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Abstract

This thesis investigates the impact of green roofs on the energy labels of buildings in Amsterdam, a city facing both climate-related and spatial constraints. Combining machine learning and empirical energy-saving estimates, this research simulates how the retrofitting of green roofs affects regulatory energy classifications. A unique dataset was assembled by integrating official energy label records, green roof suitability scores, building attributes, and roof geometry across more than 450,000 addresses. Two counterfactual scenarios were developed to estimate what energy labels buildings would have without green roofs, and what they could achieve if retrofitted. Additionally, empirical heating and cooling reductions from literature (Virk et al., 2015) were applied to estimate potential improvements across the city. Results show that while green roofs offer measurable reductions in energy demand, their effect on energy label classifications is limited: only 3% of existing green-roof buildings saw label degradation when hypothetically removed, and just 1.9% of non-green-roof buildings improved when simulated green roofs were added. City-wide application of empirical energy savings showed a modest 19% improvement rate, mostly among inefficient, uninsulated buildings. These findings suggest that while green roofs contribute positively to energy efficiency and climate resilience, their impact on standardized energy labels is constrained, highlighting the need for broader evaluative frameworks that account for co-benefits beyond regulatory classification.

Quantifying the Impact of Green Roofs on Building Energy Labels: A Case Study of Amsterdam

1. Introduction

It is not today's breaking news that the climate crisis is constantly and continuously worsening. Projections show that by 2050, urban areas could reach an additional 2°C above the average temperatures (Klimaateffectatlas, 2025). Consequently, the Urban Heat Island (UHI) effect, the phenomenon where heat in urban areas is amplified by infrastructures blocking wind and capturing warm, namely polluted air, runs the risk of being exacerbated (Klimaateffectatlas, 2025). This puts the elderly and other vulnerable segments of the population at risk, as higher temperatures have been shown to increase their mortality rates (García-León et al., 2024). Moreover, as urban populations have steadily grown, today more than half the world's population lives in cities. This figure is projected to reach seventy percent in 2050 (World Bank, 2025). Rural to urban migration is not only linked to political and economic reasons, but to environmental ones too. Thus, as increasingly more people are going to be forcefully displaced by the consequences of climate change, the density of urban centers is going to grow. This may result in higher energy demand and emissions, adding to the growing UHI effect.

A potential solution is found in horizontal green spaces, meaning parks, gardens, cool islands, and trees. Research has extensively demonstrated that horizontal green spaces improve the quality of life of urban dwellers by lowering temperatures, improving the quality of air, protecting from heavy rains and overall help in climate resilience, while also providing spaces for communities to gather and to exercise, culminating in improved mental and physical health (McDonald et al., 2023). As negative correlations have been established between urban population density and the amount of horizontal green spaces in urban areas, another challenge arises (McDonald et al., 2023). One where overpopulated urban areas, coupled with high energy demands and emissions, are going to be stuck in mutually worsening loops, exposing urban dwellers to higher risks of extreme heat, drought and flooding (*Figure 1*). Such risk increases as the socio-economic status of a neighbourhood lowers, consequently raising questions about climate justice (OECD, 2024).

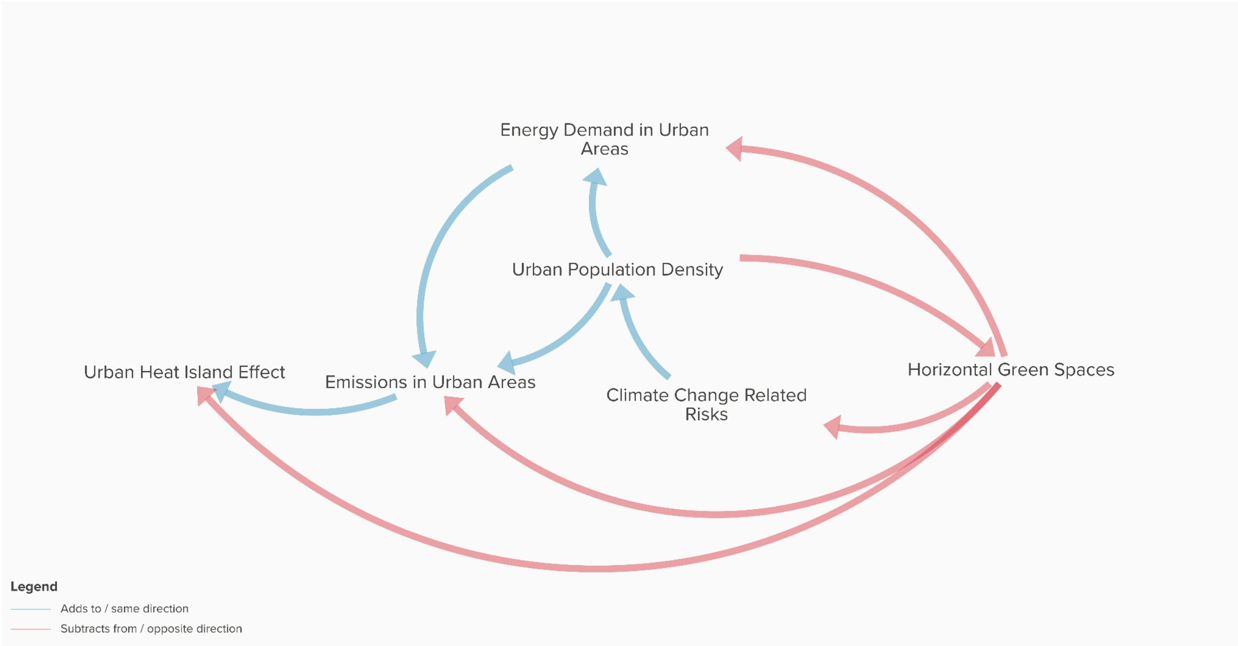

Figure 1. System dynamics of current state of risk of urban areas

It is exactly in this conundrum to overcome the obstacle of lack of space for horizontal green in urban areas, and help prevent the consequences of climate change, that the idea of nature-based solutions in the form of green roofs and green facades can come to aid. Green roofs and green façades are also broadly categorized as vertical green spaces. As these can be retrofitted on buildings and do not require land uniquely devoted to green space, they can be used even in densely populated areas. Green roofs are vegetated rooftops systems, which are often broadly categorized either as extensive, meaning they are lightweight as the vegetation is low and does not require intensive maintenance, or intensive, meaning they are deeper and are able to host bigger plants. Green roofs have been shown to lower surface and indoor temperatures, as they add an insulative layer to buildings, thus lowering the energy demand of buildings and consequently their emissions. Moreover, green roofs mitigate climate change risks, as they alleviate the urban heat island effect as well as support wastewater infrastructure during heavy rains (Susca, 2019).

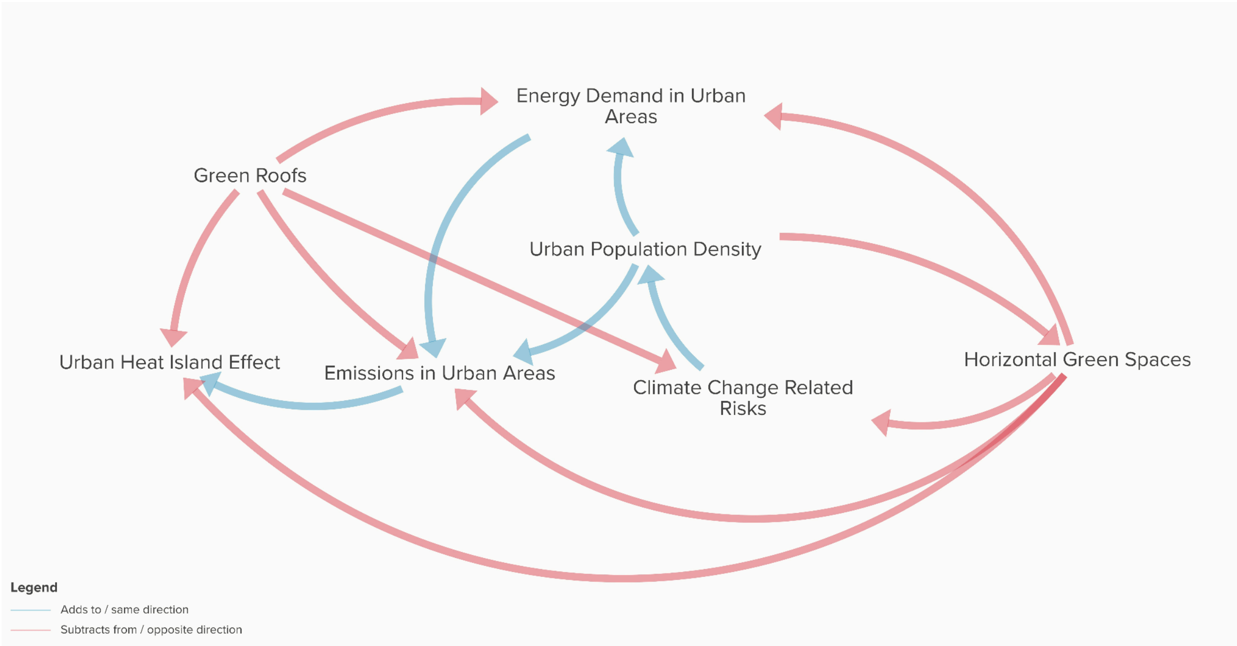

Figure 2. System dynamics of potential state of cities with the implementation of green roofs

It is for the aforementioned reasons, that, in urban contexts, thinking about the energy transition and the green transition as inherently intertwined, is essential. While this link may seem obvious, it has not been seen as such until recently, especially when looking at building level analysis rather than city level ones. In academia, this has only recently changed. This can be credited to new economic schools of thought, such as the one of *Degrowth*.

1.2 Degrowth: Technological Overreliance, Social Justice and Nature-Based Solutions

Degrowth is an interdisciplinary movement that questions the very founding principle of western societies to continuously strive for economic growth, as it has depleted our planet's resources, creating climate change, through the oppression of minorities, of lower income communities and of the Global South (Kallis et al., 2015; Hickel, 2021). Degrowth is a climate justice movement and an anti-colonial movement, as it recognizes that such economic growth was enabled by the oppression of those who were consuming the least and who are now disproportionately exposed to the consequences of climate change, through the process of externalization of costs (Hickel, 2021; Moore, 2011; Westra, 2023). This last concept comes from marxist political economy, especially from the theory of metabolic rift, which depicts society as an exchange of matter between mankind and nature. A rift happens when capitalism destroys the very thing it depends on, nature (Moore, 2011; Westra, 2023). Therefore, to cope with such destruction the western world has either moved production to lower-income areas, often inhabited by minorities, or to the Global South. This is how externalisation of costs can be understood, and Degrowth critiques not only the paths that lead us there, but how we think about moving forward when looking at reparative justice and how to approach solving the climate crisis. This critique is rooted in the understanding that capitalism has created a technological overreliance (McFarlane et al., 2017), based on the dogmatic belief that the same technology whose production is destroying the planet, will solve climate change. Here, Degrowth scholars argue that climate challenges should be tackled in a way that does not destroy the planet nor further oppresses those most vulnerable, through what are called nature-based solutions (Perveen et al., 2022). These are defined as solutions "to protect, sustainably manage, and restore natural or modified ecosystems that address societal challenges effectively and adaptively, simultaneously providing human well-being and biodiversity benefits" (IUCN, 2016, p.1; IUCN, 2020). In the context of this paper, this would entail understanding how the nature-based solution of a green roof can help insulate a building, lowering its heating and cooling load, consequently lowering the energy demand of the building itself while also increasing biodiversity, creating community and lower temperatures on a city level (IUCN, 2020; Susca, 2019).

2. Research Questions

While the effectiveness of green roofs on a building level has been widely explored, the implications on the energy class of a building of green roofs have not yet been studied to the best of our knowledge. In this study, we will explore, in the context of Amsterdam, whether and by how much the energy label of a building can be changed by adding a green roof. This research is going to investigate *How do energy labels change when a green roof is retrofitted?*. To answer this question, the analysis is broken down into five different parts.

Firstly, this study is going to answer the question *Can energy label patterns observed in conventional buildings be transferred to ones with green roofs?* Secondly, a counterfactual scenario is simulated to answer the question of *What would the energy label of a green-roof building have been in the absence of the green roof?* Therefore, allowing us to infer whether a green roof might be improving or worsening the building's energy class. Thirdly, a second counterfactual scenario is going to be simulated, answering the question *What would be the expected energy label of buildings if they were retrofitted with a green roof?*

Furthermore, deviating from the modelling, this study conducts estimation about the energy savings of retrofitting green roofs by applying empirically tested heating and cooling reduction percentages found by Virk et al., 2015, to the energy consumption of buildings. This answers the question *According to empirical examples, how much energy is a green roof going to save for every building?* Lastly, the study is going to see if the energy demand has decreased enough for the energy label to improve, and with this the question of *Can retrofitting a green roof on a building improve its energy label?*

3. Literature Review

The efficacy of green roofs has been widely studied for the past 35-40 years. While the literature dating until around 2010 has mainly focused on proving the generic positive effects of green roofs, more recent studies tend to focus on the structural differences within different typologies of green roofs and how to best combine them.

Green roofs can be broadly categorized on a spectrum from extensive green roof to intensive. The first is made up of moss-sedum and grass, is lightweight and requires little to no maintenance. The latter is made of plants, shrubs and trees, it has a weight that needs to be accounted for and requires regular maintenance.

Extensive green roof   Semi intensive green roof   Intensive green roof

Figure 3. Visualization of extensive to intensive green roofs (Besir et al., 2018)

Structural differences include type of vegetation, leaf area index (LAI - the density of foliage), height, albedo (the reflectivity of the roof), irrigation, soil thickness, intensive versus extensive green roofs, green roofs with(out) water collection systems, roof insulation level, retrofitted versus original to the design and more. Crucially, the literature shows that there isn't one type of green roof that outperforms the others, but that different climates and existing infrastructure drastically change their performance (Susca, 2019). The reason why there are such wide differences in green roof performances across climates is due to the process of evapotranspiration, how water moves between soil, grass, plants and the atmosphere through evaporation and transpiration, and therefore, humidity, solar exposure, precipitation have to be taken into account (Sailor, 2008; Susca; 2019). Susca (2019) has summarised the efficiency of green roofs, making a distinction between non-insulated and insulated roofs, for both heating and cooling across different Köppen-Geiger climate classification. As visible in *Figure 4-7*, green roofs have significantly different efficacies across the different climate areas. Thus, to have the findings be valid for Amsterdam, it was important to find heating and cooling percentages aligned with the relevant Köppen-Geiger climate classification, which for this case study is Cfb, a temperate oceanic climate (*Figure 6 and 7*).

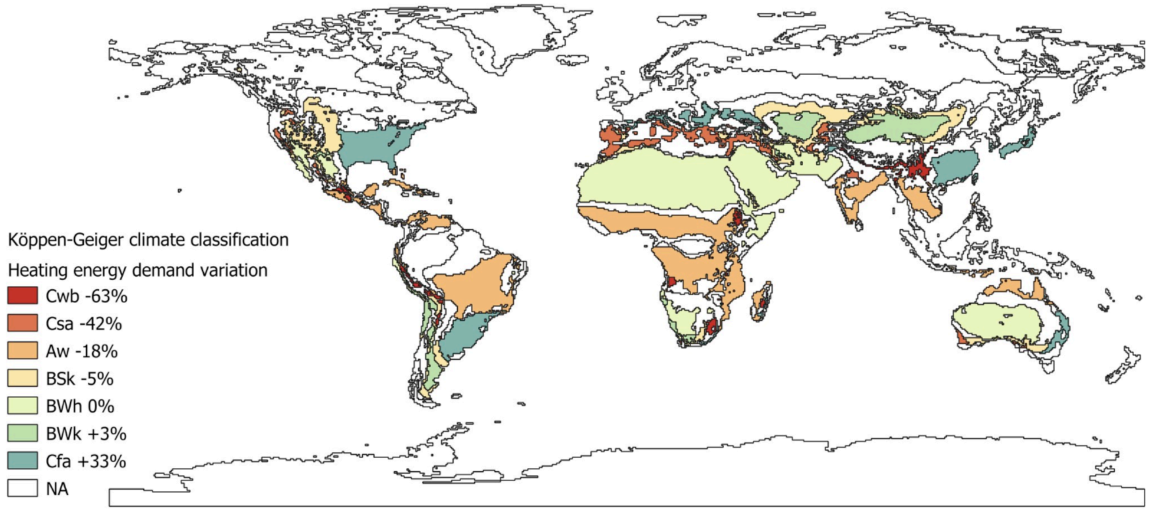

Figure 4. Variation in heating building energy-demand due to the installation of green roofs on non-insulated rooftops (Susca, 2019).

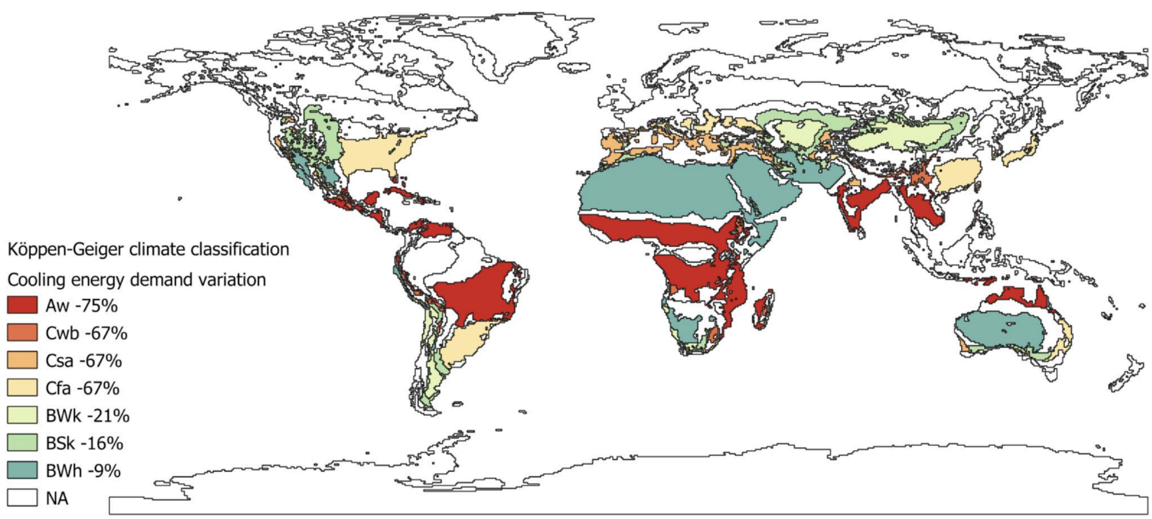

Figure 5. Variation in cooling building-energy demand due to the installation of green roofs on non-insulated rooftops (Susca, 2019).

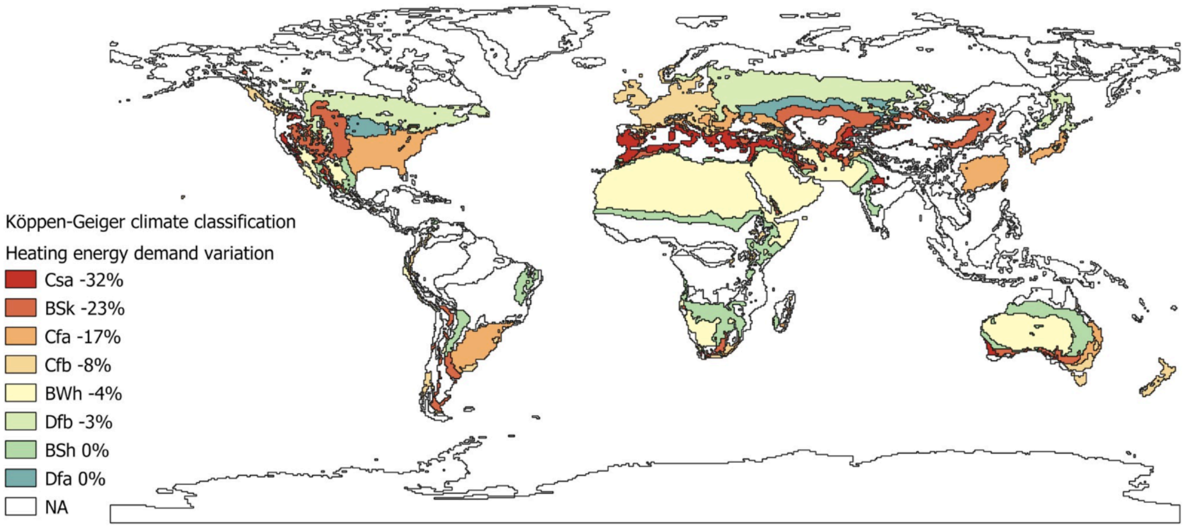

Figure 6. Variation in heating building-energy demand due to the installation of insulated green roofs (Susca, 2019).

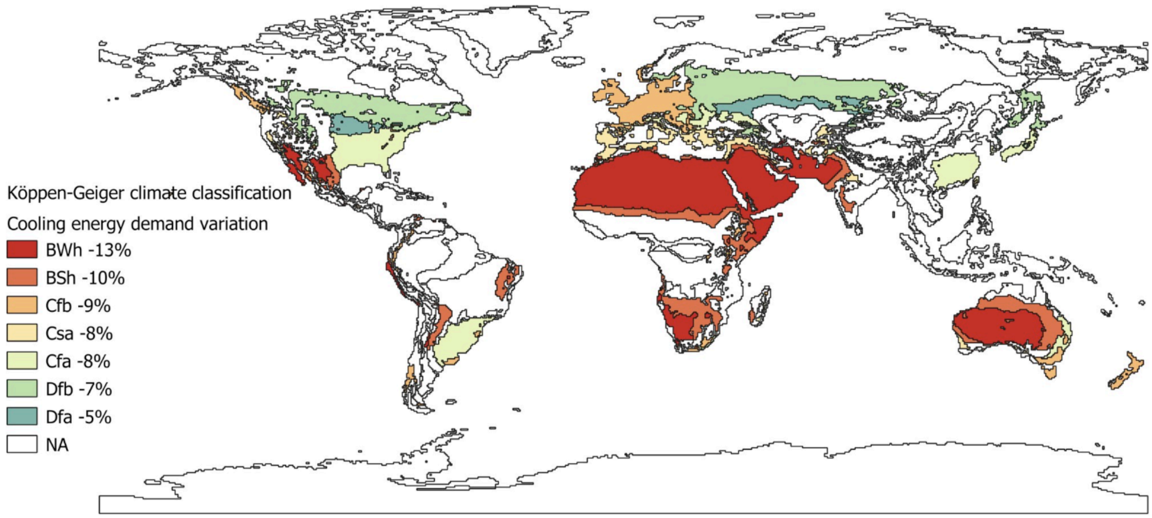

Figure 7. Variation in cooling building-energy demand due to the installation of insulated green roofs (Susca, 2019).

The selected research, with the same Köppen-Geiger climate classification, is the one of Virk et al. (2015), *Microclimatic effects of green and cool roofs in London and their impacts on energy use for a typical office building.* London and Amsterdam have similar climates and both have temperate oceanic climates. The research, as mentioned in the title, was conducted on an office building roof, and compared a traditional roof, made of asphalt with albedo 0.1, to a green roof, whose characteristics are specified in *Table 1*, a dry green roof, a green roof with lower irrigation, and a cool roof, also an asphalt roof but with a reflective paint that bright the albedo to 0.7 (Virk et al., 2015).

Green roof		Units
Soil thickness	0.15	m
Height of plants	0.1	m
Leaf area index	2	LAI
Leaf reflectivity	0.22	
Leaf emissivity	0.95	
Mean stomatal resistance	100	$s\,m^{-1}$
Max volumetric moisture content at saturation	0.5	
Min residual volumetric moisture content	0.01	
Initial volumetric moisture content	0.15	

Table 1. Characteristics of the green roof (Virk et al., 2015)

From these values, we can infer that this type of green roof would be considered an extensive green roof, as the substrate is shallow and the height of plants is low, with a moderate LAI. This paper is going to simulate that this type of green roof and dry green roof are retrofitted to Amsterdam's roofs by taking the percentage of the difference between the energy demand (kWh/m2 /yr) of the base roof and of the (dry) green roof. The original values per kWh/m2/yr can be observed in *Table 2.*

		Current climate				2050s climate			
		Base case	Green roof	Dry green roof	Cool roof	Base case	Green roof	Dry green roof	Cool roof
Modelled: energy demand (kWh/m^2/yr) for the uninsulated building									
Perturbed weather file	Heating	69.3	61.2	61.5	76.1	50.5	42.8	42.8	56.6
	Cooling	13.9	10.9	11	8.8	27.6	23.2	23.8	19.6
Basecase weather files	Heating	As above	60.2	60.5	75.1	As above	41.9	41.9	55.7
	Cooling	As above	11.6	11.3	9.7	As above	24.2	24.2	21.2
Modelled: energy demand (kWh/m^2/yr) for the insulated building									
Perturbed weather file	Heating	53.4	53.8	53.9	54.3	36.4	36.7	36.7	37.5
	Cooling	13.2	12.1	12.4	12.1	26.8	25.1	25.7	24
Basecase weather files	Heating	As above	52.9	53	54	As above	35.8	35.8	36.8
	Cooling	As above	12.7	12.7	12.4	As above	26.2	26.2	25.8

Table 2. Energy demand modelling results for the uninsulated and the insulated case study building. (Virk et al., 2015)

Here, an important assumption is made for the sake of the feasibility of this research, namely that all roofs in Amsterdam have the same characteristics as that of the base case in Virk et al. (2015). Furthermore, as mentioned above, large differences in the efficacy of green roofs have been noted between insulated and non-insulated green roofs. Hence, the distinction is also made in this article, and it is going to be applied in this research. Lastly, the selected values are the ones from the perturbed weather file, as that is a modified version of the basecase file, where the temperature and humidity data have been adjusted based on the microclimatic changes caused by green or cool roofs. Therefore, it offers a more realistic simulation of the efficacy of green roofs.

4. Methodology

4.1 Case Study Area: Amsterdam

The selected study area is the Municipality of Amsterdam. Unfortunately, due to the (un)availability of data, Stadsdeel Weesp is not included. This is because the now former Municipality of Weesp was merged into the Municipality of Amsterdam in March 2022, which is only relatively recently.

As of 2024, the Municipality of Amsterdam, has a total population of around 931,748 residents. As Stadsdeel Weesp 25,409 residents, the people living within the boundaries of the case study area are 90,6339 (Onderzoek en Statistiek - Gemeente Amsterdam, 2024 [A]). The population is not evenly distributed across neighbourhoods, with the highest density being in the most central neighbourhoods (*Figure 8*) (Onderzoek en Statistiek - Gemeente Amsterdam, 2024 [B]).

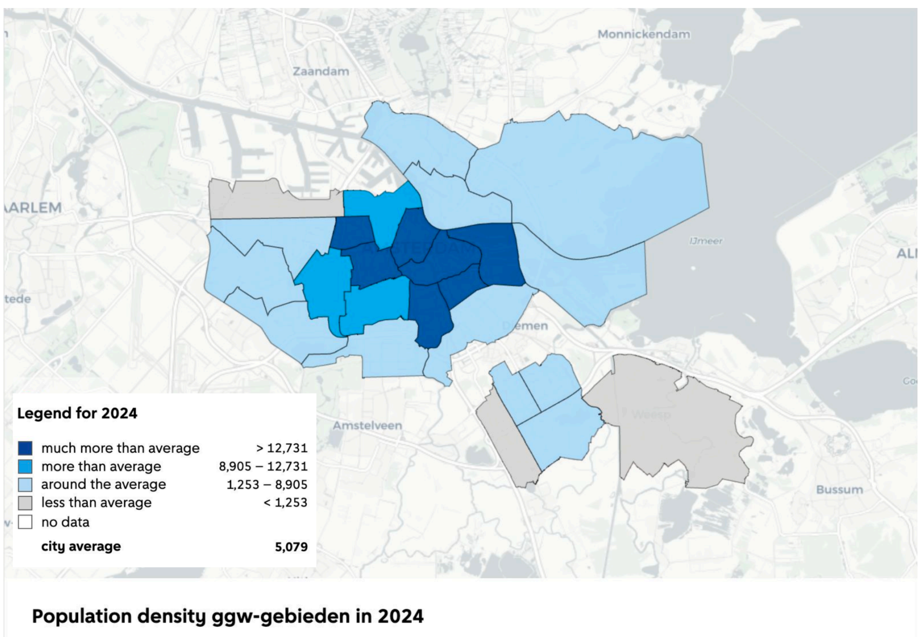

Figure 8. Population density in Amsterdam (Onderzoek en Statistiek - Gemeente Amsterdam, 2024[B])

The Municipality of Amsterdam is one of the many cities that is part of the Carbon Neutral Cities Alliance (CNCA), an international collaboration of cities that have set the goal to reach carbon neutrality within the next decades (CNCA, n.d.). The plan was laid out in a document titled Amsterdam Green Infrastructure Vision 2050 (2020) which explains through a philosophy of "Green as Default" how by greening buildings and neighborhoods, increasing park areas and preserving the landscape surrounding the city, the municipality aims to improve the city by making it more climate resilient, while bettering the social and economic welfare of its citizens. When looking at the interventions of greening on the building level, the expected outcomes are to “contribute to lowering temperatures in the city on hot days and reduce the strain on sewers during heavy rain” while supporting biodiversity and creating “space for activities” (Amsterdam Green Infrastructure Vision 2050, 2020, p.46).

In parallel, the Municipality of Amsterdam has also released the *New Amsterdam Climate: A Roadmap for Amsterdam Climate Neutral 2050* (2020), a report which maps the steps to implement an energy transition, structurally changing how energy is sourced, supplied and consumed in Amsterdam. In this report, solutions to improve the energy consumption of buildings were primarily related to placing solar panels on roofs.

Once again, it is when looking at these two reports that it becomes increasingly striking how the energy transition and green transition have been reflected upon only separately at the building level.

4.2 Data Collection

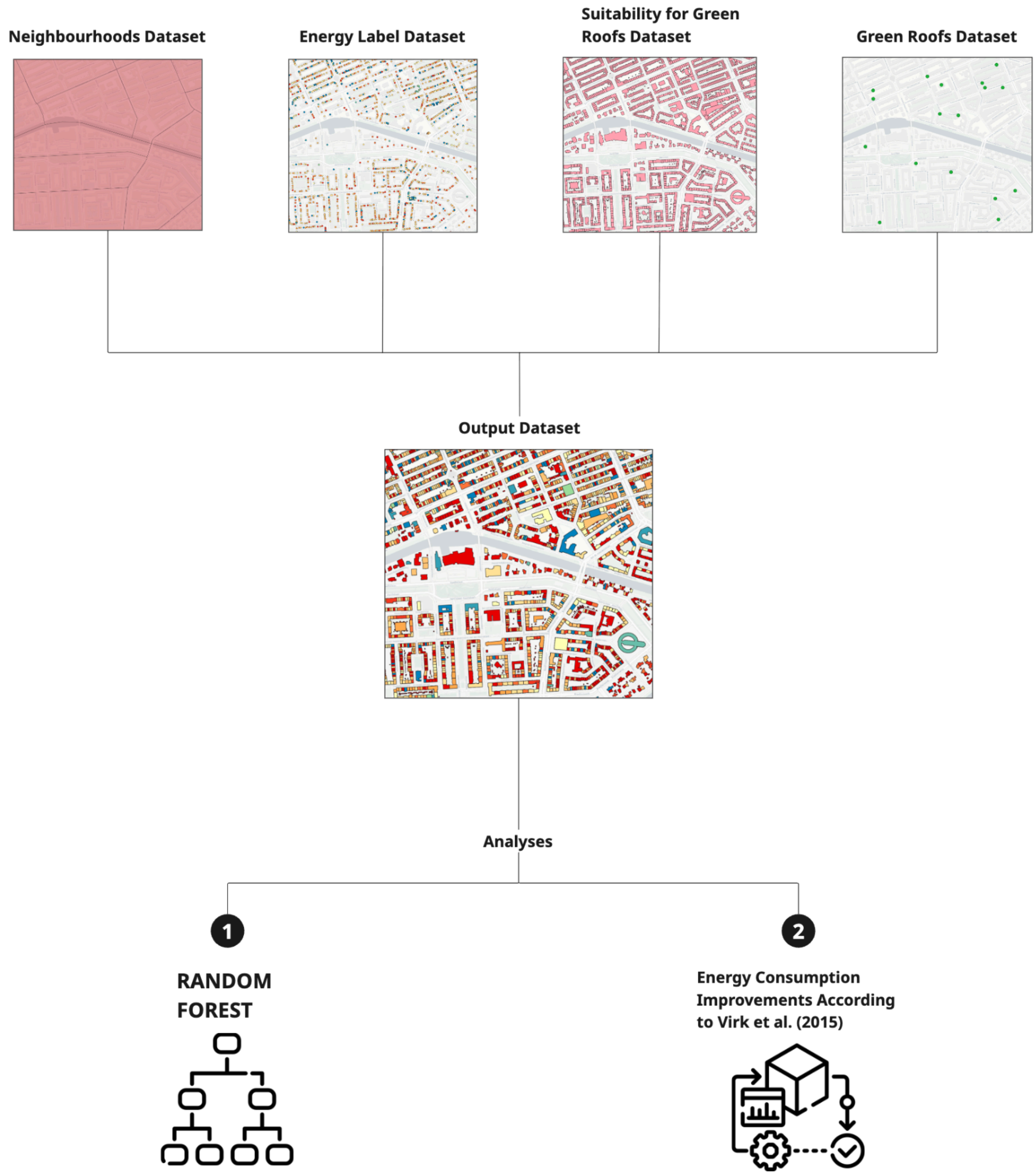

Figure 9. Overview of Data Integration and Processing

This research required multiple datasets to be integrated and preprocessed. An overview of these can be seen in *Table 3*.

Dataset Name	Source	Description	Use Case
Energy Label	ArcGIS, 2025	Point layer of energy labels of the whole of the Netherlands for 2025.	Find the energy label of a selected amount of buildings.
Suitability for Green Roofs, buildings of Amsterdam	Peranović, 2024	Building polygons from the BAG in Amsterdam that have been assigned a score based on average height, slope, area, and age.	Predict the energy label after retrofitting of green roofs
Green Roofs of Amsterdam	Maps Amsterdam, 2025	Existing green roofs (and walls) in Amsterdam.	Predict patterns of roofs with greenery
Neighbourhoods of Amsterdam	Maps Amsterdam, 2025	Neighbourhoods of Amsterdam in 2025.	Delineate the study area.

Table 3. Overview of datasets

Energy label Dataset

The energy label dataset can be downloaded freely from the ArcGIS website after login. It was downloaded as a csv, as the Geojson and the GeoPackage were not actually working files. When downloaded two files appeared, a polygon file without WTK, which meant that it could not be mapped and used in QGIS, and a point file with coordinates. The latter was selected for use, but as it was a country-wide file, it was narrowed down to include only the energy labels of Amsterdam.

Roofs of Amsterdam

The dataset with the suitability for green roof data of buildings in Amsterdam was sourced from Peranović (2024). This dataset is made up of polygons and it collects the BAG of buildings and their roofs' average height, slope, area, and age, along with a green roof suitability score.

Green Roofs Dataset

This dataset was found on the open-source data platform of the Municipality of Amsterdam, Open Geodata. It can be found when searching for ‘Groene en multifunctionele daken’, which means green and multifunctional green roofs. For this paper it was obtained by copying the geojson LngLat link into QGIS. This is a point layer.

Neighbourhoods of Amsterdam Dataset

This dataset was also found on the open-source data platform of the Municipality of Amsterdam, Open Geodata, when searching for 'Buurten', which are polygons delimiting the neighbourhoods of Amsterdam. These were used to identify the area of study. For this paper it was obtained by copying the geojson LngLat link into QGIS.

4.3 Data Integration and Preprocessing

Firstly, the green roof dataset was cleaned by delimiting it to the boundary of Amsterdam, as defined by the datasets of the neighbourhoods of Amsterdam. Moreover, as the dataset also included green facades, those were removed, as they fall outside of the scope of this research, leaving 471 buildings with a green roof. Secondly, the energy label dataset, which is at an address level, was spatially joined with the dataset containing buildings and the data of their suitability for green roof. Lastly, the previously cleaned roof dataset was also spatially joined. This enabled the computation of an additional variable that indicated whether an address was in a building with an already existing green roof. It is important to notice that some buildings had more than one green roof, while many green roofs were in buildings with many addresses. As a result, while there were 471 buildings with green roofs, a total of 6608 addresses were found to be located within these buildings.

4.4 Energy Framework

In the Netherlands from January 2021, how a building's energy performance is quantified is described by the Rijksdienst voor Ondernemend Nederland (RVO) in the NTA 8800 to align with European level standards (NTA 8800:2024, 2024). There are 3 core performance indicators, called BENG requirements, namely EP1, EP2 and EP3. EP1 calculates the energy demand of a building for heating, cooling and ventilation; it reflects the insulation, compactness, orientation and passive energy gains of a building. It is calculated as kWh/m²·year but it is not used to directly calculate the label class of building. Rather, EP1 is used in EP2 to calculate the real efficiency of a building. EP2 calculates the total primary fossil energy consumption by accounting for inefficiencies and distributions losses, it reflects how the demand of buildings for heating, cooling and ventilation, calculated in EP1, actually is and the energy source used. It is also calculated in kWh/m²·year. EP2 is the key determinant of the energy label of a building. Lastly, EP3 measures what percentage of energy demand calculated in EP2 comes from renewable sources. EP3 is also not used to determine the energy label of a building, but it is rather shown as an estimation of the cost for heating and cooling a building (NTA 8800:2024, 2024; RVO, 2017).

Therefore, when looking at how the performance of a green roof could affect the energy demand and performance of a building, and potentially affect the energy label of a building we would have to look at the EP2 table, as it looks at the whole system dynamics that dictate a building's energy demands and as it is the key determinant of energy labels. Moreover, It is crucial to stress that energy classification does change across different building types. The buildings type, translated from Dutch are housing (*Appendix 1*), offices, meeting function with daycare, meeting function without daycare, education, (health)care without a bed (*Appendix 2*), (health)care with a bed, shopping, accommodation and cell (*Appendix 3*). These functions do not completely match the ones of the dataset used in this research, therefore some generalizations were made as they can be seen in *Table 4*.

Research Dataset Categorization	**RVO Category**
Residential	Residential
Commercial	Commercial
Sport	Sport
Other uses	-
Education	Education
Lodging	Lodging
Office	Office
Industrial	-
Healthcare	Healthcare with bed, Healthcare without bed
Prison	Prison
Meeting	Meeting without childcare, Meeting with childcare

Table 4. Matching of building function between RVO categories and the Dataset of this Research

Furthermore, as many addresses had more than one building function, it was necessary to rank them from most to least restrictive, as can be seen in *Table 5* . This allows us to define the mean consumption per square meter. The most restrictive function was assigned to avoid overestimations (*Table 5*). Moreover, as there are two categories of the dataset of this research that are not in the RVO, namely ‘Other uses’ and ‘Industrial’ function, they were assigned to the category ‘Meeting without childcare’, as that is the most generic of the RVO categories.

Rank	RVO Category	Reason
1	Residential	Lowest mean consumption (0-160)
2	Prison	Low (60-500 range)
3	Office	Ranges start low
4	Education	Moderate ranges
5	Lodging	Mid-range
6	Sport	Higher but not extreme
7	Commercial	Gets into high values
8	Healthcare with bed, Healthcare without bed	One of the highest
9	Meeting without childcare, Meeting with childcare	Highest ranges (up to 445+)

Table 5. RVO Categories listed from most to least restrictive

4.5 Description of the Data

The dataset used in this research includes a range of address-level and roof-level variables. These encompass the energy label of each address, its primary and most restrictive use function, the year of construction, and a normalized building age. Roof characteristics include the minimum and maximum roof area, total roof area, median roof height and slope, as well as normalized values for area, height, and slope. The dataset also contains the number of residential units within each building, a suitability score for green roof retrofitting as developed by Peranović (2024), and a binary indicator denoting whether a roof is suitable. Energy-related features include the address-level heat requirement, CO_2 emissions, and energy consumption. Additionally, the dataset records whether a building already has a green roof, whether the roof is considered insulated (defined as having an energy label of C or better), and an estimate of the mean energy consumption per square meter. This last value was derived by linking each building's use function to the midpoint of the corresponding energy label's expected consumption range. Finally, each address is uniquely identified by its BAG number, which is also linked via a URL to the Dutch cadastre for external reference and verification.

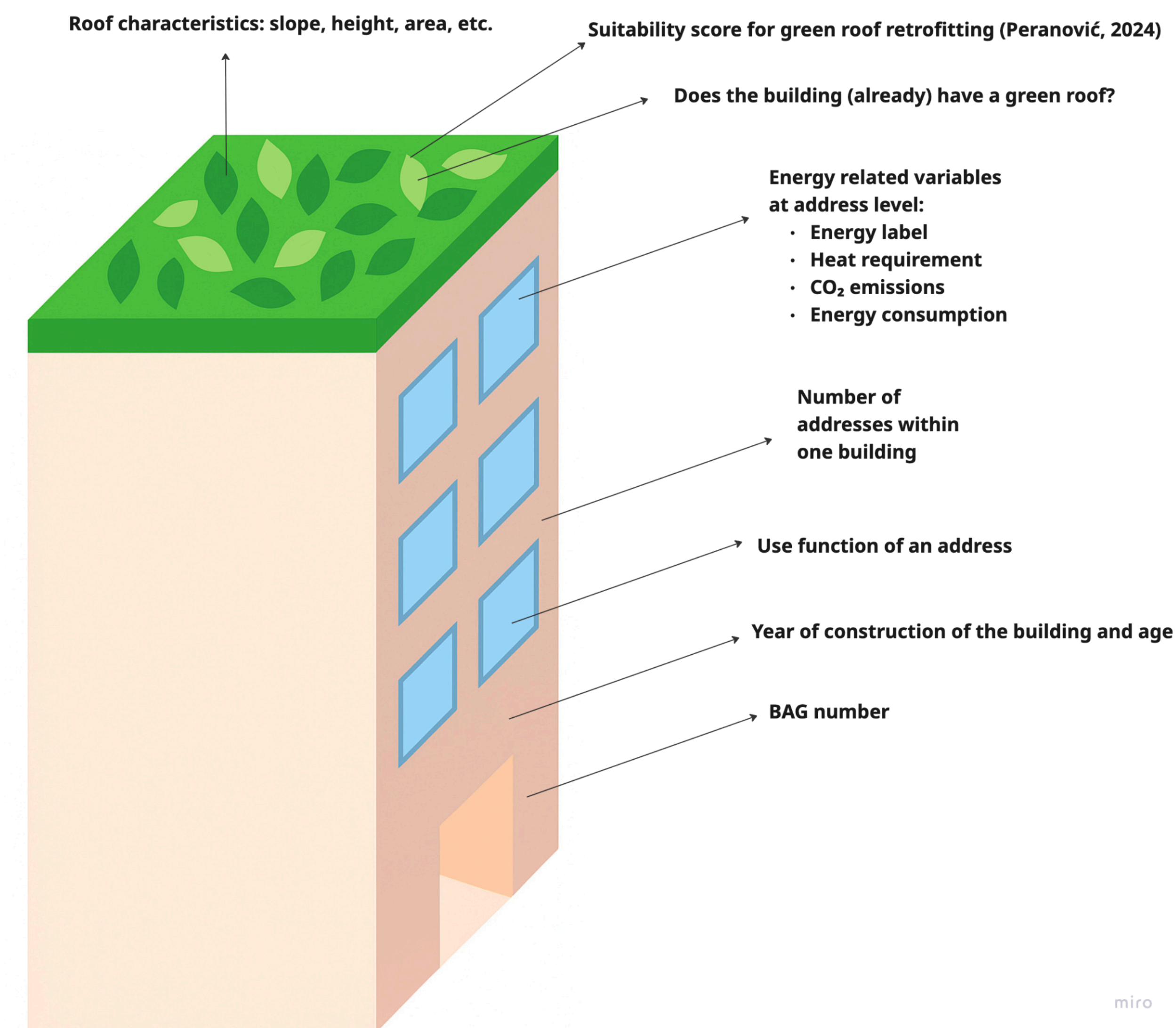

Figure 10. Dataset Visualization

The distribution of the most restrictive use function is highly unbalanced, with the majority of addresses having a residential function (93.84%), followed by the function of meeting without childcare (3.69%) and then by the function of office (1.26%). All other functions are below 1%.

Use Function (Most Restrictive)	Amount
Meeting with childcare	1442 (0.31%)
Meeting without childcare	16930 (3.69%)
Prison	7 (0.0015%)
Office	5793 (1.26%)
Lodging	701 (0.15%)
Education	649 (0.14%)

Sport	358 (0.08%)
Commercial	2369 (0.52%)
Residential	430763 (93.84%)
Healthcare with bed	212 (0.05%)

Table 6. Distribution of the Use Functions

Lastly, the distribution of the energy labels is similarly very unbalanced, with the most numerous being energy labels 'A' (25.54%), 'C' (16.82%), 'B' (11.33%) and 'D' (9.30%). These percentages are over the total dataset, including those that are missing which are around 20.48%.

Energy Label	Amount
A+++++	32 (0.0070%)
A++++	624 (0.14%)
A+++	4096 (0.89%)
A++	9433 (2.05%)
A+	17865 (3.89%)
A	117279 (25.54%)
B	52066 (11.33%)
C	77271 (16.82%)
D	42691 (9.30%)
E	21274 (4.63%)
F	10432 (2.27%)
G	12088 (2.63%)
Missing	94073 (20.48%)

Table 7. Distribution of Energy Labels

4.5 Modelling

4.5.1 Understanding Generalization Patterns Between Buildings With and Without Green Roofs

To start the modelling, a random forest is computed with the aim to find generalization patterns between buildings with a green roof and buildings without it. This answers the question *Can energy label patterns learned from conventional buildings be transferred to buildings with green* *roofs?*. The target variable is the energy label of the address. As feature variables the following were used: the year of construction of the building, the minimum and maximum area of the building, the number of addresses within the building, the median height and slope of the roof, the normalized building age, roof area, height and slope of the roof, a suitability score for retrofitting a green roof as calculated by Peranovic (2024), the heat requirement of the address, the energy consumption of the address, the primary most restrictive use function of the building and lastly, whether the address is in a building that already has a green roof.

A first challenge was encountered due to heavy class imbalances. The dataset has 459224 features, with 6608 addresses being in a building with a green roof and 452616 in a building without. Furthermore, as the target variable is the energy label, only 6464 of addresses with green roofs were left as they had a value for the variable energy label. Therefore, the random forest is going to be tested on the 6464 addresses with green roofs, while it is going to be trained on 10 randomly selected samples, through undersampling therefore, with each of 25856 addresses without green roofs. Therefore, making the training testing split 80:20. As the target variable is energy label, a categorical variable, the results of the 10 runs are then assembled through a majority vote. Another challenge can be noted here, as the distribution of the green roofs per energy label is not evenly distributed, as can be observed in *Table 8*.

Energy Label	Ordinal Classification	Count
A+++++	0	0
A++++	1	5
A+++	2	97
A++	3	270
A+	4	569
A	5	3090
B	6	1299
C	7	790
D	8	138
E	9	68
F	10	26
G	11	112

Table 8. Green Roofs Distribution for Energy Label

Due to the severity of the imbalance, undersampling would have resulted in a dataset of green roofs too small for any significant analysis. To partially handle this both in training and in the output, the results were aggregated in classes in the following way, A+++++ to A+, from A to C, and D to G.

4.5.2 Counterfactuals Scenarios

Two counterfactual scenarios were performed. The first was to answer the question *What would the energy label of a green-roof building have been in the absence of the green roof?*. This is achieved by forcefully coding the addresses with a green roof to be without it and then analyzing whether the energy label worsened or improved. This first counterfactual is going to be evaluated on the random forest built for the first question.

On the other hand, for the second counterfactual scenario a new random forest is going to be computed, in order to answer the question *What would be the expected energy label of buildings if they were retrofitted with a green roof?*. This model is going to use the same 6464 addresses with green roof and then randomly select 6464 addresses without green roof, stratified per energy label. The total is then going to be shuffled and split in a 80:20 training testing split. This is going to be repeated 10 times and the results are going to be assembled through majority vote, while the output is going to be displayed through aggregated classes, same as for the first random forest. This model is used to predict the energy label of a sample of 6464 addresses without green roof which are randomly selected.

4.5.3 Testing Possible Changes in Energy Label

The predicted labels from the last iteration of the random forest are then combined with those that are not missing. Moreover, by using the primary most restrictive use and the mean consumption per meter square, described in the energy framework section, and the empirical findings of Virk et al. (2015), a new energy consumption is computed. Virk et al. (2015) found how green roofs and dry green roofs changed the energy consumption per kWh/m2/yr of a base case roof. The percentage reduction is calculated with the formula below:

$$\text{Percentage Reduction} = \frac{\text{Base Case} - \text{Roof Case}}{\text{Base Case}} \times 100$$

In *Table 9,* the calculated percentage reductions can be observed. They are divided by roof type and by insulation scenario. As mentioned above, the efficacy of different types of green roofs also depends on the insulation of the roof itself. The most drastic improvements are found in uninsulated roofs, as there is more margin of improvement. Hence why, when the energy label of an address was between A+++++ to C, the roof is considered insulated, while between D to G, the roof is considered uninsulated.

Scenario	Type	Roof Type	Base Case (kWh/m2/yr)	Roof Case (kWh/m2/yr)	% Reduction
Uninsulated	Heating	Green Roof	69.3	61.2	11.69
Uninsulated	Cooling	Green Roof	13.9	10.9	21.58
Insulated	Heating	Green Roof	53.4	53.8	-0.75
Insulated	Cooling	Green Roof	13.2	12.1	8.33
Uninsulated	Heating	Dry Green Roof	69.3	61.5	11.26
Uninsulated	Cooling	Dry Green Roof	13.9	11	20.86
Insulated	Heating	Dry Green Roof	53.4	53.9	-0.94
Insulated	Cooling	Dry Green Roof	13.2	12.4	6.06

Table 9. Transformation in percentage of Virk et al.(2015) findings

As the heating and cooling are separated in the Virk et al. (2015), but in the dataset used for this research, there is one combined value of energy consumption per address, a split had to be defined. Firstly, the analysis is conducted with a heating to cooling ratio of 80:20. This is followed by a sensitivity analysis where the ratio is moved to 65:35.

Lastly, the energy consumption after the retrofitting of green roofs and dry green roofs in both the 80:20 and 65:35 heating to cooling ratio, is computed to the corresponding energy label, once again also relative to the use function of the building.

4.5.4 Sensitivity Analysis

The heating and cooling split of a building's energy consumption in a Cfb, temperate oceanic climate, as defined by Köppen-Geiger climate classification, heavily depends on the use function of a building. Offices, commercial spaces, facilities tend to have cooling demands around 20% of the total energy demand. This is similar in newly built residential buildings but in older ones this is closer to 4-5% (Virk et al., 2015; International Energy Agency, 2022; Openresearch Amsterdam, 2020). Furthermore, it is important to notice that the projection of cooling demand is increasing. While temperatures are rising and summers are longer and warmer, the reason for the increase is the cooling energy demand is the popularisation of air conditioners. 90% of air conditioners in the Netherlands were installed in the last 5 years (TNO, n.d.; International Energy Agency, 2022). Therefore, as suggested by Virk et al. (2015), the first splitting ratio of heating to cooling is 80:20, while the second is 65:35.

4.6 Computational Resources

All data processing, modeling, and analysis for this thesis were performed in Python using Jupyter Notebooks on a personal laptop equipped with an Apple M3 Pro chip (12-core CPU, 18-core GPU) and 18GB of RAM. This configuration is comparable to a mid-range NVIDIA RTX 4050 laptop GPU in terms of performance, enabling efficient handling of both machine learning and geospatial data. Core libraries included pandas, geopandas, scikit-learn, imbalanced-learn, matplotlib, and seaborn for data manipulation, modeling, and visualization. Geospatial validation and exploratory analysis were conducted in QGIS. The full pipeline, from data preprocessing and model training to counterfactual simulation and energy label prediction, required approximately 1.5 to 2 hours to run. All code and datasets are publicly available on GitHub at GreenRoofs_to_EnergyLabel to support reproducibility and open research.

5. Results

5.1 Understanding Generalization Patterns Between Buildings With and Without Green Roofs

As mentioned above, the results of the random forest classifier for the variable containing the energy labels were aggregated. For the highest tier, A+++++ to A+, the model assigns a top-tier label to green-roof buildings with 53% precision, and recalls 92% of truly top-performing cases. This suggests that many green-roof buildings had features associated with high energy performance even without the green roof. The model tends to overestimate this group, perhaps due to shared characteristics like roof structural features or building age. For the middle tier, A to C, the model predicts a precision of 95% and a recall of 84%; this group represents the model's strongest performance. The majority of green-roof buildings (5,179 out of 6,464) were predicted to fall in this class, indicating a conservative and accurate estimate of baseline energy efficiency. Lastly, for the lowest tier, D to G, the model correctly identifies poor-performing buildings 82% of the time (precision), but only recalls 53%, meaning it misses nearly half of the green-roof buildings that had low baseline performance.

The overall performances were 83.9% grouped accuracy and 73.8% for the grouped F1 score (macro). These results indicate a robust ability to generalize patterns from non-green-roof to green-roof buildings. The model performs particularly well in distinguishing middle- and top-tier energy labels, but shows some conservatism in predicting poor performance, supporting the idea that green roofs may have helped low-performing buildings improve.

	Precision	Recall	F1-Score	Support
A+++++ to A+	0.53	0.92	0.67	941
A to C	0.95	0.84	0.89	5179
D to G	0.82	0.53	0.64	344

Accuracy			0.84	6464
Macro Average	0.77	0.77	0.74	6464
Weighted Average	0.88	0.84	0.85	6464
Grouped Accuracy	0.8394183168			
Grouped F1 Score (macro)	0.7376032982			

Table 10. Accuracy Reports 1

When looking at the features importance of this random forest, the most impactful ones were, in order of importance, the energy consumption of the address (0.213) , the CO2 emissions (0.190), the heat requirement (0.089), the normalized building age (0.056) and the year of construction of the building (0.055). These were followed by variables capturing the structural features of buildings, such as surface, height, slope and their normalized counterparts. Moreover, came the categorical variable indicating the most restrictive function of the address which by function did not heavily impact the model. Lastly, came the variable indicating whether an address was a building with a green roof, but as expected since the model was trained on only addresses without green roofs, this was equal to zero. These can be observed in *Table 11*.

Feature	Importance %
Energy Consumption	0.213235
CO2 Emissions	0.190026
Heat Requirement	0.089277
Normalized Building Age	0.056665
Year of Construction of the Building	0.055507
(Roof) Minimum Surface Area	0.043837
Suitability Score for Green Roof Retrofitting	0.041028
Normalized Roof Height	0.040298
Median Roof Height	0.039791
(Roof) Maximum Surface Area	0.038697
Normalized Roof Area	0.037177
Roof Area	0.037148
Normalized Roof Slope	0.033059
Median Roof Slope	0.033002
Number of Addresses in the Building	0.027391

Primary Most Restrictive Building Function: Residential Function	0.011374
Primary Most Restrictive Building Function: Office Function	0.006815
Primary Most Restrictive Building Function: Meeting without Daycare Function	0.003849
Primary Most Restrictive Building Function: Commercial Function	0.000589
Primary Most Restrictive Building Function: Education Function	0.000588
Primary Most Restrictive Building Function: Meeting with Daycare Function	0.0003
Primary Most Restrictive Building Function: Lodging Function	0.000146
Primary Most Restrictive Building Function: Sport Function	0.000094
Primary Most Restrictive Building Function: Prison Function	0.000055
Primary Most Restrictive Building Function: Healthcare with Bed Function	0.000051
Already Green Roofs	0

Table 11. Feature Importance Table

Lastly, a partial dependence plot was performed to understand the type of relationship between the energy labels, which is the target variable, and the features that were established to be the most relevant for the random forest. The plots in *Figure 11-13* show the marginal effect of each feature on the predicted probability of an address being classified in each energy label group, holding all other features constant. For energy consumption and CO2 Emissions, in all three tiers, higher values of energy consumption and emissions greatly reduce the likelihood of receiving a high-performing label, while increasing the likelihood of being in the lowest tier. Lastly, the normalized building age and the year of construction of the building both show a non-linear increase in the probability of being classified in the highest tier as buildings become newer.

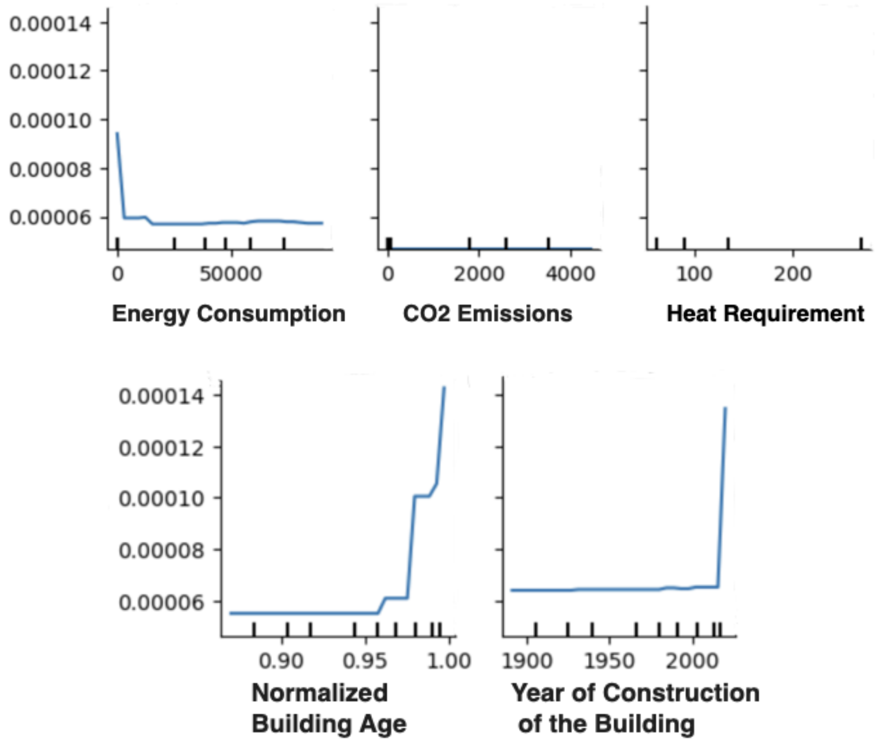

Figure 11. Partial Dependence Plot Class 0

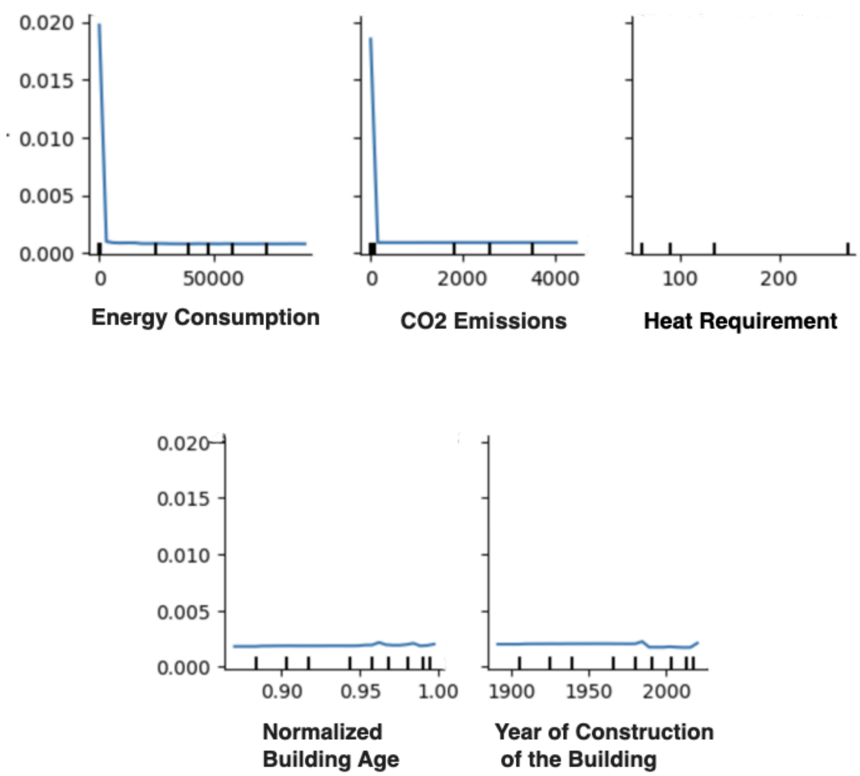

Figure 12. Partial Dependence Plot Class 1

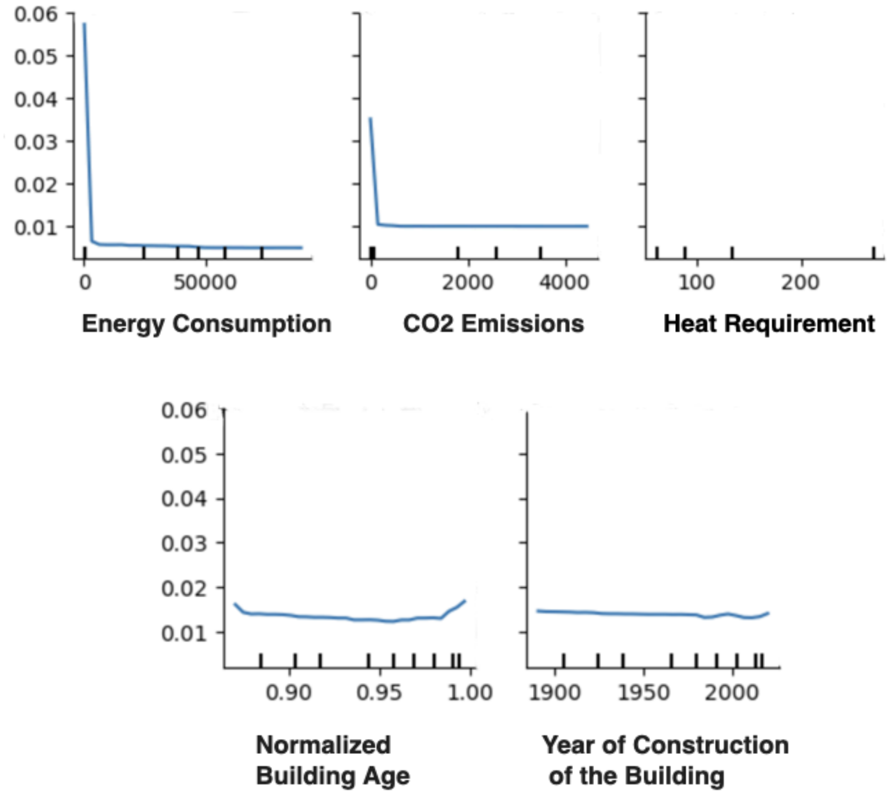

Figure 13. Partial Dependence Plot Class 2

5.2 Counterfactuals Scenarios

5.2.1 First Counterfactual

When evaluating the set of 6464 buildings with a green roof on the random forest previously discussed, to understand how their energy label would change if the green roof was simulated to be removed, the results were the following. The majority of labels did not change, that corresponded to 5945 out of 6464, around 91.96%. Around 42 buildings improved their labels by two classes (0.65%); while around 283 improved by one class (4.38%). Thus, around 5.03% of the total buildings with green roof, when it was simulated that the latter was removed, the label improved. On the other hand, around 166 buildings worsened their labels by one class (2.75%), around 24 worsened by two classes (0.37%), around 2 worsened by three classes (0.03%) and the same number worsened by four classes. Thus, a total of 194 of the labels of buildings worsens when it is simulated that the green roof is removed, corresponding to 3% of the total.

Label Change	Amount of Addresses	Meaning
-2	42	Improved by 2 labels without a green roof
-1	283	Improved by 1 label without a green roof
0	5945	No change
1	166	Worsened by 1 label without a green roof --> green roof helps improve the energy class
2	24	Worsened by 2 labels without a green roof --> green roof helps improve the energy class
3	2	Worsened by 3 label without a green roof --> green roof helps improve the energy class
4	2	Worsened by 4 label without a green roof --> green roof helps improve the energy class

Table 12. Label Change for Counterfactual Scenario 1

5.2.2 Second Counterfactual

For the second counterfactual, 6464 buildings without a green roof were simulated to be given a green roof. The results showed that the majority of buildings, 6295 out of 6464, or approximately 97.38%, did not experience any change in energy label. However, 3 buildings improved their energy label by six classes, another 3 improved by five, and a further 3 improved by four, indicating significant potential gains in a small subset of cases. A total of 20 buildings improved by three classes (0.31%), 57 by two classes (0.88%), and 37 by one class (0.57%). In total, 123 buildings (1.9%) saw improvements in their energy label with the simulated addition of a green roof. On the other hand, a small number of buildings experienced a worsening in their energy label: 27 by one class (0.42%), 16 by two classes (0.25%), and 3 by three classes (0.05%), amounting to 46 buildings (0.71%) in total.

Label Change	Amount of Addresses	Meaning
-6	3	Improved by 6 labels with a green roof --> green roof helps improve the energy class
-5	3	Improved by 5 labels with a green roof --> green roof helps improve the energy class
-4	3	Improved by 4 labels with a green roof --> green roof helps improve the energy class

-3	20	Improved by 3 labels with a green roof --> green roof helps improve the energy class
-2	57	Improved by 2 labels with a green roof --> green roof helps improve the energy class
-1	37	Improved by 1 labels with a green roof --> green roof helps improve the energy class
0	6295	No change
1	27	Worsened by 1 labels with a green roof
2	16	Worsened by 2 labels with a green roof
3	3	Worsened by 3 labels with a green roof

Table 13. Label Change for Counterfactual Scenario 2

In addition to the total number of label changes, the results were disaggregated to assess which types of buildings and which energy label were more likely to experience a shift. These proportions were calculated within each category, as the fraction of addresses that experienced any change relative to the total number of addresses in that category. This analysis revealed that buildings with, as baseline performance, the labels D, C, and A++, were the most likely to benefit from a green roof retrofit, with approximately 13.0%, 12.7%, and 10.4% showing a change, respectively. Conversely, buildings already performing efficiently (i.e. A+++, A++++, and A) were almost entirely unaffected (*Table 14*).

Energy Label	**Proportion of Change within Energy Label**
D	0.130137
C	0.127389
A++	0.104478
F	0.076923
B	0.071287
G	0.052632
A+	0.05
E	0.025316
A	0.00666
A++++	0
A+++	0

Table 14. Proportion of Change within Energy Label

Regarding building function, lodging exhibited the highest responsiveness (15.4% changed), followed by education (5.0%) and office (3.6%) uses. Residential buildings, meeting facilities without childcare, and commercial spaces showed relatively low responsiveness, while buildings categorized under healthcare or those with integrated childcare showed no observable change (*Table 15*).

Use Function	**Proportion of of Change within Use Function**
Lodging	0.153846
Education	0.05
Office	0.036364
Residential	0.026435
Meeting without Childcare	0.026217
Commercial	0.012987
Meeting with Childcare	0
Healthcare with Bed	0

Table 15. Proportion of Change within Use Function

5.3 Testing Empirical Reduction Percentages of Virk et al. (2015)

The results presented in *Table 16* and *Table 17* show how energy labels responded to the introduction of either a green roof or a dry green roof across 452,616 buildings, under two heating-to-cooling ratios: 80:20 and 65:35. For both green roof and dry green roof scenarios, the majority of buildings, around 80.89% (366059 addresses), exhibited no change in energy label.

In the case of green roofs, about 19.13% of buildings improved their energy label under both heating-cooling splits. A closer look reveals that under the 80:20 split, 16.44% improved by one label and 2.68% by two labels. The share of buildings improving by two labels slightly increased to 2.72% under the 65:35 assumption, even though the share improving by one label slightly decreased to 16.4%.

The dry green roof results followed a similar trend. Overall improvement remained at 19.13%, identical to the green roof. However, there was a marginal redistribution between the one-label and two-labels improvements. Under the 80:20 assumption, 16.46% improved by one label and 2.67% by two labels, while under the 65:35 setting, 16.4% improved by one label and again 2.72% by two labels.

	Total Buildings	No Change	Improved Total	Improved by One Energy Label	Improved by Two Energy Label
Heating:Cooling 80:20	452616	366059 (0.8089)	86557 (0.1913)	74407 (0.1644)	12150 (0.0268)
Heating:Cooling 65:35	452616	366059 (0.8089)	86557 (0.1913)	74233 (0.164)	12324 (0.0272)

Table 16. Label Change for Green Roof

	Total Buildings	No Change	Improved Total	Improved by One Energy Label	Improved by Two Energy Label
Heating:Cooling 80:20	452616	366059 (0.8089)	86557 (0.1913)	74480 (0.1646)	12077 (0.0267)
Heating:Cooling 65:35	452616	366059 (0.8089)	86557 (0.1913)	74233 (0.164)	12324 (0.0272)

Table 17. Label Change for Dry Green Roof

In order to better understand which addresses benefited the most from (dry/) green roof retrofitting, energy label improvements were further analyzed by both original energy label and use function. Results show that addresses initially rated with poorer labels, particularly label D (49.59%), followed by E (24.52%), G (13.88%), and F (12.02%), were the most likely to experience improvements across all four retrofit scenarios (*Table 18*).

	Green Roof (80/20)	Green Roof (65/35)	Dry Green Roof (80/20)	Dry Green Roof (65/35)
D	42920 (49.59%)	42920 (49.59%)	42920 (49.59%)	42920 (49.59%)
E	21220 (24.52%)	21220 (24.52%)	21220 (24.52%)	21220 (24.52%)
G	12011 (13.88%)	12011 (13.88%)	12011 (13.88%)	12011 (13.88%)
F	10406 (12.02%)	10406 (12.02%)	10406 (12.02%)	10406 (12.02%)

Table 18. Label Change by Energy Label

When looking at building function, residential buildings accounted for 97.92% of all improvements, with over 84,000 addresses improving under each scenario. Other use categories contributed marginally: office buildings (0.62%), education (0.14%), and commercial spaces (0.25%) formed small shares of the total (*Table 19*).

	Green Roof (80/20)	Green Roof (65/35)	Dry Green Roof (80/20)	Dry Green Roof (65/35)
Residential	84759 (97.92%)	84759 (97.92%)	84759 (97.92%)	84759 (97.92%)
Office	533 (0.62%)	533 (0.62%)	533 (0.62%)	533 (0.62%)
Meeting without Childcare	509 (0.59%)	509 (0.59%)	509 (0.59%)	509 (0.59%)
Commercial	216 (0.25%)	216 (0.25%)	216 (0.25%)	216 (0.25%)
Meeting with Childcare	216 (0.25%)	216 (0.25%)	216 (0.25%)	216 (0.25%)
Education	120 (0.14%)	120 (0.14%)	120 (0.14%)	120 (0.14%)
Lodging	97 (0.11%)	97 (0.11%)	97 (0.11%)	97 (0.11%)
Sport	52 (0.06%)	52 (0.06%)	52 (0.06%)	52 (0.06%)
Healthcare with Bed	52 (0.06%)	52 (0.06%)	52 (0.06%)	52 (0.06%)
Prison	3 (0%)	3 (0%)	3 (0%)	3 (0%)

Table 19. Label Change by Use Function

6. Discussion and Limitations

This research aimed to understand whether, and by how much, the energy label of a building could change when a green roof is retrofitted. Two complementary approaches were used, namely random forest classifiers, and an energy demand reduction scenario based on values from Virk et al. (2015). While both methods offer valuable insight, the results should be interpreted with caution given certain methodological limitations, particularly the relatively small number of buildings with green roofs in the dataset.

The first random forest model showed a reasonable ability to generalize energy label patterns from buildings without green roofs to those with green roofs. However, the test set included 6,464 addresses derived from only 471 actual green-roof buildings. To increase statistical power, all individual addresses associated with a green-roof building were included. While this decision was necessary to ensure sufficient test size, it may have introduced some bias, particularly where different units in the same building shared structural features of the roof.

The model performed best when predicting middle-tier labels (A to C), with a satisfying precision and recall, indicating conservative and reliable classification. Top-tier labels (A+ to

A+++++) were somewhat overpredicted, likely due to shared features like newer construction or efficient structural building characteristics. For low-performing buildings (D to G), the model showed lower recall, despite decent precision, implying that many green-roof buildings with low baseline performance were missed. This under-identification may indicate that green roofs played a corrective role, helping buildings escape the lowest energy classes, an interpretation supported by the literature (Susca, 2019; Virk et al., 2015), which found stronger green roof effects in poorly insulated buildings.

The feature importance analysis provides further insight into these patterns. The three most influential variables, energy consumption, CO2 emissions, and heat requirement, are direct measures of building energy performance, making them central to the prediction of energy labels. The next most important features, normalized building age and year of construction, suggest that newer buildings are more likely to receive better labels, likely due to recent stricter energy efficiency policies. Several variables relating to structural characteristics followed, which likely capture differences in thermal performance related to building design and construction standards. These relationships were further explored using partial dependence plots. For the most important features, energy consumption and CO2 emissions, PDPs showed that higher values greatly decreased the likelihood of a high-performing label, and increased the chance of being in the lowest tier. For normalized building age and year of construction, the PDPs revealed a non-linear increase in the probability of being assigned a top-tier label as buildings became newer. However, for low-performing labels, the pattern flattened, implying that age becomes a less distinctive predictor for poor performance beyond a certain threshold. This suggests that while age helps predict efficiency gains, it may not capture the full picture of underperformance.

The first counterfactual, simulating the removal of green roofs, showed that 91.96% of buildings saw no change in label. While 5% of the labels improved, implying that for these addresses a green roof increases their energy demand, for 3% the label worsened, suggesting that for these addresses a green roof lowers their energy demand enough to improve their energy label. The fact that more labels improved than worsened could point to model overfitting, or indicate that energy label performance is heavily driven by factors other than the green roof itself, such as roof structural features, or building age. These findings suggest that, under the current model and dataset, green roofs do not universally improve energy labels.

The second counterfactual, simulating the addition of green roofs to non-green-roof buildings, also showed limited impact. While 97.38% remained unchanged, 1.9% improved, and 0.71% worsened. Although a few buildings experienced drastic label improvements, up to six classes, these were outliers. Most buildings that benefited had low initial performance, confirming the broader pattern that green roofs are most impactful for inefficient or high-demand buildings. When breaking it down by label, buildings originally classified as D and C, were most likely to shift. Buildings already in top categories (A+, A+++, etc.) were largely unaffected, reinforcing the notion that green roofs provide diminishing returns for already efficient structures. Lastly, on the analysis by use function, the results were inconclusive as the effect of green roofs on energy labels is unevenly distributed across their use function.

This was further confirmed in the second part of the study, which applied empirically observed heating and cooling reductions from Virk et al. (2015) to the whole dataset, with the expulsion of the roofs that already had a green roof. Despite the fact that energy demand inevitably dropped for every building, due to the initial results of Virk et al. (2015), only 19.13% improved their energy label. Similarly to above, most improvements happened in the addresses with a baseline energy label below D. Moreover, improvements were primarily found in residential addresses (97.92%), but this can mainly be attributed to the fact that those were the majority of the overall sample to begin with (93.84%). Over 80% remained unchanged, highlighting that even with consistent energy savings, energy labels may not be sensitive enough to reflect small or moderate performance gains. This emphasizes a potential disconnect between demand reductions and label-based classifications. Dry green roofs performed nearly identically to conventional green roofs, suggesting that the most significant gains stem from the insulative layer itself, rather than from evapotranspiration or irrigation-related cooling, which is most likely linked to the Köppen-Geiger climate classification in which this research takes place. Temperate Oceanic climates are by nature humid and rainy. Differences between heating-cooling ratios (80:20 vs. 65:35) showed only marginal effects, though the 65:35 configuration slightly increased the share of buildings improving by two labels. This implies that heating-cooling dynamics may influence the intensity, but not the likelihood, of label change. Such findings could be important if there is a need to understand whether the efficacy of green roofs would change in future scenarios, where air conditioners are more widely used and where heating demand declines with higher average temperatures.

Taken together, these findings suggest that green roofs are not the ultimate solution for improving building energy labels. Their effectiveness is unevenly distributed and highly context-dependent, with greater potential impact in inefficient, uninsulated, or cooling-demand-heavy buildings. In this sense, energy labels may be too coarse a tool to capture the nuanced benefits of green infrastructure. As such, label-based policies alone may not provide a compelling case for green roof retrofitting, especially where buildings already perform moderately well. Although it is important to notice, as reported in the literature, that the type of green roof heavily affects its performance. This aspect had to be overlooked in this research analysis, as in the first part there was no available information on the types of green roof that already exist in Amsterdam, and in the second part, in the application of Virk et al. (2015) an extensive green roof was simulated. These, once again as discussed above, while they are cheap, low-maintenance options they have been found to be less efficient compared to intensive green roofs. Thus, this leaves hope that perhaps intensive green roofs could shift energy labels more significantly.

6. Conclusion

This study set out to quantify the impact of green roofs on building energy labels in Amsterdam, using a combination of machine learning and empirical energy reduction values. By leveraging a random forest model and simulating two counterfactual scenarios, it was possible to estimate how energy labels might change if green roofs were added or removed. Additionally, energy savings observed in the literature were applied across the city's building stock to examine broader implications.

The results show that while green roofs do have the potential to improve a building's energy label, this effect is limited and highly context-dependent. In the first counterfactual, only 3% of green-roof buildings experienced a worse energy label when the green roof was hypothetically removed, evidence that green roofs contribute to improved energy performance in a minority of cases. Similarly, only 1.9% of buildings improved when green roofs were simulated to be added in the second counterfactual. These effects were most pronounced in poorly performing buildings (D–G) and in certain underperforming building types such as lodging or education facilities.

When applying empirically derived energy savings from Virk et al. (2015) city-wide, about 19% of buildings improved their energy label, with the majority of improvements concentrated again in initially inefficient buildings. The modest performance of dry green roofs compared to green roofs suggests that the key benefits may derive primarily from insulation, particularly in uninsulated buildings.

These findings highlight that while green roofs provide multiple environmental benefits, their impact on regulatory energy performance classification, at least in temperate, humid climates like Amsterdam's, is not dramatic. Energy labels may not be sensitive enough to reflect the moderate but consistent energy savings green roofs provide. As a result, relying solely on label improvement as a policy driver for green roof adoption may be insufficient. More holistic evaluation frameworks are needed, ones that account for co-benefits such as heat mitigation, stormwater management, and biodiversity enhancement.

Future research should explore how different types of green roofs (i.e. intensive vs. extensive) impact energy label changes and assess their long-term thermal performance using primary empirical data. This could be achieved through controlled experiments that account for variations in green roof type, insulation levels, baseline energy labels, building use functions, sun orientation, and the location of units within a building (i.e. comparing ground-floor vs. top-floor apartments). Notably, the findings of Virk et al. (2015) are based on extensive green roofs, while other studies (Susca, 2019) suggest that intensive green roofs may offer greater efficacy. Therefore, future research should investigate whether intensive green roofs yield more significant improvements in energy performance. Such work would contribute to building a stronger case for integrating green infrastructure with energy transition strategies, enabling cities like Amsterdam to pursue climate resilience alongside just and sustainable urban development.

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7. Appendix

Energy RVO

BIJLAGE BIJ ARTIKEL I, ONDERDEEL B

Bijlage I. bij artikel 2, derde lid, van de Regeling energieprestatie gebouwen

Tabel 1: Klassenindeling energielabel woningen naar primair fossiel energiegebruik (in kWh/m^2.jr)

Letter of lettercombinatie	Primair fossiel energiegebruik (in kWh/m^2.jr)
A++++	Kleiner of gelijk aan 0,00
A+++	0,01 t/m 50,00
A++	50,01 t/m 75,00
A+	75,01 t/m 105,00
A	105,01 t/m 160,00
B	160,01 t/m 190,00
C	190,01 t/m 250,00
D	250,01 t/m 290,00
E	290,01 t/m 335,00
F	335,01 t/m 380,00
G	Groter dan 380,00

Appendix 1. Ministerie van Binnenlandse Zaken en Koninkrijksrelaties. (2020)

BIJLAGE BIJ ARTIKEL I, ONDERDEEL B

Bijlage Ia. bij artikel 3, derde lid, van de Regeling energieprestatie gebouwen

Tabel 2.a: Klassenindeling energielabel utiliteitsgebouwen voor de gebruiksfuncties 1 t/m 5 naar primair fossiel energiegebruik (in kWh/m^2.jr)

	1. kantoor	2. bijeenkomst zonder kinderdagverblijf	3. bijeenkomst met kinderdagverblijf	4. onderwijs	5. zorg zonder bed
Letter of lettercombinatie	Primair fossiel energiegebruik (in kWh/m^2.jr)				
A^{+++++}	Kleiner of gelijk aan 0,00	Kleiner of gelijk aan 0,00	Kleiner of gelijk aan 0,00	Kleiner of gelijk aan 0,00	Kleiner of gelijk aan 0,00
A^{++++}	0,01 t/m 40,00	0,01 t/m 50,00	0,01 t/m 55,00	0,01 t/m 50,00	0,01 t/m 45,00
A^{+++}	40,01 t/m 80,00	50,01 t/m 100,00	55,01 t/m 110,00	50,01 t/m 100,00	45,01 t/m 90,00
A^{++}	80,01 t/m 120,00	100,01 t/m 150,00	110,01 t/m 165,00	100,01 t/m 150,00	90,01 t/m 135,00
A^{+}	120,01 t/m 160,00	150,01 t/m 200,00	165,01 t/m 220,00	150,01 t/m 200,00	135,01 t/m 180,00
A	160,01 t/m 180,00	200,01 t/m 230,00	220,01 t/m 265,00	200,01 t/m 235,00	180,01 t/m 210,00
B	180,01 t/m 200,00	230,01 t/m 255,00	265,01 t/m 290,00	235,01 t/m 260,00	210,01 t/m 230,00
C	200,01 t/m 225,00	255,01 t/m 285,00	290,01 t/m 330,00	260,01 t/m 295,00	230,01 t/m 260,00
D	225,01 t/m 250,00	285,01 t/m 320,00	330,01 t/m 365,00	295,01 t/m 330,00	260,01 t/m 295,00
E	250,01 t/m 275,00	320,01 t/m 355,00	365,01 t/m 405,00	330,01 t/m 360,00	295,01 t/m 325,00
F	275,01 t/m 300,00	355,01 t/m 385,00	405,01 t/m 445,00	360,01 t/m 395,00	325,01 t/m 355,00
G	Groter dan 300,00	Groter dan 385,00	Groter dan 445,00	Groter dan 395,00	Groter dan 355,00

Appendix 2. Ministerie van Binnenlandse Zaken en Koninkrijksrelaties. (2020)

Tabel 2.b: Klassenindeling energielabel utiliteitsgebouwen voor de gebruiksfuncties 6 t/m 10 naar primair fossiel energiegebruik (in kWh/m^2.jr)

	6. zorg met bed	7. winkel	8. sport	9. logies	10. cel
Letter of lettercombinatie	**Primair fossiel energiegebruik (in kWh/m^2.jr)**				
A^{+++++}	Kleiner of gelijk aan 0,00	Kleiner of gelijk aan 0,00	Kleiner of gelijk aan 0,00	Kleiner of gelijk aan 0,00	Kleiner of gelijk aan 0,00
A^{++++}	0,01 t/m 90,00	0,01 t/m 60,00	0,01 t/m 35,00	0,01 t/m 50,00	0,01 t/m 60,00
A^{+++}	90,01 t/m 180,00	60,01 t/m 120,00	35,01 t/m 70,00	50,01 t/m 100,00	60,01 t/m 120,00
A^{++}	180,01 t/m 270,00	120,01 t/m 180,00	70,01 t/m 105,00	100,01 t/m 150,00	120,01 t/m 180,00
A^{+}	270,01 t/m 360,00	180,01 t/m 240,00	105,01 t/m 140,00	150,01 t/m 200,00	180,01 t/m 240,00
A	360,01 t/m 430,00	240,01 t/m 285,00	140,01 t/m 155,00	200,01 t/m 230,00	240,01 t/m 300,00
B	430,01 t/m 470,00	285,01 t/m 315,00	155,01 t/m 170,00	230,01 t/m 255,00	300,01 t/m 330,00
C	470,01 t/m 530,00	315,01 t/m 355,00	170,01 t/m 195,00	255,01 t/m 285,00	330,01 t/m 370,00
D	530,01 t/m 595,00	355,01 t/m 395,00	195,01 t/m 215,00	285,01 t/m 320,00	370,01 t/m 415,00
E	595,01 t/m 655,00	395,01 t/m 435,00	215,01 t/m 240,00	320,01 t/m 355,00	415,01 t/m 455,00
F	655,01 t/m 715,00	435,01 t/m 475,00	240,01 t/m 260,00	355,01 t/m 385,00	455,01 t/m 500,00
G	Groter dan 715,00	Groter dan 475,00	Groter dan 260,00	Groter dan 385,00	Groter dan 500,00

Appendix 3. Ministerie van Binnenlandse Zaken en Koninkrijksrelaties. (2020)

Modelling Results Extra Tables

	Precision	Recall	F1-Score	Support
A+++++ to A+	0.56	0.92	0.69	941
A to C	0.94	0.86	0.9	5179
D to G	0.78	0.45	0.57	344
Accuracy			0.85	6464
Macro Average	0.76	0.74	0.72	6464
Weighted Average	0.88	0.85	0.85	6464
Grouped Accuracy	0.8457611386			
Grouped F1 Score (macro)	0.7224546801			

Appendix 4. Accuracy Report Counterfactual 1

	Precision	Recall	F1-Score	Support
A+++++ to A+	0.98	0.94	0.96	233
A to C	0.99	1	1	5931
D to G	0.99	0.91	0.95	302
Accuracy			0.99	6464
Macro Average	0.99	0.95	0.97	6464
Weighted Average	0.99	0.99	0.99	6464
Grouped Accuracy	0.9927289604			
Grouped F1 Score (macro)	0.9686100977			

Appendix 5. Accuracy Report Counterfactual 2