-2.80	-1.24	2.52	-0.99	null	0.86 (0.19)
	fall	-2.12	0.13	1.00	-0.24	therm + twind	2.04 (0.44)
135425	fall	-2.29	-1.37	1.81	0.51	twind	1.78 (0.36)
142404	spring	-2.90	3.31	1.71	-2.62	full	1.01 (0.12)
142405	spring	2.34	1.06	1.93	-0.96	full / oro + therm	0.90 (0.22)
142407	spring	-2.11	-0.16	2.72	2.98	therm + twind / full	0.67 (0.12)
	fall	-0.57	-1.22	0.37	0.23	full / oro + therm	1.32 (0.24)
142408	spring	-2.66	-2.13	-0.06	-0.90	-	0.69 (0.19)
	fall	-4.82	2.61	2.32	-1.00	oro + therm	1.05 (0.16)
142409	spring	-1.29	0.67	2.16	0.33	-	0.54 (0.11)
142415	fall	-4.26	1.16	0.61	2.63	oro + twind	1.10 (0.24)
142417	spring	-0.83	-2.72	3.43	-0.23	-	0.69 (0.16)
157895	fall	-0.65	0.88	1.12	0.04	therm / oro	0.74 (0.38)
157896	fall	-0.73	0.63	1.48	-0.40	-	1.44 (0.48)
157899	fall	-2.10	1.89	6.47	0.47	oro / therm + twind / therm	1.00 (0.50)
157900	fall	-0.42	-0.05	2.98	-0.27	null / therm + twind	1.41 (0.47)
157902	fall	-1.98	-1.44	7.56	-0.38	oro + therm	2.30 (0.94)
157903	fall	-0.74	1.14	0.71	0.59	full	3.10 (2.16)
157904	fall	-1.31	3.60	2.55	0.51	oro / oro + therm	0.34 (0.22)
157906	fall	-1.16	1.33	4.52	-0.55	twind	1.25 (0.35)
mean	spring	-2.10	-0.46	1.81	-0.10		0.76
	fall	-1.83	0.29	2.33	0.35		1.56
sd	spring	1.57	1.64	1.13	1.31		0.31
	fall	1.34	1.72	2.18	0.96		0.79

[a]individual eagles; blank indicates second season for previous ID
[b]posterior means of parameter estimates
[c]model with lowest looic (Vehtari etal., 2016); all models within two looic of the top model listed in order of fit (separated by /); - indicates null did not converge
[d]oro + therm + twind
[e]the mean across pointwise estimates of the expected log pointwise predictive density estimated with PSIS-LOO (Vehtari etal., 2017, 2016)

Table S2: Pearson's correlations among estimated effects of thermal uplift, orographic uplift, and wind support on eagle movements during fall migration.

	Orographic	Thermal	Wind
Orographic	-	0.15	-0.11
Thermal	-	-	-0.35
Wind	-	-	-

Table S3: Pearson's correlations among estimated effects of thermal uplift, orographic uplift, and wind support on eagle movements during spring migration.

	Orographic	Thermal	Wind
Orographic	-	0.11	-0.22
Thermal	-	-	-0.06
Wind	-	-	-

Table S4: Estimates of environmental covariate effects on golden eagle behavior and movements during migrations. Parameter estimates are from the correlated random walk model with full behavioral process modified to assume equal variance in the x and y dimensions, which assures invariance under linear transformation of the coordinate system. Note that these estimates are similar to those in table S1, despite the modification.

ID[a]	**Season**	**Parameter**[b]			
		β_0	β_{ou}	β_{tu}	β_{tw}
135411	spring	-2.79	-2.77	1.75	-0.44
135414	spring	-1.09	-1.36	-0.48	1.01
135417	spring	-2.52	-1.41	2.30	0.07
	fall	-3.13	-0.76	1.29	2.39
135423	spring	-2.59	-1.51	2.41	-0.05
	fall	-1.81	0.07	0.67	0.16
135425	fall	-2.70	-1.47	2.20	0.88
142404	spring	-2.40	2.99	1.11	-2.71
157902	fall	-2.23	-1.36	7.43	-0.55
157904	fall	-1.28	3.48	2.42	0.04

[a]individual eagles; blank indicates second season for previous ID
[b]posterior means of parameter estimates

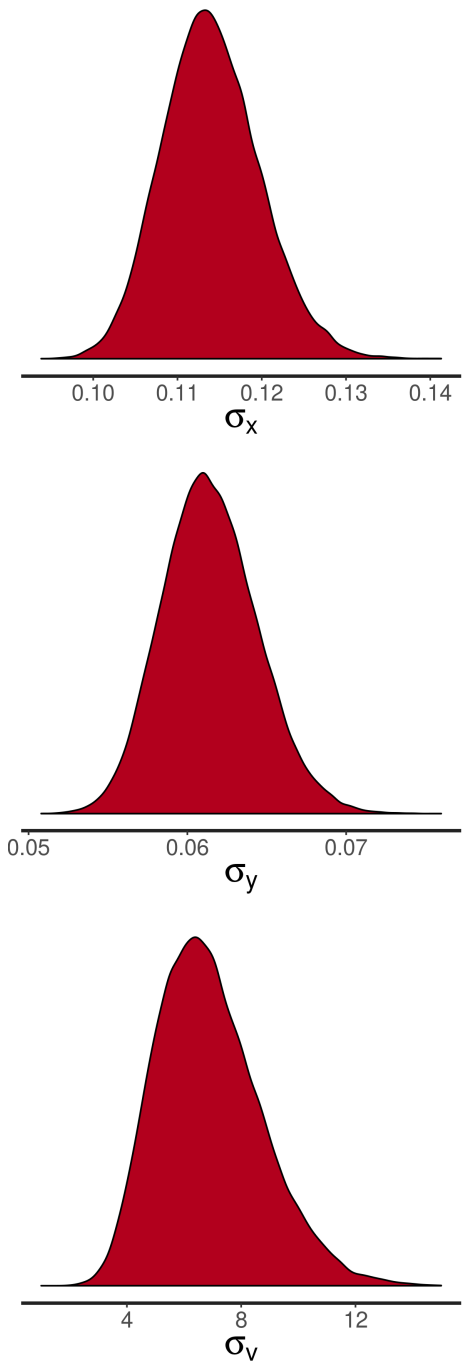

Figure S1: Posterior plots of variance components of the correlated random walk model with orographic uplift, thermal uplift, and wind support as behavioral predictors for the spring track of golden eagle 135423. Curves are approximately Gaussian, indicating the model was well behaved and likely converged to the posterior.

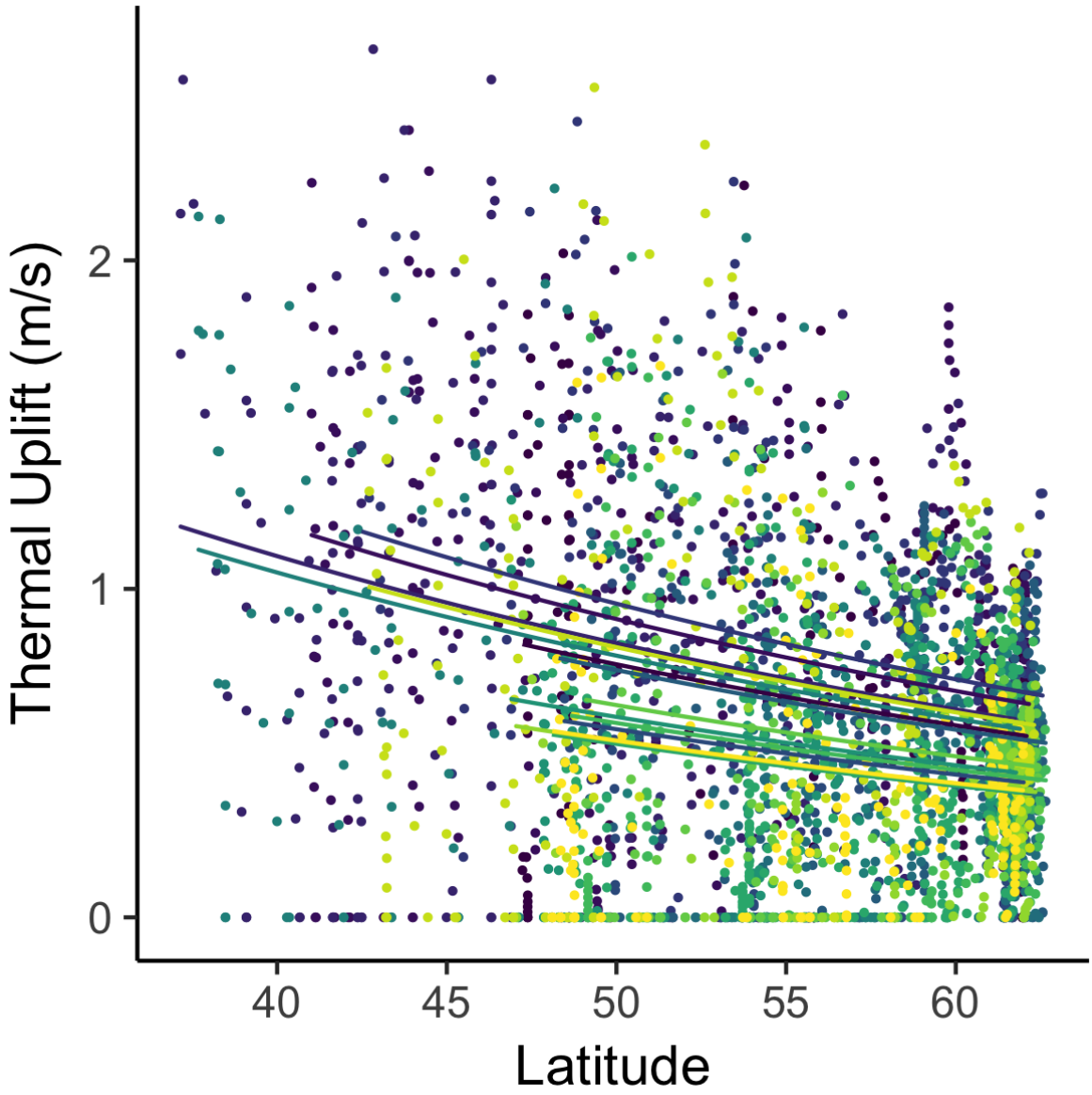

Figure S2: Interpolated thermal uplift as a function of latitude during spring migration. Hue corresponds to individual. Curves are from the individual level of a Bayesian hierarchical Gamma regression. The 95% Bayesian credible interval for the latitude coefficient was $-0.040 < \beta_{lat} < -0.015$, strong evidence for a decreasing trend in thermal uplift with increasing latitude.

Appendix 2: code

Stan model

```
data {

  int N;                // # of fixes in track
  vector[N] x;          // x coordinates
  vector[N] y;          // y coordinates
  vector[N] dt;         // time intervals

  vector[N] oro;        // covariates
  vector[N] therm;
  vector[N] twind;
  vector[N] tod;

}

transformed data {

  vector[N] c_oro;
  vector[N] c_therm;
  vector[N] c_twind;
  vector[N] oro_inter;
  vector[N] therm_inter;
  vector[N] twind_inter;

  // shifted log transform and standardize
  c_oro = ( log( oro + 1 ) * ( 0.5 / sd( log( oro + 1 ) ) ) );

  c_therm = ( log( therm + 1 ) * ( 0.5 / sd( log( therm + 1 ) ) ) );
```

```
  // center and standardize twind
  c_twind = ( ( twind  ) * ( 0.5 / sd( twind ) ) )
  - mean( twind * ( 0.5 / sd( twind ) ) );

  // interactions
  oro_inter = c_oro .* tod;
  therm_inter = c_therm .* tod;
  twind_inter = c_twind .* tod;

}

parameters {

  vector[N] gamma_raw;                // logit behavior parameter
                                      //-- time-varying, correlates steps
  real<lower=0> sigmax;               // variance in x
  real<lower=0> sigmay;               // variance in y
  real<lower=0> sigmav;               // behavior variance
  vector[4] beta;                     // covariate coefficients

}

transformed parameters{

  // introduce logit link
  vector<lower=0,upper=1>[N] gamma;

  for(j in 1:N){
```

```
    gamma[j] = inv_logit( gamma_raw[j] );
  }

}

model {

  // NOTE: Stan uses st. dev. for normals, whereas JAGS uses precision
  // Stan also truncates appropriately based on specified constraints

  // prior on behavior process noise
  // prior density away from zero--assume there is variability in behavior
  sigmav ~ normal( 3 , 3 );

  // priors on movement process noise--close to zero
  sigmax ~ normal( 0 , 1 );
  sigmay ~ normal( 0 , 1 );

  // priors on coefficients
  // prior density on zero--assume no effect of covariates on behavior
  beta ~ student_t( 5, 0 , 2.5 );

  for (i in 3:N) {

    // behavior linear combination of covariates plus previous behavior
    // this can be modified to make candidate formulations
    gamma_raw[i] ~ normal( gamma_raw[i-1] + beta[1]
    + beta[2] * oro_inter[i] + beta[3] * therm_inter[i]
    + beta[4] * twind_inter[i] , dt[i] * sigmav );
```

```
    // movement process is independent in x and y
    x[i] ~ normal( x[i-1] + gamma[i] * ( dt[i] / dt[i-1] )
    * ( x[i-1] - x[i-2] ) , dt[i] * sigmax );

    y[i] ~ normal( y[i-1] + gamma[i] * ( dt[i] / dt[i-1] )
    * ( y[i-1] - y[i-2] ) , dt[i] * sigmay );

  }

}

generated quantities {

  // generate log likelihoods for PSIS-LOO
  // test prediction of next step from previous with estimated gamma
  vector[N] log_lik;
  log_lik[1] = 0.1;  // need something here; simplest to fix across tracks
  log_lik[2] = 0.1;

  for (n in 3:N){

    log_lik[n] = normal_lpdf( x[n] | x[n-1] + gamma[n]
    * ( dt[n] / dt[n-1] ) * ( x[n-1] - x[n-2] ) , dt[n] * sigmax )
    *normal_lpdf( y[n] | y[n-1] + gamma[n] * ( dt[n] / dt[n-1] )
    * ( y[n-1] - y[n-2] ) , dt[n] * sigmay );

  }
```

```

}
```

R code

```
library(rstan)
library(loo)

################################
## model variables
# x -- vector of x coordinates
# y -- vector of y coordinates
# dt -- vector of time intervals
# N -- number of fixes in track
# oro -- vector of raw orographic uplift data
# therm -- vector of raw thermal uplift data
# twind -- vector of raw tailwind data
# tod -- vector of times of day (1=day, 0=night)
################################

dat = read.csv('examp_dat.csv')

x = dat$x
y = dat$y
dt = dat$dt
N = nrow(dat)
oro = dat$oro
therm = dat$therm
twind = dat$twind
tod = dat$tod

# fit Stan model with HMC, using default no-u-turn sampler
# model code should be saved as a .stan file
```

```
# arguments should be modified as required
stan.fit = stan("model.stan",
                data = list(x, y, dt, N, oro, therm, twind, tod),
                chains = 2,
                iter = 1000,
                thin=1,
                cores = 1,
                control = list(adapt_delta = 0.9))
# last argument helps with divergent transitions

# PSIS-LOO
log_lik = extract_log_lik(stan.fit)
loo = loo(log_lik_00)
print(loo)
# use compare(loo1, loo2, ...) to rank candidate models
```

Appendix 3: additional mathematical details

From combing components of equations 1 and 5 from the main text, we see that Δt_i is accounted for when introducing the linear combination of environmental covariates, despite that Δt_i is not explicitly included in equation 5:

$$\gamma_i \frac{\Delta t_i}{\Delta t_{i-1}} = \frac{\exp(\gamma'_{i-1} + \mathbf{Z}_i^{\mathrm{T}}\boldsymbol{\beta} + \epsilon_i)}{\exp(\gamma'_{i-1} + \mathbf{Z}_i^{\mathrm{T}}\boldsymbol{\beta} + \epsilon_i) + 1} \frac{\Delta t_i}{\Delta t_{i-1}} = \frac{\exp(\gamma'_{i-1} + \mathbf{Z}_i^{\mathrm{T}}\boldsymbol{\beta} + \epsilon_i)\Delta t_i}{\exp(\gamma'_{i-1} + \mathbf{Z}_i^{\mathrm{T}}\boldsymbol{\beta} + \epsilon_i)\Delta t_{i-1} + \Delta t_{i-1}}.$$

Equation 1, then, can be rewritten in its entirety as

$$\mathbf{x}_i | \mathbf{x}_{i-1}, \mathbf{x}_{i-2} \sim \mathcal{N}_2 \left(\mathbf{x}_{i-1} + \frac{\exp(\gamma'_{i-1} + \mathbf{Z}_i^{\mathrm{T}}\boldsymbol{\beta} + \epsilon_i)\Delta t_i}{\exp(\gamma'_{i-1} + \mathbf{Z}_i^{\mathrm{T}}\boldsymbol{\beta} + \epsilon_i)\Delta t_{i-1} + \Delta t_{i-1}} (\mathbf{x}_{i-1} - \mathbf{x}_{i-2}),\ \boldsymbol{\Sigma}_i \right),$$

or equivalently as

$$\mathbf{x}_i | \mathbf{x}_{i-1}, \mathbf{x}_{i-2} \sim \mathcal{N}_2 \left(\mathbf{x}_{i-1} + \frac{\exp(\gamma'_{i-1} + \mathbf{Z}_i^{\mathrm{T}}\boldsymbol{\beta} + \log\Delta t_i + \epsilon_i)}{\exp(\gamma'_{i-1} + \mathbf{Z}_i^{\mathrm{T}}\boldsymbol{\beta} + \log\Delta t_{i-1} + \epsilon_i) + \Delta t_{i-1}} (\mathbf{x}_{i-1} - \mathbf{x}_{i-2}),\ \boldsymbol{\Sigma}_i \right).$$