

# **Towards an Integrated Surveillance for Lassa fever: Evidence from the Predictive Modeling of Lassa fever Incidence in Nigeria.**

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# Outline

Dataset: Overview

Modeling Choices

Non-linear: Long short-term memory recurrent neural network (LSTM)

One Model Per State - Climate + Cases Predictions

One Model Per State - Cases Only Predictions

LSTM Model Per State Model Comparison

Linear: Multivariate Autoregressive Model (Mar)

All Variable: One Mar Model Per State

One Mar Model Per State - Cases Only Predictions

Mar Model Per State Model Comparison

## Dataset: Overview

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# Climate and Case Count Data

## Data Overview:

Weekly Lassa fever case counts for Bauchi, Edo, and Ondo states (Nigeria)

Time period: January 2018 – December 2024

Corresponding weekly climate data collected over the same period

## Climate Variables (per week):

Minimum Temperature

Maximum Temperature

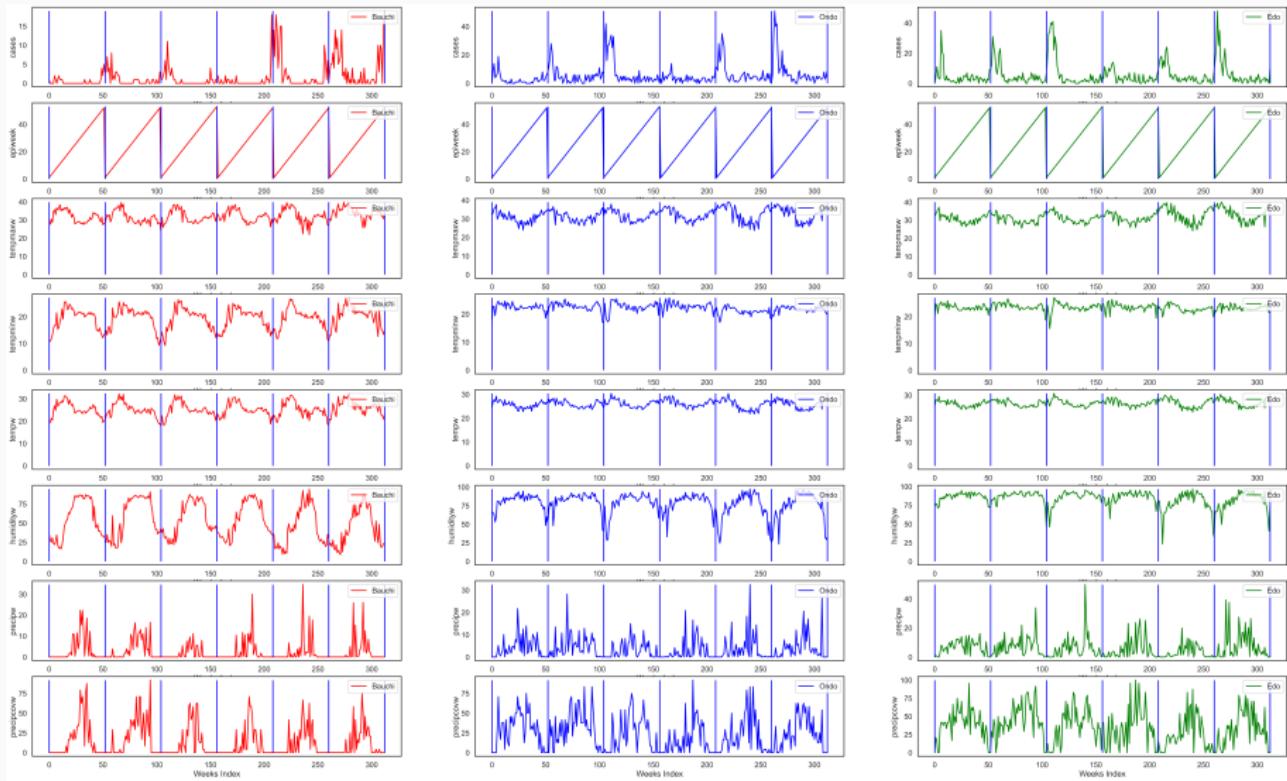
Average Temperature

Precipitation

Precipitation Coverage

Average Humidity

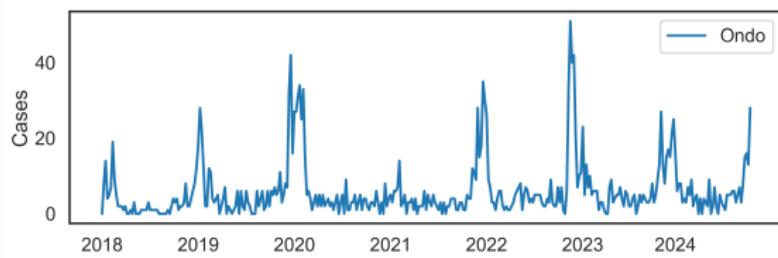
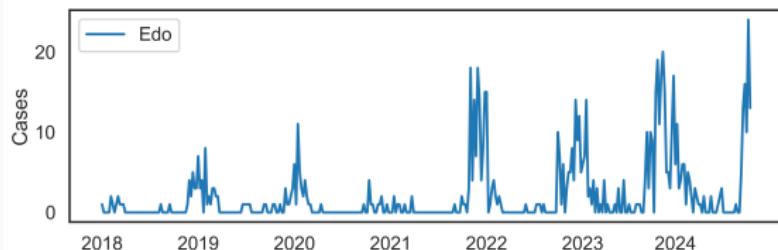
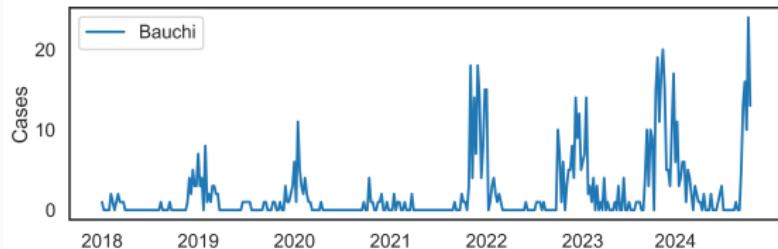
# Dataset: Plots



Observations - The data appears to exhibit characteristics of a **stationary stochastic process**.

# Dataset

## Data - Per State



# Data Split and Training Plan

## Data Split:

**Train:** 2018–2022 (per-state data)

**Test:** 2023, 2024 (with prior context)

## Modeling Strategies:

LSTM

MAR

## Experiment Variants:

**State-wise:** One model per state

7D input → 7D output (climate + cases)

7D input → 1D output ((climate , previous cases)→ cases)

**Unified:** One model across all states

## Modeling Choices

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# Non-linear Model: Long Short-Term Memory (LSTM)

## Prediction Variants:

**Single-output (Lassa case count only):**

$$y_t = f(\{y_{t-i}\}_{i=1}^4; \mathbf{w})$$

**Multivariate output (case count + climate variables):**

$$\mathbf{y}_t = f(\{y_{t-i}\}_{i=1}^4; \mathbf{w})$$

Where:

$f$  : LSTM prediction function

$y_t \in \mathbb{Z}^+$  : Predicted Lassa fever case count at time  $t$

$\mathbf{x}_{t-i} \in \mathbb{R}^6$  : Climate variables at time  $t - i$

$\mathbf{y}_t = (\mathbf{x}_t, y_t) \in \mathbb{R}^7$  : Full observation vector (climate + cases)

$t$  : Discrete time step (e.g., week)

$\mathbf{w}$  : Trainable parameters of the LSTM model

# LSTM Model: Training Loss Function

**Given:** Training dataset (time index omitted for clarity)

$$\mathcal{D} = \{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^n, \quad \mathbf{x}_i \in \mathbb{R}^d, \quad \mathbf{y}_i \in \mathbb{R}^m$$

**Loss Function:**

$$\mathcal{L}(\mathbf{w}) = \frac{1}{n} \sum_{i=1}^n \underbrace{\|f_{\mathbf{x}_i} - f(\mathbf{x}_i; \mathbf{w})\|^2}_{\text{MSE loss (climate features)}} + \underbrace{\sum_{i=1}^n [f_y - y_i \log f_y]}_{\text{Poisson loss (case count)}} + \lambda \underbrace{\sum_{i=1}^n (\Delta f_y)^2}_{\text{Smoothness penalty}}$$

**Where:**

$f(\mathbf{x}_i; \mathbf{w})$ : LSTM output for all targets

$f_y$ : LSTM prediction of Lassa fever cases (scalar)

$f_{\mathbf{x}_i}$ : LSTM prediction of climate variables (multi-output case)

$\Delta f_y = f_{y,t+1} - f_{y,t}$ : First-order difference (temporal smoothness)

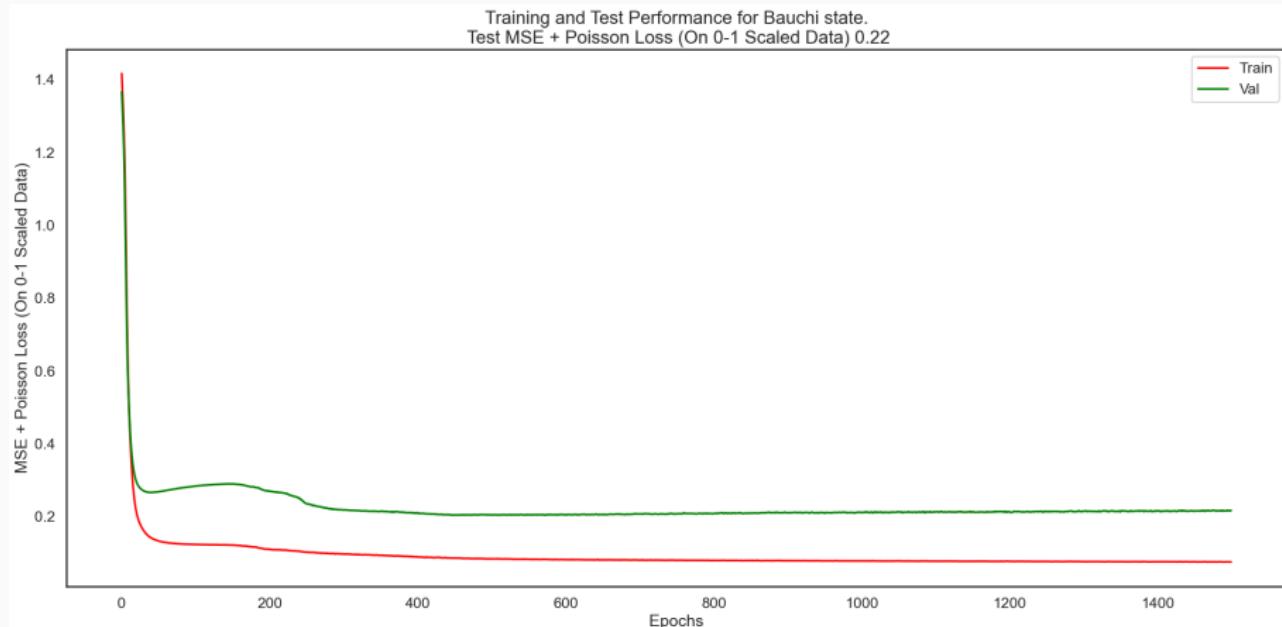
$\mathbf{w}$ : Trainable LSTM parameters

$\lambda$ : Smoothness regularization weight (e.g., 0.3)

# LSTM (Per-State Model) — Bauchi: Training Loss

**Variant:** All Variables — One Model per State

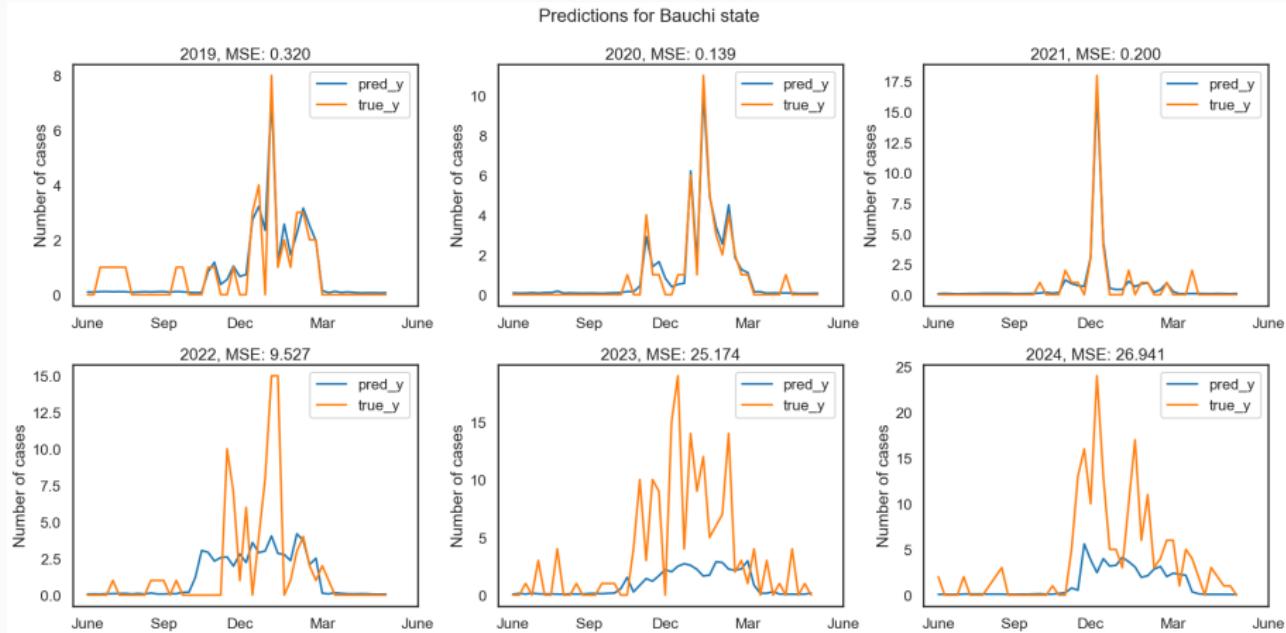
## Training Loss Curve



# LSTM (Per-State Model) — Bauchi: Predictions

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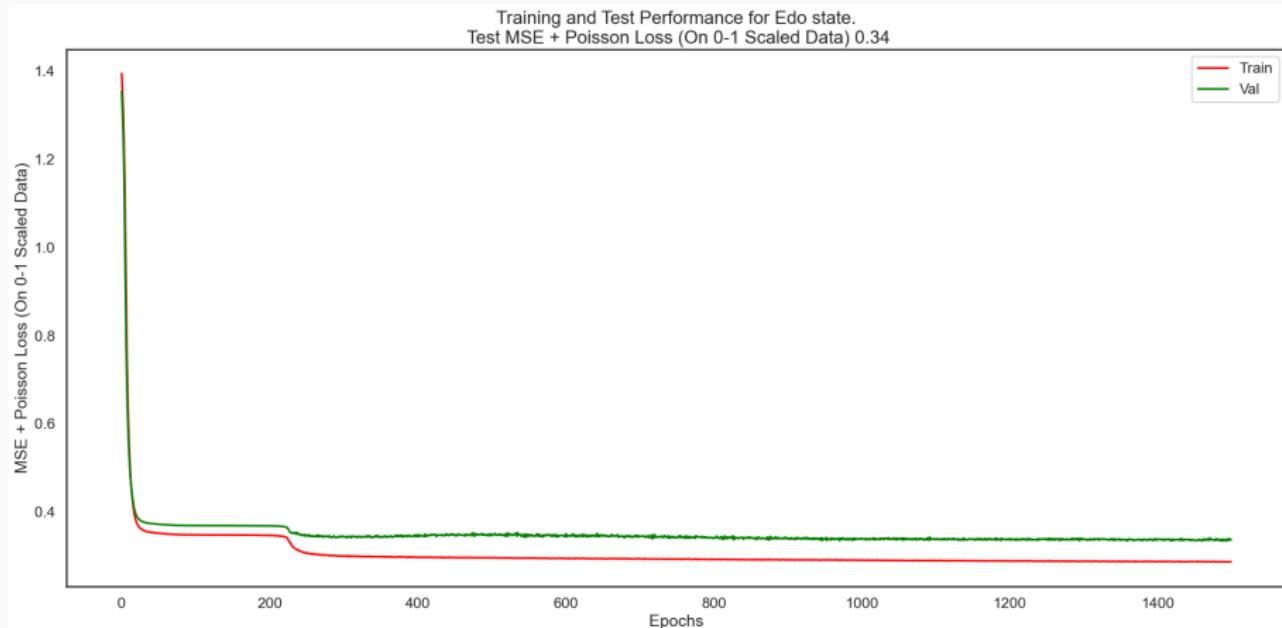
## Training and Test Predictions



# LSTM (Per-State Model) — Edo: Training Loss

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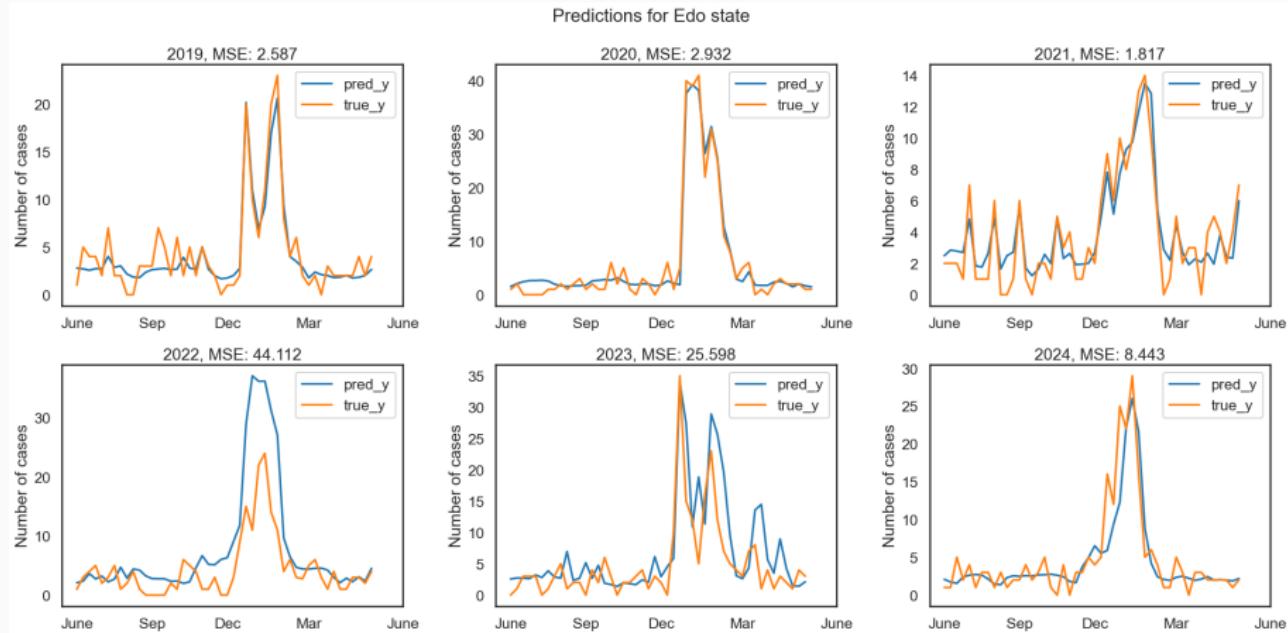
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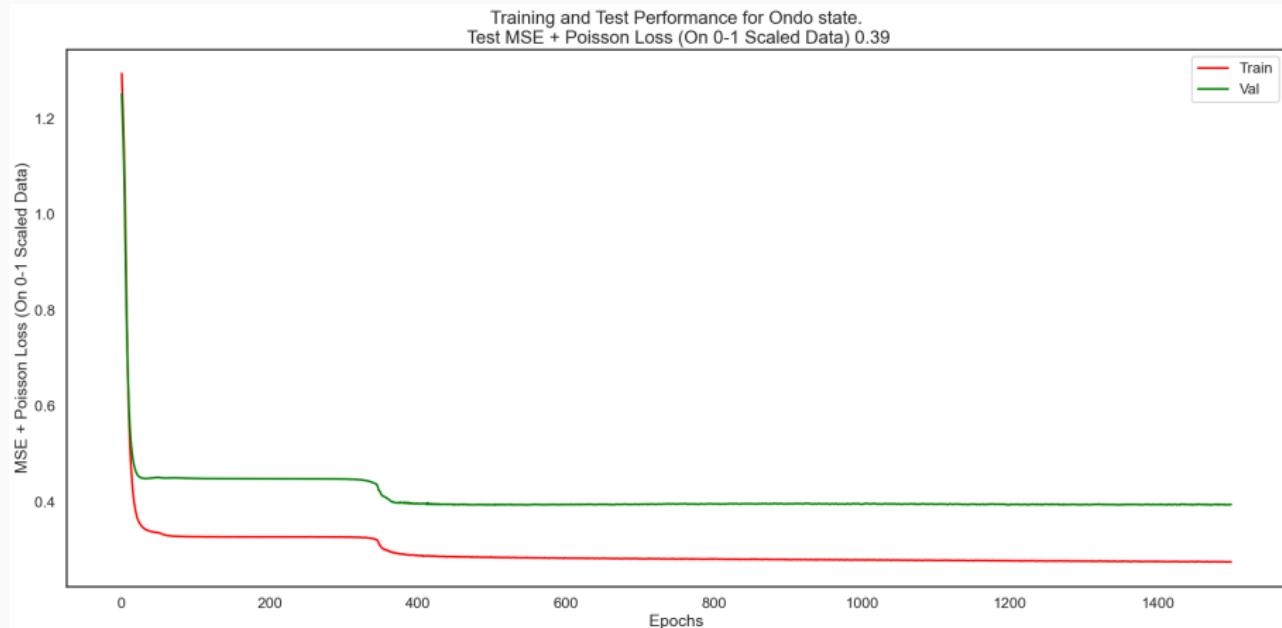
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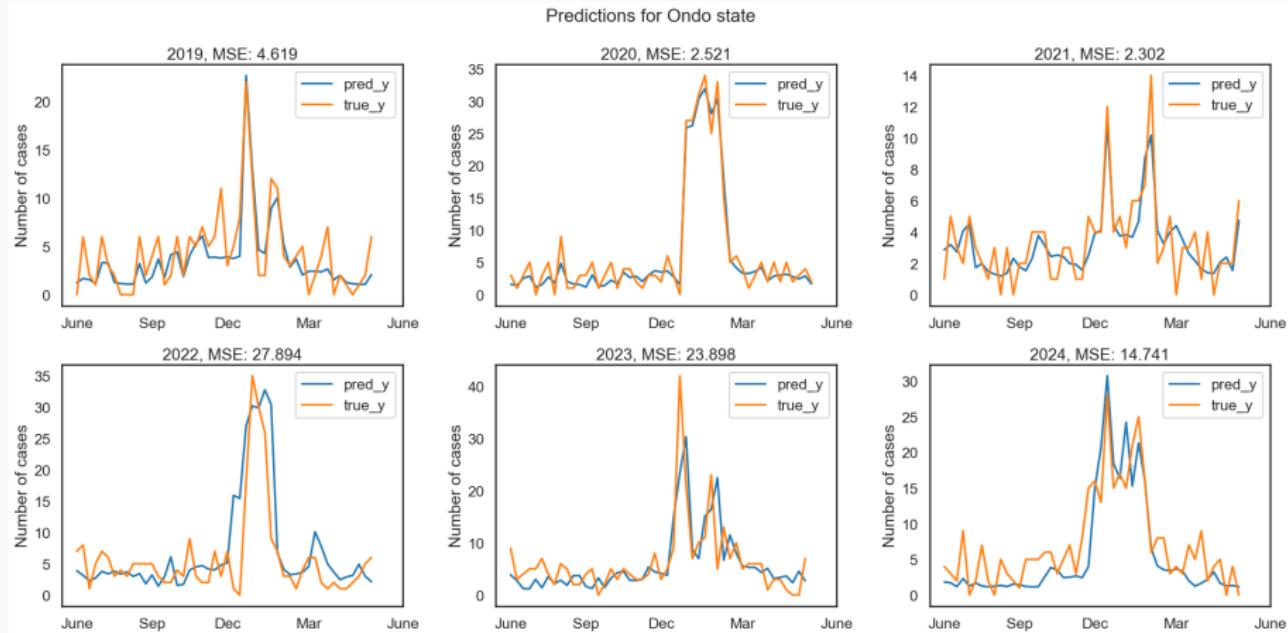
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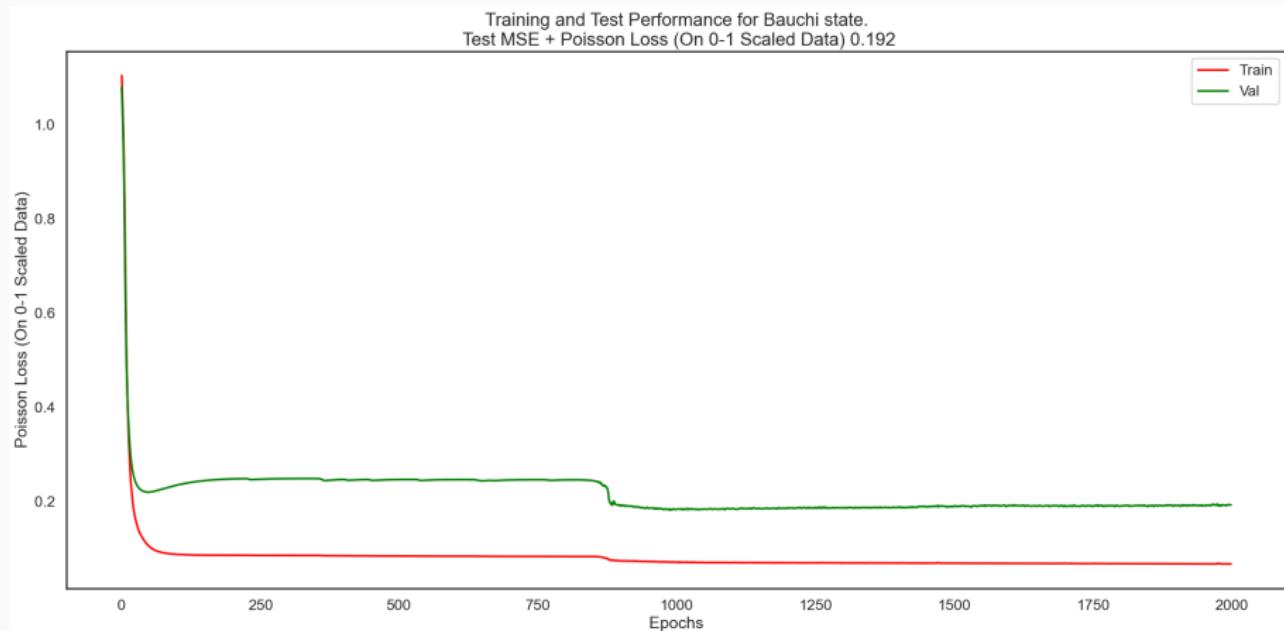
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# LSTM (Per-State, One-Output) — Bauchi: Training Loss

**Variant:** One Output — One Model per State

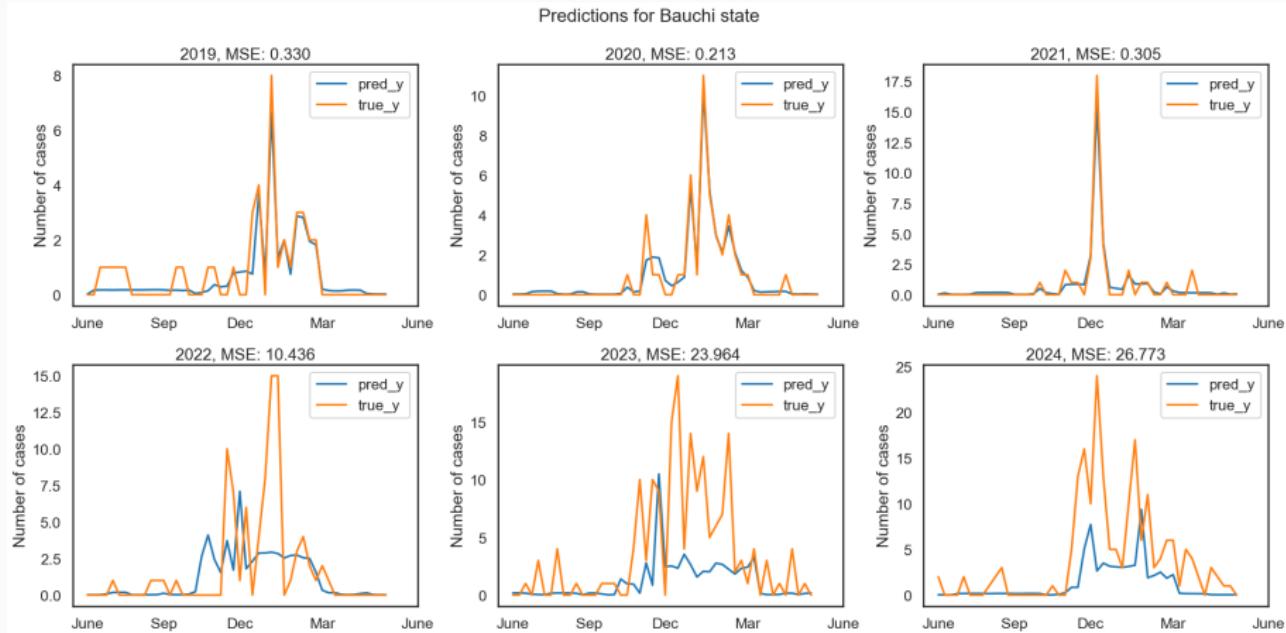
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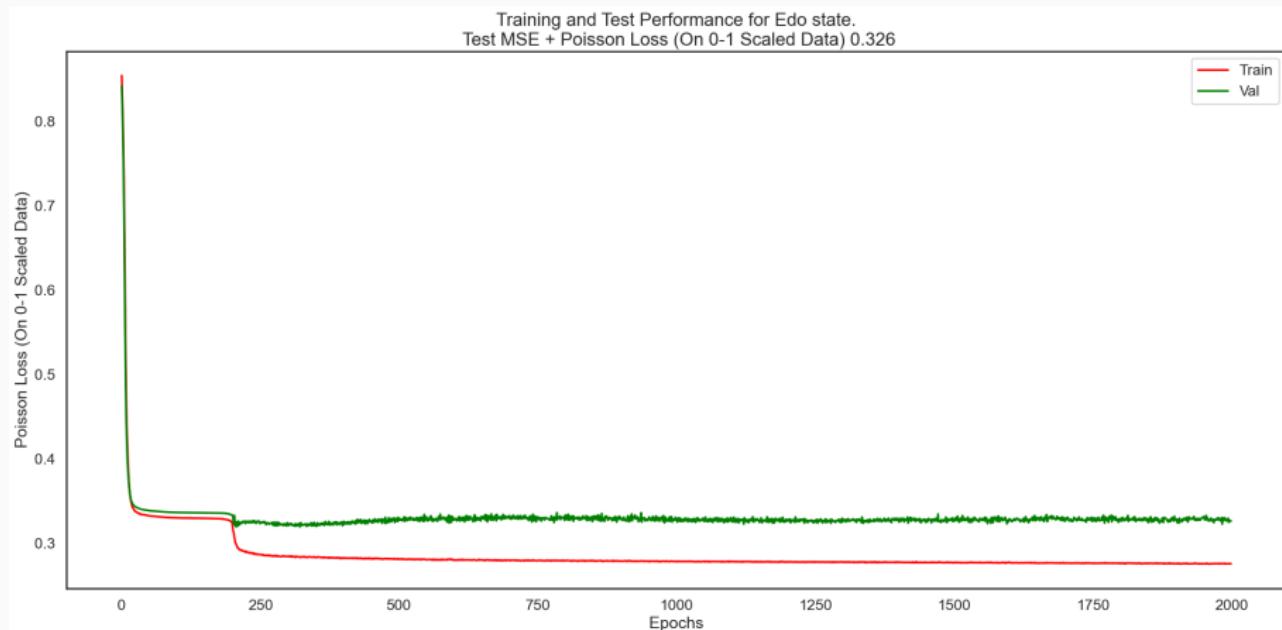
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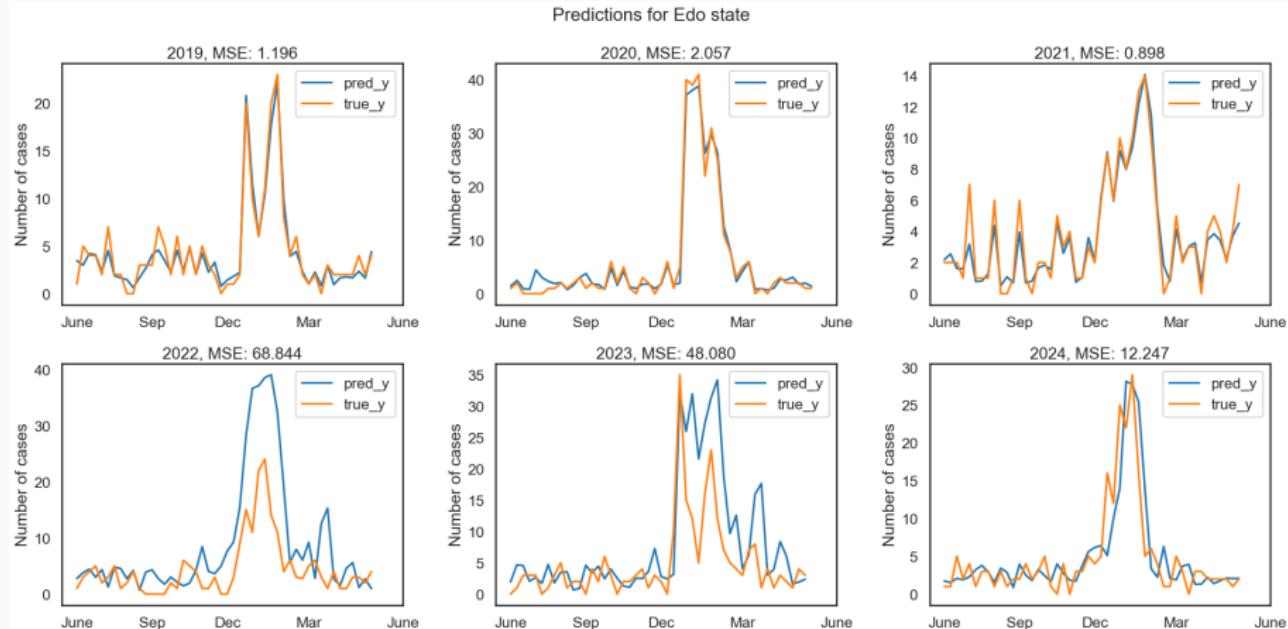
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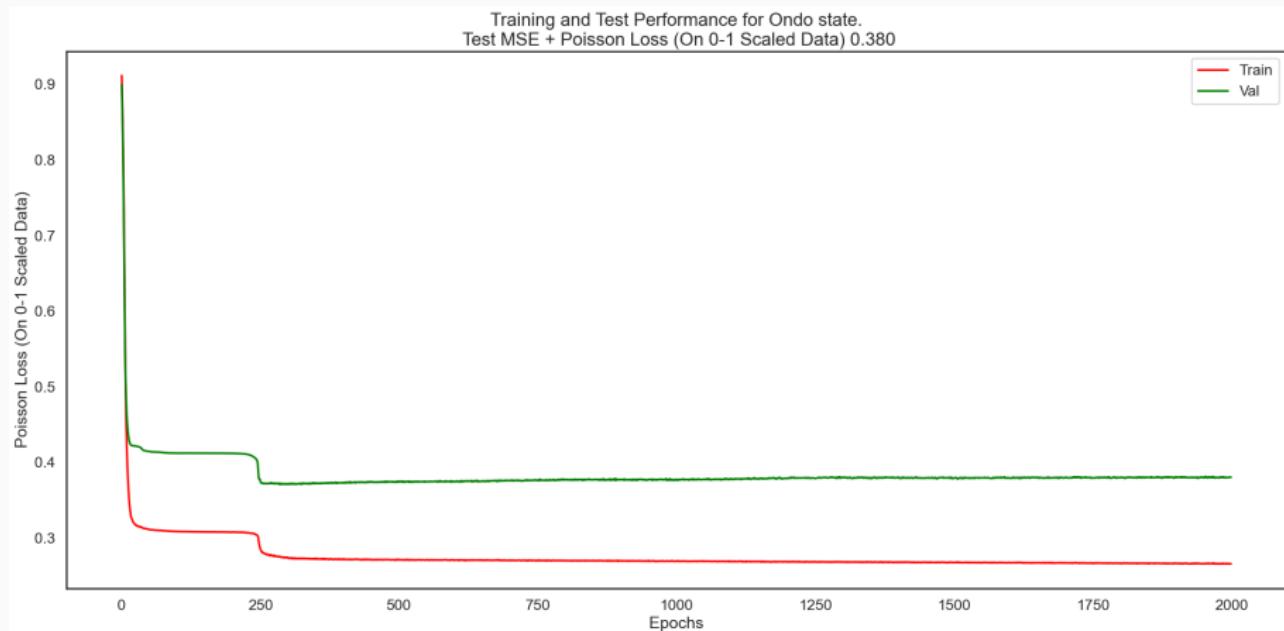
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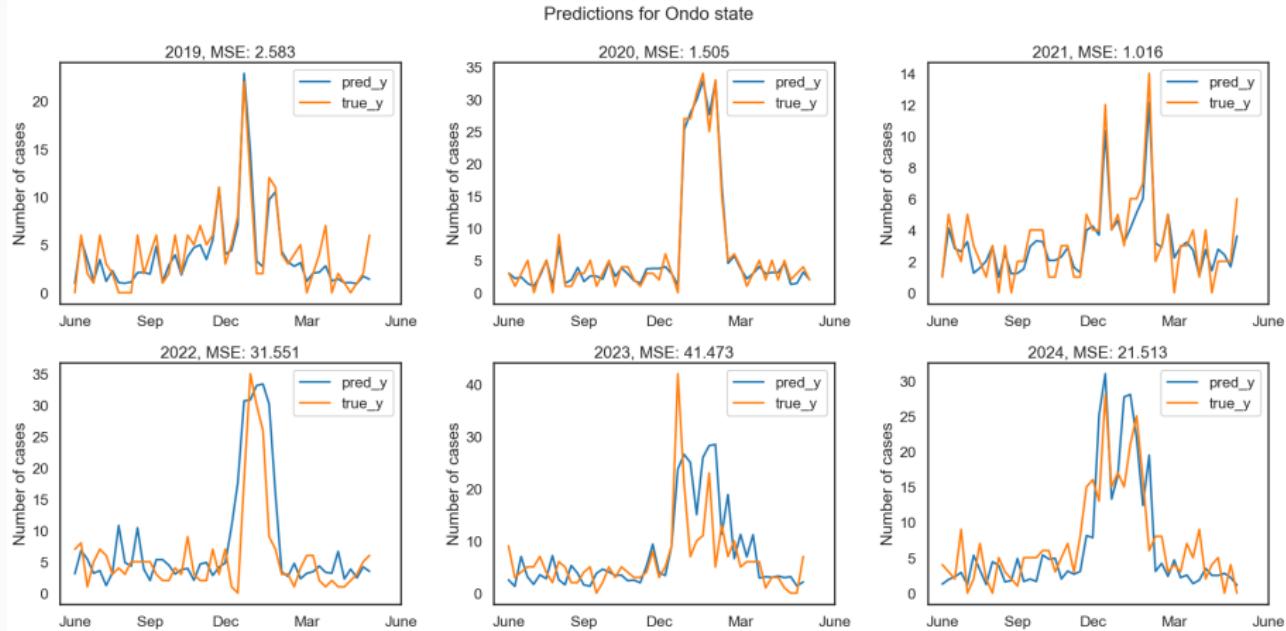
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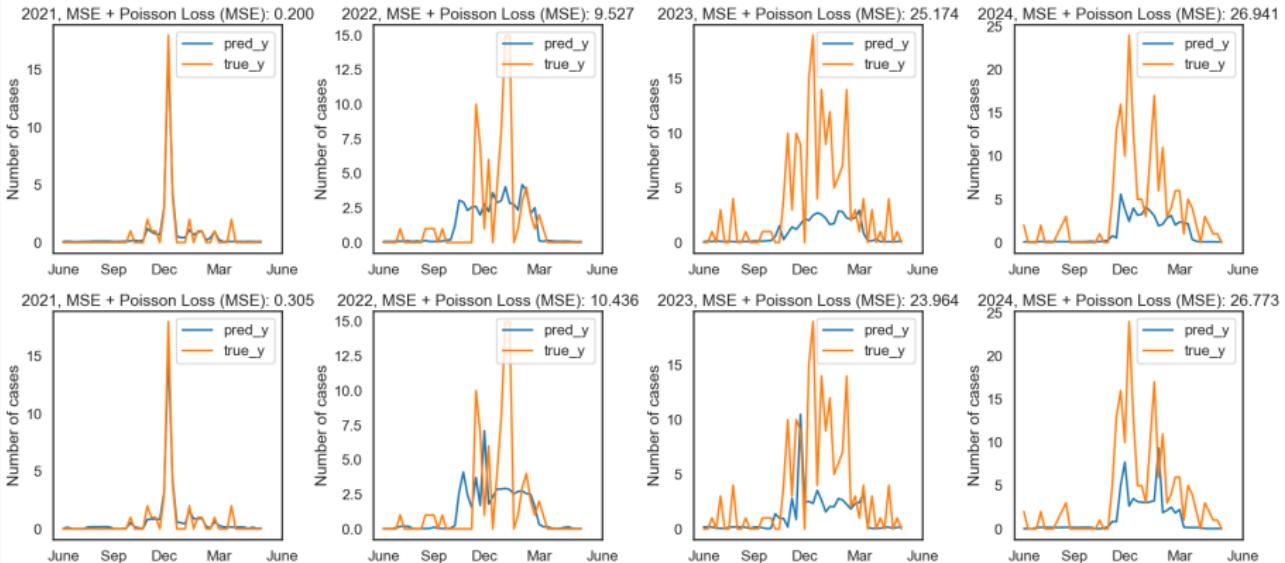
## Training and Test Predictions



# Per-State Model Comparison: All vs One – Bauchi Predictions

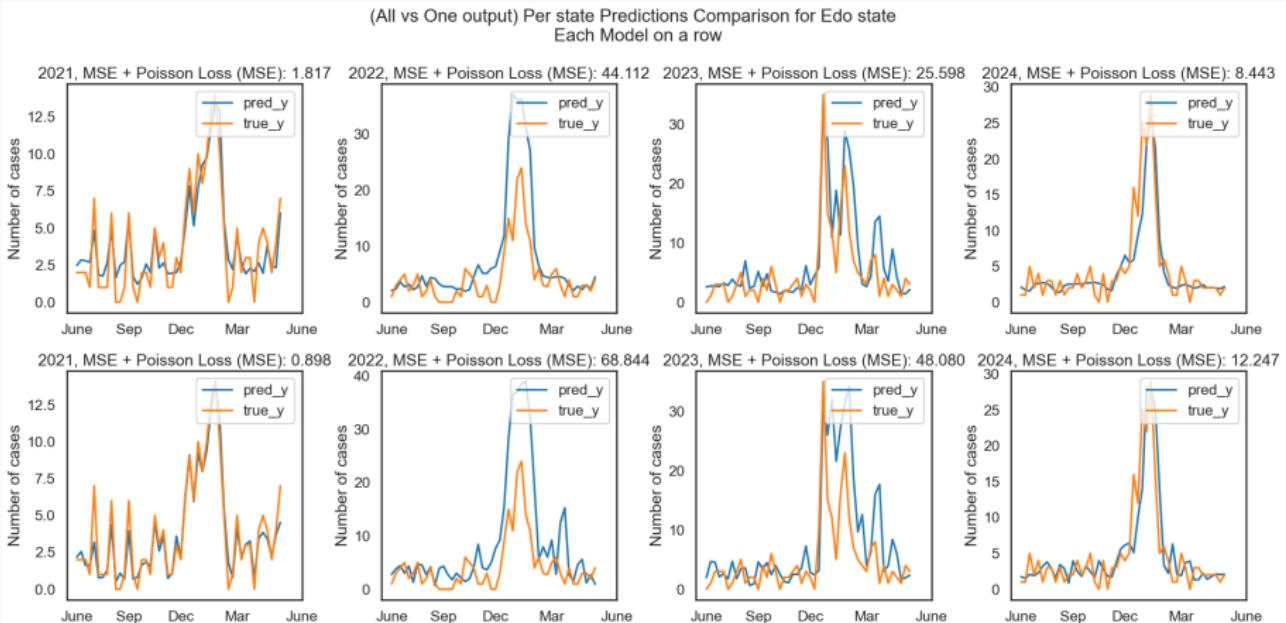
## All vs One – Output: Bauchi Predictions

(All vs One output) Per state Predictions Comparison for Bauchi state  
Each Model on a row



# Per-State Model Comparison: All vs One – Edo Predictions

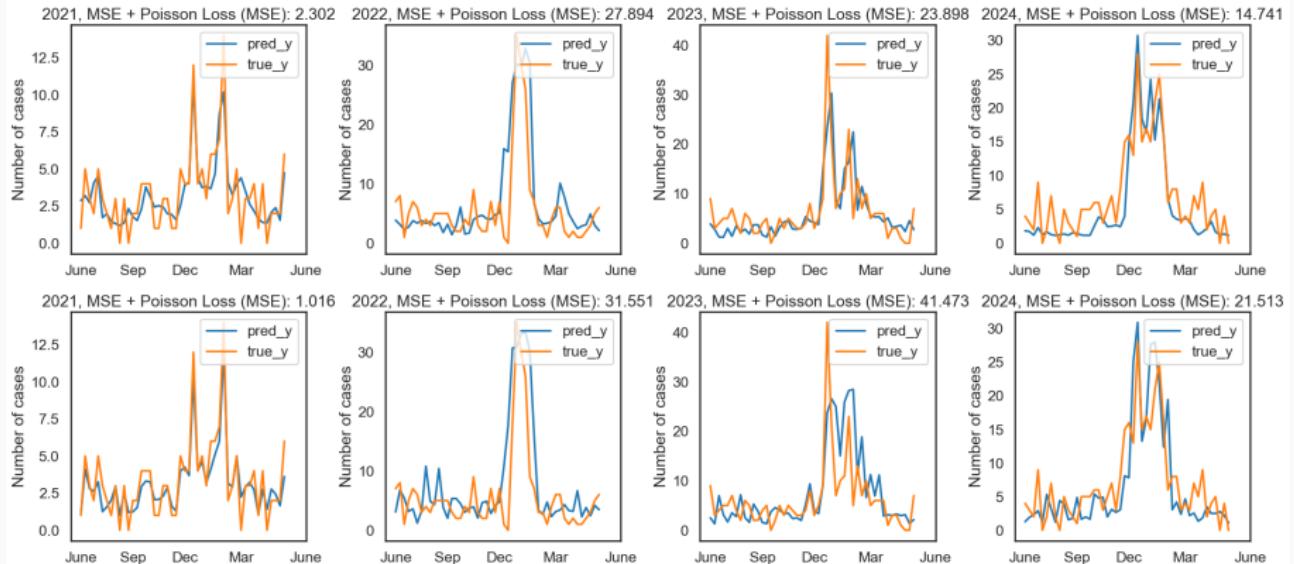
## All vs One – Output: Edo Predictions



# Per-State Model Comparison: All vs One – Ondo Predictions

## All vs One – Output: Ondo Predictions

(All vs One output) Per state Predictions Comparison for Ondo state  
Each Model on a row



## MAR(4) Model for Climate and Lassa Fever Cases

Let  $\mathbf{x}_t \in \mathbb{R}^7$  be the multivariate time series defined by:

$$\mathbf{x}_t = \begin{bmatrix} x_t^{(1)} \\ x_t^{(2)} \\ \vdots \\ x_t^{(6)} \\ x_t^{(7)} \end{bmatrix} = \begin{bmatrix} \text{climate}_t^{(1)} \\ \text{climate}_t^{(2)} \\ \vdots \\ \text{climate}_t^{(6)} \\ \text{lassa}_t \end{bmatrix}$$

The MAR(4) model is given by:

$$\mathbf{x}_t := f(\mathbf{x}_{t-1}; \mathbf{A}) = \sum_{k=1}^4 A_k \mathbf{x}_{t-k} + \boldsymbol{\epsilon}_t, \quad \boldsymbol{\epsilon}_t \sim \mathcal{N}(\mathbf{0}, \Sigma)$$

**Lassa fever dynamics** (7th component):

$$x_t^{(7)} = \sum_{k=1}^4 \sum_{j=1}^7 A_k^{(7,j)} x_{t-k}^{(j)} + \epsilon_t^{(7)}$$

## MAR(4) Model — One-Output Variant

In the one-output version of the MAR(4) model, only Lassa fever cases are predicted based on the past values of climate variables:

$$y_t = \sum_{k=1}^4 A_k \mathbf{x}_{t-k} + \epsilon_t, \quad \epsilon_t \sim \mathcal{N}(0, \sigma^2)$$

Where:

$\mathbf{x}_t \in \mathbb{R}^7$ : vector of climate variables and the number of cases at time  $t$

$A_k \in \mathbb{R}^{1 \times 7}$ : autoregressive weight matrices

$y_t$ : predicted number of Lassa fever cases at time  $t$

# Training Objective

Let  $\mathcal{D} = \{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^n$  be the dataset, and let  $f(\mathbf{x}_i; \mathbf{A})$  denote the model's prediction. To reduce clutter, we omit the explicit time index  $t$ .

## Training Loss Function:

$$\mathcal{L}(\mathbf{A}) = \frac{1}{n} \sum_{i=1}^n \|\mathbf{x}_i - f(\mathbf{x}_i; \mathbf{A})\|^2 + \lambda \sum_{j=1}^d \max(0, -\mathbf{y}_j)$$

## Where:

$\mathbf{A}$ : model coefficient matrices (e.g., MAR parameters)

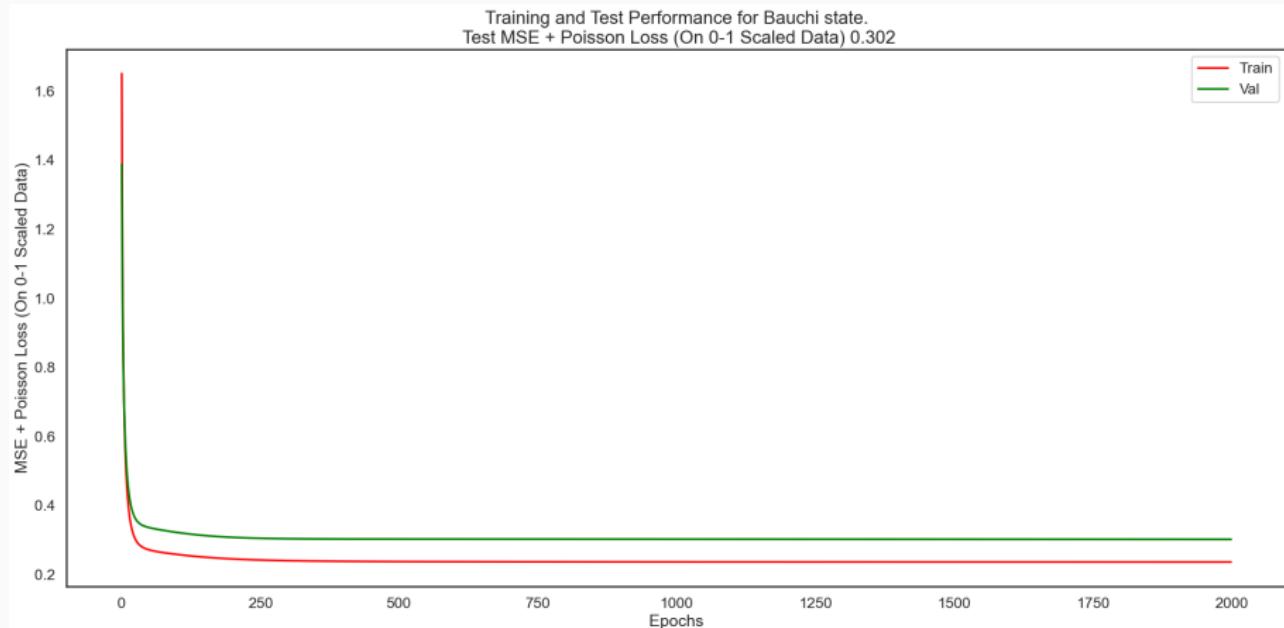
$\max(0, -\mathbf{y}_j)$ : regularization term penalizing negative outputs, enforcing  $\mathbf{y}_j \geq 0$  for  $j = 1, \dots, d$

$\lambda > 0$ : regularization hyperparameter

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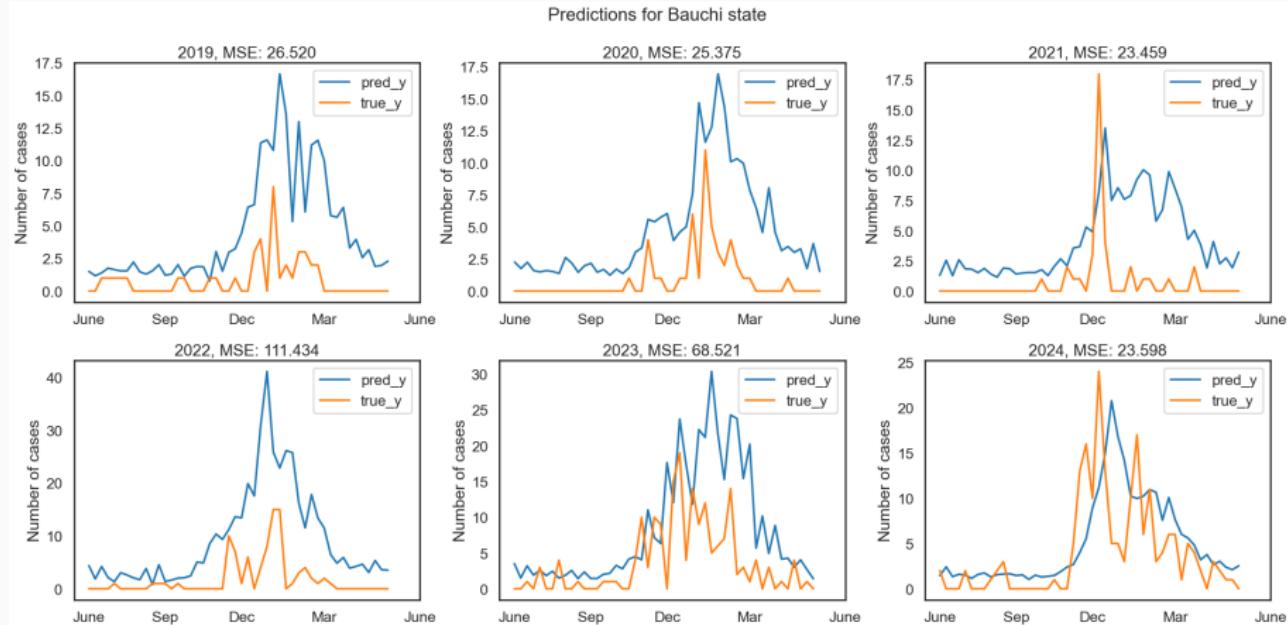
## Training Loss Curve



## MAR (Per-State Model) — Bauchi: Predictions

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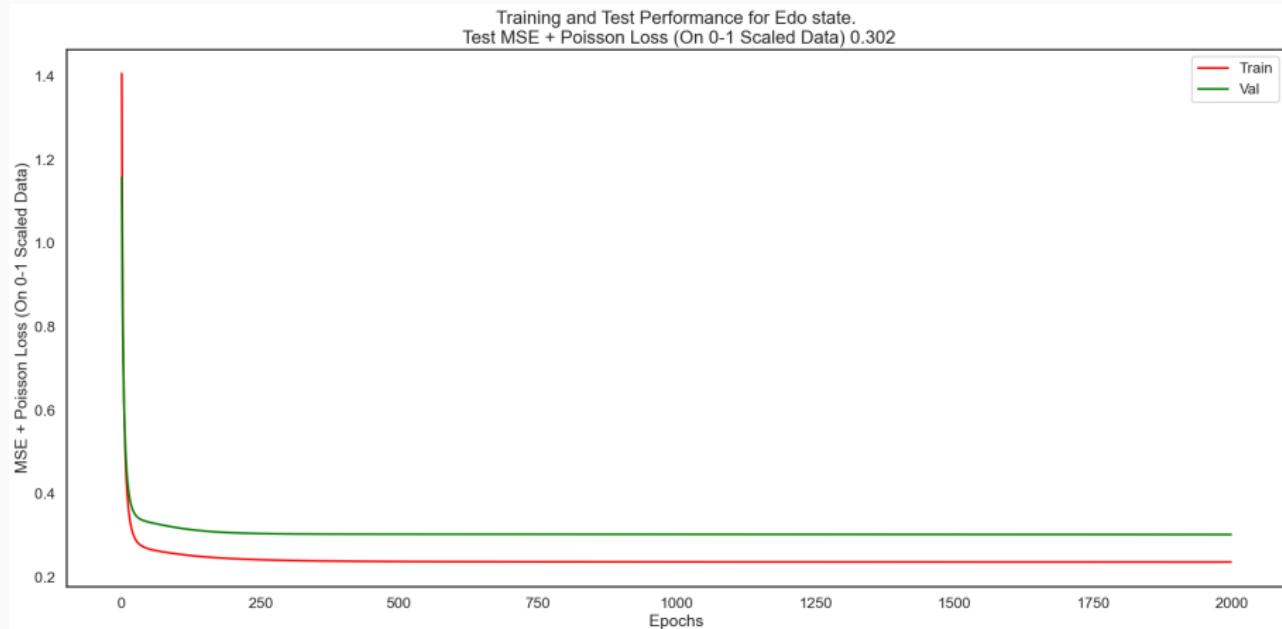
## Training and Test Predictions



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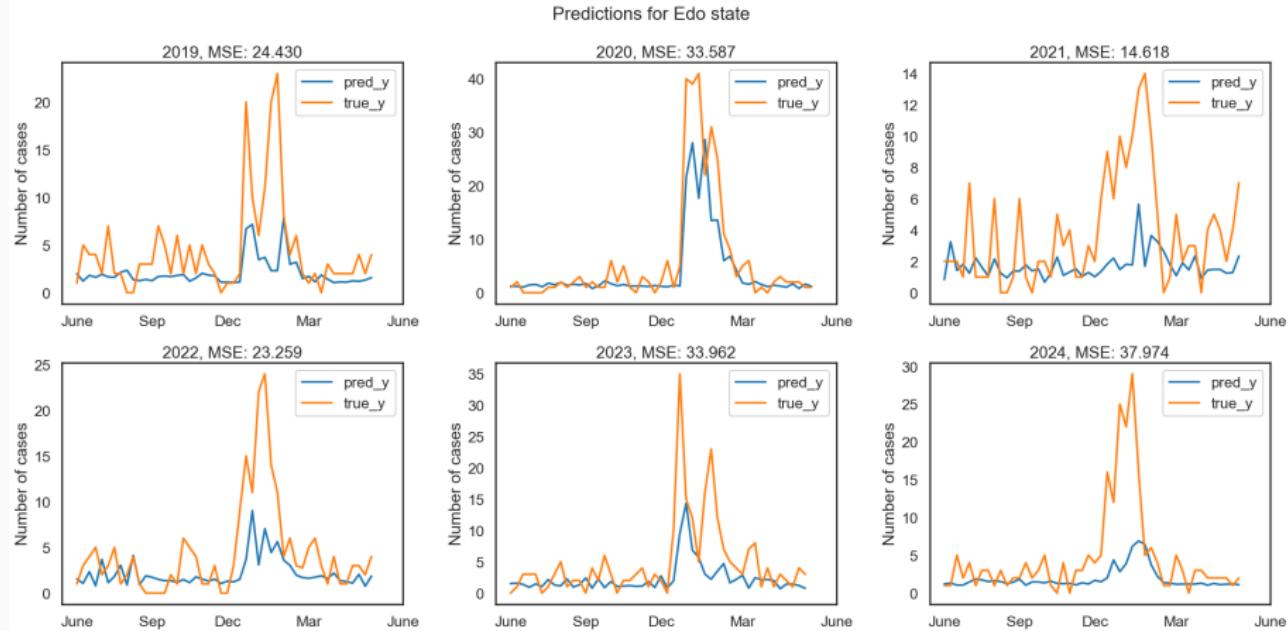
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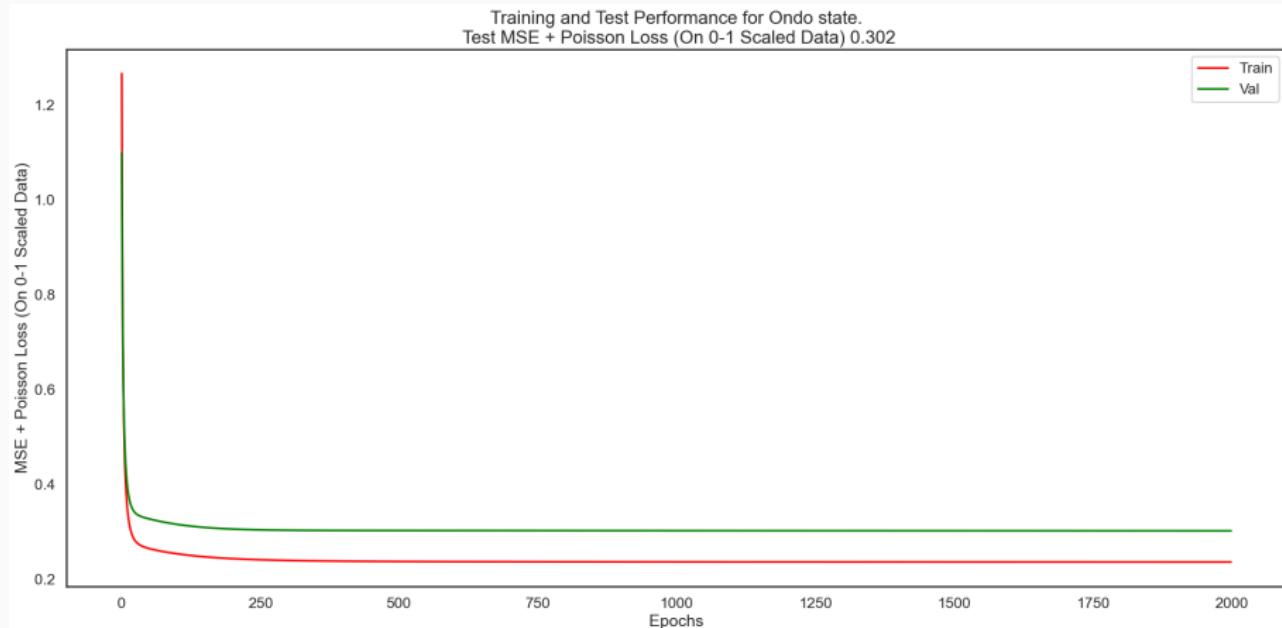
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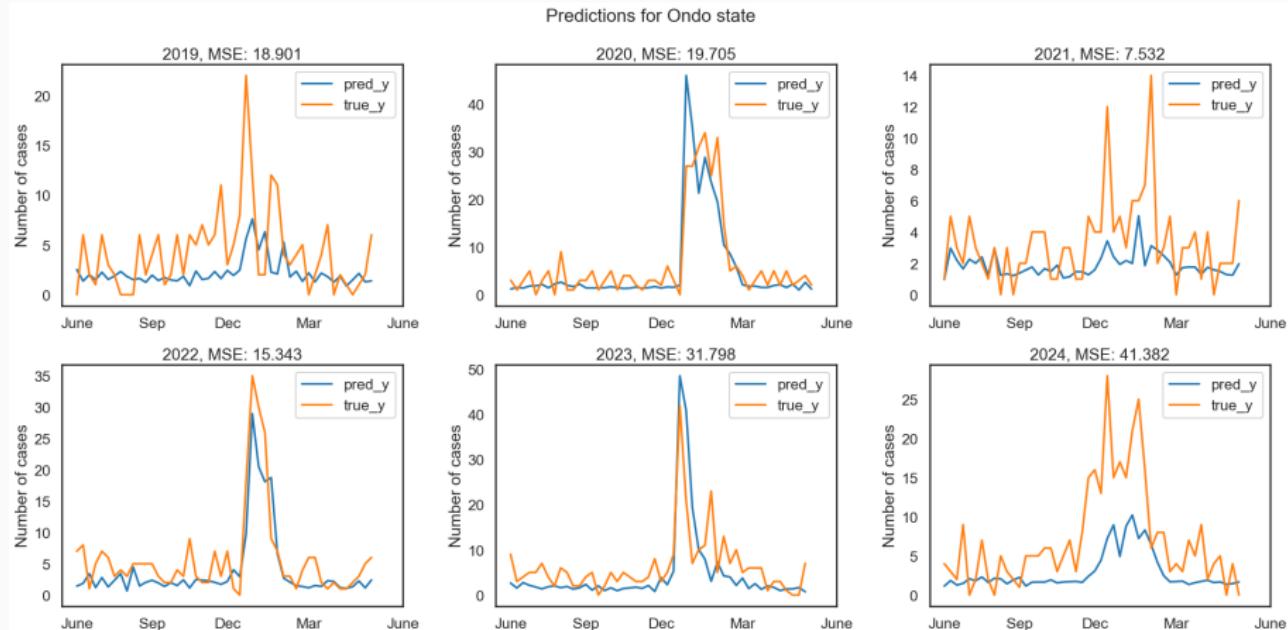
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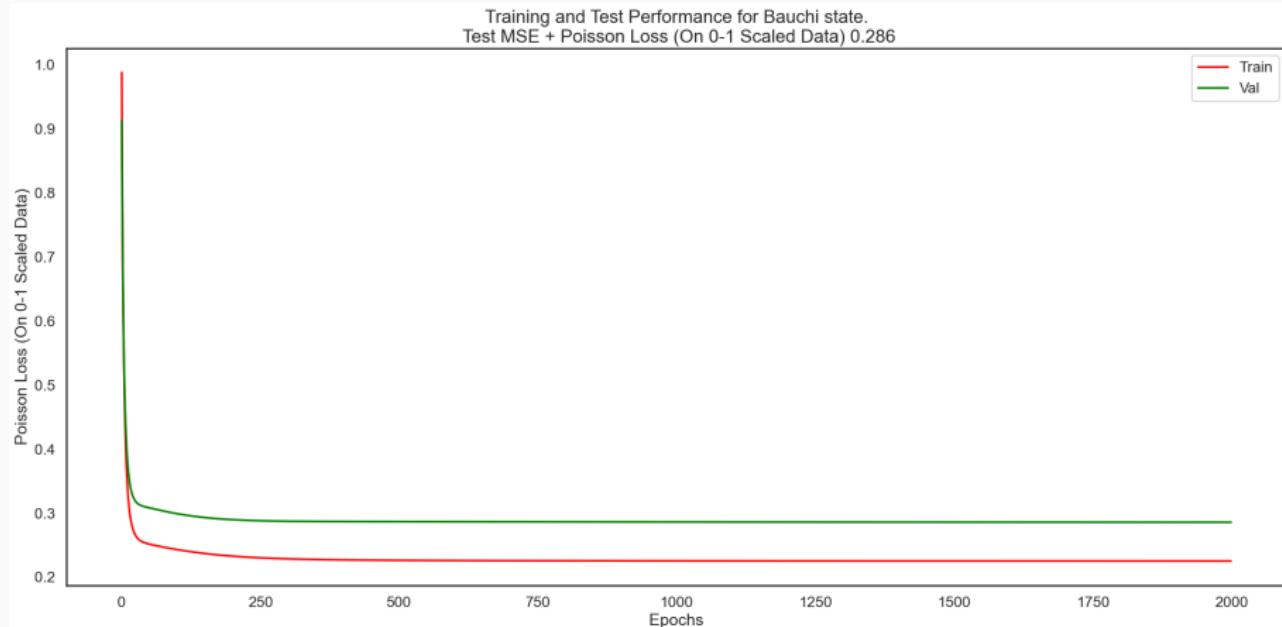
## Training and Test Predictions



# Mar (Per-State, One-Output) — Bauchi: Training Loss

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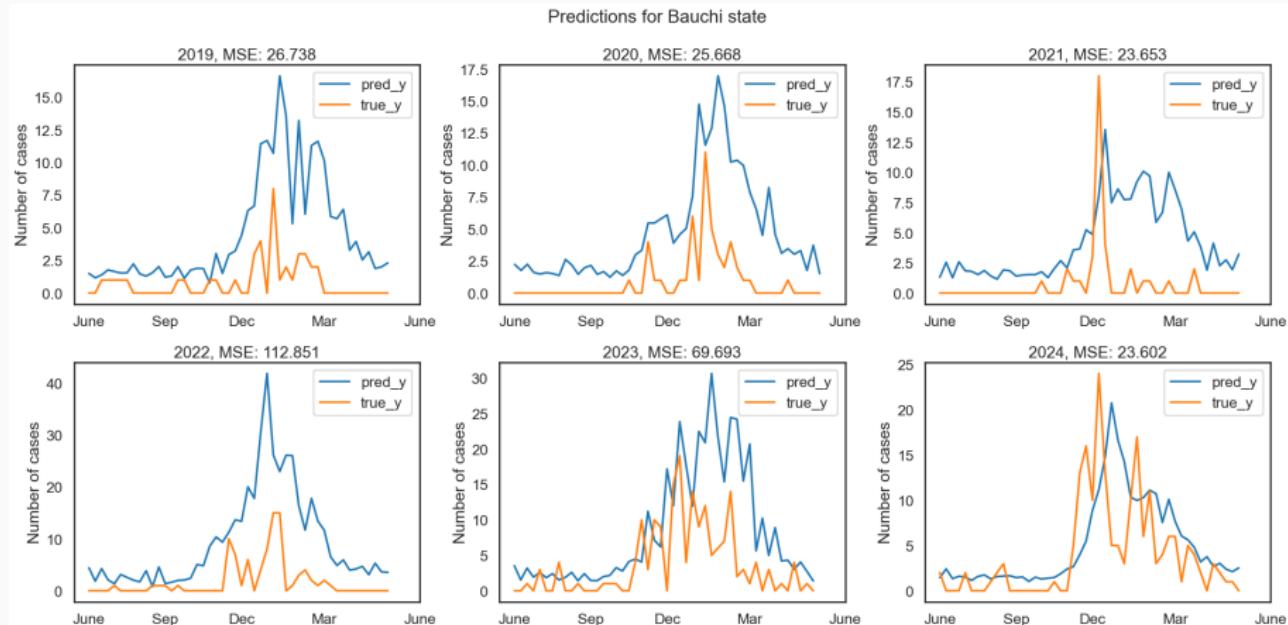
## Training Loss Curve



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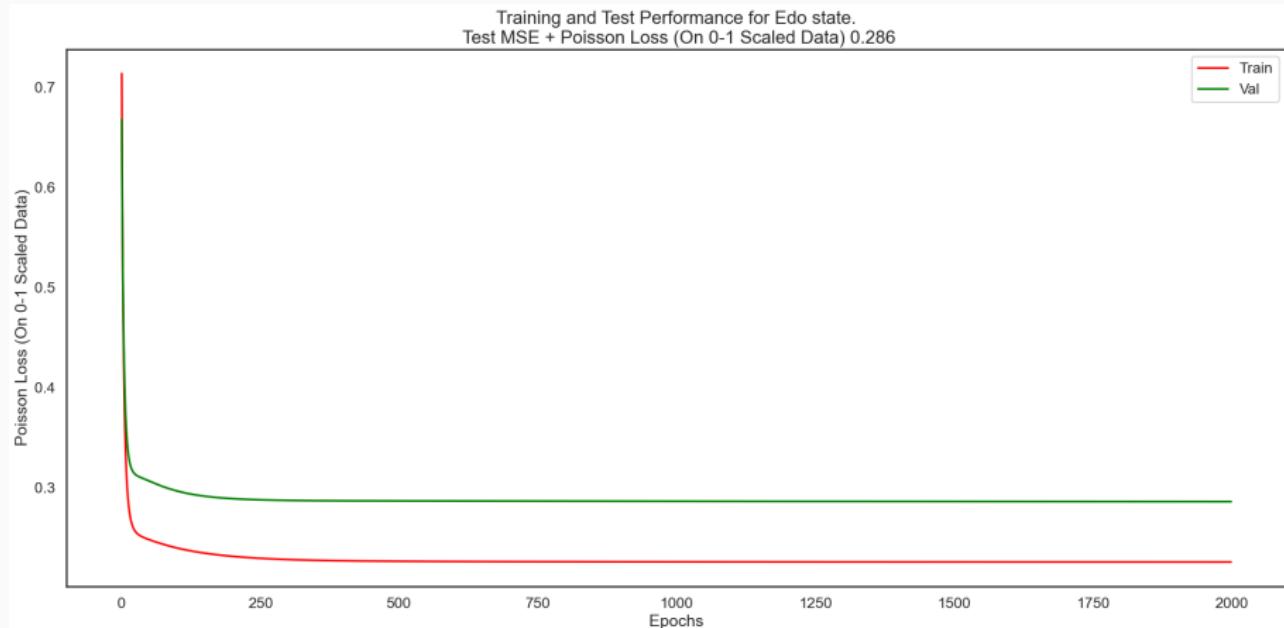
## Training and Test Predictions



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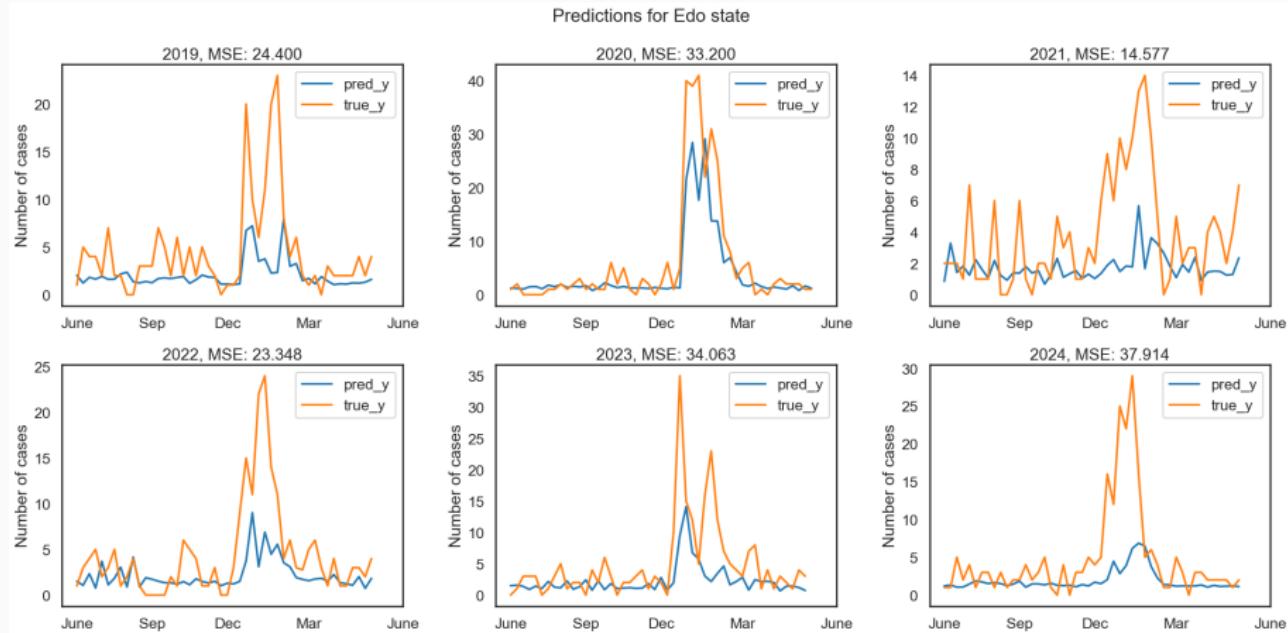
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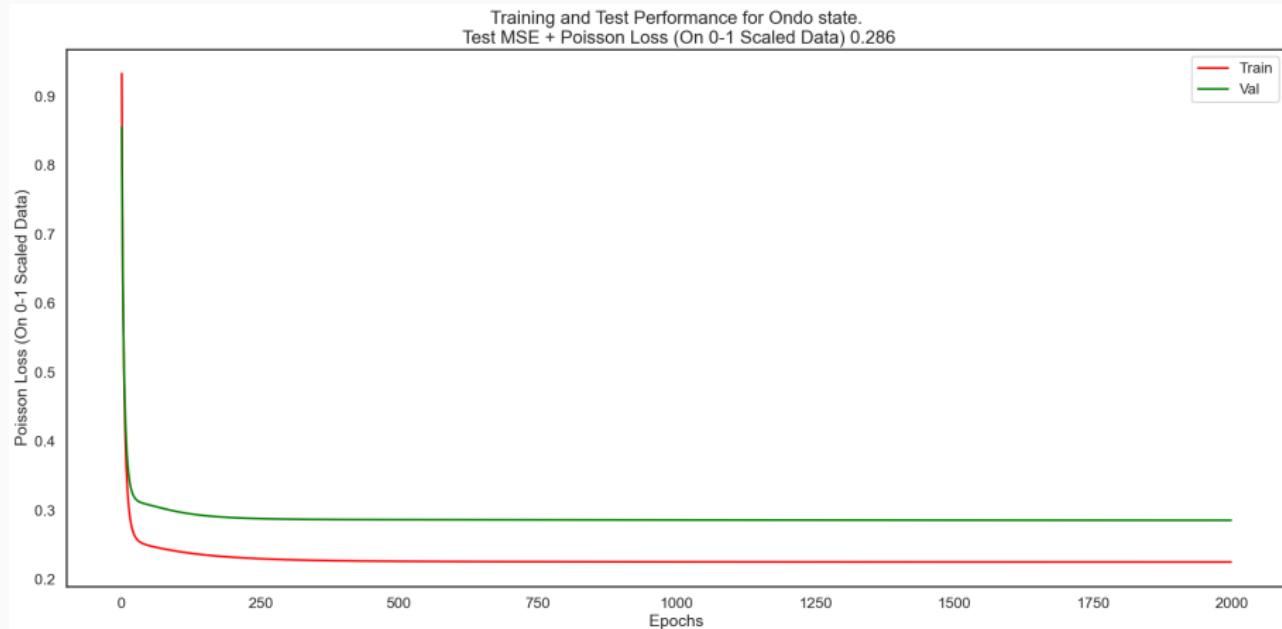
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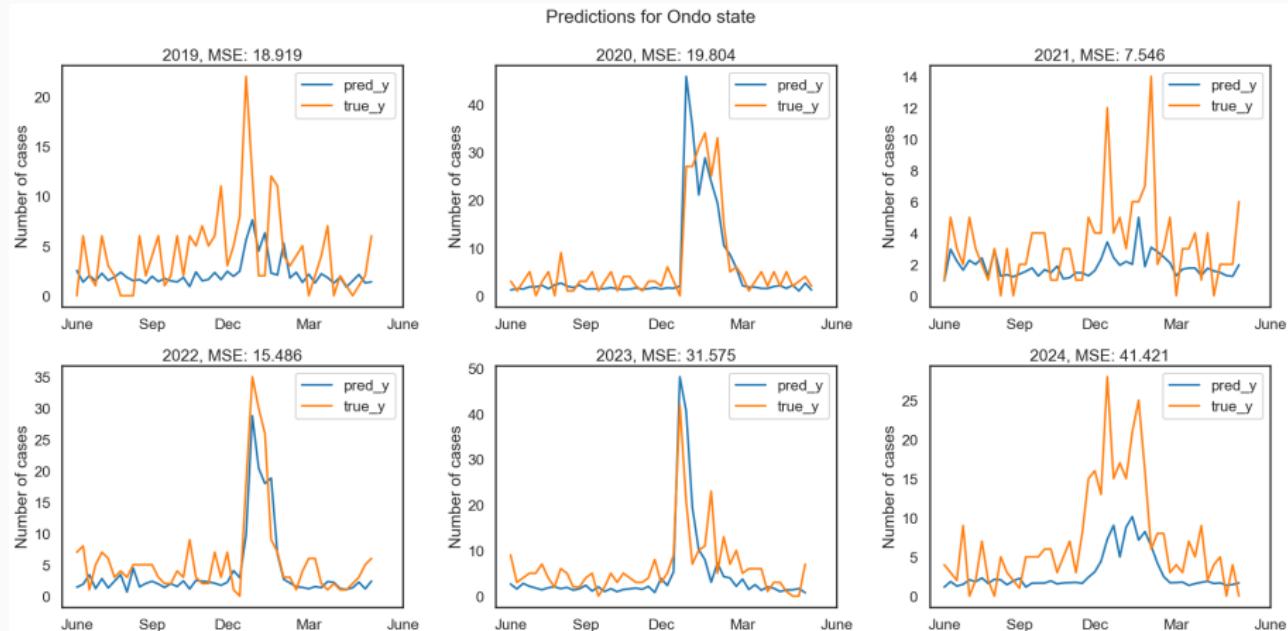
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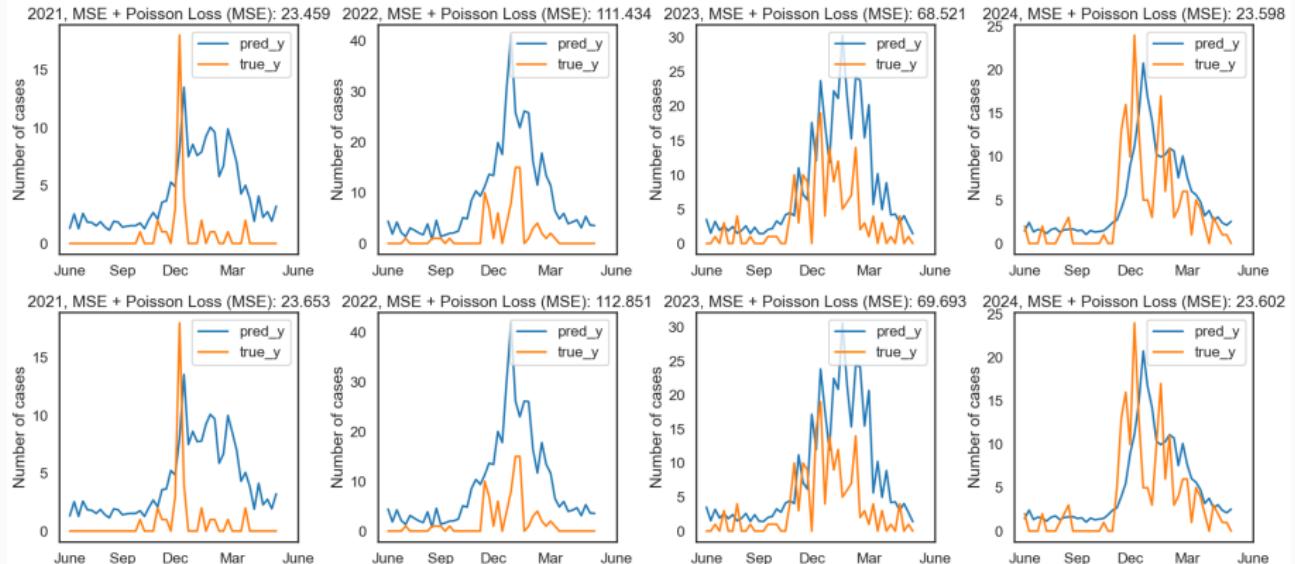
## Training and Test Predictions



## Per-State Model Comparison: All vs One – Bauchi Predictions

## All vs One – Output: Bauchi Predictions

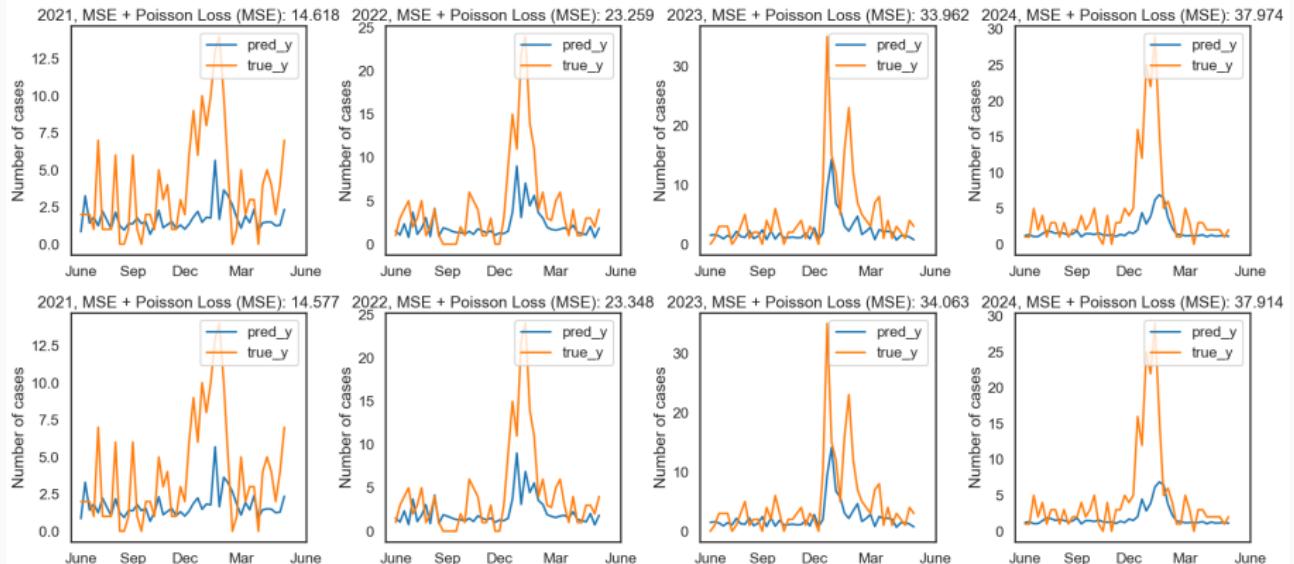
### (All vs One output) Per state MAR(4) Predictions Comparison for Bauchi state Each Model on a row



# Per-State Model Comparison: All vs One – Edo Predictions

## All vs One – Output: Edo Predictions

(All vs One output) Per state MAR(4) Predictions Comparison for Edo state  
Each Model on a row



# Per-State Model Comparison: All vs One – Ondo Predictions

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Each Model on a row

