UCLA Department of Statistics

Spatial Models for Bird Origin Assignment Using Genetic and Isotopic Data

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Project Background

Ongoing research at the Center for Tropical Research (CTR) at UCLA seeks to identify patterns of continental scale migratory connections

- Current methods are too coarse for most applications
- ullet Large amounts of data are available (>150,000 feather samples from >500 species)
 - Genetic data microsatellites, mitochondrial haplotypes, SNPs (soon)
 - Isotopic data $\delta^2 H$



Species of interest

Hermit Thrush Catharus guttatus



138 Individuals 14 Locations 6 Loci 9-27 Alleles

Wilson's Warbler Wilsonia pusilla



163 Individuals 8 Locations 9 Loci 15-31 Alleles

Model Framework

Background

Assuming that the genetic (G) and isotopic (I) models are conditionally independent, then for a sample S and location k:

$$P(k|S, G, I) \propto P(S|k, G, I) \pi(k)$$

$$= P(S_G, S_I|k, G, I) \pi(k)$$

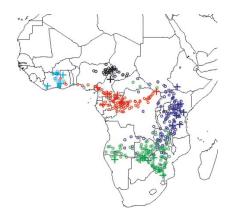
$$= P(S_G|k, G, I) P(S_I|k, G, I) \pi(k)$$

$$= P(S_G|k, G) P(S_I|k, I) \pi(k)$$



Previous work

Wasser, et. al [2004] developed an approach for assigning genetic samples from illegal ivory shipments to geographic locations.





Model Basics

Using a multinomial error structure

$$p(y_{l\cdot k}|f_{l\cdot k}) = \frac{s_{lk}!}{\prod_i y_{lik}!} \prod_i (f_{lik})^{y_{lik}}$$

where:

- f_{lik} is the allele frequency of allele i from locus I at location k.
- y_{lik} is the count of allele i from locus I at location k.
- $s_{lk} = \sum_{i} y_{lik}$ is the total count of alleles from locus l at location k.



Modeling allele frequency

Allele frequencies are modeled using normalized values:

$$f_{lik} = \frac{\exp(\theta_{lik})}{\sum_{j} \exp(\theta_{ljk})}$$

where θ_{li} is a gaussian process:

$$oldsymbol{ heta_{li}}_{[r imes1]} \sim \mathsf{MVN}(oldsymbol{\mathsf{M}}_{li}\,, oldsymbol{\Sigma}_{[r imesr]})$$



Model Parameters

Mean

$$\mathbf{M}_{li} = \xi_l \ \eta_{li} \ \mathbf{1}_{[r,1]}$$

$$\xi_I \sim \mathsf{Unif}(-\infty, \infty)$$

$$\eta_{li} \sim \mathsf{N}(0, \beta_l)$$

 $\beta_l \sim \mathsf{Unif}(0, 10^6)$

Variance

$$\{\Sigma\}_{k_1,k_2} = \sigma(d_{k_1,k_2}|\alpha)$$

Assumes process is stationary and isotropic



Covariance Functions

Powered Exponential Covariance:

$$\sigma(d|\alpha) = \alpha_0 \exp\left[-\left(\frac{d}{\alpha_1}\right)^{\alpha_2}\right] + \alpha_3 I_{d=0}$$

Matérn Covariance:

$$\sigma(d|\alpha) = \alpha_0 \frac{1}{\Gamma(\alpha_2) 2^{(\alpha_2 - 1)}} \left(\frac{d}{\alpha_1}\right)^{\alpha_2} K_{\alpha_2} \left(\frac{d}{\alpha_1}\right) + \alpha_3 I_{d=0}$$

with the following priors on α :

$$\alpha_0, \log(\alpha_1), \log(\alpha_2), \alpha_3 \sim \text{Unif}$$



Model Fitting via MCMC

All parameters are updated by random walk Metropolis Hasting with normal jump proposals.

However, we first reparameterize as follows:

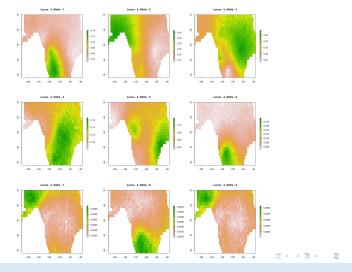
$$egin{aligned} \mathbf{V}_{li} &\sim \mathsf{MVN}(0, \ \Sigma) \ [r imes r] \end{aligned} \ \mathbf{V}_{li} &= \mathsf{Chol}(\Sigma) \cdot \mathbf{X}_{li} \ [r imes 1] & [r imes 1] \end{aligned}$$

where

$$\{X_{li}\}_k \sim N(0,1)$$



Allele Frequency - Hermit Thrush - Locus 3



Probability of a Sample

For a sample S with alleles i_l and j_l at locus l and location k

$$p(S|f,k) = \prod_{l} p_{l}(i_{l},j_{l}|f,k)$$

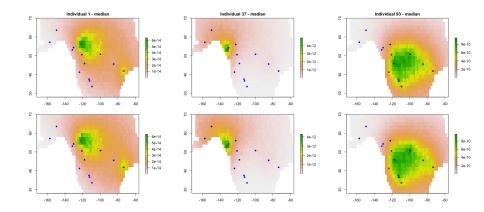
$$p_{l}(i_{l},j_{l}|f,k) = \begin{cases} \gamma \ p_{l}(i_{l}|f,k) + (1-\gamma) \ p_{l}(i_{l}|f,k)^{2} & \text{if } i_{l} = j_{l} \\ (1-\gamma) \ p(i_{l}|f,k) \ p(j_{l}|f,k) & \text{if } i_{l} \neq j_{l} \end{cases}$$

$$p_l(i_l|f,k) = (1-\delta)f_{lik} + \delta/m_l$$

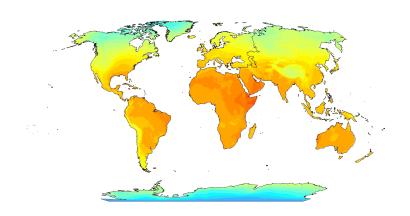
where δ is the probability only one of the alleles amplified and γ is the probability of a genotyping error.



Spatial Posteriors - Hermit Thrush





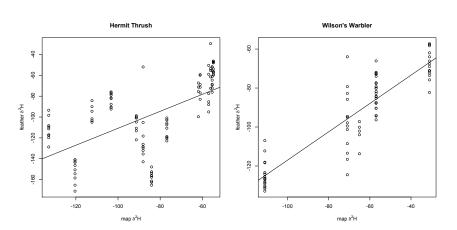


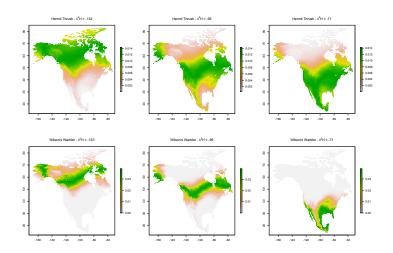
δ²H of Annual Precipitation





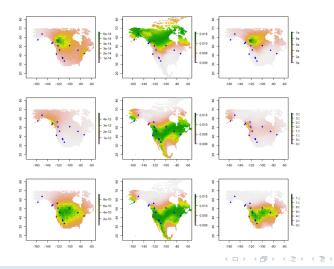
Mapping isotope values



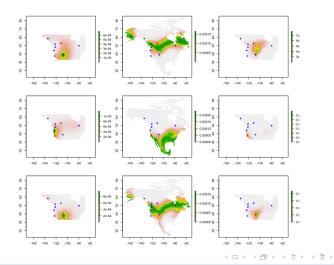




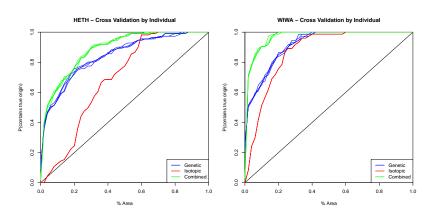
Combined - Hermit Thrush



Combined - Wilson's Warbler

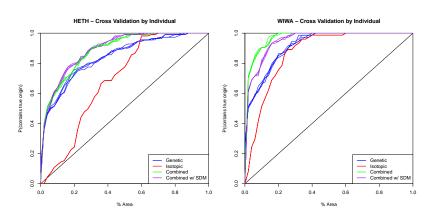


Classifier Results





Classifier Results + SDM





Conclusion

- Simple unified framework for combining Genetic and Isotopic models
- Combined results dramatically outperform either model alone
- Future Work
 - Fully bayesian isoscape model
 - Refine SDM priors
- R packages (available soon):
 - Genetic Rscat
 - Isotopic isoscape



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Genetic Methods:

- John Novembre, UCLA
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Isotopic Methods:

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