Forecasting Crime Trends in Toledo, Ohio: A Prophet-Based Modeling Approach to Neighborhood-Level Analysis of Crime Trends

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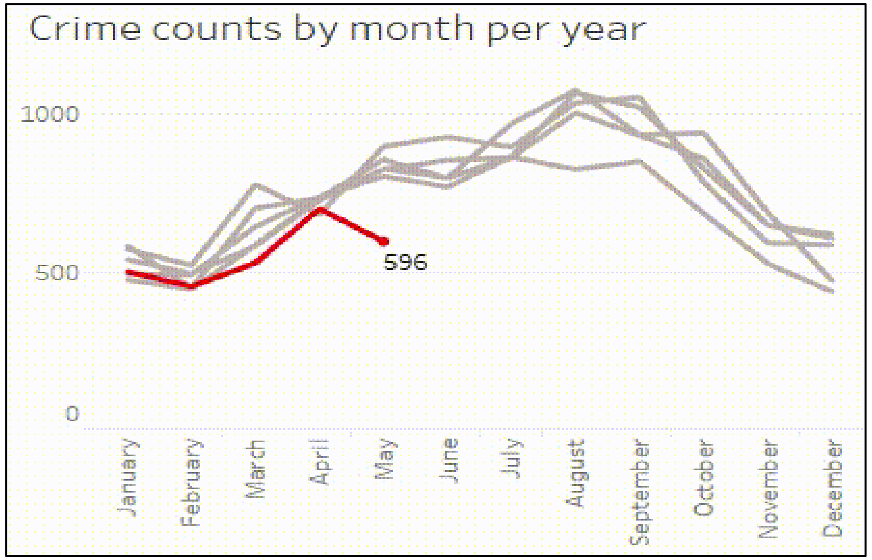
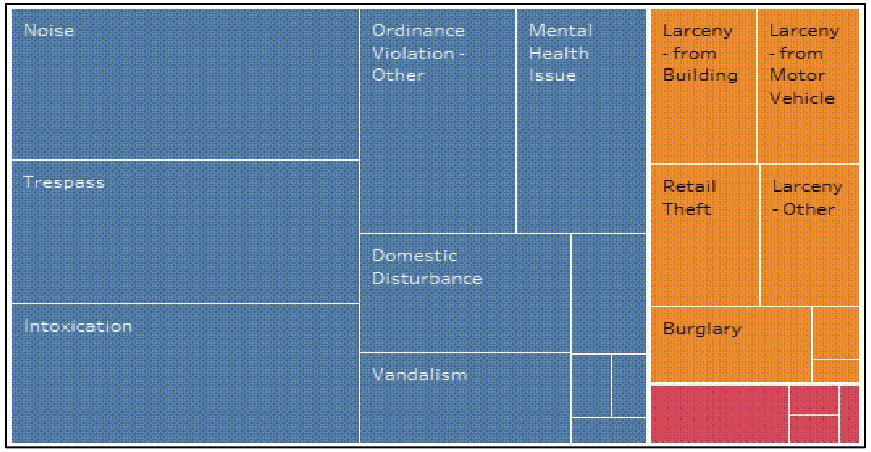
Background

- State of crime prediction research
  - Evolution of crime analysis
    - Growing emphasis on machine learning (ML) and AI-driven solutions
    - 59% of current approaches use supervised learning techniques
  - Spatial crime dynamics
    - 6-12% of urban areas identified as high-crime clusters
    - Temporal stability in neighborhood crime patterns





Source: Andrew Wheeler's blog

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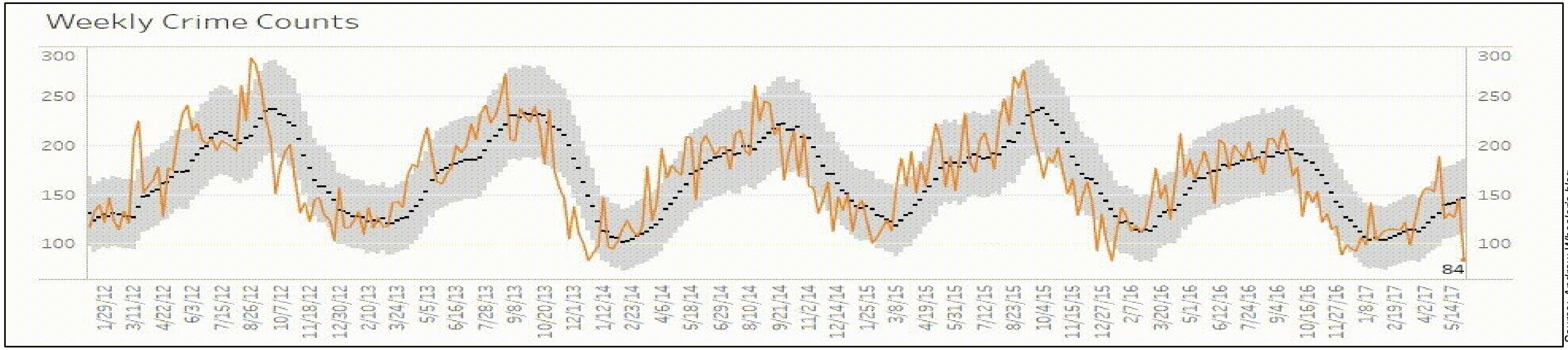
Background

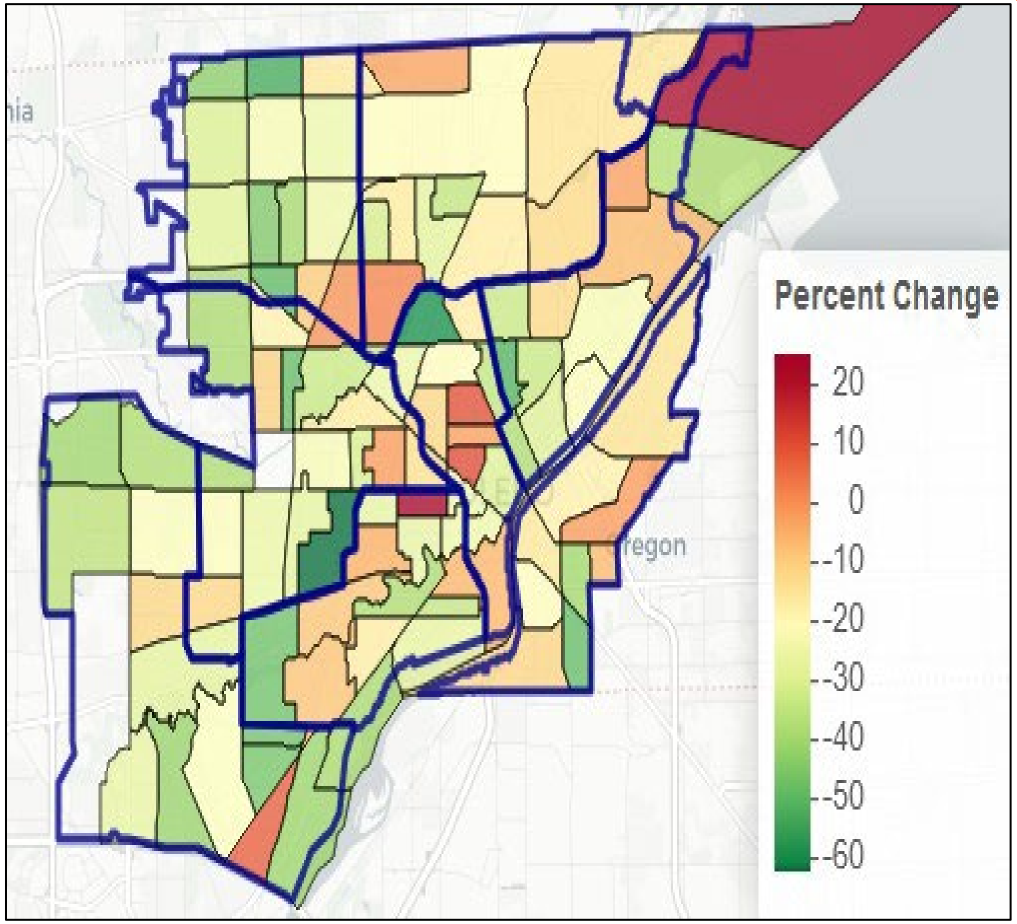
- Gaps in current advanced forecasting
  - Limited integration of multiple temporal scales
  - Need for improved, lower-level, granularity
  - Lack of comprehensive seasonal pattern analysis
- Prophet model advantages
  - Reliable time-series predictive modeling
  - Accounts for seasonal variations and “holiday” effects
  - Robust to missing data and trend changes



Source: Andrew Wheeler's blog

Purpose of the Study

- Develop data-driven tract-level crime forecasts
  - Part 1 and part 2 personal and property crimes
  - Public Order offenses
  - Substance-related offenses
- Examine predictive accuracy through Prophet modeling



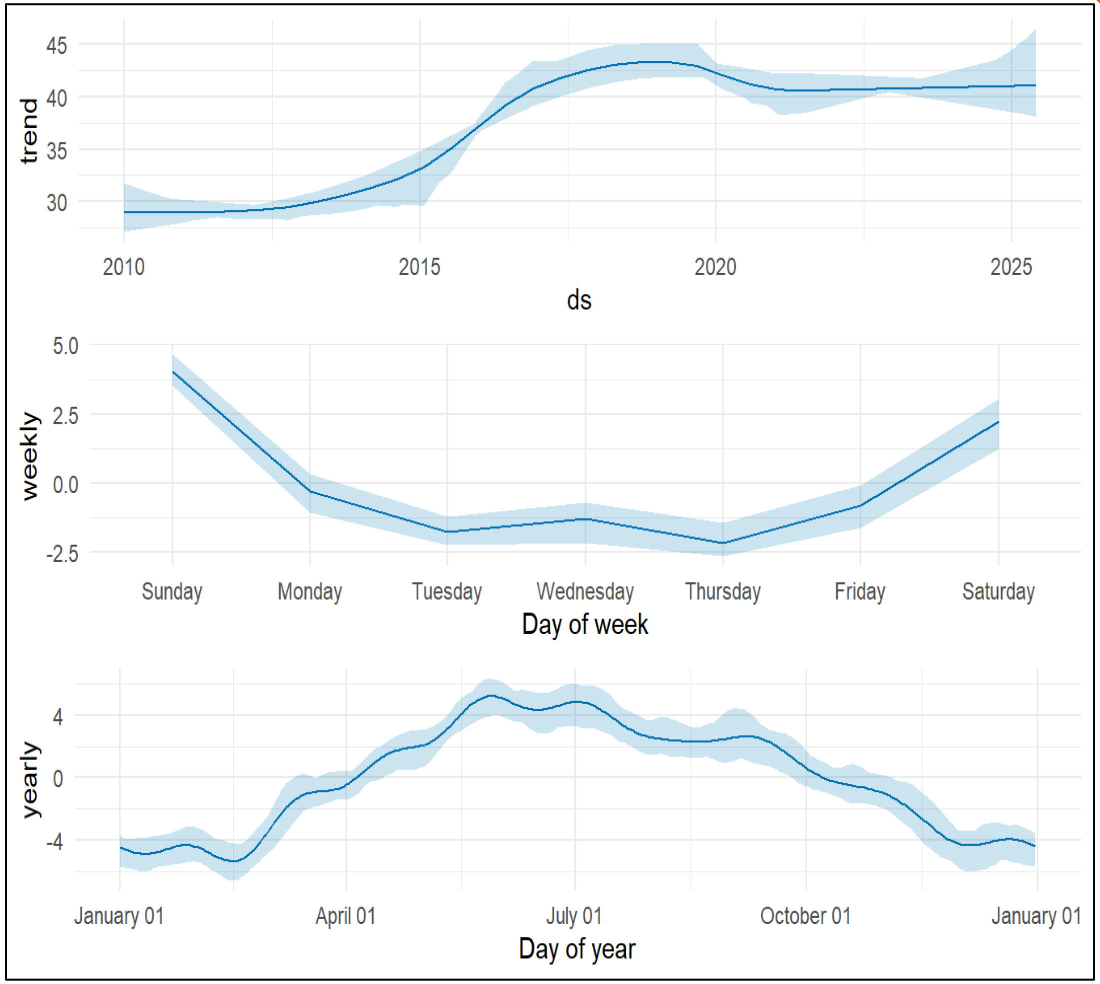
Method

- Data integration
  - Toledo Police Department (TPD) offense categories
  - Clean and prepare data for geocoding
  - Process geocodes for tract-level analysis

- Prophet model implementation
  - Additive regression model with trend components
  - Fourier series for seasonal patterns
  - Holiday effect integration

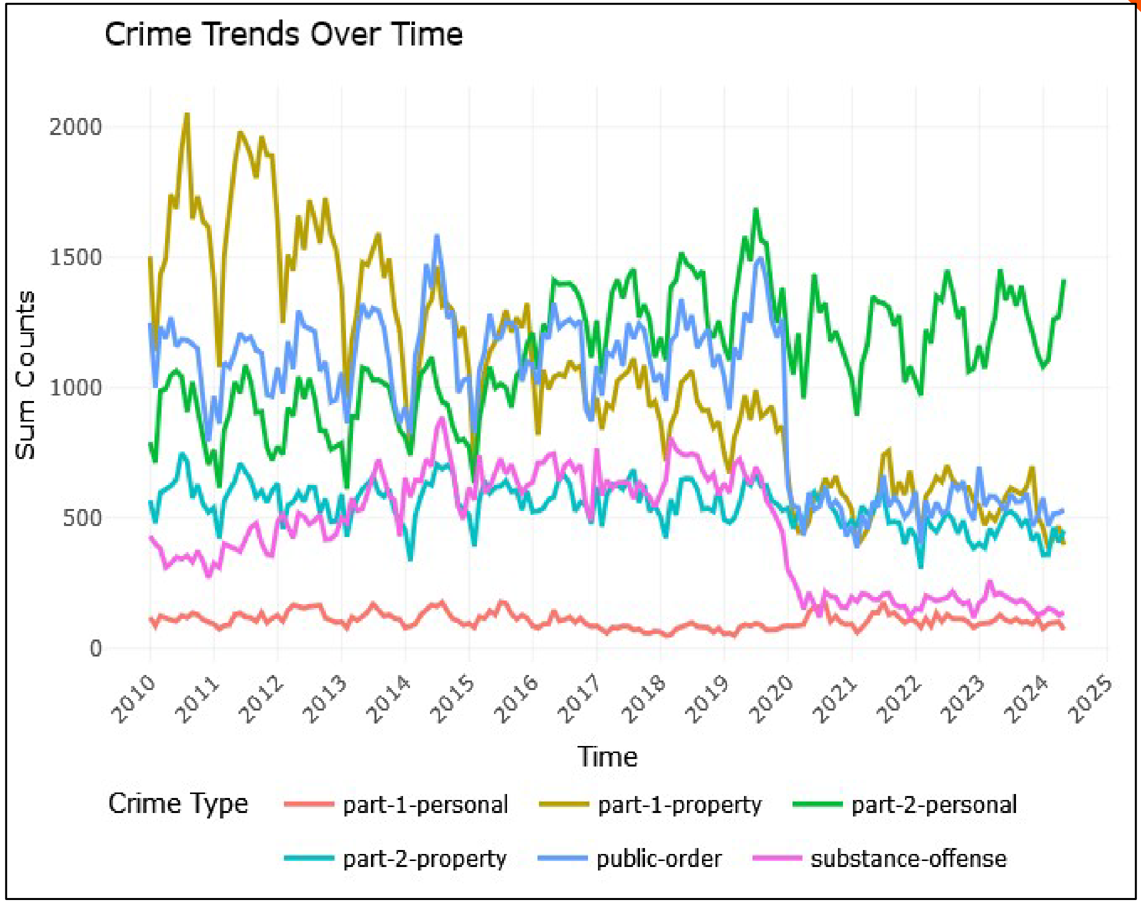
Analytic Framework

- Multi-scale analysis
  - Daily patterns
  - Monthly and yearly trends
- Model validation
  - Cross-validation across time periods
  - Comparative analysis with baseline model
  - RMSE, MAPE, & AIC comparison



Layered Crime Trend Plots: Toledo, Ohio

- Stacked visualization of offense categories from 2010-2025
- Monthly crime counts of each offense type
- Shows seasonal patterns and long-term trends across offense types



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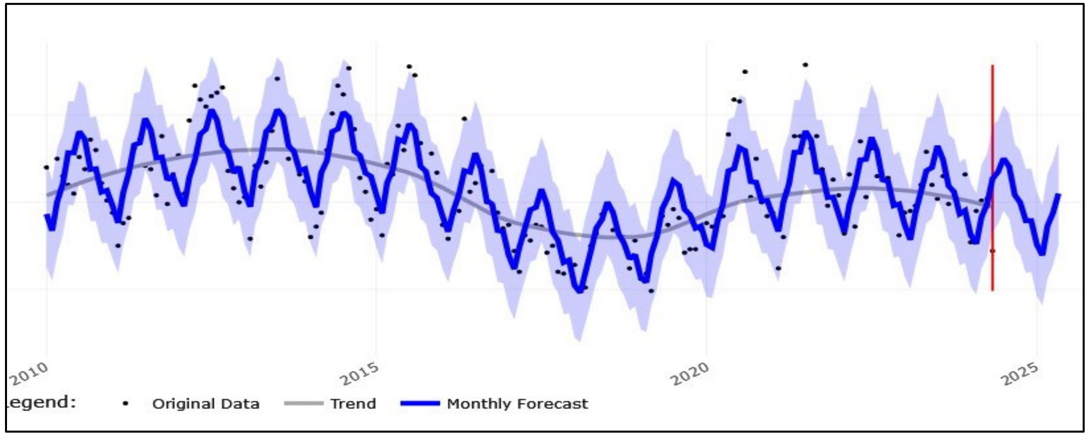
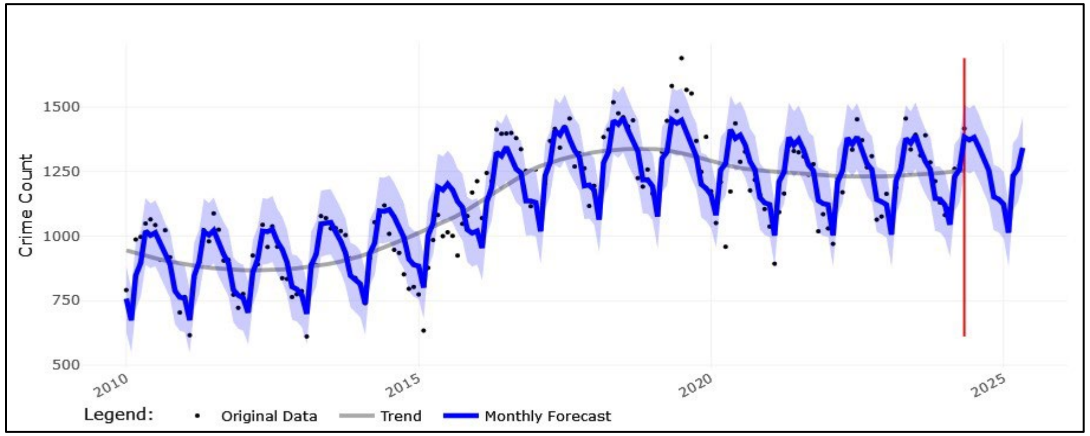
Part I and Part II Personal Crimes



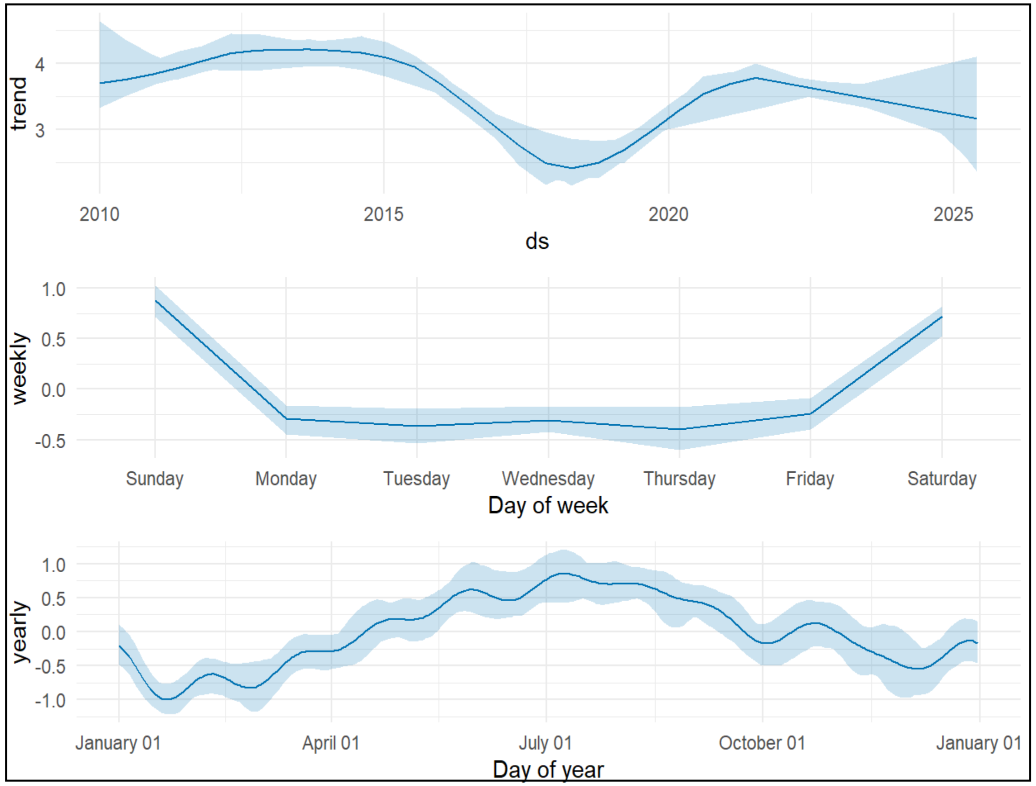
Part I Personal Crimes



Part II Personal Crimes

Part I and Part II Personal Crimes - Decomposition

Part I Personal Crimes



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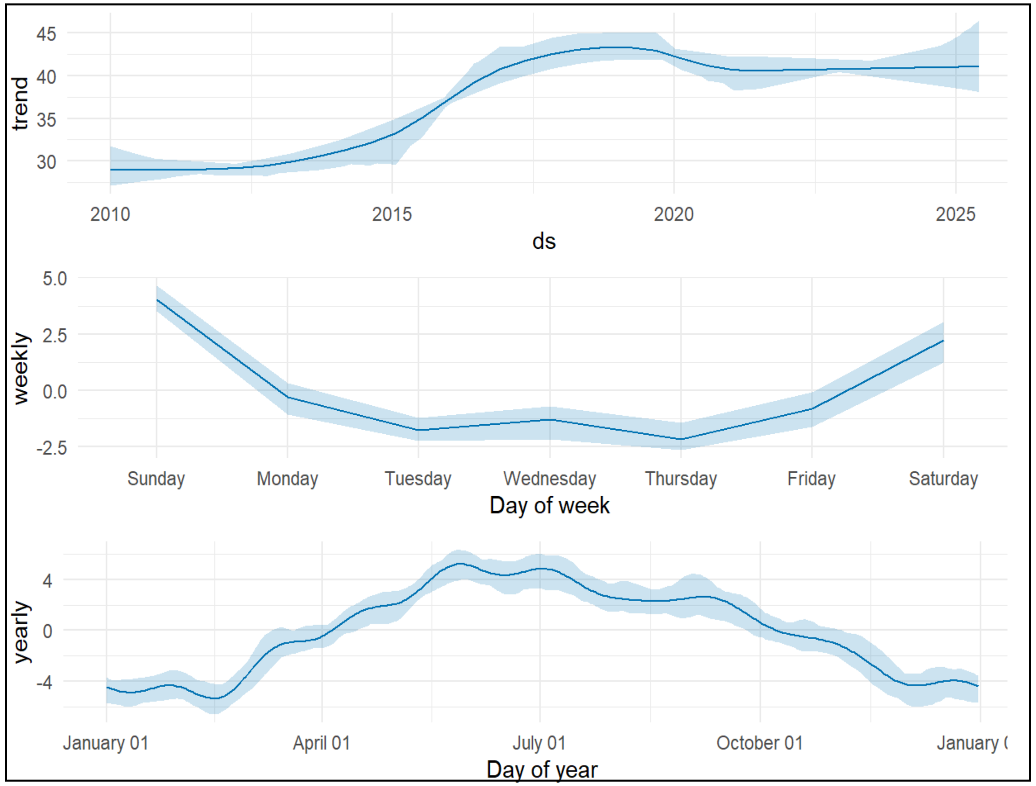
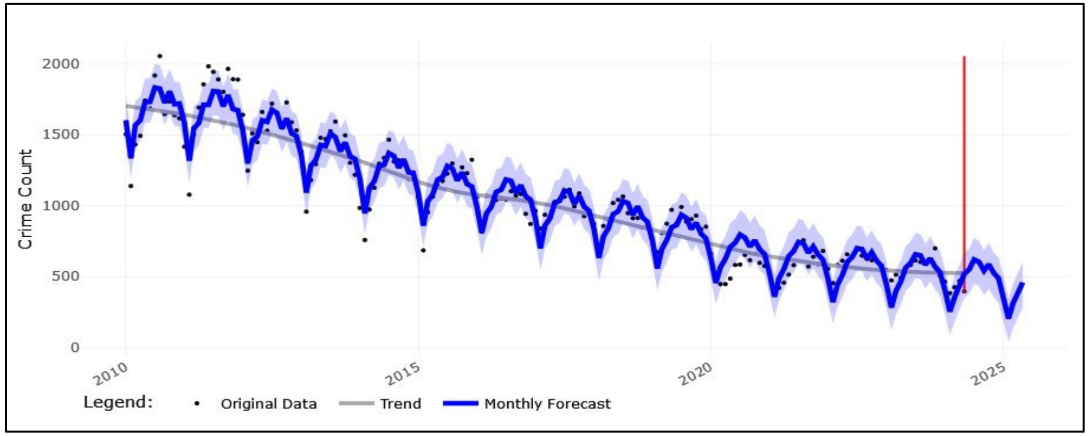
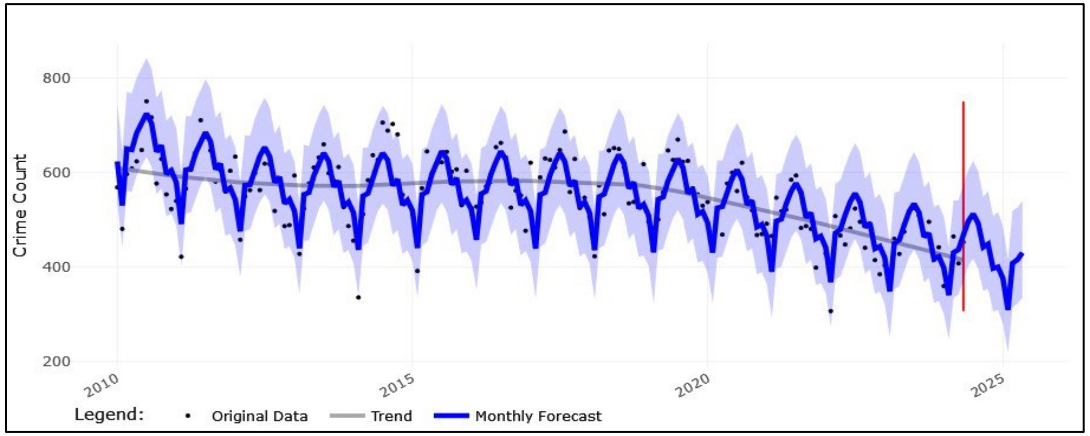


Part I and Part II Property Crimes



Part I Property Crimes



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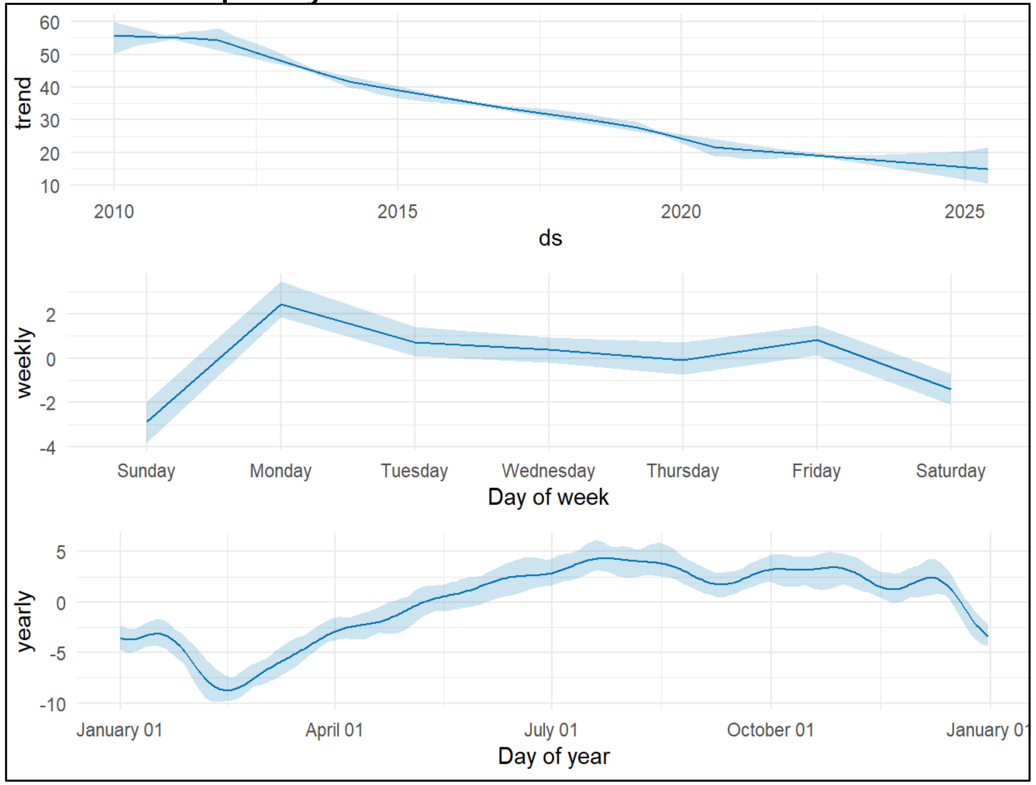

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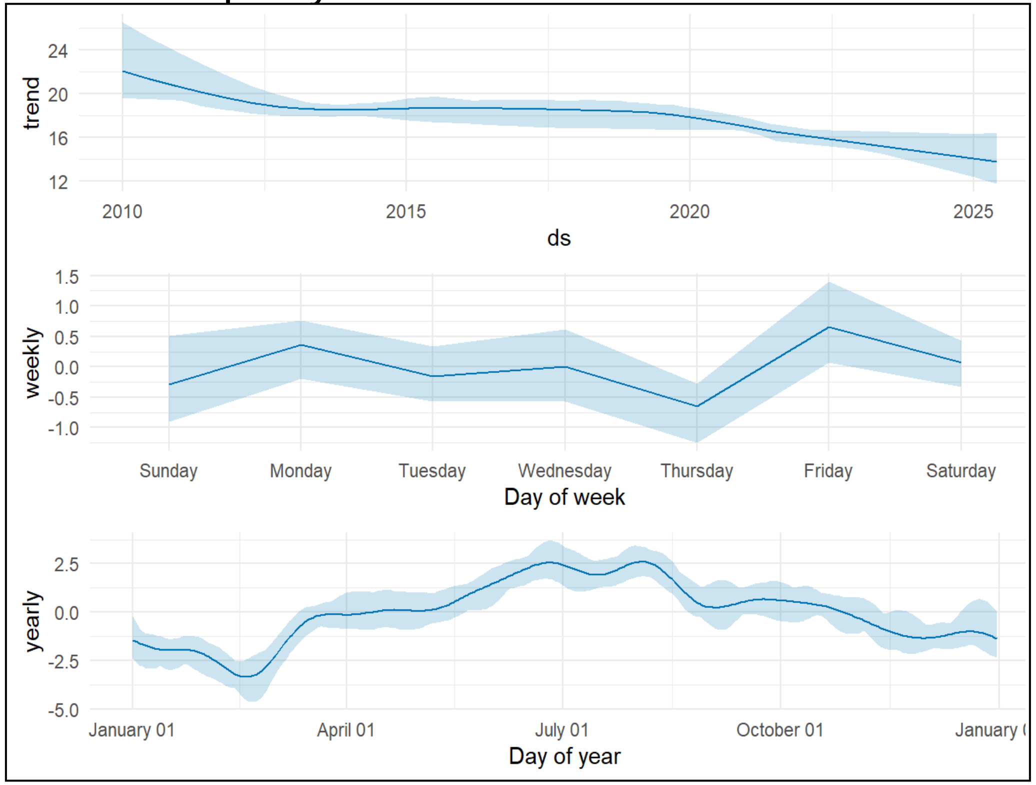
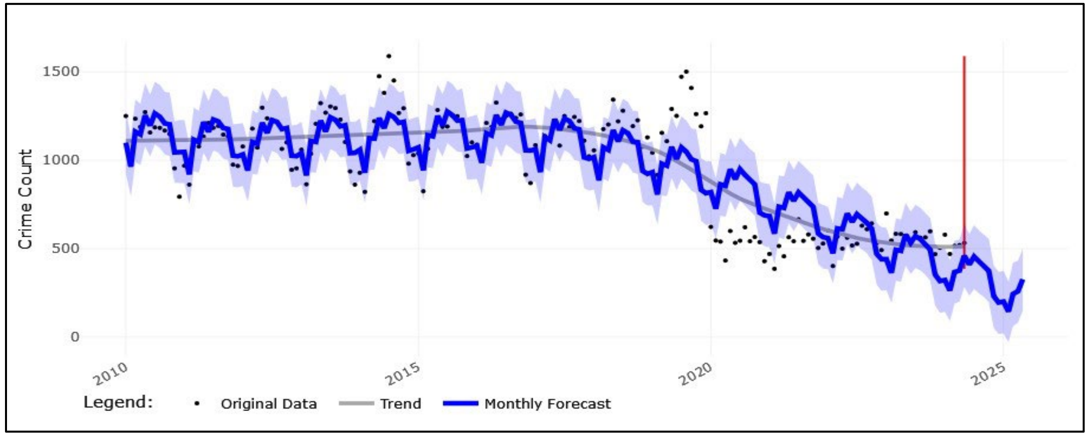


Public Order and Substance Offenses



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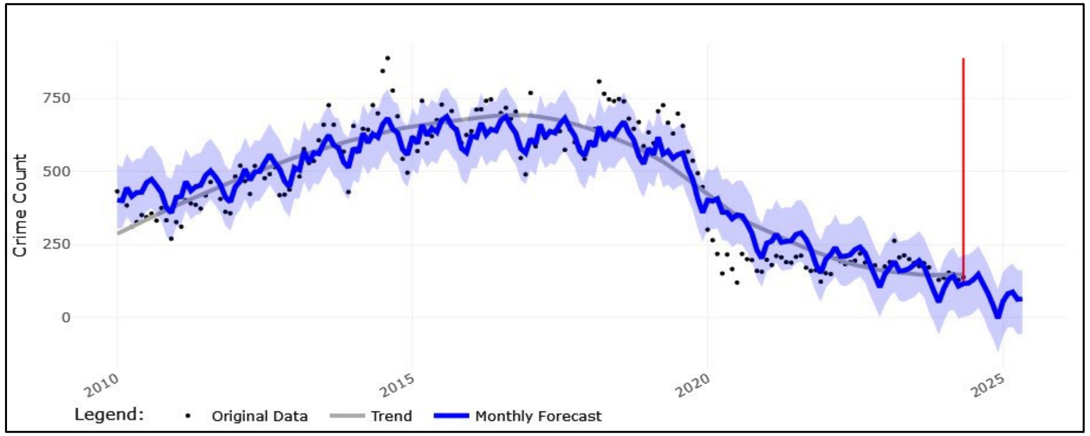
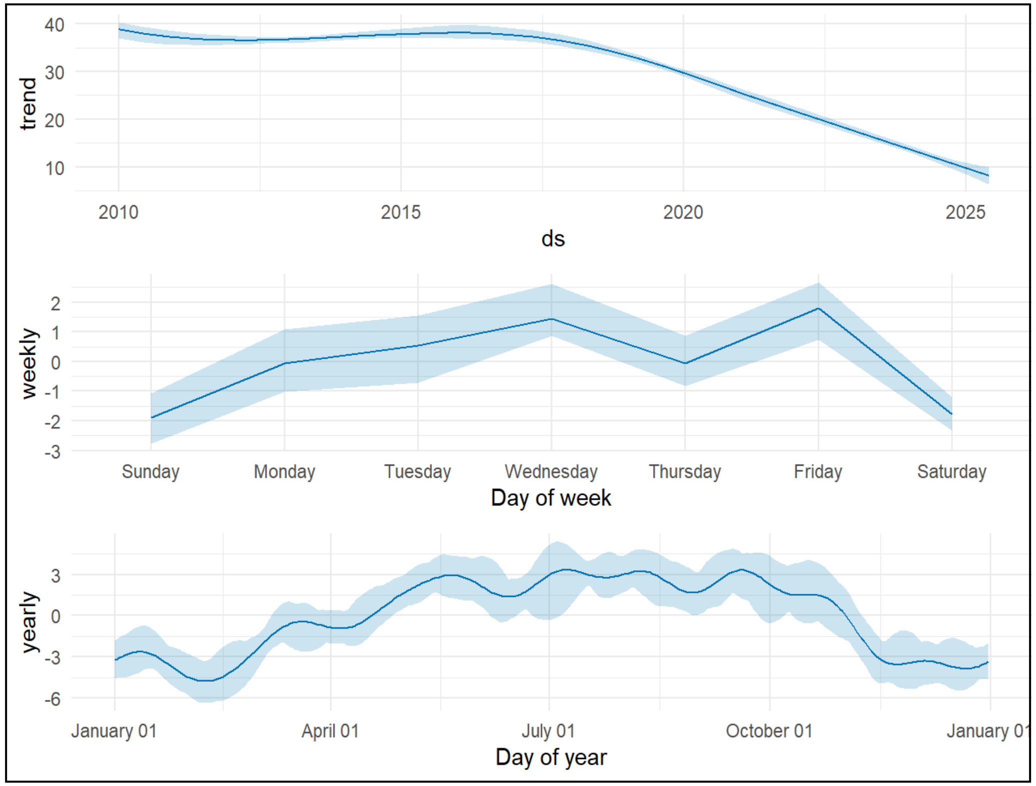


Substance-Related Offenses

Public Order and Substance Offenses- Decomposition

Public Order Offenses



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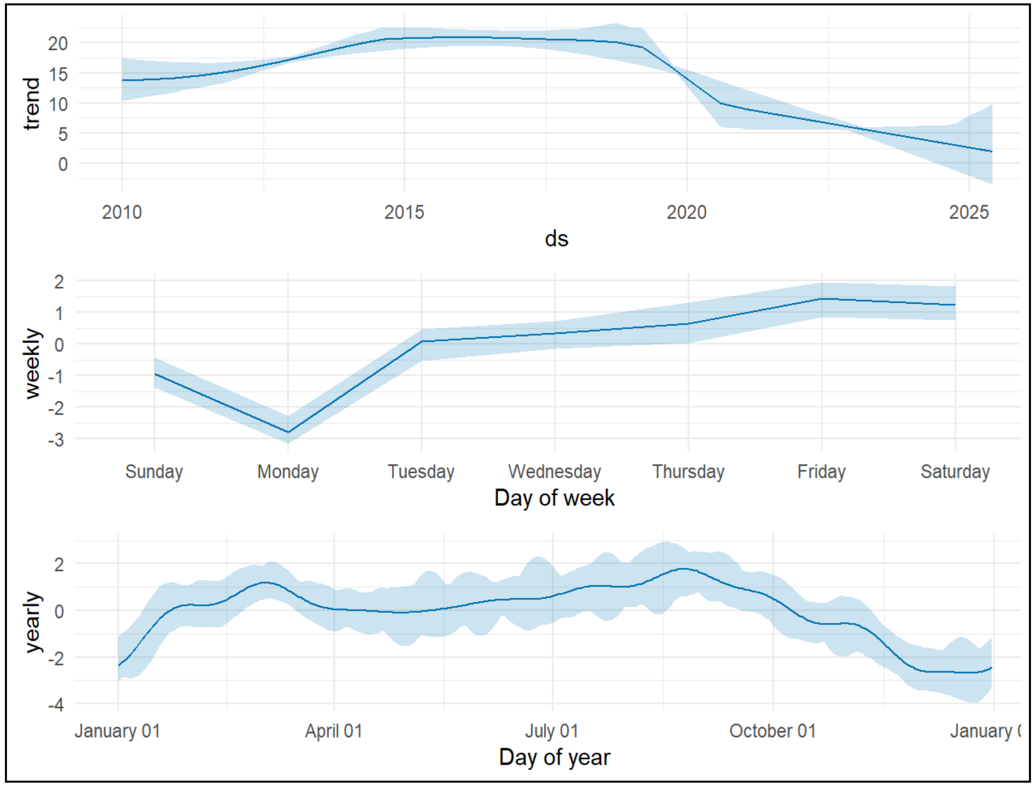

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Summary

Personal crimes

- Inverse relation between Part 1 and Part 2
- High variability in both categories
- Possible zero-sum dynamics between types

Property crimes

- Both categories showing general decline
- Part 1 exhibits stronger downward trend
- Lower variability than personal crimes

Public order and substance-related offenses

- Significant 2020 distribution in both
- Pre-2020: Different trajectories
- Post-2020: Similar stabilization patterns

Future Directions

- **Model baselines**: Comparative analysis of Prophet forecasts against ARIMA benchmarks and other ML models (e.g., XGBoost, Random Forest, LSTM, & GRU)
- **Validation enhancements**: Implementation of rolling window and sliding window cross-validation
- **MLOps pipeline**: Development of end-to-end system for:
  - **Data ingestion**: Automated data storage and versioning
  - **Feature engineering**: Streamlined feature engineering and pre-processing
  - **Model training**: Reproducible model training workflows
  - **Model management**: MLflow integration for experiment tracking, model registry, and metadata logging
  - **Operationalization**: Deployment architecture for production forecasting with performance monitoring

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Thank you!

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