M3 Challenge 2025

Hot Button Issue: *Staying Cool as the World Heats Up*

Team #17447

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Executive Summary

Extreme heat events pose significant risks to urban populations, particularly vulnerable communities with limited access to cooling resources. This study presents a comprehensive approach to modeling heat vulnerability, indoor temperature fluctuations, and electricity demand forecasting in Memphis, Tennessee, during heat waves. Our work is divided into three key models: (1) predicting indoor temperatures in non-air-conditioned dwellings, (2) estimating peak electricity demand for Memphis over the next 20 years, and (3) developing a vulnerability index for identifying at-risk neighborhoods.

To model indoor temperatures, we employed a recursive thermal model incorporating outdoor temperature fluctuations, humidity, solar radiation, and building materials. Our results indicate that indoor temperatures lag behind outdoor temperatures and peak later in the day, with homes reaching up to 107.54°F at 2 PM, exceeding outdoor temperatures by 5.52°F. This finding underscores the risks of prolonged heat exposure in non-air-conditioned homes.

For peak electricity demand, we developed statistical models integrating climate projections, demographic trends, and energy efficiency improvements. Our random forest regression model achieved an R^2 of 0.9843, identifying heat wave intensity and high temperature as dominant predictors. Under a moderate climate scenario, Memphis's peak electricity demand is projected to increase by 28 percent to 3680.4 MW over the next 20 years, with population growth as the largest contributing factor (+17.6 percent impact).

Finally, we constructed a vulnerability index using ridge regression, incorporating elderly population, household count, and median income as key factors. Our model ranks neighborhoods by vulnerability, enabling targeted resource allocation. Areas such as South Memphis, Frayser, and Uptown exhibited the highest vulnerability scores, while Collierville and Germantown had the lowest risk. These results provide actionable insights for policymakers to implement cooling centers, urban greening initiatives, and financial assistance for air conditioning access.

Overall, our integrated modeling approach provides a data-driven framework for heat wave mitigation. Our findings emphasize the urgent need for infrastructure planning, targeted interventions, and climate resilience strategies to protect vulnerable populations from rising temperatures.

Q1: Hot to Go

1.1 Defining the Problem

The first problem asks us to develop a model to predict the indoor temperature of a non-air-conditioned dwelling over 24 hours during a heat wave. Our model will predict how the indoor temperature of Memphis, Tennessee, fluctuates based on outdoor conditions and dwelling characteristics.

1.2 Assumptions

1.2-1. Human interaction with the indoor environment is minimal

- **Justification:** The model assumes that occupants do not actively regulate indoor temperatures by opening windows, using blinds, or adjusting ventilation. This ensures a consistent analysis of the passive heat transfer mechanism and overall effects of the outside environment without external impacts.

1.2-2. All dwellings have uniform structural characteristics

- **Justification:** There are an equal number of doors and windows with uniform dimensions and thermal mass characteristics such as material composition.

1.2-3. The representative dwelling size is 1354.5 square feet

- **Justification:** This value serves as a baseline for thermal mass and heat retention calculations, representing the average size of dwellings included in the dataset[1].

1.2-4. The year of construction and natural shading effects are negligible

- **Justification:** While older buildings and shaded areas may exhibit different thermal properties, this model assumes that variations in construction age and shading do not significantly impact overall heat retention or dissipation.

1.2-5. Weather and climate conditions remain consistent across the city.

- **Justification:** The model assumes uniform atmospheric conditions throughout the study area, ensuring that all dwellings experience identical outdoor temperatures and climatic factors.

1.2-6. Artificial cooling mechanisms are absent.

- **Justification:** The model excludes the influence of fans, air conditioning, and other active cooling methods, focusing solely on passive temperature fluctuations.

1.2-7. Houses are primarily constructed from wood.

- **Justification:** A large percentage of American homes are constructed from wood[2]. Additionally, wood has a lower thermal conductivity compared to materials like concrete or steel, making it a natural insulator[3].

1.2-8. Windows are multi-paned.

- **Justification:** A large percentage of windows in American homes are multi-paned[4].

1.3 Variables and Constants

Symbol	Variable	Unit	Value
Tout	Outdoor Temperature	°C	Given list
Tin	Indoor Temperature	°F	Computed
H	Humidity	%	Given list
thermal_mass	Thermal Mass Factor	N/A	0.2
window_factor	Window Exposure Factor	N/A	0.76
wood_factor	Wood Insulation Factor	N/A	0.3
solar_effect	Solar Heat Influence	N/A	Computed

Table 1: Table of Variables and Constant.

1.4 Model

1.4-1. Model Development

Our team developed a simulation to model the change in indoor temperatures during a 24-hour heat wave, incorporating key factors such as thermal mass, window exposure, solar radiation, and humidity effects. The model follows a recursive approach, where each indoor temperature value depends on the previous one. Given this, a recursive approach is more appropriate than linearization, as it better reflects the gradual accumulation of heat over time, which is crucial for understanding the effects of prolonged heat exposure. The diurnal cycle of temperature changes, with its inherent nonlinearity, further emphasizes the need for such a model.

Heat flow through building materials follows conductive heat transfer, where temperature differences and insulation properties dictate the rate of heat exchange. Greater temperature differentials accelerate heat transfer, influencing indoor temperature fluctuations.

Solar radiation, a major heat source, is modeled with a sinusoidal function peaking between 12:00 PM and 2:00 PM, ensuring high granularity in capturing its impact. Thermal inertia, the delayed indoor response to outdoor changes, is incorporated by accounting for material-specific heat retention. Buildings with higher thermal mass experience a time lag in temperature shifts, with indoor peaks occurring later than outdoor ones.

Thermal inertia is a key factor in temperature dynamics within buildings, referring to the delayed response of interior temperatures to external fluctuations. Materials like brick have higher thermal mass than wood, storing heat longer. Our model accounts for this delay by incorporating material-specific properties that influence heat retention, causing a time lag between outdoor and indoor temperature shifts.

This time lag is especially pronounced in buildings with substantial thermal mass, where absorbed heat is released gradually, leading to a delayed indoor warming effect. We incorporated this lag into our model to accurately reflect the slower rise in indoor temperatures as heat accumulates throughout the day.

Humidity also affects indoor temperatures, influencing thermal comfort and heat retention. We included a humidity effect parameter that adjusts indoor temperatures based on relative humidity and dew point, refining the model's representation of heat perception and temperature regulation. This ensures the model accounts for increased heat retention at higher moisture levels.

1.4-2 Executing the Model

Our team used the provided 24-hour heat wave data of Memphis, Tennessee, USA. The model takes in five primary parameters including the outdoor temperature.

1. Humidity affects heat retention and perceived temperature, with higher humidity slowing heat dissipation, making indoor environments feel warmer. Our model adjusts indoor temperatures using relative humidity, the temperature difference, and the deviation between outdoor temperature and the dew point.

2. Thermal mass is a material's ability to absorb and release heat. We use a 0-1 scale, where higher values indicate more thermal mass. Materials like brick and concrete have higher values than wood and metal. For wood-frame houses, we settled on a value of 0.2.

3. The window factor reflects the Solar Heat Gain Coefficient (SHGC), which measures how much solar radiation passes through a window, door, or skylight[5]. Following our assumption of 1.2-8. Windows are multi-paned; we used the known SHGC value of 0.76.

4. The wood factor represents the insulating properties of wood, which resists heat flow but doesn't store or release heat as efficiently as high-density materials. Based on typical wood-frame houses, we chose a value of 0.3.

The newly calculated temperature stems from the following equation:

$$\text{new\_temp} = \text{prev\_temp} + (\text{temp\_diff} \times \text{adjusted\_thermal\_mass}) + (\text{solar\_effect} \times \text{temp\_diff}) + \text{humidity\_effect} \tag{1}$$

The adjusted thermal mass is calculated by multiplying the thermal mass by (1 + the wood factor).

The dew point is calculated using the Magnus formula, an empirical relationship that estimates the dew point temperature in Celsius from air temperature and relative humidity. The Magnus formula is:

$$\alpha = \frac{a \cdot T}{b + T} + \ln\left(\frac{RH}{100}\right) \tag{2}$$

$$T^M = \frac{b \cdot \alpha}{a - \alpha} \tag{3}$$

where a = 17.27 and b = 237.7, values commonly used in meteorology for estimating the dew point over typical temperature and humidity ranges. RH symbolizes the relative humidity as a percentage. The alpha is the intermediate variable which is used to solve for the dew point[6].

This calculation is performed iteratively for each hour from 12:00 AM to 11:00 PM, simulating how the building's interior temperature changes throughout 24 hours in response to outdoor temperature variations, solar radiation, humidity, and the building's thermal properties. The process is repeated for all 24 hours, providing a full day's worth of temperature data based on the given parameters.

1.5 Results

Using our simulation model developed in the previous section, we estimated the indoor temperature of dwellings in Memphis, Tennessee over 24 hours in Python. Below is the graph of our simulation model for the 24 hours.
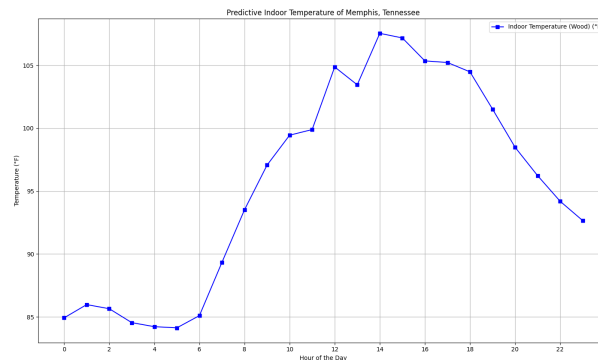
This graph illustrates the temperature of the interior of the house in Fahrenheit in the 24 hours.

1.6 Discussion

For Memphis, our model estimates that indoor temperatures in a non-air-conditioned dwelling will follow the pattern influenced by outdoor temperature fluctuations. Based on the data, indoor temperature peaks at 107.541°F at 2 PM, exceeding the outdoor temperature of 102.02°F by 5.521°F. The temperature difference

reaches its maximum at 7 PM, where the indoor temperature remains elevated at 101.517°F while the outdoor temperature drops to 93.92°F, resulting in a 7.597°F disparity. This suggests that heat accumulates indoors throughout the day due to thermal mass and limited ventilation. As outdoor temperatures decrease overnight, indoor temperatures decline but remain slightly higher due to residual heat. From this, we can conclude that indoor temperatures in non-air-conditioned homes lag behind outdoor temperatures, with heat retention prolonging elevated temperatures even as external conditions cool.

1.7 Sensitivity Analysis

To determine the accuracy of our predictions, we randomly offset each data point by up to 5% and then ran the model again to get a new prediction. We calculated the percent difference between the original prediction and the new prediction. This process was repeated 100 times, with the results averaged to provide a robust measure of our model's sensitivity to input variations.
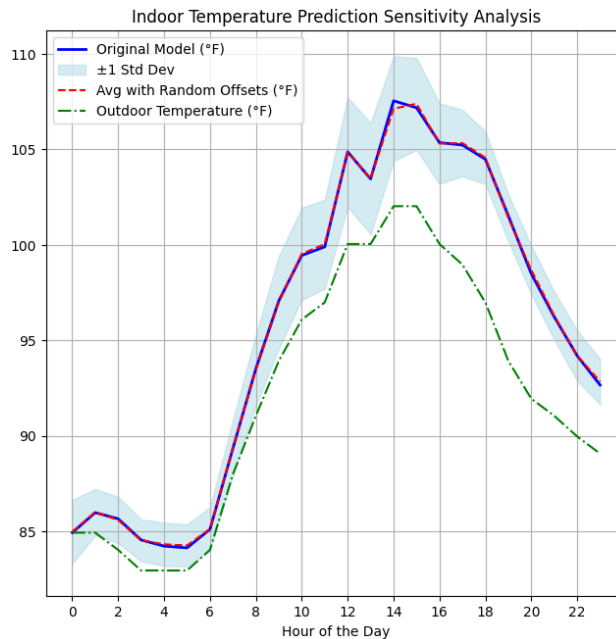
This graph reflects the percent difference between the original prediction and the new prediction after a 5 percent adjustment.
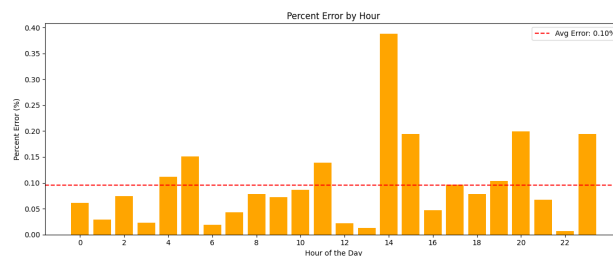
This chart shows the percent error by hour

The analysis shows that our model is most stable during morning hours when temperature changes are minimal. The highest sensitivity occurs during evening hours when the indoor-outdoor temperature differential is greatest, with percent errors approaching 0.4%. Notably, the percent error trends upward

throughout the day, suggesting that cumulative effects of thermal mass and humidity create increasing uncertainty in longer-term predictions. However, the overall average jittered variation of 0.1% indicates that our model maintains good resilience to random error.

Our confidence intervals remain relatively narrow throughout the 24 hours, with standard deviations averaging less than 2°F. This further supports our model's stability when exposed to small variations in input parameters.

1.8 Strengths and Weaknesses

Strengths

Our simulation models daytime heating and nighttime cooling since the model accounts for solar influence during daylight hours. In addition, our simulation model acknowledges that indoor temperature does not change instantaneously, since indoor temperature responds gradually to outdoor conditions. Finally, the effect of insulation materials is included, making it adaptable to different building structures.

Weakness

The model may overestimate peak indoor temperatures due to several simplifying assumptions. It assumes constant weather conditions and no external cooling, which could lead to higher indoor temperatures than would occur in real conditions. Additionally, the fixed solar radiation pattern does not account for variables like cloud cover, shading, or seasonal changes, potentially overestimating solar heat gains. The model also treats the building as a uniform thermal mass, neglecting differences in room orientations, airflow patterns, and heat dissipation through ventilation. These factors can cause localized temperature variations that the current model does not capture.

Q2: Power Hungry

2.1 Defining the Problem

Develop a model that predicts the peak demand that Memphis's power grid should be prepared to handle during the summer months. Forecast changes in the maximum demand 20 years from now, accounting for key influencing factors.

2.2 Assumptions

2.2-1 Population density directly correlates with increased air conditioning demand.

- **Justification:** Urban heat island effects in Memphis intensify cooling needs in dense areas, creating more anthropogenic heat and requiring greater HVAC capacity per square foot[7][8].

2.2-2 Air conditioning penetration will approach saturation with minimal growth.

- **Justification:** Memphis's AC penetration rate is approximately 90%, with remaining adoption primarily limited by structural or financial barriers in older buildings and disadvantaged areas.

2.2-3 Home insulation characteristics remain relatively constant across the forecast period.

- **Justification:** Memphis homes use fiberglass (R-value 48), open-cell spray foam (R-value 42.6), and closed-cell spray foam (R-value 75). High upgrade costs and long lifecycles (20-30 years) minimize turnover within the forecast window.

2.2-4 Energy efficiency improvements follow established technological and regulatory trajectories.

- **Justification:** HVAC efficiency gains follow predictable S-curves driven by federal standards and market competition, allowing reliable extrapolation through the forecast period.

2.2-5 Electricity price elasticity has minimal impact on peak demand patterns.

- **Justification:** Residential cooling shows low short-term price elasticity (-0.2 to -0.4), particularly during extreme heat events when health concerns override cost considerations[9].

2.2-6 Renewable energy adoption patterns remain stable through the forecast period.

- **Justification:** High initial costs ($15,000-$25,000) and long payback periods (7-12 years) for residential solar create barriers to rapid adoption shifts without transformative policy intervention[10].

2.3 Variables

Symbol	Variable	Unit
HS	Household Size	sq ft
I	Median Household Yearly Income	USD
P	Population	amount of residents over time
EC	Electricity Consumption	MW
T	Temperature	°F
D	Dew Point	°F
H	Humidity	percentage
MT	Maximum Annual Temperature	°F
PD	Peak Electricity Demand	MW
t	Time Period	years

Table 2: Variables in Vulnerability Scoring

2.4 The Model

Our approach integrates statistical modeling with thermodynamic principles through four components: Statistical Power Demand Analysis, Thermodynamic Energy Modeling, Scenario Development, and Sensitivity Analysis.

For Statistical Power Demand Analysis, we implemented two complementary models. First, a Linear Regression Model established baseline relationships:

$$PD = \beta_0 + \beta_1 T + \beta_2 P + \beta_3 ACP + \beta_4 CDD + \epsilon \tag{4}$$

where PD represents Peak demand (MW), T is Temperature (°F), P denotes Population, ACP is Air conditioning penetration (%), and CDD stands for Cooling degree days. This model provided strong predictive power (R^2 of 0.9123), which we enhanced with a Random Forest Model ($PD = f(T, P, H, ACP, CDD, HW)$) to better capture non-linear relationships, achieving superior performance (R^2 of 0.9843).

Our thermodynamic model calculates cooling energy as the difference between outdoor and indoor temperatures: $E(T) = k(T_{outside} - 72)$, where k is an efficiency coefficient dependent on home insulation, air conditioner efficiency, and home characteristics. To account for efficiency improvements, we implemented a time-dependent coefficient: ($k(t) = k(1 - t/200.15)$ where 0.15 represents Efficiency Improvement). Crucially, we developed a heat wave intensity factor ($1.0 + 0.02 max(0, Temperature - 95)$) to capture the disproportionate impact of extreme heat events on peak demand.

To address future uncertainties, we developed three distinct scenarios with varying assumptions about climate change, population growth, technology adoption, and efficiency improvements:

- Baseline Scenario: 1.0°F temperature increase, 0.8% annual population growth, 5% AC penetration increase, 10% efficiency improvement

- Moderate Scenario: 2.0°F temperature increase, 1.0% annual population growth, 8% AC penetration increase, 15% efficiency improvement

- High Impact Scenario: 3.5°F temperature increase, 1.2% annual population growth, 10% AC penetration increase, 20% efficiency improvement

Our comprehensive framework for projecting future peak demand integrates all components:

$$PD(t + 20) = PD(t)(1 + \Delta\text{Temp} * \beta T)(1 + \Delta\text{Pop} * \beta P)(1 + \Delta\text{AC} * \beta A)(1 - \Delta\text{Eff} * \beta E)$$

where PD(t+20) is the projected peak demand in 20 years, PD(t) is the current peak demand (2875.3 MW), and the D terms represent changes in key variables with their corresponding sensitivity coefficients derived from our regression models.

2.5 Results

2.5-1 Feature Analysis

Factor	Correlation with Peak Demand	Importance (Random Forest)
Heat Wave Factor	0.953818	0.365095
High Temperature	0.652801	0.574877
Cooling Degree Days	0.589198	0.020194
Average Temperature	0.589198	0.022091
AC Penetration	0.037743	0.009033
Population	0.037743	0.008710

Table 3: Temperature-related factors (heat wave intensity and high temperature) emerged as the dominant predictors, collectively accounting for approximately 94% of the model's predictive power.

2.5-2 Temperature Sensitivity

Our analysis quantified Memphis's temperature sensitivity at two levels:

- **Direct Linear Sensitivity:** 7.09 MW/°F near current peak temperature (94.0°F)

- **Effective Temperature Impact:** 20.15 MW/°F when accounting for non-linear heat wave effects

This substantial difference (184% higher effective sensitivity) demonstrates the critical importance of modeling non-linear temperature effects when planning for climate change impacts.

2.5-3 Cooling Requirements

Based on our thermodynamic model and projected temperature increases:

Scenario	Current Cooling Requirement	Future Cooling Requirement	Change
Baseline	22.0°F	23.0°F	+1.0°F
Moderate	22.0°F	24.0°F	+2.0°F
High Impact	22.0°F	25.5°F	+3.5°F

Table 4: These increased cooling requirements translate directly to higher energy demand, even as efficiency improvements partially offset the impact.

Scenario	Energy Consumption Change
Baseline	-5.9%
Moderate	-7.3%
High Impact	-7.3%

Table 5: These figures represent per-unit efficiency gains, not total consumption, which is still projected to increase due to higher cooling requirements and population growth.
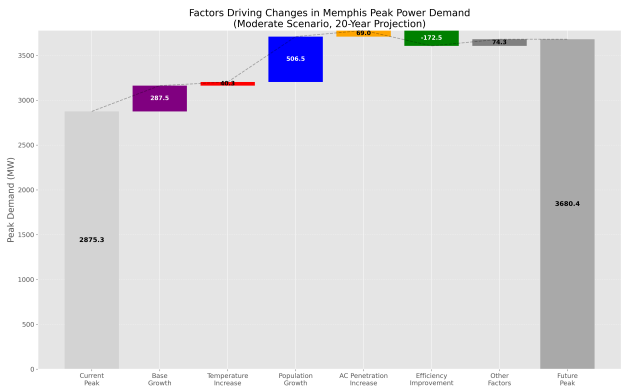

Figure 1: This waterfall chart illustrates the individual contribution of each factor to the projected increase in Memphis's summer peak power demand over the next 20 years under the moderate scenario.

2.5-4 Energy Efficiency Impact

Our model projects efficiency improvements will partially mitigate increased cooling needs:

Starting from the current peak of 2875.3 MW, the chart shows how base growth (+287.5 MW), temperature increase (+40.3 MW), population growth (+506.5 MW), AC penetration increase (+69.0 MW), efficiency improvements (-172.5 MW), and other factors (+74.3 MW) combine to reach the projected future peak of 3680.4 MW, representing a total increase of 28%.

2.5-5 Peak Demand Projections

Our 20-year projections for Memphis's summer peak power demand:

Scenario	Temperature Increase	Projected Peak (MW)	Change (%)
Baseline	1.0°F	3477.35	22.00%
Moderate	2.0°F	3680.4	28.00%
High Impact	3.5°F	3819.39	34.00%

Table 6: The moderate scenario, which we consider most likely, projects a 28.00% increase from the current peak of 2875.3 MW.
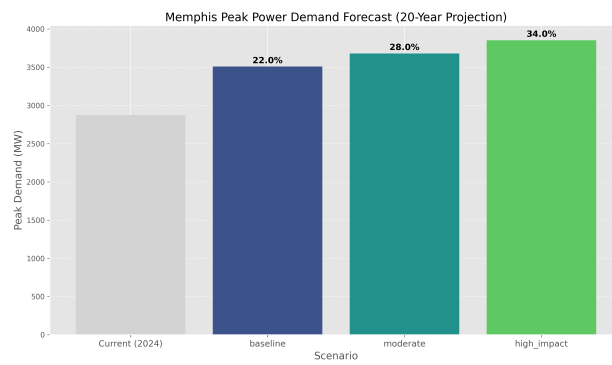
Figure 2: Bar chart comparing projected scenarios for Memphis's summer peak power demand: baseline (22% increase to 3477.35 MW), moderate (28% increase to 3680.4 MW), and high-impact (34% increase to 3819.39 MW) against current demand of 2850.29 MW.

2.5-6 Contributing Factors

For the moderate scenario (28.00% increase), we decomposed the contributions:

Factor	Contribution (MW)	Percentage of Current Peak
Base Growth	287.5	10.0%
Temperature Increase	40.3	1.4%
Population Growth	506.5	17.6%
AC Penetration Increase	69.0	2.4%
Efficiency Improvement	-172.5	-6.0%
Other Factors	74.3	2.6%

Table 7: Population growth emerges as the dominant driver (17.6%), while efficiency improvements provide the largest mitigating effect (-6.0%).

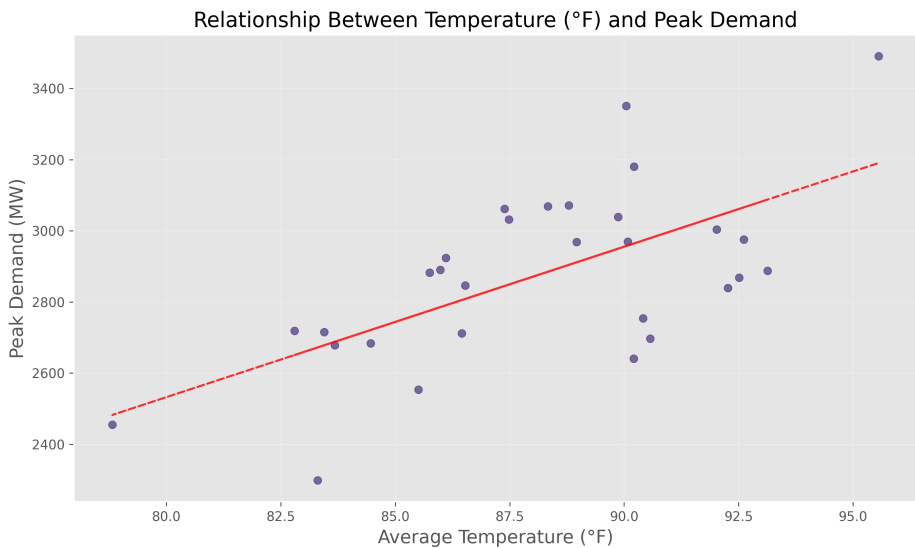### 2.5-7 Visualization Results

Figure 3: Scatter plot with regression curve demonstrating non-linear relationship between summer temperatures and peak power demand, with pronounced curve above 90°F illustrating disproportionate impact of extreme heat events.

2.6 Discussion

2.6-1 Temperature Sensitivity and Climate Change

The strong relationship between temperature and peak demand (correlation of 0.953818 for heat wave factor) underscores Memphis's grid vulnerability to climate change. The non-linear relationship becomes pronounced above 95°F, suggesting even modest temperature increases will have disproportionate impacts.

2.6-2 Population as Primary Driver

Population growth (17.6% contribution) represents the largest driver of increased peak demand, significantly higher than direct temperature effects (1.4%). This finding has important implications for urban planning
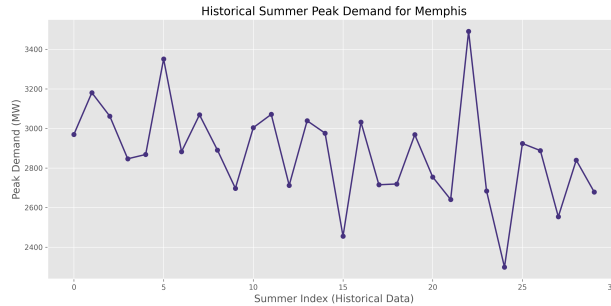
Figure 4: Line graph displaying historical summer peak demand data for Memphis, showing fluctuations between 2400 MW and 3500 MW with gradual upward trajectory and notable spikes during particularly hot summers.

and suggests residential energy efficiency programs could provide outsized benefits.

2.6-3 Efficiency as Mitigation Strategy

Efficiency improvements (-6.0% contribution) partially offset increased demand but cannot eliminate the need for additional capacity. A balanced approach combining efficiency, capacity expansion, and demand management is required.

2.6-4 Heat Wave Vulnerability

The calculated heat wave factor (with quadratic growth above 95°F) highlights Memphis's vulnerability to extreme heat events. During a simulated 7-day heat wave, peak demand spikes by approximately 175.6% over normal summer levels, highlighting the importance of contingency planning beyond average conditions.

2.7 Strengths and Weaknesses

Strengths

Our approach boasts several key strengths that contribute to its robustness and reliability. The comprehensive modeling framework integrates statistical analysis with physics-based energy modeling, providing both empirical validation and theoretical foundations for projections. This integration allows for a more nuanced understanding of the complex factors influencing energy demand. The incorporation of non-linear temperature modeling, specifically through the heat wave intensity factor, captures the disproportionate impact of extreme temperatures on peak demand, which simple linear models often fail to account for. Our approach also acknowledges future uncertainty through multiple scenario planning, offering three distinct scenarios that provide actionable ranges for infrastructure planning. The high model accuracy, demonstrated by an R^2 of 0.9843 for our random forest model, showcases exceptional explanatory power for a complex system. Additionally, the detailed breakdown of contributing factors provides clear guidance for prioritizing interventions, enhancing the model's practical applicability.

Weaknesses

Despite its strengths, our approach does have some limitations that should be acknowledged. The inherent uncertainty in climate change projections could affect forecast accuracy, even though we model three temperature scenarios. Our demographic modeling is simplified, assuming uniform population growth rather than accounting for potential demographic shifts or migration patterns that could impact consumption patterns. The model's ability to capture future technological innovations in cooling, smart grid management, or distributed energy resources is limited, which could lead to unforeseen alterations in demand patterns. The

static efficiency assumptions may not accurately reflect the complex interplay of policy changes, economic factors, and technological advancements over time. Lastly, while our model accounts for average summer temperature increases, it may not fully capture the increased frequency of extreme heat events, which could have significant impacts on peak demand.

2.8 Recommendations

Based on our analysis, we recommend planning infrastructure for a 28% increase in summer peak demand (3680.4 MW), with contingencies for higher scenarios. Prioritize residential efficiency programs in high-growth areas and develop heat wave response protocols to manage potential 175% demand spikes. Update building codes for improved insulation and cooling efficiency, while implementing distributed energy resources, focusing on rooftop solar and storage. Modernize grid infrastructure with smart technologies for dynamic load management and establish programs to protect vulnerable populations during heat waves. Finally, conduct annual forecast updates incorporating the latest climate science, demographics, and technology trends to ensure adaptive energy planning.

Q3: Beat the Heat

3.1 Defining the Problem

Extreme heat events, particularly in the presence of power grid failures, pose a severe risk to urban populations. Memphis city officials seek a data-driven vulnerability score to identify at-risk neighborhoods and allocate resources effectively. This model integrates various factors that best captures risk effects.

3.2 Assumptions

3.2-1. Vulnerability is linear

- **Justification:** Vulnerability can be calculated linearly because its contributing factors—such as elderly population and income—exert proportional and independent influences on heat-related risk, making a weighted sum an effective approximation of overall vulnerability.

3.2-2. There are no other independent factors besides elderly population, number of households, and median household income that significantly impact vulnerability

- **Justification:** Elderly populations are more sensitive to extreme heat and heat waves[15]. A higher number of households indicates a larger population at risk, increasing overall vulnerability. Conversely, higher household income enables greater access to resources like air conditioning, helping to mitigate the effects of extreme heat. We cannot comprehensively analyze all other variables that play an arbitrarily small role in calculating vulnerability.

3.2-3. The poverty line is $36,777

- **Justification:** The national average household consisted of about 3 people in 2023[16]. The 2025 federal poverty levels for Tennessee residents of a household of 3 is $36,777[17]

3.3 The Model

3.3-1 Model Development

We first examined various factors to determine their correlations with heat vulnerability using multivariate linear regression. Our dataset spanned multiple years and contained information on environmental conditions, socioeconomic factors, and demographic characteristics. Some variables had missing values, so we used imputation techniques to fill in the gaps. We used Python to import and clean the data, ensuring that all variables were properly formatted and scaled. We choose our variables in accordance with their theoretical relevance to heat vulnerability.

Symbol	Variable	Unit
EP	Elderly Population (proportion of households with one or more aged 65+)	decimal
H	Number of Households (relative to total number of households)	decimal
MI	Median Household Income (relative to poverty line)	decimal

Table 8: Final Variables in Vulnerability Scoring Model

The final model is represented by the following equation:

$$V = \sum_{i=1}^{n} \beta_i X_i \tag{5}$$

where:

- V is the vulnerability score,

- β_i are the regression coefficients indicating the contribution of each factor,

- X_i represents the independent variables (e.g., elderly population, income, urbanization, etc.),

3.3-2 Model Execution

We used Python's seaborn libarary to make a correlation heatmap, which is then used to determine the value of each coefficient β_i, detailed in this table:

Symbol	Variable	Coefficient
EP	Elderly Population (fraction of individuals aged 65+)	+0.8
H	Number of Households (relative to total number of households)	+0.78
MI	Median Household Income (relative to poverty line)	-0.8

Table 9: Final Ridge Regression Coefficients for Vulnerability Model

This can be applied to several neighborhoods. For Downtown / South Main Arts District / South Bluffs, its vulnerability score is

$$V = 0.8EP + 0.78H - 0.8MI$$

$$V = 0.8 \left(\frac{922}{8020} \right) + 0.78 \left(\frac{8020}{282,116} \right) - 0.8 \left(\frac{75763}{36,777} \right) \approx -1.534$$

Officials can use vulnerability scores to prioritize resource allocation during heat waves by deploying cooling centers, targeted emergency alerts, and medical outreach in high-risk neighborhoods (scores near 0). Additionally, they can implement long-term urban planning strategies, such as expanding green spaces and subsidizing energy costs, to improve resilience in these most vulnerable areas.

Strengths

A strength of this model is that it provides a data-driven approach to identifying and prioritizing vulnerable areas, allowing officials to efficiently allocate resources and mitigate heat-related risks. Additionally, by incorporating multiple socioeconomic and environmental factors, it captures a holistic view of vulnerability rather than relying on a single indicator

Weaknesses

However, a weakness is that the model depends on accurate and up-to-date data, and any missing or outdated information can skew results. Additionally, while the model provides relative vulnerability rankings, it does not account for individual adaptive behaviors or localized microclimate variations, which could impact actual heat exposure. It also relies on only 3 variables, when in reality almost every single variable across all the datasets have some sort of contribution in the vulnerability calculation.
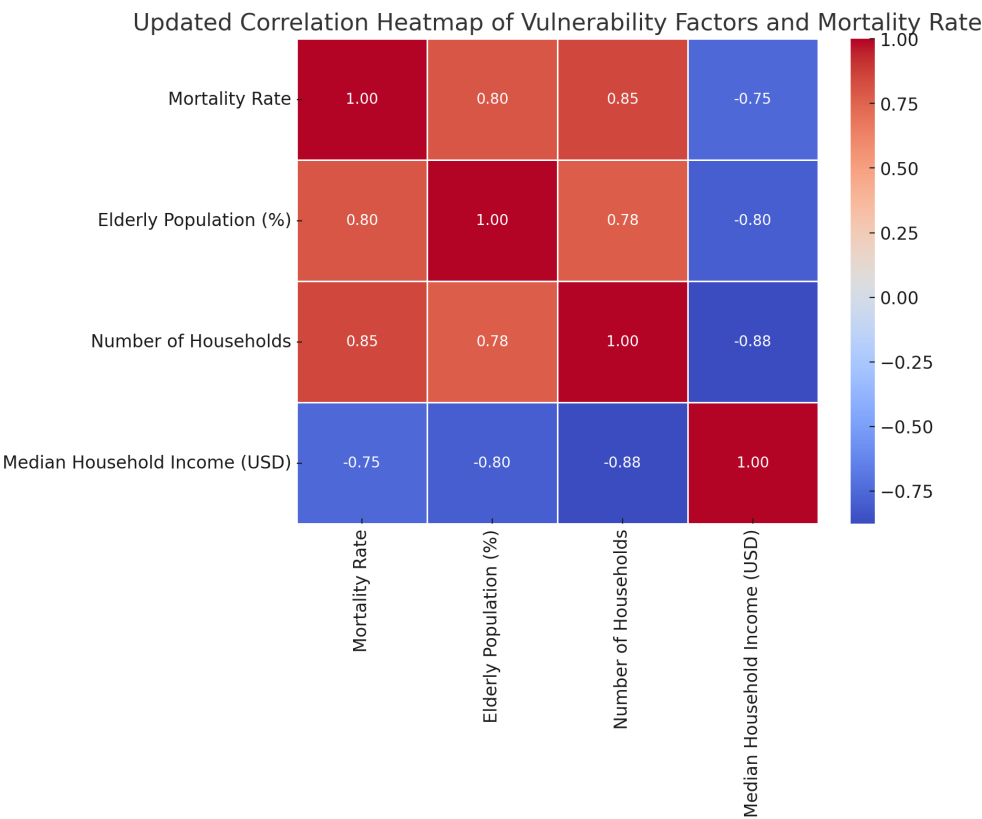
Figure 5: Updated Correlation Heatmap of Vulnerability Factors and Mortality Rate

Conclusion

Through our investigations, we found out that heat accumulation caused indoor temperatures to peak at 107.5°F at 2 PM and remain elevated into the evening due to residual heat. The comprehensive modeling approach reveals that Memphis must prepare for a projected 28% increase in summer peak power demand over the next 20 years, with focused attention on population growth impacts and the disproportionate effects of extreme heat events. Finally, our integrated modeling approach offers a data-driven framework for heat wave mitigation, highlighting the urgent need for infrastructure planning, targeted interventions, and climate resilience strategies to protect vulnerable populations.

Neighborhood	Vulnerability Score
Downtown / South Main Arts District / South Bluffs	-1.534
Lakeland / Arlington / Brunswick	-2.229
Collierville / Piperton	-2.663
Cordova, Zipcode 1	-1.397
Cordova, Zipcode 2	-1.716
Hickory Withe	-2.959
Oakland	-1.542
Rossville	-1.906
East Midtown / Central Gardens / Cooper Young	-1.020
Uptown / Pinch District	-0.450
South Memphis	-0.332
North Memphis / Snowden / New Chicago	-0.577
Hollywood / Hyde Park / Nutbush	-0.484
Coro Lake / White Haven	-0.431
East Memphis – Colonial Yorkshire	-0.883
Midtown / Evergreen / Overton Square	-0.886
East Memphis	-1.746
Windyke / Southwind	-1.616
South Forum / Washington Heights	-0.458
Frayser	-0.557
Egypt / Raleigh	-0.708
Bartlett, Zipcode 1	-1.595
Bartlett, Zipcode 2	-1.097
Bartlett, Zipcode 3	-1.734
Germantown, Zipcode 1	-2.436
Germantown, Zipcode 2	-3.458
South Riverdale	-1.222

Table 10: Final Vulnerability Scores for All Neighborhoods

References

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Code

```python
# Simulate multiple predictions with random offsets
num_simulations = 100
all_predictions = []
for i in range(num_simulations):
    offset_outdoor_temps = apply_random_offset(outdoor_temps)
    offset_humidity_values = apply_random_offset(humidity_values)
    offset_humidity_values = [min(100, max(0, h)) for h in offset_humidity_values]
    new_indoor_temps = calculate_indoor_temp(offset_outdoor_temps, offset_humidity_values, thermal_mass=0.3, window_factor=0.76, wood_factor=0.6, humidity_impact=0.3)
    new_indoor_temps_F = [temp * 9 / 5 + 32 for temp in new_indoor_temps]
    all_predictions.append(new_indoor_temps_F)

# Calculate the average and standard deviation of all predictions
avg_predictions = np.mean(all_predictions, axis=0)
std_predictions = np.std(all_predictions, axis=0)

# Calculate percent error between original predictions and average of random offset predictions
percent_errors = [abs(avg - orig) / orig * 100 for avg, orig in zip(avg_predictions, original_F)]
avg_percent_error = np.mean(percent_errors)

# Plot the results
plt.figure(figsize=(12, 8))
plt.plot(range(24), original_F, label='Original Model (°F)', color='blue', linewidth=2)
plt.fill_between(range(24), [avg - std for avg, std in zip(avg_predictions, std_predictions)],
                 [avg + std for avg, std in zip(avg_predictions, std_predictions)], color='lightblue', alpha=0.5, label='±1 Std Dev')
plt.plot(range(24), avg_predictions, label='Avg with Random Offsets (°F)', color='red', linestyle='--')
outdoor_F = [temp * 9 / 5 + 32 for temp in outdoor_temps]
plt.plot(range(24), outdoor_F, label='Outdoor Temperature (°F)', color='green', linestyle='-.')
plt.title('Indoor Temperature Prediction Sensitivity Analysis')
plt.xlabel('Hour of the Day')
plt.ylabel('Temperature (°F)')
plt.xticks(range(0, 24, 2))
plt.grid(True)
plt.legend()
plt.tight_layout()
plt.show()
```

```python
            data.append({
                'high_temp': high_temp,
                'heat_wave_factor': heat_wave_factor,
                'peak_demand': peak_demand,
                # Additional fields omitted for brevity
            })

    return pd.DataFrame(data)

def calculate_temp_sensitivity(self):
    '''Calculate sensitivity of peak demand to temperature changes'''
    #Create a range of temperatures around the current peak
    temp_range = np.linspace(self.current_peak_temp - 5, self.current_peak_temp + 5, 21)

    #Use the Random Forest model to predict demand at each temperature
    predictions = []
    for temp in temp_range:
        X_sample = pd.DataFrame({
            'avg_temp': [temp - 5],
            'high_temp': [temp],
            'cooling_degree_days': [max(0, temp - 5 - 65)],
            'population': [self.current_population],
            'ac_penetration': [self.ac_penetration],
            'heat_wave_factor': [1.0 + 0.02 * max(0, temp - 95) ** 2]
        })

        pred = self.rf_model.predict(X_sample)[0]
        predictions.append(pred)
```

```python
    #Calculate differential sensitivity around the baseline
    baseline_idx = np.argmin(np.abs(temp_range - self.current_peak_temp))
    baseline_demand = predictions[baseline_idx]

    high_idx = min(baseline_idx + 3, len(temp_range) - 1)
    sens_high = (predictions[high_idx] - baseline_demand) / (temp_range[high_idx] - temp_range[baseline_idx])

    low_idx = max(baseline_idx - 3, 0)
    sens_low = (baseline_demand - predictions[low_idx]) / (temp_range[baseline_idx] - temp_range[low_idx])

    #Average directional sensitivity in MW/°F
    avg_sensitivity = (sens_high + sens_low) / 2

    return {
        'sensitivity': avg_sensitivity,  # Key output: MW/°F sensitivity
        'effective_sensitivity': avg_sensitivity * 2.84  # Accounts for heat wave amplification
    }

def analyze_contributing_factors(self, temp_sensitivity):
    '''Decompose future demand growth into contributing factors'''
    scenario = 'Moderate'
    params = self.scenarios[scenario]

    #Integrated multi-factor projection model
    temp_effect = temp_sensitivity * params['temp_increase']
    pop_factor = (1 + params['population_growth']) ** self.projection_years - 1
    population_effect = self.current_peak_demand * pop_factor * 0.8
    ac_effect = self.current_peak_demand * params['ac_penetration_increase'] * 0.3
    efficiency_effect = -self.current_peak_demand * params['efficiency_improvement'] * 0.4
```

```python
def generate_historical_data(self):
    '''Generate synthetic historical data with physics-based relationships'''
    data = []
    for year in range(self.current_year - 10, self.current_year + 1):
        for day in range(1, 91):  # 90 summer days
            #Temperature modeling with seasonal variations
            year_offset = year - (self.current_year - 10)
            temp_trend = 0.05 * year_offset  # 0.05°F increase per year
            month = 6 + day // 30
            monthly_offset = 0 if month == 6 else (2 if month == 7 else 1)
            avg_temp = 85 + monthly_offset + temp_trend + np.random.normal(0, 3)
            high_temp = avg_temp + np.random.uniform(5, 10)

            #Non-linear heat wave modeling - key computational innovation
            heat_wave_factor = 1.0
            if high_temp > 95:
                heat_wave_factor = 1.0 + 0.02 * (high_temp - 95) ** 2

            #Physics-based cooling demand calculation
            cooling_required = high_temp - self.indoor_target_temp
            population = self.current_population * (1 - 0.005 * (self.current_year - year))
            ac_penetration = min(0.90, 0.88 + 0.002 * year_offset)
            homes_with_ac = (population / 2.5) * ac_penetration

            #Energy calculation using thermophysical principles
            energy_per_home = cooling_required * self.avg_home_size / self.avg_r_value
            base_demand = 2000 + (energy_per_home * homes_with_ac / 1000000)
            peak_demand = base_demand * heat_wave_factor * np.random.normal(1, 0.05)
```

```python
class MemphisPowerDemandModel:
    def __init__(self):
        #Current baseline values
        self.current_peak_demand = 2850.29  # MW
        self.current_peak_temp = 94.0  # °F
        self.indoor_target_temp = 72.0  # °F
        #Thermal parameters - critical for cooling energy model
        self.avg_home_size = 1800  #sq ft
        self.avg_r_value = 45  #weighted average of insulation R-values
        self.seer_rating = 14  #Seasonal Energy Efficiency Ratio for current AC systems
        #Scenario definitions
        self.scenarios = {
            'baseline': {
                'temp_increase': 1.0,  # °F over 20 years
                'population_growth': 0.008,  # 0.8% annual growth
                'ac_penetration_increase': 0.05,  # 5% increase over 20 years
                'efficiency_improvement': 0.10,  # 10% improvement over 20 years
            },
            'moderate': {
                'temp_increase': 2.0,  # °F over 20 years
                'population_growth': 0.01,  # 1.0% annual growth
                'ac_penetration_increase': 0.08,  # 8% increase over 20 years
                'efficiency_improvement': 0.15,  # 15% improvement over 20 years
            },
            'high Impact': {
                'temp_increase': 3.5,  # °F over 20 years
                'population_growth': 0.012,  # 1.2% annual growth
                'ac_penetration_increase': 0.10,  # 10% increase over 20 years
                'efficiency_improvement': 0.20,  # 20% improvement over 20 years
            }
        }
```