Modeling Species Distribution Dynamics with Spatiotemporal Exploratory Models: *Inter-annual Bird Migrations*

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NSF

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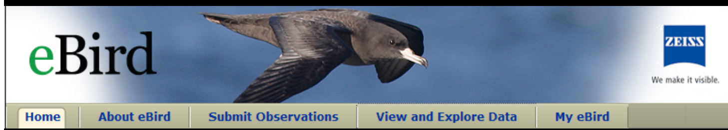
Goal: Modeling Species Distribution Dynamics

We need to understand how species distributions change and evolve through time

- Phenology – annual cycle dynamics
- Conservation - migration corridors & stopover sites
- Spread of invasive species, diseases, dispersal, etc.
- Anthropogenic changes to environment
- ➔ *Large spatial & temporal extent*
- ➔ *Fine spatial & temporal scale*

Exploratory analysis:

1. Little a priori knowledge
2. Facilitate Discovery & Description



eBird Data

- Traveling Count
- Lat - Lon
- Year (2004 – 2008)
- Julian Date (1-365)

- Observation Effort
- Observation Time
- Number of Observers

➔ Presence/absence

<= 8 km long

<= 3 hours

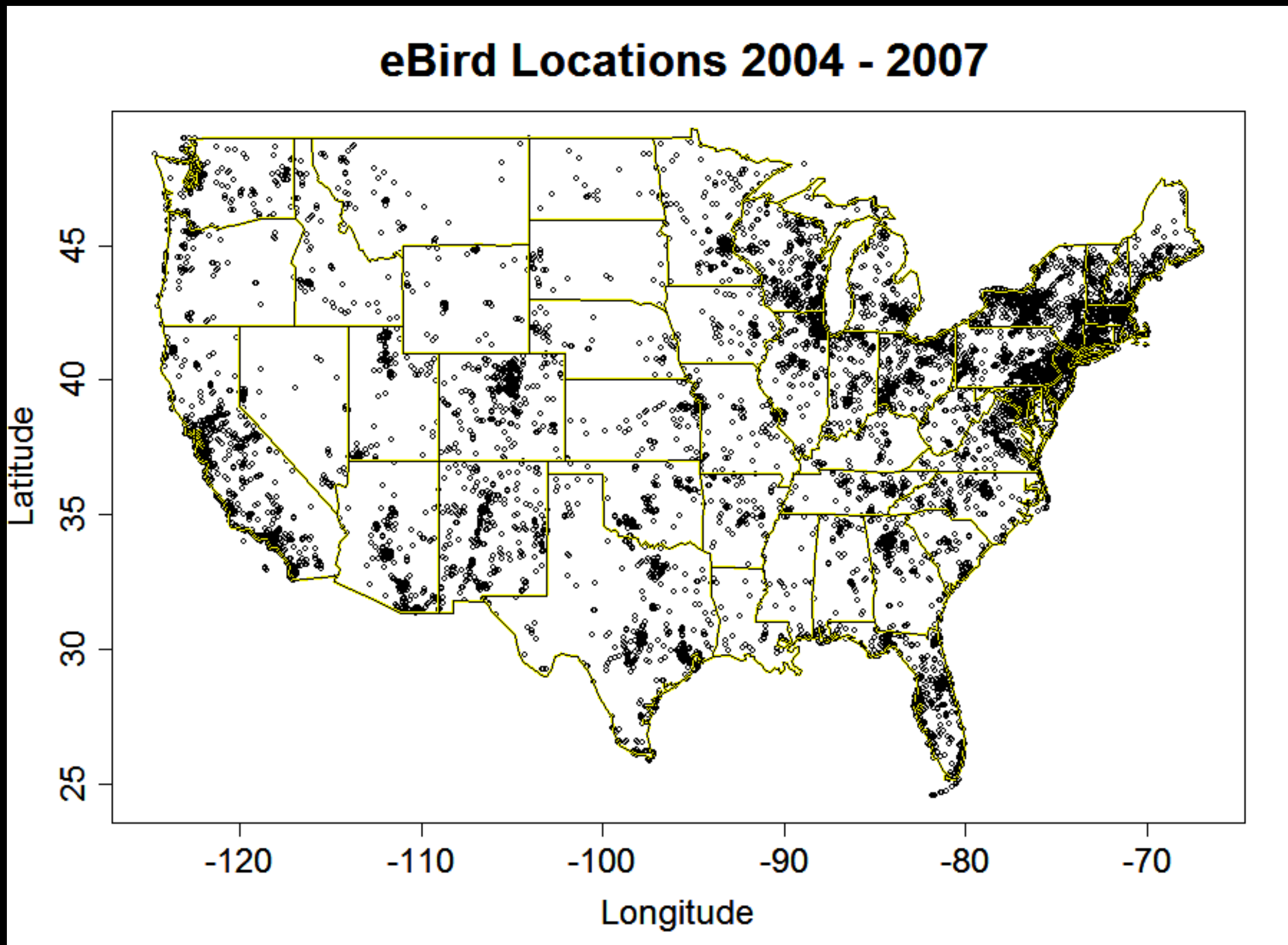
~150,000 observations

~30,000 locations

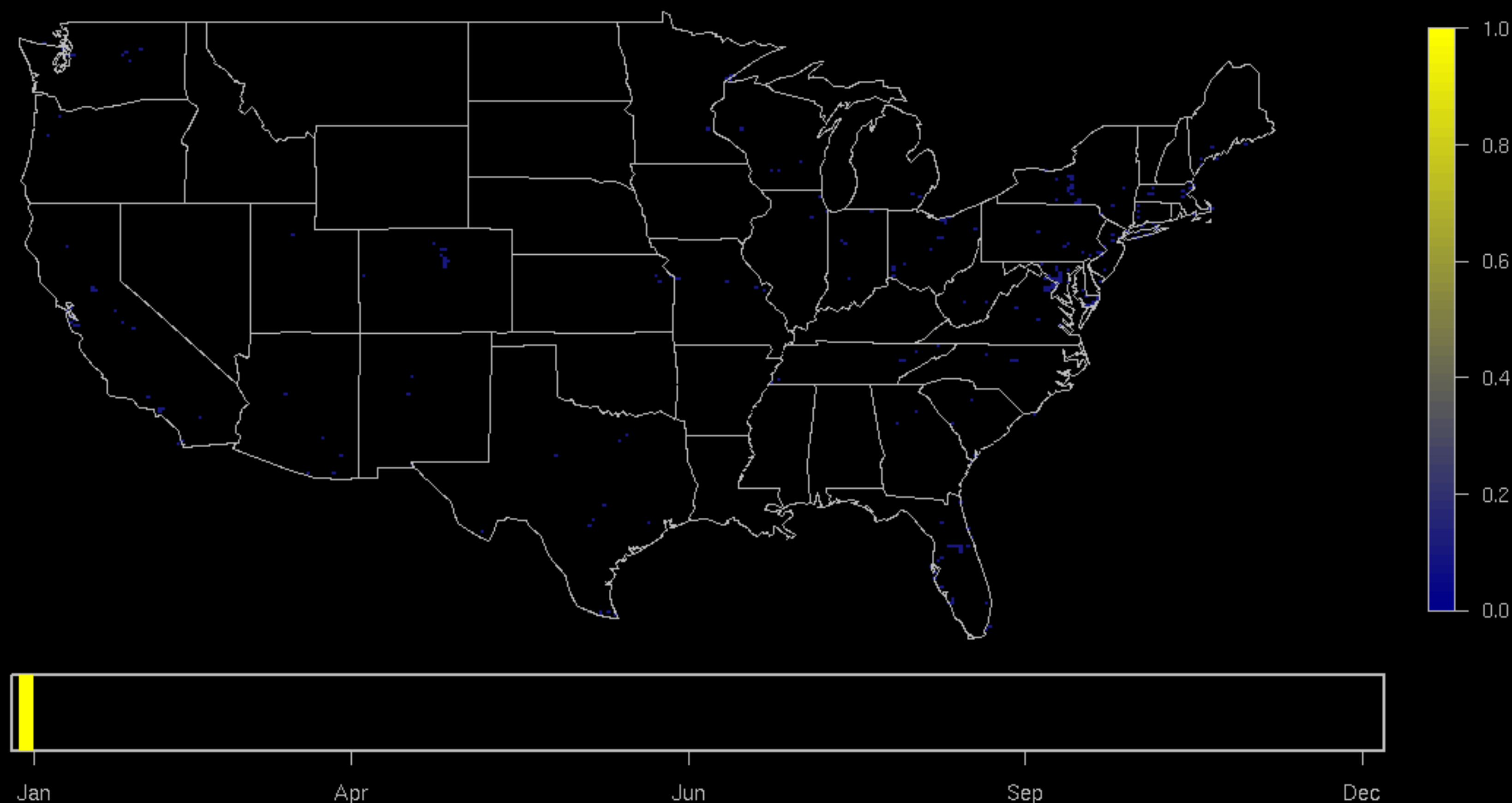
National Landcover Data (NLCD)

– 2001
– 16 Classes
– 1.5 km pixel
– Spatial Composition (% coverage)
– Spatial Configuration (Fragstats)

- Elevation
- Climate (30 yr average)
- Housing Density


eBird Locations 2004 - 2007
Latitude
Longitude
25
30
35
40
45
-120
-110
-100
-90
-80
-70

eBird data | 2008 traveling count protocol



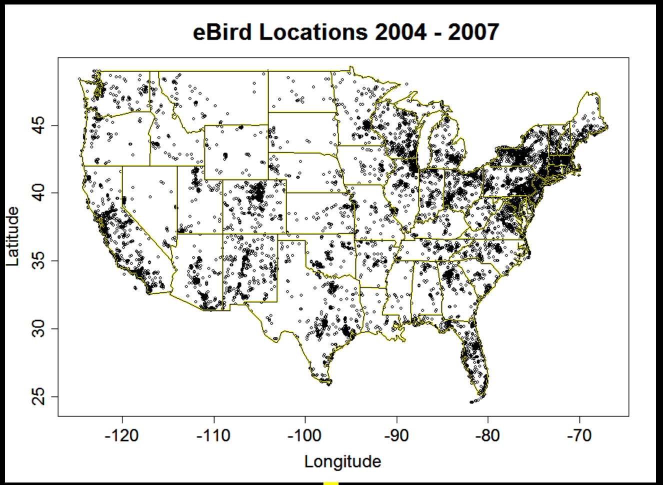
Species Distribution Modeling

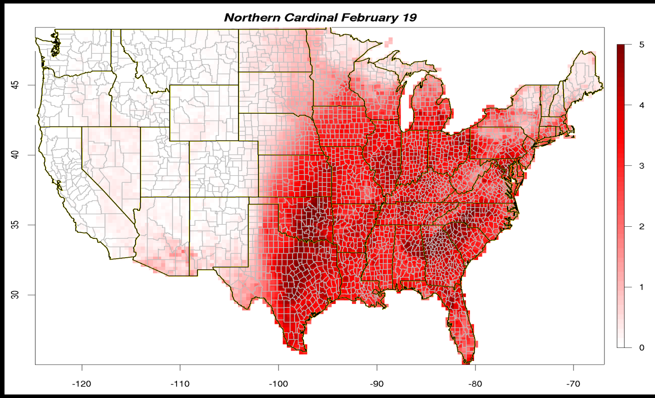
Goal: broad-scale & fine resolution

- Observational data are sparsely distributed in space and time
- Interpolation is essential

Modeling also buys us

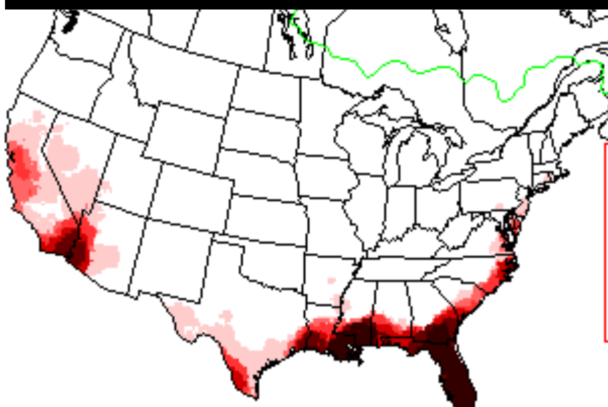
- Control bias
- Quantify uncertainty
- Framework for predictive experimentation



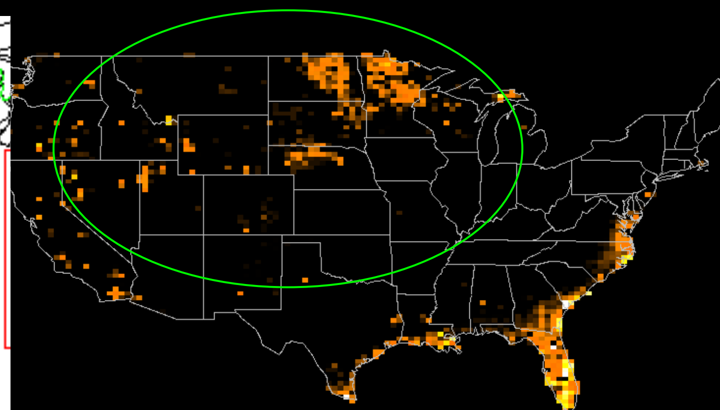


Tree Swallow
Winter Distribution Analysis
Bagged Decision Tree

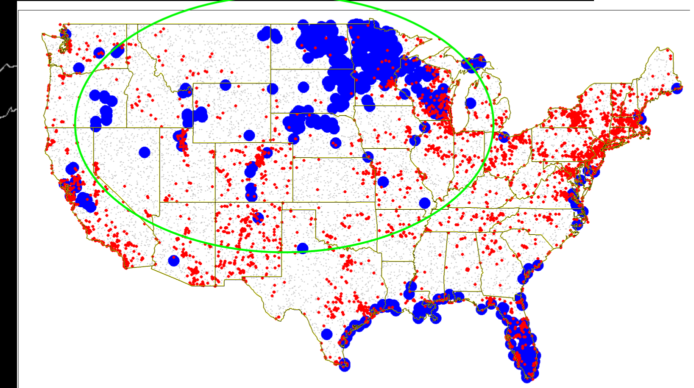
(Tachycineta bicolor)



Christmas Bird Count



eBird BDT



Wetland Coverage > 5%

- *Nonparametric model with global support may aggregate data in ways that are ecologically impossible*
- *SDM shares habitat information across regions and seasons where Tree Swallows do not coexist.*

The Multi-scale Challenge

Goal: Analysis at broad-scale with fine resolution

Challenge: spatiotemporal patterning at multiple scales

- Local-scale Homogeneity
  - Fine-scale spatial and temporal resource patterns
  - Local-scale dispersal
- Large-scale Heterogeneity
  - Regional & seasonal variation in species' habitat utilization
  - Source-sink dynamics & Allee effects
  - La Nina & North Atlantic Oscillation

SpatioTemporal Exploratory Model (STEM)

Current nonparametric SDM's are very good for local-scale modeling by relating environmental predictors (X) to observed occurrences (y)

$$y = f(X)$$

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Multi-scale strategy: differentiate between local and global-scale ST structure.

1. Make explicit time (t) and location (s)

$$f(X, s, t)$$

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Restricted Support Set (Q)

$$f(X,s,t)I(s,t \in \theta)$$

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Multi-scale strategy: differentiate between local and global-scale ST structure.

1. Make explicit time (t) and location (s)
2. "Regionalize" by restricting support
3. Predictions at time (t) and location (s) are made by averaging across a set of local models containing that time and location

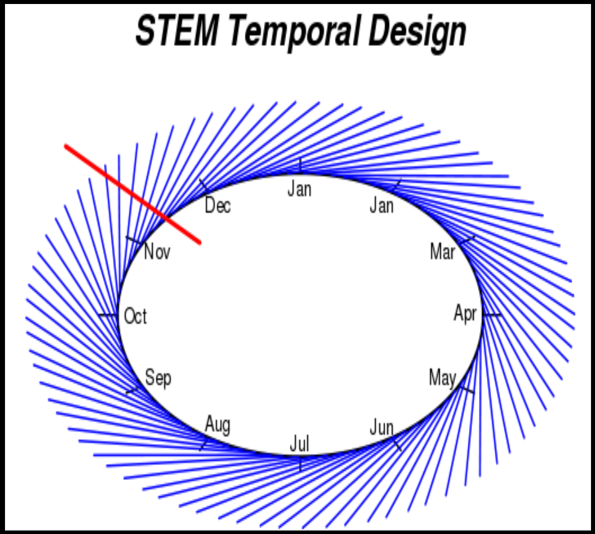
i^{th} ST explicit base model

Number of models supporting (s,t)

$$\frac{1}{n(s,t)} \sum_{i=1}^{m} f_i(X, s, t) I(s, t \in \theta_i)$$

Theta: The Spatio-Temporal Design

IDEA: ST Slice and dice sufficient overlap

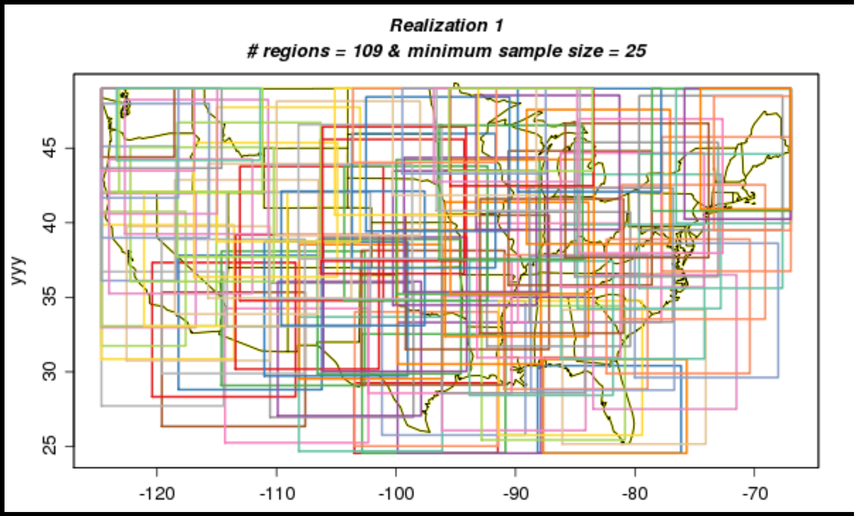


Temporal Design:

- 40 day windows
- 80 evenly spaced windows throughout year

Spatial Design

- For each time window
- Random Sample rectangles (constant size)
- With at least 25 unique locations.



The Spatio-Temporal Ensemble

$$F(X,s,t) = \frac{1}{n(s,t)} \sum_{i=1}^{m} f_i(X,s,t) I(s,t \in \theta_i)$$

<u>Quantitative Intuition</u>

Statistical Experimental Design:
Block over ST regimes to control variance

Bagging: resample block-level variance and average

<u>Ecological Intuition</u>

Local predictor-response learning
No “long-range” learning

“Local” averaging allows large-scale patterns emerge from local-scale

- *Add essential spatiotemporal structure to existing techniques*
- *Models a wide variety of dynamic processes automatically*

Base Models: Decision Trees

f(Predictors)

Predictors → → Observations

f(Habitat, Effort, LAT, LON, Year, Julian Date) = Predicted Count

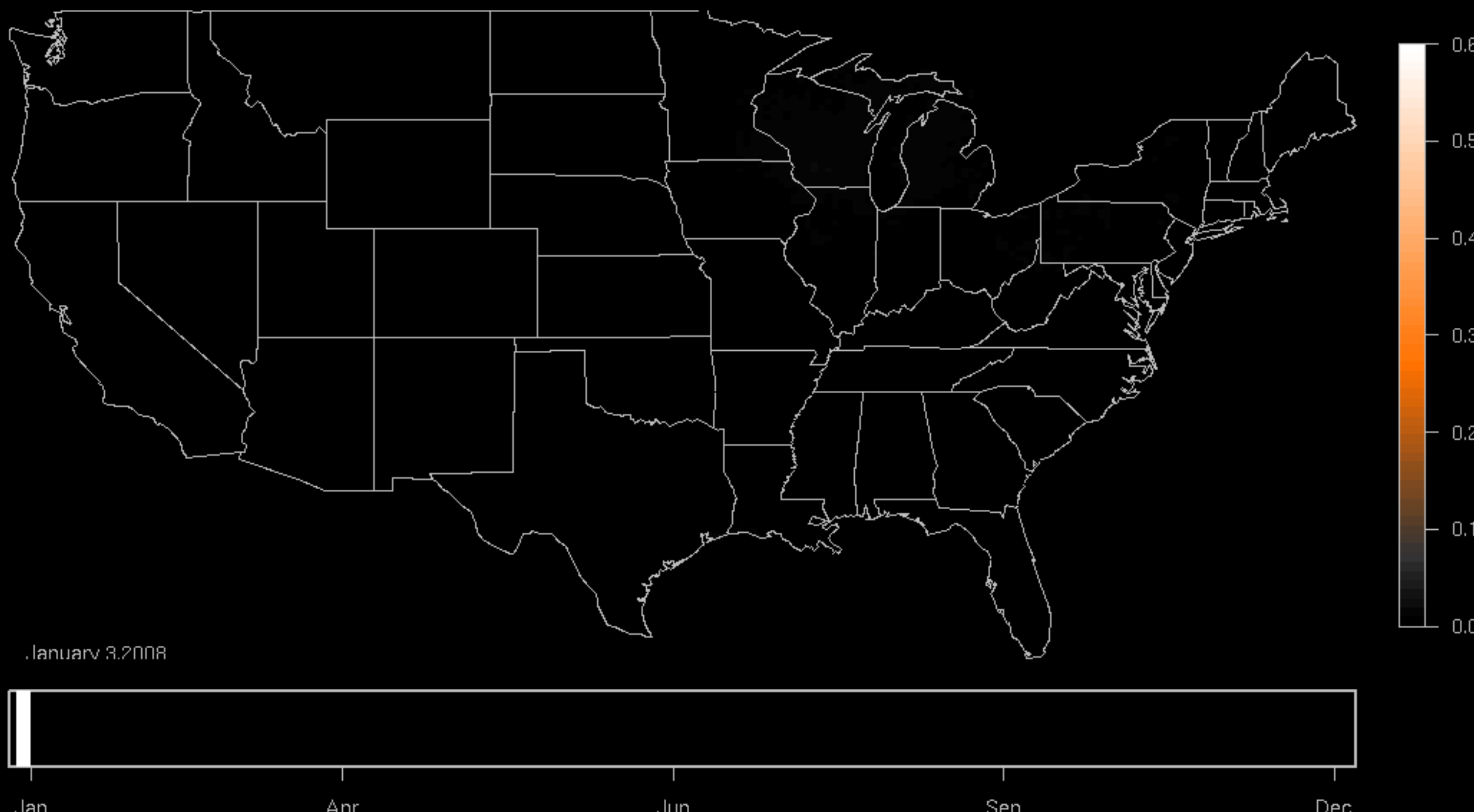
Strengths

- Automatic
- Good Predictive Performance
- Scale well to large data sets

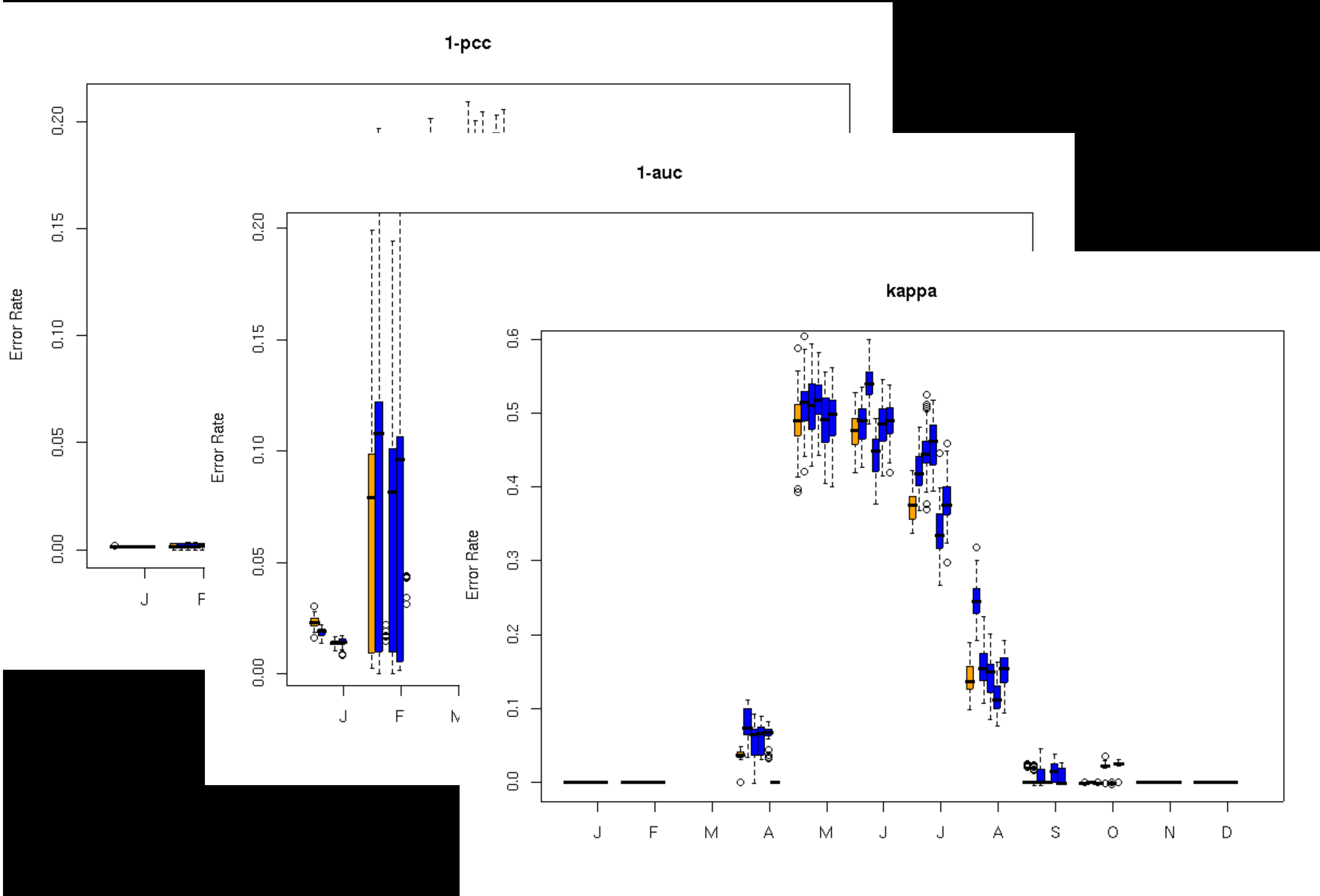
- Monotone transformations
- Nonlinear predictor effects
- Automatic interaction modeling
- Missing covariates

➔ Predictor Selection is the main analyst decision

Indigo Bunting | Full Year

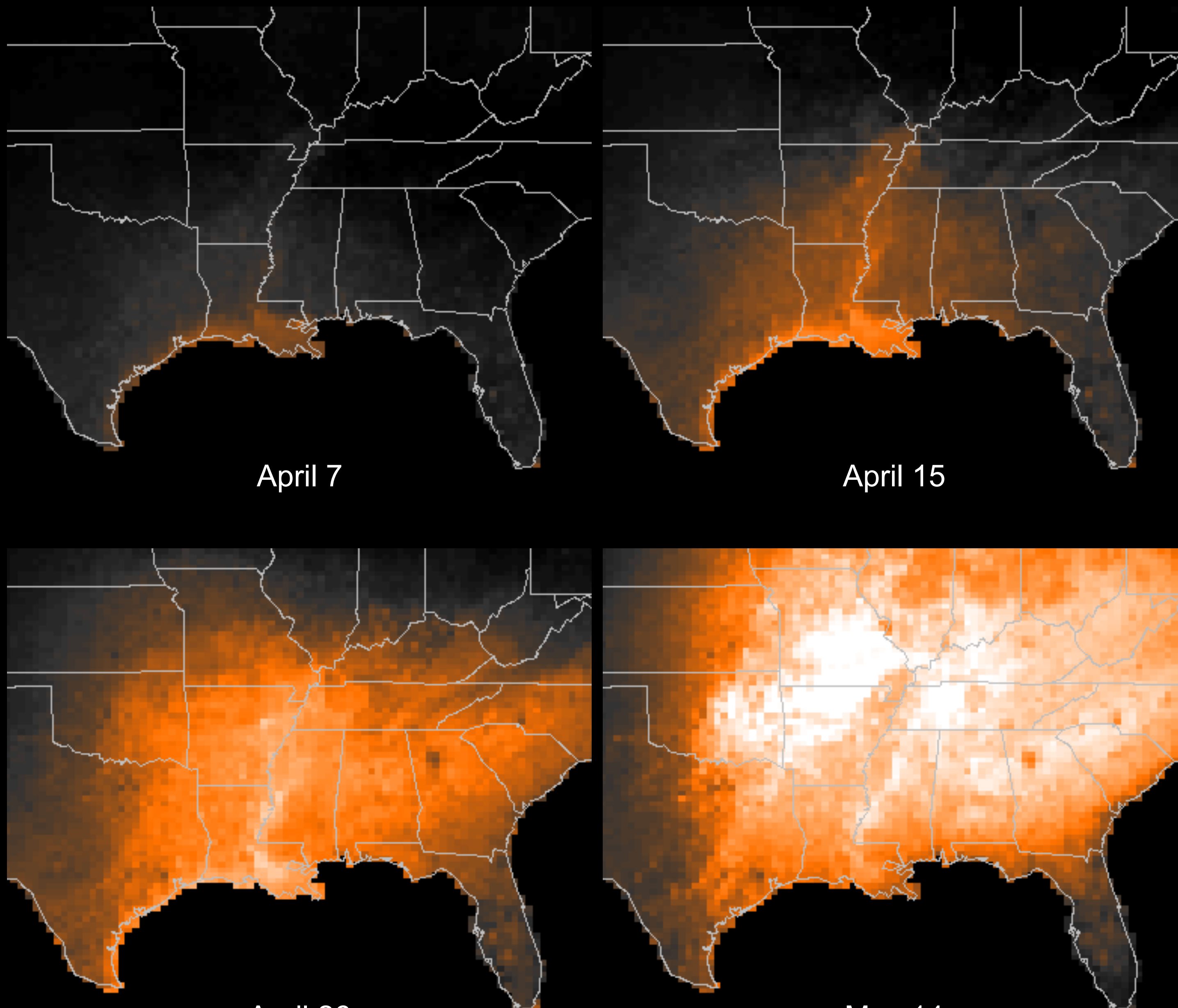


Indigo Bunting | Monthly Predictive Performance



Indigo
Bunting

Spring
Migration



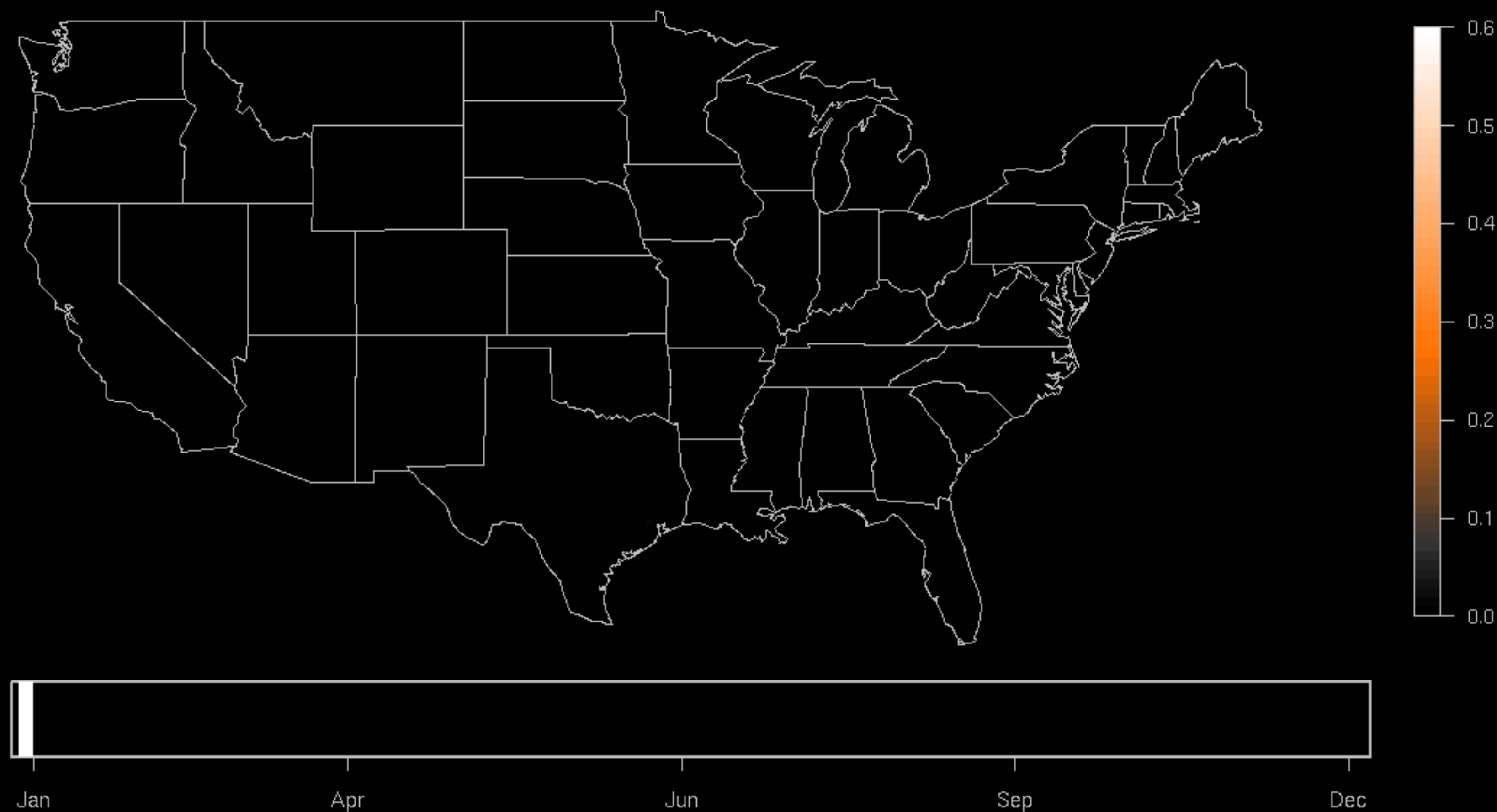
April 7

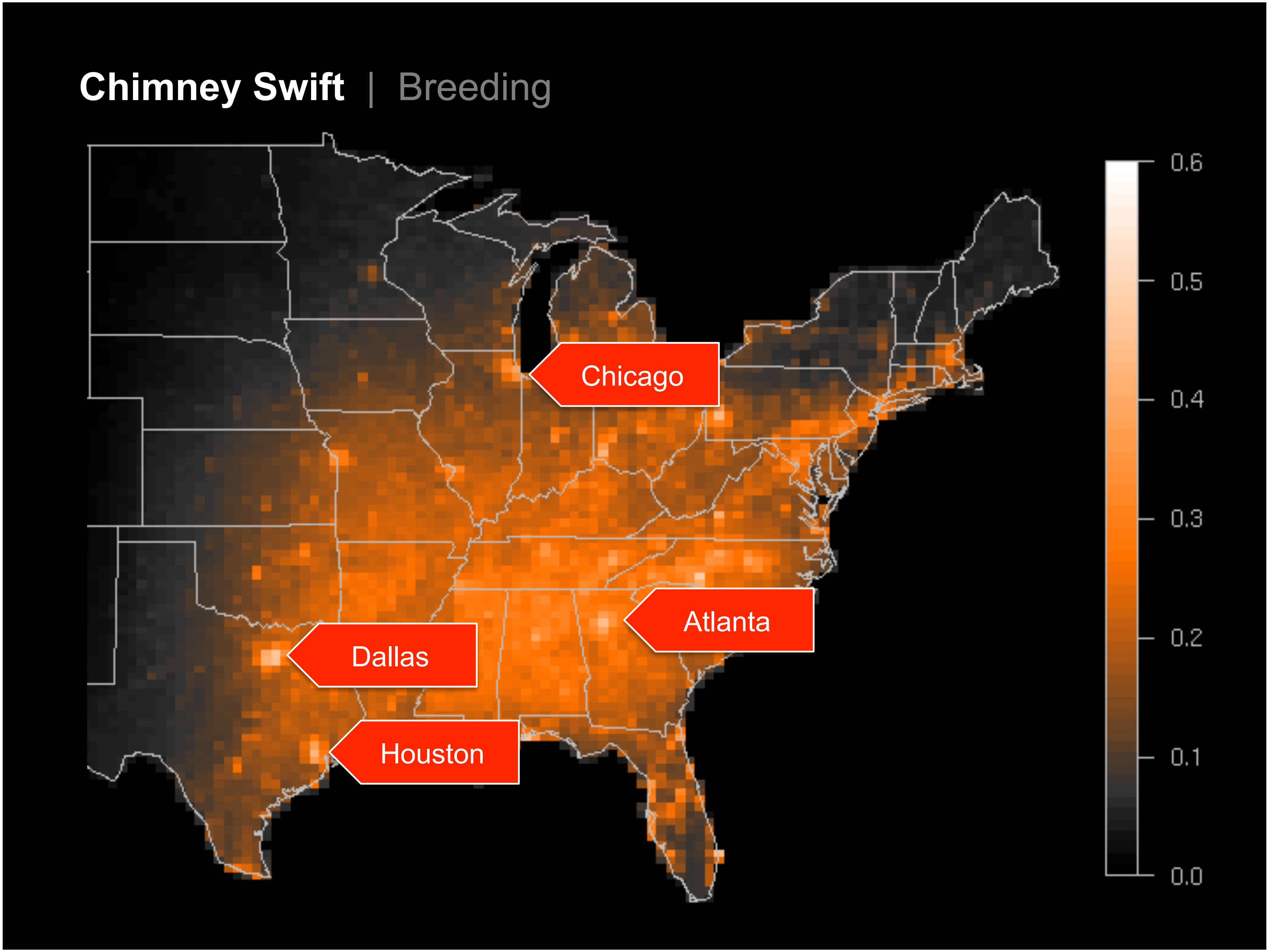
April 15

April 26

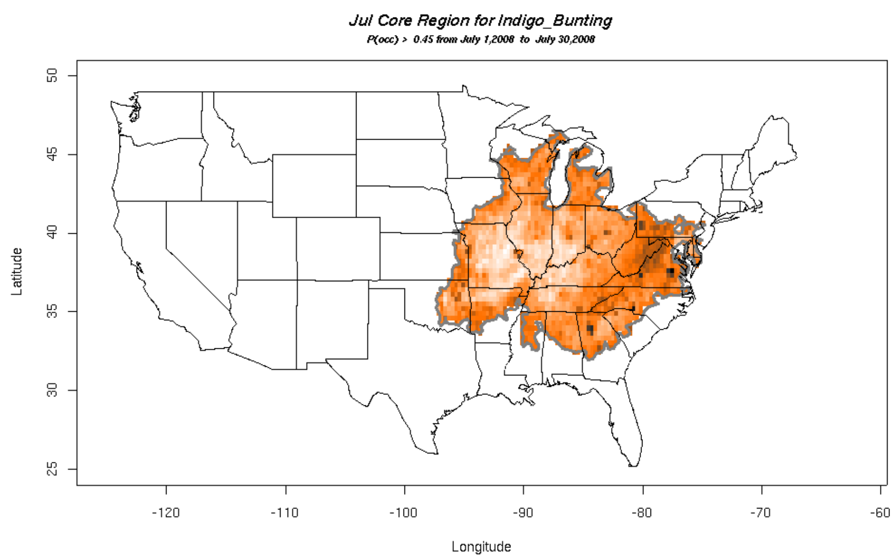
May 14

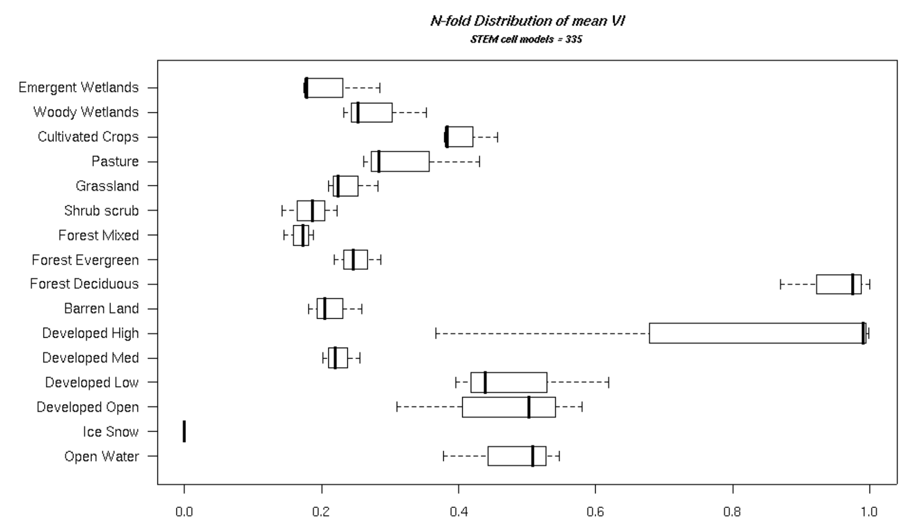
Chimney Swift | Full Year



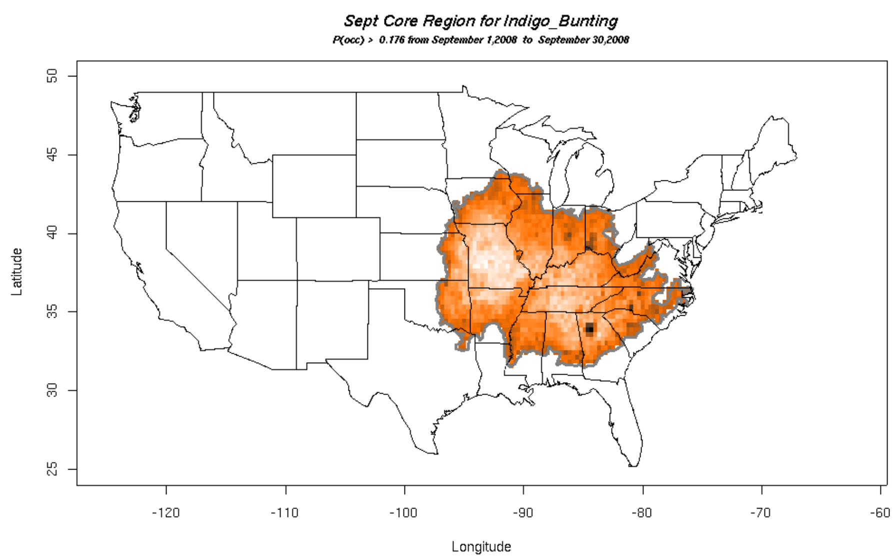

Chimney Swift | Breeding
Chicago
Atlanta
Dallas
Houston
0.6
0.5
0.4
0.3
0.2
0.1
0.0

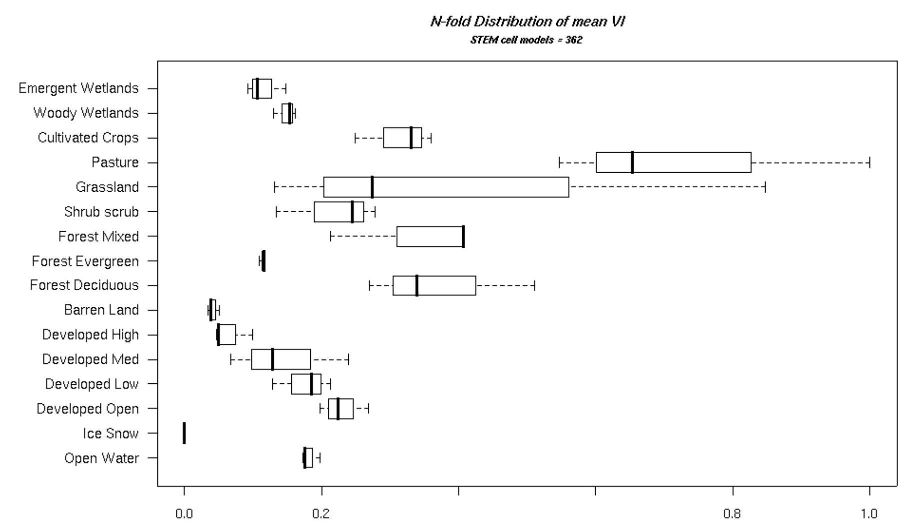
Indigo Bunting | Relative Variable Importance



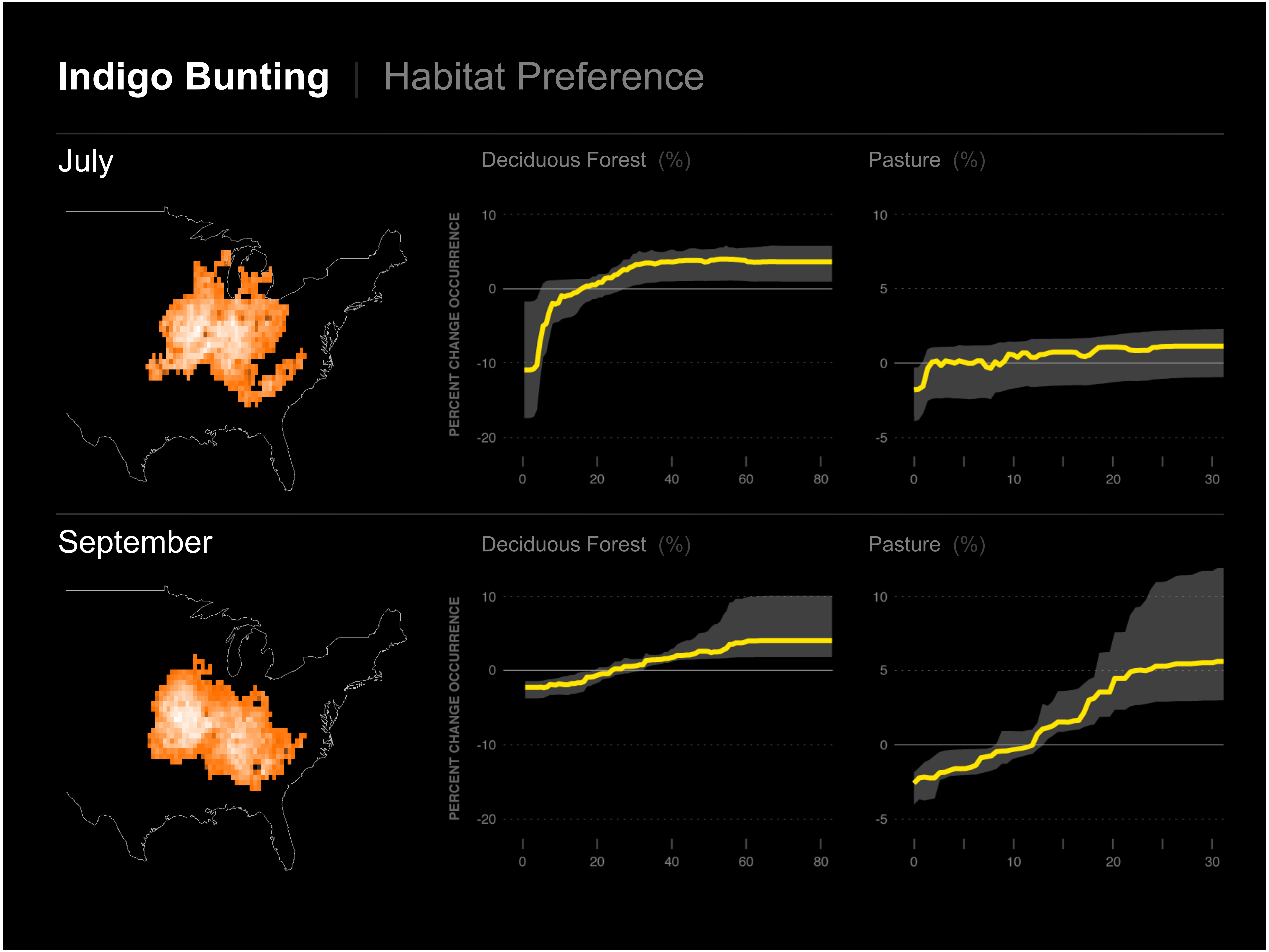


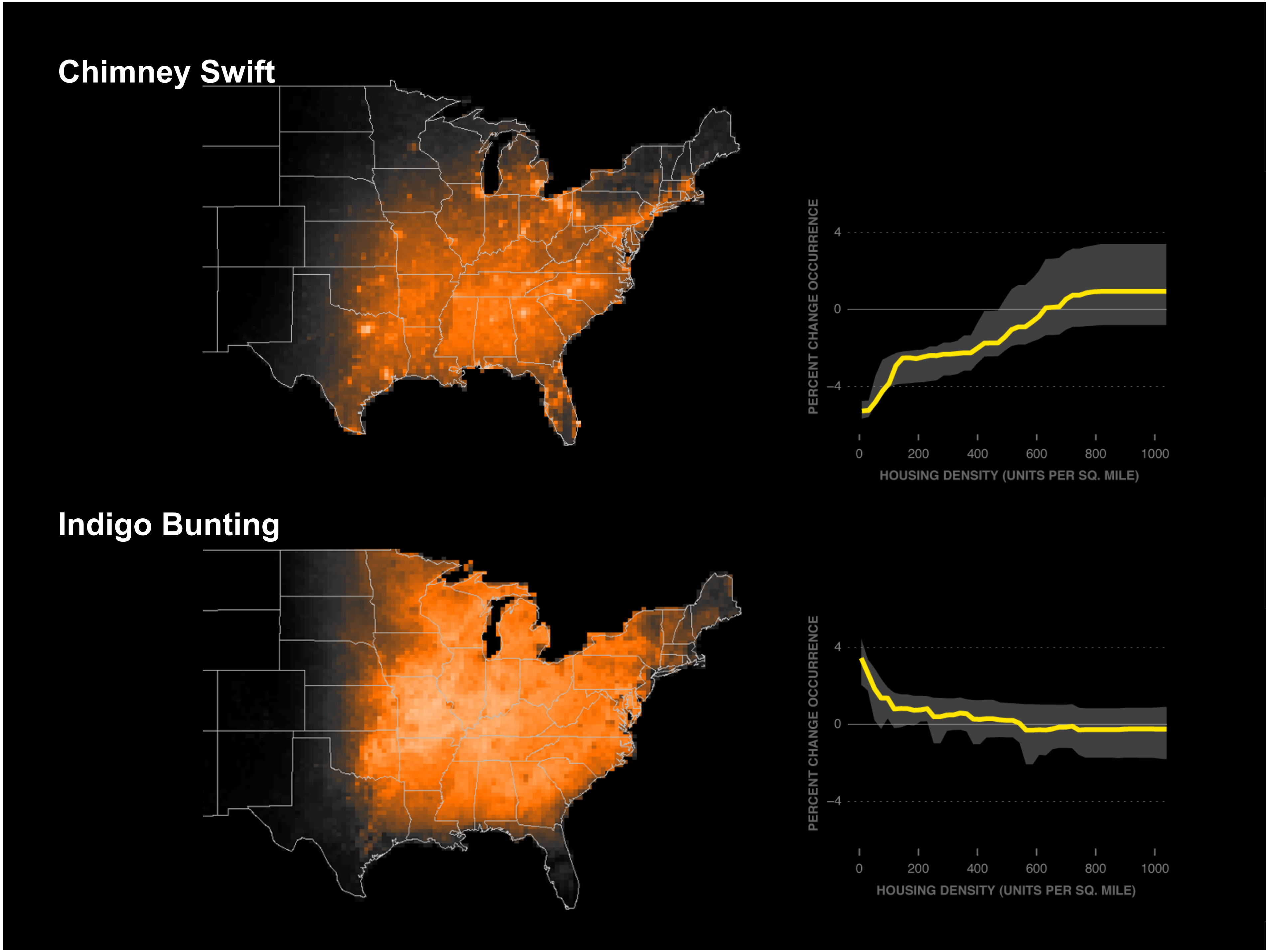
Relative Importance →

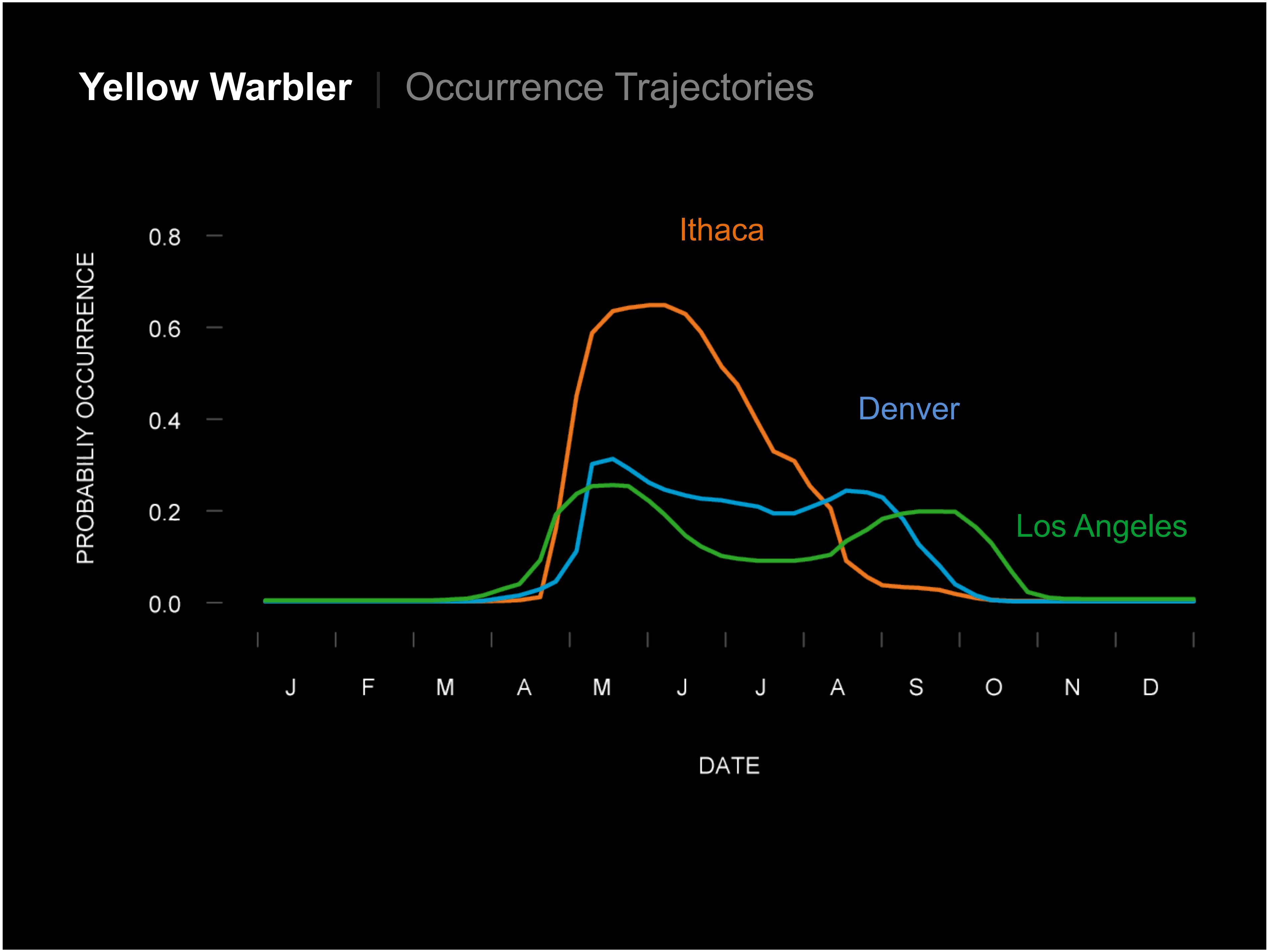




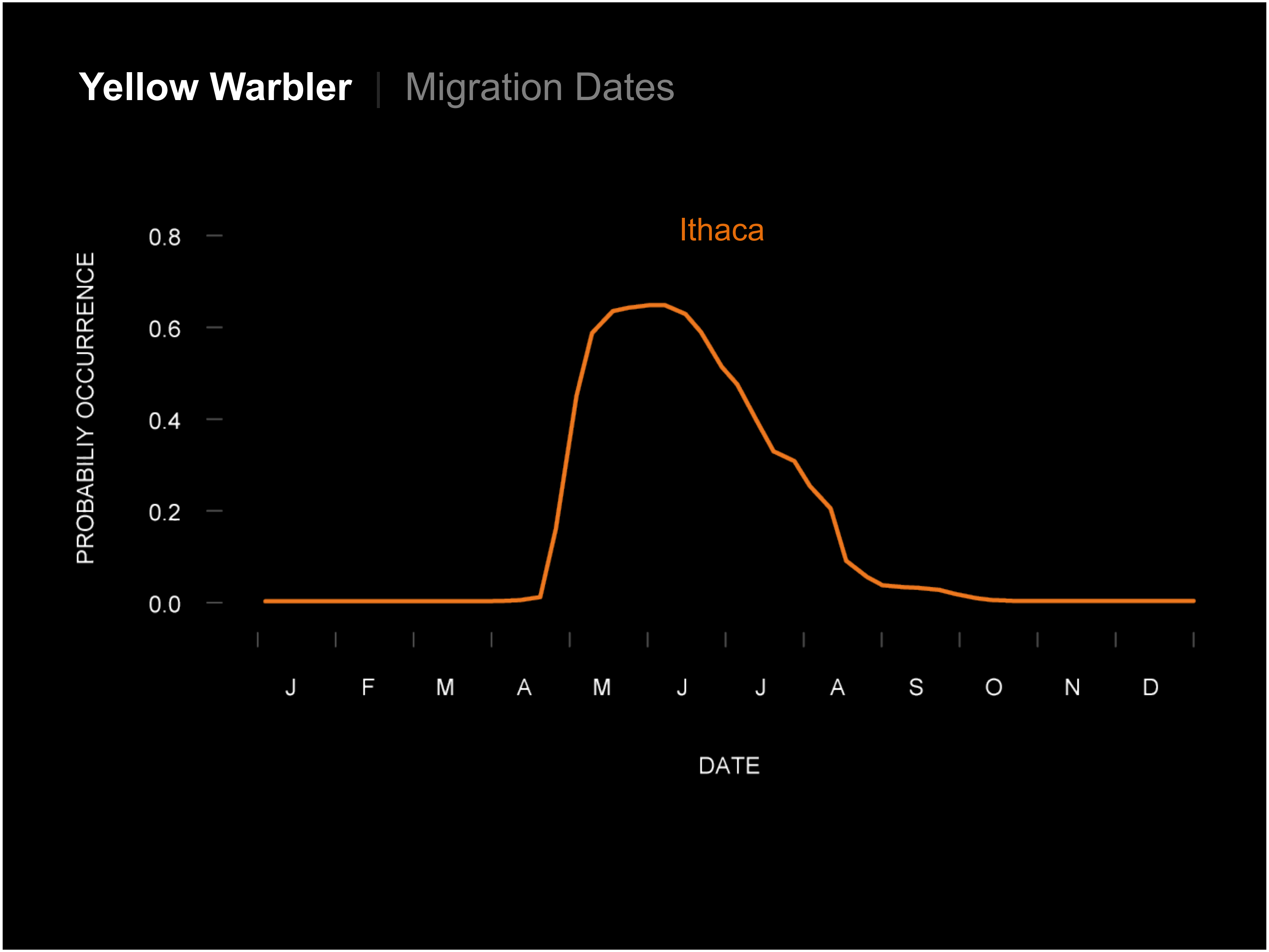
Relative Importance →

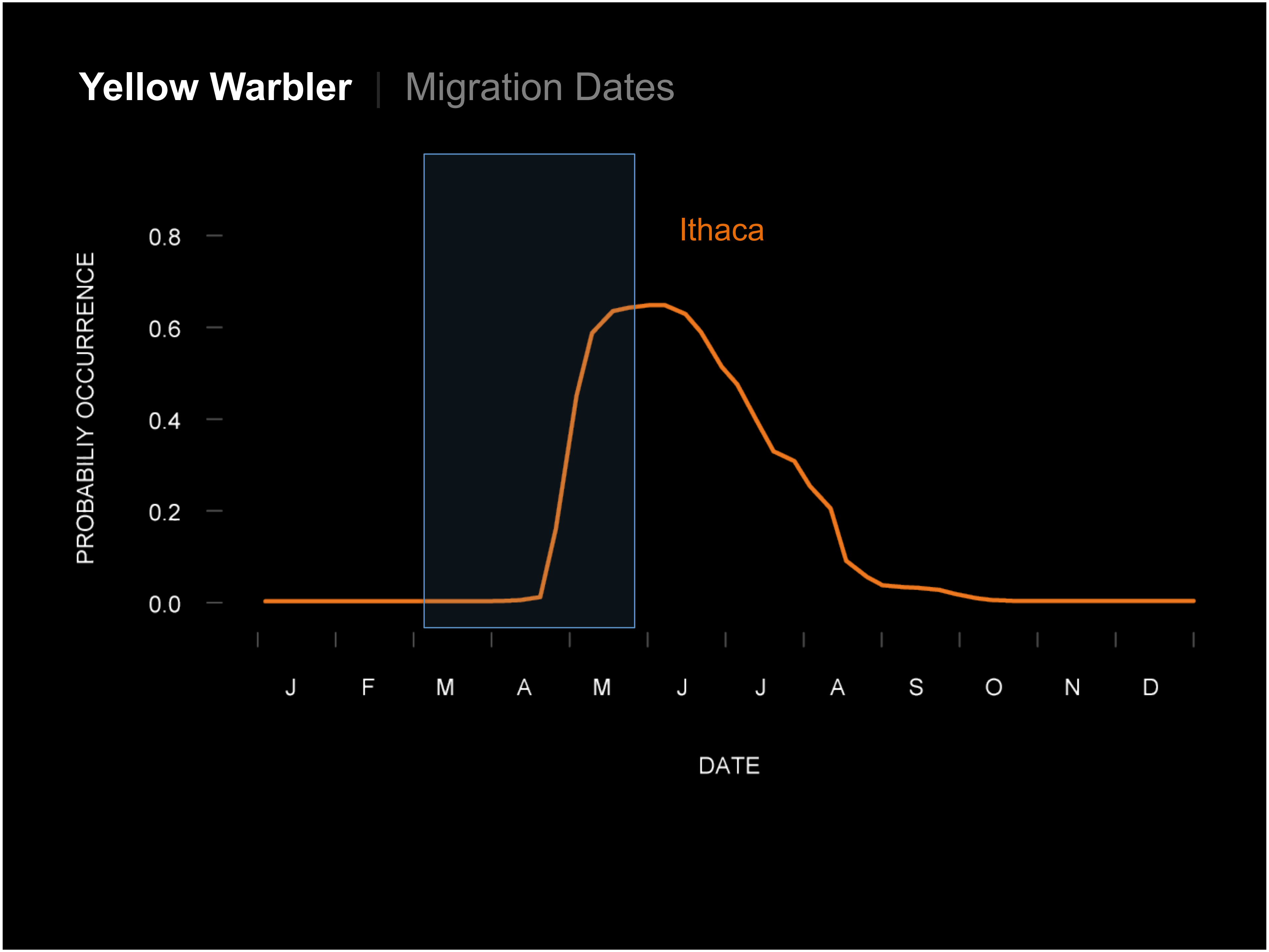

Indigo Bunting | Habitat Preference
July
Deciduous Forest (%)
Pasture (%)
PERCENT CHANGE OCCURRENCE
10
0
-10
-20
0
20
40
60
80
10
5
0
-5
0
10
20
30
September
Deciduous Forest (%)
Pasture (%)
PERCENT CHANGE OCCURRENCE
10
0
-10
-20
0
20
40
60
80
10
5
0
-5
0
10
20
30

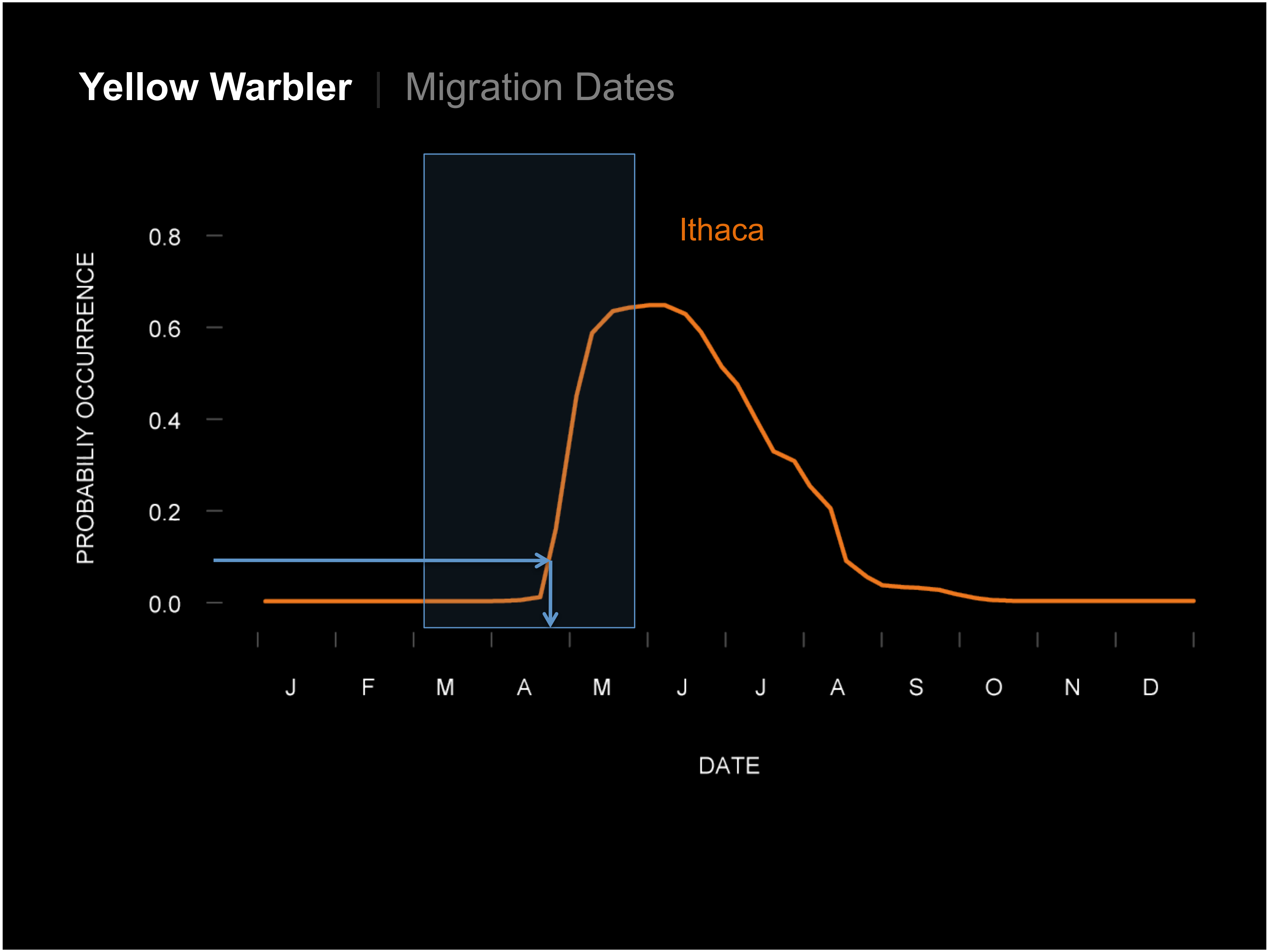

Chimney Swift
PERCENT CHANGE OCCURRENCE
4
0
−4
0
200
400
600
800
1000
HOUSING DENSITY (UNITS PER SQ. MILE)
Indigo Bunting
PERCENT CHANGE OCCURRENCE
4
0
−4
0
200
400
600
800
1000
HOUSING DENSITY (UNITS PER SQ. MILE)

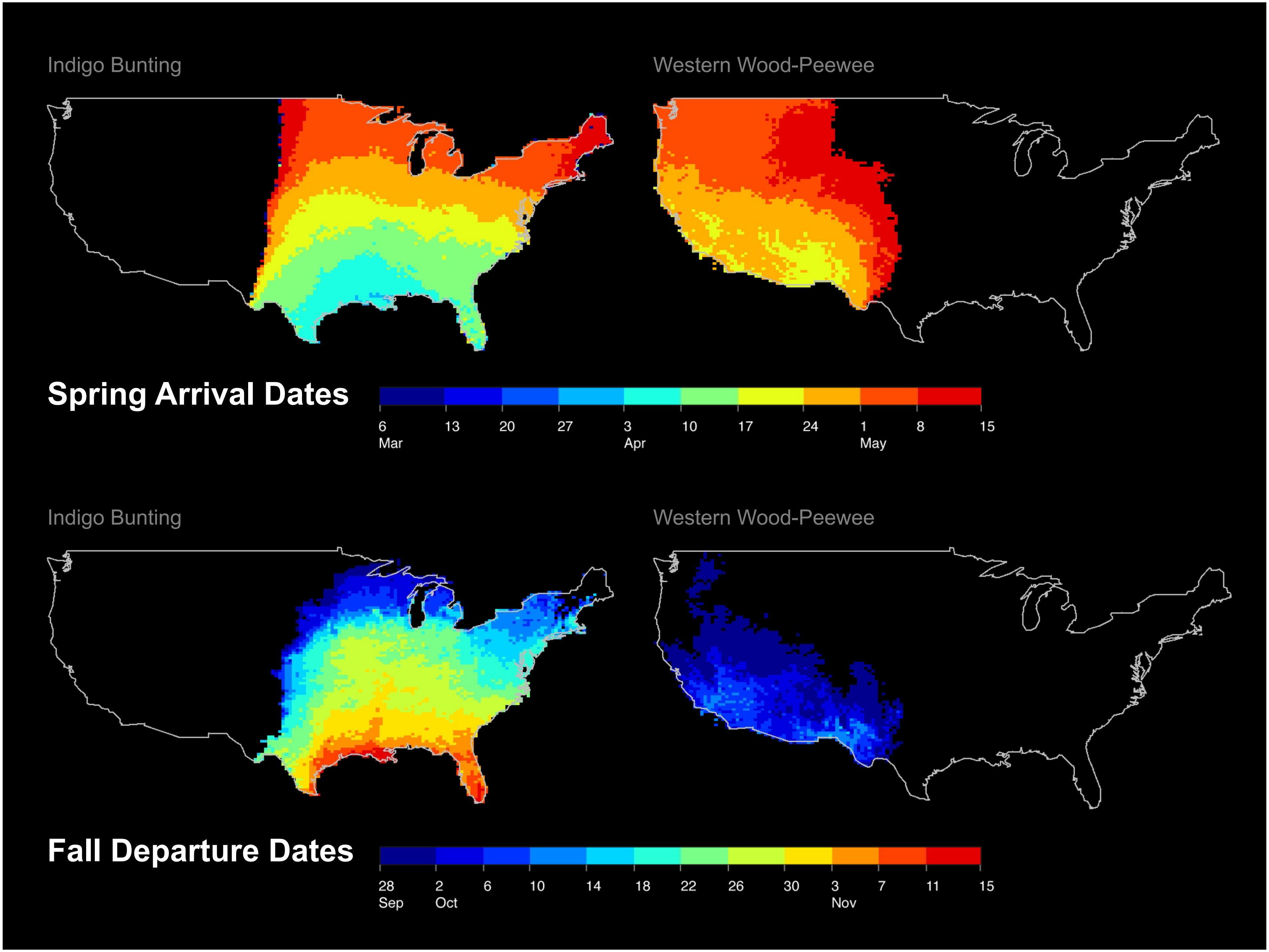


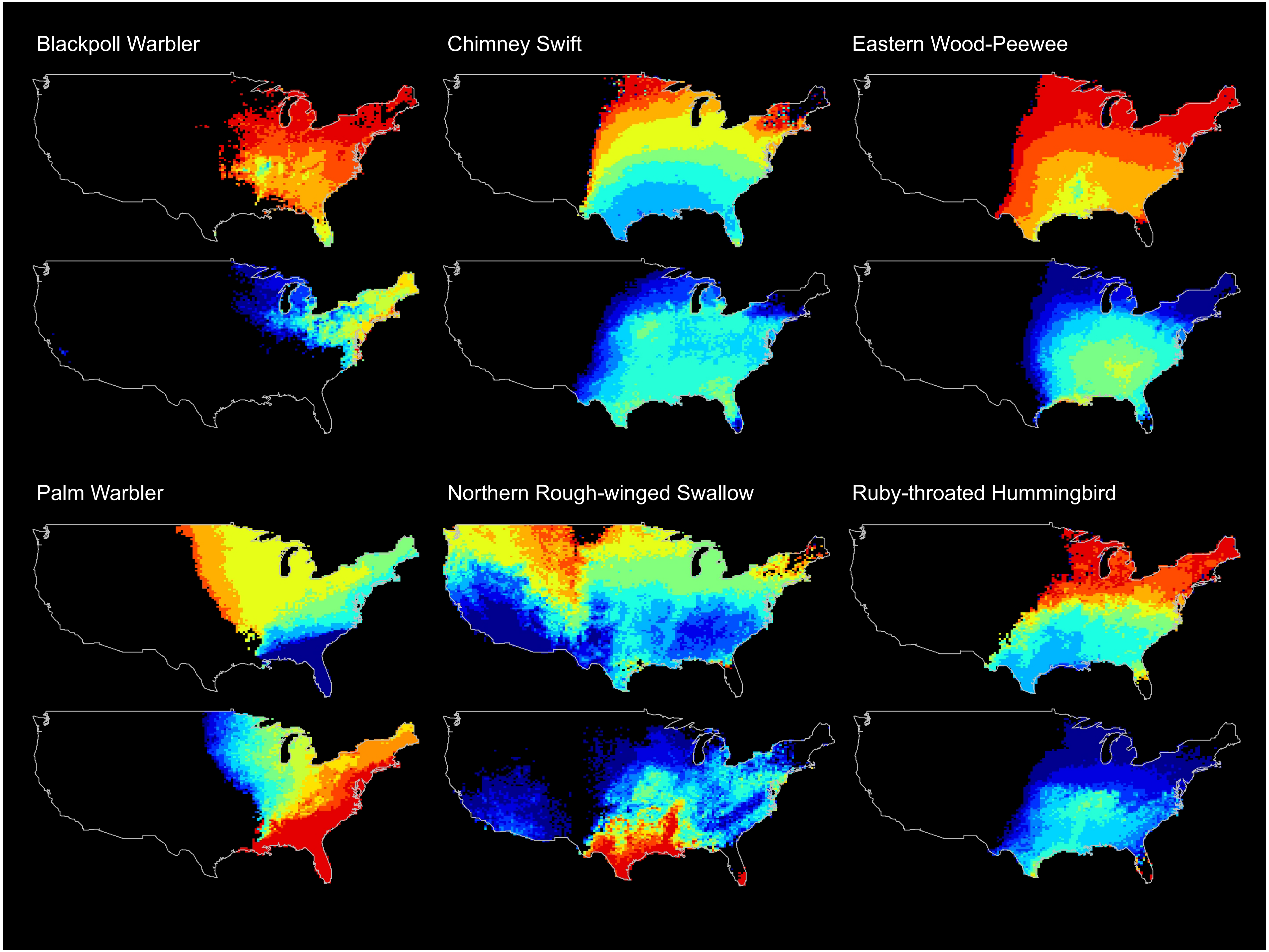
Yellow Warbler | Occurrence Trajectories
Ithaca
Denver
Los Angeles
PROBABILIY OCCURRENCE
0.8
0.6
0.4
0.2
0.0
J
F
M
A
M
J
J
A
S
O
N
D
DATE


Yellow Warbler | Migration Dates
Ithaca
PROBABILIY OCCURRENCE
0.8
0.6
0.4
0.2
0.0
J F M A M J J A S O N D
DATE


Yellow Warbler | Migration Dates
Ithaca
PROBABILIY OCCURRENCE
0.8
0.6
0.4
0.2
0.0
J F M A M J J A S O N D
DATE


Yellow Warbler
Migration Dates
Ithaca
PROBABILIY OCCURRENCE
0.8
0.6
0.4
0.2
0.0
J
F
M
A
M
J
J
A
S
O
N
D
DATE


Indigo Bunting
Western Wood-Peewee
Spring Arrival Dates
6 Mar
13
20
27
3 Apr
10
17
24
1 May
8
15
Indigo Bunting
Western Wood-Peewee
Fall Departure Dates
28 Sep
2 Oct
6
10
14
18
22
26
30
3 Nov
7
11
15


Blackpoll Warbler
Chimney Swift
Eastern Wood-Peewee
Palm Warbler
Northern Rough-winged Swallow
Ruby-throated Hummingbird

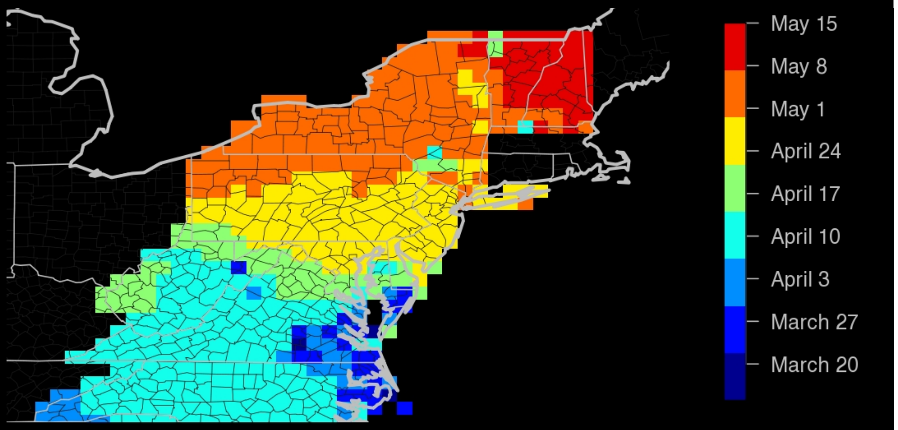
Environmental Cues of Migration

Include spatiotemporally varying covariates to study environmental cues of migration timing: NDVI

Questions

1. Is Red-eyed Vireo migration timing associated with NDVI?
2. If so, how is migration timing, direction, and speed affected by NDVI?

Spring Arrival Dates



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Experiment

1. Fit STEM with NDVI predictor
2. Advance "greening dates" by 14 days

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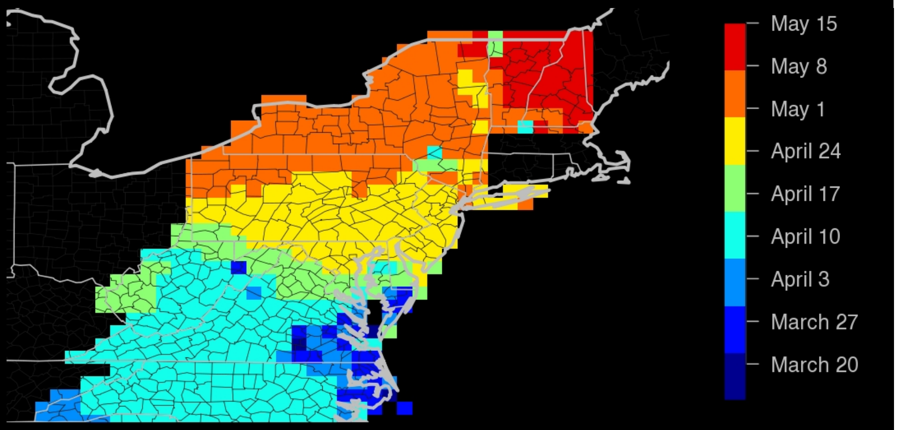

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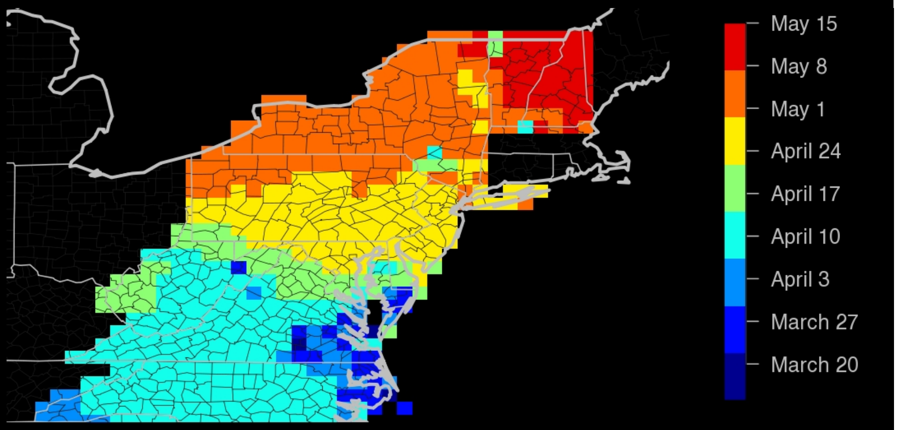

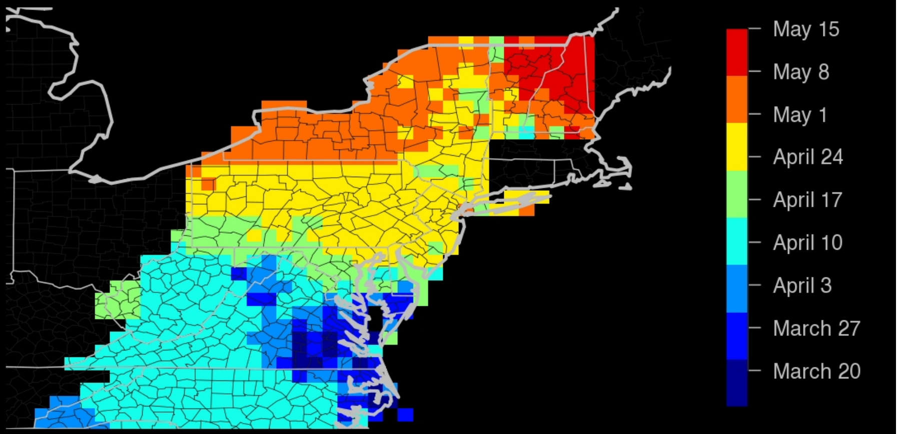

Spring Arrival Dates with Advanced Greening

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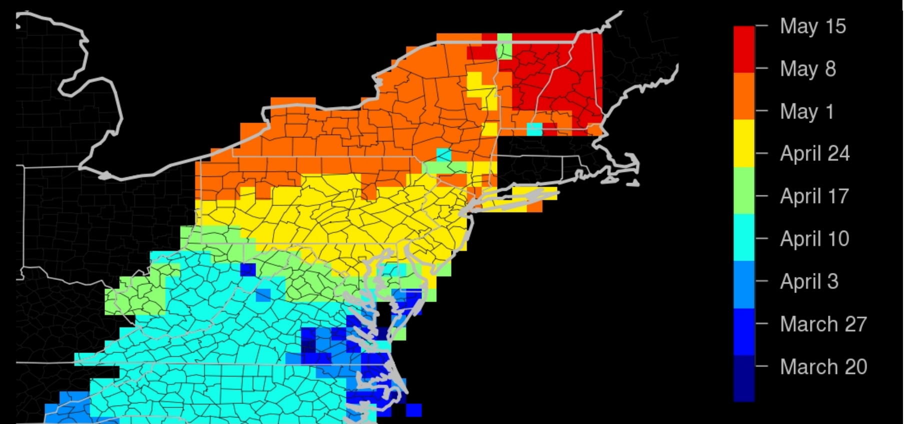

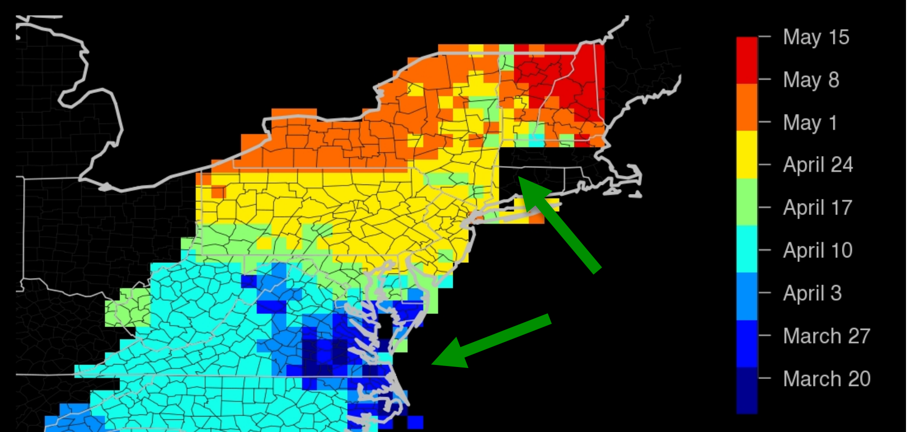

Spring Arrival Dates with Advanced Greening

Overview

- Exploratory Dynamic Spatiotemporal Modeling
- Automatically adapts to many dynamic processes
- Multi (bi)–scale approach

Next Steps

- Replicate over Years to explore inter-annual differences
- Improve Validation Methods – Spatial & Temporal correlation
- Identify & control sources of bias
  - Spatial sampling bias
  - Habitat sampling bias
  - Temporal variation in detection rates
  - Etc.
- Expand NDVI analysis
  - More species – compare different migration strategies
  - VI & Partial Dependence for NDVI
  - Explore other ST covariates