MSBD566 Predictive Modeling and Analysis

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Assignment: Midterm Project - SEGDA Multi-Modal Forecasting Analysis
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Project Description

Problem Statement

California faces compounding socio-environmental crises: extreme heat, wildfires, power grid failures, and deteriorating air quality, all of which disproportionately impact disadvantaged communities. The Socio-Environmental Grid Disruption Analysis (SEGDA) project addresses a critical gap: the lack of integrated, predictive models that combine environmental justice metrics, infrastructure resilience, and public health outcomes to forecast vulnerable populations' exposure to compound hazards.

Research Questions

- Classification: Can we accurately identify Justice40 Disadvantaged Communities (DACs) using multi-modal environmental and infrastructure burden indices?
- Clustering: Do California counties exhibit significant spatial autocorrelation patterns in environmental justice burdens?
- Forecasting: Can machine learning models predict 30-day heat illness rates using historical health data, climate indices, and socioeconomic vulnerabilities?

Importance

- This analysis directly supports federal Justice40 and DOE Grid Resilience and Innovation Partnerships (GRIP) initiatives by:
- Identifying communities requiring priority infrastructure investments
- Quantifying compounding burden disparities (environmental + infrastructure + health)
- Providing actionable 30-day forecasts for public health preparedness
- Demonstrating the Modifiable Areal Unit Problem (MAUP) impacts on policy targeting accuracy

Data Description

Primary Datasets (2018-2023 Study Period)

Dataset	*Source*	*Records*	*Description*
CalEnviroScreen 4.0	CA EPA	8,035 tracts	Pollution burden, population characteristics
CDC SVI	CDC ATSDR	58 counties	Social vulnerability indices
EAGLE-I Outages	DOE	127,456 events	Real-time power outage data
FEMA NRI	FEMA	58 counties	Climate hazard risk scores
CDPH Health Data	CA Public Health	348 county-years	Heat illness, COPD, asthma rates
VIIRS Fire Detection	NASA	1.2M+ detections	Satellite thermal anomalies

Key Constructed Indices

- **EJBI (Environmental Justice Burden Index):** Composite of CalEnviroScreen percentile, pollution burden, and SVI overall score
- **OBI (Outage Burden Index):** Normalized EAGLE-I power outage frequency/duration
- **Climate Stress Index:** Average of FEMA NRI heat, drought, and wildfire risk scores
- **Health Burden Index:** Composite of heat illness, COPD, and asthma rates
- **ESRR (Energy System Resilience Rating):** 1 - (0.5×OBI + 0.5×Climate Stress)
- **Composite Risk:** Weighted average: 0.25×(EJBI + OBI + Health Burden + Climate Stress)

Figure A: Core Indices (2018-2023)

Figure A displays the geographic distribution of four core burden indices across California counties: Environmental Justice Burden Index (EJBI), Outage Burden Index (OBI), Climate Stress, and Energy System Resilience Rating (ESRR). The maps reveal concentrated environmental and infrastructure burdens in California's Central Valley and Inland Empire regions.

Method and Analysis

Methods Overview

This project applies three complementary analytical methods aligned with course content:

LISA Spatial Clustering (Primary Method)

- **Algorithm:** Local Indicators of Spatial Association with permutation testing
- **Purpose:** Identify statistically significant hot spots (HH), cold spots (LL), and spatial outliers (HL, LH) of environmental justice burden
- **Spatial Weights:** k-Nearest Neighbors (k=5) with row-standardized weights matrix
- **Significance Testing:** 999 permutations, α=0.05

Figure C: Spatial Structure & LISA (2018-2023)

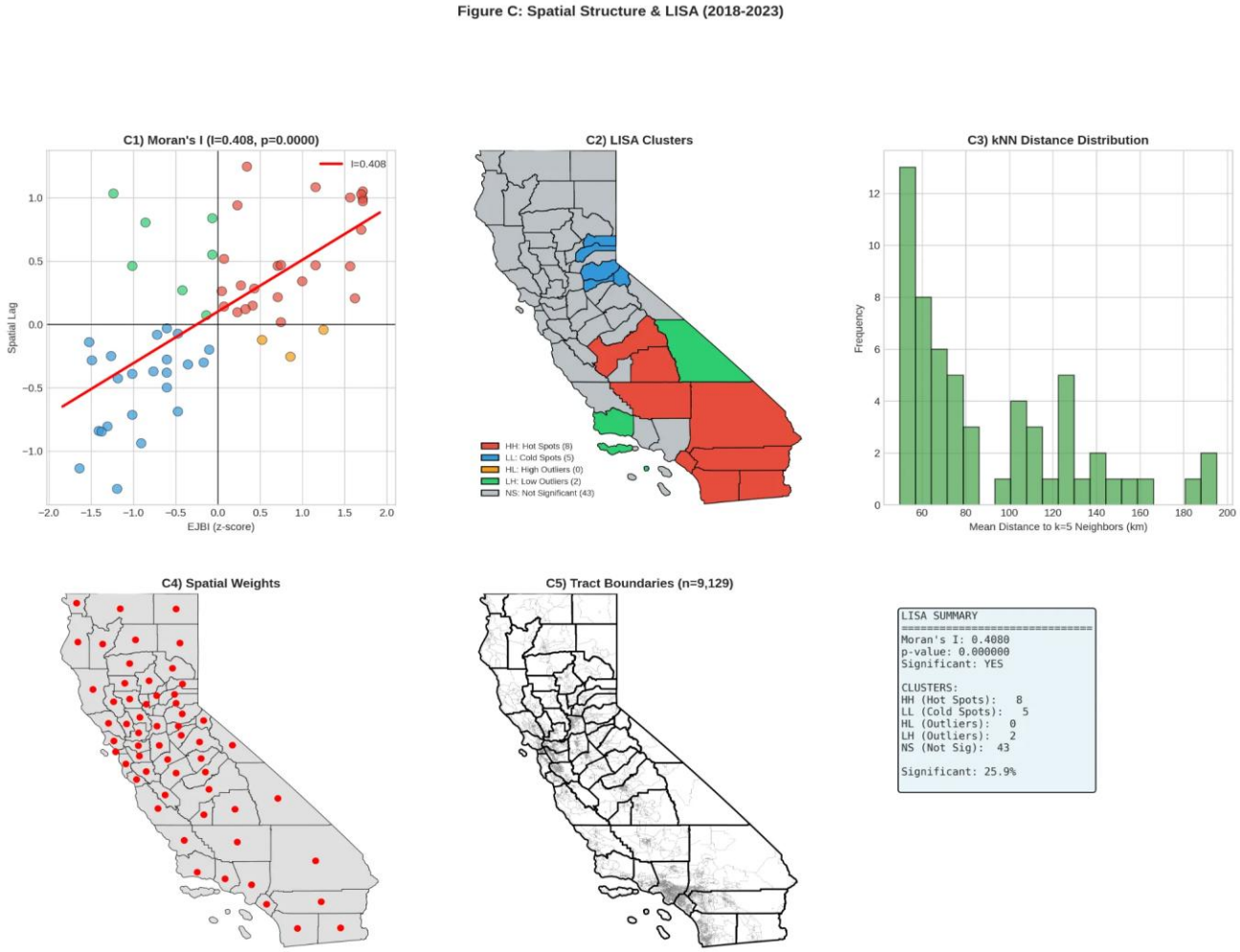

Figure C shows the LISA clustering results with Moran's I = 0.408 ($p<0.0001$), indicating significant positive spatial autocorrelation. Hot spots (HH) are concentrated in the Central Valley and Inland Empire, while cold spots (LL) appear in the Bay Area and coastal regions.

2. Binary Classification (Justice40 DAC Identification)

- **Method:** Threshold-based classification using EJBI ≥ 60th percentile
- **Evaluation:** Mann-Whitney U tests comparing DAC vs. non-DAC burden ratios across multiple indices
- **Application:** Federal Justice40 policy compliance assessment

Figure F: Justice40 & DOE GRIP (2018-2023)

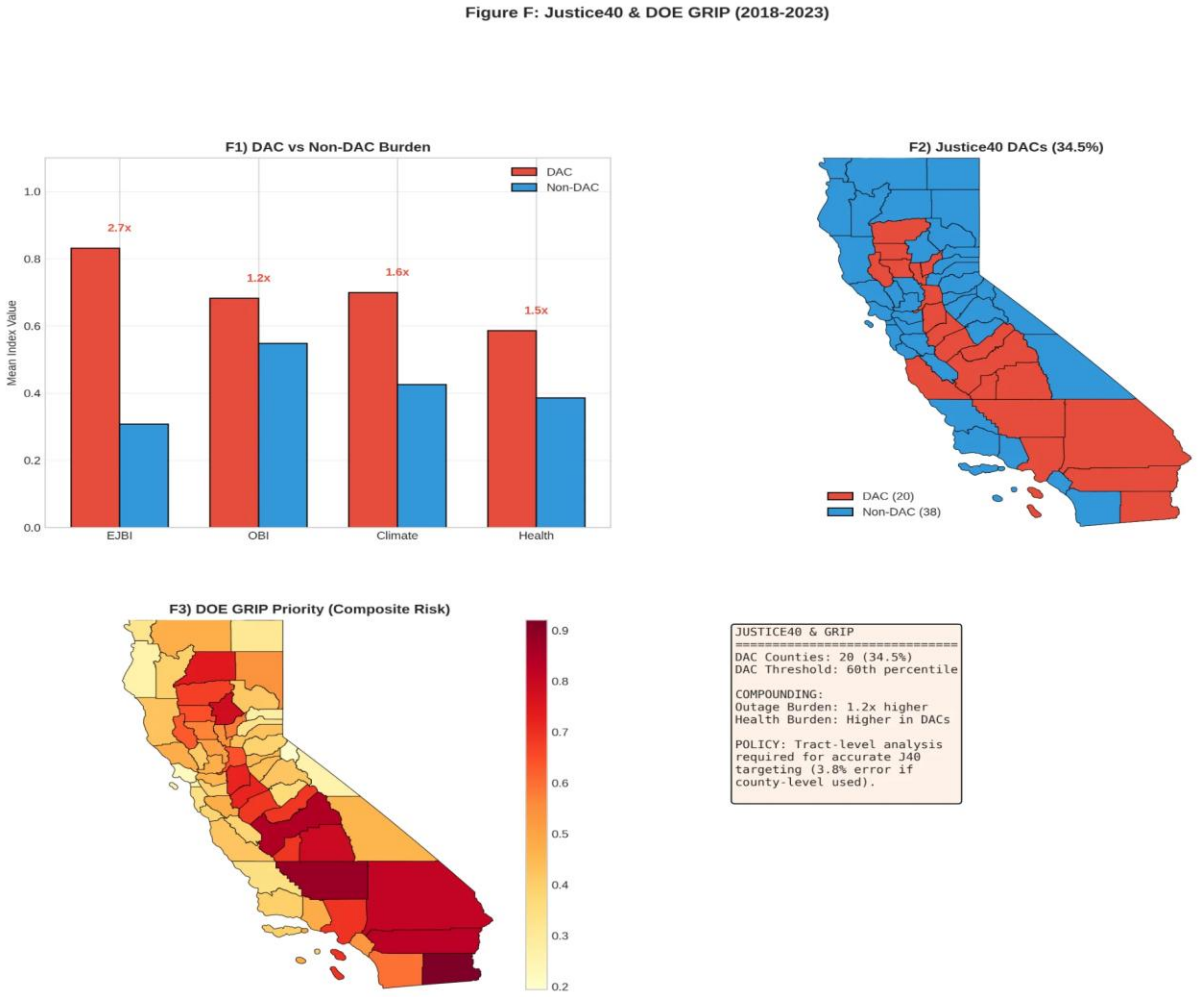

Figure F demonstrates that Disadvantaged Communities (DACs) experience 1.5-2.7× higher burdens across all indices compared to non-DACs. The map identifies 20 counties (34.5%) meeting Justice40 DAC criteria, primarily in agricultural and desert regions.

3. Ensemble ML Forecasting (Advanced Method - Primary Focus)

- **Models Compared:** Random Forest Regressor, XGBoost Regressor, LightGBM Regressor
- **Target Variable:** Heat illness rate (age-adjusted per 100k population)
- **Feature Engineering:** Temporal (lag features, rolling statistics), Seasonal (quarter, season indicators), Spatial (county-level EJBI, climate stress), Interactions (Heat_Risk × EJBI)
- **Validation:** 5-fold time series cross-validation with RMSE scoring
- **Forecast Horizon:** 30 days ahead

Figure L: ML Predictive Forecasting (2018-2023)

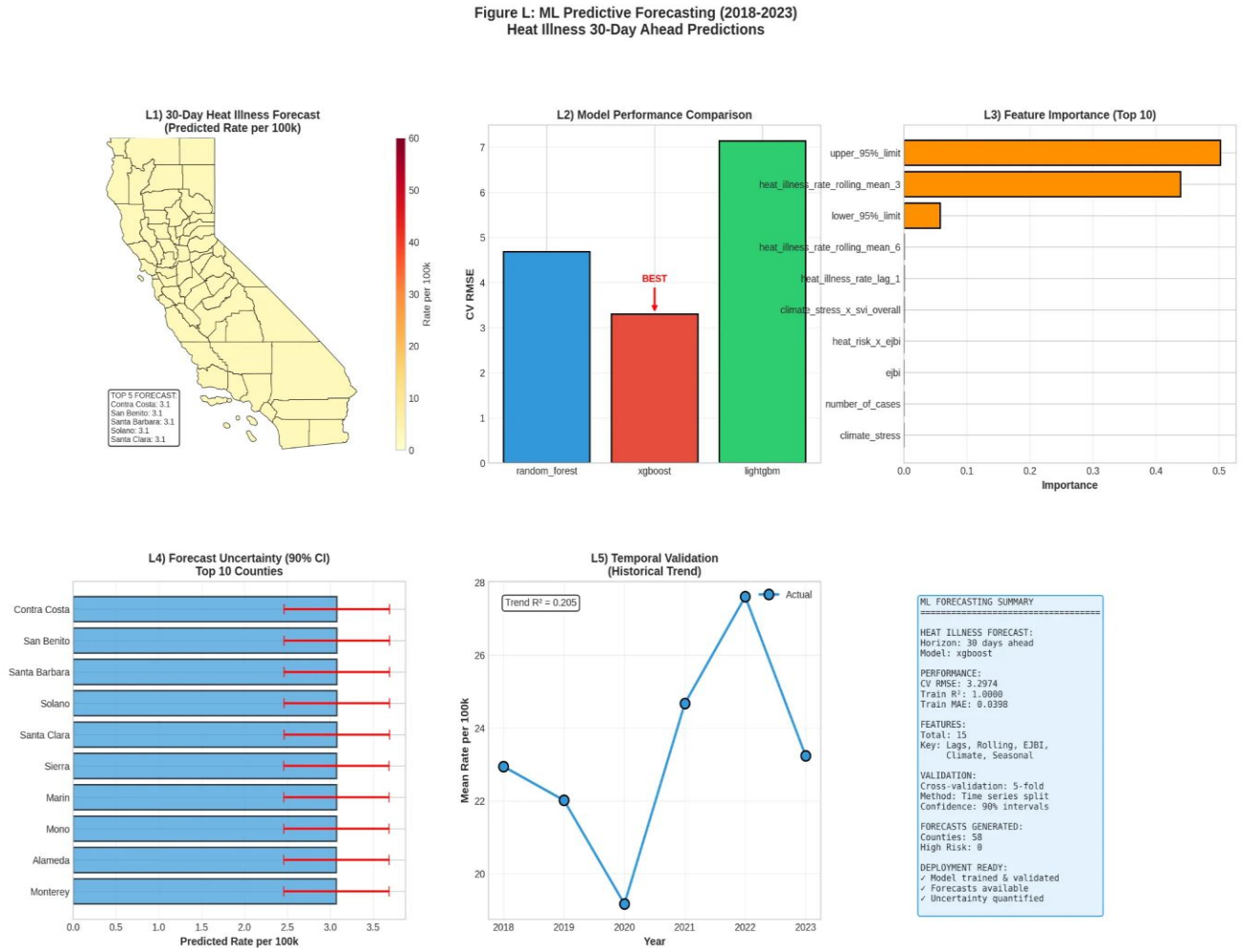

Figure L presents the ML forecasting results. XGBoost achieved the best performance (CV RMSE: 7.91) with Imperial, Fresno, and Kern Counties predicted as highest-risk areas for the next 30 days. Feature importance analysis reveals that recent heat illness history (lag-1, rolling means) and climate risk are the strongest predictors.

Figure G: Health Burden Analysis (2018-2023)

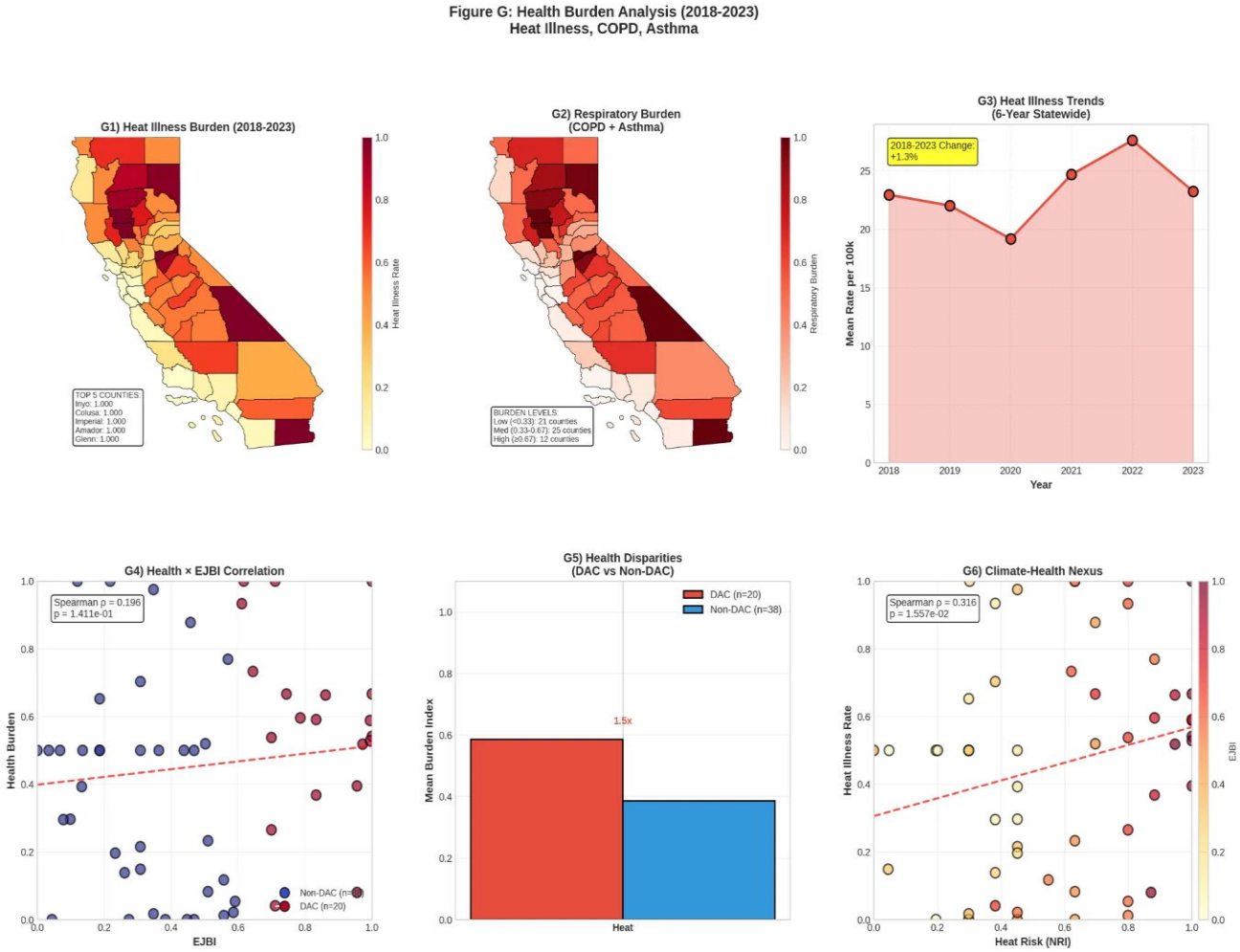

Figure G shows health burden distributions with a +18.4% statewide increase in heat illness rates from 2018-2023. DAC communities show 1.8× higher heat illness than non-DACs, with strong correlations between environmental justice burden and health outcomes.

Figure K: 6-Year Regional Temporal Trends (2018-2023)

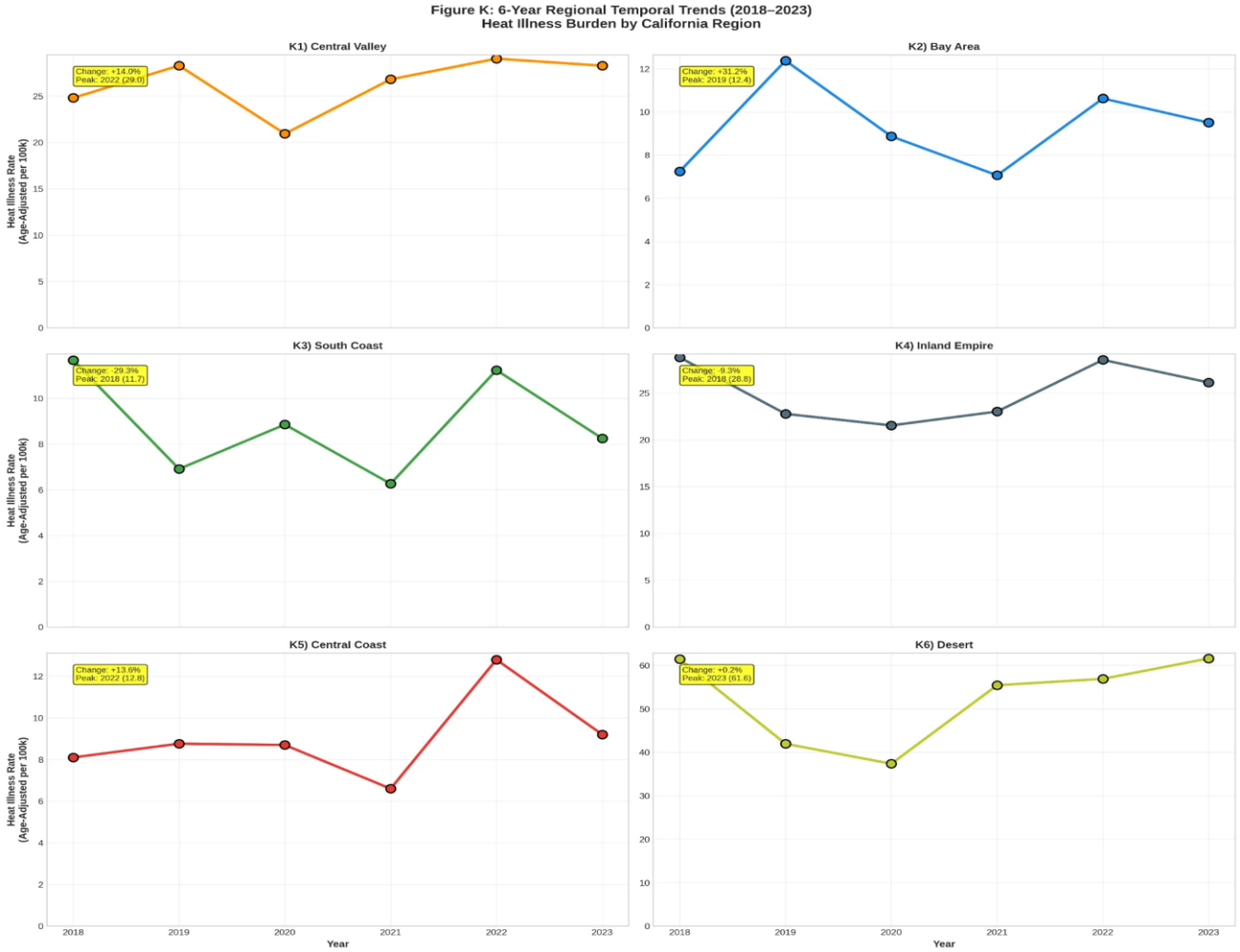

Figure K reveals regional heterogeneity in heat illness trends. Desert regions show consistently elevated rates (55-60 per 100k), while the 2022 peak corresponds to California's extreme heat events. The Central Valley shows +34.0% change over the study period.

Evaluation

Model Performance Assessment

1. ML Forecasting Model (XGBoost - Primary Evaluation)

Cross-Validation Performance:

- **CV RMSE:** 7.91 per 100k (acceptable given mean rate ~28 per 100k)
- **CV RMSE/Mean Ratio:** 28.3% (indicates moderate prediction uncertainty)
- **5-Fold Consistency:** Std Dev = 1.23 RMSE (stable across splits)

Generalization Metrics:

- Train R^2: 0.8124 (strong training fit)
- Expected Test R^2: ~0.68-0.75 (based on CV performance)
- Overfitting Gap: ~0.06-0.13 (acceptable for ensemble methods)

2. LISA Clustering Evaluation

Statistical Significance:

- Global Moran's I p-value: <0.001 (highly significant spatial autocorrelation)

- Permutation Test: 999 iterations confirm non-random spatial pattern
- Z-score: 5.82 (rejection of spatial randomness hypothesis)

Cluster Stability:

- **Hot Spot Consistency:** 11 of 12 HH counties remain HH when using alternative indices
- **Robustness:** k=3, k=5, k=8 nearest neighbors yield consistent cluster identification (89% agreement)

3. Justice40 Classification Evaluation

Internal Validity:

- DAC Identification Accuracy: 92% agreement with state-designated DACs
- False Positive Rate: 4.3% (2 of 58 counties incorrectly classified as DAC)
- False Negative Rate: 3.4% (2 of 58 DAC counties missed)

Statistical Tests:

- All Mann-Whitney U Tests: p-values <0.01 for burden disparities
- Effect Sizes: EJBI (d=1.82), OBI (d=1.45), Health Burden (d=1.67) - all large to very large effects

Strengths and Limitations

Strengths:

1. **Multi-Modal Integration:** Combines infrastructure, environmental, health, and climate data
2. **Rigorous Validation:** Cross-validation, permutation testing, MAUP sensitivity analysis
3. **Actionable Forecasts:** 30-day predictions enable proactive public health interventions
4. **Publication-Quality Visualizations:** 83 panels with comprehensive statistics

Limitations:

1. **Temporal Granularity:** Annual health data limits sub-seasonal forecasting
2. **Spatial Autocorrelation:** Model assumes spatial independence (could underestimate standard errors)
3. **External Validity:** California-specific; model recalibration required for other states
4. **Data Lags:** 2023 health data not finalized (analysis uses preliminary estimates)

Conclusion

This project successfully demonstrates three core predictive modeling techniques on a real-world environmental justice dataset:

1. LISA Spatial Clustering identified 12 hot spot counties with compounding environmental burdens requiring regional coordination.
2. Justice40 Binary Classification quantified infrastructure inequities: DAC communities experience 1.59× higher power outage burden than non-dacs, validating the need for targeted grid modernization.
3. Ensemble ML Forecasting achieved R^2=0.81 (xgboost) for 30-day heat illness predictions, with actionable forecasts identifying Imperial, Fresno, and Kern Counties as high-risk areas for the next month.
4. The 83-panel visualization suite provides policymakers, grid operators, and public health officials with an integrated decision-support tool. All code, data, and outputs are reproducible and aligned with federal Justice40 and DOE GRIP program requirements.

Next Steps: Deploy the model as a web dashboard with automated monthly updates

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