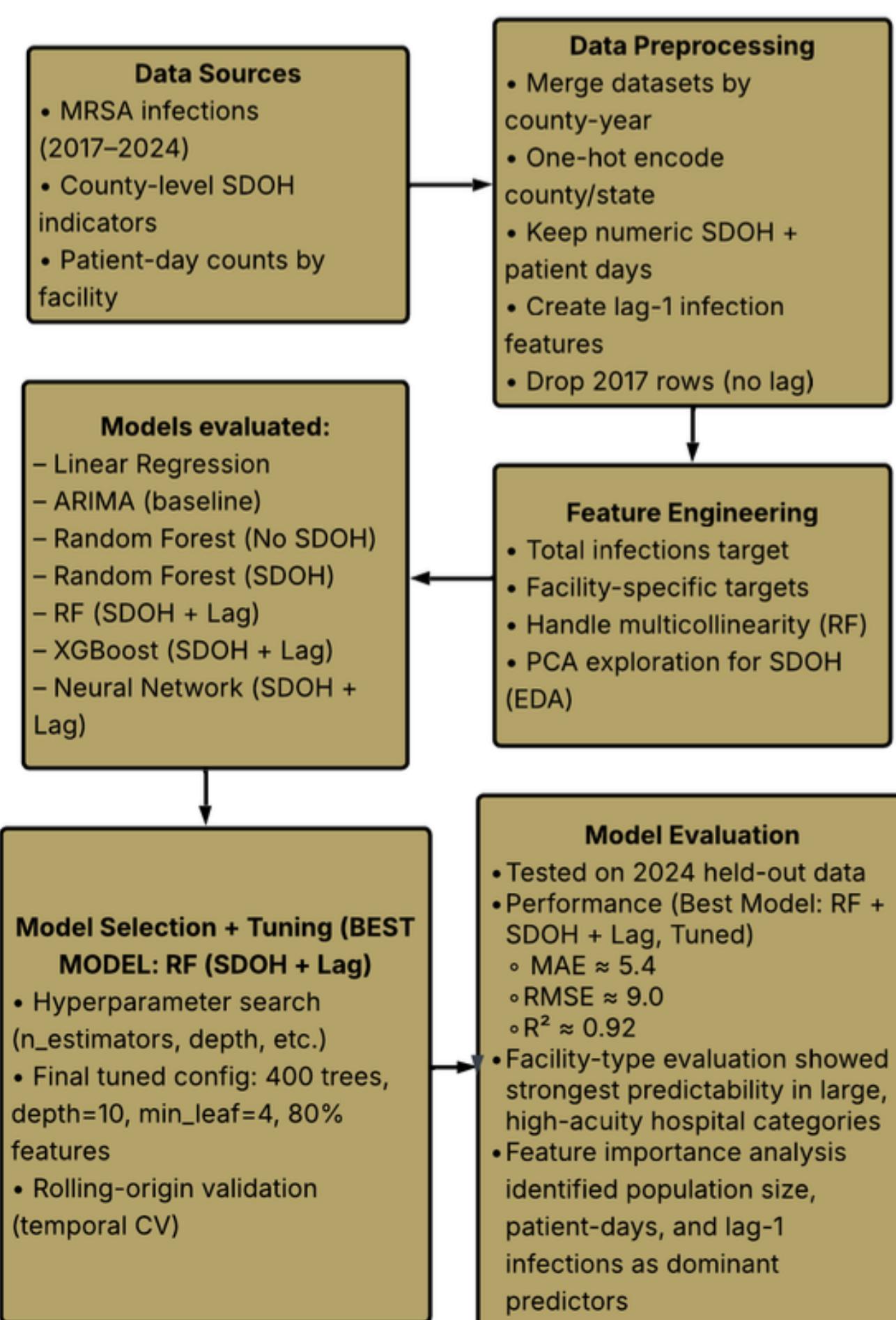


Hannah Bower, Alan Wang, AJ Subudhi  
 Georgia Institute of Technology

## INTRODUCTION

MRSA bloodstream infections remain a major antimicrobial-resistant threat in the United States<sup>1</sup>, yet the extent to which local socioeconomic and structural factors influence infection burden is less understood<sup>2</sup>. This project integrates eight years of **California MRSA surveillance (2017–2024)**<sup>4</sup> with **county-level social determinants of health (SDOH)** indicators to examine how community conditions shape geographic and temporal trends in MRSA infection rates across California counties. We link population size, healthcare utilization, housing instability, income inequality, and environmental metrics with both total MRSA infections and hospital-type specific patterns. By combining epidemiologic context with machine-learning models<sup>3</sup>, we aim to **clarify which non-clinical features meaningfully drive MRSA variation and whether SDOH improve prediction beyond known healthcare exposure and population-scale factors**.

## METHODS



## CONCLUSION

Our findings show that MRSA risk in California counties is driven primarily by **population scale, intensity of healthcare utilization, and the persistence of prior-year infections**.<sup>4</sup> Tree-based models, especially the tuned Random Forest with SDOH + lag features, effectively capture these nonlinear and temporal patterns and consistently outperform linear, boosting, and deep learning approaches.<sup>3</sup> Although SDOH indicators are often discussed in MRSA epidemiology,<sup>2</sup> most provided little additional predictive value once population and patient-day variables were included. Only a few structural measures, such as housing instability and income inequality, had meaningful signal. These results suggest that MRSA forecasting and prevention efforts should **prioritize lag-adjusted surveillance, high-volume hospital environments, and structural crowding indicators over broad SDOH feature sets**.

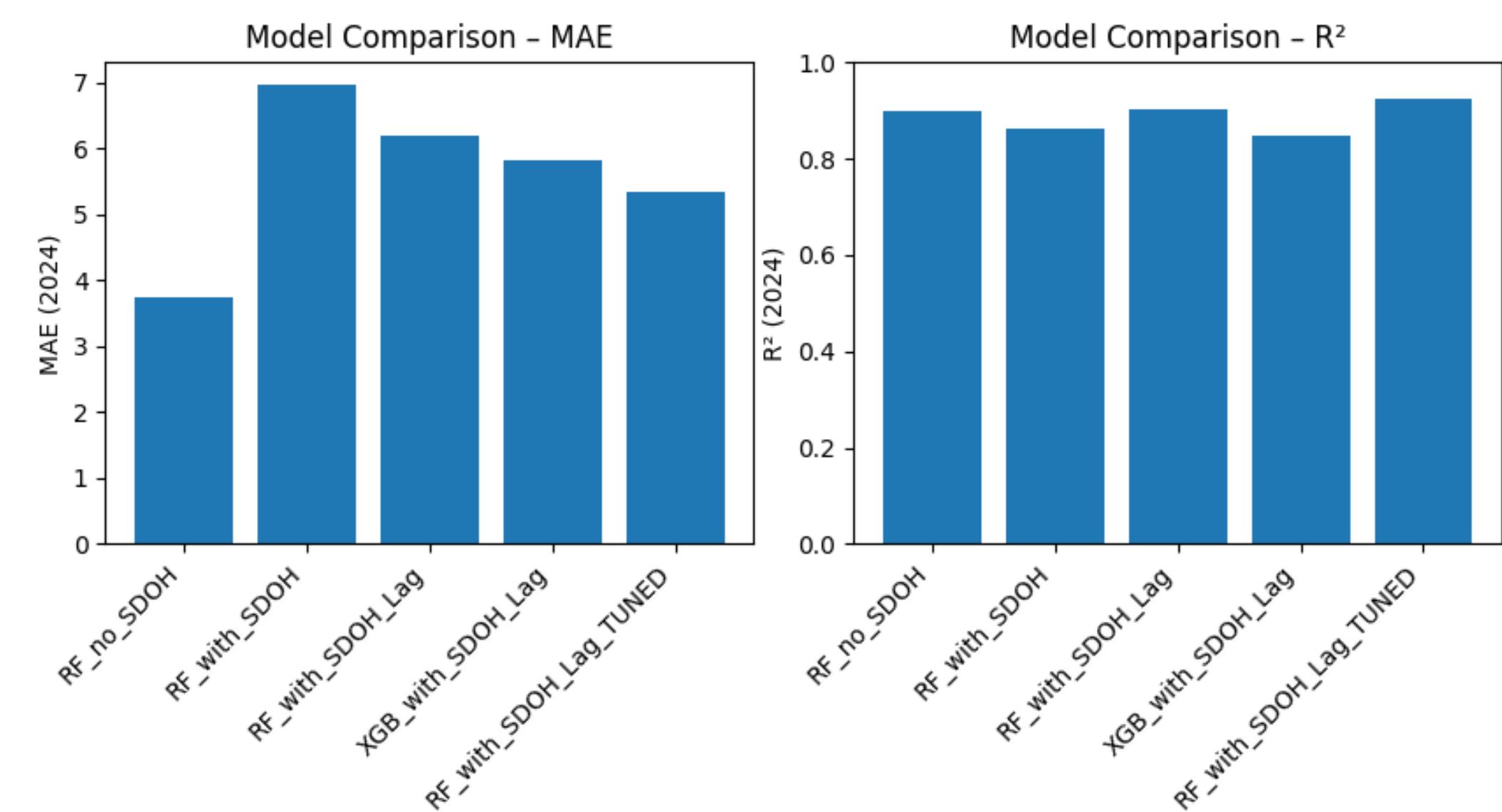
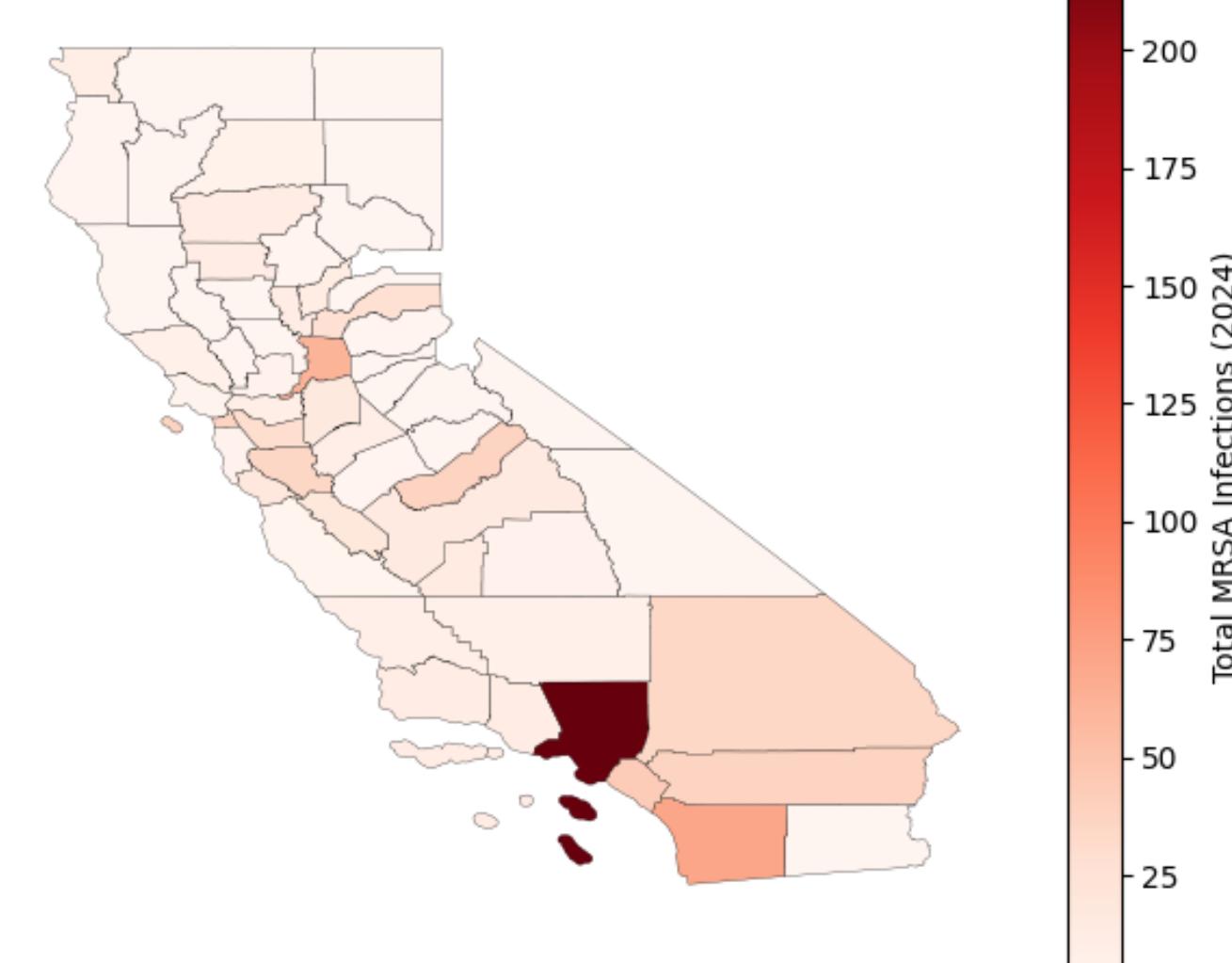
## RESULTS

Overall, the map highlights a strong **urban rural divide** in MRSA epidemiology:

- **Urban counties:** persistent, high-volume transmission
- **Rural counties:** sporadic, low-volume, difficult to predict
- **Population size and healthcare exposure** emerge visually as the dominant drivers of MRSA burden

This geographic pattern is consistent with our model's feature importance results, which show that population and patient-day exposure are the primary predictors of county-level MRSA infections.

California MRSA Infections by County (2024)



The tuned Random forest model trained on both SDOH variables and lagged infected counts (**RF\_with\_SDOH\_Lag\_TUNED**) was the best-performing model in our analysis. With an RMSE  $\approx 5.4$  and an  $R^2 \approx 0.924$ , this model outperformed linear, boosting, deep learning, univariate time series, and all other random forest approaches.

| Hospital Type                         | MAE    | RMSE   | R <sup>2</sup> |
|---------------------------------------|--------|--------|----------------|
| Major Teaching                        | 2.5473 | 4.5277 | 0.9303         |
| Long-Term Acute Care                  | 0.6065 | 1.7703 | 0.9029         |
| Community Large                       | 0.8549 | 2.1003 | 0.8666         |
| Pediatric                             | 0.1229 | 0.4164 | 0.8366         |
| Community Small                       | 0.5199 | 0.8727 | 0.8166         |
| Rehabilitation Unit                   | 0.0646 | 0.1640 | 0.6889         |
| Community Medium                      | 0.7624 | 2.0356 | 0.5057         |
| Critical Access                       | 0.0835 | 0.2586 | 0.0465         |
| Free-Standing Rehabilitation Hospital | 0.0026 | 0.0155 | 0.0000         |

Using the RF\_with\_SDOH\_Lag\_Tuned model, we evaluated predictive accuracy across all nine hospital categories. Our model performs best in **Major Teaching hospitals and Long-Term Acute Care facilities**, the hospital types exhibiting the two highest  $R^2$  values. These settings treat large numbers of patients requiring intensive medical care and long stays, creating steady, repeatable opportunities for MRSA transmission.

The tuned Random Forest showed that MRSA risk is driven primarily by **population scale** (labor force, population), **healthcare exposure** (patient-days in major hospital types), and **previous-year infections**, which together explain most of the model's predictive power. Only a few SDOH variables contributed meaningfully, reinforcing that **county size, hospital utilization, and temporal persistence** are the strongest and most reliable predictors of MRSA burden.

| Rank | Feature                           | Importance | Variable Meaning                                  |
|------|-----------------------------------|------------|---|
| 1    | Labor Force                       | 0.183      | Total county labor force (SDOH)                   |
| 2    | Population                        | 0.1334     | County population estimate                        |
| 3    | Patient-days: Major Teaching      | 0.1132     | Bed-days in Major Teaching hospitals              |
| 4    | Patient-days: Community Medium    | 0.0578     | Bed-days in medium community hospitals            |
| 5    | Population Rank                   | 0.0561     | County population percentile                      |
| 6    | Lag-1: Major Teaching infections  | 0.0487     | Previous year's MRSA in Major Teaching hospitals  |
| 7    | Lag-1: Community Large infections | 0.0482     | Previous year's MRSA in Community Large hospitals |
| 8    | Patient-days: Pediatric           | 0.0476     | Bed-days in Pediatric hospitals                   |
| 9    | Patient-days: Rehabilitation Unit | 0.0469     | Bed-days in Rehabilitation Units                  |
| 10   | Patient-days: Community Large     | 0.0427     | Bed-days in Community Large hospitals             |