

# A Probabilistic Framework for Imputing Genetic Distances in Spatiotemporal Pathogen Models

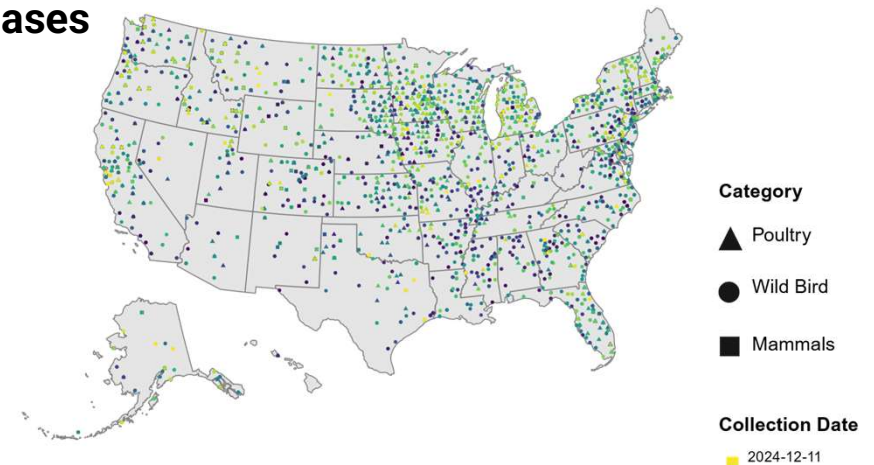
*Bridging genomic and spatial data to infer evolutionary relationships under sparse sequencing.*

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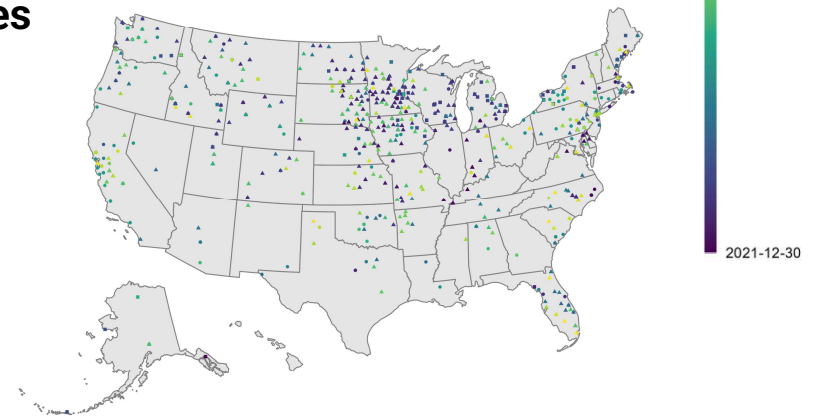
# The Problem

- Only a small fraction of detected cases are genetically sequenced
- Without sequences, we lose the ability to measure evolutionary relatedness between detections
- This limits how well spatial models can track viral movement and emergence

Reported Cases

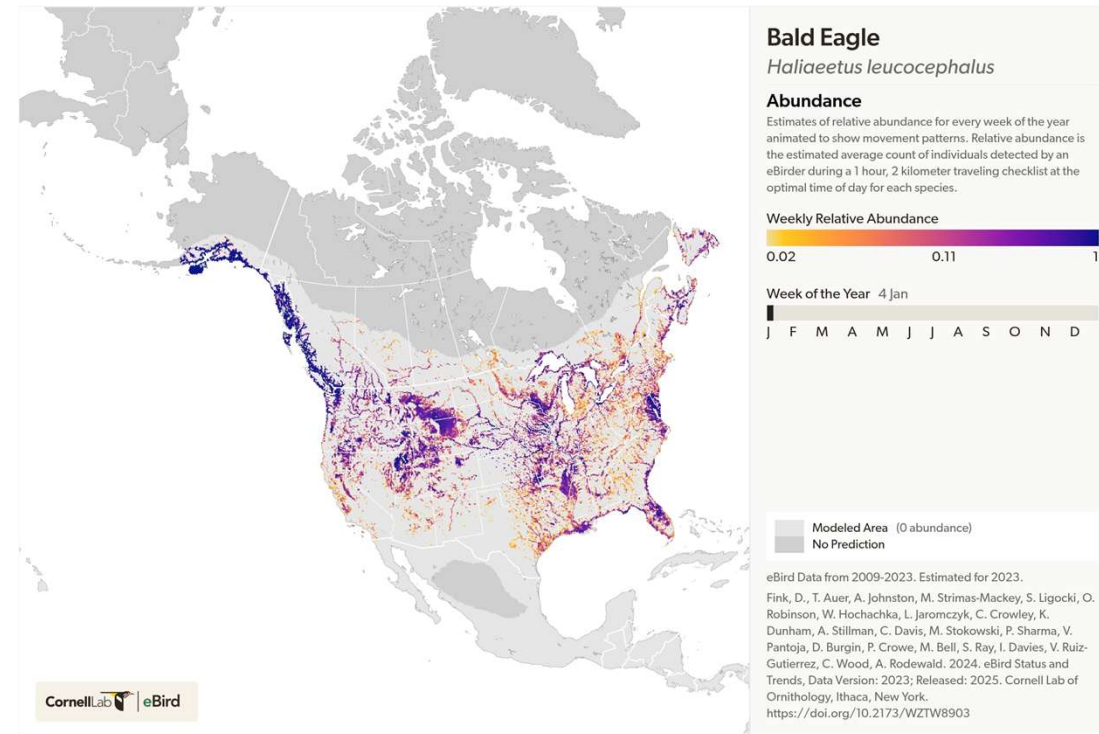


Sequences



# Background

- Long-distance migration spreads viruses across continents
- Wildlife–livestock interfaces drive spillover
- Animal surveillance detects risk before human cases appear



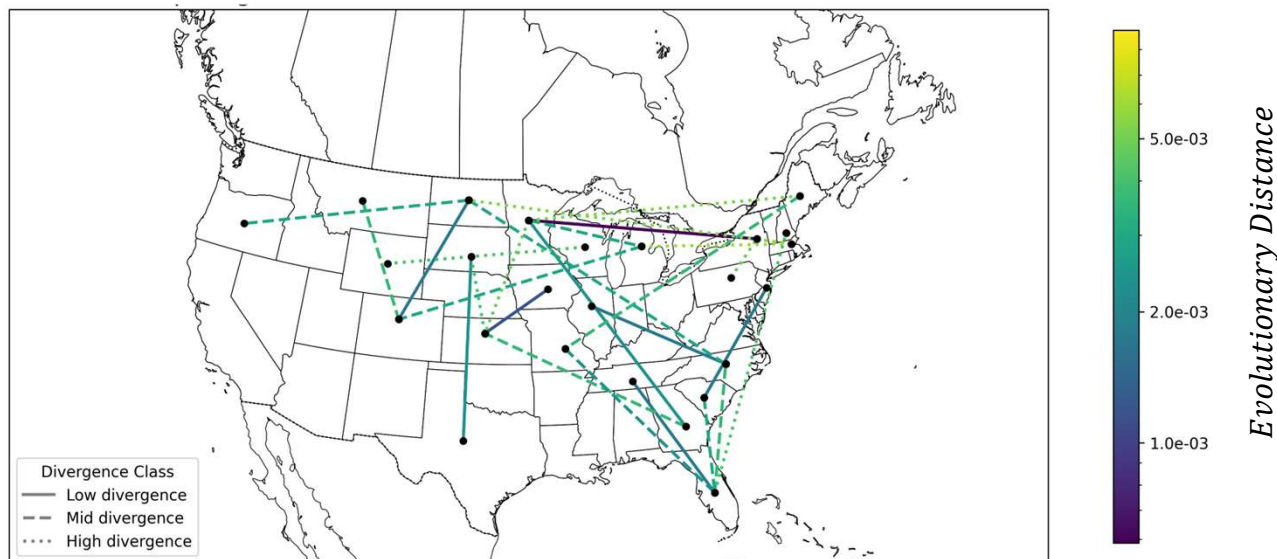
# What are evolutionary distances?

- Measure of evolutionary divergence between two genomes
- Counts the number of nucleotide changes, adjusted for multiple substitutions
- Often inferred from a phylogenetic tree as the *path length* between two samples
- Sequence comparisons produce genetic distance matrices that underpin clustering, diffusion, and phylogenetic models

[illegible]

# Why Not Just Use Space or Time?

- Without divergence, we lose the evolutionary structure of spread
- Two distant detections can be genetically identical if linked by migration
- Evolution introduces non-Euclidean, asymmetric divergence patterns that simple spatial metrics can't capture



# Problem Formulation

Let  $S = \{s_1, \dots, s_n\}$ : sequenced cases  
     $A = \{a_1, \dots, a_n\}$ : unsequenced cases

For  $i \in S \cup A, j \in S$ :  
    metadata vector  $x_{ij} \in \mathbb{R}^p$

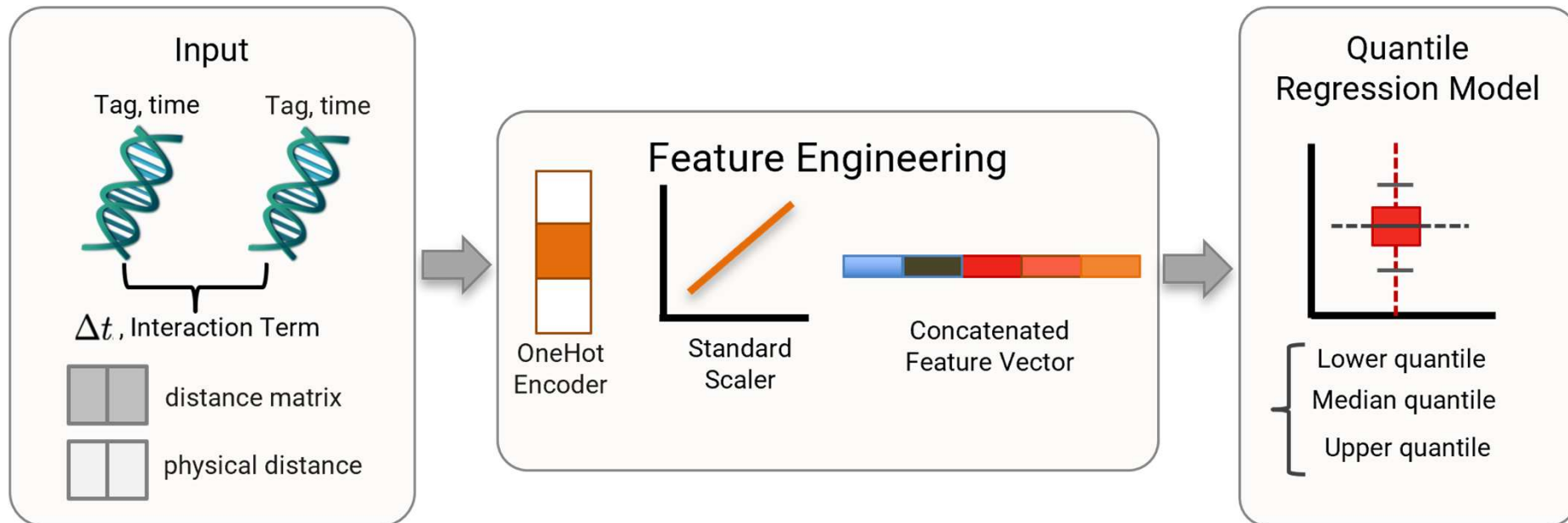
Observed divergence( only for  $S \times S$ ):  
     $d_{ij} = K80(s_i, s_j)$

Learn conditional quantiles:  
     $Q_\tau(d_{ij} \mid x_{ij}), \quad \tau \in \{0.05, 0.5, 0.95\}$

Train on  $S \times S$ ; infer on  $A \times S$

# Metadata-Driven Genetic Distance Imputation

- Learn how metadata explain evolutionary separation between cases
- Train on sequenced pairs to learn the relationship between:
  - Time difference ( $\Delta t$ )
  - Spatial distance ( $\Delta_{\text{geo}}$ )
  - Host taxonomy
  - Year
- Once trained, apply the model to unsequenced detections to infer plausible divergence intervals
- Predicted intervals capture biological uncertainty arising from mutation variability and incomplete sampling



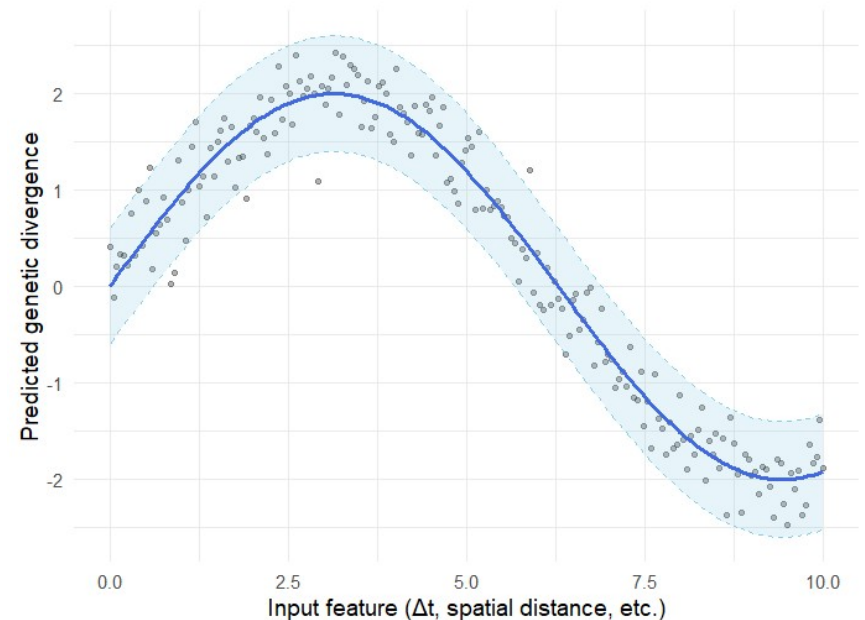
# Evolutionary Distance Measure

- We use the Kimura two-parameter model (K80) to quantify genetic divergence
  - Corrects for unobserved mutations and distinguishes transitions vs. transversions
- Provides a biologically meaningful, continuous distance between sequences
- Serves as our ground truth target for learning

$$d = -\frac{1}{2}\ln(1 - 2P - Q) - \frac{1}{4}\ln(1 - 2Q)$$

# Quantile Regression Framework

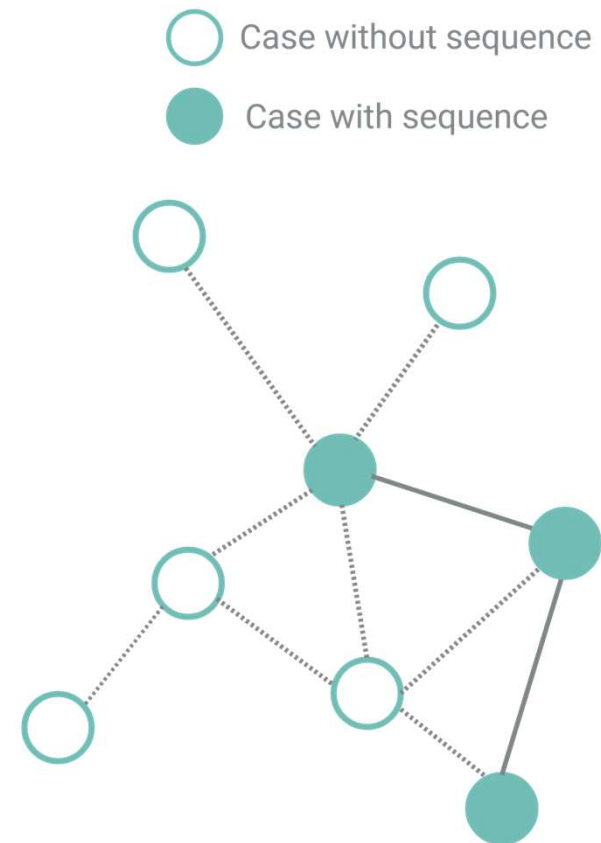
- Three models estimate the 5th, 50th, and 95th percentiles using gradient-boosted trees
- Quantile (pinball) loss allows asymmetric treatment of over- vs under-prediction
- The resulting interval represents expected evolutionary variability



| Class | Distance Range       | Mean Distance    |
|-------|----------------------|------------------|
| LOW   | [0.000000, 0.003246] | $\approx 0.0020$ |
| MID   | [0.003246, 0.006632] | $\approx 0.0045$ |
| HIGH  | [0.006632, 0.492703] | $\approx 0.0193$ |

# Data & Training Setup

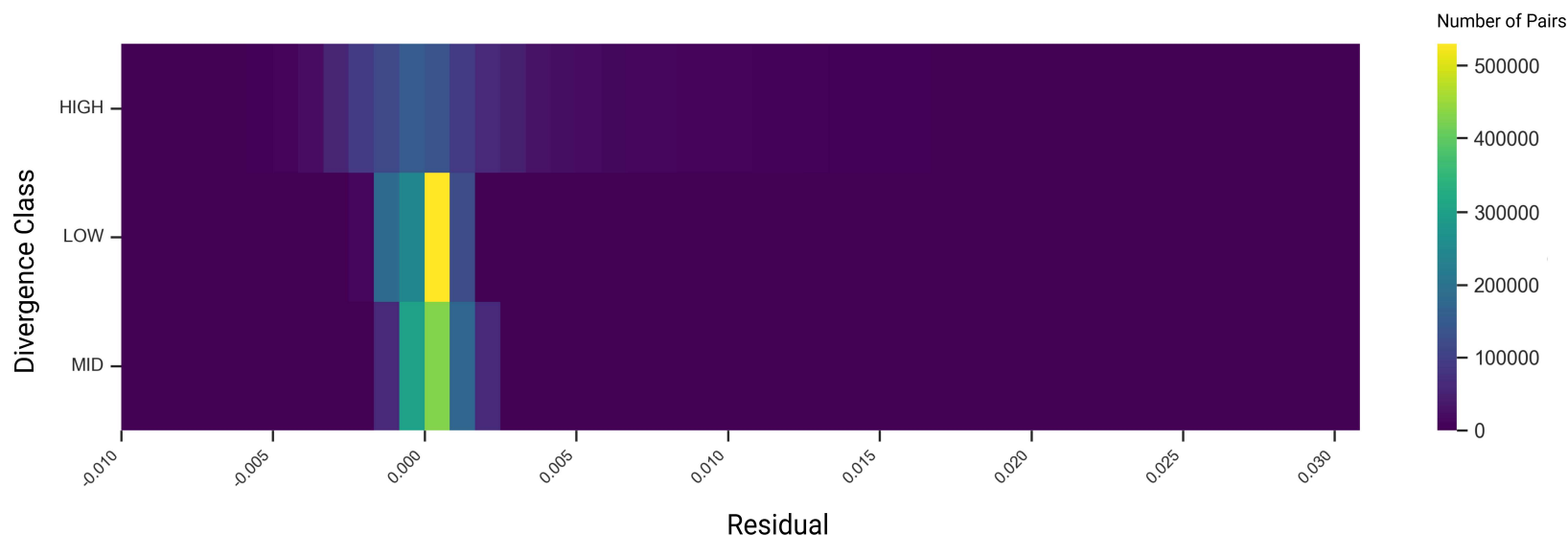
- *AvianUS* Dataset:
  - 2,143 wild bird detections (2021–2024)
  - ~1 M valid sequence pairs used for training
- Cross-validated by region and year to avoid spatial autocorrelation
- Model then applied to all unsequenced detections for nationwide inference



# Model Performance

- Model reproduces observed divergence patterns across evolutionary scales
- Intervals are sharp and well-calibrated & uncertainty reflects real biological variability
- Strongest correspondence in local and regional transmission contexts

| Class | MAE     | RMSE    | R <sup>2</sup> | Coverage (%) |
|-------|---------|---------|----------------|--------------|
| LOW   | 0.00060 | 0.00077 | 0.03           | 94.95        |
| MID   | 0.00064 | 0.00080 | 0.07           | 92.63        |
| HIGH  | 0.01074 | 0.04352 | 0.03           | 90.07        |
| TOTAL | 0.00283 | 0.00542 | 0.19           | 92.60        |

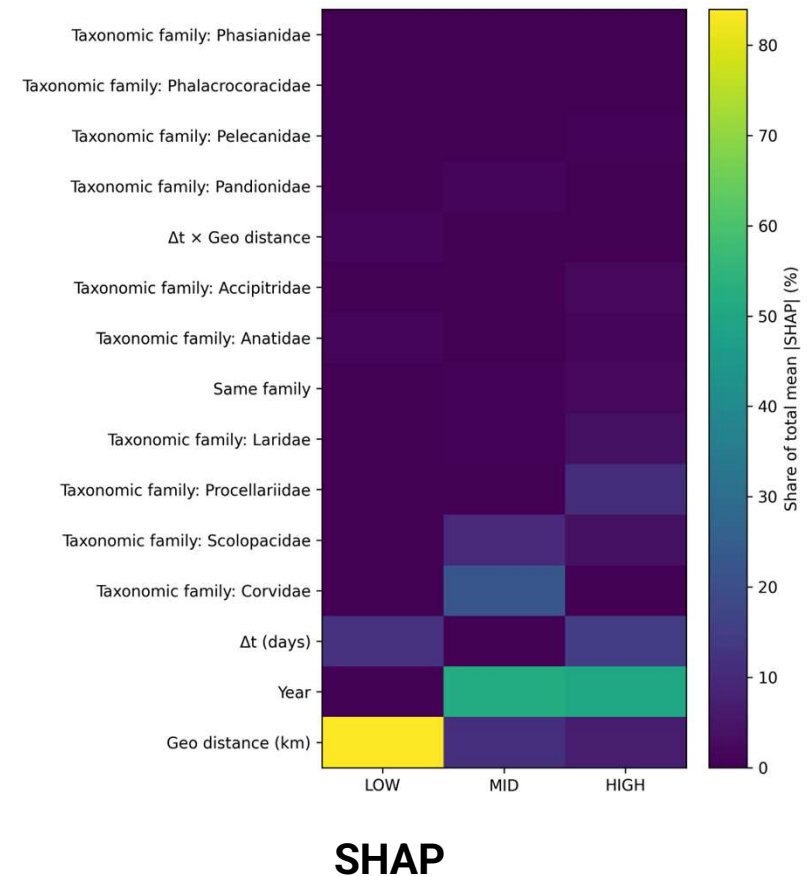


# Feature Effects & Interpretability

- *Low divergence*: spatial and temporal separation dominate
- *Mid divergence*: time × host interactions gain influence
- *High divergence*: host taxonomy and year explain most variation
- The model learns biologically interpretable transitions: from within-lineage drift to cross-lineage diversity

## Ablation Study

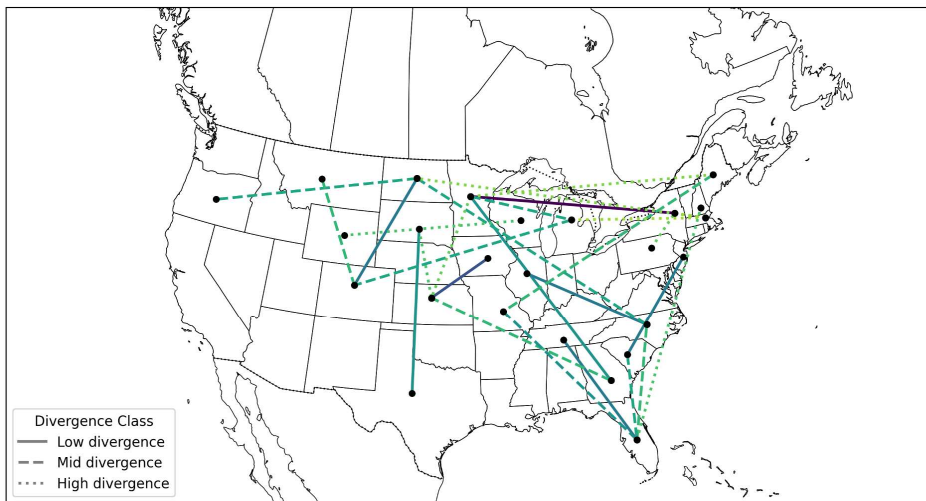
| Feature Removed       | $\Delta$ MAE | $\Delta$ Interval Width |
|-----------------------|--------------|-------------------------|
| $\Delta t$            | +0.00021     | +0.00085                |
| Physical Distance     | +0.00013     | +0.00049                |
| Same Taxonomic Family | +0.00009     | +0.00026                |
| Interaction Term      | +0.00015     | +0.00037                |
| Year                  | +0.00007     | +0.00031                |



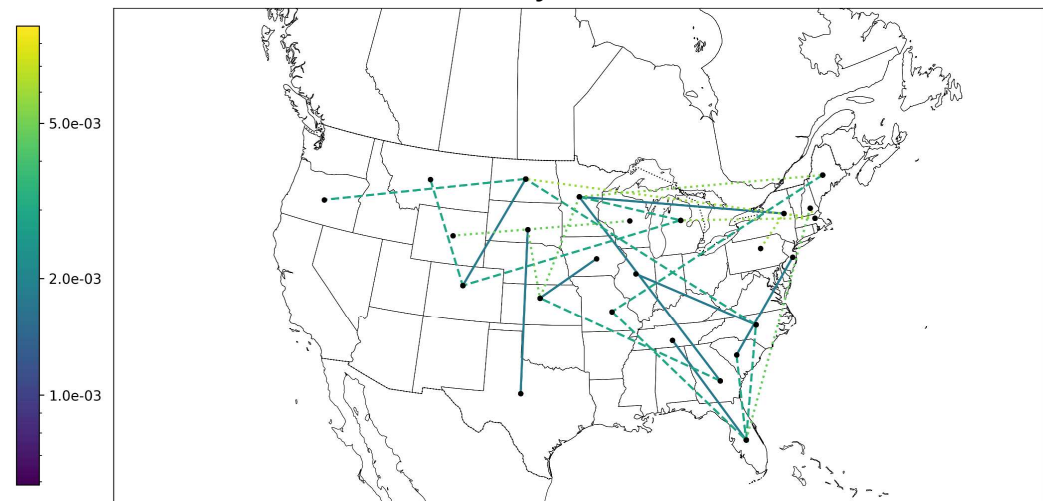
# Case Study

- Observed vs. predicted divergence maps show parallel gradients across regions
- Predicted divergence mirrors observed evolutionary gradients across space and host ecology
- Accurately reflects local transmission, regional mixing, and independent introductions

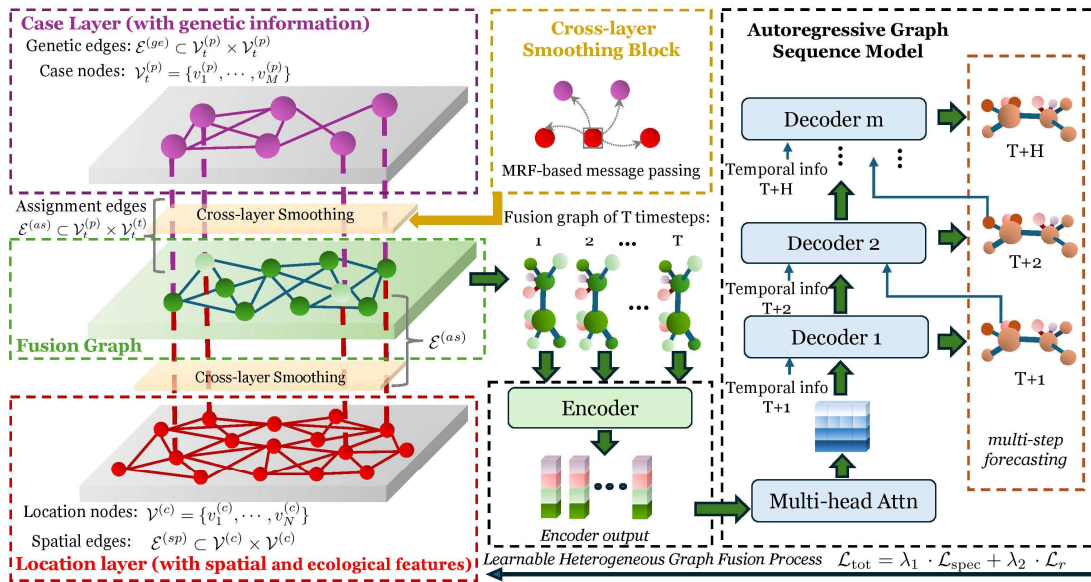
Observed Evolutionary Distance



Predicted Evolutionary Distance



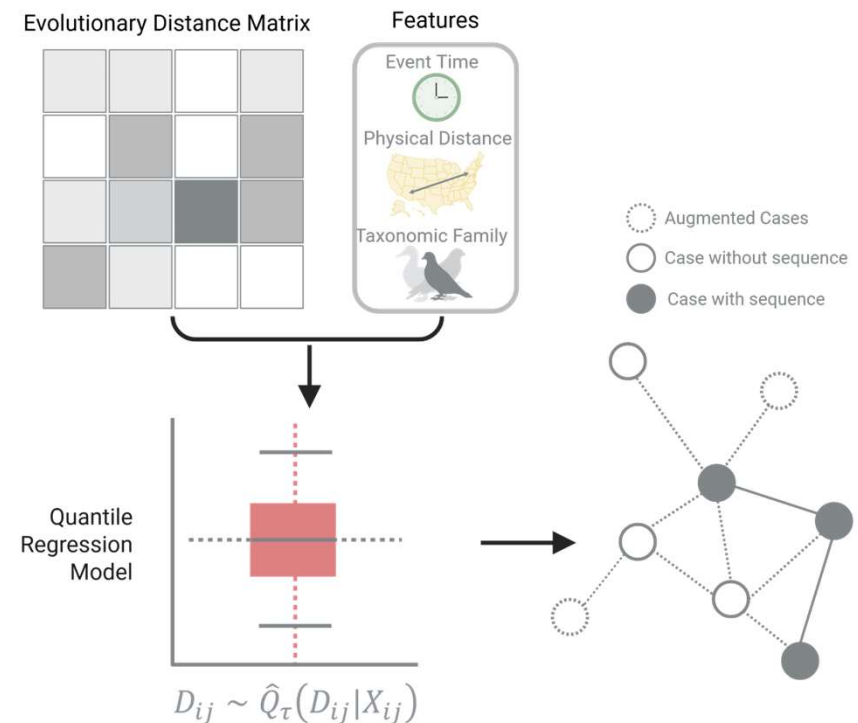
# Integrating Imputed Distances into Spatiotemporal Graphs



- Each node = detection; edges weighted by observed or imputed divergence
- Supports diffusion modelling and cluster detection under missing data
- Supports our broader BLUE framework for pathogen forecasting

# Summary

- Metadata-driven imputation of genetic distances under missing data
- Quantile regression provides interpretable, uncertainty-aware predictions
- Scales to continental surveillance systems with minimal sequence coverage



# Acknowledgements

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Link to the Paper

