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Definition of Criteria for Determining Homogeneous Zones for Photovoltaic "Embodied Emissions" in Europe

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Abstract

This study develops a systematic framework to classify European regions into homogeneous zones, allowing for a more data-driven and efficient strategy for integrating photovoltaic (PV) systems into the energy mix. In addition to assessing PV potential, it introduces average embodied emissions values for each category, providing a comprehensive evaluation of both feasibility and environmental impact. Given the significant variability in solar irradiance, grid carbon intensity, electricity demand, and land availability, a structured classification is essential to assess the feasibility of PV deployment beyond national or geographic boundaries. By grouping regions with similar characteristics, this approach enables a standardized evaluation of PV potential, ensuring that energy investments and policies align with regional conditions.

Using a multi-criteria analysis (MCA), key variables were analyzed to determine potential for PV deployment. The study defines four homogeneous zones, each representing a distinct level of feasibility based on solar resource availability, energy demand, and infrastructure compatibility. The results highlight substantial differences in PV potential across these zones, with some regions offering optimal conditions for large-scale deployment, while others require grid adaptation, policy interventions, or alternative renewable integration strategies to enhance viability.

By establishing a standardized classification system and integrating embodied emissions considerations, this research provides a transparent and scalable methodology for assessing PV feasibility across Europe. The findings contribute to smarter policy decisions, optimized investment strategies, and a more sustainable expansion of solar energy, ensuring that PV deployment is both technically viable and aligned with carbon neutrality goals.

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1. Introduction

Problem Definition

The transition to renewable energy is a key component of the European Union's (EU) climate strategy, particularly in achieving net-zero emissions by 2050. To meet this ambitious target, multiple sectors must undergo rapid decarbonization, with aviation being one of the most challenging industries to reform due to its reliance on liquid fossil fuels. One major strategy to address this challenge is the deployment of sustainable aviation fuels (SAFs) as a cleaner alternative to conventional jet fuels. In addition, electrofuels (e-fuels) have been identified as key low-carbon alternatives across various transport modes. However, the large-scale production of both SAFs and e-fuels requires significant amounts of renewable electricity, not only for fuel synthesis such as hydrogen production but also for powering the operation of production facilities. This makes the availability and strategic deployment of clean energy sources, particularly solar photovoltaics (PV), a critical factor in enabling a truly sustainable fuel transition.

One of the primary strategies proposed by the EU is the promotion of sustainable aviation fuel (SAF) production. Despite technological improvements in aircraft efficiency, aviation emissions continue to rise, necessitating alternative solutions. SAFs have the potential to significantly reduce the lifecycle greenhouse gas (GHG) emissions associated with air travel. However, the large-scale production of SAFs requires substantial amounts of renewable energy, both for fuel synthesis (e.g., green hydrogen and power-to-liquid processes) and for the operation of production facilities(Prussi et al., 2021). As a result, strategic planning is essential to determine where SAF production plants should be located, ensuring that they are powered by low-carbon electricity sources and aligned with sustainability goals.

A critical aspect often overlooked in EU renewable energy policies is the role of embodied emissions—the CO_2 emissions associated with manufacturing, transporting, and installing renewable energy infrastructure. Most current policies focus primarily on direct emissions reductions (e.g., phasing out coal plants, promoting electric vehicles) but do not comprehensively account for the carbon footprint embedded in clean energy technologies themselves.

This is particularly concerning for photovoltaic (PV) installations, which play a vital role in decarbonizing SAF production but are also highly dependent on imported solar panels. A large share of Europe's PV modules are sourced from China, where coal-based electricity dominates manufacturing processes (Philipps et al., 2023). As a result, while PV deployment in Europe is accelerating, the actual climate benefits of these installations may be undermined by their embodied emissions.

Currently, in European Union (EU) energy policies, embodied emissions are not explicitly accounted for in PV deployment strategies, whereas other international regulatory frameworks, such as ICAO's CORSIA (Carbon Offsetting and Reduction Scheme for International Aviation), are actively investigating them. This creates a potential regulatory gap in how emissions are evaluated and reported in Europe.

Moreover, Europe is not homogeneous in terms of solar irradiance, energy demand, grid carbon intensity, and available land for PV deployment. Therefore, a methodology is required to classify different European regions based on their actual potential for PV installation while also considering the embodied emissions impact.

These policy gaps create an important question: How should Europe balance the rapid expansion of renewable energy with the need to minimize embodied emissions? This challenge is further complicated by the fact that Europe is not homogeneous in terms of solar irradiance, energy demand, and grid carbon intensity, making it essential to define regional variations when planning large-scale PV installations.

This study aims to address two critical questions that influence the sustainability of PV-powered SAF production:

1. Where should PV installations be prioritized in Europe to support low-carbon SAF production?
2. How do embodied emissions vary across different locations, and how can they be minimized when expanding PV infrastructure?

Goal of the Project

The significance of this research lies in the fact that while sustainable aviation fuels (SAFs) and e-fuels offer a significant reduction in lifecycle emissions, their true climate impact depends on how they are produced. Although SAFs reduce net CO_2 emissions by utilizing biogenic carbon uptake, the high energy demands of their production processes, particularly in pathways like HEFA and SIP, pose a major challenge. The HEFA process, as the most commercially developed SAF pathway, requires large amounts of electricity and hydrogen for hydroprocessing(Prussi et al., 2021). If these inputs are sourced from fossil fuels, the overall emissions of HEFA-derived fuels remain high, diminishing their environmental advantages.

Similarly, SIP fuels, derived from fermentation-based processes, rely on hydrogen for stabilization, and their emissions are directly affected by how this hydrogen is produced. Conventional steam methane reforming (SMR) for hydrogen production generates significant CO_2 emissions, offsetting some of SAFs' climate benefits. However, replacing fossil-based hydrogen with green hydrogen—produced via electrolysis using electricity from renewable systems—can drastically lower emissions, making SIP and other SAF pathways more sustainable.

This study focuses specifically on photovoltaic (PV) electricity as the primary energy source for SAF production, rather than considering all renewable energy options. Given the growing scalability and cost-effectiveness of PV technology, integrating solar power into SAF production processes can provide a reliable, sustainable, and low-carbon energy solution. Without this shift, even the most advanced SAF pathways will remain partially dependent on fossil-based energy inputs, limiting their ability to achieve full decarbonization. This research aims to bridge this gap by assessing how PV-powered electricity and hydrogen can be effectively integrated into SAF production, ensuring maximum emissions reduction while maintaining economic viability. By focusing on the role of solar energy in decarbonizing SAF supply chains, this study contributes directly to the development of a truly low-carbon aviation fuel industry, aligning with long-term sustainability goals for the aviation sector.

One of the fundamental challenges in the large-scale production of Sustainable Aviation Fuels (SAF) and synthetic jet fuels (e-fuels) is securing sufficient renewable energy resources while minimizing the reliance on energy and raw material imports. Given Europe's geographical constraints, varying access to energy resources, and the need to minimize environmental impact, choosing high-efficiency locations for establishing these facilities is crucial.

Recent studies indicate that large-scale e-fuel production in Europe may be unsustainable due to the immense electricity demand for hydrogen production via electrolysis and DACCS operations (Sacchi et al., 2023). This underscores the necessity of prioritizing regions with high photovoltaic (PV) capacity and strong renewable energy potential to support the required energy supply.

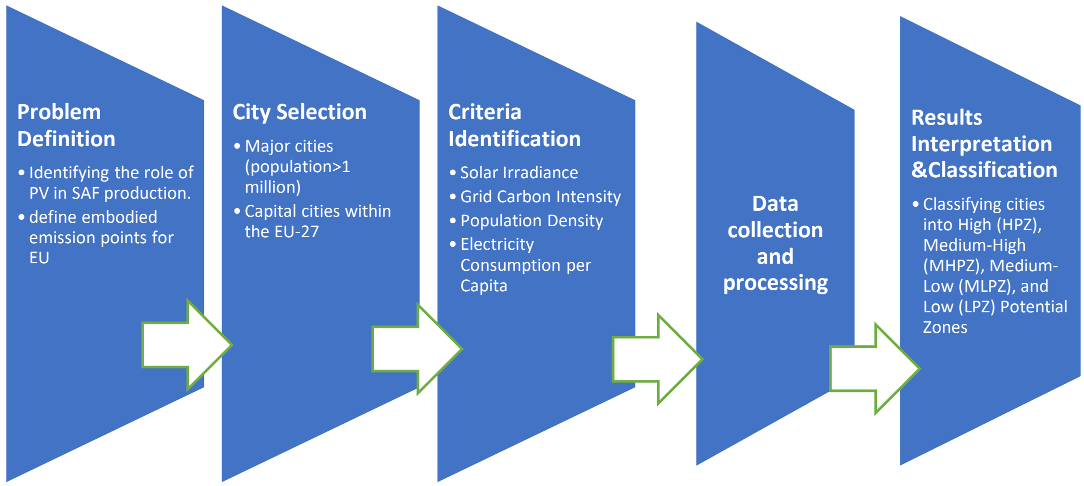
My research addresses this critical issue by exploring optimal site selection for SAF and e-fuels production, identifying high-potential regions in Europe where renewable energy availability, infrastructure, and resource efficiency align to support sustainable aviation fuel production.

The primary goal of this research is to develop a systematic framework to evaluate the optimal locations for PV deployment in Europe, considering both technical feasibility (solar potential, energy demand, and grid carbon intensity) and environmental sustainability (embodied emissions of PV systems). The key objectives include:

1. Defining homogeneous zones within the EU for optimal PV deployment based on factors such as solar irradiance, energy consumption, and grid carbon intensity.
2. Quantifying the embodied emissions of PV installations across different European regions to assess their environmental impact.
3. Developing a multi-criteria ranking system to assess and prioritize cities for PV investment based on their potential to contribute to a low-carbon SAF production network.
4. Providing policy recommendations on how the EU can integrate embodied emissions considerations into renewable energy expansion strategies.

By incorporating embodied emissions into renewable energy decision-making, this research will contribute to more effective climate policies and ensure that the EU’s renewable energy investments truly align with long-term carbon neutrality objectives.

Flow of the work



The research follows a structured methodology to systematically analyze the potential for photovoltaic (PV) deployment in Europe while considering embodied emissions. The workflow is divided into five key stages, each contributing to the identification and classification of optimal locations for PV installations.

The first stage, Problem Definition, establishes the research focus by identifying the role of PV in sustainable aviation fuel (SAF) production and the need to define embodied emission points for PV deployment in the European Union. This step ensures that the study addresses both energy sustainability and life-cycle emissions to provide a comprehensive evaluation of PV expansion.

The second stage, City Selection, involves selecting major cities with populations exceeding one million and all capital cities within the EU-27. This approach ensures broad geographical representation and captures variations in solar potential, energy demand, and grid carbon intensity across different regions.

The third stage, Criteria Identification, defines the four key factors used to assess the feasibility of PV deployment: solar irradiance, grid carbon intensity, population density, and electricity consumption per capita. These criteria allow for a multi-dimensional evaluation of each city's potential, considering both technical and environmental sustainability.

In the Data Collection and Processing stage, relevant data for each criterion is gathered and standardized. This ensures that the comparisons between cities are consistent and enables accurate ranking based on their suitability for PV deployment.

Finally, in the Results Interpretation & Classification stage, cities are categorized into four groups based on their total potential scores: High Potential Zones (HPZ), Medium-High Potential

Zones (MHPZ), Medium-Low Potential Zones (MLPZ), and Low Potential Zones (LPZ). This classification allows for targeted policy recommendations and investment strategies to optimize PV deployment while minimizing embodied emissions.

This structured flow ensures that the research effectively integrates sustainability considerations into the expansion of solar energy infrastructure, offering a data-driven approach for optimizing renewable energy investments in Europe.

2. Literature review

SAFs

The aviation sector is a significant contributor to global CO_2 emissions, accounting for 2.4% of global emissions in 2019, with projections indicating a potential threefold increase by 2050 if no mitigation strategies are implemented (ICAO, 2022). Unlike other transportation sectors, aviation faces unique decarbonization challenges due to its reliance on high-energy-density fuels and limited technological alternatives for long-haul flights. The sector's environmental impact extends beyond CO_2 emissions, as nitrogen oxides (NOx) and contrail-induced radiative forcing further amplify its contribution to climate change. Given that air travel demand is expected to double by mid-century, immediate action is required to curb emissions growth through sustainable aviation fuels (SAFs), efficiency improvements, and regulatory measures (ICAO, 2022).

Despite advancements in fuel efficiency, decarbonizing the aviation sector remains a major challenge due to its rapid growth. While alternative propulsion technologies such as electric and hydrogen-based systems are being explored, their large-scale deployment faces technical and logistical barriers (Hileman & Stratton, 2014). As a result, sustainable aviation fuels (SAFs) are considered the most viable near-term solution, as they require no modifications to existing aircraft or fueling infrastructure (Hileman & Stratton, 2014; ICAO, 2019).

Sustainable Aviation Fuels (SAFs) play a pivotal role in reducing CO_2 emissions in the aviation sector, particularly in the context of the Long-Term Aspirational Goal (LTAG) study conducted by ICAO. The LTAG report outlines three integrated scenarios (IS1, IS2, and IS3) that project different levels of technological advancement, operational efficiency, and SAF adoption. Across all scenarios, SAFs contribute significantly to emissions reduction, yet their impact depends on policy implementation, investment, and infrastructure development (ICAO, 2022).

The contribution of SAFs to emissions reduction varies significantly across the three LTAG scenarios, depending on the level of ambition, investment, and technological advancement. In the Low Ambition Scenario (IS1), SAF adoption remains limited due to minimal policy intervention and insufficient investment in production capacity. As a result, only 15% of CO_2 reductions come from SAFs, with the majority of improvements driven by aircraft efficiency and operational optimizations. The slow transition to SAFs in this scenario underscores the risks of relying on conventional fossil fuels, as emissions remain relatively high (ICAO, 2022).

In contrast, the Medium Ambition Scenario (IS2) envisions a more proactive approach, where SAFs account for 41% of total CO_2 reductions. This scenario assumes a moderate level of investment in SAF production, along with policy incentives that encourage airlines to integrate SAFs into their fuel mix. While aircraft efficiency and operational advancements continue to play a role, SAFs emerge as the dominant strategy for emissions mitigation. The increasing reliance on SAFs in this scenario highlights the aviation sector's growing commitment to alternative fuels, yet widespread adoption remains constrained by economic and logistical challenges (ICAO, 2022).

The High Ambition Scenario (IS3) represents the most aggressive strategy for emissions reduction, in which SAFs contribute 55% of total CO_2 reductions. This scenario assumes rapid expansion of SAF production infrastructure, significant technological advancements, and strong regulatory frameworks supporting widespread adoption. Unlike the previous scenarios, IS3 envisions a near-complete transition away from fossil-based aviation fuels, making SAFs the primary means of decarbonization. Achieving this level of SAF integration requires coordinated global efforts, substantial financial investments, and innovative breakthroughs in feedstock sourcing and fuel conversion technologies. The reliance on SAFs in IS3 illustrates their potential to transform aviation into a low-carbon industry, but it also underscores the challenges of scaling up production to meet future demand (ICAO, 2022).

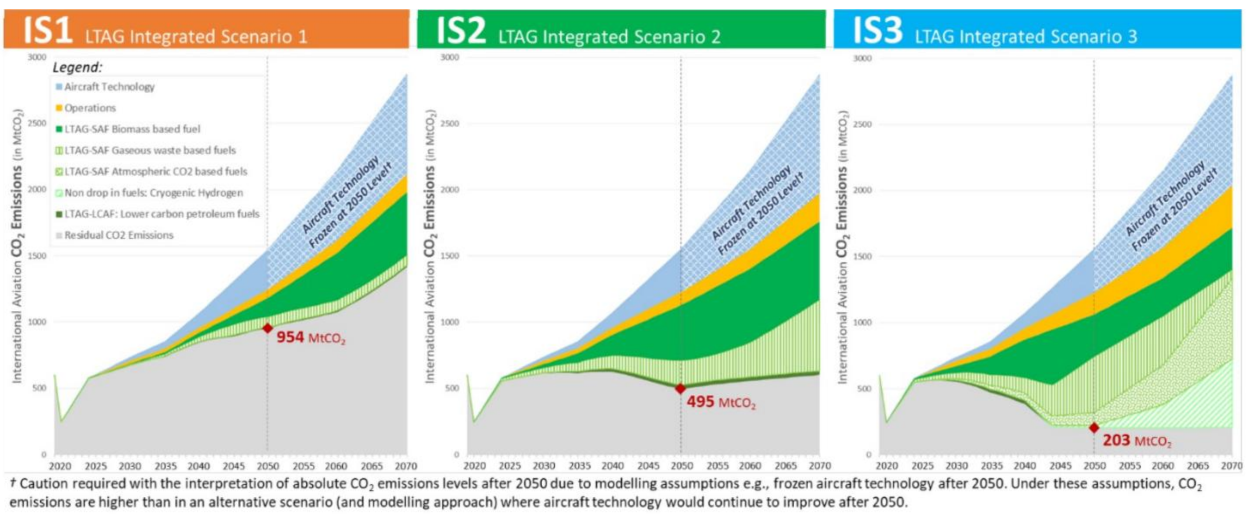


Fig1. CO_2 emissions from international aviation associated with LTAG Integrated Scenarios

The role of SAFs in mitigating aviation emissions extends beyond simple fuel substitution, as they provide a long-term pathway for reducing the industry's reliance on fossil-based jet fuel. SAFs have a significantly lower carbon footprint over their life cycle compared to conventional jet fuels, particularly when produced from waste materials, biomass, or synthetic processes powered by renewable energy. The adoption of SAFs leads to direct reductions in CO_2 emissions from aircraft operations while also mitigating upstream emissions associated with fuel extraction, refining, and distribution.

In the LTAG scenarios, SAFs consistently outperform other mitigation strategies, such as aircraft efficiency improvements and operational optimizations, in achieving meaningful CO_2 reductions. Unlike technological advancements, which take decades to reach full-scale deployment, SAFs can be integrated into existing aircraft with minimal modifications, making them a viable near-term solution for emissions reduction. However, the feasibility of large-scale SAF adoption depends on key factors such as production scalability, feedstock availability, and economic viability. While current SAF production remains limited, advancements in synthetic fuels and waste-based alternatives have the potential to expand supply and reduce costs.

A major challenge in SAF adoption is ensuring that production remains sustainable and does not contribute to unintended environmental consequences, such as deforestation or excessive land use for biofuel crops. The LTAG report incorporates safeguards against land-use change and deforestation, emphasizing the need for sustainable feedstock sourcing. Additionally, economic considerations remain a significant barrier, as SAFs are currently more expensive than traditional jet fuel. The successful deployment of SAFs will require government incentives, subsidies, and long-term investment strategies to bridge the cost gap and encourage widespread adoption.

SAFs are positioned as the most impactful decarbonization strategy for aviation, but their success depends on industry-wide collaboration and policy alignment. With sufficient investment and regulatory support, SAFs can lead to substantial CO_2 reductions, enabling the aviation sector to move toward net-zero emissions by mid-century.

To mitigate the aviation sector's environmental impact, ICAO introduced the Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA), which mandates that airlines offset emissions exceeding 2019 levels through carbon credits or CORSIA-compliant fuels(Climate, 2019) .This initiative aims to facilitate carbon-neutral growth in international aviation.

Under the CORSIA framework, sustainable aviation fuels (SAFs) are evaluated using a life-cycle assessment (LCA) methodology approved by ICAO in 2018, making it the first internationally recognized approach for assessing aviation fuel emissions (Prussi et al., 2021). The method considers all stages from feedstock cultivation to fuel combustion, accounts for factors such as indirect land use change (ILUC) and safeguards against deforestation, ensuring that SAFs contribute to emission reductions while mitigating environmental risks and also is highlighting the sustainability challenges associated with SAF production (Prussi et al., 2021).

To qualify as a sustainable aviation fuel (SAF) under ICAO's CORSIA framework, a fuel must meet strict sustainability criteria, including a minimum of 10% life-cycle GHG reduction compared to conventional jet fuel and compliance with land-use restrictions (ICAO, 2019). The standard life-cycle GHG intensity for fossil jet fuel has been set at 89 gCO_2e/MJ, and SAFs with emissions below 80.1 gCO_2e/MJ are eligible for CORSIA certification (Prussi et al., 2021). This approach ensures that SAFs contribute to aviation decarbonization while maintaining environmental and social sustainability.

The system boundary for CORSIA's core LCA covers all key stages in SAF production and utilization. These stages include feedstock cultivation, harvesting and collection, feedstock processing and extraction, transportation, jet fuel production (conversion), fuel transportation and distribution, and final combustion in aircraft engines. The methodology also considers upstream energy and material inputs, including diesel, natural gas, and hydrogen, which are necessary for fuel production. The distinction between different feedstock categories impacts the system boundary, as emissions from feedstock cultivation are excluded for residues, wastes, and by-products but included for main and co-product feedstocks. This systematic approach ensures that the LCA results accurately reflect the carbon intensity of SAFs and their potential role in mitigating aviation emissions (Prussi et al., 2021).

SAFs are obtained from different reactions, so there are multiple pathways to generate them. The Fischer-Tropsch (FT) process converts biomass, municipal solid waste (MSW), or other carbonaceous feedstocks into synthetic hydrocarbons via gasification followed by Fischer-Tropsch synthesis. FT generally has low conversion-related emissions, as it can utilize syngas combustion heat, but when MSW with non-biogenic carbon (NBC) is used, emissions increase significantly(Prussi et al., 2021).

The Hydroprocessed Esters and Fatty Acids (HEFA) process utilizes waste oils, animal fats, or vegetable oils and converts them into jet fuel through hydrodeoxygenation (HDO) and hydrocracking. The process requires hydrogen and high-temperature hydroprocessing, making it one of the most energy-intensive SAF pathways. HEFA emissions are largely driven by fossil-based hydrogen production via steam methane reforming (SMR). Replacing fossil hydrogen with green hydrogen produced via electrolysis using renewable electricity could significantly lower its carbon footprint (Prussi et al., 2021).

The Synthesized Iso-Paraffins (SIP) process uses sugarcane or sugar beet as feedstock, converting sugars into farnesene via fermentation, followed by hydrogenation to produce a drop-in jet fuel. The process requires hydrogen input for fuel stabilization, making its emissions highly dependent on the hydrogen source. If fossil-based hydrogen is replaced with electrolytic hydrogen from renewable electricity, the overall emissions of SIP fuels can be greatly reduced (Prussi et al., 2021).

The Alcohol-to-Jet (ATJ) and Ethanol-to-Jet (ETJ) processes convert isobutanol or ethanol into jet fuel through dehydration, oligomerization, and hydroprocessing. Their carbon intensity depends largely on feedstock type, with sugarcane-based ETJ having lower emissions due to higher yields and lower fossil input reliance, while corn grain-based ETJ has higher emissions due to fertilizer use and natural gas consumption(Prussi et al., 2021).

CORSIA default life-cycle emission values are calculated as the sum of the "core LCA" values (adding up direct emissions along the supply chains of individual SAFs) and the estimated "ILUC" (Induced land use change) emission values (Prussi et al., 2021).

In the CORSIA LCA methodology, emissions from fuel conversion are allocated among co-products based on energy content. This prevents the overestimation of SAF emissions and maintains consistency in comparing fuel pathways (Wang et al., n.d.). For biomass-derived SAFs, CO_2 emissions from combustion are considered neutral, as the carbon released is offset by uptake during biomass growth. In contrast, fossil-based jet fuel emissions contribute directly to atmospheric CO_2 accumulation. This distinction highlights the carbon cycle benefits of SAFs in mitigating aviation emissions (Prussi et al., 2021).

The core LCA methodology can be summarized in Equation (1), including terms for feedstock cultivation ($e_{fe\text{-}c}$); feedstock harvesting and collection ($e_{fe\text{-}hc}$); feedstock processing ($e_{fe\text{-}p}$); feedstock transportation to processing and fuel production facilities ($e_{fe\text{-}t}$); feedstock- to-fuel conversion processes ($e_{fefu\text{-}p}$); fuel transportation and distribution ($e_{fu\text{-}t}$); and fuel combustion in an aircraft engine ($e_{fu\text{-}c}$). For purposes of reporting or accounting emissions from biofuels combustion, the latter term ($e_{fu\text{-}c}$) is considered as being zero for the fuel fraction produced from biomass (Prussi et al., 2021).

$$\text{Core LCA}[gCO_{2e} / MJ] = e_{fe\text{-}c} + e_{fe\text{-}p} + e_{fe\text{-}t} + e_{fefu\text{-}p} + e_{fe\text{-}t} + e_{fu\text{-}c}$$

In the CORSIA LCA methodology, emissions are measured in gCO_2e per MJ of fuel combusted, incorporating CO_2, N_2O, and CH_4 based on IPCC AR5 100-year GWPs (IPCC. & Assessment, 2013). Infrastructure-related emissions are excluded due to their minimal impact. The fossil jet fuel baseline used for CORSIA assessments was established by analyzing the average GHG intensity of petroleum-derived jet fuel across various global refinery configurations, ensuring a standardized benchmark for SAF comparisons (Prussi et al., 2021).

Indirect land use change (ILUC) emissions result from the expansion of cropland due to increased biofuel demand, potentially leading to significant GHG emissions beyond biofuel-producing regions. ILUC emissions for SAFs are estimated through a two-step process: First, economic models quantify land-use changes due to biofuel demand; second, GHG emissions are calculated based on terrestrial carbon fluxes, including changes in biomass carbon stock, soil carbon stock, and forgone carbon sequestration(Prussi et al., 2021).

SAFs provide significant life-cycle GHG reductions compared to fossil jet fuels due to the carbon uptake of biomass feedstocks. As CO_2 emissions from fuel combustion are offset by photosynthetic carbon sequestration, SAFs achieve net-zero combustion emissions. Since combustion accounts for 83% (74 gCO_2e/MJ) of petroleum jet fuel's total life-cycle emissions, avoiding this results in substantial climate benefits (Prussi et al., 2021).

e-fuels

E-fuels (that is, electrofuels, powerfuels or electricity-based synthetic fuels) are hydrocarbon fuels synthesized from hydrogen and CO2 (that is, carbon capture and utilization (CCU)), where hydrogen is produced from electricity and water (via electrolysis), and CO2 is captured from either fossil sources (for example, industrial plants) or the atmosphere (biomass or direct air capture (DAC)). E-fuels can thereby tap into the low-cost and vast global potentials of low-carbon wind and solar photovoltaic (PV) power. The resulting gaseous and liquid fuels feature characteristics that make them perfect substitutes for their fossil counterparts: a high energy density, storability, transportability and combustibility. While these characteristics already improve in the conversion of electricity to hydrogen, adding carbon in a second step also circumvents the challenges of handling hydrogen (Sacchi et al., 2023).

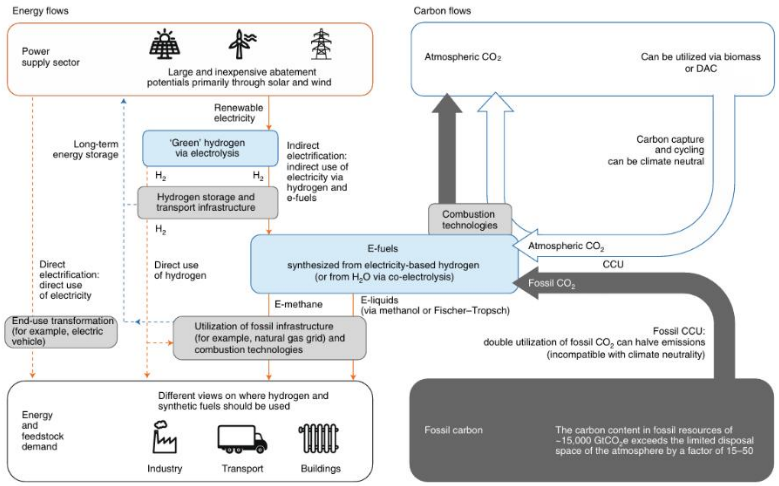


Fig2.Basic principle of e-fuels in an energy system (Sacchi et al., 2023)

Recent reports point to the potential value of e-fuels and hydrogen in overcoming the limitations of other mitigation options in difficult-to-decarbonize sectors (Davis et al., 2018). The requirement of carbon neutrality creates increasing awareness of residual hydrocarbon demands as bottlenecks for climate stabilization (Luderer et al., 2018). E-fuels could help out in sectors and applications such as long-distance aviation, shipping, feedstocks in the chemical industry, high-temperature industrial processes, long-haul heavy-duty road transport and long-term energy storage(Munnings et al., n.d.; Report, 2020).

Policy roadmaps, such as Destination 2050, aim for net-zero aviation; however, many fail to account for non-CO_2 effects and the critical role of low-carbon electricity in the production of synthetic jet fuels. Without decarbonizing the energy inputs for SAF and e-fuel production, the aviation sector cannot fully achieve its climate goals (Kallbekken & Victor, 2022).

Despite industry commitments, aviation has failed to meet efficiency and alternative fuel targets over the past two decades (Asher et al., n.d.). Additionally, carbon offset schemes face credibility issues due to challenges in preventing double-counting and ensuring permanent CO_2 removal (October, 2019). Recognizing these limitations, the European Union has mandated that synthetic fuels must achieve at least 70% GHG reductions and be produced almost exclusively using additional renewable electricity (eurostat. Electricity production, 2020). This highlights the necessity of integrating low-carbon electricity sources such as photovoltaic (PV) power into SAF and e-fuel production to achieve true climate benefits.

While synthetic jet fuel produced via direct air capture (DAC) and electrolysis offers a theoretically climate-neutral alternative, its large-scale deployment remains constrained by technological readiness and high energy demand (Sacchi et al., 2023). Compared to DAC-based pathways, bio-based SAFs offer a more immediate and scalable solution, though biomass availability remains a limiting factor (Bergero et al., 2023). Thus, optimizing SAF production through photovoltaic (PV) electricity integration presents a promising path toward aviation decarbonization.

The long-term feasibility of synthetic jet fuels depends on the availability of low-carbon electricity, as mandated by European regulations requiring GHG emissions below 65 gCO_2/kWh for their production (Sacchi et al., 2023). If electricity generation remains carbon-intensive, these fuels will struggle to achieve meaningful emissions reductions. This highlights the importance of integrating renewable electricity into aviation fuel production to ensure true climate benefits.

Synthetic jet fuels (e-fuels) produced via Fischer-Tropsch synthesis using DAC-derived CO_2 and hydrogen from electrolysis can significantly reduce aviation-induced warming compared to fossil jet fuels (Sacchi et al., 2023). However, their large-scale deployment remains constrained by high electricity demand, increased CO_2 emissions from DAC and hydrogen production, and potential methane lifetime extension due to hydrogen leakage (Sacchi et al., 2023). This highlights the importance of low-carbon electricity sources enabling the sustainable production of both SAFs and e-fuels.

A complete life-cycle assessment (LCA) is essential when evaluating alternative aviation fuels, as neglecting upstream emissions can underestimate their true climate impact by over one-third (Brazzola et al., 2023). While synthetic jet fuels reduce direct flight CO_2 emissions, their large-scale deployment still requires significant carbon dioxide removal (CDR), particularly due to emissions from DAC and hydrogen production (Sacchi et al., 2023). Additionally, decreasing cirrus cloud formation through syn-jet fuel usage partially offsets warming effects, underscoring the complex interplay of factors influencing aviation decarbonization (Sacchi et al., 2023).The necessity of low-carbon electricity sources remains a crucial factor in minimizing these emissions.

The electricity supply for DACCS significantly impacts the overall CDR requirement, increasing it by 13% in 2050, though this reduces as electricity decarbonizes (Sacchi et al., 2023). This highlights the necessity of low-carbon electricity sources, such as photovoltaic (PV) power, to minimize emissions from e-fuel and SAF production. Moreover, while synthetic jet fuels can help achieve warming neutrality by 2050 without DACCS, their reliance on hydrogen production still contributes to surface CO_2 emissions, emphasizing the importance of renewable energy integration in aviation fuel decarbonization.

Large-scale deployment of synthetic jet fuels (e-fuels) faces significant resource constraints, particularly in terms of electricity demand. Achieving climate neutrality using syn-jet fuel and DACCS could require nearly 70 times the European Union's 2020 electricity output, with the majority needed for hydrogen production (eurostat. Electricity production, 2020). While alternative low-carbon electricity mixes may reduce land and water use, the sheer scale of renewable power required suggests that syn-jet fuel production may not be entirely feasible within Europe (Sacchi et al., 2023).This highlights the importance of integrating photovoltaic (PV) power into SAF production pathways, which offer lower electricity requirements compared to e-fuels.

Achieving net-zero aviation emissions requires more than just offsetting flight CO_2 emissions. Without fully decarbonized electricity, synthetic jet fuels would merely shift emissions upstream (Sacchi et al., 2023). This highlights the necessity of integrating photovoltaic (PV) power in SAF production to minimize CDR dependency and ensure meaningful climate impact mitigation.

3. Methodology

To achieve the objectives outlined above, a data-driven methodology is employed, consisting of following steps: city selection, criteria identification, data collection and normalization, multi-criteria ranking, and embodied emissions assessment. The methodology of this research work is a combination of MCDA (multi-criteria decision analysis), data normalization, squaring, and embodied carbon analysis.

Multiple-Criteria Decision Making (MCDM) is a subfield of operations research that develops computational and mathematical methods to assist decision-makers in the rational evaluation of multiple criteria (Mardani et al., 2015). It provides a structured framework for selecting among alternatives to solve complex problems or prioritize a set of choices based on predefined criteria. MCDM has been widely applied in various fields, including energy planning, transportation, financial decision-making, corporate activities (e.g., mergers and acquisitions), and resource allocation (Saaty, 1990). Given the multifaceted nature of energy transition challenges, MCDM is particularly useful in balancing technical, economic, environmental, and social factors when evaluating sustainable energy solutions(Kshanh & Tanaka, 2024).

Multi-criteria decision Analysis (MCDA) methods are frequently used for sustainability assessment of energy systems, which requires a range of indicators from the economy, environment, and society pillars (Grondin et al., 2025). MCDA analysis improves the decision-making process in energy planning by providing decision recommendations such as ranking, sorting, selecting, and clustering of alternatives.

MCDA has found application in diverse fields and problem typologies. In general, it serves as a versatile framework within which multiple objectives and decision criteria (or attributes) can be systematically integrated into the analysis of a given problem (*Multi-Criteria Analysis : A Manual*, n.d.).

Three main reasons why a multi-criteria approach is well-suited for the multidimensional nature of sustainability assessments are: - It allows formally incorporating multiple objectives and decision criteria, very often conflicting, thus aligning them with the complexity of multi-dimensional sustainability assessments (Dean, 2022) - It enables participatory and non-participatory weighting procedures, allowing the prioritization of specific criteria and the evaluation of qualitative and quantitative performances based on the specific research objectives. It guarantees a transparent and structured process, enhancing stakeholders' engagement and communication.(Poulsen, 2022)

Also defined as Multiple Criteria Decision Making (MCDM) or Multiple Attribute Decision Making (MADM), MCDA is a process that assesses alternatives by identifying the evaluation criteria, eliciting the preferences of the stakeholders and using the preference information to build a preference model that aggregates the multiple criteria evaluations of alternatives. This model permits the comparison of alternatives comprehensively (with, e.g., a ranking, a classification) and leads to a decision recommendation (Cinelli et al., 2014). Each MCDA process is composed of different characteristics, which can be defined as features or elements that belong to the MCDA process and serve to identify (parts of) it(Cinelli et al., 2020).

The use of MCDA has increased consistently over the years, due to recognition of the need to address challenges from a multitude of perspectives while dealing with several trade-offs, which calls for multiple criteria assessments. This trend has been particularly marked in complex decision making domains like energy technologies and systems evaluations, urban regeneration planning, policy analysis, health technology management, ecosystem services governance, sensors placement, resilience and sustainability quantification, energy policy ranking, product recovery activities, supply chain management, waste recycling, freight selector, housing affordability, raw material supply risk assessment, water supply systems, and polluted land remediation(Cinelli et al., 2020).

MCDA has different methods which makes it suitable for different applications. The Weighted Sum Model (WSM) is one of the most straightforward and widely used MCDA methods. It operates by assigning numerical weights to each criterion and computing a weighted sum to rank alternatives. Each criterion is given a relative importance score, which is multiplied by the normalized value of that criterion for each alternative. The sum of these weighted values determines the overall ranking. The main advantage of WSM is its simplicity, making it well-suited for problems where all criteria are measured on the same scale. It is particularly effective in cases where decision-makers have quantitative data and need a clear, numerical ranking of options. However, one of its limitations is that it assumes complete compensability, meaning a poor performance in one criterion can always be offset by a high score in another, which might not always be desirable in complex decision-making contexts (Kshanh & Tanaka, 2024).

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is a method designed to rank alternatives based on their relative distance from an ideal and an anti-ideal solution. The ideal solution represents the best possible performance for each criterion, while the anti-ideal solution is the worst. Each alternative is evaluated based on how close it is to the ideal and how far it is from the anti-ideal. The method relies on Euclidean distance calculations to determine the ranking, favoring alternatives that have the shortest distance from the ideal and the longest distance from the worst-case scenario. TOPSIS is particularly useful when decision-makers want to balance multiple criteria without necessarily prioritizing any single factor. Its main advantage lies in its ability to capture both the best and worst possible cases, but its effectiveness can be influenced by how criteria weights are assigned, which may introduce subjectivity into the decision process (Kshanh & Tanaka, 2024).

The VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) method is a compromise-ranking technique that helps decision-makers find an optimal balance among conflicting criteria. Unlike other MCDA methods that seek an absolute best option, VIKOR focuses on identifying a compromise solution that minimizes the distance from an ideal point while also considering the worst possible performance. This is particularly valuable when trade-offs must be made between competing priorities. The method introduces a regret measure, which quantifies the extent to which an alternative fails to achieve the ideal across different criteria. VIKOR is particularly suitable when decision-makers must reach a consensus-driven decision, making it applicable in policy planning, environmental management, and infrastructure development. However, one of its limitations is that it requires careful weight assignment and a clear understanding of decision-makers' preferences, which may not always be well-defined (Kshanh & Tanaka, 2024).

The Weighted Aggregated Sum Product Assessment (WASPAS) method combines elements of the Weighted Sum Model (WSM) and the Weighted Product Model (WPM) to improve ranking accuracy. It accounts for both additive and multiplicative relationships between criteria, making it more robust than simple weighted models. WASPAS assigns a weight to each criterion and calculates a final score by combining both summation and multiplication of weighted values. This dual approach reduces inconsistencies and improves decision reliability. WASPAS has been widely applied in industrial decision-making, transportation planning, and renewable energy project evaluations, as it provides a comprehensive ranking mechanism that considers multiple dimensions of performance. While more computationally intensive than WSM, its advantage lies in its ability to balance multiple factors effectively, making it a practical tool for complex decision problems (Kshanh & Tanaka, 2024).

The Preference Ranking Organization Method for Enrichment of Evaluations (PROMETHEE) is an outranking-based MCDA method that ranks alternatives based on pairwise comparisons. Instead of assigning absolute scores, PROMETHEE evaluates alternatives by comparing them directly across multiple criteria. It uses a preference function to determine how much one alternative is preferred over another for each criterion, then aggregates these preferences to produce a final ranking. One of the strengths of PROMETHEE is its ability to handle both qualitative and quantitative data, making it useful for problems where subjective judgments must be incorporated alongside objective measurements. It is widely applied in areas such as supply chain management, environmental impact assessment, and business strategy formulation. However, PROMETHEE is more complex than scoring-based methods like WSM, requiring careful definition of preference functions, which can be challenging when dealing with large datasets (Kshanh & Tanaka, 2024).

The Analytic Hierarchy Process (AHP) is a structured decision-making framework that uses pairwise comparisons to determine the relative importance of criteria. Instead of assigning weights arbitrarily, AHP asks decision-makers to compare each criterion against the others, creating a hierarchical structure that breaks down a decision problem into different levels. These comparisons generate a consistency ratio, ensuring that decision-makers' judgments are logically consistent. AHP is widely used in policy analysis, engineering, and urban planning, as it allows for an intuitive yet mathematically rigorous way to prioritize multiple factors. However, AHP can be time-consuming and may introduce bias if decision-makers' subjective judgments are not carefully managed (Kshanh & Tanaka, 2024).

The Fuzzy Analytic Hierarchy Process (FAHP) is an extension of AHP that incorporates fuzzy logic to handle uncertainty in decision-making. Traditional AHP requires crisp numerical comparisons, which may not always reflect real-world complexity, especially when dealing with qualitative criteria. FAHP allows decision-makers to express preferences using fuzzy numbers, which are then processed mathematically to derive priority weights. This method is particularly useful in risk assessment, environmental management, and infrastructure planning, where criteria may be difficult to quantify precisely. While FAHP improves flexibility, it also increases computational complexity and requires expertise in fuzzy mathematics (Kshanh & Tanaka, 2024).

This study employs a direct scoring-based MCDA approach, which aligns most closely with Weighted Sum Model (WSM). Unlike AHP, FAHP, or PROMETHEE, which require pairwise comparisons and preference functions, this approach involves predefined weighting and normalization. The research assigns numerical weights to selected criteria, normalizes the data for comparability, and uses a scoring mechanism to rank potential locations for SAF and e-fuel production. This method is effective for large-scale spatial analysis where decision factors are quantifiable and objective. While more advanced MCDA methods offer deeper decision insights, the chosen approach ensures computational efficiency and transparency, making it well-suited for optimizing geographical siting of sustainable fuel production plants.

3.1 Selection of European Cities for Analysis

A total of 36 major cities across the EU-27 were selected to ensure a broad geographical representation while capturing diverse urban, energy, and policy landscapes.

The selection of cities for this study was based on specific criteria to ensure comprehensive geographical representation and meaningful comparisons in photovoltaic (PV) deployment potential. Capital cities were included regardless of their population size to ensure that each country within the EU-27 was represented, acknowledging their central role in national energy policies and infrastructure development. In addition to capitals, non-capital cities with populations exceeding one million were selected to capture major urban centers with significant energy demand and potential for large-scale PV deployment.

The geographical distribution of selected cities reflects a balanced approach to regional diversity. Countries with larger populations and more extensive energy infrastructures, such as Germany, Italy, and France, were represented by four cities each. Spain and Portugal were assigned two cities each, while all other countries, including the Netherlands, Belgium, Luxembourg, Austria, Slovakia, Czech Republic, Poland, Hungary, Slovenia, Cyprus, Romania, Greece, Ireland, Croatia, Bulgaria, Lithuania, Estonia, Latvia, Sweden, Finland, Malta, and Denmark, were represented by a single city.

This selection approach ensures that the study effectively captures variations in solar irradiance, grid carbon intensity, and electricity consumption across different regions. By incorporating cities with diverse climatic conditions, energy profiles, and policy environments, the research provides a fair and comprehensive basis for assessing PV deployment potential in different urban contexts across Europe.

3.2 Identification of Key Criteria for Homogeneous Zones

We analyzed various criteria and ultimately identified four key factors: Solar Irradiance, Grid Carbon Intensity, Population Density, and Electricity Consumption per Capita. These factors help define homogeneous zones based on PV feasibility and sustainability.

3-2-1. Solar Irradiance (kWh/m²/year)

Definition: Yearly in-plane irradiation (kWh/m²) measures the amount of solar energy available for PV systems in each city.

Data Source: Obtained from PV-GIS, a reliable database for solar energy potential.

Normalization: All values were normalized using the min-max technique to ensure consistency across cities.

Cities with higher IRR values show more potential for PV installations.

In this analysis, the normalized annual solar irradiance (Normalized Yearly Irradiance) is examined, along with the distribution of this parameter across European cities. A detailed box plot and bar chart analysis has been conducted to highlight the differences among cities, identify outliers, and assess the logical consistency of the observed data.

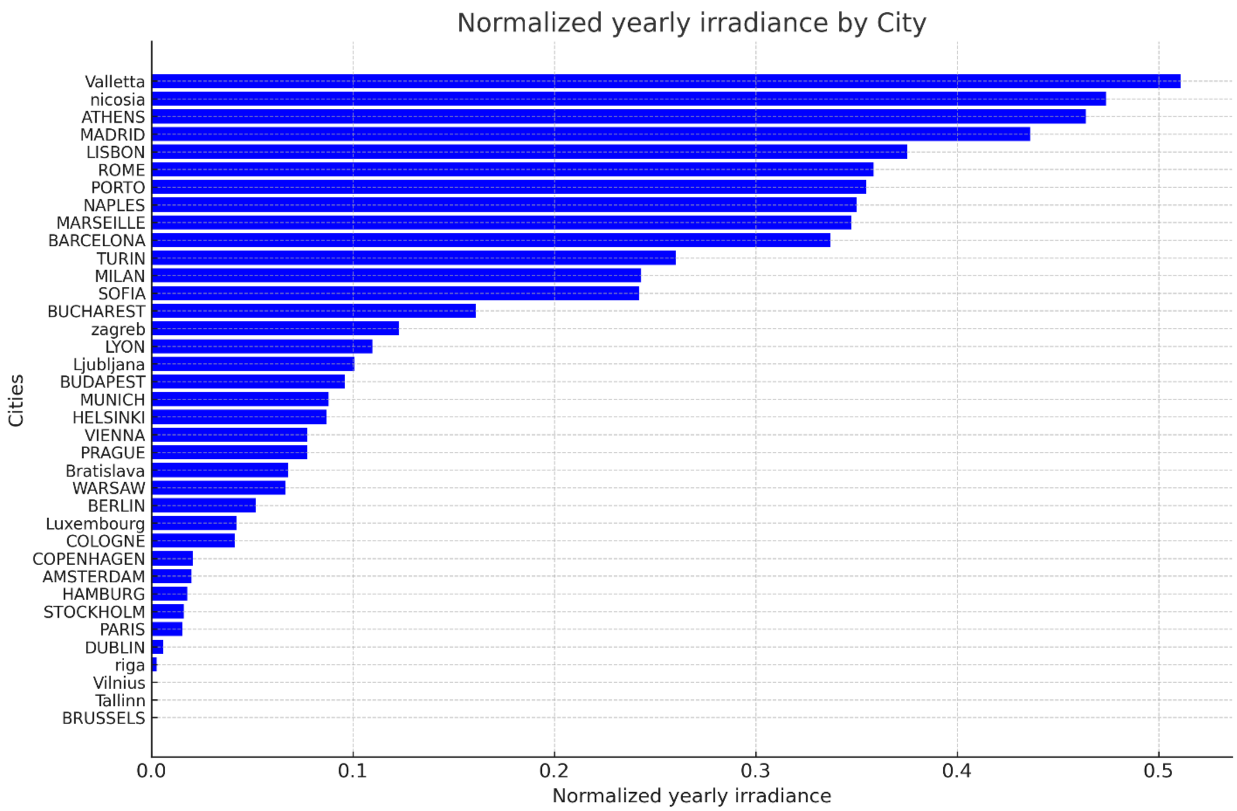


Fig 3. Bar chart of Normalized Yearly Irradiance of European cities

The box plot of normalized solar irradiance reveals a wide range of values, demonstrating significant variations in sunlight exposure across Europe. The key statistical insights derived from the box plot are as follows:

Minimum and Maximum Values:

The lowest normalized solar irradiance is close to 0, indicating extremely low solar exposure in Northern European cities such as Helsinki (Finland), Stockholm (Sweden), and Dublin (Ireland).

The highest value is around 1, corresponding to southern cities like Athens (Greece), Valletta (Malta), Nicosia (Cyprus), Madrid (Spain), and Rome (Italy), which receive abundant sunlight throughout the year.

Median and Mean Values:

The median value is approximately 0.4 to 0.5, suggesting that half of the analyzed cities receive annual solar irradiance above this value, while the other half receive less.

In boxplots, when the mean value is slightly higher than the median, it indicates a right-skewed (positively skewed) distribution. This means that while most of the data points are concentrated around lower values, a few higher-than-usual values (outliers or extreme values) are pulling the mean upwards. For example, in the context of solar irradiance and carbon intensity, if the mean carbon intensity is higher than the median, it suggests that most cities in that region have relatively lower carbon intensity, but a few cities with very high carbon intensity significantly affect the overall average. This pattern is especially important in understanding energy distribution because it helps policymakers identify the cities that deviate significantly from the norm and may require targeted interventions to reduce carbon emissions.

Data Distribution and Outliers:

The distribution is relatively broad and uniform, with a more concentrated data range in the mid-level irradiance values. Outliers exist at both ends of the distribution. Northern European cities such as Helsinki and Stockholm exhibit significantly lower irradiance values than the majority, while Mediterranean cities (e.g., Athens, Nicosia, and Madrid) are at the upper extreme of the distribution.

The presence of high and low outliers suggests that latitude strongly influences solar energy potential in European cities.

Interquartile Range (IQR) and Spread of Data:

The interquartile range (IQR) is relatively large, reflecting the substantial variance in solar irradiance between northern and southern regions.

A few extreme values (beyond 1.5 times the IQR) exist but are limited, meaning that while differences are significant, most values fall within a logical range.

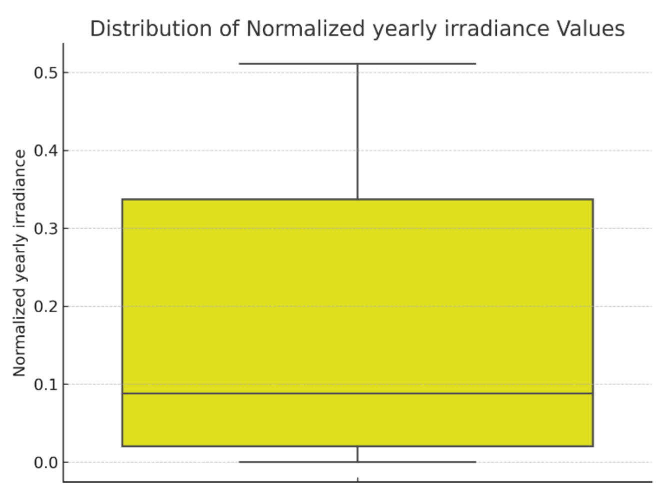


Fig 4. Box and Whisker Plot of normalized yearly irradiance of European cities

The selected data appears to be well-distributed in terms of irradiance values, meaning that the selection is not biased toward only high-irradiance or low-irradiance locations. The lack of extreme outliers and the relatively symmetric spread indicate that the selection effectively represents a diverse range of solar exposure conditions in Europe. This is ideal for analyzing the relationship between latitude and solar energy production, as it ensures that the dataset is comprehensive and not skewed toward specific geographic conditions.

3-2-2. Grid Carbon Intensity (gCO_2e/kWh)

Definition: Carbon intensity measures the amount of CO_2 emissions per unit of electricity generated (gCO_2e/kWh). Lower values indicate cleaner electricity grids.

Data Source: Country-level data was obtained from Eurostat and other reliable sources.

Relation to Cities: Since carbon intensity data is typically available at the country level, we assigned the same value to all cities within the same country. For example:

All cities in Germany (Berlin, Munich, Hamburg, Cologne) share the same carbon intensity value.

All cities in France (Paris, Lyon, Marseille) share the same carbon intensity value.

Normalization: Country-level carbon intensity values were normalized to a 0–1 scale for comparison.

Higher carbon intensity of grid shows more need and potential for new renewable source plant installations.

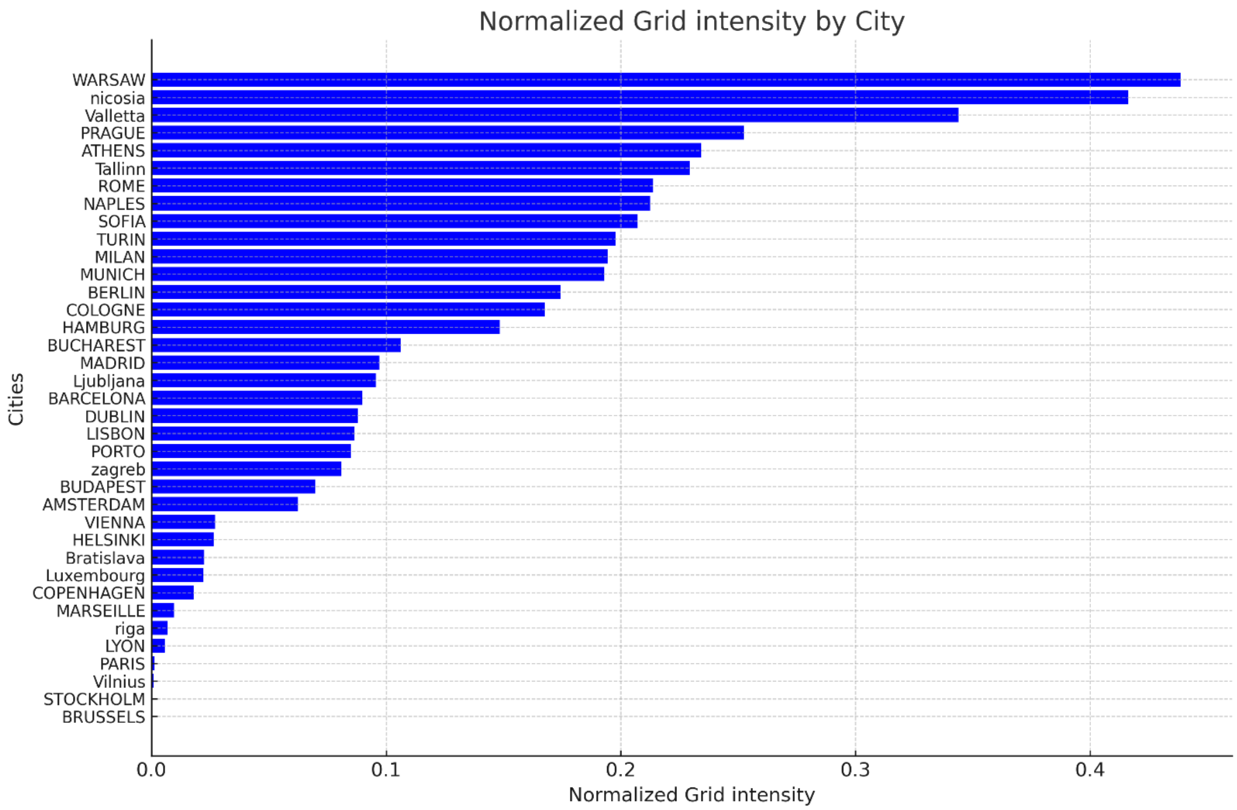


Fig 5. Bar chart of Normalized Grid Intensity of European cities

The Normalized Grid Intensity metric represents the amount of carbon dioxide (CO_2) emissions per kilowatt-hour of electricity produced. This indicator is crucial for assessing the environmental impact of energy consumption in different cities and plays a significant role in determining the feasibility of sustainable energy transitions.

The carbon intensity of electricity generation varies substantially across Europe, mainly due to differences in energy sources, national policies, and infrastructure development. Some cities operate on clean electricity grids, predominantly powered by nuclear, hydro, and wind energy, whereas others still rely heavily on fossil fuels, particularly coal and natural gas. Understanding this variation is essential for identifying which cities are leading in decarbonization and which require urgent policy interventions to transition towards cleaner energy systems.

This section provides a detailed statistical analysis of the distribution of grid intensity across European cities, using box plots and bar charts to examine key trends, identify outliers, and assess the implications of carbon-intensive electricity production.

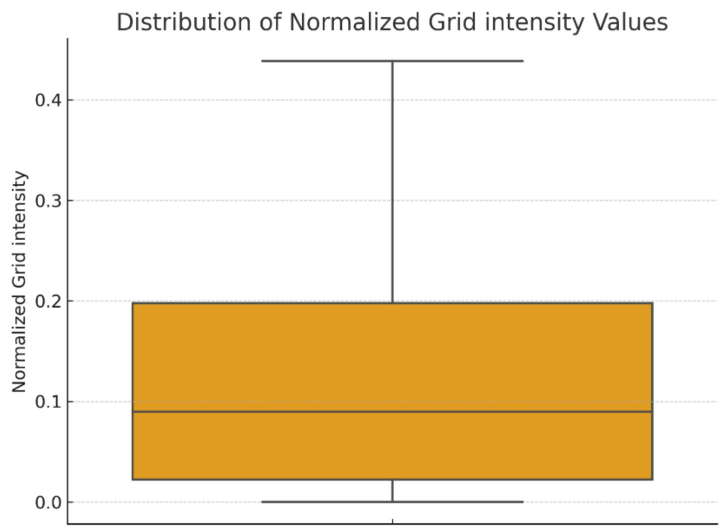


Fig 6. Box and Whisker Plot of normalized Grid Intensity of European cities

The box plot and bar chart of normalized grid intensity reveal significant disparities among European cities. The following key insights emerge:

Minimum and Maximum Values:

The lowest values (close to 0) belong to cities with ultra-low-carbon electricity grids, such as Stockholm (Sweden) and Paris (France). These cities benefit from widespread use of nuclear, hydro, and wind power, resulting in carbon intensities of approximately 50–100 g CO_2/kWh (NomadElectric, 2022).

The highest values (close to 1) are observed in cities such as Warsaw (Poland), Nicosia (Cyprus), and Valletta (Malta), where the electricity grid is still heavily dependent on coal and fossil fuels, reaching carbon intensities of around 700 g CO_2/kWh (NomadElectric, 2022).

Median and Mean Values:

The median grid intensity is around 0.4, meaning that half of the cities have a carbon intensity lower than this value, while the other half have higher intensities.

The mean is slightly above the median (around 0.5), indicating that the distribution is slightly skewed to the right due to a few cities with extremely high carbon emissions.

Data Distribution and Outliers:

The distribution is highly asymmetrical, with a majority of cities having moderate to low grid intensity, while a few cities exhibit significantly higher emissions.

Cities in Poland, Malta, and Bulgaria have exceptionally high values and appear as upper outliers.

Conversely, French and Scandinavian cities are lower outliers, as they operate on exceptionally clean electricity grids.

The box plot shows a long whisker on the high-emission side, reflecting the presence of a few highly polluting cities compared to the majority.

Interquartile Range (IQR) and Data Spread:

The spread of values within the IQR is moderate, indicating that most cities have similar carbon intensities, except for a few extreme cases at both ends.

The primary driver of grid intensity is the share of fossil fuels (coal, oil, and gas) in electricity production. Cities with high reliance on these sources exhibit higher carbon intensity, while cities that have invested in renewables and nuclear energy maintain significantly lower emissions. For instance, Warsaw (Poland), Sofia (Bulgaria), Valletta (Malta), and Nicosia (Cyprus) generate a large portion of their electricity from fossil fuels, leading to high carbon intensity. In contrast, cities like Stockholm (Sweden) and Paris (France) benefit from extensive hydropower and nuclear energy infrastructure, resulting in much lower grid emissions. Since cities with high carbon intensity grids face greater pressure to decarbonize, they present an ideal opportunity for PV installation, as solar energy can significantly reduce dependency on fossil-fuel-based electricity in these areas.

The extent to which cities have invested in renewable energy directly affects their grid intensity. Cities like Helsinki (Finland), Stockholm (Sweden), and Lisbon (Portugal) have made substantial progress in wind, hydro, and solar power, lowering their carbon intensity relative to other regions. However, cities such as Warsaw (Poland), Prague (Czech Republic), Valletta (Malta), and Nicosia (Cyprus) still face challenges in transitioning to renewable energy due to coal dependency or geographic constraints. These cities not only contribute to higher carbon emissions per kilowatt-hour but also have significant potential for PV installations, as increasing solar energy production could directly lower grid intensity and support decarbonization efforts.

3-2-3. Population Density (people/km²)

Definition: Population density (people/km²) reflects the concentration of people in a country, which can influence the availability of land for PV installations.

Normalization: Values were normalized to ensure comparability.

Lower population density is preferable, as it indicates more available land for building PV plants. High population density areas often lack sufficient space for large-scale PV installations. So this factor is inversely related to high potential zones.

The Normalized Inverse Population Density (1/Population Density) metric indicates the availability of land in a city for the development of renewable energy infrastructure. A higher value of this indicator suggests more open space, making a city more suitable for large-scale renewable energy projects, such as solar farms and wind farms. Conversely, a lower value signifies high population density, which limits land availability and necessitates alternative energy solutions, such as rooftop solar installations and urban energy storage systems.

This analysis examines the distribution of inverse population density across European cities, utilizing box plots and bar charts to assess variations, identify extreme cases, and highlight the implications for energy planning.

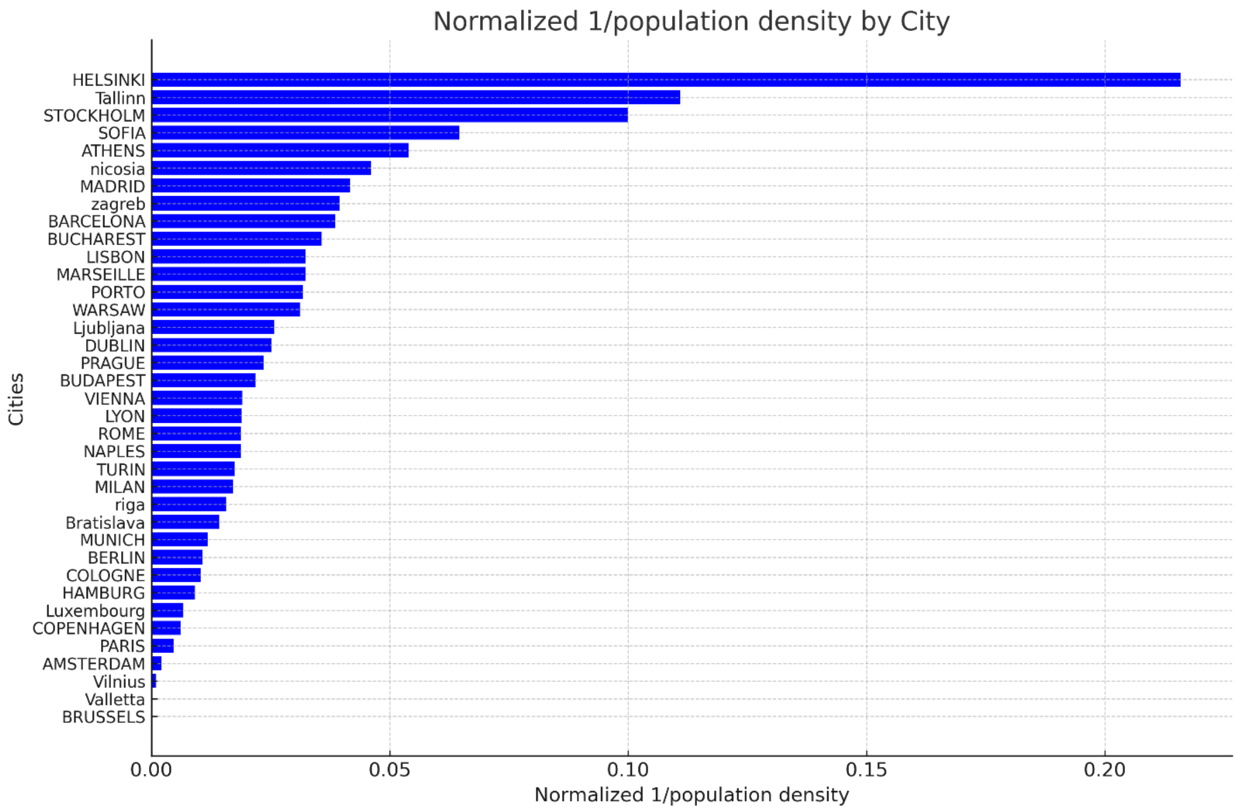


Fig 7. Bar chart of normalized inverse population density of European cities

The box plot and bar chart of normalized inverse population density reveal a bimodal distribution, meaning that cities tend to cluster into two groups—high-density and low-density cities. The key statistical observations are as follows:

Minimum and Maximum Values:

The lowest values (close to 0) correspond to highly dense cities, such as Paris, Amsterdam, and Copenhagen, where land availability is severely limited.

The highest values (close to 1) are observed in low-density cities, such as Rome, Warsaw, and Zagreb, which have a relatively large land area compared to their population size (Global Cities Population Density Index, 2022).

Median and Mean Values:

The median is around 0.5, indicating that half of the analyzed cities have relatively limited space for large-scale renewable energy projects, while the other half have more open land.

The mean is close to the median, suggesting that the distribution is somewhat balanced, though some extreme values exist on both ends.

Data Distribution and Outliers:

The distribution follows a bimodal pattern, with one cluster of cities having very low inverse density (high urban density) and another cluster with significantly higher values (low urban density).

Outliers exist at both ends of the distribution:

Paris and Amsterdam are extreme low outliers, as they have some of the highest population densities in Europe. Rome and Warsaw appear as high outliers, as they are expansive cities with relatively low population density.

Interquartile Range (IQR) and Data Spread:

The IQR is relatively wide, reflecting the substantial difference between compact cities and sprawling cities.

The presence of both extremely high-density and low-density cities increases the overall data variability, making the box plot display elongated whiskers.

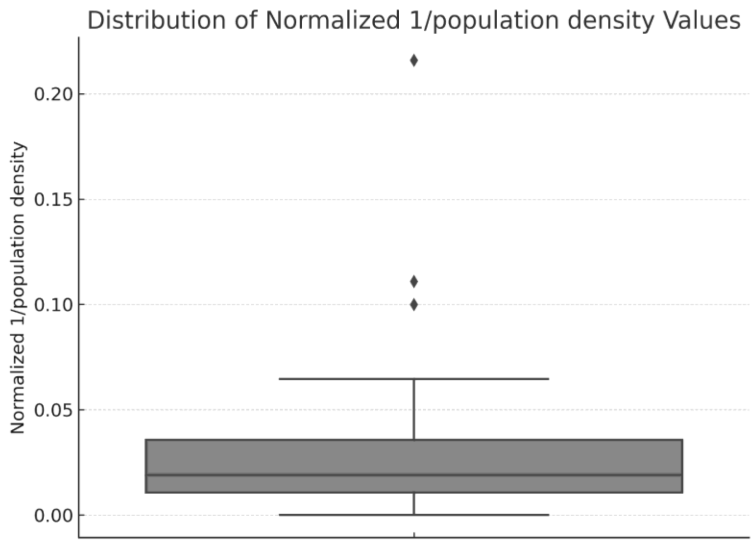


Fig 8. Box and Whisker Plot of normalized inverse population density of European cities

The design and expansion of a city play a crucial role in determining its land availability for renewable energy projects.

Low Inverse Population Density (High Urban Density Cities):

Paris, Amsterdam, Brussels: These cities were historically designed with compact urban centers, resulting in limited open land for large-scale energy infrastructure.

Such cities need to focus on alternative solutions, such as rooftop solar PV systems, vertical wind turbines, and decentralized energy storage (European Urban Development Report, 2021).

High Inverse Population Density (Low Urban Density Cities):

Warsaw, Rome, Zagreb: These cities have expansive urban layouts, providing ample space for the development of large solar and wind farms.

The meaning of the distribution of the data provides the following insights:

- The interquartile range (IQR) is relatively small, meaning that the majority of cities have similar values for the normalized inverse of population density. This suggests that population density does not vary drastically among most of the selected cities.
- A narrow IQR indicates that this parameter does not introduce significant differences between cities, making it less impactful in comparison to other parameters with wider distributions.
- The boxplot shows multiple high outliers, meaning that a few cities have exceptionally low population densities compared to others.

The boxplot of the normalized inverse of population density shows that the majority of cities have similar values, as indicated by the relatively small interquartile range. This suggests that population density does not vary significantly across most locations, meaning it does not create substantial differences between cities in terms of available space for solar installations. Additionally, the presence of a few high outliers shows that some cities have exceptionally low population densities, but these cases do not represent the overall dataset. Since urban space availability tends to be relatively fixed, population density alone is not a strong determining factor for solar panel feasibility. Furthermore, alternative solutions such as rooftop and parking lot solar installations provide practical ways to integrate solar energy in high-density areas, making open land availability a less critical constraint. Compared to other parameters that exhibit greater variation and influence on solar energy potential, population density is a relatively stable factor and has less impact on the overall feasibility of photovoltaic installations.

3-2-4. Electricity Consumption per Capita (MWh/capita)

Definition: Annual electricity consumption per capita [MWh/capita] was gathered for deferent countries.

Normalization: Values were normalized to a 0–1 scale.

Higher electricity consumption indicates greater potential zones, making PV plants more beneficial to meet local needs and reduce reliance on external energy sources.

Each of these four factors plays a crucial role in defining optimal zones for PV deployment, ensuring that investments align with both technical feasibility and climate goals.

The Normalized Electric Consumption metric reflects the per capita electricity usage in each city, which is influenced by climatic conditions, economic development, industrial activity, and energy efficiency policies. Understanding the variations in electricity consumption across different European cities is crucial for assessing energy demand, evaluating sustainability policies, and optimizing renewable energy distribution.

Some cities exhibit significantly higher per capita electricity consumption due to their cold climates, requiring extensive heating in winter. Others have high industrial activity, leading to greater electricity demand. Conversely, certain cities demonstrate lower consumption levels, which can be attributed to energy efficiency policies, warmer climates, or lower economic activity.

This analysis explores the distribution of normalized electricity consumption across European cities, utilizing box plots and bar charts to highlight disparities, identify outliers, and evaluate key drivers behind variations in energy demand.

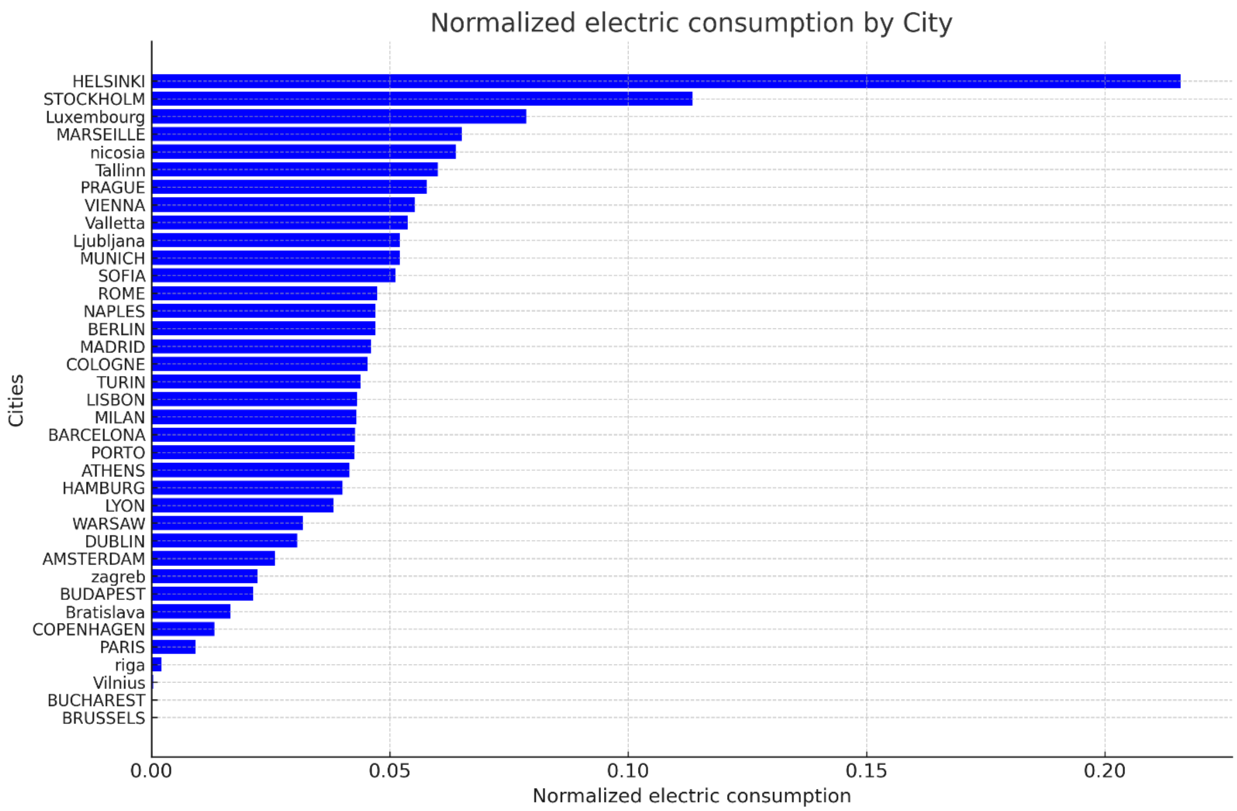


Fig 9. Bar chart of normalized electric consumption of European cities

The box plot and bar chart of normalized electric consumption reveal a right-skewed distribution, indicating that a majority of cities have moderate consumption levels, while a few Northern European cities exhibit significantly higher usage. Key statistical observations are as follows:

Minimum and Maximum Values:

The lowest values (close to 0) correspond to cities with low per capita electricity consumption, such as Bucharest (Romania) and Sofia (Bulgaria). Bucharest, for example, has a per capita electricity consumption of around 2.6 MWh per year, one of the lowest in Europe (Wikipedia, 2022; WorldData, 2022).

The highest values (close to 1) are seen in cities from wealthy Nordic countries, such as Helsinki (Finland), which records per capita consumption of approximately 14.7 MWh per year, among the highest in Europe (Wikipedia, 2022).

Median and Mean Values:

The median is around 0.4, meaning that half of the cities have a per capita electricity consumption below this level, while the other half are above it.

The mean is slightly above the median (around 0.45–0.5), indicating that the distribution is slightly skewed to the right, due to the presence of a few high-consumption cities.

Data Distribution and Outliers:

The distribution is skewed to the right, as most cities fall within a moderate consumption range (5–7 MWh per capita, normalized between 0.4–0.6).

Cities from Northern Europe (Helsinki, Stockholm) appear as upper outliers, with significantly higher per capita electricity consumption than the average. Finland's electricity consumption, for instance, is 3–4 times higher than some Eastern European countries.

Cities with the lowest consumption (e.g., Bucharest, Sofia) appear as lower outliers, but their numbers are limited, as most European cities maintain at least a moderate level of electricity usage.

Interquartile Range (IQR) and Data Spread:

The IQR is moderately wide, showing significant variability in consumption across cities.

A long right tail in the distribution indicates that a small number of cities (mostly Nordic) have exceptionally high electricity consumption, increasing overall variance.

Key Observations:

Cities with High Electricity Consumption: Helsinki, Luxembourg, Vienna.

Cities with Low Electricity Consumption: Paris, Dublin, Riga.

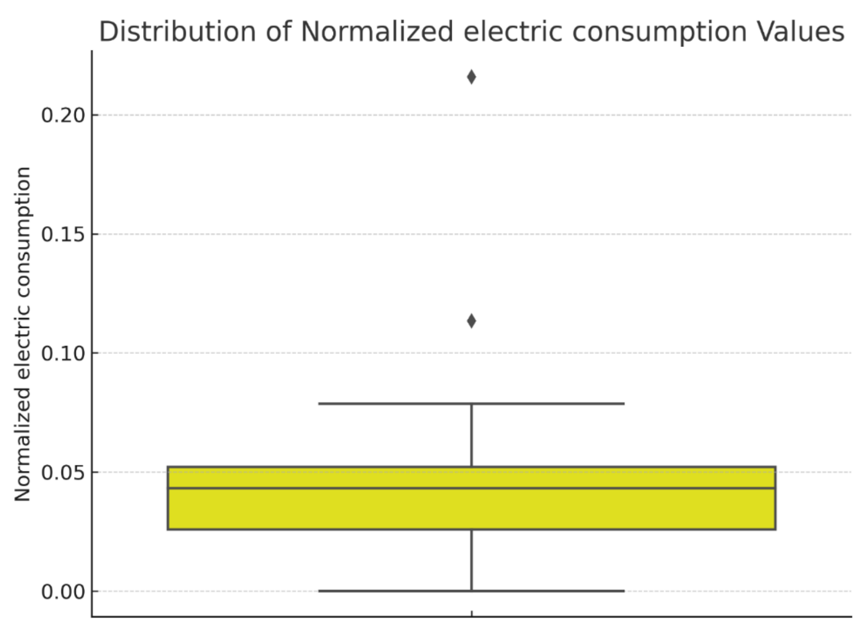


Fig 10. Box and Whisker Plot of normalized electric consumption of European cities

Cold weather conditions significantly increase electricity consumption, particularly in cities with long winters. High Consumption Cities (Cold Climates) like as Helsinki (Finland), Stockholm (Sweden), Warsaw (Poland) experience severe winters, requiring extensive electric heating, which significantly raises per capita energy consumption (IRENA, 2022).In Scandinavian countries, the use of electric heating is widespread, contributing to their high electricity demand (European Energy Report, 2021).

Low Consumption Cities (Mild Climates) like as Paris (France), Dublin (Ireland), and Lisbon (Portugal) have milder climates, reducing the need for electricity-powered heating or cooling systems. Southern European cities generally consume less electricity per capita, as heating demands are lower, and air conditioning usage is seasonal (European Climate Report, 2021).

Cities with strong industrial sectors and high economic output typically consume more electricity per capita. High Consumption Cities (Industrial & High-Income Economies) namely Luxembourg and Vienna exhibit high electricity demand, largely due to their industrial and commercial sectors, which require large-scale energy inputs.

Countries with high GDP per capita tend to have higher electricity consumption, as they host energy-intensive industries and extensive commercial infrastructure (IEA, 2022). Low Consumption Cities (Lower Industrial Activity) like as Bucharest (Romania) and Sofia (Bulgaria) have lower per capita electricity consumption, reflecting weaker industrial activity and lower overall energy demand. Eastern European cities tend to have less energy-intensive economies, contributing to lower average electricity consumption per capita (Romania Insider, 2022). Industrialized cities have higher energy demands, whereas cities with smaller economies consume less electricity per capita.

The boxplot of normalized electric consumption shows a similar pattern to the previously analyzed population density parameter, suggesting that its impact on the overall assessment should be lower. The interquartile range is relatively narrow, indicating that most cities have similar electricity consumption levels, meaning this parameter does not introduce significant variation across different locations. Although there are a few extreme outliers with very high values, these cases do not represent the majority of cities and do not strongly affect the general trend.

The limited variability within the core data implies that electricity consumption is relatively stable across cities, and it does not create substantial differences between them. Additionally, electricity consumption is inherently difficult to alter in the short term since it is influenced by structural factors such as industrial activity, economic development, and climate conditions. Unlike parameters such as solar irradiance or energy mix, which can significantly impact carbon intensity, electricity consumption itself does not provide strong differentiation between cities regarding their suitability for photovoltaic installations.

Given that the distribution of this parameter is compact, with most cities falling within a similar range, and considering that electric consumption is not easily modifiable, it makes sense to assign a lower weight to it in comparison to other parameters that exhibit greater variability and direct impact on renewable energy feasibility.

3.3 Data Collection and Normalization

To ensure consistency and comparability across different cities, a min-max normalization technique was applied to scale all values between 0 and 1. This method standardizes the data, allowing for an unbiased evaluation of each city's potential for PV deployment. The normalization process ensures that cities with widely varying values for solar irradiance, grid carbon intensity, population density, and electricity consumption can be assessed on a common scale. By transforming the raw data into a standardized range, this approach prevents any single factor from disproportionately influencing the ranking of cities and facilitates meaningful cross-regional comparisons.

$$Xnorm = \frac{X - Xmin}{Xmax - Xmin}$$

where:

- X is the original value,
- Xmin and Xmax are the minimum and maximum values in the dataset.

By applying this method, all criteria were standardized, ensuring fair weight distribution in multi-criteria ranking.

3.4 Multi-Criteria Ranking and Classification of Cities

To evaluate the PV potential of each city, a composite Total Score (TS) was calculated using the following equation:

TS = Normalized Solar Irradiance + Normalized Grid Carbon Intensity + (0.5× 1/Population Density) + (0.5×Electricity Consumption)

Given the significant variability in solar irradiance, grid carbon intensity, population density, and electricity demand across Europe, defining homogeneous regions is essential for standardizing embodied emissions values for photovoltaic (PV) installations. This study employs a multi-criteria approach to classify European regions into distinct zones where similar environmental and technical conditions allow for the application of average embodied emissions values.

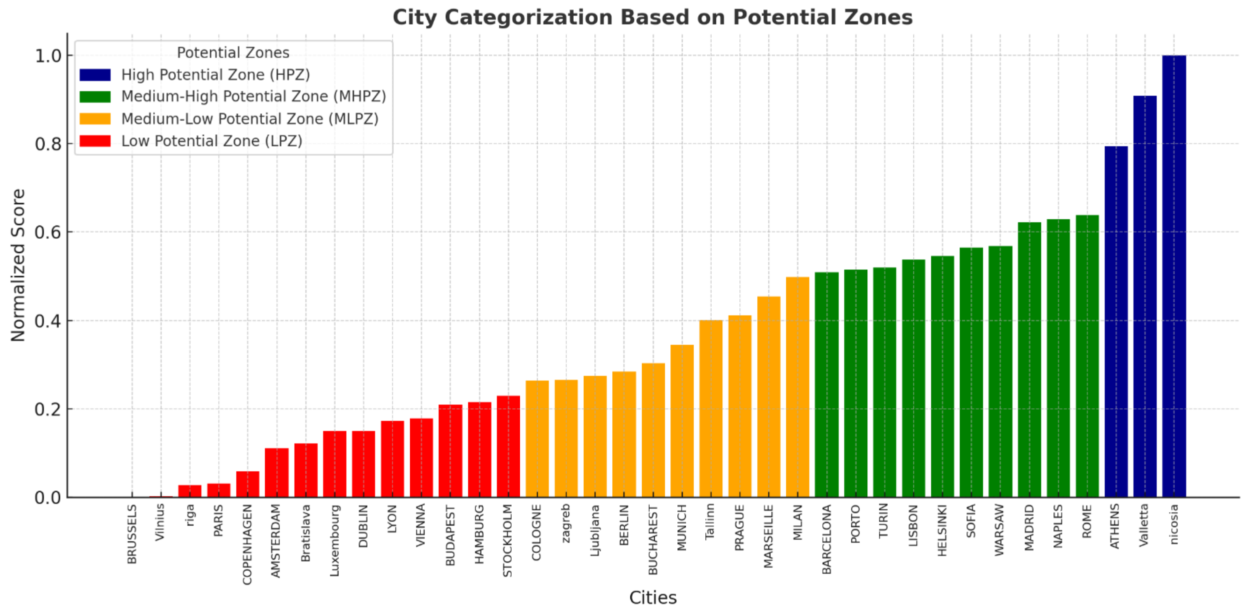


Fig 11. Bar chart of potential homogenous zones in European cities

Based on the total score, cities were categorized into four homogeneous zones:

High Potential Zones (HPZ): [1.00 – 0.75)

Medium-High Potential Zones (MHPZ): [0.75 – 0.50)

Medium-Low Potential Zones (MLPZ): [0.50 – 0.25)

Low Potential Zones (LPZ): [0.25-0]

These categories allow for a structured evaluation of PV feasibility, ensuring that higher-priority zones are targeted for sustainable investment. **High Potential Zones (HPZ)** represent the most suitable regions for PV deployment, predominantly located in Southern Europe, including Greece, Cyprus, Malta, Spain, Portugal, and Southern Italy. These regions benefit from consistently high levels of solar irradiance, which ensures greater electricity generation efficiency and shorter energy payback times. The strong solar potential in these locations maximizes PV performance, making large-scale solar investments particularly effective. Additionally, the energy demand in these regions is significant, reinforcing the role of PV as an energy provider for SAFs. Grid carbon intensity in these areas varies, with some regions still dependent on fossil fuels, making PV a strategic option to accelerate the transition toward cleaner energy sources. The favorable combination of solar exposure, energy demand, and grid conditions establishes these regions as the primary candidates for PV expansion.

Medium-High Potential Zones (MHPZ) encompass Mediterranean and Central European cities such as Rome, Madrid, Warsaw, Lisbon, Barcelona, Turin, and Sofia. These cities maintain relatively strong solar resources, though their irradiance levels are slightly lower than those found in HPZ regions. As a result, PV systems in these locations experience somewhat longer energy payback times but remain viable for significant deployment. Many of these cities are undergoing energy transition efforts, and while grid carbon intensity is still moderate, continued grid decarbonization will further enhance the benefits of PV. Electricity consumption remains high, indicating strong demand for locally produced solar energy. The potential for PV in these regions remains substantial, provided that supportive policies and infrastructure improvements facilitate further integration into the energy system.

Medium-Low Potential Zones (MLPZ) include several Northern and Central European cities such as Milan, Munich, Berlin, Prague, Ljubljana, and Cologne. These locations experience lower solar irradiance levels, which extends energy payback times and reduces the overall efficiency of PV installations. The decarbonization of electricity grids in these cities varies, with some countries already advancing towards cleaner energy sources, limiting the additional benefits that PV might provide in terms of emission reductions. Although electricity consumption remains high in these areas, the efficiency of PV installations is reduced due to climatic limitations, making large-scale deployment less favorable compared to regions with higher solar potential. In these areas, successful PV integration depends on optimizing system design, implementing hybrid energy solutions, and improving energy storage to compensate for lower generation efficiency.

Low Potential Zones (LPZ) are primarily located in Northern and Western Europe, including cities such as Stockholm, Hamburg, Amsterdam, Brussels, Paris, Dublin, and Copenhagen. These regions face considerable limitations for large-scale SAFs deployment due to low solar irradiance levels, resulting in significantly longer energy payback times. The reduced solar exposure limits PV efficiency, requiring larger installation areas to achieve the same energy output as higher-potential zones. Additionally, many of these regions have highly decarbonized electricity grids, meaning that PV does not offer the same level of emissions reduction benefits as in regions with fossil-fuel-based grids. High population density in many LPZ cities further restricts the availability of land for large-scale ground-mounted SAFs installations. While PV can still play a role in these areas, the tendency to invest in these areas are not considerably high.

The classification of European regions into these four homogeneous zones offers a structured approach to assessing the feasibility and potential of PV deployment. High Potential Zones provide the most efficient conditions for solar energy investment, while Medium-High and Medium-Low Potential Zones remain strong candidates for PV expansion with additional policy support. In Low Potential Zones, the role of PV may be more limited, requiring a diversified approach that integrates other renewable energy sources. By incorporating factors such as solar availability, grid carbon intensity, energy consumption, and land availability, this classification framework helps policymakers and energy planners optimize PV deployment strategies, ensuring a balanced and effective transition to the production of SAFs in order to reduce emissions in the aviation industry

The following analysis evaluates the potential for new PV installations across 36 major European cities based on key factors: solar irradiance, grid carbon intensity, population density, and electricity consumption per capita. These factors were normalized and combined to generate a total score for each city, as illustrated in the bar chart below.

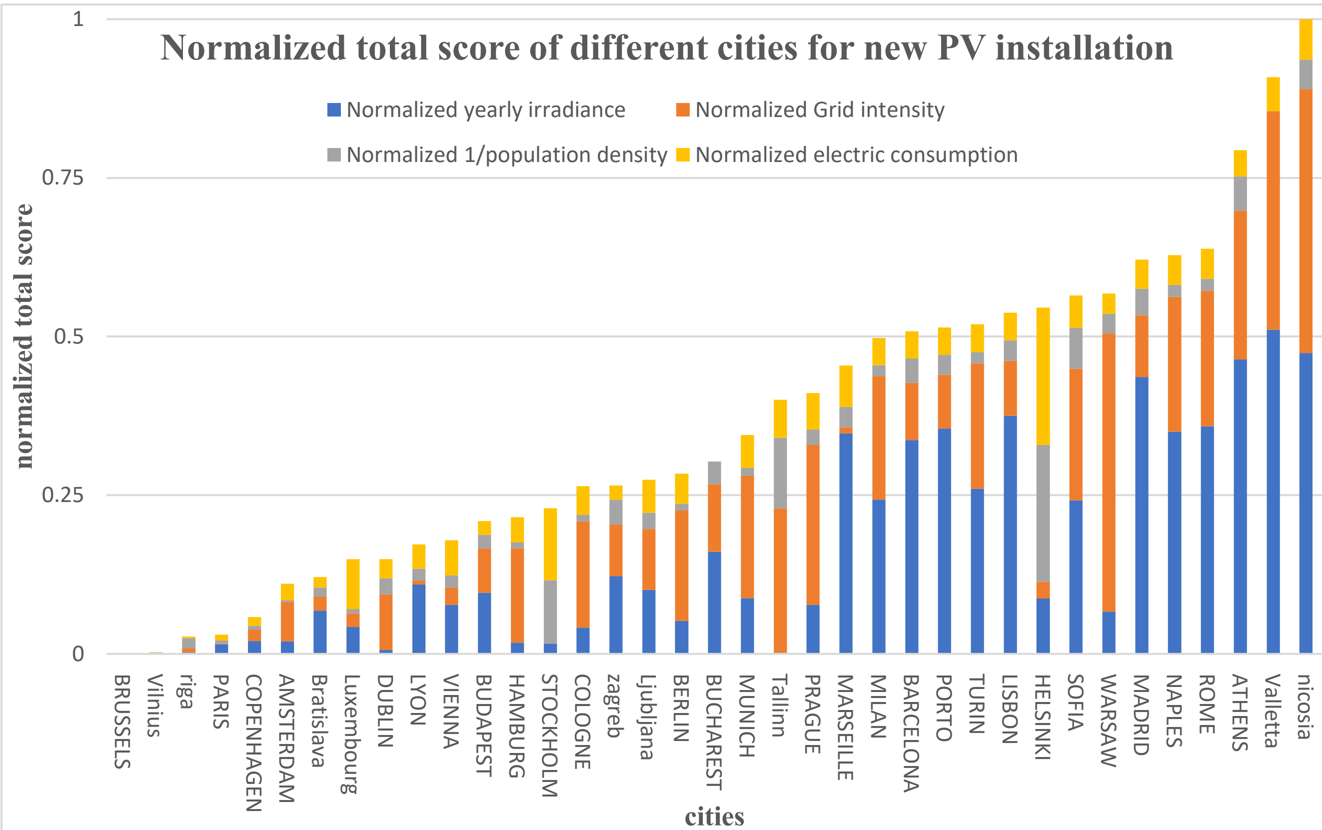


Fig 12. Bar chart of the normalized total score of EU cities

The final ranking of European cities in renewable energy potential is based on four key normalized parameters: solar irradiance, grid intensity, inverse population density, and electricity consumption. These factors collectively determine the suitability of each city for renewable PV investments and its ability to transition towards a sustainable energy system through SAFs and e-fuels production.

The stacked bar chart provides a visual representation of how each parameter contributes to the total score of each city. Cities with higher total scores are better suited for large-scale renewable energy adoption, whereas those with lower scores face challenges that limit their renewable energy potential. The breakdown of these components allows us to analyze the weight of each factor in shaping the final ranking and potential policy interventions.

Impact of Solar Irradiance on the Final Score

The solar irradiance parameter (blue segment in the graph) is the dominant factor in cities located in Southern Europe, where solar energy potential is significantly higher. Cities such as Athens, Valletta, Nicosia, and Madrid have the highest values of normalized yearly irradiance, reinforcing their potential for solar energy investments.

However, the total score is not solely determined by solar irradiance, as seen in the case of Valletta and Nicosia. Despite high solar potential, they do not achieve the highest final rankings due to the negative impact of other parameters, particularly grid intensity and electricity consumption. On the other hand, cities such as Madrid and Lisbon, which benefit from high solar irradiance along with relatively cleaner grid intensity, maintain strong rankings.

While solar irradiance significantly boosts the total score, cities with high solar potential but unfavorable grid conditions struggle to rank at the top. Clean energy grids enhance the benefits of high solar potential, making cities like Madrid and Athens highly favorable for solar energy deployment.

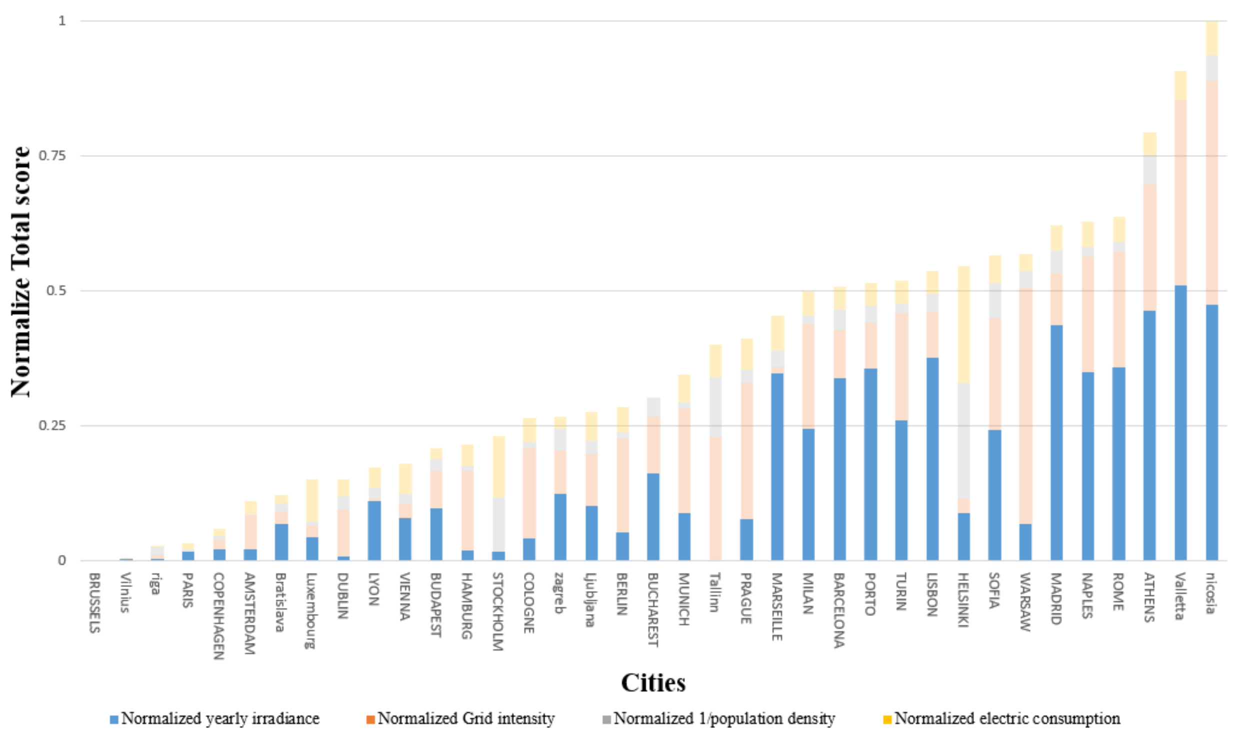


Fig 13. Share of yearly irradiation in normalized total score of European cities.

Impact of Grid Intensity on the Final Score

The grid intensity parameter (orange segment in the graph) represents the carbon footprint of electricity generation, significantly influencing the renewable energy feasibility of each city.

Cities with low grid intensity, such as Paris, Stockholm, and Helsinki, gain a competitive advantage in renewable energy transition, even when solar irradiance is moderate or low. On the other hand, cities with high solar potential but dirty electricity grids, such as Valletta and Nicosia, experience a reduction in their total score.

Cities that suffer the most from high grid intensity include Warsaw and Prague, where the heavy reliance on coal-based power generation lowers their ranking. The strongest-ranked cities, such as Madrid and Lisbon, benefit from both solar potential and relatively moderate grid intensity, positioning them higher in the final ranking.

Reducing grid intensity is a key policy priority for cities aiming to maximize renewable energy integration. Cities with high solar potential but carbon-intensive grids (e.g., Valletta, Nicosia) face challenges in sustainability, while those with clean grids (e.g., Stockholm, Paris) enhance their renewable energy feasibility.

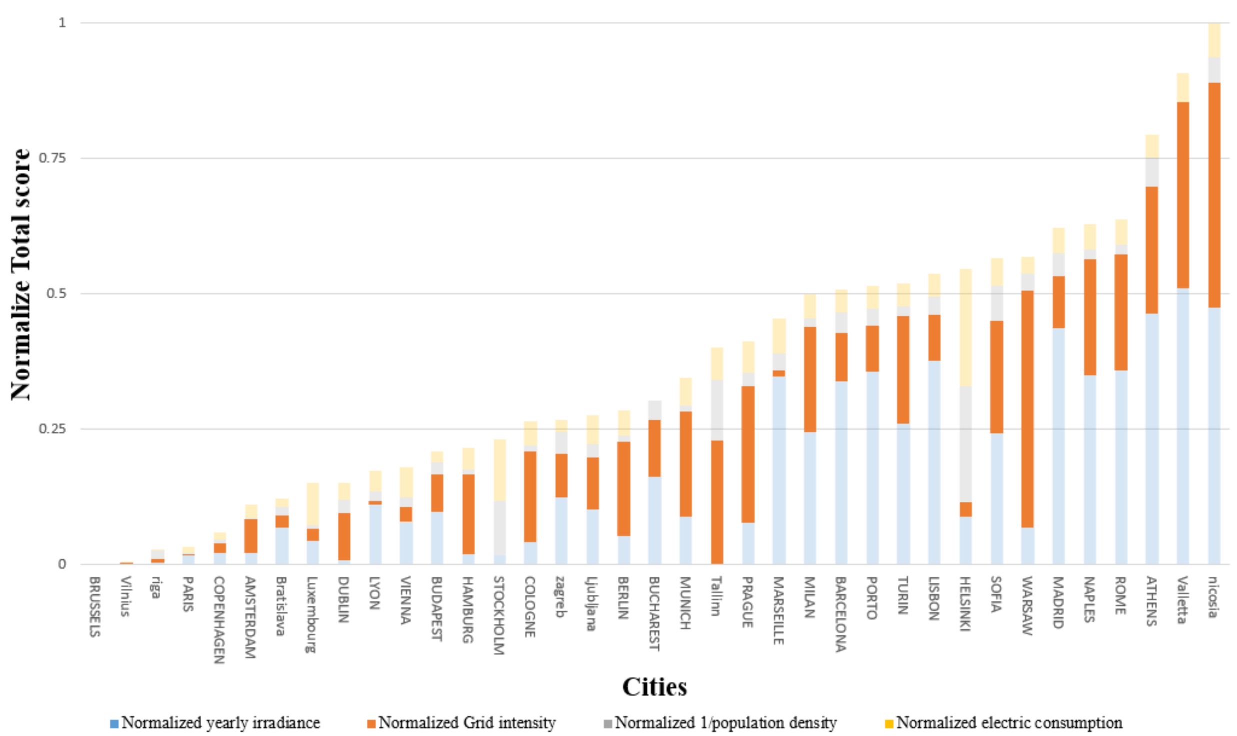


Fig 14. Share of grid intersity in normalized total score of European cities.

Impact of Inverse Population Density on the Final Score

The inverse population density parameter (gray segment in the graph) plays a critical role in determining land availability for large-scale renewable projects. Cities such as Rome, Zagreb, and Sofia benefit from higher inverse population density, meaning they have more available land for solar and wind farms. This increases their total score and makes them attractive locations for large-scale renewable energy deployment.

Conversely, compact urban centers like Paris, Amsterdam, and Copenhagen have low inverse population density values, indicating limited land availability for large-scale projects. These cities must rely on alternative renewable energy strategies, such as rooftop solar panels and energy efficiency measures.

Land availability plays a crucial role in renewable energy planning. Cities with lower population density can accommodate large-scale projects, whereas high-density cities must focus on innovative urban renewable energy integration.

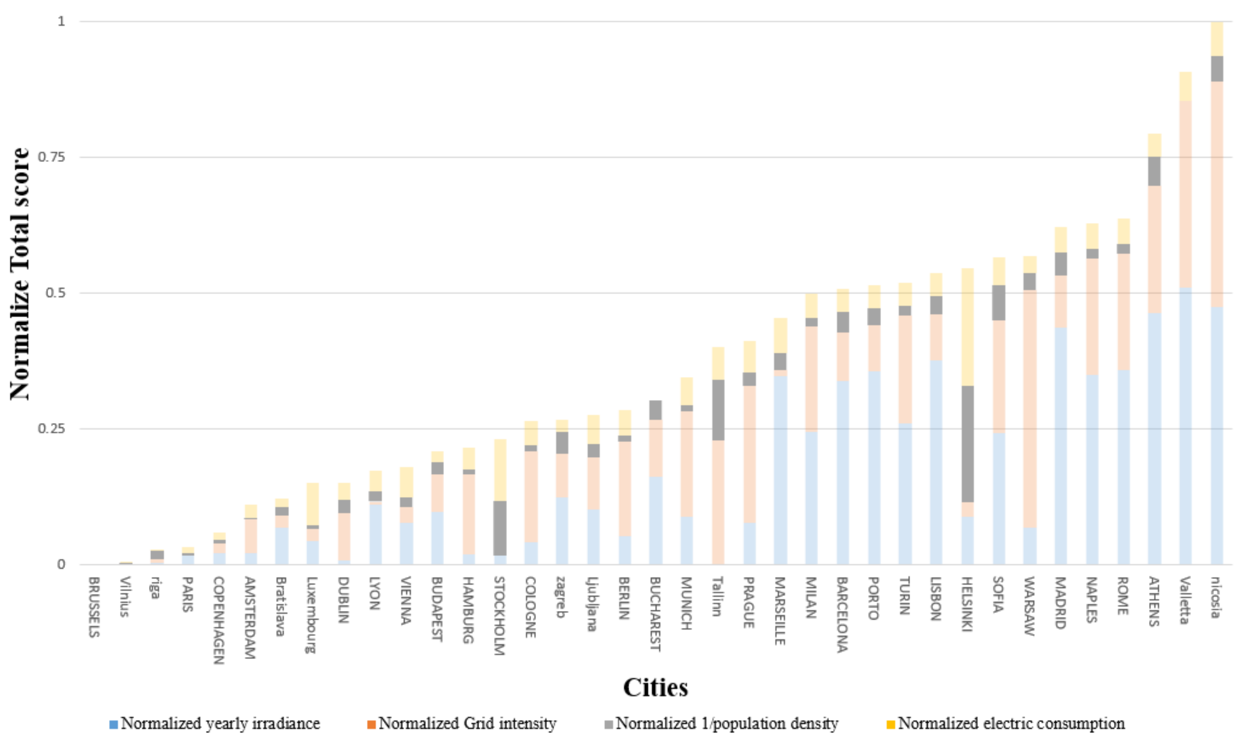


Fig 15. Share of reverse of population density in normalized total score of European cities.

Impact of Electricity Consumption on the Final Score

The electricity consumption parameter (yellow segment in the graph) is an indicator of energy demand per capita. The higher the consumption, the greater the need for renewable energy expansion.

Cities with high electricity consumption, such as Helsinki, Warsaw, and Sofia, require greater renewable energy investments to offset fossil fuel use. Meanwhile, cities with lower energy consumption, such as Paris and Dublin, benefit from energy efficiency policies, reducing the need for large-scale additional power generation.

One of the most challenging scenarios is for cities with high energy consumption and high grid intensity, such as Warsaw and Sofia. These cities face significant obstacles in reducing carbon emissions, emphasizing the need for urgent grid decarbonization and energy efficiency improvements.

Cities with high electricity consumption must prioritize renewable energy expansion, while low-consumption cities should enhance energy efficiency to optimize their sustainability strategy.

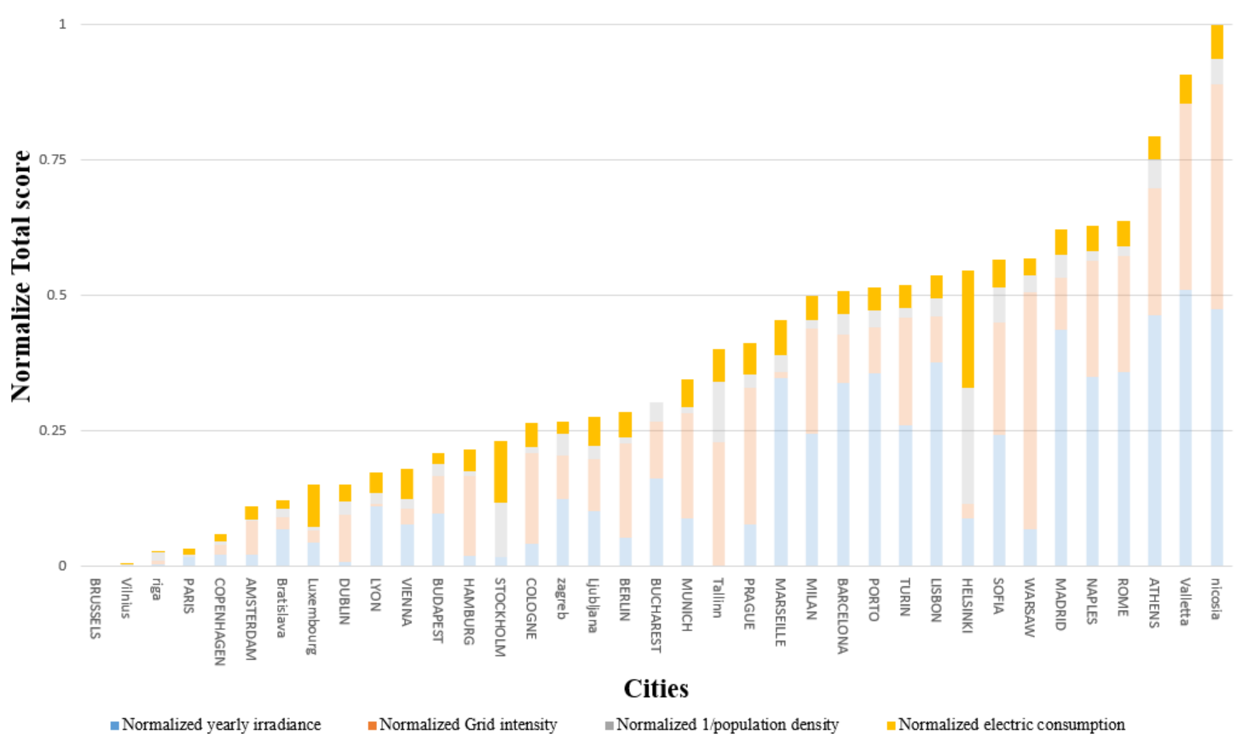


Fig 16. Share of electric consumption in normalized total score of European cities.

Final Integration of All Parameters and City Rankings

The stacked bar chart confirms that no single parameter alone determines a city's renewable energy feasibility. Instead, the combination of solar irradiance, grid intensity, land availability, and energy consumption collectively shape the final ranking.

Cities with strong solar irradiance and moderate grid intensity rank the highest (e.g., Athens, Madrid, Lisbon). Cities with high solar potential but poor grid intensity struggle to achieve top scores (e.g., Valletta, Nicosia). Cities with clean electricity grids compensate for lower solar irradiance, achieving strong rankings despite limited solar energy potential (e.g., Stockholm, Paris).

The final renewable energy potential ranking reflects a complex interaction of multiple factors. High solar potential enhances a city's feasibility for renewables, but it must be supported by a clean grid, available land, and sustainable energy consumption patterns.

3.5 Embodied Carbon Intensity Calculation

Life-Cycle assessment of photovoltaic technologies

Life Cycle Assessment (LCA) enables us to take into account life cycle stages, from cradle to grave, in measuring environmental and resource sustainability. There has been continuous and remarkable progress in photovoltaic (PV) technologies during the last two decades as governments and the industry stepped up investments in solar energy. Economies of scale and improvements in material utilization and process and module efficiencies have contributed to drastic reductions in production costs and to lower environmental footprints (IEA PVPS, 2020).

The ISO 14040- and 14044-standards provide the framework for LCA. However, this framework leaves the individual practitioner with a range of choices that can affect the results and thus the conclusions of an LCA study (IEA PVPS, 2020). As with many LCA applications, variations in methodologies, system boundaries, and underlying assumptions can lead to significant discrepancies in results. To establish a consistent framework for comparison, the IEA Photovoltaic Power System Programme (PVPS) has developed standardized methodologies for life-cycle and energy analysis. These guidelines emphasize the need for a precise definition of assumptions when conducting LCA studies on PV systems. Several key factors can influence the outcome of these analyses, including:

•The timeframe of the data used in the assessment, which impacts the relevance and accuracy of the results.

•The specific life-cycle stages considered, as different studies may include or exclude various phases such as raw material extraction, manufacturing, installation, operation, and end-of-life disposal.

•The country of origin of PV manufacturing components, since production emissions and energy inputs vary by region.

•The electricity mix used in the production process, as the carbon intensity of the grid supplying electricity to PV manufacturing significantly affects the overall environmental impact.

Tools for life-cycle assessment of photovoltaic systems

Several tools have been developed to assess the life-cycle emissions of photovoltaic (PV) systems, each offering distinct analytical capabilities. Notably, PARASOL-LCA and ENVI-PV are among the most recognized tools for conducting comprehensive LCA studies on PV technologies. These tools provide valuable insights into the environmental impact of PV systems by evaluating emissions across various life-cycle stages. Additionally, while PVGIS does not directly assess LCA emissions, it serves as a useful resource for estimating PV system performance, making it a valuable tool for preliminary evaluations of solar energy potential.

PARASOL-LCA is a customized Life Cycle Assessment (LCA) model developed specifically for silicon-based photovoltaic (PV) systems, addressing the limitations of outdated life-cycle inventory (LCI) data in environmental impact assessments. While photovoltaic energy is a renewable and sustainable electricity source, its manufacturing, maintenance, dismantling, and recycling require significant energy and material inputs, leading to associated carbon emissions. Traditionally, the carbon footprint of silicon-based PV electricity has been estimated between 40 and 110 gCO_2eq/kWh. However, these estimates often rely on LCI datasets from early-stage PV technologies, which fail to reflect the rapid advancements in efficiency and manufacturing processes within the PV industry. PARASOL-LCA was developed to parametrize LCI data, ensuring that assessments better represent current and emerging PV technologies. The model demonstrates that using outdated datasets can lead to a significant overestimation of environmental impacts, sometimes by a factor of two or more. Recent findings using PARASOL-LCA indicate that the carbon footprint of modern PV electricity has decreased substantially, from 70 gCO_2eq/kWh to a revised range of 15–30 gCO_2eq/kWh, reflecting technological progress in solar cell efficiency, manufacturing processes, and supply chain optimizations. Furthermore, the model incorporates multicriteria sensitivity analysis, identifying key strategies for further reducing environmental impacts, making it an essential tool for assessing the future sustainability of PV technologies (IEA PVPS, 2020) . The tool, developed in the python environment, is available as a Jupyter notebook, but a handy web interface with part of its functionalities has also been made available.

ENVI-PV is an interactive, web-based tool designed to assess the current and future environmental performance of photovoltaic (PV) systems on a global scale. As solar photovoltaics continue to expand—projected to reach 4674 GW by 2050—minimizing their environmental footprint becomes increasingly critical. ENVI-PV enables decision-makers to evaluate the life-cycle environmental impacts of PV technologies, considering factors such as production, transportation, and electricity generation. The tool integrates state-of-the-art life-cycle inventories (LCIs) developed by TREEZE within the framework of IEA PVPS Task 12, along with solar irradiation estimates derived from NASA's SSE database. It provides spatially resolved maps comparing the environmental footprint of different PV technologies with national electricity mixes, allowing users to assess regional variations in environmental performance. By utilizing multi-criteria assessment, ENVI-PV offers a screening-level analysis of both current and prospective scenarios (2050), enabling users to identify optimal PV deployment strategies based on location-specific techno-economic factors (Perez-lopez et al., 2017).

The **PVGIS** software is a freely accessible tool designed to estimate the energy output of photovoltaic (PV) systems installed at various locations worldwide. This tool is available through a GIS-based web interface, allowing users to customize PV system configurations within a defined range of parameters. Users can specify installation site characteristics, PV technology type, mounting configurations, and system losses to tailor the assessment to their specific needs. PVGIS generates energy production estimates for the selected PV system at different temporal resolutions, including yearly, monthly, and hourly outputs, making it a valuable resource for evaluating the performance of PV installations under diverse environmental conditions.

Photovoltaics-specific aspects

Life expectancy

The recommended life expectancy used in life cycle assessments of photovoltaic components and systems differentiates between the components:

• Modules: 30 years for mature module technologies (e.g., glass-glass or glass-Tedlar backsheet) used in ground mounted, building attached and building integrated PV modules. life expectancy may be lower for foil-only encapsulation; this life expectancy is based on typical PV module warranties (i.e., 20 % or less efficiency degradation after 25 years) and the expectation that modules last beyond their warranties (IEA PVPS, 2020).

• Inverters: 15 years for small plants (residential PV); 30 years with 10 % part replacement every 10 years (the parts that are assumed to be replaced need to be specified) for large size plants utility PV (IEA PVPS, 2020);

• Transformers: 30 years;

• Mounting and supporting structures: 30 years for building attached roof-top and façade installations, and between 30 to 60 years for building integrated installations and for ground-mount installations on metal supports. Sensitivity analyses should be carried out by varying the service life of the ground-mount supporting structures within the same time span (IEA PVPS, 2020).

Irradiation

The irradiation collected by modules depends on their location and orientation. Depending on the goal of the study, four main recommendations are given:

• Analysis of systems based on average technologies or on specific products: Assume for all ground-mounted systems that the panels on an array plane are optimally oriented and tilted at angles equal to the latitude (except when a specific system under study is laid out differently, which should be reported). Also, assume that roof-top installations are optimally oriented and tilted. Assume either optimally oriented or case-specific orientation of panels of façade systems. Additionally, 1-axis tracking systems may be assumed. All assumptions, especially deviations from these general recommendations, should be reported (IEA PVPS, 2020).

• Analysis of the average of installed systems in a grid network: The average actual orientation, shading and irradiation should be used;

• Analysis of building-integrated PV systems in a given building context: annual irradiation incident on the PV surface should be determined using state-of-the-art modelling software (the choice of software may depend on the planning stage of the building);

• Analysis of bifacial PV modules: annual irradiation, in particular the additional irradiation on the backside, should be determined using state-of-the-art modelling software (IEA PVPS, 2020).

Performance ratio

The performance ratio (PR) is defined by IEC 61724 as the ratio between the system's final yield (actual AC generation) and the reference or ideal yield (DC rated performance) and is widely used as a performance metric to quantify the overall system losses due to temperature effects, soiling, shading and inefficiency of its components. In general, PR increases with 1) decline in temperature and 2) early monitoring of PV systems to detect and rectify defects. Shading, if any, and soiling would have an adverse effect on PR. This means that welldesigned, well-ventilated, well-maintained, and large-scale systems generally have a higher PR. Average annual PR data collected from many residential systems show an upward trend from typical 0.7 in the 1990'ies with widely ranging values, to current values between 0.8 and 0.9 with less variance (Fraunhofer ISE 2019).

Using either site-specific PR values or a default value of 0.75 is recommended for roof-top installations and 0.80 for ground-mounted utility installations (Fthenakis et al. 2008; Mason et al. 2006; Pfatischer 2008); these default values include degradation caused by age. The performance ratio of building-integrated PV systems and bifacial PV panels should be determined individually for each application, due to the impacts of irradiance for each case and the changes in DC:AC ratios that these systems might require. When site-specific PR values are used based on performance from previous years, degradation-related losses should be added to longer-term projections of the performance (IEA PVPS, 2020).

It is recommended to use actual performance data (actual energy yield in kWh per kWp) of installed technology whenever available or make reasonable assumptions that reflect actual performance data when analyzing the average of installed PV systems in a grid network. This can be aided by the use of PV system modelling software. Such software can calculate the output of the system over the duration of the project, making the calculation of the average PR possible. The PR is used in combination with solar irradiation data to determine actual yields (IEA PVPS, 2020).

Accurately assessing the embodied emissions of photovoltaic systems requires a life-cycle perspective. Life Cycle Assessment (LCA) is widely regarded as the most comprehensive method to evaluate environmental impacts of a product or system across its entire life span.(Leccisi et al., 2016). For PV systems, an LCA accounts for all stages – from raw material extraction and panel manufacturing to transportation, installation, operation, and end-of-life disposal or recycling .(Leccisi et al., 2016) Following ISO 14040/44 standards and photovoltaic-specific guidelines (e.g., IEA PVPS Task 12) ensures methodological consistency. This framework captures "embodied" greenhouse gas emissions – the CO_2-equivalent (CO_2e) emissions that occur during the production and deployment of PV infrastructure – which are then allocated over the electricity generated in the system's lifetime.

Under this LCA approach, the functional unit is often 1 kWh of electricity delivered by the PV system. The total life-cycle CO_2e emissions (from manufacturing through decommissioning) are divided by the expected lifetime electricity output to yield a carbon intensity in gCO_2e/kWh. This metric allows comparison across different energy sources and locations. In early meta-analyses of PV systems, life-cycle carbon intensities ranged widely – from as low as ~5 gCO_2e/kWh up to over 200 gCO_2e/kWh (Besseau, Tannous, Douziech, Jolivet, Julie, et al., 2023). A review of 400 studies reported interquartile ranges of roughly 45–110 gCO_2/kWh for single-crystalline silicon PV and 40–85 g/kWh for multi-crystalline Si, under various assumptions (Besseau, Tannous, Douziech, Jolivet, Julie, et al., 2023). However, much of this variability arose from inconsistent assumptions in those studies. Key factors like solar irradiation, system lifetime, module efficiency, and performance ratio can dramatically affect results; when these parameters are harmonized (e.g. assuming a common irradiance and performance), the spread in reported carbon intensities shrinks by about 65% (Besseau, Tannous, Douziech, Jolivet, Julie, et al., 2023). Under standardized conditions (e.g. Southern European sun and 2012-era technology), a median value around ~50 gCO_2e/kWh was obtained for crystalline-silicon PV(Besseau, Tannous, Douziech, Jolivet, Julie, et al., 2023). This confirms that solar resource and system performance are critical: a PV system in a high-irradiation region will generate more electricity over its lifetime, diluting its embodied emissions per kWh, whereas the same panel in a low-sunlight region yields a higher carbon intensity (since the "carbon cost" is spread over fewer kWh).

Another decisive factor is the energy mix and efficiency of the manufacturing process. PV module production is energy-intensive, so the carbon intensity of the electricity used in manufacturing substantially influences the total embodied emissions (Besseau, Tannous, Douziech, Jolivet, Julie, et al., 2023). For example, manufacturing PV modules in regions with coal-dominated grids leads to a higher embodied CO_2 footprint than manufacturing with cleaner energy (Philipps et al., 2023). Leccisi et al. (2016) demonstrate this by comparing modules made in China versus Europe: a Chinese-produced crystalline silicon module (manufactured with a coal-heavy grid) and then installed in a low-irradiation location can have a life-cycle GHG intensity up to ~80 gCO_2e/kWh, whereas the same module type produced in Europe (with a cleaner grid mix) and/or installed in a high-irradiation location can be as low as ~10–20 gCO_2e/kWh (Leccisi et al., 2016). Indeed, the electricity mix at the production stage can swing results significantly – one analysis finds that PV systems manufactured in Europe (where grids are more efficient and less carbon-intensive) have ~10% shorter energy payback times than if the same systems were made in China(Philipps et al., 2023). This underscores why our methodology explicitly considers the origin of PV modules in its emissions calculations.

Continual improvements in PV technology have been driving down the embodied energy and emissions. Over the past decade, solar panel efficiency has risen from about 15% to over 20% for typical commercial modules, meaning more wattage (and energy output) is obtained per unit of material and manufacturing input. At the same time, manufacturing processes have become more efficient and material usage has been reduced (for instance, the adoption of diamond-wire wafer cutting nearly eliminated the wasteful slurry-based cutting method) (Besseau, Tannous, Douziech, Jolivet, Julie, et al., 2023). These advancements translate directly into lower life-cycle emissions per kWh produced. According to a recent open-source LCA study (PARASOL-LCA), many LCA datasets in use were outdated and did not reflect these improvements. Earlier estimates of 40–110 gCO_2/kWh for PV electricity were based on older technology baselines. When Besseau et al. (2023) updated the life-cycle inventory parameters to current industry data, they found the carbon footprint of modern silicon PV has fallen to roughly 15–30 gCO_2e/kWh for state-of-the-art systems (Besseau, Tannous, Douziech, Jolivet, Julie, et al., 2023). In other words, using legacy LCA data can overestimate PV's climate impact by a factor of two or more . This dramatic reduction is attributed to higher module efficiencies, improvements in silicon purification and module assembly, and supply chain optimizations that have occurred over the last decade (Philipps et al., 2023). Our methodology builds on this up-to-date understanding, using current emission factors for PV components rather than older generic data, to ensure the embodied emissions calculations reflect today's PV industry and not that of a decade ago.

It is important to note that even the highest embodied emissions values for PV are far lower than the life-cycle emissions of fossil-based power. For example, modern PV systems typically emit on the order of a few tens of grams CO_2 per kWh (Leccisi et al., 2016). , whereas electricity from coal can emit ~800–1000 gCO_2/kWh and natural gas around 400–500 gCO_2/kWh when lifecycle emissions are considered (fuel extraction, transport, etc.). Thus, PV offers a clear net emissions benefit in virtually all cases. Still, quantifying the exact carbon intensity of PV in different scenarios is vital for robust climate policy: it helps identify where PV deployment yields the greatest carbon payback and how supply chain choices (like sourcing modules from lower-carbon manufacturers) could further improve outcomes.

Embodied emission calculation

Traditional life cycle assessments (LCA) of photovoltaic (PV) systems have played a significant role in evaluating the environmental impacts of solar electricity generation. These studies typically rely on fixed, historical life cycle inventory (LCI) datasets, often based on data that may no longer represent current industry practices. For example, the well-known IPCC meta-analysis reviewed over 400 PV studies and reported carbon footprint values ranging from 5 to 217 gCO_2eq/kWh(Edenhofer et al., 2011). However, this analysis — and many of the studies it includes — relied on LCI data that predates 2012 (Besseau, Tannous, Douziech, Jolivet, Prieur-Vernat, et al., 2023). Since then, the PV industry has undergone substantial changes, with module costs dropping by a factor of 10, driven largely by improvements in module efficiency and silicon production technologies(Fu et al., 2018). Yet, many widely used databases such as ecoinvent still represent PV performance as of 2005, thereby misrepresenting the actual environmental performance of today's PV systems(Wernet et al., 2016).

In addition, conventional LCAs often place strong emphasis on a few output-related parameters — such as module efficiency, irradiation level, and lifetime — while overlooking upstream improvements in manufacturing efficiency, material inputs, or technology evolution. These approaches also tend to assess only a narrow set of impact categories, focusing heavily on carbon footprint, while neglecting other environmental dimensions such as acidification potential or resource use. The lack of flexible, up-to-date, and multi-criteria modeling capabilities leads to results that are static, outdated, and potentially misleading for eco-design and policy-making(Besseau, Tannous, Douziech, Jolivet, Prieur-Vernat, et al., 2023).

To overcome these limitations, the PARASOL_LCA model introduces a parameterized and open-source framework that allows for the dynamic customization of input variables. Unlike traditional models that require rebuilding the entire LCI when new data or assumptions are introduced, PARASOL_LCA enables users to vary a wide range of parameters — including electricity mix, wafer slicing efficiency, silicon purification energy, material intensity, and more — through a single interface. This flexibility allows for the rapid assessment of not only current configurations, but also future, prospective scenarios, making it highly valuable for stakeholders engaged in eco-design and technology planning.

Moreover, PARASOL_LCA is not limited to production-side assumptions. It expands the scope of parametrization beyond electricity generation and includes manufacturing-level innovations, such as changes in energy intensity per kg of silicon or efficiency gains in wafer production. This holistic view ensures that environmental performance reflects real-world technological progress. It also facilitates uncertainty and sensitivity analysis by allowing users to sample parameter values from distributions, which makes the model robust and adaptable to a range of conditions and assumptions.

Importantly, the model is designed to be open-source, user-friendly, and reproducible. Its core objective is to provide an LCA tool that is not only rigorous and multi-dimensional, but also fast and transparent, removing the typical barriers associated with time-consuming and non-transparent LCI construction. This is particularly critical given that industrial data is often inaccessible due to confidentiality, and primary data collection can be costly and labor-intensive.

For the calculation of carbon intensity (CI), the PARASOL-LCA tool was used. Within this platform, several key parameters are customizable, and were adjusted in line with the specific goals of our project. The following section outlines the selected parameters along with the rationale and modifications applied in our analysis.

Silicon_production_electricity_intensity: This parameter represents the amount of electricity (in kWh per kg) required to transform metallurgical-grade silicon into solar-grade crystalline silicon, which is used in photovoltaic (PV) modules. In earlier life cycle assessment (LCA) databases such as ecoinvent, the total electricity consumption for this transformation process was estimated to be very high, reaching up to 195 kWh per kg of silicon. This figure included around 110 kWh/kg for the purification of silicon and an additional 85 kWh/kg for crystallization. However, such estimates are now outdated, as significant technological improvements have taken place in the PV industry over the last decade. In particular, the adoption of fluidized bed reactor (FBR) technologies by some manufacturers has drastically reduced electricity consumption to around 30–40 kWh/kg, with some certified production processes—such as those reported by REC Solar—achieving values as low as 11 kWh/kg(Woodhouse et al., 2019).

These variations underscore the importance of using a flexible and adaptable model to account for a broad range of industrial practices and technological efficiencies. The PARASOL-LCA tool integrates this parameter into its simulation environment as a customizable and highly sensitive variable. Rather than relying on a single fixed value, the tool allows users to either input a specific number or use a statistical distribution, which reflects the real-world variability of electricity consumption in silicon production. In the interactive web version of the model, the default setting for this parameter is a distribution ranging approximately from 20 to 100 kWh/kg, with a mode (most likely value) around 40–45 kWh/kg. This approach makes it possible to perform uncertainty analysis through Monte Carlo simulations, leading to a more robust estimation of environmental impacts. By using the distribution mode, the carbon footprint calculation reflects not just one hypothetical manufacturing scenario but a spectrum of possibilities—from energy-efficient to energy-intensive processes.

When the electricity mix is set to a country with a carbon-intensive grid such as China, the impact of this parameter becomes even more significant.

According to the sensitivity analysis presented in the article, this specific parameter alone accounts for 26% of the total variation in the final carbon footprint result(Besseau, Tannous, Douziech, Jolivet, Prieur-Vernat, et al., 2023).

Module Efficiency: The amount of electrical power output (in kWp) per square meter of installed module area (kWp/m²). This essentially reflects how much sunlight the module can convert into electricity.

The module efficiency is a key driver in determining the environmental performance of PV systems. Higher efficiency modules convert more sunlight into electricity per unit area, meaning that for a given energy output over the system's lifetime, fewer materials and manufacturing energy are required, ultimately leading to a lower carbon footprint per kilowatt-hour produced. The module efficiency is a parameterized input in the PARASOL-LCA model and states that it plays a significant role in reducing environmental impacts when improved.

PV panel's efficiency has also remarkably evolved over time. The ecoinvent datasets consider around 12% efficiency, whereas recent commercialized PV panels can reach 20% efficiency, with a maximum of 22.8% for already commercialized products. PARASOL_LCA therefore includes the PV panel's efficiency ('PV_module_efficiency') as additional parameter. Based on current technologies available in the market, the model assumes a typical efficiency range between 16% and 22% (i.e., 0.16–0.22 kWp/m²). The most likely values are centered around 18% (i.e., 0.18). This distribution accounts for the variability across different PV technologies, ranging from older, less efficient modules to modern high-efficiency monocrystalline ones.

The Fraunhofer report states that in Q4 2022, the average efficiency of crystalline silicon (c-Si) wafer-based PV modules was 20.9%, with values ranging from 17.2% to 23.2%, based on total shipments. This aligns well with the PARASOL_LCA model, which uses a similar efficiency range (approximately 16%–22%) as a distribution input for module efficiency, confirming its relevance and realism in modeling current commercial technologies.

In PARASOL-LCA's web interface, this parameter is again defined as a distribution rather than a fixed value, allowing the model to simulate various real-world scenarios using Monte Carlo simulations. When efficiency is lower, the system must use more modules (and thus more materials and energy) to deliver the same energy output over its lifetime. Consequently, carbon emissions per kWh increase. Conversely, higher efficiency means a lower material and energy footprint per unit of energy produced, which directly lowers the numerator in the carbon intensity (CI) calculation.

Electricity mix: Electricity mix refers to the source and composition of electricity used during the manufacturing of PV modules. This includes what proportion of electricity is generated from coal, natural gas, nuclear, hydro, solar, etc. Since electricity generation is a major contributor to greenhouse gas emissions in PV production (especially in silicon processing), the carbon intensity of this electricity — which depends on the country — becomes a key factor in calculating the overall carbon footprint of solar panels.

According to Fraunhofer report in 2021, producers from Asia accounted for 94% of total c-Si PV module production, with China holding a 75% share. Europe contributed only 1%. For this reason, the emission profile from China has been used as proxy for the production in Asia and therefore used for the estimation of the embodied emissions of the PV panels (Philipps et al., 2023). electricity mix parameter is fixed to China to align with real-world supply chains. Most PV modules deployed in Europe are manufactured in China, where the electricity grid is heavily fossil-fuel-based, especially coal. Therefore, assuming a Chinese electricity mix introduces higher carbon intensity values during the production phase — resulting in a more conservative (i.e. higher) carbon footprint estimate.

Wafer manufacturing efficiency gain: This parameter represents the efficiency improvements in wafer manufacturing, particularly in terms of reduced electricity consumption per wafer. It is expressed as a fraction — from 0 (no gain) to 1 (100% gain).

Regarding the climate change impact, apart from the parameters determining the amount of electricity produced over the lifetime of the PV panel, the amount of electricity used to produce the silicon wafer ('Silicon production electricity intensity') and the carbon content of the electricity mix used ('Electricity mix CO2 content') throughout the systems' lifecycle are also key parameters(Besseau, Tannous, Douziech, Jolivet, Prieur-Vernat, et al., 2023).

this parameter reflects recent technological improvements in the wafer production step of PV manufacturing. Wafer manufacturing is highly energy-intensive, especially during the crystallization and slicing phases. Over the past decade, manufacturers have introduced techniques like diamond wire sawing and improved slicing yields, leading to a reduction in material waste and electricity use.

This parameter reflects technological improvements in wafer manufacturing that reduce electricity demand. In the PARASOL-LCA model, it is defined as a fractional gain (from 0 to 1), and the web interface uses a probability distribution to simulate variability in how much efficiency has been gained. As a result, this parameter helps lower the total carbon footprint, especially when electricity sources are carbon-intensive. According to the article, wafer efficiency gain accounts for 13% of the uncertainty in the final carbon footprint estimates.

The PVGIS tool was used to extract yearly PV energy production for each city, considering:

- System loss: 20%
- Installed power per unit: 1 kWp
- Azimuth: 0°
- Optimized slope for each location

These parameters ensure consistency across all selected cities, allowing for a fair comparison of embodied emissions per kilowatt-hour of generated electricity across different PV potential zones. By standardizing these variables, the analysis provides a reliable framework for assessing the sustainability of PV deployment in diverse European urban contexts.

$$CI_{pv\,elc}\left[\frac{gCO_{2eq}}{kWh}\right] = \frac{CI_{pv}\left[\frac{gCO_{2eq}}{kWp}\right]}{\sum_{i}^{L} P_{elc,i}\left[\frac{kWh}{kWp \cdot year}\right]}$$

Where:

- CI_{pv} : total emissions occurring in the production, distribution and operations stages of the life of the various components of the PV system.
- P_{elc} : electricity produced by a 1-kWp PV system in one year.
- L : lifetime of the PV system. This was assumed to be 25 years for all configurations.

By computing average embodied emissions per category, this research provides a more accurate representation of the true environmental benefits of PV deployment across Europe.

The relationship between latitude and carbon intensity is visualized in the provided bubble chart, while the box plot analysis categorizes carbon intensity distribution across three latitude-based regions.

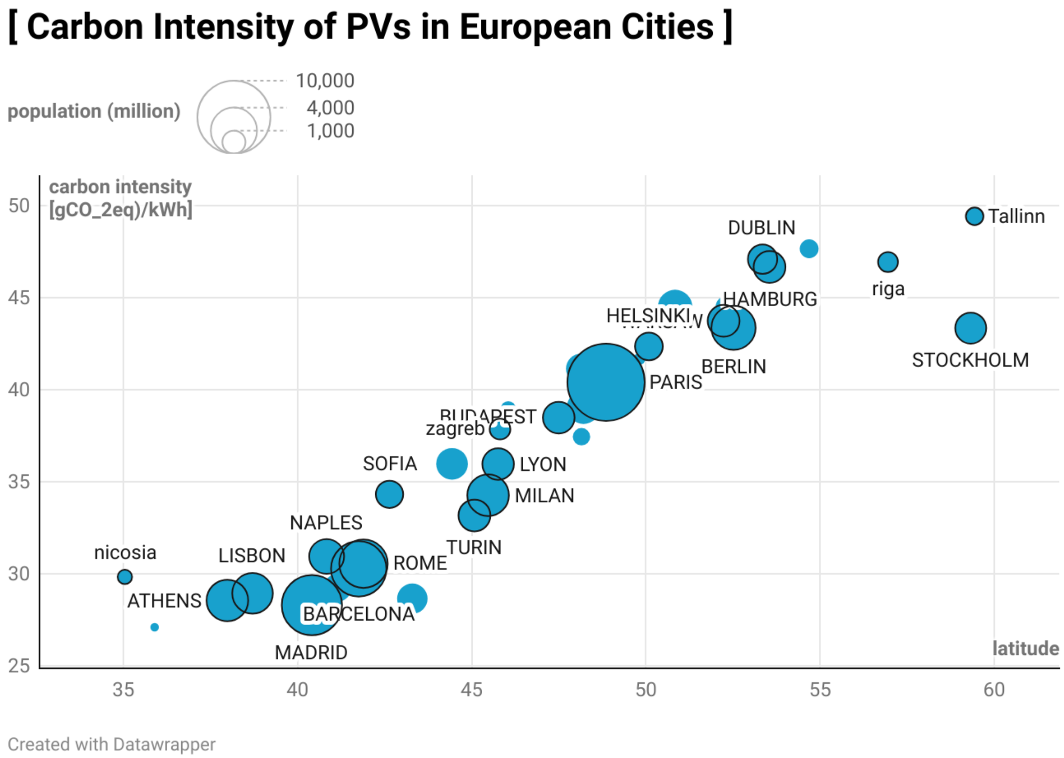


Fig 17. carbon intensity of PVs in European cities

The bubble chart illustrates the relationship between latitude and the carbon intensity of photovoltaic (PV) installations in various European cities. The size of each bubble represents the population of the corresponding city. The PV modules used in these cities were imported from China, meaning that during their manufacturing and transportation, they contributed to carbon emissions. However, once installed, their carbon intensity depends on the amount of electricity they generate, which varies with latitude.

Since solar irradiance levels change based on geographic location, PV panels installed at different latitudes produce varying amounts of electricity. In regions with higher solar potential (lower latitudes), PV systems generate more electricity, effectively distributing the embodied emissions over a larger energy output, leading to a lower carbon intensity. Conversely, in northern cities with lower solar exposure, PV systems produce less electricity, resulting in a higher carbon intensity as the same embodied emissions are spread over a smaller energy output.

From the chart, a clear trend is observable: carbon intensity tends to increase with latitude. Cities such as Athens, Nicosia, and Barcelona, located in southern Europe, exhibit lower carbon intensity values, likely due to higher solar irradiance and greater energy production from PV systems. On the other hand, northern cities like Tallinn, Stockholm, and Riga show significantly higher carbon intensity values. This suggests that PV modules in these regions are less efficient in energy generation due to lower solar exposure, making the relative environmental impact of their embodied emissions greater.

Larger cities like Paris, Berlin, and Helsinki are positioned in mid-to-high latitudes and show moderate-to-high carbon intensity values. Their energy mix and urban energy demand may also influence these values, along with latitude. Some cities, such as Dublin and Hamburg, appear as outliers with higher carbon intensity than other cities at similar latitudes, which could be attributed to specific climate conditions or local energy policies.

Overall, this graph highlights the crucial role of geographic location in determining the effectiveness of PV installations in reducing carbon emissions. While PV modules inherently contribute to carbon emissions during production, their actual environmental impact depends on where they are installed and how much electricity they generate. Policymakers and energy planners should consider these geographic variations when promoting solar energy deployment in Europe to maximize efficiency and minimize environmental costs.

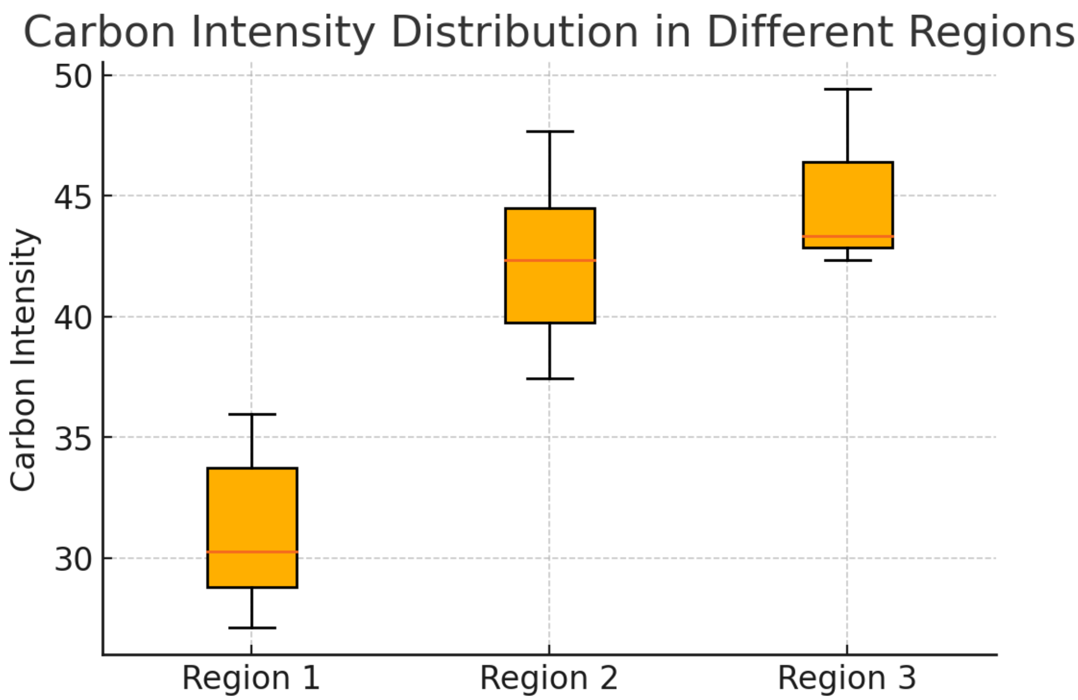


Fig 18. carbon intensity of PVs distribution in different regions in Europe

The boxplot represents the distribution of carbon intensity across three geographic regions in Europe, categorized based on latitude. The dataset used for this visualization was previously analyzed, and the three regions are divided as follows:

- Region 1: Latitudes between 34°N and 46.67°N
- Region 2: Latitudes between 46.67°N and 58.33°N
- Region 3: Latitudes between 58.33°N and 70.00°N

Summary Statistics for Each Region

The boxplot provides key insights into the minimum, maximum, median, and distribution of carbon intensity values for each region:

Region 1 (Southern Europe)

- Minimum Carbon Intensity: ~27 gCO_2eq/kWh
- Maximum Carbon Intensity: ~36 gCO_2eq/kWh
- Median (Q2 - 50th Percentile): ~30 gCO_2eq/kWh
- Mean (Average): ~31 gCO_2eq/kWh
- Interquartile Range (IQR - 25th to 75th percentile): ~28 to 34 gCO_2eq/kWh
- Outliers: No significant outliers.

Region 2 (Central Europe)

- Minimum Carbon Intensity: ~37 gCO_2eq/kWh
- Maximum Carbon Intensity: ~47 gCO_2eq/kWh
- Median (Q2 - 50th Percentile): ~42 gCO_2eq/kWh
- Mean (Average): ~42.56 gCO_2eq/kWh
- Interquartile Range (IQR - 25th to 75th percentile): ~39 to 45 gCO_2eq/kWh
- Outliers: No major outliers observed.

Region 3 (Northern Europe)

- Minimum Carbon Intensity: ~42 gCO_2eq/kWh
- Maximum Carbon Intensity: ~49 gCO_2eq/kW
- Median (Q2 - 50th Percentile): ~44 gCO_2eq/kWh
- Mean (Average): ~45 gCO_2eq/kWh
- Interquartile Range (IQR - 25th to 75th percentile): ~43 to 47 gCO_2eq/kWh
- Outliers: A possible high outlier close to 49 gCO_2eq/kWh.

In analyzing boxplots, the position of the mean relative to the interquartile range (IQR) can reveal important insights into data distribution:

- If the mean is lower than the median (50% range of data): The data is left-skewed (negatively skewed), meaning that most values are higher, but a few significantly lower values are pulling the mean downward. This could indicate that a majority of cities have higher carbon intensity, but a few with low emissions influence the overall mean.
- If the mean is higher than the median: The data is right-skewed (positively skewed), meaning that most values are lower, but a few extremely high values are increasing the

mean. This scenario suggests that a few cities have exceptionally high carbon emissions compared to the rest.

- If the mean is close to the median: The data is approximately symmetrically distributed, meaning carbon intensity is fairly balanced across cities in that region.

Regional Observations

Region 1: The average carbon intensity (31.08 gCO2eq/kWh) lies within the interquartile range. If it is positioned lower than the median, this suggests that many cities have lower emissions, but a few high-carbon-intensity cities are skewing the mean.

Region 2: The average carbon intensity (42.56 gCO2eq/kWh) suggests a balanced distribution, but if lower than the median, it indicates that most cities have lower emissions while a few have extremely high emissions.

Region 3: With an average carbon intensity of 45.04 gCO2eq/kWh, if the mean is below the median, this means that while a few cities have significantly high emissions, most cities in this region have relatively lower emissions.

The distribution of carbon intensity data in different regions provides key insights into the relationship between latitude and emissions. In Region 1, the data distribution is slightly right-skewed, meaning that a few cities have higher-than-average carbon intensity while most maintain lower values. This suggests that while the general trend in the region is toward low emissions, some urban centers or industrial areas may exhibit significantly higher carbon intensity.

In Region 2, the distribution is more balanced, with the mean and median values closely aligned. This indicates that carbon intensity in this region is fairly evenly distributed, meaning that most cities share similar energy characteristics, likely due to a mix of solar exposure and diversified energy sources.

Region 3 exhibits a stronger right-skewed distribution, meaning that while most cities have a moderate level of carbon intensity, a few exhibit extremely high values, pulling the mean upwards. This suggests that in the northernmost areas, certain locations have inefficient energy production, leading to significantly higher emissions.

This analysis highlights the variation in carbon intensity across European regions and its underlying factors. Additionally, the relationship between the mean and the interquartile range of carbon intensity distributions indicates whether certain cities are significantly influencing overall regional averages. The skewness of the data distribution provides meaningful insights: right-skewed distributions in Region 1 and Region 3 suggest that a small number of high-emission cities drive up the mean, while a more balanced distribution in Region 2 indicates that emissions are relatively uniform across cities. This trend aligns with the expected variation in solar potential and energy policies across Europe. Policymakers can use these insights to design strategies for reducing emissions and improving PV deployment in higher-latitude regions.

4. The EU photovoltaic market

A significant portion of the PV modules installed in Europe are imported from regions with high-carbon electricity grids, such as China, where coal is still a dominant energy source for manufacturing. According to the Fraunhofer ISE report, Asia accounted for 93% of global PV module production in 2021, with China alone producing 75%. This means that while PV technology is enabling a cleaner energy transition in Europe, a substantial hidden carbon footprint is embedded in the lifecycle of these panels, making it necessary to reassess the sustainability of current PV expansion plans (Philipps et al., 2023).

The Role of Photovoltaics in Europe's Energy Transition

The European Union has committed to achieving carbon neutrality by 2050, and photovoltaics (PV) are at the core of its renewable energy strategy. As a scalable and increasingly cost-effective technology, solar PV provides a sustainable solution for reducing greenhouse gas (GHG) emissions across multiple sectors, including industrial processes and transportation. The aviation sector, one of the most challenging industries to decarbonize, is exploring alternative fuels such as Sustainable Aviation Fuels (SAFs) and synthetic e-fuels. Both rely heavily on electricity, making the availability of low-carbon energy sources a crucial factor in determining their environmental and economic feasibility. Given the high energy demand for hydrogen electrolysis, direct air carbon capture, and fuel synthesis, PV-generated electricity is a key enabler of aviation decarbonization. The geographical siting of PV infrastructure across Europe will directly impact the cost, efficiency, and sustainability of fuel production (Philipps et al., 2023).

The Growth and Current State of the EU Photovoltaic Market

Over the last two decades, the European PV sector has experienced exponential growth, driven by technological advancements, supportive policies, and declining costs. In 2022, the EU's cumulative installed PV capacity surpassed 200 GW, reflecting a significant expansion from 16 GW in 2010. The largest contributors to this growth include Germany, Spain, Italy, and France, which collectively account for the majority of PV installations. The sector's expansion aligns with the European Commission's RePowerEU Plan, which aims to double PV capacity to 600 GW by 2030 to strengthen energy security and reduce reliance on fossil fuels. This rapid development has been enabled by falling costs, with solar panel prices dropping by over 80% since 2010, making PV one of the most competitive energy sources in Europe. The levelized cost of electricity (LCOE) for PV has reached as low as €30/MWh in some regions, further reinforcing its viability as a primary energy source for SAF and e-fuel production (Philipps et al., 2023).

Technological Advancements and Efficiency Improvements

Photovoltaic technology has undergone continuous advancements, improving energy conversion efficiency and reducing system costs. Over the past decade, commercial solar cell efficiency has increased from 15% to over 22%, with next-generation technologies such as tandem perovskite-silicon cells expected to exceed 30% efficiency in the coming years. The performance ratio (PR) of PV systems, which measures their actual energy output relative to theoretical maximum performance, varies by region. Southern European countries such as Spain and Italy achieve PR values above 85%, whereas Northern Europe, due to lower solar radiation levels, has

PR values between 75% and 80%. However, advancements in bifacial panels, smart inverters, and energy storage systems are optimizing PV system performance, ensuring that solar power remains viable even in less sunny regions (Philipps et al., 2023).

Energy Payback Time (EPBT) and Carbon Footprint of PV Systems

One of the critical advantages of PV technology is its low energy payback time (EPBT), referring to the duration required for a solar system to generate the energy used in its production. In the EU, modern PV systems have an EPBT of 1–3 years, depending on geographic location and system efficiency. Once installed, PV panels operate for 25–30 years, producing emissions-free electricity for the majority of their lifespan. In terms of life-cycle carbon emissions, PV systems generate between 20–50 gCO_2e/kWh, significantly lower than fossil fuels, which exceed 400 gCO_2e/kWh. The use of solar electricity in SAF and e-fuel production processes dramatically reduces the carbon intensity of aviation fuels, making PV an essential component of sustainable fuel production. As the European electricity grid continues to decarbonize, the emissions associated with PV will decrease further, enhancing its long-term sustainability (Philipps et al., 2023).

Policy Framework and Market Incentives

The European Union has implemented a range of policies to support PV deployment and ensure its integration into industrial applications. The Renewable Energy Directive (RED III) mandates a higher share of renewables in the EU's energy mix, setting ambitious national targets for solar expansion. The Solar Strategy for Europe introduces additional incentives such as streamlined permitting processes, rooftop solar mandates, and investment subsidies. Market-based mechanisms such as Feed-in Tariffs (FiTs), Power Purchase Agreements (PPAs), and Contracts for Difference (CfDs) have encouraged private-sector investment, reducing reliance on government subsidies. Furthermore, carbon pricing through the EU Emissions Trading System (ETS) has made fossil-fuel-based electricity less competitive, accelerating the shift toward solar energy. These regulatory frameworks are essential for supporting the large-scale deployment of PV systems necessary for aviation fuel production and industrial decarbonization (Philipps et al., 2023).

Regional Variations in PV Potential Across Europe

Solar radiation levels across Europe vary significantly, influencing the feasibility of large-scale PV deployment. The highest Global Horizontal Irradiance (GHI) values, exceeding 1,800 $kWh/m^2/year$, are concentrated in Southern Spain (Andalusia), Italy (Sicily, Apulia), Southern France, Greece, and Portugal. These regions offer the most favorable conditions for high-yield PV electricity generation, making them ideal locations for SAF and e-fuel production plants. Conversely, Northern Europe, including Germany, the Netherlands, and Scandinavia, has lower solar radiation levels, typically 800–1,200 $kWh/m^2/year$. However, strong policy support, advanced grid infrastructure, and innovations in energy storage and hybrid PV systems ensure that these regions remain competitive. Selecting optimal locations for PV-powered fuel production is crucial for minimizing energy costs and maximizing environmental benefits (Philipps et al., 2023).

Future Outlook for the EU Photovoltaic Market

The European PV sector is expected to expand further, driven by increased demand for low-carbon electricity and advancements in solar energy storage and grid integration. By 2030, installed PV capacity in the EU is projected to surpass 500 GW, making solar power the dominant electricity source. The transition toward large-scale solar farms dedicated to industrial applications is already underway, with major investments in hybrid systems that integrate PV with battery storage and green hydrogen electrolysis. Additionally, the modernization of cross-border electricity grids will allow for more efficient solar energy distribution across EU member states, optimizing renewable energy utilization. As synthetic aviation fuel production scales up, PV electricity will be instrumental in ensuring that the aviation sector transitions toward full decarbonization (Philipps et al., 2023).

The Role of PV in SAF and e-Fuel Production

The European photovoltaic market is a driving force behind the region's transition to a net-zero economy, providing a scalable and cost-effective source of clean energy. For aviation fuel production, the availability of low-carbon electricity is a decisive factor, influencing both the environmental impact and economic feasibility of SAF and e-fuel technologies. While SAFs provide an immediate, operationally feasible solution, e-fuels require significant long-term energy investments. The strategic siting of fuel production facilities in high solar potential regions is crucial for ensuring their sustainability. This study highlights the need for optimizing SAF and e-fuel plant locations based on solar energy availability, land use, and grid infrastructure. By leveraging Europe's abundant PV resources, the aviation industry can transition toward a cleaner and more sustainable future.

5. Average values of "embodied emissions" for photovoltaic installations in Europe

The following analysis evaluates the potential for new PV installations across 36 major European cities based on key factors: solar irradiance, grid carbon intensity, population density, and electricity consumption per capita. These factors were normalized and combined to generate a total score for each city, as illustrated in the bar chart below.

Based on the normalized total score, cities were classified into four categories to evaluate their potential for PV installation. To analyze the embodied emissions associated with PV electricity generation in each group, the median city of each category was selected as a representative case.

Table 1. Embodied emission for each homogenous zone

Category	Embodied Emissions [gCO_2eq)/kWh]
HPZ	27.1103
MHPZ	34.3259
MLPZ	41.1483
LPZ	37.4551

The table presents the embodied emissions associated with PV electricity generation for four distinct categories of cities, classified according to their overall suitability for new photovoltaic installations. These categories were established based on a multi-criteria analysis using four key parameters. This integrated approach allows for a deep understanding of PV deployment potential beyond simple geographic or climatic distinctions.

As expected, the HPZ group shows the lowest embodied emissions, averaging 27.11 gCO_2eq/kWh. These cities benefit from favorable solar conditions and relatively high grid carbon intensity, which are the most favorable cities for new PV installations.

The MHPZ group follows with an average of 34.33 gCO_2eq/kWh, reflecting a slight drop in solar resource availability and/or lower grid emissions. These cities still offer relatively good potential for PV deployment but face slightly less favorable conditions than the HPZ cities.

In the MLPZ group, the embodied emissions rise to 41.15 gCO_2eq/kWh, the highest among all categories. These cities generally have lower solar irradiance and lower carbon-intensive grids, resulting in longer EPBTs and greater emissions per unit of electricity generated.

Interestingly, the LPZ group, typically considered the least favorable for PV deployment, shows a slightly lower embodied emission value of 37.46 gCO_2eq/kWh compared to MLPZ. This result is not due to better potential but rather reflects the multidimensional nature of the classification. The grouping of cities was not based solely on solar irradiance or emissions, but on the combined evaluation of all four parameters. As such, some cities with relatively favorable solar or grid conditions may still fall into the LPZ category due to high population density or low electricity demand, which can hinder PV expansion from a systemic perspective.

This result underscores the importance of using a comprehensive and integrated methodology when assessing the carbon and strategic performance of PV systems across regions. It demonstrates that embodied emissions do not always follow a linear or geographic gradient but taking into account environmental, demographic, and infrastructural factors which is essential for identifying realistic and effective solar deployment strategies across Europe.

6. Conclusion

This study introduces a systematic and data-driven framework for identifying optimal locations for photovoltaic (PV) deployment across Europe. By incorporating four key parameters—solar irradiance, grid carbon intensity, electricity consumption per capita, and population density—the analysis classifies 36 major cities into four homogeneous zones of deployment potential. This multi-criteria approach offers a more comprehensive basis for evaluating PV suitability than traditional models based solely on solar availability.

The results reveal considerable variation in embodied emissions among the identified zones, with the lowest values found in HPZ cities and the highest in MLPZ cities. Notably, LPZ cities performed slightly better than MLPZ in terms of embodied emissions. This outcome underscores the non-linear relationship between emissions and any single factor. Instead, the findings highlight the complex interplay of environmental, demographic, and infrastructural variables in shaping PV performance. Cities with strong solar or grid attributes may still rank lower in overall suitability due to factors such as limited electricity demand or high population density. These insights emphasize the necessity of applying a holistic, multi-dimensional framework when evaluating the sustainability of PV systems.

Building on this analysis, the research underscores the importance of integrating embodied emissions into renewable energy policy, an element still largely absent from current EU strategies. While high-potential zones offer the clearest path for efficient PV expansion, lower-ranked regions may require tailored policy support to justify investment and ensure equitable energy transitions. This zone-based classification enables more targeted and regionally sensitive recommendations, aligning with the EU's climate objectives.

By establishing default embodied emissions values for each potential zone, the study contributes to a more consistent and transparent life-cycle assessment of PV technologies. It also draws attention to the indirect environmental costs associated with imported PV modules from carbon-intensive manufacturing regions—an aspect often overlooked in deployment planning.

Moreover, the framework developed here has broader applicability beyond solar. Its structure can be adapted for other renewable technologies, such as wind or battery storage, providing a foundation for more integrated and cross-sectoral carbon planning. Incorporating embodied emissions into multi-technology assessments can enhance policy coherence and improve infrastructure allocation across EU member states.

Looking forward, this framework could be extended to include economic and social criteria such as cost-effectiveness, employment potential, or social acceptance, offering policymakers, utilities, and investors a more inclusive decision-support tool. Such an evolution would better reflect the multidimensional nature of sustainability and improve long-term planning effectiveness.

In summary, this research offers both strategic insights and practical tools for accelerating Europe's transition to clean energy. By integrating embodied emissions into the core of PV planning, it supports the development of more effective, inclusive, and sustainable energy policies, reinforcing the EU's commitment to achieving carbon neutrality by 2050.

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Appendix

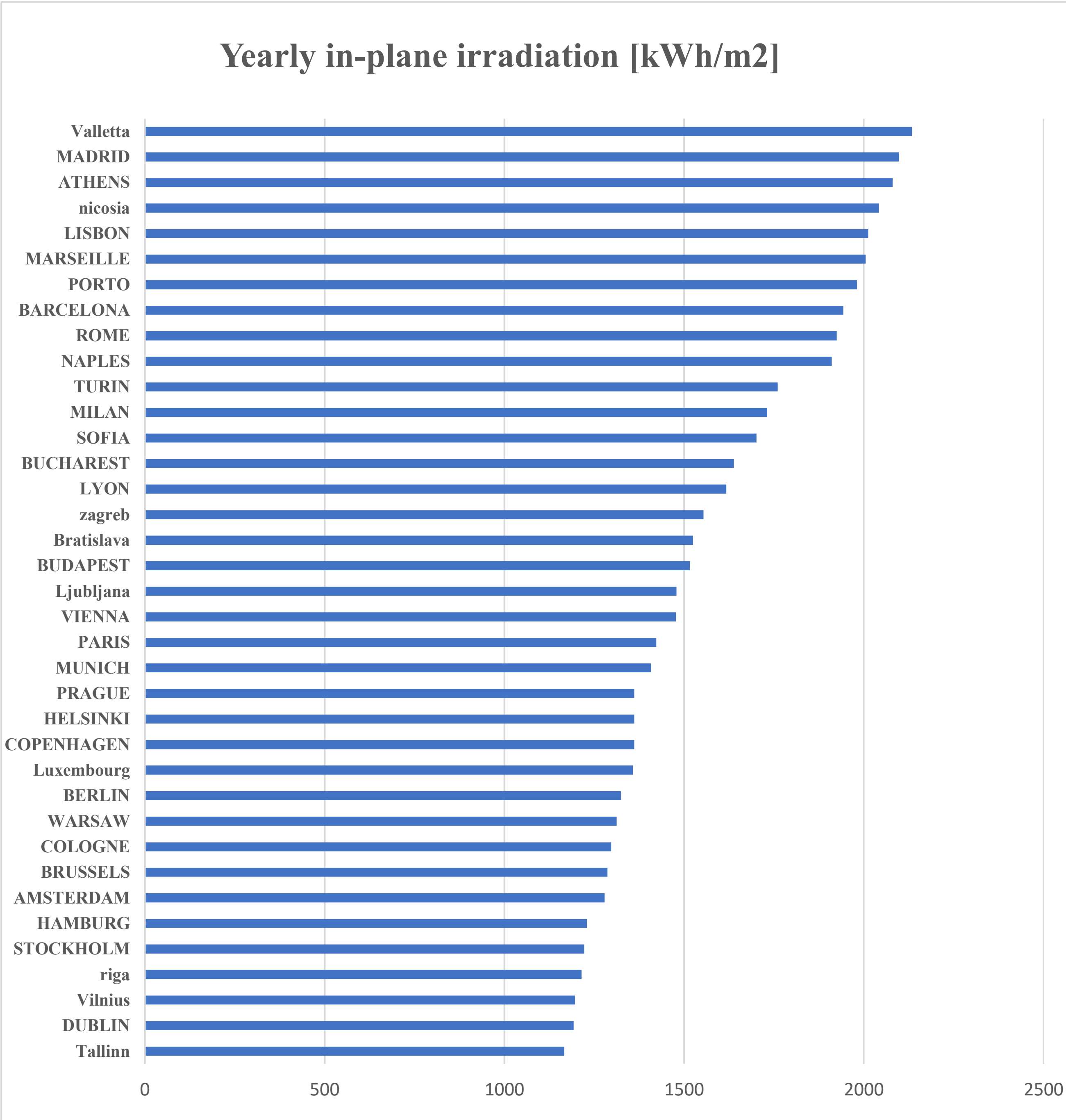

Fig 19. Yearly in-plane irradiation values [kWh/m2] in different cities

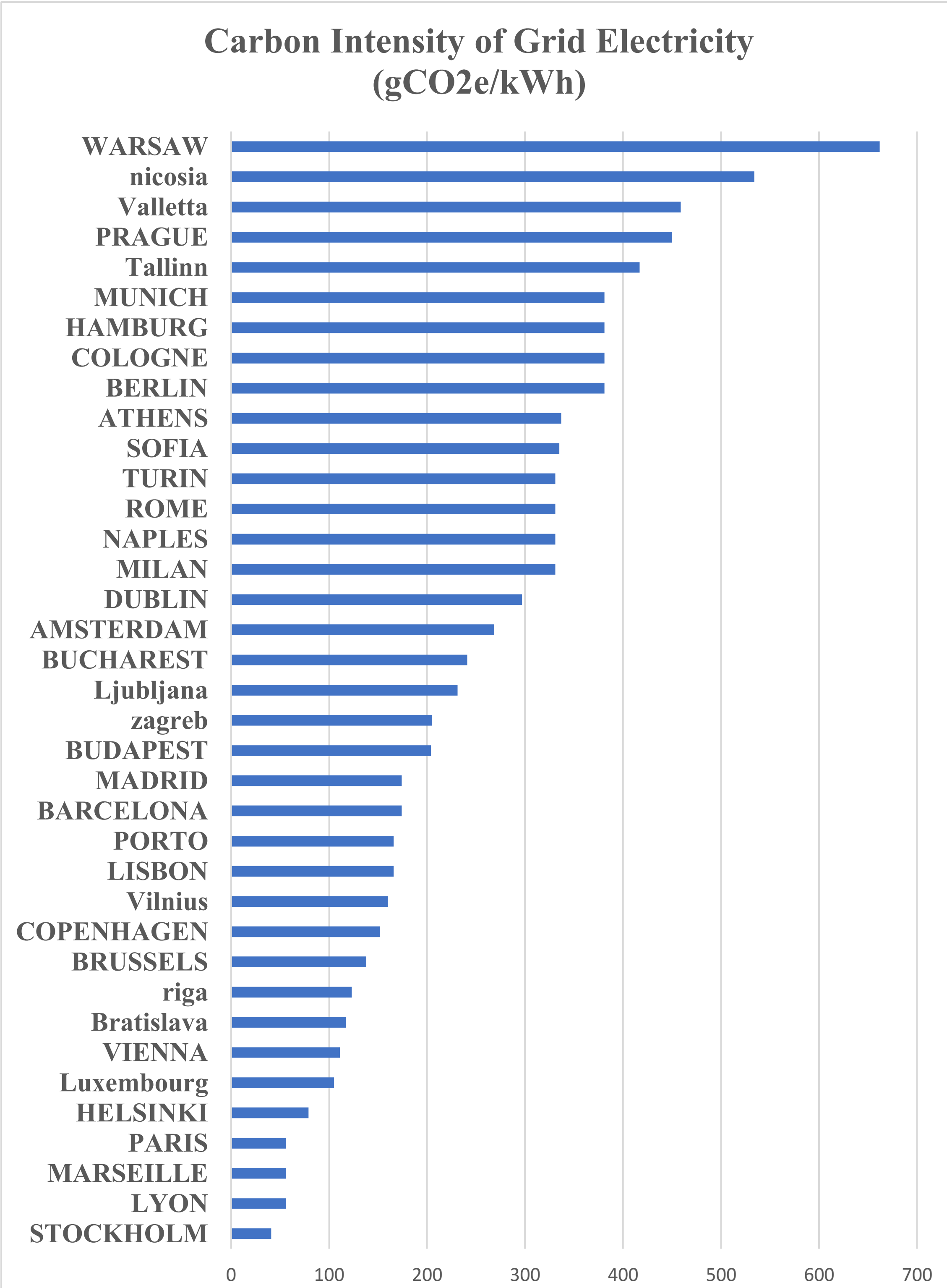

Fig 20. Carbon intensity of the grid electricity values (gCO2e/kWh) in different cities

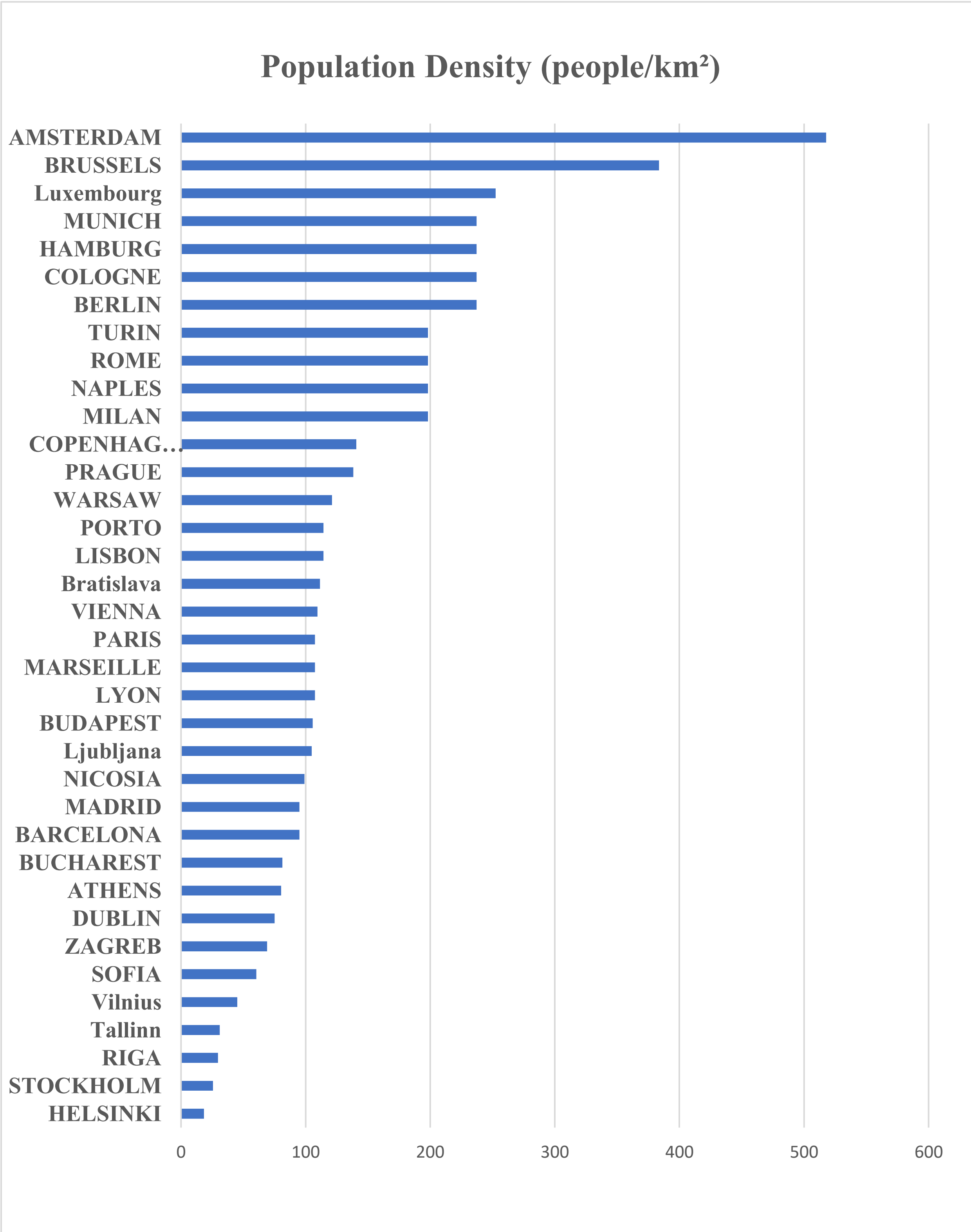

Fig 21. Population density [people/km2] values of different cities

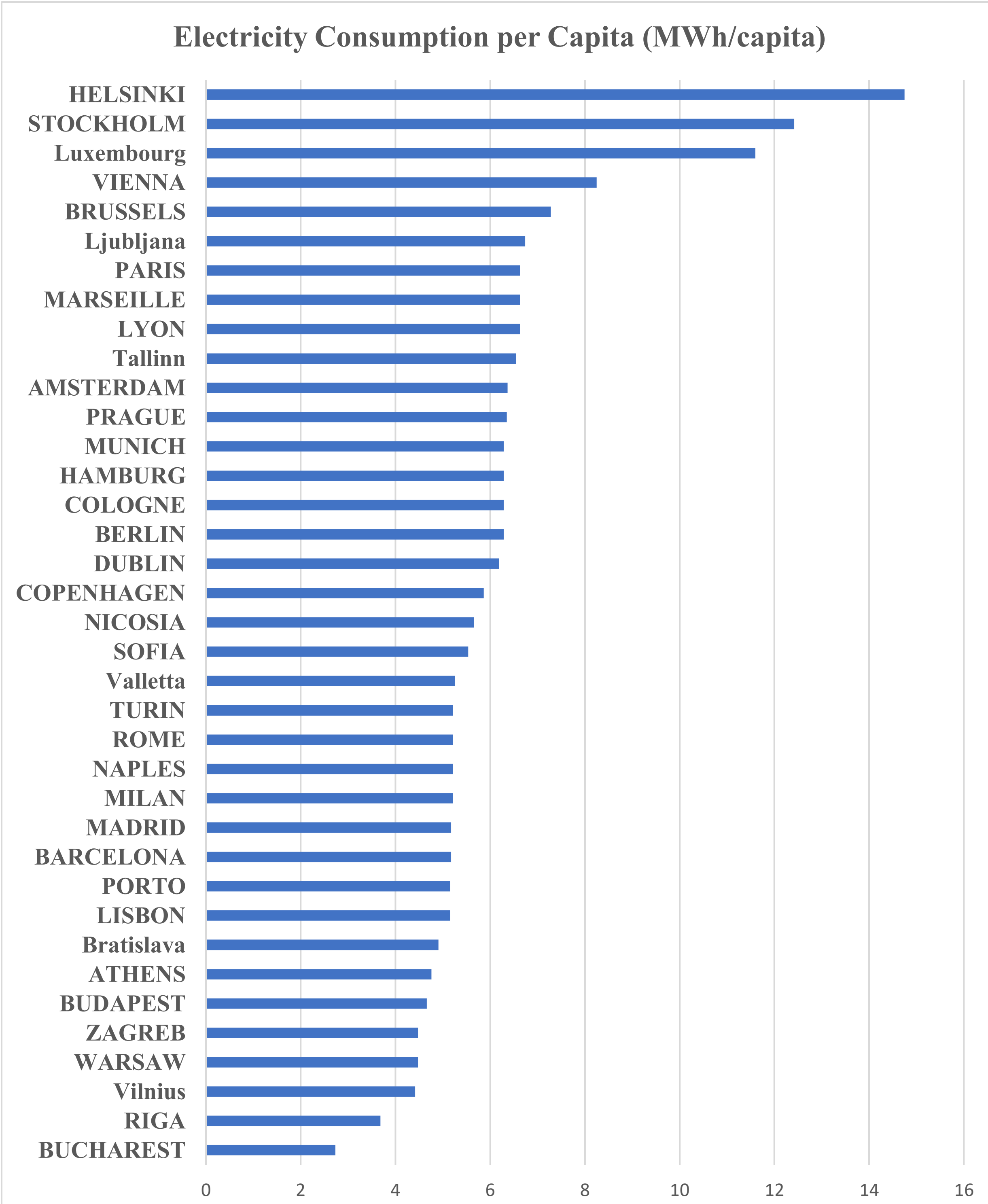

Fig 22. Electricity Consumption per Capita (MWh/capita) values of different cities