# SAMPLE PAPER: AVERAGE

The executive summary is extremely terse. The team provides an overview of their activities. Few insights into the problem, the approach, or the results are given. The introduction, however, includes a much better overview of the problem.

The team made use of linear regression for the first question. A written description of the relationships is provided, but it is difficult to follow. Python code is included within the narrative, but it is not well formatted. It is also difficult to parse the code. Results are provided in a long table, and very little residual analysis is provided.

The description of the methodology used in the second question is vague. The team used a spreadsheet to examine the data, but the procedures they used are not clear. Little analysis of their results is discussed. One nice aspect, though, is the team's use of data from another region to obtain a sanity check on their results.

To address the third question the team first examined a long list of factors. The different factors are examined and their relative impacts are compared. Based on their comparison a linear combination of the factors is created, and a brief argument for their choices of the relative weights are given based on their initial exploration of the data. Many teams examined a similar kind of weighted sum, but this team did a very nice job of justifying the final weights that were employed. The results of their final conclusions are stated with appropriate graphical representations.

# M3 Modelling Challenge: Hot Button Issue, Staying Cool as the World Heats Up

Team number : 18***

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# Summary

In recent years, global temperatures have been rising causing more and more extreme weather to occur in the UK. One notable example that we will be investigating in our project are heatwaves.

In this project we aimed to create models that would successfully predict information that's relevant to how climate change and heatwaves are going to impact residents' lives in Birmingham, UK. To do this we have researched online and used software such as Excel and Kaggle to create models that can recognise and describe patterns in order to make predictions.

First, we created a model to predict indoor temperatures in heatwaves using linear regression. Following this, we analysed energy demand to find the maximum energy demand that the Birmingham grid should be prepared to handle during the summer months and how this could change over the next 20 years. Finally, we created an index to find the vulnerability of different boroughs and created a plan for the council to spread resources more equitably to minimise the impact of power outages and heatwaves.

# Contents

# Heatwaves in Birmingham, England

## 1 Introduction

Within this report, we aimed to answer three main questions regarding the extreme weather in the UK and its consequences in Birmingham specifically. The first question we aimed to solve was to predict the temperature of a non-air conditioned dwelling over 24 hours, during a heatwave, where a heatwave is defined as three consecutive days with temperatures over 20 degrees Celsius. This forecasting takes in multitudinous different factors which we will come across later on.

The second problem, we aimed to find a solution for, was predicting the peak power demand on the city's grid in the summer and how that could change over the next 20 years. This also, is dependent on many factors and required us to research both past events and sets of data as well as data and trends from foreign countries in order to give us a holistic view which we then managed to create our models from.

Finally, we developed a vulnerability scoring system for various neighbourhoods within Birmingham to determine which communities are most at risk during a heatwave to support the local authority in distributing resources equitably to minimise the impact of a heatwave or a power outage. This uniquely designed scoring system also takes into account a variety of factors which were all weighted independently depending on their impact on the vulnerability of a community.

# 2 Q1: Predict the indoor temperature of non-air-conditioned dwelling during a heat wave over a 24-hour period in Birmingham

## 2.1 Initial ideas

We attempted to find the indoor temperature trend in a 24-hours period, we used a dataset,[1] which has collected data from 20 houses over the course of the year, tracking indoor and outdoor temperatures, humidity, the total amount of insulation and the type of house.

## 2.2 Model

### 2.2.1 Assumptions Made

1. All houses let in the same amount of sunlight proportional to floor area as the difference in shading causes a variation in indoor temperature.[2]
2. Above 20 degree Celsius people don't have their heating on
3. We have assumed different types of houses with different amounts of insulation have relatively similar coefficients in high temperatures.[3]

### 2.2.2 Variables: Factors Affecting Indoor Temperature

1. Outdoor temperature
2. Outdoor humidity
3. Time of day

### 2.2.3 The Model

In creating this model, we have considered the minimum temperature for overheating to occur to be when temperatures are greater than or equal to 20°C.[4] We have also assumed that the relationship between the above three parameters in some way form a linear relationship that can be used to calculate the indoor temperature.

The parameters we have used are shown above, with outdoor temperature given by $T_o$ in Celsius, coded time of day that these measurements were taken, $t_c$ in hours, calculated as a variable by calculating $|12 - t|$ where $t$ is the time of day of measurement to the nearest hour and outdoor humidity given by $H_u$. We have chosen to use humidity as this is a measure of water in the air, and because water has an extremely high specific heat capacity of $4184Jkg^{-1}K^{-1}$,[5] thus humidity in the air can show how long heat takes to dissipate. We have chosen to code the data as such as $12pm$ is midday, and because time cycles, across 24 hours, we can thus code more efficiently using a linearly regressive model. We have rounded to the nearest hour as all measurements in our dataset have been taken at 59 minutes past the hour, or on the hour, and have assumed the resulting one minute discrepancies are statistically insignificant.

These data points were taken from a large data set.[6] This data set allowed us to form a linear regression model using Python, with the Pandas library for data analysis and the Sklearn model for forming the linear regression model.

Using these input fields, we have formed the following code:

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
```

```
#Access the dataset
df=pd.read_csv('IN-HALE_indoor_outdoor_hourly_db(IN-HALE_indoor_outdoor_hourly_d).csv')
df['Outdoor Air Temperature (?C) Prev'] = df['Outdoor Air Temperature (?C)'].shift(24)
df = df.iloc[24:]

#Only for temperatures at which there is risk of overheating
df = df[df["Outdoor Air Temperature (?C)"] > 19]


#Create a measure of relative time of day to 12pm
df["Time (dd/mm/yyyy hh:mm)"] = pd.to_datetime(df["Time (dd/mm/yyyy hh:mm)"], format="%d/%m/%y %H:%M", 
df["Hour Integer"] = abs(12-(df["Time (dd/mm/yyyy hh:mm)"].dt.round("H").dt.hour))


#Define variables
X = df[["Outdoor Air Temperature (?C)", "Hour Integer", "Outdoor Relative Humidity (%)"]]
y = df["Indoor Air Temperature (?C)"]

#Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

#Create and train the model
model = LinearRegression()
model.fit(X_train, y_train)

#Predict on test set
y_pred = model.predict(X_test)

#Evaluate the model
mse = mean_squared_error(y_test, y_pred)
print(f"Mean Squared Error: {mse}")

#Print model coefficients
print("Coefficients:", model.coef_)
print("Intercept:", model.intercept_)
```

#### 2.2.4 Solution(s)

The above code leads to the output:

```
Mean Squared Error: 1.6871857711657523
Coefficients: [0.27189907 0.16016037 0.02179863]
Intercept: 17.064310319046342
```

This provides the model where the indoor temperature, $T_i^{\circ}C$ in dwellings is given by:

$$T_i = 0.272 \times T_o + 0.160 \times t_c + 0.0218 \times H_u.$$

Via substituting the respective values for $T_o, t_c$ and $H_u$, indoor temperature can thus be found. Via use of the provided compiled data,[7] the following values for calculated indoor data were calculated:

| $T_o/°C$ | $t_c/h$ | $H_u/\%$ | $T_i/°C$ |
|---|---|---|---|
| 21.1 | 12 | 60 | 26.0 |
| 18.9 | 11 | 68 | 25.4 |
| 17.8 | 10 | 68 | 25.0 |
| 17.2 | 9 | 72 | 24.8 |
| 17.2 | 8 | 68 | 24.5 |
| 16.1 | 7 | 72 | 24.1 |
| 18.9 | 6 | 73 | 24.8 |
| 25.0 | 5 | 44 | 25.6 |
| 27.8 | 4 | 35 | 26.0 |
| 32.2 | 3 | 27 | 26.9 |
| 33.9 | 2 | 24 | 27.1 |
| 36.1 | 1 | 23 | 27.5 |
| 37.2 | 0 | 19 | 27.6 |
| 37.2 | 1 | 21 | 27.8 |
| 37.2 | 2 | 24 | 28.0 |
| 35.0 | 3 | 28 | 27.7 |
| 35.0 | 4 | 28 | 27.8 |
| 32.8 | 5 | 29 | 27.4 |
| 32.8 | 6 | 29 | 27.6 |
| 32.2 | 7 | 31 | 27.6 |
| 27.8 | 8 | 45 | 26.9 |
| 27.8 | 9 | 45 | 27.0 |
| 27.2 | 10 | 48 | 27.1 |
| 26.1 | 11 | 54 | 27.1 |

#### 2.2.5 Discussion

This model is accurate in terms of the limited amount of data that we can find online. We used Python to build a linear regression model which accounts for outdoor temperature, time of day and outdoor humidity based on the dataset.[6] This is useful because outdoor temperature affects the indoor temperature heavily by influencing the amount of heat which transfers through a building's walls, windows, and roof; essentially, when it's hot outside, heat naturally flows into a cooler indoor space, causing the indoor temperature to rise, but the degree of this effect depends on the building's insulation and air sealing quality as well.

Nonetheless, our model will still have some flaws as it does not account for the previous day's temperatures which may affect the indoor temperature of homes. Additionally, the model acts under the assumption that all dwellings have the same structure, however for example flats on higher levels may have higher indoor temperature than those lower down, due to lack of insulation between floors and that heat rises. However, we do not have enough temperature data specifically for the level of flat, so we cannot take that into account.

A model that considers the flow of temperature through use of aerodynamic software may be more effective for comparing temperatures across different dwellings in the same building an calculation of internal temperatures of individual flats. This can be done in future studies where we can collect primary data in flats.

Additionally, this model assumes that there is a linear relationship between these factors and internal temperature. This may not be the case, as these are complicated variables. Thus a range of models should be tested, however this could not be done due to time restraints.

Overall, the model is quite strong at estimating internal temperatures of the given dataset. With a mean squared error of $1.7°C^2$, it appears to have relatively accurately measured risk of overheating. This means it may be adequate to assess if weather conditions are high enough to pose a significant risk of harm from overheating.

#### 2.2.6 Sensitivity Analysis

For our model we look at parameters such as the outdoor temperature in order to aid us in making a prediction about the indoors temperature. We also made a few assumptions while working on this problem and we acknowledge that without these assumptions the model would have a more accurate set of results, with a smaller degree of inaccuracy, and the prediction of the indoors temperature would differ depending on the location.

# 3 Q2: Predicting peak demand in Birmingham's power grid during summer months and foreseeing any changes in the maximum demand 20 years from now

## 3.1 Initial ideas

For this questions we focus on the two areas of the problem: what the peak demand in summer is and how this may change in 20 years time. We first conducted research about the factors that may affect the demand for energy as well as looked into the daily energy usage patterns. Sources such as[8,9] aided us greatly and provided a dataset and information for us to work with.

## 3.2 Further exploring

Firstly, in the future, due to the warmer projected summers, it's forecasted that in the next year there is an anticipated volume growth of AC units of 2.8%,[10] and this figure is only set to increase more rapidly in next 20 years, reaching a point where 27% of the general population will have their own AC units. This means that inevitably, more energy will be consumed.

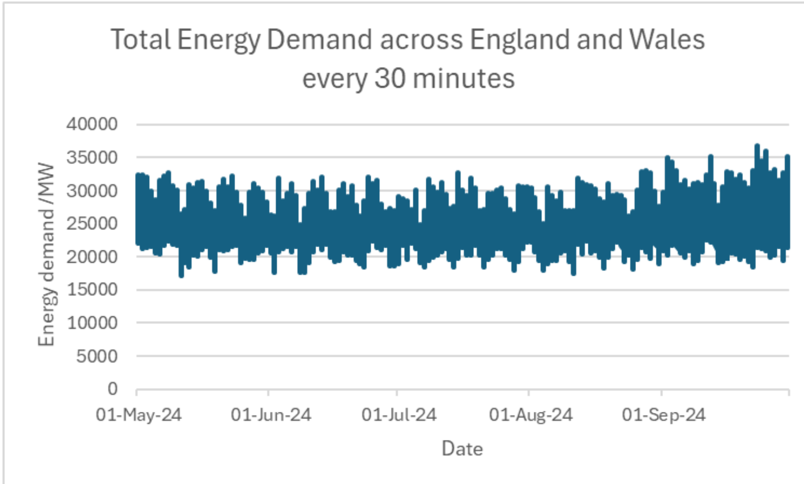
However, in 20 years time, renewable energy will become a larger percentage of the UK's energy mix as there has been more of a push for such a shift due to climate change and global warming. It has been prioritised as goal 7 on the UN's 17 Goals for a better future.[11] This means that although there will be higher demand for energy during these warmer seasons, due to the theoretically more prominently implemented renewable energy sources such as solar energy, there wouldn't be as much pressure relatively due to the extra energy simultaneously being produced from the sun.

When looking at the estimated temperature increase of the future, we can see that we can approximate the future weather forecasts to be similar to other warmer European countries such as Spain. This means that we can, in turn, also compare the energy consumption of Spain in the summer to the UK's in the summer and we can get a sense of how much it would increase by. This is a fairly good estimate at the most basic level due to the similarities between the UK and Spain in terms of their socio-economic states. In the summer in Spain, the power demand is just below 40,000 MW,[12] equivalent to $827W$ per capita and in the UK, the demand averages around 30,000 MW,[8] equivalent to $439W$, so now we can roughly gauge by how much the demand for energy may be set to increase.

Another factor which is likely to change the electricity demand is the the fact that over time, home insulation will improve, as it has historically,[13] due to government schemes such as the Great British Insulation Scheme.[14] The aim of this scheme is to improve insulation in peoples homes so that in turn, their energy bills are lowered. This means that although the temperature will increase over the next 20 years and so in turn the electricity usage, this factor would be slightly limited by schemes such as this. However, there is then also the question of whether this factor would impact the energy usage at all due to the fact that schemes such as this target lower-income households who probably will not be able to afford AC units regardless.

## 3.3 Analysing the dataset and solution

We used Excel to analyse the data set and determine the average energy used in the UK over summer.
This shows that between May and September there was minimal variation in energy use as it is warm enough that the heating is not used and, although the temperature rises in June and August, the energy use stays stable as less than 5% of people have air conditioning units.[15] It is worth noting that, whilst Birmingham uses less energy per capita than the rest of the UK, it is a city and relatively south so it is likely to get hotter than much of the UK, which could lead to higher energy use. The maximum peak that the England and Wales energy grid should be prepared to handle in summer would be 35000 MW which was obtained from the National Energy System Operation's dataset[9] and as the population of Birmingham (1.2 million) is 2% of the population of England and Wales, its local power grid should be prepared to handle around 680 MW.




## 3.4 Model

### 3.4.1 Assumptions Made

1. Unpredictable events that affect the energy demand are not taken into account such as extreme weather, television pickups (people watch a TV show at the same time)
2. Not considered humidity which affects air conditioner use as humidity affects how hot it feels

### 3.4.2 Variables: Factors Affecting Peak demand

1. Energy prices
2. GNP (Gross National Product)
3. Energy demand index
4. Population
5. Temperature
6. Socioeconomic status (income)
7. Number of appliances

### 3.4.3 Discussion

This model has many variables taken into account which makes it more reliable however this may also suggest that there's more applicable factors that we haven't explored. As well as the fact that since all our data is secondary data from the past, we cannot be certain that the trend will follow in the future and would have to account for this.

### 3.4.4 Sensitivity Analysis

For this model we assumed that unpredictable events did not occur and our data is heavily affected by this assumption as if it were to occur the prediction could be much greater/less than what was calculated.

# 4 Q3: Developing a vulnerability index to support the local authority in equitably allocating resources for minimizing the effects of a heat wave or a power grid failure.

## 4.1 Initial ideas

For this question, we define the term 'effects' as how severely the heat wave affects the residents living in the neighbourhood instead of the effects on the physical utilities, however we are still considering the damage to utilities as it can further impact the residents' life.

We considered many different variables, from environmental, social to economics, then weighted them based on how much they affect the residents' life in the region. Birmingham is ranked the third most deprived English Core City after Liverpool and Manchester. While deprivation is widely spread, it is most densely clustered in the area surrounding the city centre.

For the vulnerability index we thought that it would work best to first list out factors that may determine how susceptible to the dangers of heatwave people are and to rank them in terms of importance so that we could create weightings for these factors.

## 4.2 Model

### 4.2.1 Assumptions Made

1. There are no other key factors affecting the data
2. The weightings are accurate

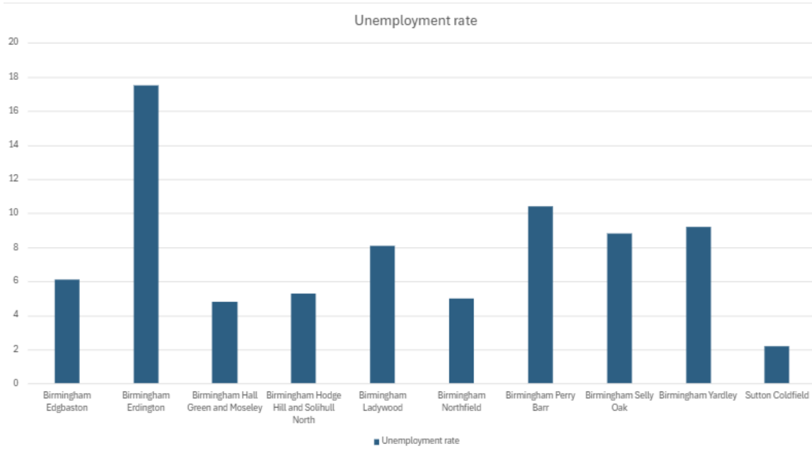
### 4.2.2 Variables: Factors that could affect the vulnerability score

Social

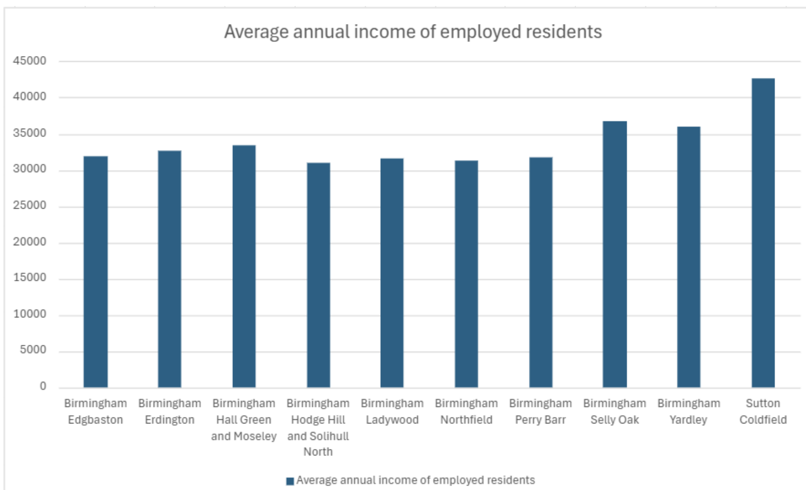
1. The Human Development Index (HDI) is calculated from life expectancy index, Education index, Mean years of schooling index, Expected years of schooling index, Income index
2. Life Expectancy
3. Literacy Rate
4. Population Density

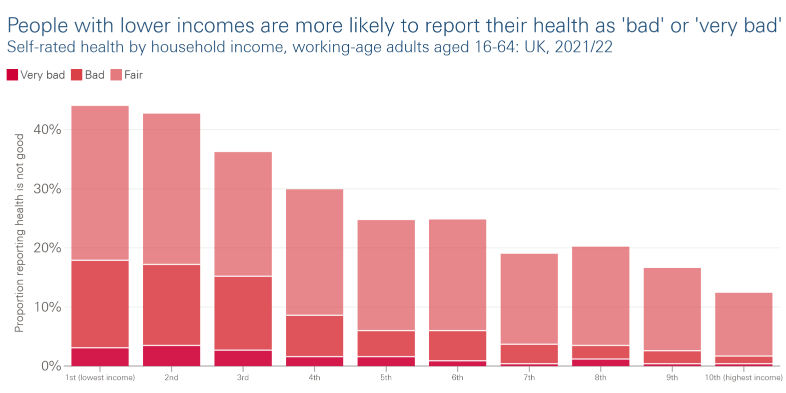
Economics

1. Multiple Deprivation Index is calculated from Income (22.5%), Employment (22.5%), Health Deprivation and Disability (13.5%), Education, Skills, and Training (13.5%), Crime (9.3%), Barriers to Housing and Services (9.3%), Living Environment (9.3%).
2. Unemployment rate


Unemployment rate
20
18
16
14
12
10
8
6
4
2
0
Birmingham Edgbaston
Birmingham Erdington
Birmingham Hall Green and Moseley
Birmingham Hodge Hill and Solihull North
Birmingham Ladywood
Birmingham Northfield
Birmingham Perry Barr
Birmingham Selly Oak
Birmingham Yardley
Sutton Coldfield
Unemployment rate

3. Income


Average annual income of employed residents
45000
40000
35000
30000
25000
20000
15000
10000
5000
0
Birmingham Edgbaston
Birmingham Erdington
Birmingham Hall Green and Moseley
Birmingham Hodge Hill and Solihull North
Birmingham Ladywood
Birmingham Northfield
Birmingham Perry Barr
Birmingham Selly Oak
Birmingham Yardley
Sutton Coldfield
Average annual income of employed residents


People with lower incomes are more likely to report their health as 'bad' or 'very bad'
Self-rated health by household income, working-age adults aged 16-64: UK, 2021/22
Very bad
Bad
Fair
Proportion reporting health is not good
40%
30%
20%
10%
0%
1st (lowest income)
2nd
3rd
4th
5th
6th
7th
8th
9th
10th (highest income)
Net household income – deciles

<u>Environmental</u>

1. Green space

We were able to rule out multiple factors. We did not include literacy rates, as they are very high in Birmingham so there would not be much variation as well as life expectancy for the same reason. We also excluded the type of job as that is impacted by income, which is included and the type of house as that is also impacted by income and population density which are both included.

<u>Justification of variables being used</u>

Overall, we chose to use general health index, income, population density,[16] general environmental index, proportion over 65 and employment rate[17] as these are the most applicable and influential indicators in finding a vulnerable area.

For general health index, we weighted it 25% of the score, since it is extremely influential in terms of risks introduced by heat waves. This is because healthier people, have a lower risk of developing any health issues during the heat wave. Also, if the people are healthier, this puts a smaller pressure on the public health system generally, which means that more resources is available when there is any emergencies and this can reduce the impact of heat waves on people's health.

We believe that income is the second important factor so we weighted it 20%. This is because it can affect the population economically, socially and environmentally. Higher income suggests higher quality housing which may include air-conditioner or better ventilation to keep the temperature lower. Moreover, higher income of the area also recommend that more resources is available when there is any damage due to the heat wave since people are more capable to afford medical services. From medical support, to repairing of facilities to maintenance of the power grid, all of these requires financial support from the council or general public. Furthermore, as shown in figure,[18] the poorer the population, the more likely to report their health as bad. This indicates that income also heavily impact the health of the general population which links back to our first factor, general health index.

The third factor is population density which is weighted 20%. Environmentally, there will be less green space and more flats in the area due to higher demand for housing. This leads to an even larger increase in temperature due to "urban heat island effect," where concentrated buildings, roads, and infrastructure in cities absorb and re-emit more heat from the sun compared to natural landscapes, which introduces higher risk. Socially, The denser the population, the larger demand on public health services which mean more pressure. This results in the lack of extra services that can be provided when there is a heat wave.

We weighted general environment index as the forth, which is 15%. The larger green area, the greater the cooling effect because of their ability to provide shade, absorb solar radiation, and release moisture through transpiration, essentially acting as a natural cooling mechanism.

The fifth factor is proportion over 65, which takes 10% of our calculation. This is because older people tends to put more pressure on public services and they are more easily affected by the extreme weather. This is because as we age, we have a reduced ability to thermoregulate our bodies.

The last factor we chose is unemployment rate, which is weighted at 10%. This is the least weighted feature since we have taken income into consideration earlier since it affects a larger proportion of the population economically.

### 4.2.3 Model

To create the model, we set up 6 separate indexes with a maximum of 1 and a minimum of zero. These were:

**Income Index (II):**
Income Index = Average Income/45000
When income is £45000, the Income index would be 1.

**General Health Index (GHI):**
General Health Index = Health score/5
The Health Score is collected in the census and asks participants to rate their health as "Very bad", "Bad", "Fair", "Good" and "Very Good" which we transferred into numbers meaning that a constituency can have a maximum of 5 as its average score, therefore the index has a maximum of 1.

**Employment Index (EI):**
Employment index = Employment rate/100
where the maximum possible employment rate is 100%

**Population Density Index (PDI):**
Population Density Index = Population Density/10000
Where the index is 1 when the population density is 10,000 people/km$^2$

**The Environmental Index (TEI):** Environmental Index = 1- Environmental Score
This ensures that the larger the Environmental Index is, the better the local environment.

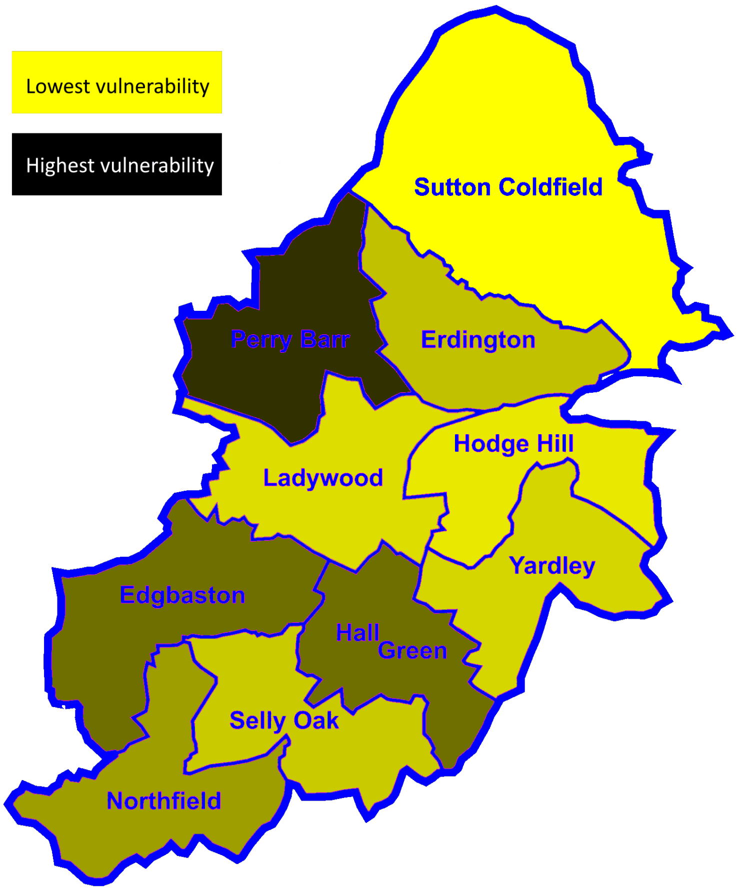
**The 65 Index (65I):**
65 Index =$(proportion > 65)/0.25$

If we combine this with the earlier discussed weightings to find a vulnerability index with a maximum of 1 and minimum of 0, we get :

Vulnerability Index (VI)* = $\frac{1}{4}$*GHI + $\frac{1}{5}$*II +$\frac{1}{5}$*PDI + $\frac{3}{20}$*TEI+ $\frac{1}{10}$*EI + $\frac{1}{10}$*65I
$VI = 2VI^{3**}$

*The lower the VI, the more vulnerable the community is

**To increase the variation without changing the distribution, the VI was then cubed and multiplied by 2.




Here, you will actually present the results, so you need to decide the best way to do that. Do you need separate sections that describe how your model works for different cases? Should you use a graph or a table? Point out the general trends and any exceptions to the rules. See Section **??** for guidance about including tables and graphs.

#### 4.2.4 Discussion

The Vulnerability Index we designed takes into account a number of factors which are heavily correlated with, if not the cause of suffering during heat waves. From this index, local authorities are then able to identify areas which may need more support during these extreme weather conditions.

The general process of choosing which factors to include in the calculations and which to rule out was very informative due to the fact that you can see how closely related these factors all are i.e. a community having a high unemployment rate is also likely to have an overall lower mean income.

The strengths of our model is that it provides an easily comparable, holistic view of the different cities in Birmingham. This means that those communities which may be in need of more support are easily identifiable. The ease of comparability is also due to our increasing the variation without changing the distribution. This was done by cubing the VI and then doubling it. This gives a larger range of values possible for the VI for the communities in Birmingham.

The weakness of our model is that it can only account for a certain number of factors and this limits

its accuracy and usefulness. Additionally, the weightings are somewhat arbitrarily chosen which also impacts the usefulness and reliability of this model. An improvement would be analysing datasets and then deriving a more intentional weighting for each factor. Another one would be calculating the VI from a larger variety of factors.

The accuracy of our model is also backed up by the 2003 heat wave, as it killed the most people in the age group of 75 and older. For age group over 75, there is a 33% excess mortality and for age group under 75: 13.5% excess mortality in this age group during the heatwave. The significant difference further proofs that our indexes are effective factors.

#### 4.2.5 Sensitivity Analysis

The assumptions we have made obviously impact our model. We have assumed that there are no other factors affecting the vulnerability of an area which is flawed. If there are other variables which have a large impact on vulnerability, it would render the vulnerability index more limited, although it could be combined with other factors to make it more accurate. Furthermore, our weightings could be flawed. If income or age, for example, are more important than the weightings suggest, then the index could be misleading as it states that it already accounts for those factors. We have also assumed that the whole borough has the same index whereas half of a borough may be very vulnerable whereas the other half may be affluent and young, hence much less vulnerable which would present the whole area as mildly vulnerable which could be misleading and leave at risk people without support.

## 5 Action Plan for the Local Authority

Based off the VI, the Local Authority should target the most vulnerable boroughs during heatwaves. They should set up temporary hubs in public buildings with air conditioning which people can spend time in to reduce heat exposure as well as ensuring that everyone has access to water, medical treatment and electrolytes. They should also ensure that everyone living in vulnerable areas is given information on how to keep their accommodation cool in the heat, such as closing curtains, keeping windows shut in the daytime, eating cold foods and minimising use of appliances.

## 6 Conclusions

Overall, climate change will cause an increase and worsening of heatwaves impacting Birmingham, UK. We also found that the outdoor temperature has direct correlation to the increase in indoor temperatures, which means people are constantly exposed to excessive heat, which could be dangerous and would also potentially cause the use of appliances such as AC to rapidly increase. Not only does this put pressure on the power grid and other services it also increase the risk to more susceptible groups. Additionally we have suggested an action plan for the local government to combat this issue, based off our vulnerability index, in order to ensure the safety of their residents.

# References

[1] Vanda Dimitriou Tarek Hassan Farid Fouchal Michael Coleman Lynda Webb Steven Firth, Tom Kane. Refit smart home dataset, 2025. [Accessed: 01.03.2025].

[2] Study on relationship between shading and outdoor air temperature based on the comparison of two high-rise residential estates with field measurements, 2025.

[3] Victoria Seabrook. Is insulation making your house hotter in summer - and how can you cool it down?, Jul 2022.

[4] S Hajat, R S Kovats, and K Lachowycz. Heat-related and cold-related deaths in england and wales: Who is at risk? *Occupational and Environmental Medicine*, 64(2):93–100, Sep 2006.

[5] The Open University. *S104 Book 3 Energy and Light, p. 179.* Open University, 2008.

[6] Lopes A. Oliveira A. Osvaldo S. Fragoso M. Correia E. Almendra R. Vasconcelos, J. Indoor/outdoor air temperature dataset - in-hale project (version v1) [data set]. 2025.

[7] MathWorks Math Modeling Challenge. Hot button issue, curated data.

[8] Claire Gavin. Seasonal variations in electricity demand, 2014. [Accessed: 01.03.2025].

[9] Historic demand data 2024, 2024. [Accessed: 01.03.2025].

[10] Air conditioners statista, 2025. [Accessed: 01.03.2025].

[11] Un 17 goals, 2015. [Accessed: 01.03.2025].

[12] Peak hourly electricity demand in mainland spain* from 2009 to 2023, 2023. [Accessed: 01.03.2025].

[13] The evolution of insulation in uk homes, 2025. [Accessed 01.03.2025].

[14] Great british insulation scheme, 2025. [Accessed: 01.03.2025].

[15] Cooling in the uk, 2021. [Accessed: 01.03.2025].

[16] United kingdom: West midlands, 2025. [Accessed 01.03.2025].

[17] Average earnings 2024, 2025. [Accessed 01.03.2025].

[18] People with lower incomes are more likely to report their health as 'bad' or 'very bad'. 2021/22. [Accessed: 01.03.2025].