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**Life Cycle Sustainability Assessment
of Local Renewable Energy Systems using Fuzzy Logic**

**by
Antonios Kalogerakis**

**Funding source:
Energy Coast Campus Project (ECCP)**

**This thesis is submitted for the degree of Doctor of Philosophy
(in accordance with University of Cumbria procedures and in
compliance with Lancaster University regulations).**

Submitted: January 2024

Word count: 64,403

Declaration

I declare that the thesis is my own work and no material in this thesis has been submitted for a degree at this or any other university.

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Abstract

Title: Life Cycle Sustainability Assessment of Local Renewable Energy Systems using Fuzzy Logic

Author: Antonios Kalogerakis

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The advocacy for renewable energy technologies as a means of establishing a more sustainable and low-carbon electricity mix is evident at the UK, as reflected in national energy and climate plans. However, it remains challenging to identify realistic scenarios and evaluate the overall performance of current renewable energy technologies, taking into account their environmental, economic, and social impacts throughout their life cycle, particularly at the local level. This thesis introduces an innovative life cycle sustainability framework. This framework involves: i) developing small scale renewable energy scenarios, ii) assessing them using environmental and social life cycle assessment and costing, and iii) conducting an integrated sustainability assessment using fuzzy logic. The method is focused on the county of Cumbria, considering three scenarios spanning from 2015 to 2030, which came from Cumbria County Council documents: 1) business-as-usual deployment projections, 2) the UK renewable strategy mix, and 3) no new development of commercial wind. The results indicate that scenario 1 is the most favorable, followed by Scenarios 2 and 3. Even though scenario 1 does not achieve the highest scores in all intermediate life cycle assessments, this framework has the potential to enhance the decision-making process for local renewable energy planning. The innovation of this thesis lies in the development of a highly specialized model – which is called iCumbRIA and it is a development of this PhD – tailored specifically for the county of Cumbria. This model, utilizing real data, uniquely integrates state-of-the-art tools such as Life Cycle Sustainability Assessment (LCSA), which considers not only environmental but also economic and social parameters. The incorporation of fuzzy logic further distinguishes this thesis as a pioneer in its field. The results generated by this approach hold practical utility for decision-makers and stakeholders, offering valuable insights applicable in real-world.

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1. Introduction

1.1 Published research outputs

Antonios Kalogerakis (Environmental Engineer/Dipl-Eng. TU-Crete, Greece and M.Sc./Univ. of Calgary, Canada), during the course of this PhD research, has participated as co-author in a number of peer-reviewed journal articles, book chapter and conference papers, along with the current thesis:

a) Viktor Kouloumpis and Antonios Kalogerakis, *"Decentralised Renewable Energy: Alleviating Conflicts at the Expense of the Environment?"*, IAFOR 2014 Conference, Brighton, East Sussex, UK, July 3-6, 2014.

b) Victor Kouloumpis, Antonios Kalogerakis, Anastasia Pavlidou, George Tsinarakis, George Arampatzis, *"Should Photovoltaics Stay at Home? Comparative Life Cycle Environmental Assessment on Roof-Mounted and Ground-Mounted Photovoltaics"*, Sustainability, 12(21), 9120, 2020. <https://doi.org/10.3390/su12219120>

c) Ioannis Vourdoubas, Antonios Kalogerakis, Kostantinos Zorbas, *"Sustainability Assessment: Offsetting Carbon Emissions from Energy Use at the Orthodox Academy of Crete (OAC)"*, American Scientific Research Journal for Engineering, Technology, and Sciences (ASRJETS), Vol. 72, No.1, 2020.

https://asrjetsjournal.org/index.php/American_Scientific_Journal/article/view/6215

d) Erden Miray Yazgan Yalkin and Antonios Kalogerakis, *"Human Domination on Environment: An Eco-Theological Analysis with Philosophical and Engineering Approach"*, article published in the book: *"Contemporary ecotheology, climate justice and environmental stewardship in world religions"*, Editors: Louk A. Andrianos and Tom Sverre Tomren, et. al., ECOTHEE volume 6th – Orthodox Academy of Crete publication, World Council of Churches, Embla Akademisk, 2021, ISBN 978-82-93689-14-0, pp. 132-139.

e) Soukouli A., Kalogerakis A., Arampatzis G. and Angelis-Dimakis A., *"Energy Supply of a Conference Center Towards Nearly Zero-Energy Building in Accordance with the Standards of the European Green Deal"*, 17th International Conference on Environmental Science and Technology (CEST), Athens, Greece, September 1-4, 2021.

Also, the following presentation was made during the Summer School of the University of Cumbria (Lancaster Campus):

Antonios Kalogerakis, *“Analysis of Decentralised Renewable Energy Sources by Using Life Cycle Approach”*, Doctoral Colloquium, University of Cumbria, Lancaster, Lancashire, United Kingdom, July 10, 2014.

1.2 Thesis organization

This thesis is organized into five main chapters. This first chapter describes the thesis organization, lists the published research outputs (in parallel to this thesis) and clearly articulates the research questions, aim and objectives. Then the literature review in chapter 2 includes an explanatory introduction that establishes the context and provides a rationale for the research, as well as evidence of critical and creative engagement with academic sources and relevant literature. Chapter 3 describes the research method to be followed and its theoretical basis. Chapter 4 provides the results of the model according to the scenarios that have been implemented based on the methodology described in chapter 3. The results are analysed and discussed for each scenario separately and also in comparison to each other. Chapter 5 includes conclusions based on the analysis and discussion from chapter 4 and provides recommendations for future research.

1.3 Research questions, aim and objectives

This analysis is focused in answering three basic research questions, based on the fact that the central point of this thesis is focusing on small scale technologies at a local scale and Cumbria is a case study. Therefore, whenever the terms “renewable energy technologies” and “renewable energy scenarios” are used, these refer to the small-scale technologies for electricity generation. The three research questions are:

- a) How the current renewable energy technologies in Cumbria are assessed in terms of their environmental, economic and social impacts?
- b) Whether it is possible to identify realistic short-term, mid-term and long-term renewable energy scenarios for the Cumbria county?

c) How these renewable energy scenarios can be assessed for their overall performance taking into account a life cycle approach?

The aim of this research is to critically answer the above mentioned three questions and give specific results about the renewable energy future of Cumbria, which could be used by the decision makers in order to improve county's energy sustainability.

Based on this aim, the objectives are being formulated with the following way:

1. Definition of different main scenarios for Cumbria.
2. Identification of the most suitable and probable electricity generation technologies for Cumbria.
3. Undertaking of Life Cycle Assessment (LCA), Life Cycle Costing (LCC), and Social Life Cycle Assessment (SLCA) for these different technologies.
4. Development of a new tool which uses as inputs the results of (4) i.e. the results from the three different types of LCA, LCC, SLCA.
5. Calculation of the impacts of each sub-scenario for each one of the: LCA, LCC and SLCA.
6. Aggregate the LCA, LCC and SLCA in the Life Cycle Sustainability Assessment (LCSA).
7. Ranking of the scenarios both for their three LCAs as well as their overall LCSA.

2. Literature review

2.1 Introduction

The worldwide ecological, economic and social problems have been discussed in the scientific community and society (Schlör et al., 2012), (Brundtland et al., 1987). In 2012, the sustainability concept was confirmed during the Rio+20 conference (Earth Summit 2012), where green economy and more specifically life cycle sustainable assessment was introduced as implementation and operationalization strategy and tool (Schlör and Hake, 2015). From a life cycle perspective the three pillars of sustainability: a) environment, b) economy and c) society, can be addressed by life cycle sustainability assessment (Schlör et al., 2015).

The United Nations Environmental Programme (UNEP) and Society of Environmental Toxicology and Chemistry (SETAC) have used life cycle approach since the 1990s and through the international UNEP/SETAC Life Cycle Initiative (LCI) partnership since 2003 (Vadlivia et al., 2011).

Three different types of life cycle analysis can be applied in order to analyze the impacts on environmental, economic and social problems:

1. Life Cycle Assessment (LCA) is focusing on environmental effects as described in ISO 14040 and ISO 14044, which identifies environmental hotspots (Dantas and Soares, 2022). The main purpose of LCA is to assess the impact on different systems on environment. This involves examining the environmental impacts associated with a product, process or activity at each stage of its life cycle from the extraction of raw material through to its waste management (Baumann and Tillman, 2004).
2. Life Cycle Costing (LCC) is used to optimize the value of money by taking into consideration all the cost factors, which are related to a specific asset during all the period of its operational life. According to (Woodward, 1997) the minimum life cycle cost of the asset can be achieved through the optimization of the trade-off between the cost factors. In order to do so, the costs should be assessed, for the whole life cycle phase prior to the purchase.

Unlike LCA, there isn't a current standardization for LCC (Hayatina et al., 2023). The levelized cost of energy (LCoE), sometimes known as the levelized cost of electricity or

the levelized energy cost (LEC), is a metric used to evaluate and compare alternative energy production systems (Kabeyi and Olanrewaju, 2023). The levelized cost of electricity (LCoE) is a useful measure for evaluating the cost competitiveness of various electricity production systems (CFI, 2022).

3. Social Life Cycle Assessment (SLCA) is used for the impacts on society. According to (Benoît et al., 2010) SLCA is a systematic process using best available science to collect best available data and report about social impacts in product life. More specifically, SLCA is a tool used to evaluate potential positive or negative effects of a product in its whole life cycle in a social aspect, including the process of raw material mining, production, distribution, application, reuse, maintenance, recycling and final disposal (Yang et al., 2020). A specific example of SLCA on renewables and more specifically on solar panels is presented on the following paper: (Bonilla-Alicea and Fu, 2022). As it is clear on this paper, too, the goal of SLCA is to identify and comprehend the social hotspots, risks, and opportunities connected with the life cycle of a product, taking into account elements such as labor conditions, human rights, community well-being, health and safety, and other social indicators. (Rob Hoogmartens et al., 2014) However, there are differences in several aspects, such as the incorporation of stakeholder perspectives, the form and source of data, and the methodology for calculating impact (Leroy-Parmentier et al., 2023).

The life cycle assessments mentioned are integral components of a broader Life Cycle Sustainability Assessment (LCSA). This comprehensive approach takes a cradle-to-grave perspective, considering the three facets of sustainability: environmental, economic, and social. LCSA is instrumental in examining the far-reaching implications of products, goods, services, usage, and waste management across the entire supply chain, encompassing environmental, economic, and ecological aspects. The ISO 14040 standard outlines a four-phase framework for Life Cycle Assessment (LCA): goal and scope definition, inventory analysis, impacts assessment, and interpretation (International Standard Organization, 2006). These phases are applicable to both Life Cycle Costing (LCC) and Social Life Cycle Assessment (SLCA). In the context of LCSA, these phases aim to provide a comprehensive evaluation of a product, capturing both positive and negative impacts. It is important to note that while LCA, LCC, and SLCA share

common phases, they serve distinct purposes. Therefore, when employing an integrated approach, it is crucial to clearly state the intended goals of each assessment type.

2.2 Methodological frameworks for LCSA

The exploration of integrating all three dimensions of sustainability, as opposed to focusing on a single aspect, paving the way for the concept of Life Cycle Sustainability Assessment (LCSA), finds its origins in the PROSA approach (Product Sustainability Assessment) introduced by (Grießhammer et al., 2007). However, the formal proposal for a comprehensive life-cycle-based sustainability assessment, LCSA, was articulated by (Klöppfer, 2008) and (Zamagni, 2012), presenting a sequential integration: $LCSA = LCA + LCC + SLCA$.

A significant challenge within the LCSA framework stems from the distinct perspectives of its three dimensions, making the development of an aggregate framework capable of simultaneously assessing impacts across these dimensions highly intricate. The emphasis is on creating a framework that is not only effective but also straightforward in its implementation. Additionally, while Life Cycle Assessment (LCA) boasts standardization by the (International Standard Organization, 2006) and widespread use in examining environmental impacts on products and services, the lack of definition and limited practical application of Life Cycle Costing (LCC) and, notably, Social Life Cycle Assessment (SLCA) pose challenges in the establishment of an LCSA framework. This incongruity prompts various studies to address these complexities.

(Parent et al., 2013) highlighted the infrequent consideration of the social dimension of sustainable development in Statistical Process Control (SPC) and underscored the inadequacy of LCSA in adequately addressing the social impacts of products on consumers, as observed by (Zamagni et al., 2013). Furthermore, for a complex framework like LCSA to be successful and efficient, it is crucial to clearly define the indicators to be used. (Niemeijer and de Groot, 2008) asserted that the challenge in assessment lies not in the absence of suitable indicators but in the manner of their selection. Also, (Alejandrino et al., 2021) has concentrated and analyzed 100 cases of LCSA and the challenges were again the same: a) clearly defined research questions, b) criteria for selecting relevant case studies and c) specific guidelines for identifying the

information to be extracted. The findings of this study underline the need for further research to establish clearer boundaries for each sustainability pillar. This would enable the development of more precise impact indicators and a better understanding of the strengths and limitations of operational research tools in supporting decision-making.

2.2.1 Analyses for LCA & LCC

The majority of existing reviews lack a comprehensive framework for assessing Life Cycle Sustainability (LCSA). Typically, these reviews either independently delve into the three dimensions of sustainability or endeavor to merge the methodologies of Life Cycle Assessment (LCA) and Life Cycle Costing (LCC). For example, (Kvarnström et al., 2003) attempted to amalgamate LCC and LCA in the context of municipal waste management systems. Despite enabling analysis, the methodology faced persistent compatibility issues between LCC and LCA approaches. Similarly, (Ristimäki et al., 2013) integrated LCA and LCC frameworks for managing the life cycle of energy-consuming products, while (Gu et al., 2008) applied LCC and LCA to address the life cycle green costs of building. Additionally, (Brown et al., 2011) introduced a life cycle management approach for large-scale development resorts, blending LCA and LCC to design environmentally beneficial structures with minimized operational costs. (Heijungs et al., 2010) proposed a computational structure for a unified LCA and LCC, accompanied by a detailed description of life cycle cost calculation.

Similarly, (Simões et al., 2013) demonstrated integration between LCA and LCC by comparing two material alternatives (stainless steel and glass fiber-reinforced polymer composite) for a storage trunk. In Finland, (Ristimäki et al., 2013) conducted a study combining LCC and LCA for energy system design in response to climate change concerns. This study focused on a residential district energy system in Finland, aiming to identify technologies that offer the highest sustainable viability. Additionally, (Kosareo and Ries, 2007) assessed the life cycle impact of green roofs, and (Arpke and Hutzler, 2005) conducted an operational LCC and LCA regarding water use in multi-occupant buildings.

2.2.2 Analyses for LCSA

Despite the considerable number of studies that have integrated Life Cycle Assessment (LCA) and Life Cycle Costing (LCC), a pressing need for a framework capable of addressing all three dimensions of sustainability remains in order to effectively advance sustainable development. Consequently, recent years have witnessed a growing body of research dedicated to developing an integrated Life Cycle Sustainability Assessment (LCSA) framework. For example, (Hacking and Guthrie, 2008) devised an LCSA framework that takes into account the three dimensions of sustainability (environment, economy, society). This comprehensive approach is essential for fully understanding the implications of sustainable development. Similarly, (Ostermeyer et al., 2013) aimed to integrate not only LCA and LCC but also Social Life Cycle Assessment (SLCA), utilizing a multidimensional Pareto-based method to visually represent the interconnectedness of results from LCA, LCC, and SLCA.

However, despite these efforts, LCSA remains a complex framework that requires simplification. Various approaches have been proposed to streamline LCSA. Building on this perspective, (Pesonen and Horn, 2013) introduced sustainability SWOT as an efficiency tool for LCSA, resembling traditional SWOT analyses by examining products and services to identify strengths, weaknesses, opportunities, and threats, although its success has been somewhat limited.

A different perspective was presented by (Guinée et al., 2011), who analyzed two sustainability frameworks within LCSA, denoted as LCSA (assessment) and LCSA (analysis). This framework amalgamates inventory analysis and impact assessment into one model, recognizing that sustainability analysis involves assumptions, scenarios, and uncertainties. Despite both frameworks falling under the LCSA umbrella, the significant distinction between "assessment" and "analysis" points to two distinct concepts, underscoring existing gaps in merging these different levels.

An alternative proposition was put forward by (Graedel et al., 2012), who incorporated criticality considerations within the LCA and LCSA framework to enable a more critical assessment of impacts on the Area of Protection Natural Resources. While this approach considered all relevant indicators for assessing criticality, it faced drawbacks that limited its effectiveness within the LCA framework, as noted by (Sonnemann et al., 2015).

Also, a more recent approach was presented by (Leroy-Parmentier et al., 2023), which includes 193 cases studies. The conclusion of this paper is that LCSA is becoming more popular as more professionals, potential users, and decision-makers learn about and share information on it. Still, there are some important challenges to putting its principles into practice. These include: to understand how the three areas of sustainability (environmental, social and economic) are connected; to choose the right impact categories for LCSA; to have clear guidance on how to make decisions using LCSA. These are exactly the reasons why a new model is required which will be tailored in the needs of a specific study area, as the model which is presented in this thesis does.

2.2.2.1 LCSD

(Traverso et al., 2012) proposed the "Life Cycle Sustainability Dashboard (LCSD)" as a tool designed to navigate the complexities inherent in Life Cycle Sustainability Assessment (LCSA). Developed within the Excel platform, the LCSD facilitates the comparative analysis of two or more products across diverse types of Life Cycle assessments. A parallel approach was employed in China to address end-of-life strategies for electrical and electronic equipment (WEEE) (Vadlivia et al., 2011), with a specific focus on the treatment of a desktop PC as the selected functional unit. Despite these endeavors, challenges persisted in effectively implementing LCSA tools.

2.2.2.2 Tiered

Another approach to implementing Life Cycle Sustainability Assessment (LCSA) is the Tiered Approach, which integrates an indicator hierarchy, as proposed by (Neugebauer et al., 2015). This method involves three tiers of indicators: Tier 1 includes simple yet essential indicators, Tier 2 builds upon these by incorporating a cumulative set of indicators, and Tier 3 encompasses a comprehensive array of indicators to thoroughly evaluate sustainability performance. The methodology is inspired by the International Reference Life Cycle Data System Handbook for Life Cycle Assessment (LCA). For the Life Cycle Costing (LCC), various cost types were integrated, representing perspectives from consumers. Additionally, Social Life Cycle Assessment (SLCA) incorporated additional

indicators addressing aspects related to human health and working conditions. In Tier 3, further supplementary indicators were introduced.

2.2.2.3 AHP-LCA & Em-LCA

The AHP-LCA framework, was introduced to assess the sustainability of sewer pipe life cycles by integrating insights from both Life Cycle Assessment (LCA) and Life Cycle Costing (LCC) (Akhtar et al., 2014). Employing a multi-criteria decision-making (MCDM) technique rooted in (Saaty, 1980) approach, this framework aimed to provide a comprehensive analysis. Another LCSA framework, Em-LCA, introduced by (Reza et al., 2013), utilized emergy synthesis to amalgamate LCA and LCC results into a unified measure of solar emergy joule. The Life Cycle Impact Assessment (LSIA) considered various categories, including resource depletion, energy consumption, and associated emissions throughout the sewer pipe life cycle. LCC components encompassed capital cost, maintenance, repair/replacement cost, and end-of-life cost. Despite both approaches yielding varied results, the broad implementation of LCSA encounters challenges and limitations, particularly in addressing gaps in Social Life Cycle Assessment (SLCA) and LCC methodologies (Vadlivia et al., 2011).

In the pursuit of advancing sustainable development, the LCSA framework emerges as a valuable tool for concurrently estimating the environmental, economic, and social impacts of products and services, aligning with sustainability objectives. Given the pressing need to tackle climate change and escalating greenhouse gas levels, the adoption of renewable energy systems becomes imperative. The LCSA framework stands out as a crucial tool for pinpointing region-specific optimal renewable energy systems. However, additional investigation and refinement are essential for the effective application of LCSA, especially in the evaluation of energy systems.

2.3 LCSA frameworks for the energy sector

The urgent challenges caused by rapid climate change and environmental pollution have underscored the need for sustainable development, emphasizing the vital role of renewable energy in addressing concerns related to energy security, ecological impact, and both global and national climate issues (Singh and Olsen, 2011). Within this context,

(Subhadra and Edwards, 2010) outlined three crucial aspects in ongoing policy discussions pertaining to energy, climate, and greenhouse gas (GHG) emissions: 1) the necessity for globally applicable and transparent energy production and conservation technologies, 2) the requirement for future emission reduction goals to align with policies promoting clean energy production and conservation, and 3) the urgency for immediate action (Singh and Olsen, 2011). Renewable energy has been proposed as a feasible solution, with assessments of renewable energy technologies relying on diverse critical sustainability indicators (Liu, 2014). Nevertheless, the comprehensive evaluation of the sustainability of entire renewable energy systems remains a highly intricate task. Numerous studies have sought to establish comprehensive frameworks to tackle climate change and environmental pollution by exploring energy systems and renewable resources. Considerable research has been dedicated to developing sustainability assessment indicators and tools, categorized into two types: single indicators and multiple indicators. For example, (Ren et al., 2015a) and (Gangadharan et al., 2012) applied a total of eight criteria for sustainability assessment in the context of polygeneration processes involving syngas derived from coal and natural gas. Similarly, (Piluso et al., 2010) utilized 11 criteria for the sustainability assessment of an industrial system.

More recently three papers: (Hallste Pérez et al., 2023), (Lassio et al., 2021) and (Rashid and Majed, 2023) have used LCSA for the electricity generation sector at a country level for Spain the first paper (more focused on social indexes), for Brazil the second one and for Bangladesh the third one. These papers verify the importance of LCSA in the energy sector, and their focus generally on the specific countries on a national level and not in specific cases points out how important is to also have tailored LCSA in specific regions, as this thesis proposes, in order to have as reliable as possible results.

Furthermore, three review papers that are worth mentioning, too, as they are at the same field as this thesis are the: (Dantas and Soares, 2022) that considered 34 publications, (Hemmati et al., 2024) that analyzed 102 papers and (Al-Kuwari et al., 2024), which took into account 443 articles. These reviews highlight how crucial it is to define the life cycle parameters, such as system boundaries and impact categories, since each study approached these elements differently. There was even greater variation when it came to the sustainability indicators used, particularly in relation to the social

and economic aspects, making the use of a decision system necessary. This is the reason why this thesis is proposing a sophisticated decision-making tool, too, as fuzzy logic is a way to reach solid conclusions.

2.3.1 GSI

(Liu, 2014) crafted a framework for a General Sustainability Indicator (GSI) designed to evaluate Renewable Energy Systems (RES). This inclusive GSI incorporated the three dimensions of sustainability – Life Cycle Assessment (LCA), Life Cycle Costing (LCC), and Social Life Cycle Assessment (SCLA) – by merging all relevant indicators and criteria into a unified metric. To accomplish this integration, Liu applied the Fuzzy Analytical Hierarch Processing (FAHP) and Fuzzy Comprehensive Evaluation (FCE) methods.

2.3.2 MCSA

(Nzila et al., 2012) employed the Multi Criteria Sustainability Assessment (MCSA) to devise a method for systematically and reliably evaluating various alternatives in biogas production. The chosen impact criteria encompassed considerations of reliability, measurability, and relevance to the specific circumstances in Kenya. SimaPro software and the Ecoinvent 2.2 database were utilized for conducting the Life Cycle Assessment (LCA), while the economic aspect involved monetary indicators like total investment, energy autonomy, and labor cost. The culmination of their approach resulted in a radial spider-gram, visually presenting the outcomes of the multi-criteria comparative analysis.

2.3.3 MAVT

(Santoyo-Castelazo and Azapagic, 2014) conducted a comprehensive assessment integrating environmental, economic, and social dimensions to envision the future electricity supply in Mexico. Their proposed framework for evaluating the sustainability of integrated energy systems involved various steps, including selecting indicators for environmental, economic, and social aspects, specifying energy technologies, defining scenarios and time horizons, and conducting life cycle assessments for each dimension. The aggregation of sustainability indicators was achieved through a multi-criteria

decision-making process. The use of Multi-Criteria Decision Analysis (MCDA) allowed for considering diverse preferences for the criteria. Among the different MCDA methods available, the authors opted for the Multi-Attribute Value Theory (MAVT) due to its widespread use. The results of the method highlighted the intricate nature of decision-making in the energy sector, emphasizing that a singular “best” solution is often elusive, and trade-offs are necessary to identify the most sustainable option (Santoyo-Castelazo and Azapagic, 2014).

2.3.4 MCDM

(Ren et al., 2015b) integrated the LCSA framework with the MCDM methodology to appraise the sustainability of bioethanol production. This amalgamation involved employing the AHP and VIKOR methods to ascertain the sustainable ranking of diverse alternatives. Social indicators were quantified by using a fuzzy set theory method. However, a notable drawback of the overall approach is its intricacy, presenting challenges for users to apply the MCDM method (Ren et al., 2015a).

2.3.5 ILCSA

(Keller et al., 2015) introduced an innovative development methodology called Integrated Life Cycle Sustainability Assessment (ILCSA), designed to provide comprehensive decision support with a sustainability perspective during the implementation of new technologies, processes, and products, especially in the context of biorefineries. Aligned with the life cycle thinking principle and following the steps proposed for Life Cycle Assessment (LCA), ILCSA incorporates a distinctive result integration step based on a benchmarking procedure. This includes selecting relevant scenarios and indicators, integrating cross-disciplinary indicators such as greenhouse gas abatement cost, compiling overview tables, and fostering discussions. The careful selection of pertinent scenarios and indicators is crucial to prevent irrelevant data overload for the assessed decision options. Ultimately, the benchmarking process compares all scenarios to a benchmark scenario. The outcomes of this approach suggest that there are no inherent limitations in combining Life Cycle Assessment (LCA), Life Cycle Costing (LCC), and Social Life Cycle Assessment (SLCA). ILCSA emerges as a practical

and flexible extension of Life Cycle Sustainability Assessment (LCSA) methodologies, allowing for the inclusion of results from intermediate assessment methodologies addressing specific sustainability aspects that go beyond the scope of LCA and LCC alone (Keller et al., 2015).

2.3.6 MOS

(Chong et al., 2016) put forth a framework for Sustainability Indicators centered on the Life Cycle of waste-to-energy (WTE), introducing a sustainability metric and unveiling a new measure named the Metric of Sustainability (MOS). The primary goal was to offer a comprehensive framework for sustainability indicators and a sustainability metric, serving as valuable benchmarks for future investigations into the sustainability of WTE systems. In structuring sustainability considerations, the framework adopted the three pillars of sustainability, encompassing indicators, underlying factors, three types of interlinking factors (eco-efficiency, social-economic, socio-environmental), and life cycle phases. MOS was applied based on three distinctive principles drawn from existing sustainability accounting methodologies. The findings underscored the significance of simultaneously addressing the three pillars of sustainability to bolster the overall sustainability of WTE systems. Furthermore, the suggested sustainability indicator framework and MOS were found to be applicable in the context of Life Cycle Sustainability Assessment (LCSA).

2.3.7 FELICITA

(Kouloumpis and Azapagic, 2018) worked on the FELICITA model (Fuzzy Evaluation for Life Cycle Integrated Sustainability Assessment), a tool aimed at enabling comprehensive assessments of life cycle sustainability. This model integrates life cycle assessment (LCA), life cycle costing (LCC), and social life cycle assessment (SLCA) into a fuzzy inference framework. By utilizing indicators derived from LCA, LCC, and SLCA as inputs, the model produces an overall life cycle sustainability indicator as its output. The fact that the LCSA can be combined successfully with fuzzy logic is verified by more scientific works like the (Fetanat et al., 2022), which helps rank technologies more effectively under uncertain conditions.

2.3.8 iCELTIC

The iCELTIC model (intelligent Community Electricity Lifecycle Technology Impact Calculator), as published by (Kouloumpis and Yan, 2021), has undergone refinements to enhance its adaptability for diverse applications, particularly for local-level energy planning. These adjustments also involve an expanded scope, incorporating social aspects for a more thorough sustainability assessment. This extension encompasses estimations of fatalities and job creation linked to activities necessary for electricity generation from specific technologies. Moreover, the energy assessment has broadened to include a diverse range of renewable sources, moving beyond conventional electricity generation technologies like photovoltaics, wind, and hydro to encompass sources such as plant biomass and energy from waste.

Concurrently, the Life Cycle Sustainability Framework (LCSF) has been expanded to facilitate the aggregation of basic Life Cycle Assessment (LCA) and other foundational indicators into more comprehensive metrics. This contributes to an overarching Life Cycle Sustainability Assessment indicator. The aggregation process involves normalizing basic indicators and applying fuzzy logic, specifically Fuzzy Inference Systems (FIS), without the use of weights.

2.3.9 iCumbRIA

To assess the sustainability of renewable energy systems, it is crucial to delve into local scenarios and conduct a thorough examination of impacts across all stages of the product life cycle. This involves scrutinizing various categories and incorporating current data for a comprehensive evaluation of environmental, economic, and social effects. The use of a reliable tool is indispensable to ensure an unbiased and holistic examination of the case study (Kouloumpis and Yan, 2021), particularly in the context of a specific region, such as the county of Cumbria. Consequently, the creation of a novel model was necessary and this is exactly what has been accomplished through this thesis. The new model is named iCumbRIA (integrated Cumbria Renewable Impact Assessment) and it is an innovative development of this PhD. iCumbRIA functions as a multi-criteria decision analysis tool, aiding stakeholders in the comprehensive assessment and ranking of

various future energy system options. Chapter 3 provides a detailed exploration of the model components.

2.4 Cumbria: an overview

Cumbria is characterized for its diverse and captivating natural landscapes, featuring attractions such as the Lake District National Park, segments of the Yorkshire Dales National Park, the Solway Coast, St Bees Heritage Coast, portions of the Arnside and Silverdale, and the North Pennines Areas of Outstanding Natural Beauty (AONBs). Additionally, the region hosts sites designated as Special Scientific Interest (Cumbria County Council, 2011). Despite its rural character, the presence of the nuclear technology industry has significantly influenced Cumbria (Marshall et al., 2013). Over many decades, nuclear energy has played a pivotal role in the local economy, providing substantial employment opportunities (West Cumbria Energy Compass, 2013). West Cumbria is acknowledged as the leading hub for nuclear and advanced engineering in the UK, contributing roughly one-third of the nation's civil nuclear sector (Britain's Energy Coast, 2008). Furthermore, the region possesses abundant natural resources conducive to renewable energy, encompassing onshore and offshore wind, small scale wind, hydro power, solar PV, solar thermal, heat pumps, biomass, and potential improvements in energy efficiency.

2.4.1 Renewable energy goals in the UK

The UK has set a formidable target to significantly diminish greenhouse gas emissions by promoting the extensive use of renewable energy across sectors such as renewable electricity generation, renewable heat, and renewable fuels for transportation. The ambitious target is to achieve a minimum 80% reduction by the year 2050. As part of the strategic plan, articulated by (Holdgate, 2009), the UK aims to generate up to half a million new jobs through the widespread adoption of renewable energy. Furthermore, there is a commitment to curbing carbon dioxide emissions by over 750 million tons by 2030, as indicated by the (Cumbria County Council, 2011).

2.4.2 The Capability of Cumbria in renewable energy

Cumbria, with its distinct climate and geographical attributes, emerges as an opportune locale for advancing Renewable Energy Sources (RES) and nuclear energy, aligning with the objective of enhancing the region's economy. The rural landscape of Cumbria offers the potential for generating plant biomass, tapping into vast woodlands and animal biomass. Particularly notable is West Cumbria's potential for harvesting woods and forests, with farm and food industry waste presenting another significant energy source in the region (West Cumbria Energy Compass, 2013).

Cumbria envisions diversifying its biomass sources, encompassing small communities, woodlands, and field crops, from decentralized outlets (Holdgate, 2009). The region boasts a substantial wind resource, especially in the Irish Sea, hosting some of the UK's largest offshore wind parks, such as Robin Rigg, Walney, and Ormond (West Cumbria Energy Compass, 2013). Despite limited sunlight, solar power holds promise in meeting the energy needs of households and businesses.

The ample rainfall, numerous lakes, and streams in West Cumbria make it well-suited for small scale hydropower. Cumbria holds a significant share of the North West's small hydropower potential, with the potential to access around 69.7MW Small scale Hydropower from the Lake District National Park (Cumbria County Council, 2011). Additionally, the tidal magnitude along the Cumbria coast is among the world's largest, with potential barrage sites identified, including the Solway in Cumbria (West Cumbria Energy Compass, 2013).

Cumbria's climatic conditions, topography, and natural resources create an environment conducive to a diversified mix of electricity developments, aiming for targeted reductions in carbon dioxide emissions and enhanced energy efficiency. This mix leverages seasonal variations for optimal renewable electricity production. Assessing the feasibility of this diversified mix at the distributed level is essential, considering its potential contribution to local demand (Gormally et al., 2012).

In September 2010, Cumbria County Council engaged SQW Ltd and Land Use Consultants to conduct an Energy Capacity and Development Study for Cumbria, with the aim of proposing measures to enhance the planning system's support for economic growth and sustainable development (Cumbria County Council, 2011). The vision set

forth by (West Cumbria Energy Compass, 2013) positions the region as the UK Centre of Excellence for Sustainable Energy, advocating for the development of a 'green' brand through a well-structured marketing plan. Cumbria County Council produced a Supplementary Planning Document (SPD) on wind energy to interpret and provide guidance on planning policies related to onshore wind turbines and their landscape impact (Cumbria County Council, 2011).

By 2030, Cumbria anticipates more than doubling its renewable energy generation from 295MW to 606MW (Cumbria County Council, 2011). This substantial increase is pivotal for Cumbria's energy security and environmental sustainability, addressing both local pollution and the impacts of climate change. While various reports, such as the Cumbria (Cumbria Clean Energy Strategy, 2022), have been published, they originate from sources outside the county and are utilized as references for cross-checking assumptions in subsequent sections.

2.5 Discussion on the contribution of the thesis

By analyzing all the literature that is presented in the subchapters from 2.1 to 2.4 of this thesis and especially the review papers (Dantas and Soares, 2022), (Hemmati et al., 2024) and (Al-Kuwari et al., 2024), which consider 579 publications in total, the novelty of the proposed method of this thesis that adds to the current scientific known is based on the following three specific facts, which proves the significance of its contribution to both academic literature and practical applications:

- a) This thesis takes a close look at electricity generation, with a particular emphasis on small-scale, local renewable energy technologies. Rather than focusing solely on high-tech solutions or national strategies, it explores options specifically designed for Cumbria, aiming to address the county's unique energy needs through more decentralized approaches.
- b) The thesis brings together an evaluation of the environmental, economic, and social (deaths and jobs creation) dimensions of small-scale renewable systems. Because of their decentralized setup and relatively modest scale, this kind of comprehensive sustainability assessment has not been carried out before, making the analysis both timely and original.

- c) Instead of using the electricity output (measured in MWh) as the focal point, this thesis takes a capacity-based perspective (measured in MW), shifting the focus toward infrastructure and supply decisions. This approach highlights the importance of choices made on the production side, rather than those driven by energy consumption.

2.6 Literature review conclusion

The outcome of the literature review is that in order to address the three main research questions, as they are mentioned on subchapter 1.3 of this thesis, a LCSA approach based on the aggregation of LCA, LCC and SLCA can be followed using a wide range of methods and models with the iCumbRIA one being the most suitable, as it was developed by this PhD and verified especially and specifically for the needs of the county.

3. Research methodology

3.1 Outline of the methodology

The research methodology of the thesis can be realized by following the procedures as illustrated in the following Figure 1, specifically for the case of iCumbRIA, as the central point of this thesis is focusing on small scale technologies at a local scale and Cumbria is a case study:

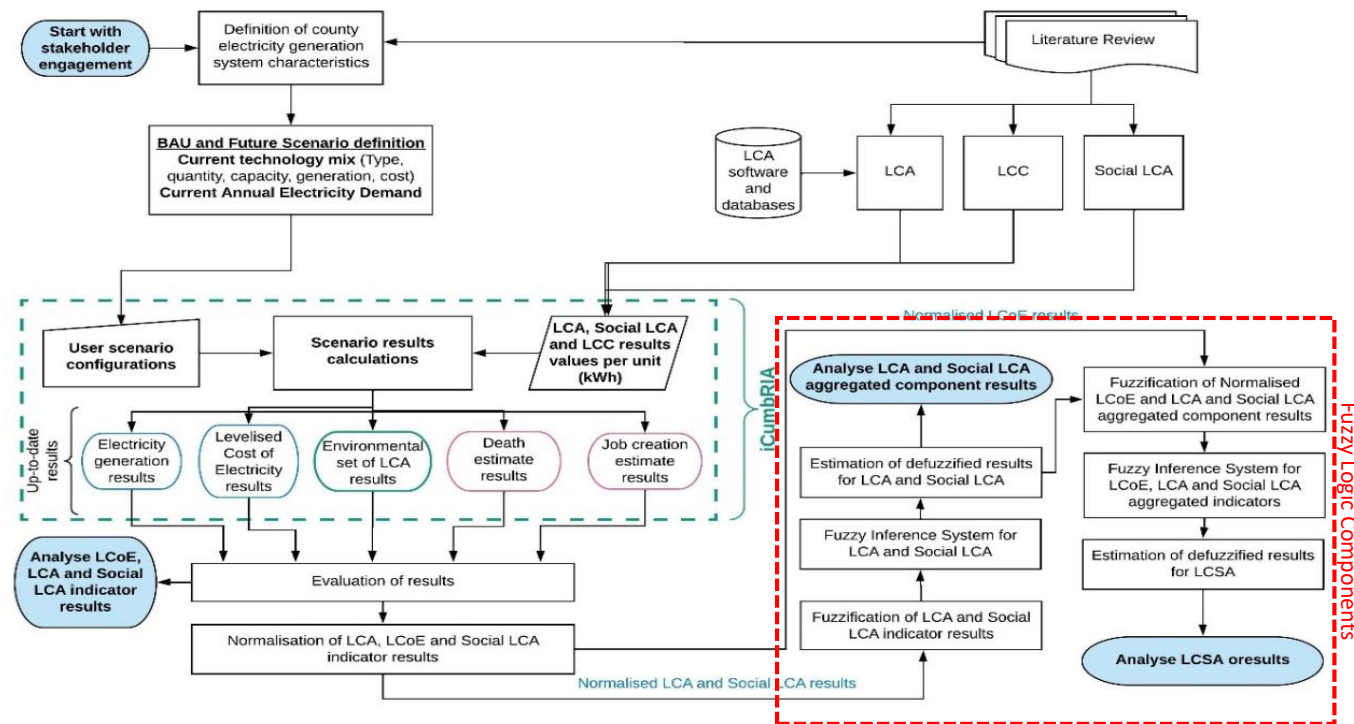


Figure 1: iCumbRIA research methodology

Starting with the stakeholder engagement to define the county's energy generation system characteristics and scenarios, a number of actors and interested parties can be involved such as the local communities, the national grid moderators and energy providers, as well as the local and national authorities (Kouloumpis and Yan, 2021). Once the scenarios are defined for the types of the technologies -including the capacity factor- they are inserted into the model and the results for the indicators of the LCA, Social LCA and LCC are calculated. On this stage, the results can be analysed further before they are normalised and undergo via the Fuzzy Logic Components (FLC). After the FLC are applied, the results for the aggregated components for LCA and Social LCA can be studied and finally, the outcomes for the overall LCSA indicator can be examined. These analyses are particularly useful for the comparison of scenarios, because they can inform the stakeholders about the strengths and weaknesses on various levels of granularity.

The following subsection for the case of Cumbria describes the current situation and how the scenarios were defined while in the next subsections the iCumbRIA model and its LCA, LCC and Social LCA components are analysed.

3.2 Data collection for current situation – Renewable Energy Foundation (REF)

The Renewable Energy Foundation (REF, 2024) is a non-profitable organization, a registered charity since 2004. It was founded in the UK by a group of people willing capturing and bringing balance in the country's energy policy. It is supported by private donations, while the members are working on releasing publications, presentations, reports. Some of the main topics are the UK's renewable energy target over the years, the renewable generation technology share, wind output and subsidy costs. REF aims to provide public knowledge on sustainable development of UK, by creating not only reports, but also online databases including different energy sources and installations across the country. For example, REF divides information into groups such as technology groups (biomass, hydro, wind etc.), technology sub-groups (onshore/ offshore wind, landfill gas, dedicated biomass, photovoltaic etc.) and subsidy (renewables obligation, feed-in-tariff, unsubsidized).

The first group made by REF includes the generators subsidized by the Feed-in-Tariff (FiT) and it is actually a financial incentive for renewable generators. The installed capacity in this group does not exceed 5MW (Cumbria County Council, 2011). The main purpose out of this project was to make renewable generation more financially viable by ensuring long term stability in terms of the produced electricity price. FiT scheme started in 2010 and there are five categories in this group considering the existing technology: Photovoltaic, Hydro, Anaerobic Digestion (AD), Wind and Micro CHP (Combined heat and power). There are 8,771 FiT generators, while 8,192 of them have an installed capacity under 10 kW and just 35 of them exceed 500 kW (REF, 2024).

The primary mechanism for fostering the extensive production of renewable electricity is known as the Renewables Obligation (RO). This group includes sub-groups based on their technology: Photovoltaic, Anaerobic Digestion, Advanced Gasification, On-shore wind, Landfill Gas, Hydro, Off-shore wind, Dedicated biomass. There are 52 RO generators, while 17 of them have an installed capacity under 1,000 kW and 6 of them have an installed capacity over 10,000 kW (REF, 2024).

This study is based on the data of 8,771 FiT generators reaching a capacity of 81,187 kW, 52 RO with a total capacity of 2,578,890 kW and 2 unsubsidized installations (REF, 2024). Based on their technology, generators are separated in 11 categories. Anaerobic Digestion (AD) is a microbial process where bacteria decompose organic materials, such as animal manure, wastewater biosolids, and food wastes, in the absence of oxygen. The process involves 21 inputs with a total capacity of 8,479 kW, as outlined by (REF, 2024). Within the AD category, there are 18 Feed-in Tariff (FiT) installations and 3 Return on Sales (RoS) initiatives (REF, 2024). Advanced gasification is a thermochemical process that transforms waste feedstocks at temperatures exceeding 700°C, utilizing a controlled supply of oxygen or steam to generate synthetic gas (syngas) without combustion. (REF, 2024) includes two processes of this nature in the datasets, with a combined capacity of 1,248 kW. Dedicated biomass entails generating electricity solely from regular biomass. The dataset provided by (REF, 2024) includes 4 inputs for dedicated biomass, contributing to a total capacity of 50,650 kW. Landfill gas is generated as bacteria decompose organic waste, resulting in a mixture containing methane, carbon dioxide, nitrogen, oxygen, ammonia, sulfides, and hydrogen (REF, 2024). There are 6 installations of 8,049 kW in total (REF, 2024). The last three categories

are ROs. There are 240 on-shore wind farms with a total capacity of 217,725 kW and there are 209 FiT generators in the category and 31 ROs (REF, 2024). Hydropower stations reach 7,071 kW with a total number of 65 installations (REF, 2024). This category includes 57 FiT generators, 2 ROs and 2 unsubsidized installations (REF, 2024). The biggest category, based on the number of installations, includes photovoltaics. There are 8,487 installations with a total capacity of 46,179 kW (REF, 2024). Photovoltaic and AD installations consist of FiT generators.

The following Figure 2 illustrate the total installations. As it was mentioned above, photovoltaic installations are 8,487 out of 8,825 (96%).

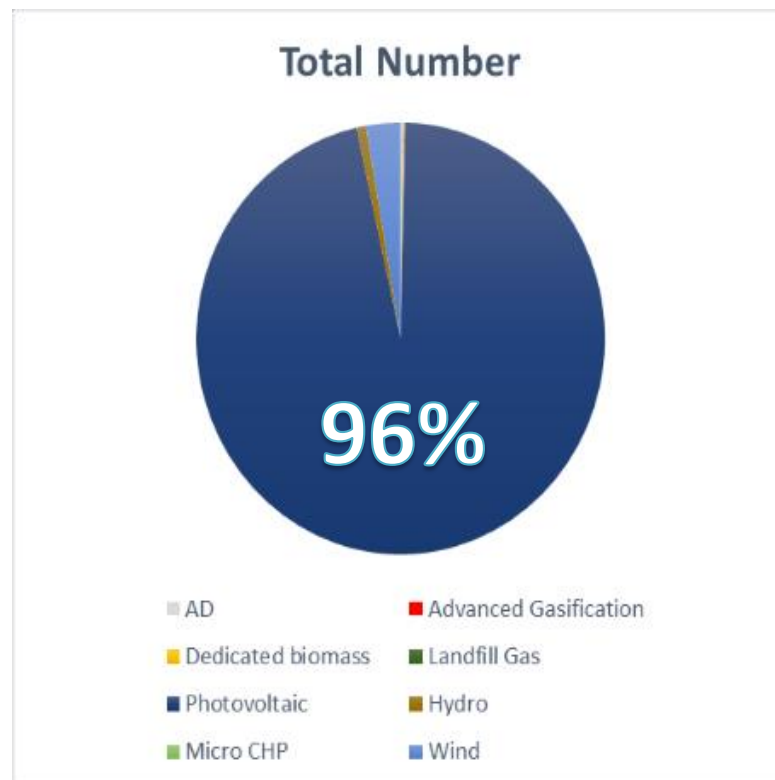


Figure 2: Total number of the installations (REF, 2024)

The categorization can also be done by using the type of installation: commercial, domestic, community, industrial, N/A. The first four categories include FiT generators, while N/A includes just ROs. Domestic installations are the most popular of the rest, reaching a number of 8,091 (92%) (REF, 2024). Commercial installations take the second place with 577 and the rest are under 100 (REF, 2024). The following Figure 3 depicts all those.

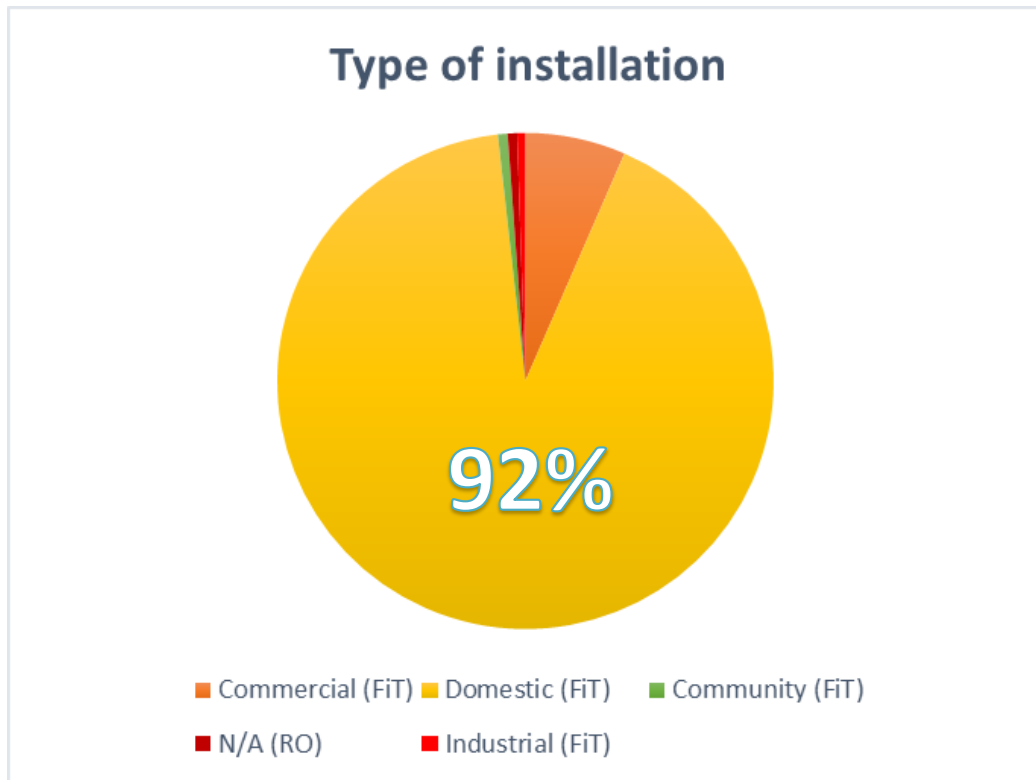


Figure 3: Categorization based on the type of the installations (REF, 2024)

3.3 Data collection for scenarios by Cumbria County Council Documents

In 2011, the Cumbria County Council initiated an extensive examination titled "Cumbria's Renewable Energy Capacity and Deployment" (Cumbria County Council, 2011). The primary objective of this study was to provide a detailed overview of Cumbria's energy landscape, emphasizing the resilience of local planning frameworks in the context of renewable energy. Additionally, the study aimed to outline the potential technical capacities of various technologies such as wind, solar, hydropower, and biomass, projecting developments until the year 2030. This analysis considered national and energy planning policies, aligning them with potential energy resources and demand. The central projection from the study suggests that a feasible deployment of 606 MW of renewable energy within Cumbria is within reach by the year 2030 (Figure 4).

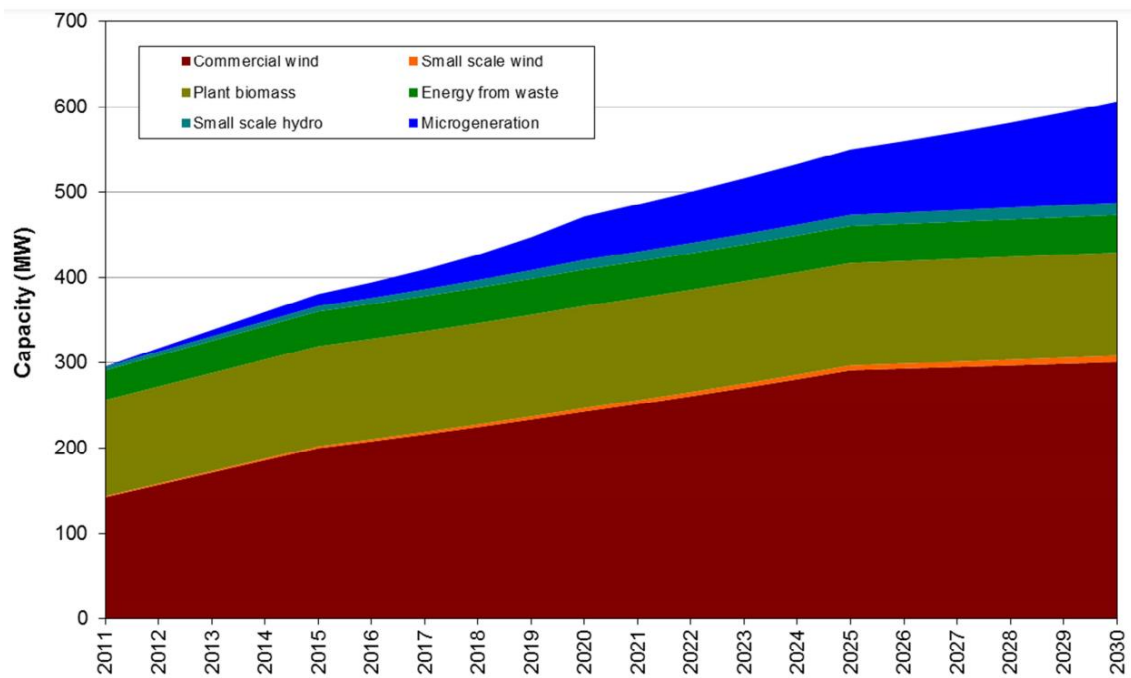


Figure 4: Cumbria renewable energy deployment curve by 2030 (Cumbria County Council, 2011)

In the report (Cumbria County Council, 2011), in addition to the deployment projections, three alternative scenarios were examined to showcase diverse technology mixes that could potentially fulfill the outlined objectives. These scenarios that came from Cumbria County Council documents (Cumbria County Council, 2011) and were used in this thesis can be briefly outlined as follows:

- “Current mix- business as usual”, where the currently installed capacity is projected to 2030 to the 606MW capacity
- “UK Renewable Strategy Mix”, where the indicative national RET proportions are the same as in the UK Renewable Strategy 2009.
- “No new commercial wind”, where there commercial wind that is already there or has already gotten consent for remains only.

Based on the above, the research is focused on: a) Deployment projections, b) UK Renewable Strategy mix and c) No new commercial wind, hereafter mentioned as Scenario 1, Scenario 2 and Scenario 3 respectively (Table 1 and Figure 5), because of their realistic approach, which has a research significance and a practical importance.

Table 1: Presentation of scenarios

Scenario envisaged capacity (MW)	Deployment projection	UK Renewable Strategy mix	Current mix- business as usual	No new commercial wind
Commercial wind	300.1	219	292	142
Small scale wind	7.4	12	9	11
Microgeneration	119.2	135	<1	181
Small scale hydro	14.5	16	9	22
Plant biomass	121.7	119	181	181
Energy from waste	43.3	106	70	66
Unallocated capacity	-	-	51.1	-

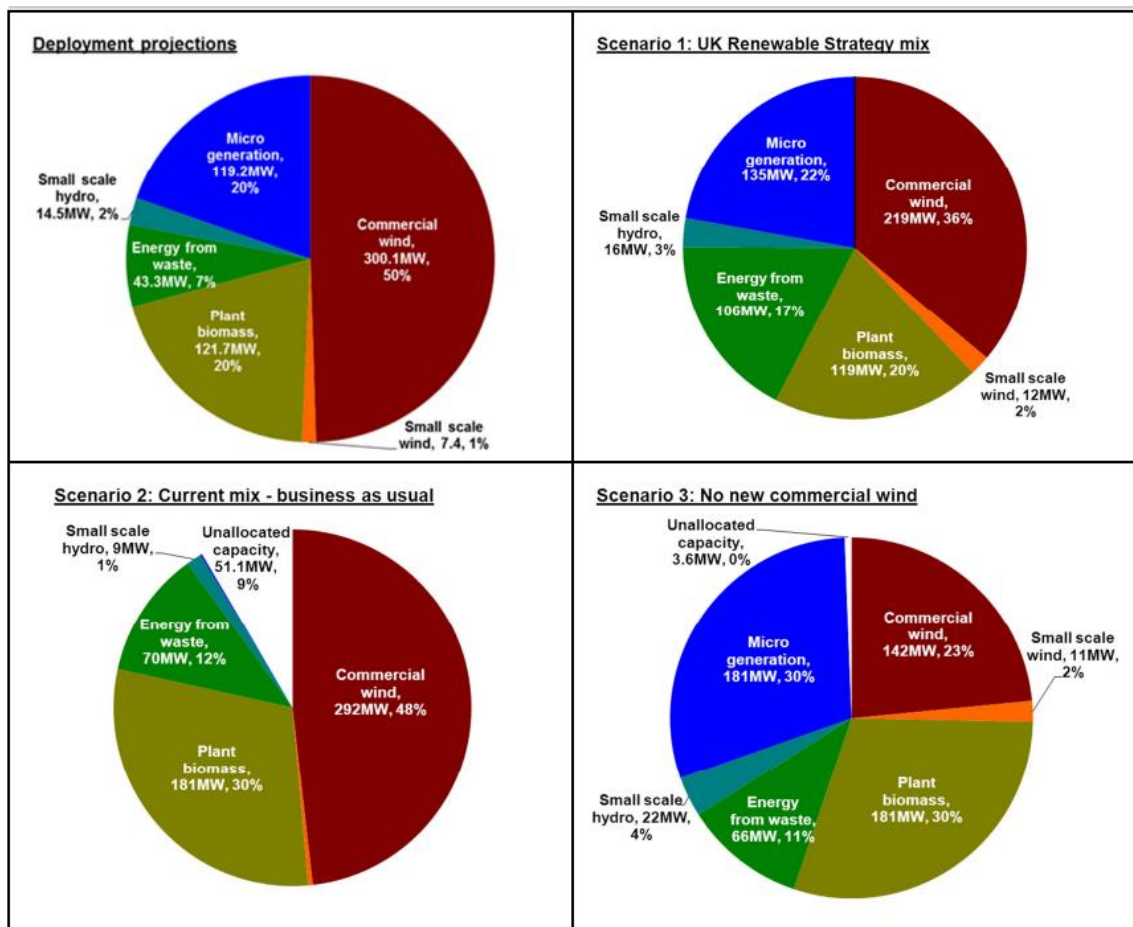


Figure 5: Overview of scanaria for Cumbria county (Cumbria County Council, 2011)

The report (Cumbria County Council, 2011) was used as a case study and although not very recent, the specific county has not officially published anything newer. This seemingly shortcoming of this analysis can be turned into an advantage, as it provides a unique opportunity to assess the progress of acting upon the specific plans and gain useful insight on the risks and update requirements in similar situations. Several other reports like (Cumbria Clean Energy Strategy, 2022) were published after that but not from the county itself and they have been used as a reference and for cross checking of the assumptions that are described in the following parts of the thesis.

So, by using the (Cumbria County Council, 2011) study as a starting point, the following six main renewable energy technologies are considered: wind (commercial and small scale), photovoltaics (as microgeneration), small hydro, plant biomass and energy from waste. The Commercial wind includes the onshore wind farms for commercial energy generation and supply with capacity over 100 kW. They are usually connected to the national grid but there may also be private-wired schemes. The small scale wind includes onshore wind installations with capacity of less than 100 kW. They are usually single turbines ground-based and supply the on-site demand first before feeding the excess to the grid (Cumbria County Council, 2011).

Offshore wind is not included in the specific study and neither are tidal and geothermal (Cumbria County Council, 2011). The microgeneration technologies typically refer to renewables that cover the on-site demand and that can be integrated into the buildings. In this case, the technologies chosen are the ones that depend directly on the built environment capacity: solar photovoltaics and heat pumps. The small hydro includes small scale hydro power under 20 MW, usually installed in small rivers and streams, which have lower ecological impacts than the larger one like the dams. The plant biomass includes resources which (via their combustion) can generate heat and electricity and they could be: unmanaged woodland, energy crops, waste wood and agricultural arisings (straw) (Cumbria County Council, 2011). The energy from waste refers to technologies that utilise waste, such as animal biomass (wet organic waste), municipal and industrial solid waste as well as biogas that could come from landfill and sewage gas.

The year 2015 was used as the starting point of the scenarios, because of the availability of data and 2030 was considered as the final year. The data which were used are

according to the publication of the spreadsheet dataset for 'Renewable_electricity_by_local_authority_2014-2021_Nov22update', part of the National Statistics publication Energy Trends produced by the UK government (Department for Energy Security and Net Zero, 2023). It was published alongside a feature article: "Renewable Electricity in Scotland, Wales, Northern Ireland and England in 2021" and it includes both the installed capacity and the generation by region and local authority from 2014-2021. Based on this, the capacity factors were calculated for the specific technologies for 2015 and 2020, for the six borrows that make up Cumbria (i.e Allerdale, Barrow-in-Furness, Carlisle, Copeland, Eden and South Lakeland) and the numbers are presented in Table 2 and Table 3.

Table 2: Cumbria renewable energy for 2015

TOTAL CUMBRIA 2015	Capacity MW	Electricity MWh	Capacity Factor
Commercial wind	145.8	376811.5	29.50%
Small scale wind	3.0	7690.0	29.50%
Microgeneration	64.6	44159.437	7.81%
Small scale hydro	5.7	11888.444	23.61%
Plant biomass	50.0	356993.077	81.55%
Energy from waste	13.209	49544.916	42.82%

Table 3: Cumbria renewable energy for 2020

TOTAL CUMBRIA 2020	Capacity MW	Electricity MWh	Capacity Factor
Commercial wind	210.1	544927.6	29.61%
Small scale wind	4.3	11121.0	29.61%
Microgeneration	113.1	102431.374	10.34%
Small scale hydro	7.0	24434.619	39.98%
Plant biomass	51.8	341186.348	75.21%
Energy from waste	16.955	44078.086	29.68%

For the year 2030, the values were based on the data retrieved by the Cumbria's report (Cumbria County Council, 2011). However, these data are based on a target 606 MW, which also includes the thermal energy from the Iggesund biomass plant. Therefore, an adjustment was made to reflect the deduction of 50 MW which brings the new expected generated electricity for 2030 to 557 MW.

For Scenario 3 'No new commercial wind energy', the values from the report for 2030 (142MW) were much lower than the ones already reported for 2020 (210.1MW), so it was decided to keep all wind (commercial and small scale) same as in 2020 and arrange the rest of the values so that their shares are based on the shares of the original Scenario 3 but representing in total 61.5% and not 75% are originally planned. For the year 2025, the average values between 2020 and 2030 were used.

Based on the above assumptions and estimations, the data used for the three scenarios in this study are shown in the Table 4.

Table 4: Presentations of the 3 scenarios for 2015/2020/2025/2030 for Cumbria

SCENARIO 1	Capacity of different electricity plants/installations (MW)			
DEPLOYMENT PROJECTIONS	2015	2020	2025	2030
Commercial wind	145.8	210.1	255.1	300.2
Small scale wind	3.0	4.3	5.9	7.5
Microgeneration	64.6	113.1	116.2	119.3
Small scale hydro	5.7	7.0	10.8	14.6
Plant biomass	50.0	51.8	61.8	71.8
Energy from waste	13.2	17.0	30.2	43.4
				≈557
SCENARIO 2	Capacity of different electricity plants/installations (MW)			
UK RENEWABLE STRATEGY MIX	2015	2020	2025	2030
Commercial wind	145.8	210.1	214.5	219.0
Small scale wind	3.0	4.3	8.1	12.0
Microgeneration	64.6	113.1	124.1	135.0
Small scale hydro	5.7	7.0	11.5	16.0
Plant biomass	50.0	51.8	60.4	69.0
Energy from waste	13.2	17.0	61.5	106.0
				≈557
SCENARIO 3	Capacity of different electricity plants/installations (MW)			
NO NEW COMMERCIAL WIND (ADJUSTED TO NO NEW AFTER 2020)	2015	2020	2025	2030
Commercial wind	145.8	210.1	210.1	210.1
Small scale wind	3.0	4.3	4.3	4.3
Microgeneration	64.6	113.1	141.8	170.4
Small scale hydro	5.7	7.0	14.8	22.7
Plant biomass	50.0	51.8	69.4	87.1
Energy from waste	13.2	17.0	39.7	62.5
				≈557

The data of the above scenario were cross referenced against the following Table 5 that was presented by the Cumbria Local Enterprise Partnership (Cumbria Clean Energy Strategy, 2022) . Table 5 verifies that the values of the scenarios 1, 2 and 3 of this thesis are very close to the ones reported at this bibliographic source.

Table 5: Actual electricity generation in Cumbria for 2020

Renewables generation capacity and actual electricity generation 2020						
Source	Installed capacity MW end of 2020			Electricity Generation in 2020 (GWh)		
	Cumbria	UK	Cumbria share	Cumbria	UK	Cumbria share
Photovoltaics	111	3,462	0.8%	104	13,158	0.8%
Offshore wind*	329	10,383	3.2%	1,289	40,681	3.2%
Onshore wind	214	4,102	1.5%	549	34,688	1.6%
Hydro	7	1,876	0.4%	24	6,754	0.4%
Anaerobic Digestion	9	38	1.6%	47	2,904	1.6%
Plant Biomass	52	4,553	1.1%	344	26,845	1.3%
Other	8	2,900	0.3%	16	9,573	0.2%
*Total	730	47,813	1.5%	2,373	134,681	1.8%
**All offshore wind allocated to Cumbria	1,656	10,383	15.9%	6,488	40,681	15.9%
Revised total renewables	2,057	47,813	4.3%	7,572	134,603	5.6%
Source: Renewable electricity by local authority 2014 – 2020. Note Cumbria offshore wind share for generation adjusted by applying share of capacity to total UK offshore wind generation in 2020. * The share is based on the wind far capacity allocated to Barrow (329 MW) and excludes the share allocated to Lancaster (1,327 MW). ** This share includes the proportion allocated to Lancaster in recognition that the six wind farms in Morecambe Bay/Irish Sea are part of the Cumbria renewable energy supply.						

Source: Cumbria Clean Energy Strategy, 2022 and Renewable electricity by local authority 2014-2020

3.4 Description of the iCumbRIA model

Once the scenarios are defined, and the components that constitute the current and future electricity generation mix (type of technology, capacity and capacity factor) are known, they are used as inputs in the iCumbRIA model.

The model already contains the values per kWh for the LCC, LCA and Social LCA indicators. This is based on the results of separate LCA studies, databases and allows for

the calculation of the numerical values as well as the graphic representation of the results for the scenarios per technology used and as a whole.

The Microsoft Excel interface of iCumbRIA facilitates the integration of outcomes derived from Life Cycle Assessment (LCA), Life Cycle Costing (LCC), and Social Life Cycle Assessment (SLCA) with existing and prospective scenario configurations. Users can input values for both current and future preferred scenarios on the designated input sheet. The output sheet then provides users with numerical and graphical representations of the results for each scenario. These outcomes can be assessed and subsequently utilized in the ensuing stages, incorporating the utilization of Fuzzy Inference Systems (FIS).

3.4.1 Environmental assessment

Specialized tools, such as GaBi v8.7 (Thinkstep A.G., 2019), and the extensive Life Cycle Inventory (LCI) database ecoinvent v3.5 (Wernet et al., 2016), were employed for conducting Environmental Life Cycle Assessments (LCAs). These assessments incorporated historical data, including information related to the Simplon (Kouloumpis and Azapagic, 2022). The chosen functional units for these assessments revolved around the "generation of 1 kWh of electricity from a single energy mix component (e.g., a wind turbine) with an expected lifespan of 20 years". Employing a cradle-to-gate perspective, these assessments deliberately exclude End-of-Life (EoL) treatment but incorporate indicators for materials anticipated to be disposed of. This deliberate exclusion stems from the inherent uncertainty associated with future scenarios, making predictions about infrastructure outcomes and material disposal methods (landfill, incineration, or recycling) challenging.

The thesis boundaries deliberately omit the local transmission and distribution (T&D) grid, presuming its integration with the existing infrastructure. The models specifically focus on electricity demand for generation, excluding losses during T&D. LCI data within these predefined boundaries were meticulously sourced from relevant literature and databases, such as Ecoinvent (Wernet et al., 2016), and processed using GaBi software version 8.7 (Thinkstep A.G., 2019). Employing the CML impact assessment method,

potential impacts were calculated for each technology based on the predefined functional unit (Kouloumpis and Yan, 2021).

A foundational assumption for the analysis involves a 20-year lifespan and a static network, negating the necessity to model additional transmission and distribution components like power lines, pylons, and substations. To ensure consistency, the capacity factors from the ecoinvent database were retained when calculating impacts per kWh generated – the functional unit. Both iCumbRIA in this thesis and iCELTIC (Kouloumpis and Yan, 2021) incorporate a function that adjusts overall impacts by dividing the LCA model's capacity factor by the user-defined capacity factor, reflecting actual electricity generation. The capacity factors for the Cumbria scenarios were derived from capacities and generation estimates, as detailed in subchapter 3.3. Table 6 provides specifications related to energy generation technology.

Table 6: Energy generation technology specifications

Energy generation plant/installation	Energy generation technology	Reference (Thinkstep A.G., 2019) (Wernet et al., 2016)
Small scale wind	Based on Simplon 30 kW assuming 8.5% capacity factor	Ecoinvent 3.5 'CH: electricity, at wind power plant Simplon 30kW'
Commercial wind	Based on a combination of the Ecoinvent onshore wind available models and 20.29% capacity factor	Ecoinvent 3.7.1 'Electricity production, wind, <1MW turbine, onshore' of the ecoinvent 3.5 Ecoinvent 3.7.1 'Electricity production, wind, 1-3MW turbine, onshore' of the ecoinvent 3.5 Ecoinvent 3.7.1 'Electricity production, wind, >3MW turbine, onshore' of the ecoinvent 3.5
Small scale hydro	Based on run-of-river and excluding pumped storage as big and commercial and 30% capacity factor	GB: electricity production, hydro, run-of-river ecoinvent 3.7.1
Microgeneration	Based on heat pump 10kW and roof-installed photovoltaics and weighted average combined capacity factor 22.45%	Europe without Switzerland: heat production, air-water heat pump 10kW ecoinvent 3.7.1 GB: electricity production, photovoltaic, 3kWp slanted-roof installation, multi-Si, panel, mounted ecoinvent 3.7.1 GB: electricity production, photovoltaic, 3kWp slanted-roof installation, single-Si, panel, mounted ecoinvent 3.7.1
Plant Biomass	Based mainly on wood, future and 8% capacity factor	GLO: electricity production, wood, future ecoinvent 3.7.1
Energy from waste	Based on biogas and waste and weighted average combined capacity factor 43.58%	GB: Electricity from biogas Sphera GB: Electricity from waste Sphera

Derived from the aforementioned LCA work, the per kWh outcomes were computed. These findings are contingent on the specific conditions and data accessible at that particular time, and they have the potential to fluctuate in the future based on varying circumstances and requirements. In this instance, a set of indicators was selected utilizing the CML2001 - Jan. 2016 (Guinée, 2002) life cycle impact assessment method. These indicators include: i) Abiotic Depletion Potential (Elements), ii) Abiotic Depletion Potential (Fossils), iii) Acidification Potential, iv) Eutrophication Potential, v) Freshwater Aquatic Ecotoxicity Potential, vi) Global Warming Potential, vii) Human Toxicity Potential (HTP), viii) Marine Aquatic Ecotoxicity Potential, ix) Ozone Layer Depletion Potential, x) Photochemical Ozone Creation Potential, xi) Terrestrial Ecotoxicity Potential.

3.4.2 Economic assessment

For evaluating economic considerations, it is advantageous to examine the stages of Development and Consenting (D&C), Production and Acquisition (P&A), Installation and Commissioning (I&C), Operation and Maintenance (O&M), and Decommission (DECOM) as outlined by (Myhr et al., 2014), employing approaches such as Life Cycle Costing (LCC) or Life Cycle Cost Analysis (LCCA). In this dissertation, the chosen metric is the Levelised Cost of Energy (LCoE), which is derived from the anticipated energy production over the project's lifespan. The levelised cost of electricity generation (LCoE) is defined as the ratio of the net present value of total capital and operating costs of a generic plant to the net present value of the net electricity generated by that plant during its operational life (Bucher et al., 2016). The data utilized in the iCumbRIA model originates from the 'Electricity Generation Cost' report by the Department of Energy and Climate Change (BEIS, 2016), and the corresponding LCoE values for various technologies are presented in Table 7. The values in this report are denominated in £/MWh and represent averages for the years 2013, 2015, 2020, 2025, and 2030.

Table 7: LCoE for each technology

Electricity generation/storage technology	LCoE £ per MWh
Small scale wind	299
Commercial wind	111
Microgeneration	183
Small scale hydro	160
Plant biomass	180
Energy from waste	45

To ascertain the Central Capital Expenditure (Capex) for Commercial wind, this study adopted the Levelised Cost of Energy (LCoE) values detailed in the report, specifically focusing on 'Onshore wind 1-5MW' (£111/MWh). Small scale wind computations involved blending 'Onshore wind 100-1500kW' (£424/MWh) and 'Onshore wind 1-5MW' LCoE values from the report, utilizing a weighted ratio of 60/40, resulting in a revised value of (£299/MWh). Microgeneration considerations were grounded in the 'Solar <4kW' LCoE values from the report, yielding a adjusted figure of (£183/MWh). Small scale hydro LCoE values were determined by referencing the 'Hydropower 100-1000kW' category in the report, resulting in a recalibrated figure of (£160/MWh). Plant biomass assessments took into consideration the 'Energy crops (small)' LCoE values from the report, generating a recalculated figure of (£180/MWh). Energy from waste considerations were based on the 'EfW' LCoE values from the report, yielding an adjusted value of (£45/MWh). It is important to note that the iCumbRIA model allows users the flexibility to modify these default values to accommodate shifts in the intricate and unpredictable economic landscape.

3.4.3 Social assessment

For the social aspect of the sustainability the two metrics used are the estimates for the deaths as well as the jobs created that can be attributed to the activities necessary for the electricity generation from these specific technologies. For the death rates from energy per kWh, the data were sourced by Deaths per TWh energy production – processed by Our World in Data: “Deaths per terawatt-hour of energy production”

[dataset¹]. Deaths per TWh energy production based on data published by Data published by (Sovacool et al., 2016) and (Markandya and Wilkinson, 2007). The mortality rates are calculated by considering fatalities resulting from accidents and air pollution per terawatt-hour of electricity generated. For the estimates of the jobs per kWh the data were sourced by the “Renewable energy and jobs: Annual review 2022” by the International Renewable Energy Agency and the International Labour Organization (IRENA, ILO, 2022). The data from the above bibliographic sources are summarized in Table 8.

Table 8: Death rates and jobs per kWh

IMPACTS PER kWh	Death-rates-from-energy per kWh	Jobs per kWh
Small scale wind	3.50E-11	5.26E-07
Commercial wind	3.50E-11	5.26E-07
Microgeneration	1.90E-11	5.27E-07
Small scale hydro	1.30E-09	1.90E-07
Plant biomass	4.63E-09	1.05E-06
Energy from waste	4.63E-09	1.88E-06

3.4.4 Fuzzy Logic components of the framework

3.4.4.1 Normalisation of basic indicators

The first step for using fuzzy logic evaluation is the normalisation procedure based on the literature (Kouloumpis et al., 2008), (Kouloumpis and Azapagic, 2018). It is important to be mentioned that fuzzy logic can give us the tools for comparison in a unique multicriteria way (Kouloumpis and Azapagic, 2018).

Based on (Kouloumpis and Azapagic, 2018) the procedure is the following:

The model's initial phase involves preparing input data from Life Cycle Assessment (LCA), Life Cycle Costing (LCC), and Social Life Cycle Assessment (SLCA) indicators. The subsequent normalization of input data includes linear interpolation between the most

¹ <https://ourworldindata.org/grapher/death-rates-from-energy-production-per-twh?tab=table> (assessed 1.15.2024)

and least favorable values for each sustainability indicator. These values can be determined through expert consultation/reliable sources and may alternatively be based on minimum or maximum values within the range. Desirability of indicators varies; for example, optimal global warming potential aligns with the lowest range, while for employment, it's in the highest range. If the lowest value is preferred, the normalized value, " $x_{a,c}$," is computed using Equation 1, where " c_{max} " is the highest value, " $z_{a,c}$ " is the current value, and " c_{min} " is the lowest value.

Equation 1: Fuzzy – normalization – lowest value is desirable

$$x_{a,c} = \frac{c_{max} - z_{a,c}}{c_{max} - c_{min}}$$

If the preferred value is the highest within the range, then Equation 2 can be used, as follows:

Equation 2: Fuzzy – normalization – maximum value is desirable

$$x_{a,c} = \frac{z_{a,c} - c_{min}}{c_{max} - c_{min}}$$

3.4.4.2 Fuzzy inference system modelling

Fuzzy logic, applied in sustainability assessments, handles uncertainties in variable values using linguistic descriptions rather than precise numerical values. For instance, ambient temperature could be characterized as “hot” for 30°C or above and “cold” for 0°C (Kouloumpis and Azapagic, 2018). Unlike Boolean logic (Bhunja and Tehranipoor, 2019), which deals in absolute truths (0 or 1), fuzzy logic embraces "half-truths" and employs membership functions, such as " $\mu(t)$ ", which is shown in Equation 3, to represent the degree of truth for input variables, where " t " is temperature. Fuzzification involves assigning degrees of membership to linguistic values, for example, based on Equation 3, the value is 0.5 for a temperature of 25°C. In fuzzy inference, this approach aids decision-making by translating imprecise inputs into clear outputs. A Fuzzy Inference System (FIS) entails the process of fuzzifying input values through the application of membership functions and rule-based processing, typically formulated as

IF-THEN statements. The outcome is a fuzzy set characterized by specific degrees of membership, which is then subjected to defuzzification to generate precise numerical outputs. The Mamdani method, widely used for its simplicity and "min-max" operations, is a prominent choice, and various defuzzification methods, including center-of-area and mean of maxima, are available (Mamdani, 1977), (Sugeno, 1985), (Zimmermann, 2001), (Kouloumpis and Azapagic, 2018).

Equation 3: Fuzzy – indicating the degree of truthfulness

$$\mu(t) = \begin{cases} 0, & 0 \leq t < 20 \\ 0.1 \cdot (t - 20), & 20 \leq t \leq 30 \\ 1, & t \geq 30 \end{cases}$$

For the fuzzy inference system applications, the Fuzzylite 5.0 software (FuzzyLite Limited, 2015) was used as well as calculations in Microsoft Excel.

3.4.4.3 Fuzzy inference for environmental LCA

This section describes the type of fuzzy inference system used for the aggregation of the basic indicators of Environmental LCA and Social LCA into the composite indicators 'ENVIRONMENT' and 'SOCIAL'. The normalised value will be used for the aggregation with the results from the application of the FIS (Fuzzy Inference Systems) in the other two composite indicators 'ENVIRONMENT' and 'SOCIAL'.

For the application of the FIS (Fuzzy Inference System) for the Environmental LCA, the plethora of the indicators required a grouping and further aggregation in order to proceed with the calculations for the overall indicator 'ENVIRONMENT'. If all 11 indicators were synthesized and a single FIS was utilised then the number of rules required would have been $3^{11}=177,147$ which would have been difficult to calculate due to the computational effort and very time consuming. Therefore, following a rational similar to the one used in the bibliography (Kouloumpis et al., 2008). The 11 indicators were allocated in 4 main groups representing the various dimensions of the environment. Some of the indicators like the GWP were used in more than one groups because the impacts they represent affect more than one dimension. In this way, it is acknowledged that this increases their influence towards the estimation of the overall

environmental sustainability. However, this is not necessarily an issue because no other weighting factors were used. The issue of using weighting factors is not new and their use and definitions can be controversial. Only in few cases, there has been an approach where they have been adopted by a large audience like the ones used in Product Environmental Footprint (PEF) of the European Commission Joint Research Centre (Environmental Footprint methods - European Commission, 2022).

3.4.4.3.1 Fuzzy inference for LAND

For the LAND, the following basic indicators were included in the group: Abiotic Depletion Potential (ADP elements) [kg Sb-Equiv.], Abiotic Depletion Potential (ADP fossil) [MJ], Terrestrial Ecotoxicity Potential (TETP) [kg DCB-Equiv.], Acidification Potential (AP) [kg SO₂-Equiv.], Global Warming Potential (GWP) [kg CO₂-Equiv.] and Eutrophication Potential (EP) [kg Phosphate-Equiv.]. For these indicators, their normalised values were used as inputs in the FIS (Fuzzy Inference System) that included six inputs and provided as an output the aggregated indicator 'LAND'. The Linguistic Variables used for each one of them were identical and included three Liguistic Values: BAD, AVERAGE, GOOD with the same characteristics as the ones for the Social indicators:

range: 0.000 1.000

term: BAD Triangle 0.000 0.000 0.500

term: AVERAGE Triangle 0.250 0.500 0.750

term: GOOD Triangle 0.500 1.000 1.000

For brevity, the characteristics of the triangular LVs will not be analytically described from now on because they are the same for the fuzzification of all indicators.

The rule base used was consisted of 729 rules shown in Table A of the Appendices

RuleBlock: LAND; conjunction: Minimum, disjunction: Maximum, activation: Minimum

The output variable 'LAND' utilises 5 linguistic variables (VERY BAD, BAD, AVERAGE, GOOD, VERY GOOD) triangular with the same characteristics as 'Socialoutput' and all Output Variables. However, in this, as well as in the following cases for the LCA basic indicators, the rules are not allocated in a symmetric manner. The symmetry is broken so that there are less rules that give 'VERY_GOOD' as an output. In fact, only when all basic indicators have as input 'GOOD' the output is 'VERY_GOOD'. If there is at least one basic indicator input 'AVERAGE' then the output cannot be more than 'GOOD' and if

there is at least one basic indicator input 'BAD' then the output cannot be more than 'AVERAGE'. The exact outcome is defined by the number of 'GOOD' inputs and is presented at the Figure 6.

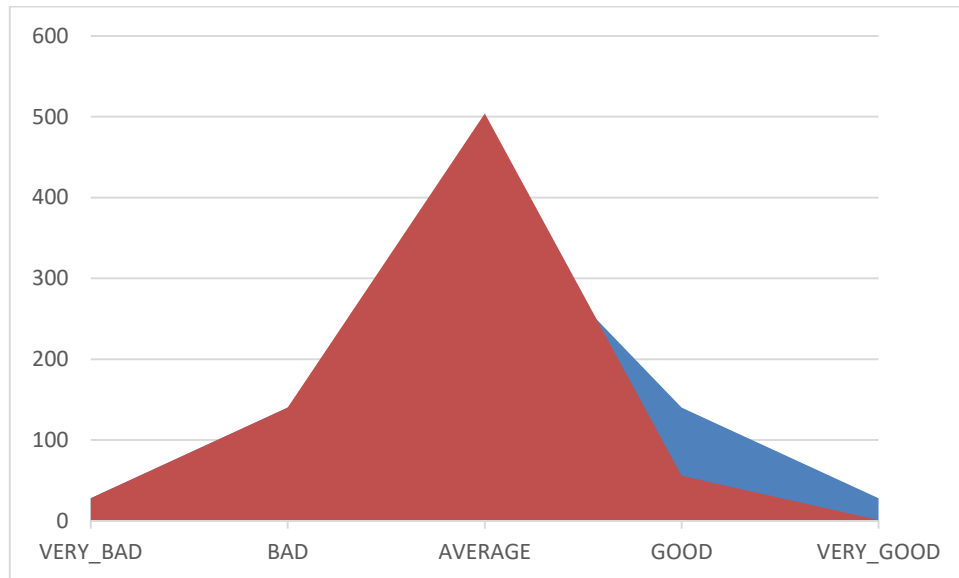


Figure 6: Fuzzy inference for land - variables

In addition, the Mamdani and Maximum-Centroid defuzzification (Pham and Castellani, 2002), were used and the result is presented at Figure 7 (scenario 1), Figure 8 (scenario 2) and Figure 9 (scenario 3).

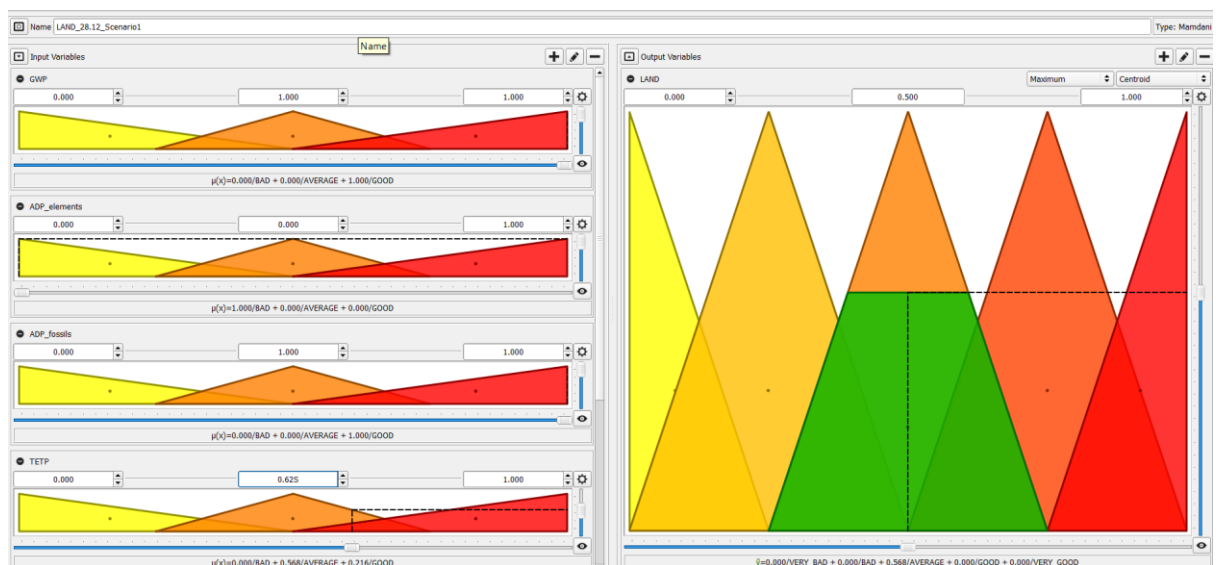


Figure 7: Fuzzy inference for land – scenario 1

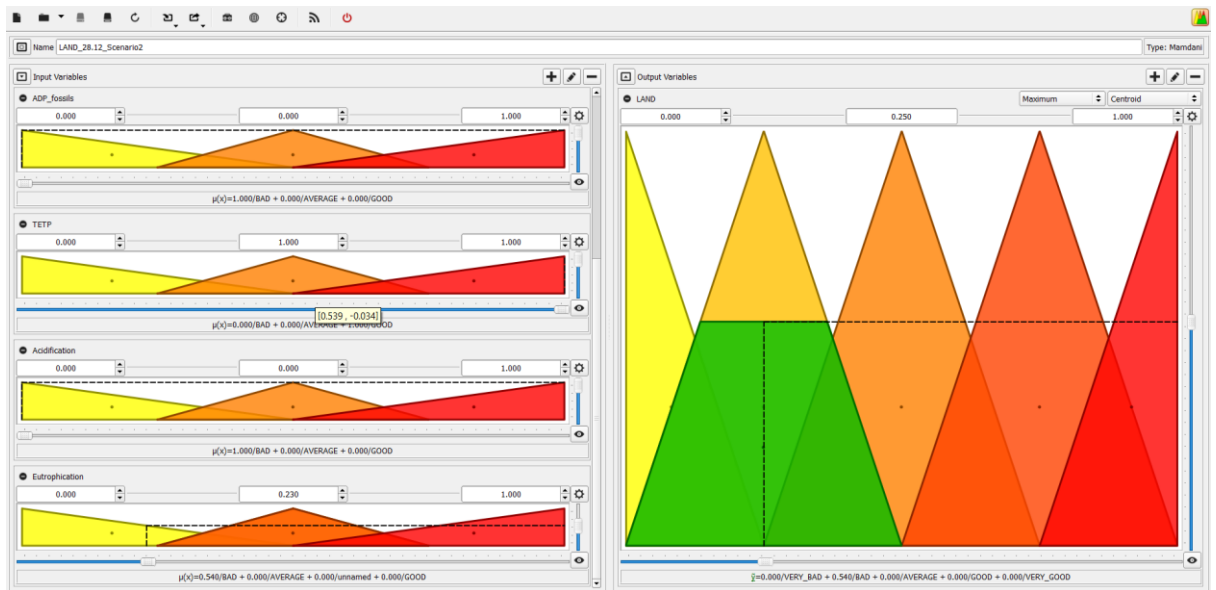


Figure 8: Fuzzy inference for land – scenario 2

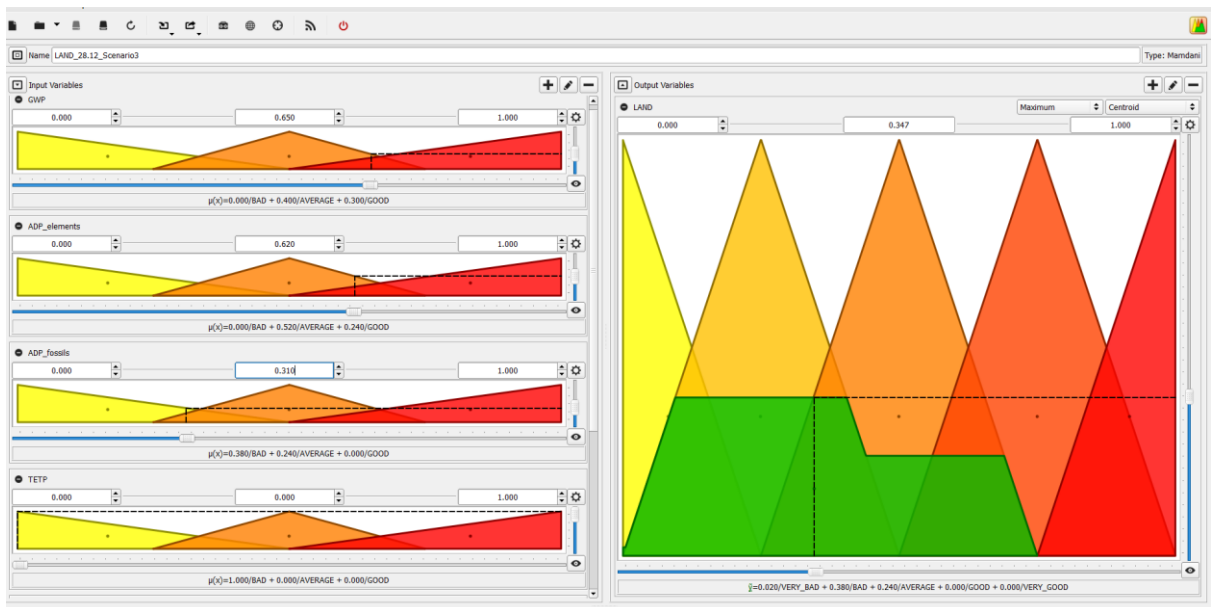


Figure 9: Fuzzy inference for land – scenario 3

3.4.4.3.2 Fuzzy inference for WATER

For the WATER, the following basic indicators were included in the group: Acidification Potential (AP) [kg SO₂-Equiv.], Global Warming Potential (GWP) [kg CO₂-Equiv.] and Eutrophication Potential (EP) [kg Phosphate-Equiv.], Freshwater Aquatic Ecotoxicity Potential (FAETP) [kg DCB-Equiv.] and Marine Aquatic Ecotoxicity Potential (MAETP) [kg DCB-Equiv.]

For these indicators, their normalised values were used as inputs in the FIS (Fuzzy Inference System) that included five inputs and provided as an output the aggregated

indicator 'WATER'. The Linguistic Variables used for each one of them were identical with all the rest and included three Linguistic Values: BAD, AVERAGE, GOOD with the same characteristics as all. The rule base used was consisted of 243 rules shown in Table B of the Appendices with conjunction: Minimum, disjunction: Maximum, activation: Minimum

The output variable 'LAND' utilises 5 linguistic variables (VERY BAD, BAD, AVERAGE, GOOD, VERY GOOD) triangular with the same characteristics as 'Socialoutput' and all Output Variables. The result is represented at the Figure 10. Also, as before, the three scenarios are presented accordingly in Figure 11, Figure 12 and Figure 13.

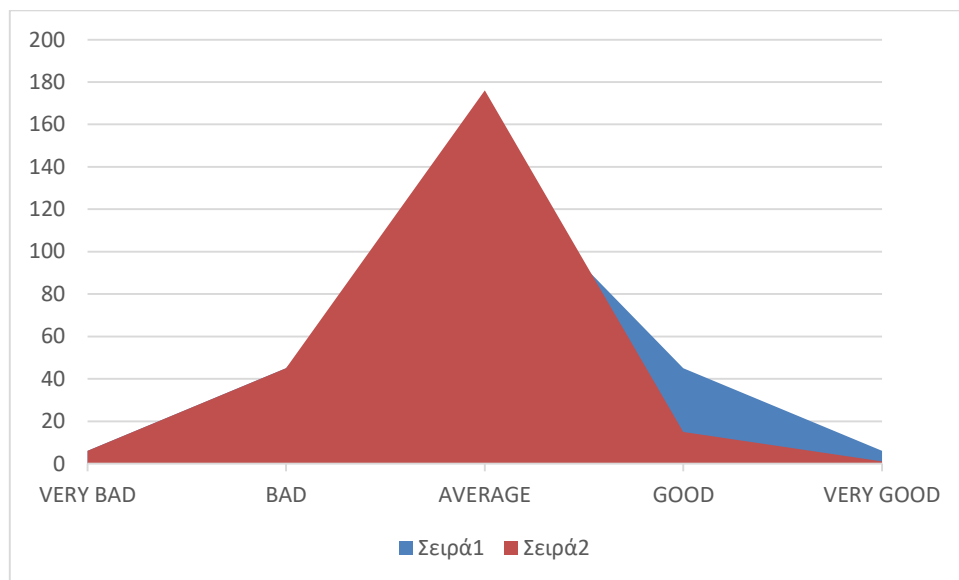


Figure 10: Fuzzy inference for water – variables

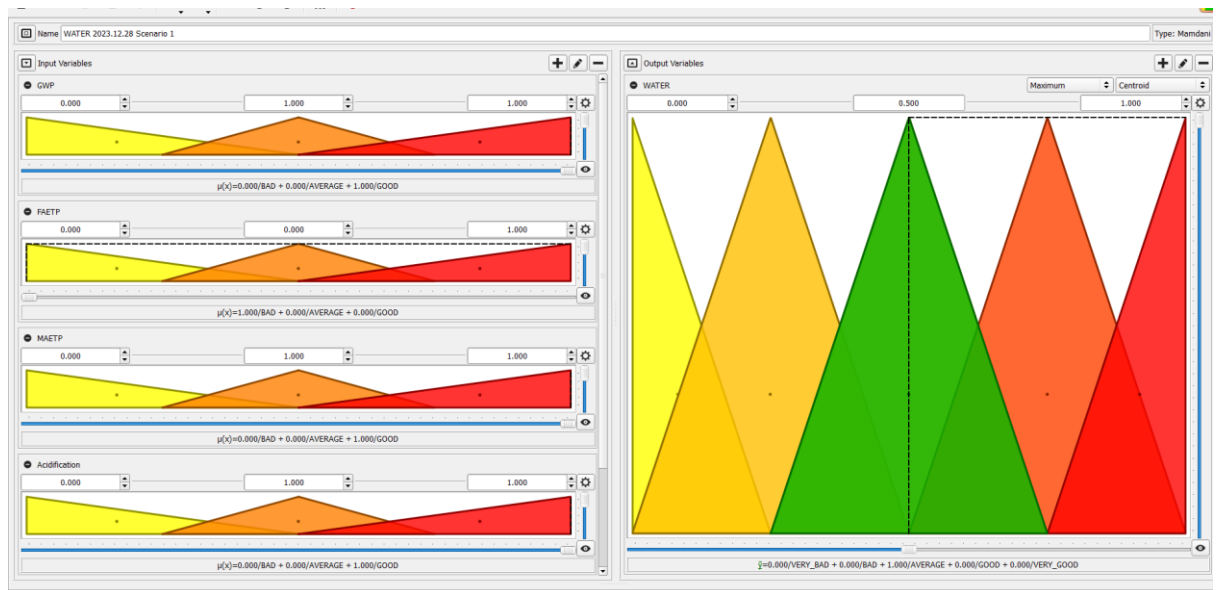


Figure 11: Fuzzy inference for water – scenario 1

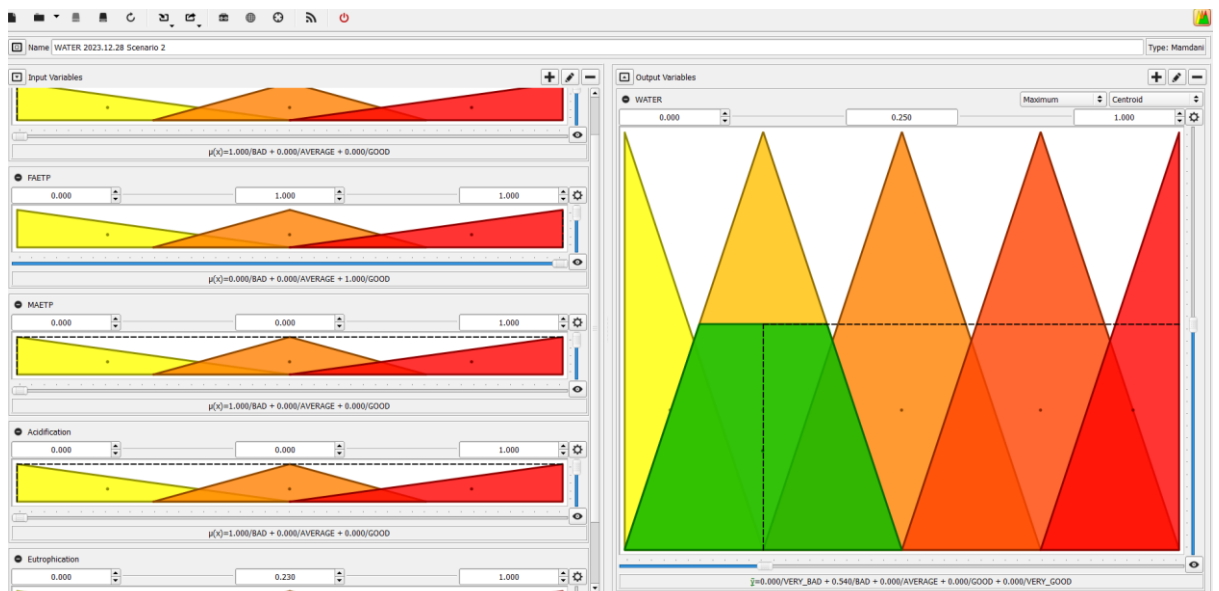


Figure 12: Fuzzy inference for water – scenario 2

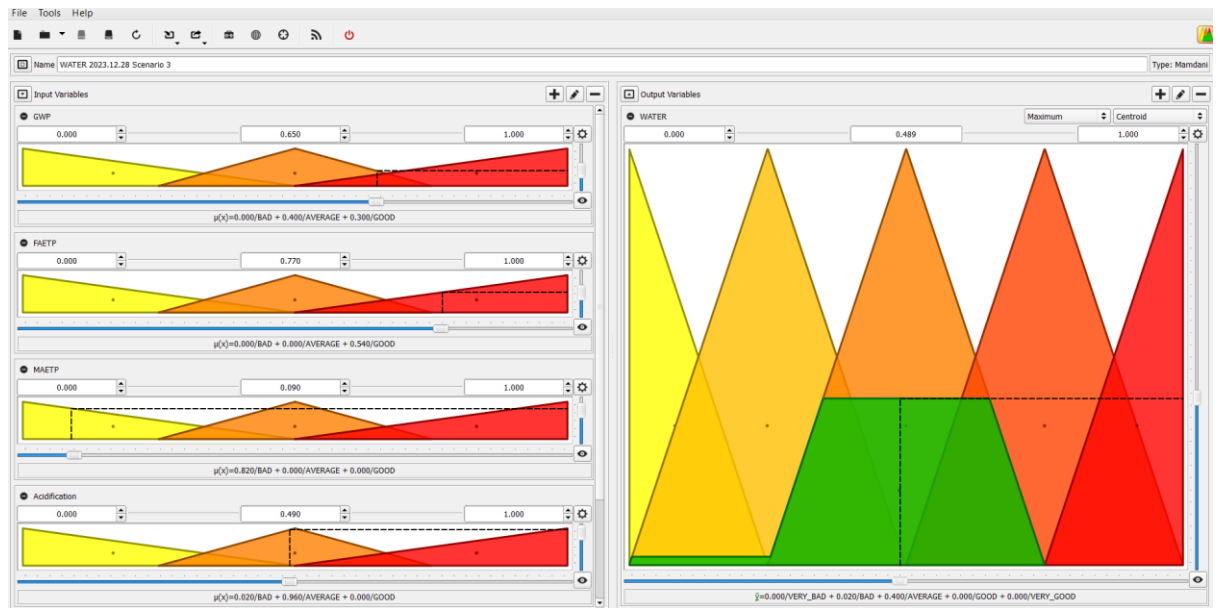


Figure 13: Fuzzy inference for water – scenario 3

3.4.4.3.3 Fuzzy inference for AIR

For the AIR, the following basic indicators were included in the group: Ozone Layer Depletion Potential (ODP) [kg R11-Equiv.], Photochemical Ozone Creation Potential (POCP) [kg Ethene-Equiv.] and Global Warming Potential (GWP) [kg CO₂-Equiv.]

For these indicators, their normalised values were used as inputs in the FIS (Fuzzy Inference System) that included three inputs and provided as an output the aggregated indicator 'AIR'. The Linguistic Variables used for each one of them were identical with all the rest and included three Linguistic Values: BAD, AVERAGE, GOOD with the same characteristics as all. The rule base used was consisted of 27 rules shown in Table C of the Appendices with conjunction: Minimum, disjunction: Maximum, activation: Minimum

The output variable 'AIR' utilises 5 linguistic variables (VERY BAD, BAD, AVERAGE, GOOD, VERY GOOD) triangular with the same characteristics as 'Socialoutput' and all Output Variables. The three scenarios are presented at the following Figure 14, Figure 15 and Figure 16.

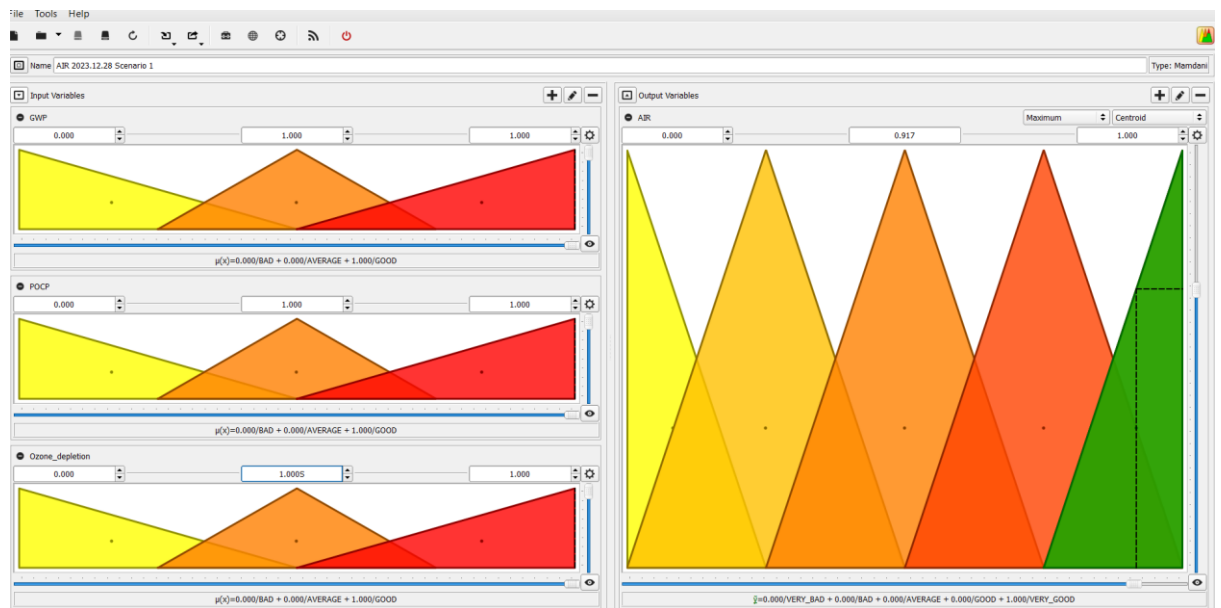


Figure 14: Fuzzy inference for air – scenario 1

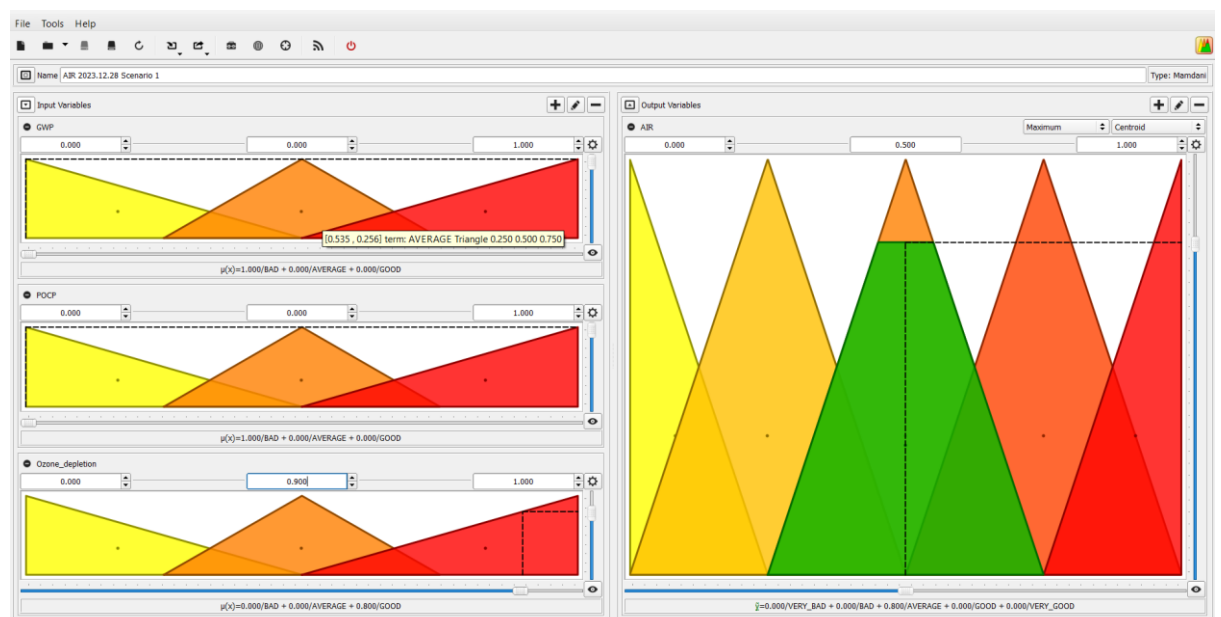


Figure 15: Fuzzy inference for air – scenario 2

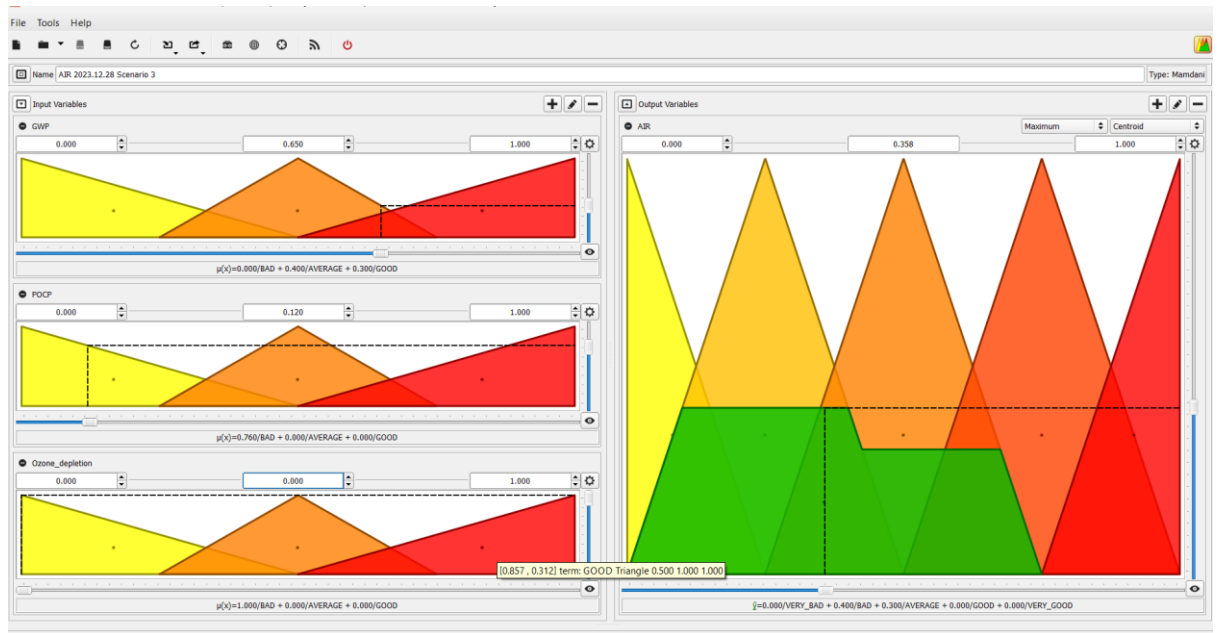


Figure 16: Fuzzy inference for air – scenario 3

3.4.4.3.4 Fuzzy inference for HUMAN

For the HUMAN, the following basic indicators were included in the group: Human Toxicity Potential (HTP) [kg DCB-Equiv.] and Global Warming Potential (GWP) [kg CO₂-Equiv.]

For these indicators, their normalised values were used as inputs in the FIS (Fuzzy Inference System) that included three inputs and provided as an output the aggregated indicator 'HUMAN'. The Linguistic Variables used for each one of them were identical with all the rest and included three Linguistic Values: BAD, AVERAGE, GOOD with the same characteristics as all. The rule base used was consisted of 9 rules shown in Table D of the Appendices with conjunction: Minimum, disjunction: Maximum, activation: Minimum

The output variable 'LAND' utilises 5 linguistic variables (VERY BAD, BAD, AVERAGE, GOOD, VERY GOOD) triangular with the same characteristics as 'Socialoutput' and all Output Variables. The three scenarios are presented at the following Figure 17, Figure 18 and Figure 19.

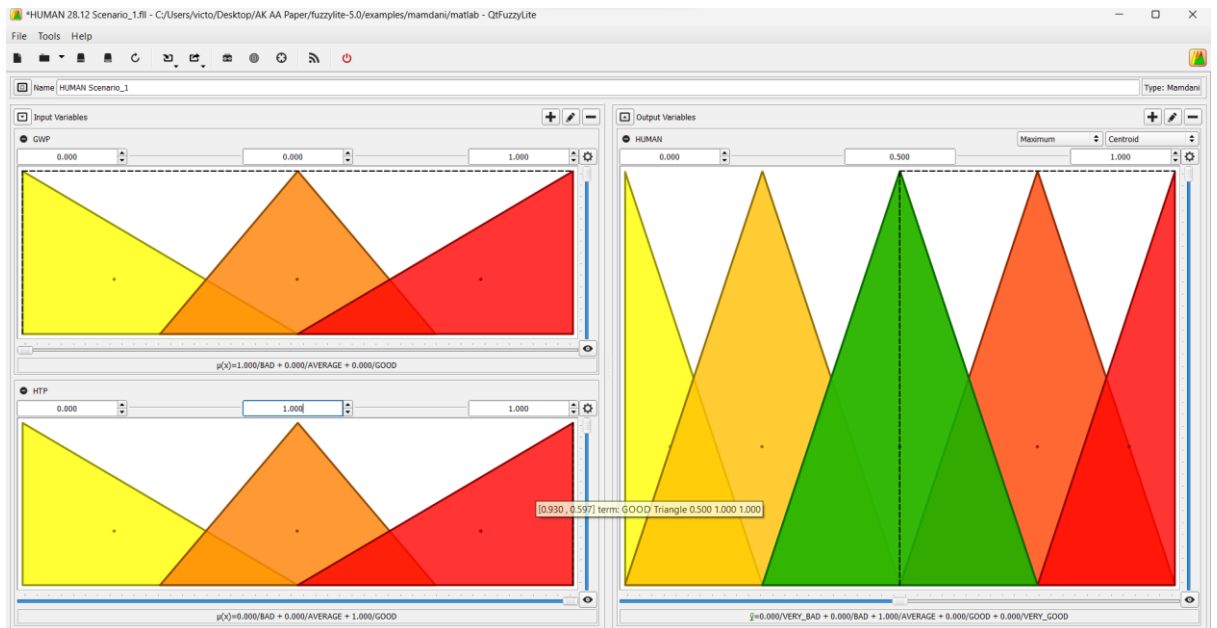


Figure 17: Fuzzy inference for human – scenario 1

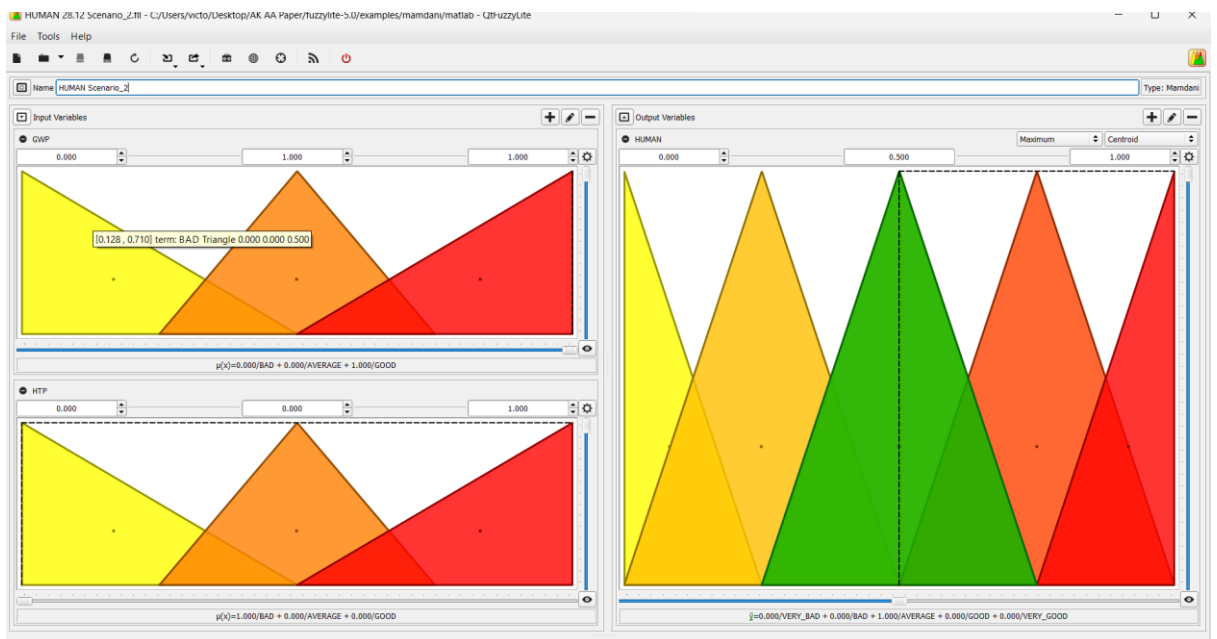


Figure 18: Fuzzy inference for human – scenario 2

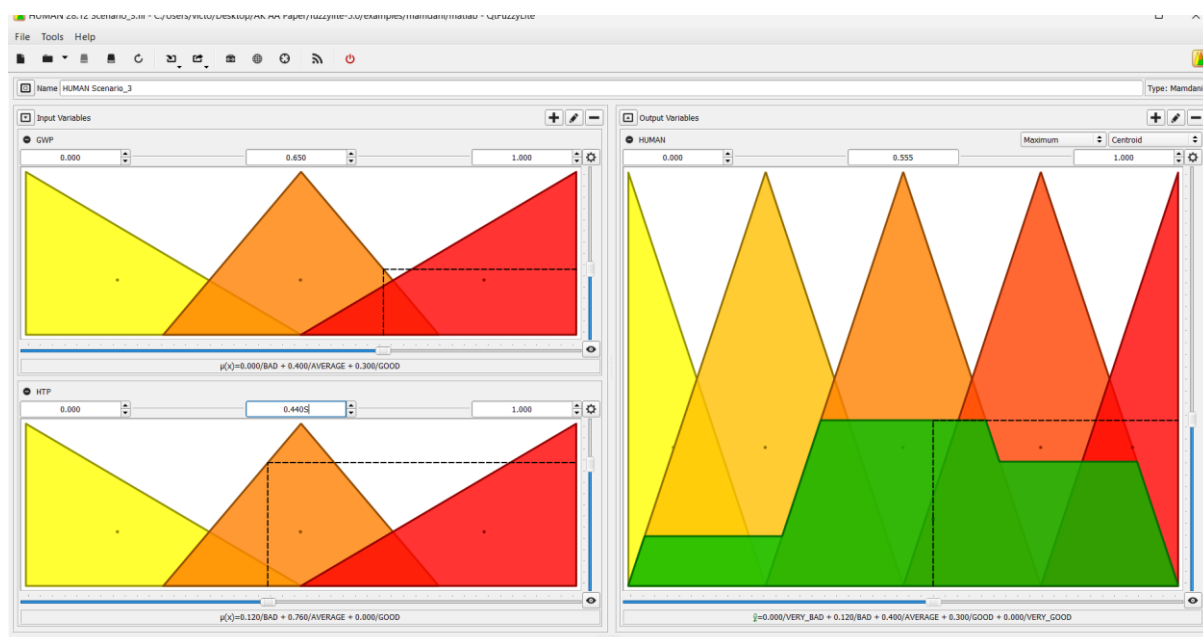


Figure 19: Fuzzy inference for human – scenario 3

3.4.4.3.5 Fuzzy inference for ENVIROMENT

For the 'ENVIRONMENT', the four indicators mentioned above were included and their defuzzified values were used as inputs in the FIS (Fuzzy Inference System) that included four inputs and provided as an output the aggregated indicator 'ENVIRONMENT'. The Linguistic Variables used for each one of them were identical with all the rest and included three Linguistic Values: BAD, AVERAGE, GOOD with the same characteristics as all. The rule base used was consisted of 81 rules shown in Table E of the Appendices with conjunction: Minimum, disjunction: Maximum, activation: Minimum

The output variable 'ENVIRONMENT' utilises 5 linguistic variables (VERY BAD, BAD, AVERAGE, GOOD, VERY GOOD) triangular with the same characteristics as 'Socialoutput' and all Output Variables. The result is represented at the Figure 20. Also, as before, the three scenarios are presented accordingly in Figure 21, Figure 22 and Figure 23.



Figure 20: Fuzzy inference for environment – variables

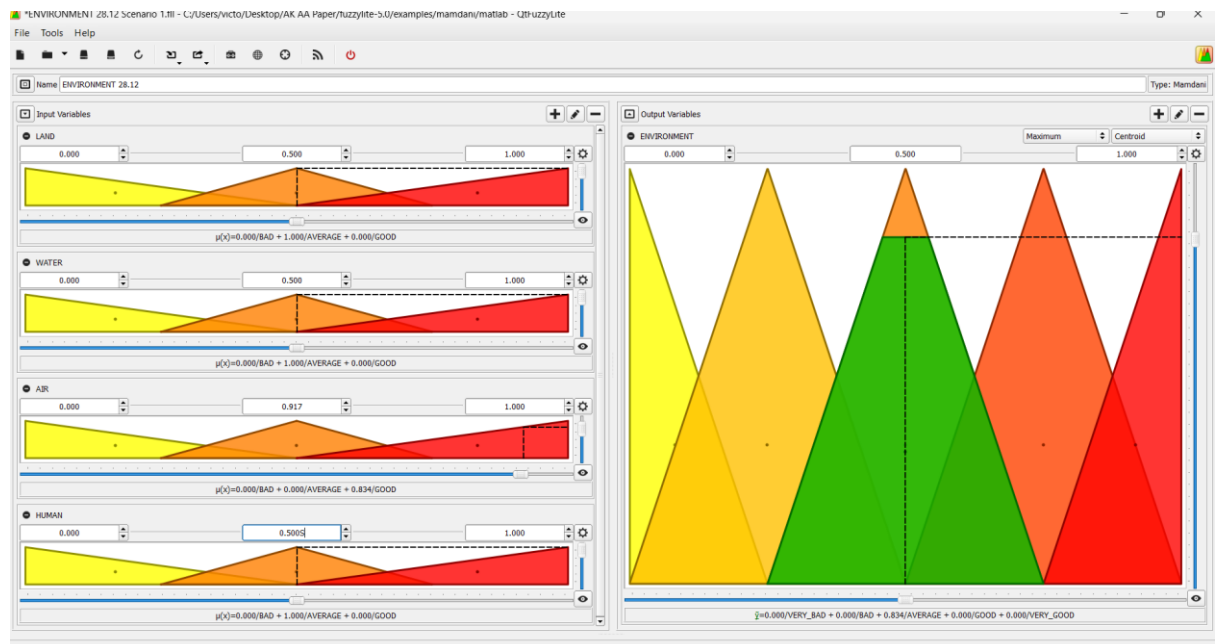


Figure 21: Fuzzy inference for environment – scenario 1

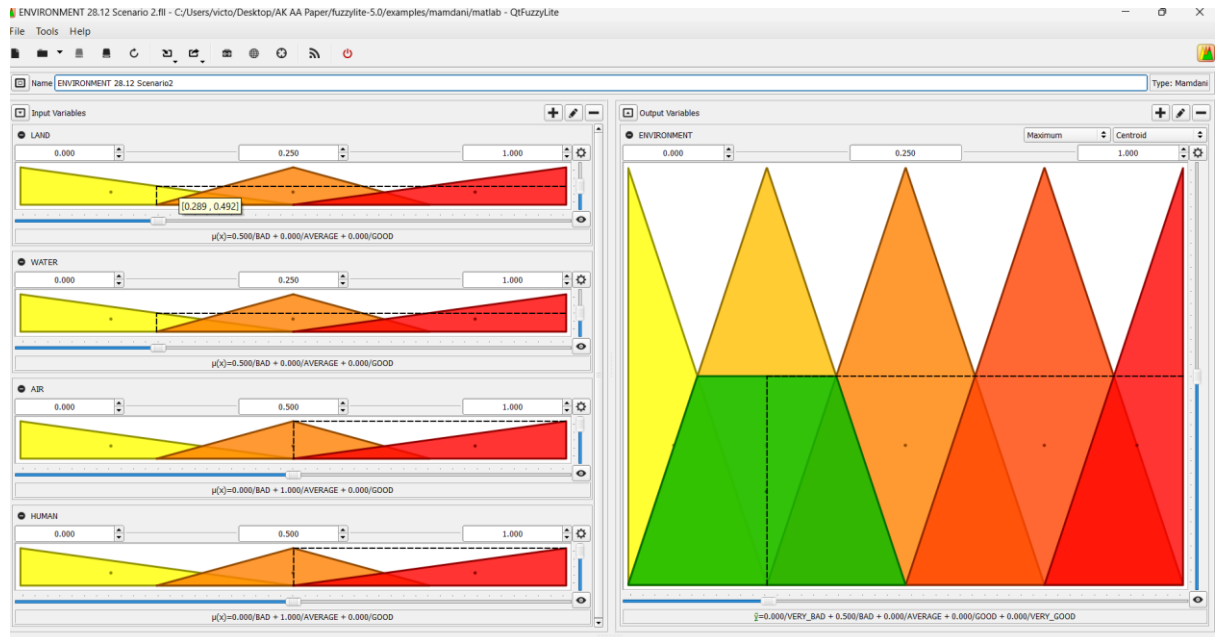


Figure 22: Fuzzy inference for environment – scenario 2

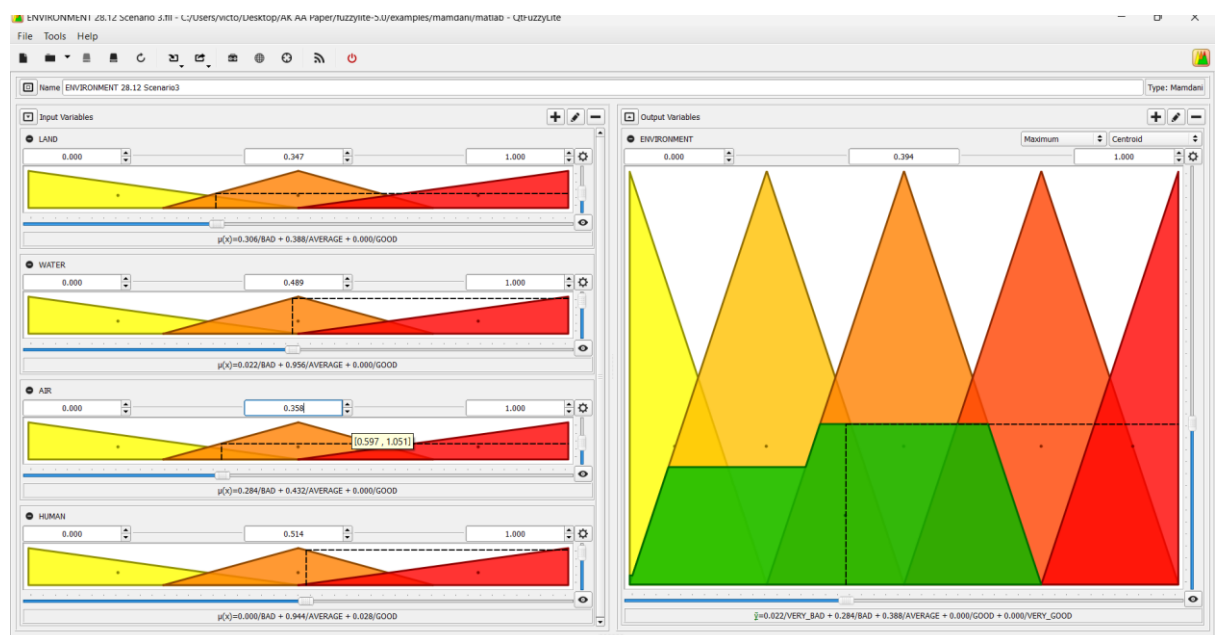


Figure 23: Fuzzy inference for environment – scenario 3

3.4.4.3.6 Fuzzy inference for economic LCA

It has to be noted that since the LCC is expressed from one indicator only, 'LCoE', the use of a fuzzy inference system is not necessary. Instead, the value from the normalisation is used as an input in the fuzzy inference system for the overall sustainability.

3.4.4.3.7 Fuzzy inference for Social LCA

For the application of a FIS (Fuzzy Inference System) for the Social component, two inputs were used that named 'Deaths_estimate' and 'Jobs_estimate' utilising 3 linguistic variables (BAD, AVERAGE, GOOD) , triangular with the following characteristics for both of them:

range: 0.000 1.000

term: Bad Triangle 0.000 0.000 0.500

term: Average Triangle 0.250 0.500 0.750

term: Good Triangle 0.500 1.000 1.000

The rule base used was consisted of 9 sub-rules shown in Table 9.

Table 9: Description of rules for fuzzy inference of social LCA

1	if Deaths_estimate is Good and Jobs_estimate is Good then Socialoutput is Very_Good
2	if Deaths_estimate is Good and Jobs_estimate is Average then Socialoutput is Good
3	if Deaths_estimate is Good and Jobs_estimate is Bad then Socialoutput is Average
4	if Deaths_estimate is Average and Jobs_estimate is Good then Socialoutput is Good
5	if Deaths_estimate is Average and Jobs_estimate is Average then Socialoutput is Average
6	if Deaths_estimate is Average and Jobs_estimate is Bad then Socialoutput is Bad
7	if Deaths_estimate is Bad and Jobs_estimate is Good then Socialoutput is Average
8	if Deaths_estimate is Bad and Jobs_estimate is Average then Socialoutput is Bad
9	if Deaths_estimate is Bad and Jobs_estimate is Bad then Socialoutput is Very_Bad

The rule base was built in a symmetric way which means that the number of rules that give 'BAD' as an output are equal to the number of rules that give 'GOOD' as an output and the same is for 'VERY_BAD' and 'VERY_GOOD'. The majority of the rules provide the output 'AVERAGE'. The Figure 24 that follows, shows the allocation of the rules to the respective Linguistic Value.

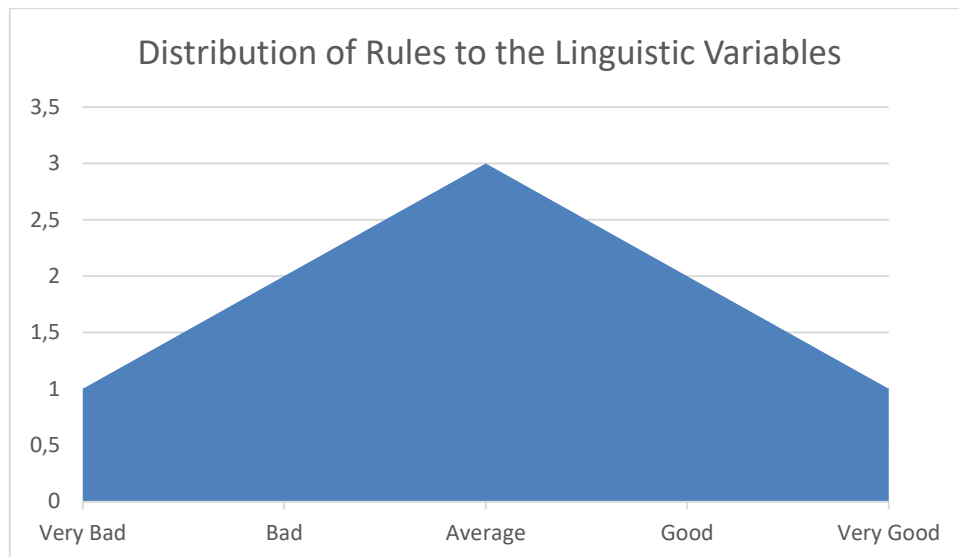


Figure 24: Fuzzy inference for social LCA – variables

For that a Mamdani type was used with the following RuleBlock characteristics:

enabled: true

conjunction: Minimum

disjunction: Maximum

activation: Minimum

The output variable 'Socialoutput' utilises 5 linguistic variables (VERY BAD, BAD, AVERAGE, GOOD, VERY GOOD) triangular with the following characteristics:

OutputVariable: Socialoutput

range: 0.000 1.000

accumulation: Maximum

defuzzifier: Centroid 200

term: Very_Bad Triangle 0.000 0.000 0.250

term: Bad Triangle 0.000 0.250 0.500

term: Average Triangle 0.250 0.500 0.750

term: Good Triangle 0.500 0.750 1.000

term: Very_Good Triangle 0.750 1.000 1.000

The three scenarios for the social inference are presented accordingly in Figure 25, Figure 26 and Figure 27.

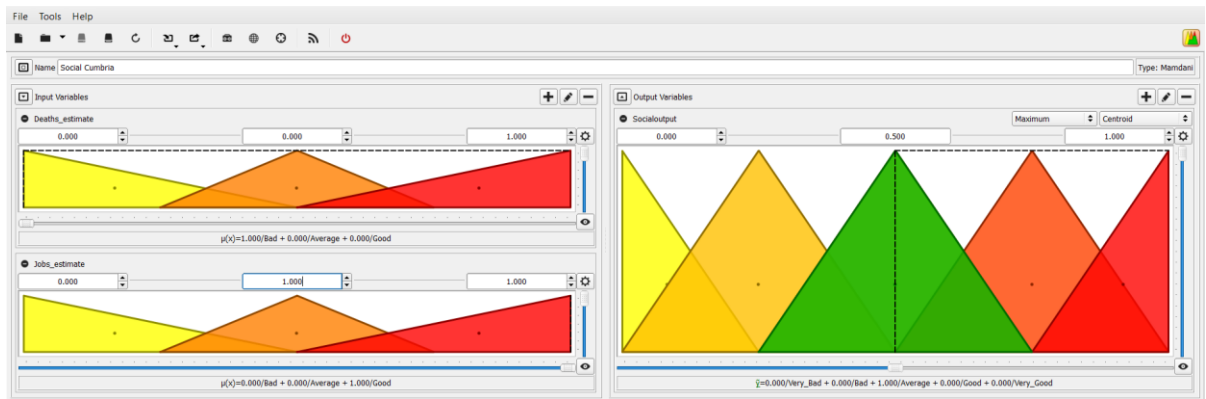


Figure 25: Fuzzy inference for social – scenario 1

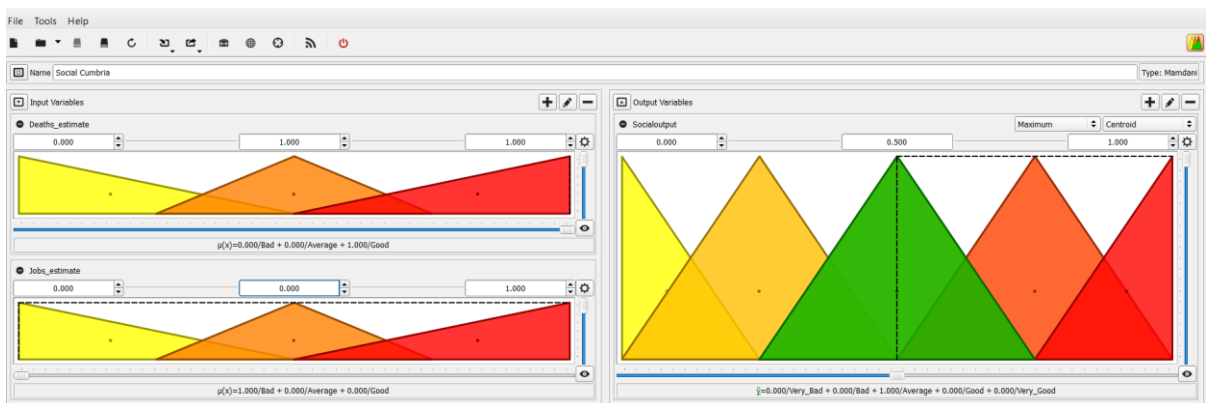


Figure 26: Fuzzy inference for social – scenario 2

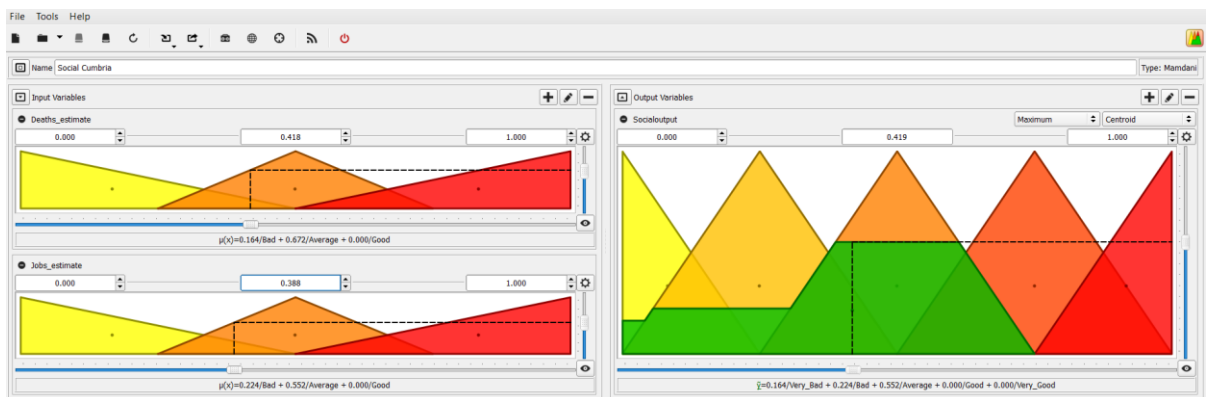


Figure 27: Fuzzy inference for social – scenario 3

3.4.4.3.8 Fuzzy inference for LCSA

Once the composite indicators for Social LCA and Environmental LCA were calculated, their defuzzified values are used as inputs in the FIS (Fuzzy Inference System) that aggregate them along with the normalised value of the LCoE into the overall LCSA.

The Linguistic Variables used for each one of them were identical with all the rest and included three Linguistic Values: BAD, AVERAGE, GOOD with the same characteristics as

all. The rule base used was consisted of 27 rules shown in Table F in the Appendices with conjunction: Minimum, disjunction: Maximum, activation: Minimum

In the final aggregation, the rules were not symmetric and a clear skew towards the 'VERY BAD' and 'BAD' values was used to express a more stringent approach. Two 'BAD' values in a rules will give an output 'VERY BAD' and one 'BAD' will give an output 'BAD' (Figure 28).



Figure 28: Final aggregation - linguistic variables

The output variable 'LCSA' utilises 5 linguistic variables (VERY BAD, BAD, AVERAGE, GOOD, VERY GOOD) triangular with the same characteristics as 'Socialoutput' and all Output Variables for the three scenarios (Figure 29, Figure 30 and Figure 31).

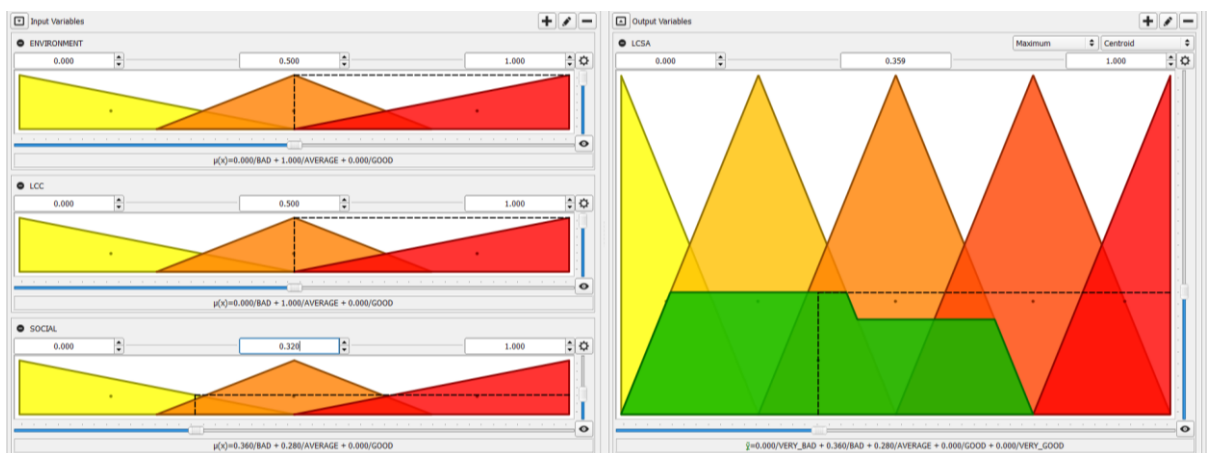


Figure 29: Final aggregation LCSA – scenario 1

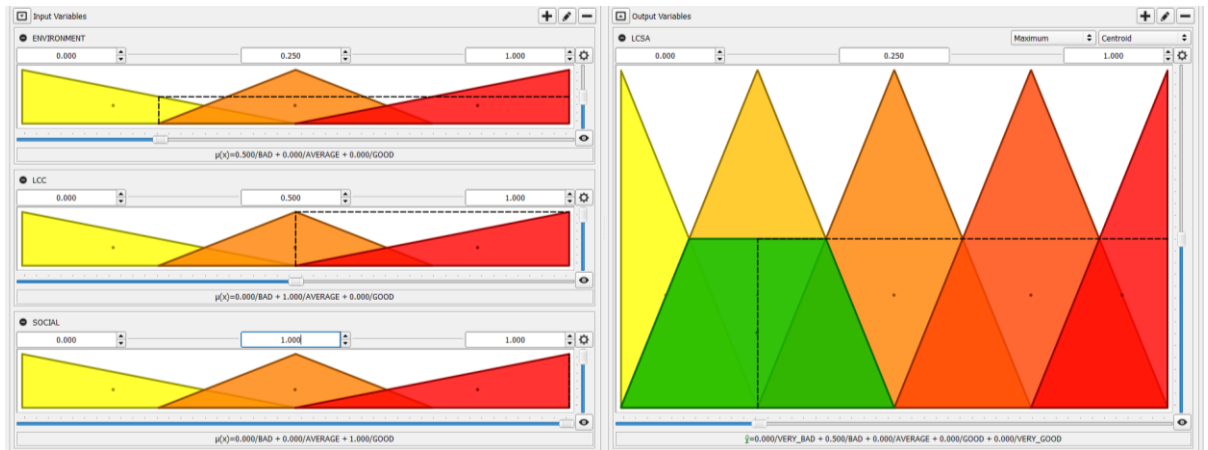


Figure 30: Final aggregation LCSA – scenario 2

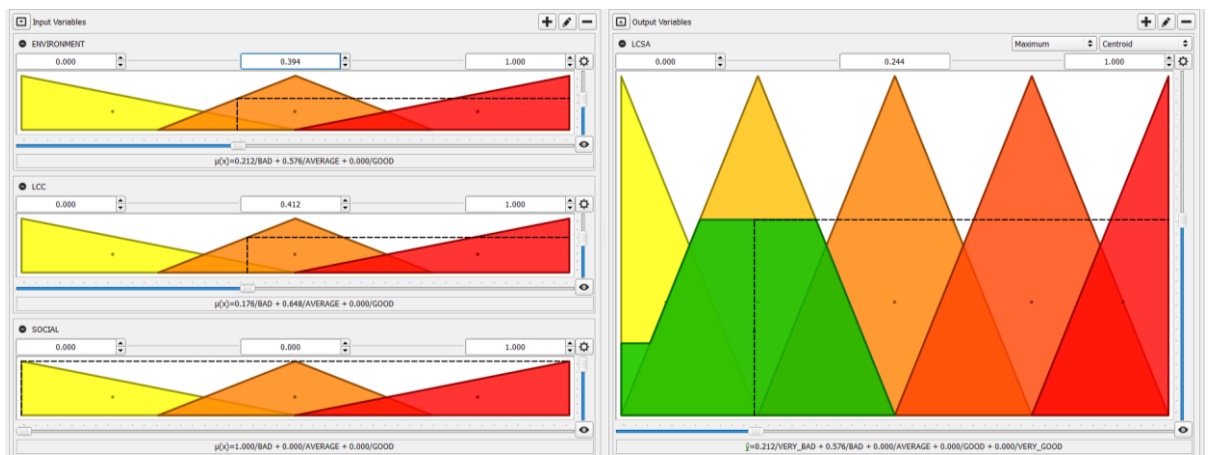


Figure 31: Final aggregation LCSA – scenario 3

4. Research results and discussion

In this chapter, the results of the assessments conducted are presented and discussed. These assessments are performed using the methodology and data inputs outlined in the scenarios described in chapter 3.

4.1 Outcomes of scenario 1: Business-as-usual deployment projections

The results of scenario 1 are shown at the following tables and figures:

Table 10: Scenario 1 - Global Warming Potential (GWP)

Global Warming Potential (GWP) [kg CO ₂ -Equiv.]	2015	2020	2025	2030
Total	5.73E+07	7.55E+07	1.14E+08	1.53E+08
Commercial wind	4.85E+06	6.98E+06	8.48E+06	9.98E+06
Small scale wind	1.20E+05	1.73E+05	2.38E+05	3.03E+05
Microgeneration	7.66E+06	1.34E+07	1.38E+07	1.42E+07
Small scale hydro	1.58E+05	1.92E+05	2.97E+05	4.02E+05
Plant biomass	9.91E+06	1.03E+07	1.23E+07	1.42E+07
Energy from waste	3.46E+07	4.44E+07	7.91E+07	1.14E+08

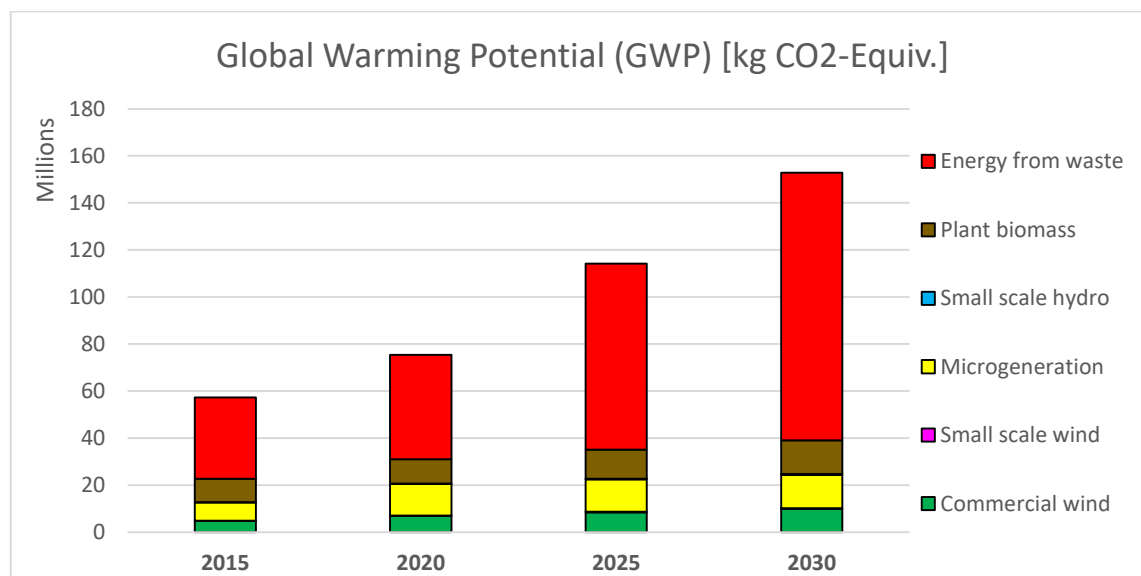


Figure 32: Scenario 1 - Global Warming Potential (GWP)

The data from Table 10 and Figure 32 present that global warming potential increases during the years for every energy source, reaching 1.53E+08 kg CO₂e until 2030. In 2015,

the energy from waste contributes the most to GWP, with 3.46E+07 kg CO₂e, following by plant biomass, microgeneration and commercial wind with 9.19E+06, 7.66E+06, 4.85E+06 kg CO₂e respectively. During this year, small scale hydro and small scale wind have the lowest contribution with 1.58E+05 and 1.20E+05 kg CO₂e. This ranking remains stable for the rest of the years, but every energy source contributes more to GWP. In 2020, energy from waste is the most significant contributor emitting 4.44E+07 kg CO₂e. Following this, with emissions of 1.34E+07 and 1.03E+07 kg CO₂e, respectively, microgeneration and plant biomass have significant contributions. Commercial wind contributes 6.98E+06 kg CO₂e. Small scale hydro and wind has the smallest values, at 1.92E+05 and 1.73E+05 kg CO₂e, respectively. With 7.91E+07 kg CO₂e, energy from waste continues to be the largest contributor in 2025. Plant biomass continues to be a significant energy source at 1.23E+07 kg CO₂e, and microgeneration remains considerable at 1.38E+07 kg CO₂e. Small scale hydro and wind remain the lowest contributors, with 2.97E+05 and 2.38E+05 kg CO₂e, respectively, while commercial wind climbs to 8.48E+06 kg CO₂e. Energy from waste continued to lead the way by 2030, contributing 1.14E+08 kg CO₂e, the highest GWP. Plant biomass and microgeneration's emissions has the same value of 1.42E+07 kg CO₂e. The amount of commercial wind rises to 9.98E+06 kg CO₂e. With 3.03E+05 and 4.02E+05 emissions, small scale wind and hydropower remain the least significant sources. The energy from waste is the most significant contributor every year, followed by microgeneration and plant biomass.

Table 11: Scenario 1 - Abiotic Depletion Potential (ADP elements)

Abiotic Depletion Potential (ADP elements) [kg Sb-Equiv.]	2015	2020	2025	2030
Total	1.20E+03	1.82E+03	2.10E+03	2.38E+03
Commercial wind	8.18E+02	1.18E+03	1.43E+03	1.68E+03
Small scale wind	2.68E+00	3.86E+00	5.31E+00	6.76E+00
Microgeneration	3.49E+02	6.11E+02	6.28E+02	6.44E+02
Small scale hydro	8.18E-01	9.92E-01	1.53E+00	2.08E+00
Plant biomass	2.51E+01	2.60E+01	3.11E+01	3.61E+01
Energy from waste	2.96E+00	3.80E+00	6.76E+00	9.73E+00

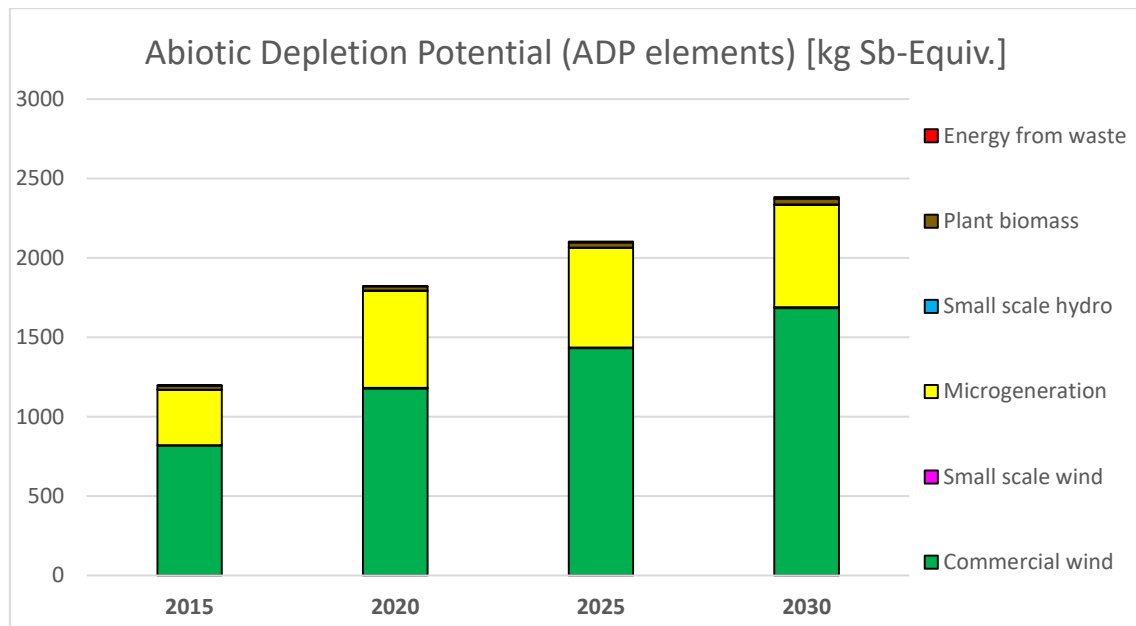
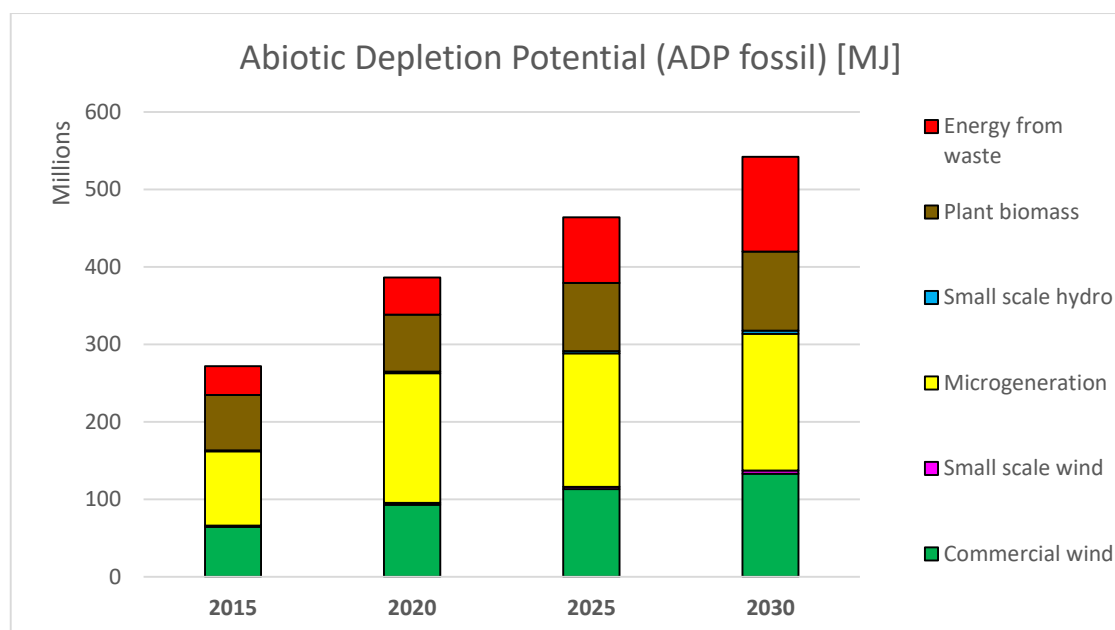


Figure 33: Scenario 1 - Abiotic Depletion Potential (ADP elements)

The data from Table 11 and Figure 33 present that abiotic Depletion Potential increases over the years for every energy source, reaching 2.38×10^3 kg Sbe by 2030. In 2015, ADP reaches 1.2×10^3 kg Sbe. Commercial wind has the highest ADP with 8.18×10^2 kg Sbe, following by microgeneration with 3.49×10^2 kg Sbe, plant biomass and energy from waste with 2.51×10^1 and 2.96×10^0 kg Sbe, respectively. Small scale wind and small scale hydro has the lowest contribution with 2.68×10^0 and 8.18×10^{-1} kg Sbe, respectively. During 2020, ADP reaches the stage of 1.82×10^3 kg Sbe. Commercial wind is the highest contributor again, with 1.18×10^3 kg Sbe, followed by microgeneration with 6.11×10^2 kg Sbe. Plant biomass contributes with 2.60×10^1 kg Sbe, while small scale wind, hydro and energy from waste reach 3.86×10^0 , 9.92×10^{-1} and 3.80×10^0 kg Sbe, respectively. The total ADP increases during 2025, to 2.10×10^3 kg Sbe. Commercial wind continues to be the top contributor, emitting 1.43×10^3 kg Sbe. The ranking keeps the same, with microgeneration at 6.28×10^2 kg Sbe, plant biomass at 3.11×10^1 kg Sbe, energy from waste at 6.76×10^0 kg Sbe, small scale wind at 5.31×10^0 kg Sbe and small scale hydro at 1.53×10^0 kg Sbe. In 2030, ADP rises to 2.38×10^3 kg Sbe. Commercial wind remains the highest contributor with 1.68×10^3 kg Sbe. Microgeneration ADP reaches 6.44×10^2 kg Sbe, while plant biomass increases to 3.61×10^1 kg Sbe. Small scale wind, small scale hydro and energy from waste also have increasing ADP values, but remain small.

Table 12: Scenario 1 - Abiotic Depletion Potential (ADP fossil)

Abiotic Depletion Potential (ADP fossil) [MJ]	2015	2020	2025	2030
Total	2.72E+08	3.86E+08	4.64E+08	5.42E+08
Commercial wind	6.46E+07	9.31E+07	1.13E+08	1.33E+08
Small scale wind	1.63E+06	2.35E+06	3.23E+06	4.11E+06
Microgeneration	9.56E+07	1.67E+08	1.72E+08	1.77E+08
Small scale hydro	1.53E+06	1.86E+06	2.88E+06	3.89E+06
Plant biomass	7.12E+07	7.38E+07	8.81E+07	1.02E+08
Energy from waste	3.72E+07	4.77E+07	8.49E+07	1.22E+08

**Figure 34: Scenario 1 - Abiotic Depletion Potential (ADP fossil)**

The data from Table 12 and Figure 34 present that abiotic Depletion Potential (fossil) increases over the years for every energy source, reaching 5.42E+08 MJ, by 2030. During 2015, the Abiotic Depletion Potential (ADP fossil) is 2.72E+08 MJ. Microgeneration has the highest ADP with 9.56E+07 MJ, followed by commercial wind, which contributes with 6.46E+07 MJ. Plant biomass and energy from waste also contributes to ADP, with 7.12E+07 MJ and 3.72E+07 MJ, respectively. Small scale wind and hydro have lower contributions with 1.63E+06 MJ and 1.53E+06 MJ, respectively. In 2020, ADP fossil increases to 3.86E+08 MJ. Microgeneration remains the highest contributor with 1.67E+08 MJ, followed by commercial wind with 9.31E+07 MJ. Plant biomass and energy from waste contributes with 7.38E+07 MJ and 4.77E+07 MJ, respectively. Small scale wind and hydro also increases a little bit with values of 2.35E+06 and 1.86E+06 MJ. In 2025, microgeneration continues to be the top contributor, emitting 1.72E+08 MJ. The

ranking remains the same. Commercial wind, plant biomass, energy from waste contributes with $1.13\text{E}+08$, $8.81\text{E}+07$, $8.49\text{E}+07$ MJ, respectively. Approaching 2030, microgeneration remains the highest contributor with $1.77\text{E}+08$ MJ and commercial wind has ADP of $1.33\text{E}+08$ MJ. Plant biomass increases to $1.02\text{E}+08$ MJ, while energy from waste to $1.22\text{E}+08$. Small scale wind and hydro have also small increased ADP values.

Table 13: Scenario 1 - Acidification Potential (AP)

Acidification Potential (AP) [kg SO₂-Equiv.]	2015	2020	2025	2030
Total	2.53E+05	3.12E+05	4.08E+05	5.04E+05
Commercial wind	2.56E+04	3.69E+04	4.48E+04	5.27E+04
Small scale wind	6.36E+02	9.16E+02	1.26E+03	1.60E+03
Microgeneration	3.47E+04	6.08E+04	6.24E+04	6.41E+04
Small scale hydro	6.28E+02	7.62E+02	1.18E+03	1.59E+03
Plant biomass	1.32E+05	1.37E+05	1.63E+05	1.90E+05
Energy from waste	5.93E+04	7.61E+04	1.35E+05	1.95E+05

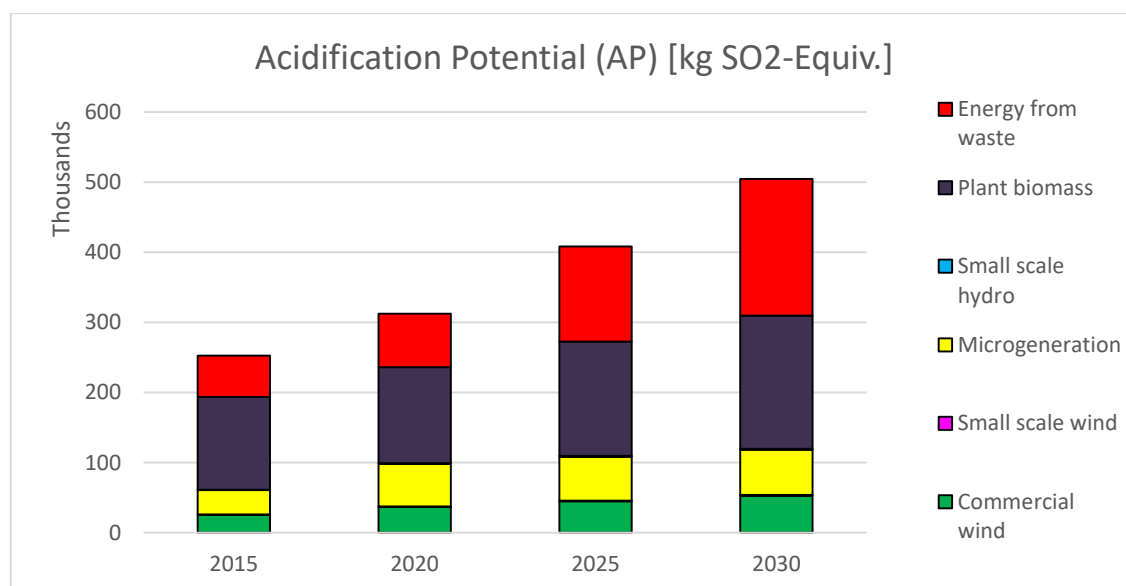


Figure 35: Scenario 1 - Acidification Potential (AP)

The data from Table 13 and Figure 35 present that Acidification (AP) increases over the years, reaching the point of $5.04\text{E}+05$ kg SO₂e, by 2030. In 2015, AP is $2.53\text{E}+05$ kg SO₂e. Plant biomass has the highest AP with $1.32\text{E}+05$ kg SO₂e, followed by energy from waste at $5.93\text{E}+04$ kg SO₂e. Commercial wind and microgeneration also contribute to AP, with $2.56\text{E}+04$ and $3.47\text{E}+04$ kg SO₂e, respectively. Small scale wind and small scale hydro have lower contributions with $6.36\text{E}+02$ and $6.28\text{E}+02$ kg SO₂e, respectively. During

2020, AP increases to 3.12E+05 kg SO₂e. Plant biomass remains the hot-spot with 1.37E+05 kg SO₂e, followed by energy from waste at 7.61E+04 kg SO₂e. Commercial wind and microgeneration also contributes to AP, with 3.69E+04 and 6.08E+04 kg SO₂e, respectively. Small scale wind and hydro have values of 9.16E+02 and 7.62E+02 kg SO₂e, respectively. In 2025, plant biomass emits 1.63E+05 kg SO₂e. Energy from waste, microgeneration and commercial wind were also significant sources, with 1.35E+05, 6.24E+04 and 4.48E+04 kg SO₂e, respectively, while small scale wind and small scale hydro contribute with 1.26E+03 and 1.18E+03 kg SO₂e. During 2030, the ranking changes: Energy from waste comes first with 1.95E+05 kg SO₂e, followed by plant biomass, microgeneration, commercial wind, small scale wind and small scale hydro contributing with 1.90E+05, 6.41E+04, 5.27E+04, 1.60E+03 and 1.59E+03 kg SO₂e, respectively.

Table 14: Scenario 1 - Eutrophication Potential (EP)

Eutrophication Potential (EP) [kg Phosphate-Equiv.]	2015	2020	2025	2030
Total	9.56E+04	1.25E+05	1.48E+05	1.71E+05
Commercial wind	1.87E+04	2.69E+04	3.27E+04	3.85E+04
Small scale wind	4.17E+02	6.00E+02	8.25E+02	1.05E+03
Microgeneration	2.31E+04	4.05E+04	4.16E+04	4.27E+04
Small scale hydro	2.38E+02	2.89E+02	4.46E+02	6.04E+02
Plant biomass	4.69E+04	4.86E+04	5.80E+04	6.74E+04
Energy from waste	6.30E+03	8.08E+03	1.44E+04	2.07E+04

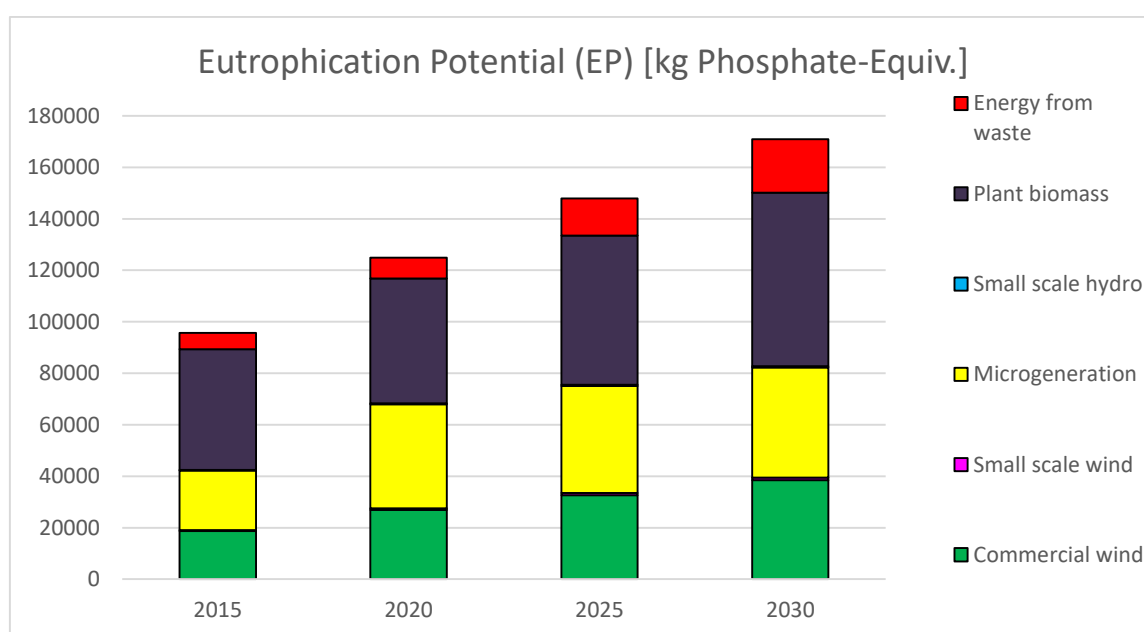


Figure 36: Scenario 1 - Eutrophication Potential (EP)

The data from Table 14 and Figure 36 present that eutrophication potential (EP) increase over the years, reaching the point of 1.71E+05 kg Phosphate Eq. In 2015, EP is 9.56E+04 kg Phosphate Eq. The most impactful energy sources are: plant biomass, microgeneration and commercial wind with 4.69E+04, 2.31E+04 and 1.87E+04 kg Phosphate Eq, respectively. Energy from waste comes next with 6.30E+03 kg Phosphate Eq. Small scale wind and hydro have lower contributions at 4.17E+02 and 2.38E+02 kg Phosphate Eq, respectively. In 2020, the total EP increases to 1.25E+05 kg Phosphate Eq, with plant biomass remaining the highest contributor with 4.86E+04 kg Phosphate Eq. Microgeneration follows with 4.05E+04 kg Phosphate Eq. Commercial wind and energy from waste are also considerable amounts also with 2.69E+04 and 8.08E+03 kg Phosphate Eq, respectively. Small scale wind and hydro have also increased a little bit. During 2025, plant biomass has the highest emissions with 5.80E+04 kg Phosphate Eq. Microgeneration comes in the second place with 4.16E+04 kg Phosphate Eq and in the third place is commercial wind again, with 3.27E+04 kg Phosphate Eq. Energy from waste emits 1.44E+04 kg Phosphate Eq. Small scale wind and small scale hydro climbs 8.25E+02 and 4.46E+02 kg Phosphate Eq. respectively. In 2030, the ranking remains the same: plant biomass, microgeneration, commercial wind, energy from waste, small scale wind and small scale hydro, contributing 6.74E+04 kg, 4.27E+04, 3.85E+04, 2.07E+04, 1.05E+03 and 6.04E+02 kg Phosphate Eq, respectively.

Table 15: Scenario 1 - Fresh Aquatic Ecotoxicity Potential (FAETP)

Freshwater Aquatic Ecotoxicity Potential (FAETP) [kg DCB-Equiv.]	2015	2020	2025	2030
Total	7.12E+07	1.06E+08	1.24E+08	1.42E+08
Commercial wind	5.26E+07	7.57E+07	9.20E+07	1.08E+08
Small scale wind	1.70E+05	2.45E+05	3.36E+05	4.28E+05
Microgeneration	1.52E+07	2.65E+07	2.73E+07	2.80E+07
Small scale hydro	1.27E+05	1.54E+05	2.39E+05	3.23E+05
Plant biomass	3.13E+06	3.24E+06	3.86E+06	4.49E+06
Energy from waste	1.24E+04	1.59E+04	2.83E+04	4.07E+04

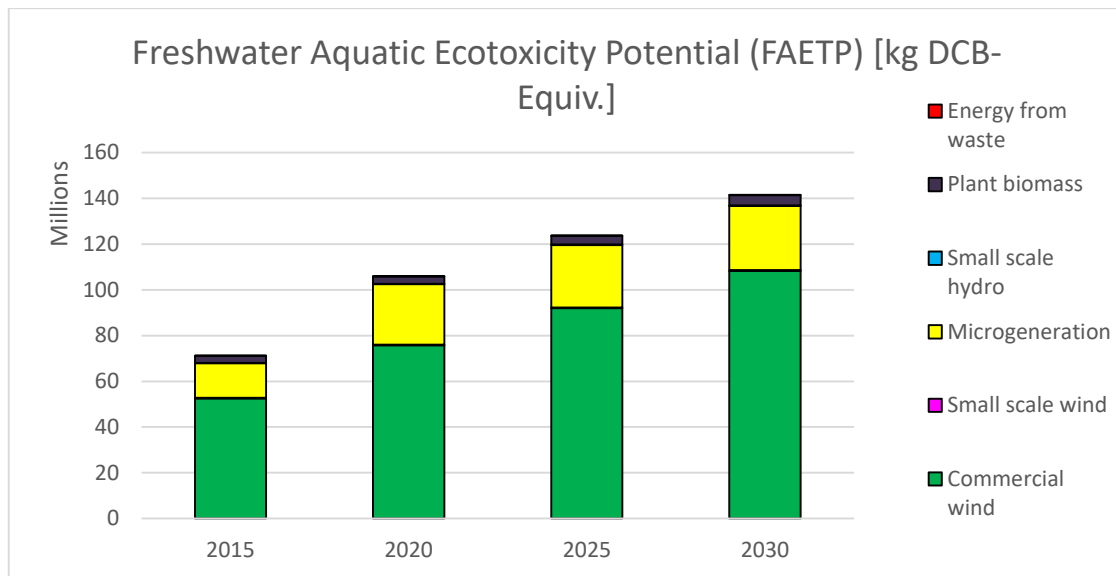
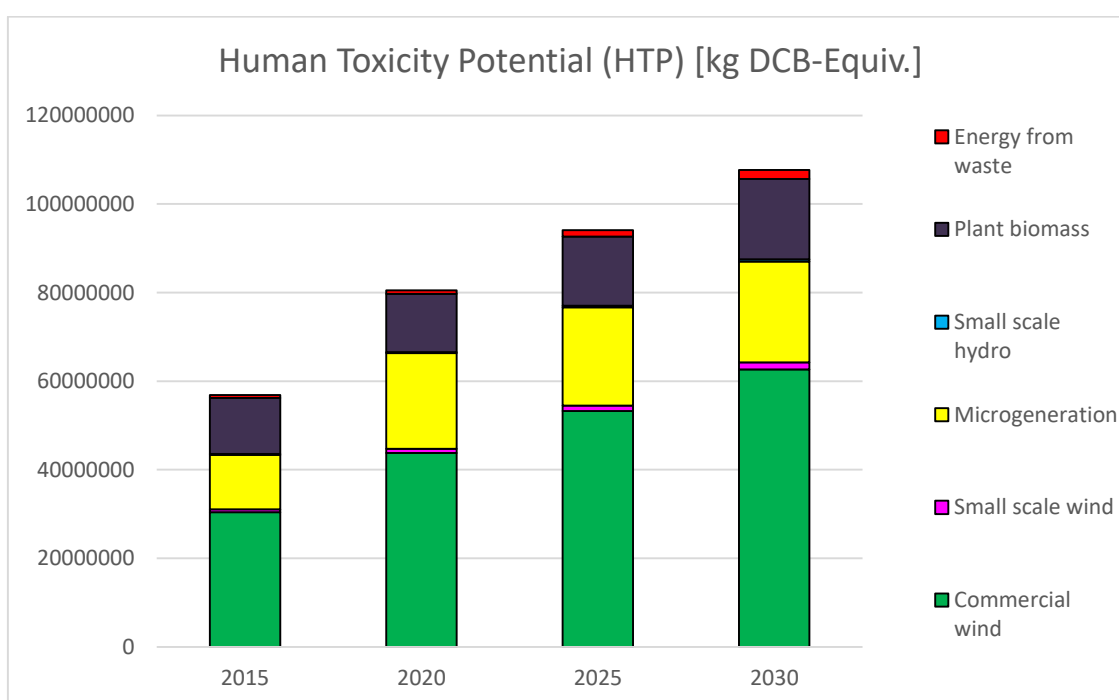


Figure 37: Scenario 1 - Fresh Aquatic Ecotoxicity Potential (FAETP)

The data from Table 15 and Figure 37 present that Freshwater Aquatic Ecotoxicity Potential (FAETP) increases over the years reaching the point of $1.42\text{E}+08$ kg DCBe by 2030. It is clear that during the years, the most significant contributor is commercial wind. In 2015, the total FAETP is $7.12\text{E}+07$ kg DCBe. Commercial wind has the highest impact with $5.26\text{E}+07$ kg DCBe, followed by microgeneration with $1.52\text{E}+07$ kg DCBe and plant biomass with $3.13\text{E}+06$ kg DCBe. Small scale wind, small scale hydro and energy from waste have the lowest contributions at $1.70\text{E}+05$, $1.27\text{E}+05$ and $1.24\text{E}+04$ kg DCBe, respectively. During 2020, the total FAETP increases to $1.06\text{E}+08$ kg DCBe, with commercial wind remaining the hot-spot at $7.57\text{E}+07$ kg DCBe, followed by microgeneration at $2.65\text{E}+07$ kg DCBe. Plant biomass is also a significant contributor with $3.24\text{E}+06$ kg DCBe. A small increase, but still not significant enough is pointed to small scale wind, small scale hydro and energy from waste. In 2025, the ranking remains the same with commercial wind and microgeneration emitting the most with $9.20\text{E}+07$ and $2.73\text{E}+07$ kg DCBe, respectively. Plant biomass is in the third place with $3.86\text{E}+06$ kg DCBe. Small scale wind, hydro," and energy from waste reach $3.36\text{E}+05$, $2.39\text{E}+05$ and $2.83\text{E}+04$ kg DCBe, respectively. In 2030, commercial wind is still the highest contributor with $1.08\text{E}+08$ kg DCBe. Microgeneration emits $2.80\text{E}+07$ kg DCBe and plant biomass increases to $4.49\text{E}+06$ kg DCBe. Small scale wind, small scale hydro and energy from waste also have higher values.

Table 16: Scenario 1 - Human Toxicity Potential (HTP)

Human Toxicity Potential (HTP) [kg DCB-Equiv.]	2015	2020	2025	2030
Total	5.69E+07	8.05E+07	9.41E+07	1.08E+08
Commercial wind	3.04E+07	4.38E+07	5.32E+07	6.26E+07
Small scale wind	6.36E+05	9.16E+05	1.26E+06	1.60E+06
Microgeneration	1.23E+07	2.16E+07	2.22E+07	2.28E+07
Small scale hydro	2.01E+05	2.44E+05	3.77E+05	5.11E+05
Plant biomass	1.26E+07	1.31E+07	1.56E+07	1.82E+07
Energy from waste	6.23E+05	8.00E+05	1.42E+06	2.05E+06

**Figure 38: Scenario 1 - Human Toxicity Potential (HTP)**

The data from Table 16 and Figure 38 present that Human Toxicity (HTP) increases over the years and commercial wind is consistently the highest contributor. In 2015, the total HTP is 5.69E+07 kg DCBe. As said above, commercial wind has the highest impact with 3.04E+07 kg DCBe, followed by plant biomass with 1.26E+07 kg DCBe. Microgeneration is in the third place with 1.23E+07 kg DCBe. Small scale wind, energy from waste and small scale hydro contribute with 6.36E+05, 6.23E+05 and 2.01E+05 kg DCBe, respectively. During 2020, the total HTP increases to 8.05E+07 kg DCBe, with "commercial wind remaining the highest contributor at 4.38E+07 kg DCBe. The second place now goes to microgeneration emitting 2.16E+07 kg DCBe, while plant biomass gets the third place with 1.31E+07 kg DCBe. The rest of the energy sources have much lower contributions. By 2025, the total HTP increases to 9.41E+07 kg DCBe, with commercial

wind emitting $5.32\text{E}+07$ kg DCBe. Microgeneration and plant biomass follow with $2.22\text{E}+07$ and $1.56\text{E}+07$ kg DCBe, respectively. Energy from waste gets the fourth place with $1.42\text{E}+06$ kg DCBe, followed small scale wind with 1.26 kg DCBe. Small scale hydro remains in the last place with 3.77 kg DBCe. In 2030, the total HTP reaches $1.08\text{E}+08$ kg DCBe. Commercial wind $6.26\text{E}+07$ kg DCBe and in the second place, microgeneration has HTP of $2.28\text{E}+07$ kg DCBe, followed by plant biomass with $1.82\text{E}+07$ kg DCBe. Energy from waste, small scale wind and hydro contribute with $2.05\text{E}+06$, $1.60\text{E}+06$ and $5.11\text{E}+05$, respectively.

Table 17: Scenario 1 - Marine Aquatic Ecotoxicity Potential (MAETP)

Marine Aquatic Ecotoxicity Potential (MAETP) [kg DCB-Equiv.]	2015	2020	2025	2030
Total	5.78E+10	8.71E+10	1.02E+11	1.16E+11
Commercial wind	3.02E+10	4.35E+10	5.28E+10	6.22E+10
Small scale wind	3.10E+08	4.47E+08	6.14E+08	7.82E+08
Microgeneration	1.97E+10	3.45E+10	3.55E+10	3.64E+10
Small scale hydro	1.75E+08	2.13E+08	3.29E+08	4.46E+08
Plant biomass	4.29E+09	4.45E+09	5.30E+09	6.16E+09
Energy from waste	3.09E+09	3.96E+09	7.06E+09	1.01E+10

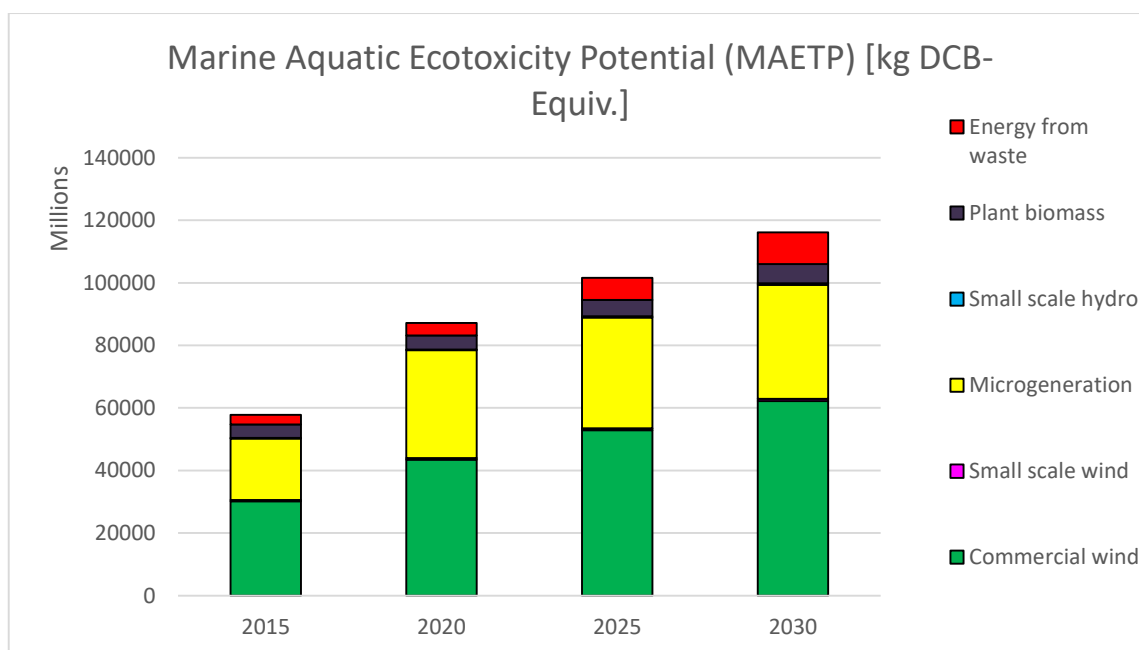


Figure 39: Scenario 1 - Marine Aquatic Ecotoxicity Potential (MAETP)

The data from Table 17 and Figure 39 present that Marine Aquatic Ecotoxicity Potential (MAETP) increases over the years, reaching $1.16\text{E}+11$ kg DCBe, by 2030, with commercial

wind being consistently the energy source with the highest contribution. In 2015, the total MAETP is 5.78E+10 kg DCBe. Commercial wind has the highest impact with 3.02E+10 kg DCBe, followed by microgeneration with 1.97E+10 kg DCBe. Plant biomass and energy from waste play a significant role emitting 4.29E+09 and 3.09E+09 kg DCBe, respectively. Small scale wind and hydro contributes with 3.10E+08 and 1.75E+08 kg DCBe, respectively. In 2020, the total MAETP increases to 8.71E+10 kg DCBe. The ranking remains the same with commercial wind remaining the highest contributor at 4.35E+10 kg DCBe, followed by microgeneration and plant biomass with 3.45E+10 and 4.45E+09 kg DCBe, respectively. Energy from waste contributes with 3.96E+09 kg DCBe. Small scale wind and hydro's emissions remain relatively low. During 2025, the commercial wind continues to be the hot-spot emitting 5.28E+10 kg DCBe. Microgeneration and energy from waste follow with 3.55E+10 and 7.06E+09 kg DCBe, respectively. Plant biomass gets the fourth place with 5.30E+09 kg DCBe. Small scale wind and hydro emit 6.14E+08 and 3.29E+08 kg DCBe. In 2030, the ranking remains the same: commercial wind, microgeneration, energy from waste, plant biomass, small scale wind and small scale hydro emitting 6.22E+10, 3.64E+10, 1.0E+10, 6.16E+09, 7.82E+08 and 4.46E+08 kg DCBe, respectively.

Table 18: Scenario 1 - Ozone Layer Depletion Potential (ODP)

Ozone Layer Depletion Potential (ODP) [kg R11-Equiv.]	2015	2020	2025	2030
Total	2.16E+00	3.20E+00	3.50E+00	3.79E+00
Commercial wind	2.95E-01	4.24E-01	5.15E-01	6.07E-01
Small scale wind	6.98E-03	1.01E-02	1.38E-02	1.76E-02
Microgeneration	1.18E+00	2.06E+00	2.12E+00	2.17E+00
Small scale hydro	1.08E-02	1.31E-02	2.02E-02	2.74E-02
Plant biomass	6.71E-01	6.95E-01	8.30E-01	9.64E-01
Energy from waste	3.57E-08	4.59E-08	8.16E-08	1.17E-07

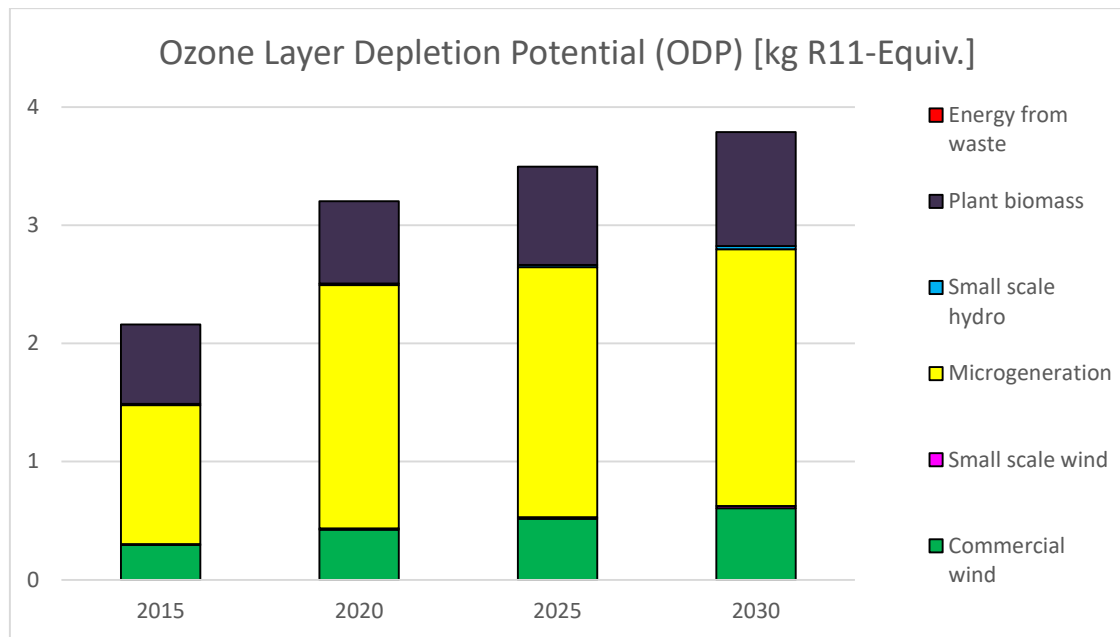
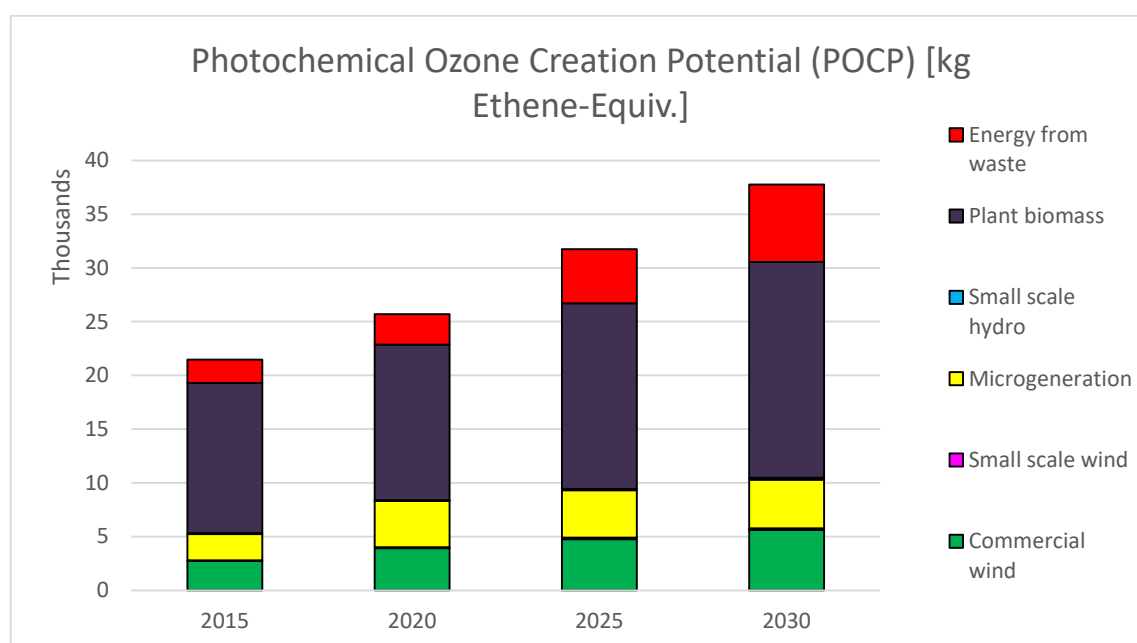


Figure 40: Scenario 1 - Ozone Layer Depletion Potential (ODP)

The data from Table 18 and Figure 40 present that Ozone Layer Depletion Potential (ODP) increases over the years, with the most significant energy source in terms of emissions is microgeneration. In 2015, the total ODP is 2.16E+00 kg R11e. Microgeneration has the highest ODP with 1.18E+00 kg R11e, followed by plant biomass with 6.71E-01 kg R11e. Commercial wind emits 2.95E-01 kg R11e. Small scale hydro, small scale wind and energy from waste contribute the least with 1.08E-02, 6.98E-03 and 3.57E-08 kg R11e, respectively. In 2020, the total ODP increases to 3.20E+00 kg R11e, with microgeneration remaining the highest contributor with 2.06E+00 kg R11e. Plant biomass and commercial wind emit 6.95E-01 and 4.24E-01 kg R11e, respectively. Small scale hydro and wind contributes with 1.31E-02 and 1.01E-02 kg R11e, while energy from waste with 4.59E-08 kg R11e. During 2025, the ranking remains the same: microgeneration, plant biomass and commercial wind emit 2.12E+00, 8.30E-01 and 5.15E-01 kg R11e. Small scale hydro, wind and energy from waste increase but not significantly. In 2030, the total ODP reaches 3.79E+00 kg R11e. Microgeneration emits 2.17E+00 kg R11e, while plant biomass and commercial wind increase to 9.64E-01 and 6.01E-01kg R11e, respectively. Small scale hydro increases to 2.74E-02 kg R11. Small scale wind and energy from waste emit 1.76E-02 and 1.17E-07, respectively.

Table 19: Scenario 1 - Photochemical Ozone Creation Potential (POCP)

Photochemical Ozone Creation Potential (POCP) [kg Ethene-Equiv.]	2015	2020	2025	2030
Total	2.15E+04	2.57E+04	3.17E+04	3.78E+04
Commercial wind	2.72E+03	3.92E+03	4.76E+03	5.60E+03
Small scale wind	6.38E+01	9.19E+01	1.26E+02	1.61E+02
Microgeneration	2.46E+03	4.30E+03	4.42E+03	4.54E+03
Small scale hydro	6.56E+01	7.97E+01	1.23E+02	1.67E+02
Plant biomass	1.40E+04	1.45E+04	1.73E+04	2.01E+04
Energy from waste	2.20E+03	2.82E+03	5.02E+03	7.22E+03

**Figure 41: Scenario 1 - Photochemical Ozone Creation Potential (POCP)**

The data from Table 19 and Figure 41 present that Photochemical Ozone Creation Potential (POCP) increases over the years, while plant biomass is the hot-spot every year. In 2015, the total POCP is 2.15E+04 kg Ethene Eq. Plant biomass has the highest impact with 1.40E+04 kg Ethene Eq, followed by microgeneration with 2.46E+03 kg Ethene Eq. Commercial wind comes in the third place and energy from waste in the fourth emitting 2.72E+03 and 2.20E+03 kg Ethene Eq, respectively. Small scale hydro and small scale wind contribute to 6.56E+01 and 6.38E+01 kg Ethene Eq, respectively. In 2020, the total POCP increases to 2.57E+04 kg Ethene Eq. Plant biomass remains on the top with 1.45E+04 kg Ethene Eq, followed by microgeneration with 4.30E+03 and commercial wind 3.92E+03 kg Ethene Eq. The lowest contributions are pointed to energy from waste, small scale hydro and wind with 2.82E+03, 7.97E+01 and 9.19E+01 kg

Ethene Eq., respectively. By 2025, the ranking changes with plant biomass emits $1.73\text{E}+04$ kg Ethene Eq, while energy from waste takes the second place and commercial wind the thirds with emissions of $5.02\text{E}+03$ and $4.76\text{E}+03$ kg Ehtene Eq. Microgeneration is also significant with $4.42\text{E}+03$ kg Ethene Eq. Small scale wind and small scale hydro, still have the lowest emissions above all and they contribute to $1.26\text{E}+02$ and $1.23\text{E}+02$ kg Ethelene Eq. In 2030, the total POCP reaches $3.78\text{E}+04$ kg Ethene Eq. Plant biomass emits $2.01\text{E}+04$ kg Ethene Eq, while energy from waste $7.22\text{E}+03$ kg Ethene Eq. Commercial wind, microgeneration, small scale wind and hydro contribute with $5.60\text{E}+03$, $4.54\text{E}+03$, $1.61\text{E}+02$ and $1.67\text{E}+02$ kg Ethene Eq, respectively.

Table 20: Scenario 1 - Terrestrial Ecotoxicity Potential (TETP)

Terrestrial Ecotoxicity Potential (TETP) [kg DCB-Equiv.]	2015	2020	2025	2030
Total	9.05E+05	1.10E+06	1.32E+06	1.55E+06
Commercial wind	2.61E+05	3.77E+05	4.57E+05	5.38E+05
Small scale wind	1.56E+04	2.25E+04	3.09E+04	3.93E+04
Microgeneration	6.51E+04	1.14E+05	1.17E+05	1.20E+05
Small scale hydro	3.93E+03	4.78E+03	7.39E+03	9.99E+03
Plant biomass	5.39E+05	5.59E+05	6.67E+05	7.75E+05
Energy from waste	1.93E+04	2.47E+04	4.40E+04	6.33E+04

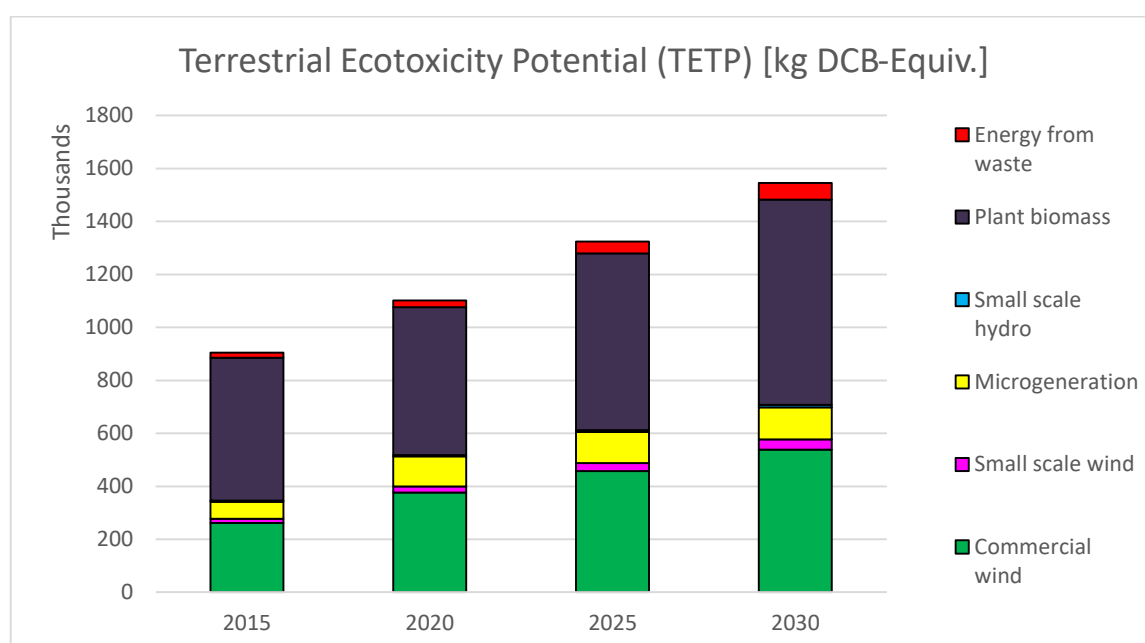


Figure 42: Scenario 1 - Terrestrial Ecotoxicity Potential (TETP)

The data from Table 20 and Figure 42 present that Terrestrial Ecotoxicity Potential (TETP) increases over the years, reaching $1.55\text{E}+06$ kg DCBe by 2030. In 2015, the total TETP is

9.05E+05 kg DCBe. Plant biomass contributes to 5.39E+05 kg DCBe, followed by commercial wind to 2.61E+05 kg DCBe and microgeneration to 6.51E+04 kg DCBe. Energy from waste, small scale wind and hydro contribute with 6.51E+04, 1.56E+04, 3.93E+03 kg DCBe, respectively. In 2020, the total TETP increases to 1.10E+06 kg DCBe. Plant biomass emits 5.59E+05 kg DCBe, while commercial wind contributes with 3.77E+05 kg DCBe. The rest of the energy sources have lower contributions compared to the sources above. By 2025, plant biomass is still on the top emitting 6.67E+05 kg DCBe. Commercial wind and microgeneration keep rising until 4.57E+05 and 1.17E+05 kg DCBe, respectively. Energy from waste, small scale wind and hydro contribute with 4.40E+04, 3.09E+04 and 7.39E+03 kg DCBe. In 2030, the ranking remains the same: plant biomass, commercial wind, microgeneration, energy from waste, small scale wind and small scale hydro reach 7.75E+05, 5.38E+05, 1.20E+05, 6.33E+04, 3.93E+04 and 9.99E+03 kg DCBe, respectively.

Table 21: Scenario 1 - Levelised Cost of Electricity (GBP)

Levelised cost of electricity (GBP)	2015	2020	2025	2030
Total	1.21E+08	1.50E+08	1.83E+08	2.14E+08
Commercial wind	4.18E+07	6.05E+07	7.35E+07	8.64E+07
Small scale wind	2.34E+06	3.38E+06	4.64E+06	5.91E+06
Microgeneration	8.09E+06	1.88E+07	1.93E+07	1.98E+07
Small scale hydro	1.90E+06	3.91E+06	4.81E+06	6.51E+06
Plant biomass	6.44E+07	6.16E+07	7.65E+07	8.89E+07
Energy from waste	2.23E+06	1.98E+06	4.31E+06	6.20E+06

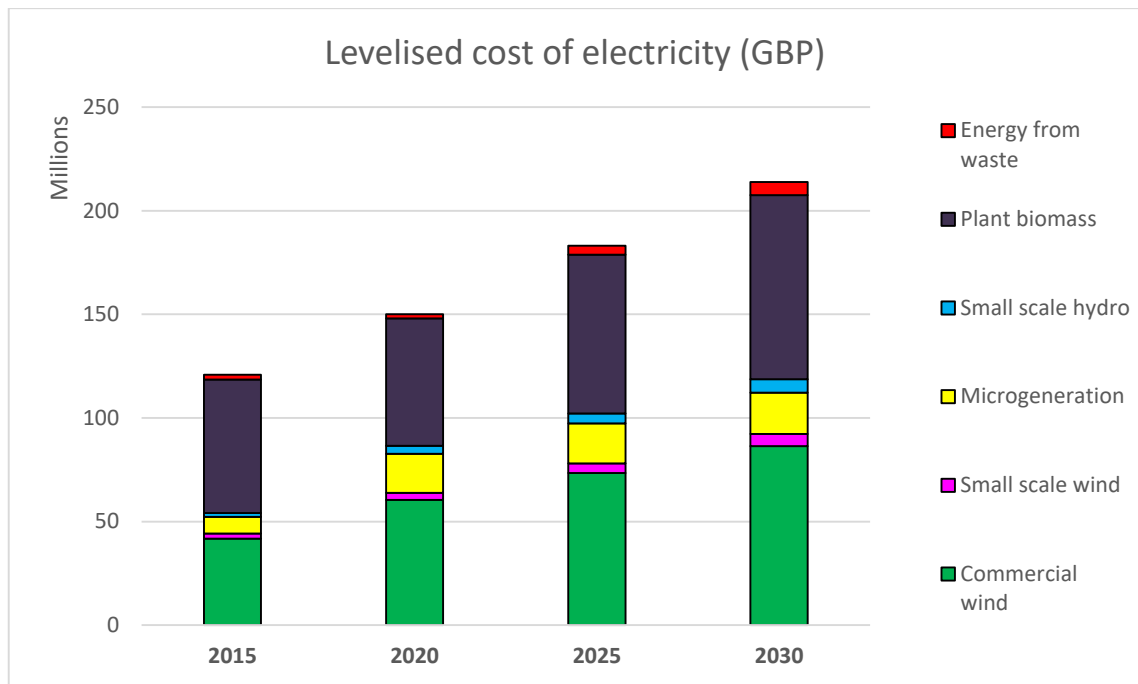
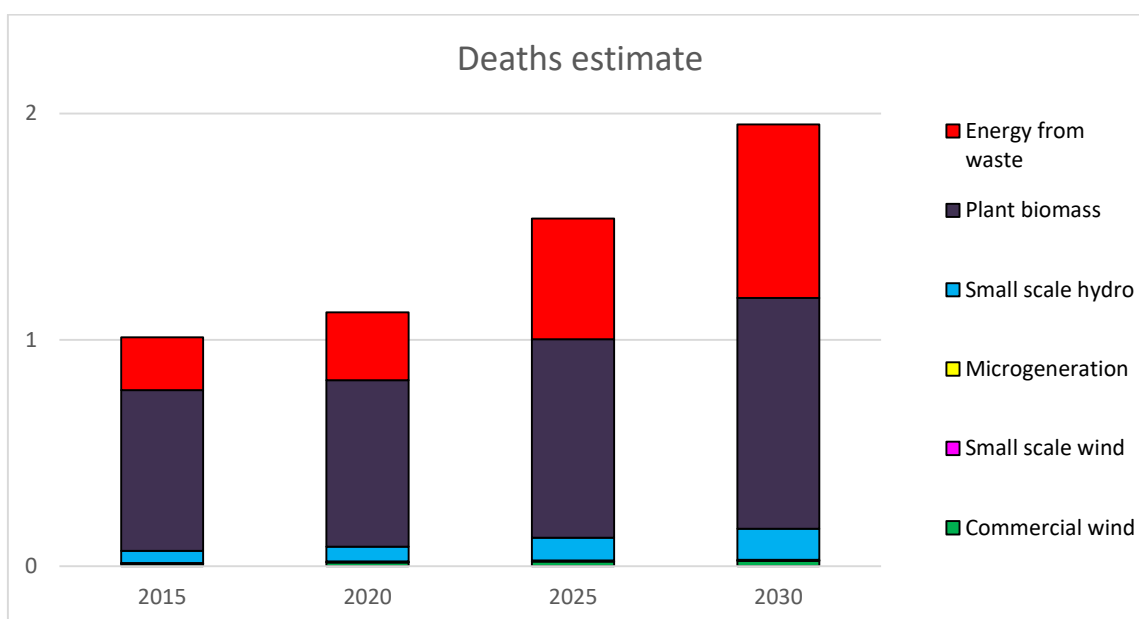


Figure 43: Scenario 1 - Levelised Cost of Electricity (GBP)

The data from Table 21 and Figure 43 present that levelised cost of electricity increases over the years and by 2030 reaches the value of $2.14\text{E}+08$ GBP. In 2015, the total Levelised cost of electricity reaches $1.21\text{E}+08$ GBP. Plant biomass and commercial wind are the most significant contributors with $6.44\text{E}+07$ and $4.18\text{E}+07$ GBP respectively, while the lowest values are pointed to microgeneration, energy from waste, small scale wind and hydro with $8.09\text{E}+06$, $2.23\text{E}+06$, $2.34\text{E}+06$ and $1.90\text{E}+06$ GBP, respectively. In 2020, the total LCOE increases to $1.50\text{E}+08$ GBP and the ranking remains the same. Although, microgeneration climbs to $1.88\text{E}+07$ GBP. By 2025, the total LCOE further increases to $1.83\text{E}+08$ GBP, with plant biomass continuing to be the top contributor, with $7.65\text{E}+07$ GBP. Commercial wind and microgeneration contribute with $7.65\text{E}+07$ and $1.93\text{E}+07$ GBP, respectively. Small scale hydro follows with $4.81\text{E}+06$ GBP and small scale wind with $4.64\text{E}+06$ GBP. Energy from waste contributes the lowest to the LCOE, $4.31\text{E}+06$ GBP. In 2030, the ranking for the highest contributors remains the same: plant biomass, commercial wind, microgeneration with $8.89\text{E}+07$, $8.64\text{E}+07$ and $1.98\text{E}+07$ GBP. Small scale hydro, energy from waste and small scale wind follow and energy from waste climbs to $6.20\text{E}+06$ GBP.

Table 22: Scenario 1 - Deaths estimate

Deaths estimate	2015	2020	2025	2030
Total	1.01E+00	1.12E+00	1.54E+00	1.95E+00
Commercial wind	1.17E-02	1.69E-02	2.05E-02	2.41E-02
Small scale wind	7.76E-05	1.12E-04	1.54E-04	1.95E-04
Microgeneration	2.41E-03	4.23E-03	4.34E-03	4.46E-03
Small scale hydro	5.37E-02	6.52E-02	1.01E-01	1.36E-01
Plant biomass	7.09E-01	7.35E-01	8.77E-01	1.02E+00
Energy from waste	2.33E-01	3.00E-01	5.33E-01	7.67E-01

**Figure 44: Scenario 1 - Deaths estimate**

The data from Table 22 and Figure 44 present that deaths estimate is a number increasing over the years. In 2015, the total estimated deaths are 1.01E+00 people. Plant biomass has the highest death estimate with 7.09E-01, followed by energy from waste with 2.33E-01 people. Small scale hydro plays also a significant role with 5.37E-02 and commercial wind 1.17E-02 deaths estimate. Microgeneration and small scale wind have the lowest death estimates with 2.41E-03 and 7.76E-05, respectively. In 2020, the total estimated deaths increase to 1.12E+00. Plant biomass remains on the top with 7.35E-01, followed by energy from waste at 3.00E-01. Small scale hydro, commercial wind and microgeneration contribute with 6.52E-02, 6.52E-02 and 4.23E-03, respectively. Small scale wind has the lowest risk with 1.12E-04 deaths estimate. By 2025, the total estimated deaths climb to 1.54E+00. The ranking remains the same, with plant biomass being on top with 8.77E-01, followed by energy from waste at 5.33E-01. In 2030, the total estimated deaths reach 1.95E+00, almost two people. Plant biomass is the hot spot

again with 1.02E+00. Energy from waste comes in the second place with 7.67E-01 deaths estimated, while small scale hydro and commercial wind contribute with 1.36E-01 and 2.41E-02, respectively. Microgeneration and small scale wind have also increased to 4.46E-03 and 1.95E-04, respectively.

Table 23: Scenario 1 - Job estimate

Jobs estimate	2015	2020	2025	2030
Total	5.08E+02	6.71E+02	8.62E+02	1.05E+03
Commercial wind	1.76E+02	2.54E+02	3.08E+02	3.63E+02
Small scale wind	1.17E+00	1.68E+00	2.31E+00	2.94E+00
Microgeneration	6.70E+01	1.17E+02	1.21E+02	1.24E+02
Small scale hydro	7.83E+00	9.50E+00	1.47E+01	1.99E+01
Plant biomass	1.61E+02	1.67E+02	1.99E+02	2.32E+02
Energy from waste	9.49E+01	1.22E+02	2.17E+02	3.12E+02

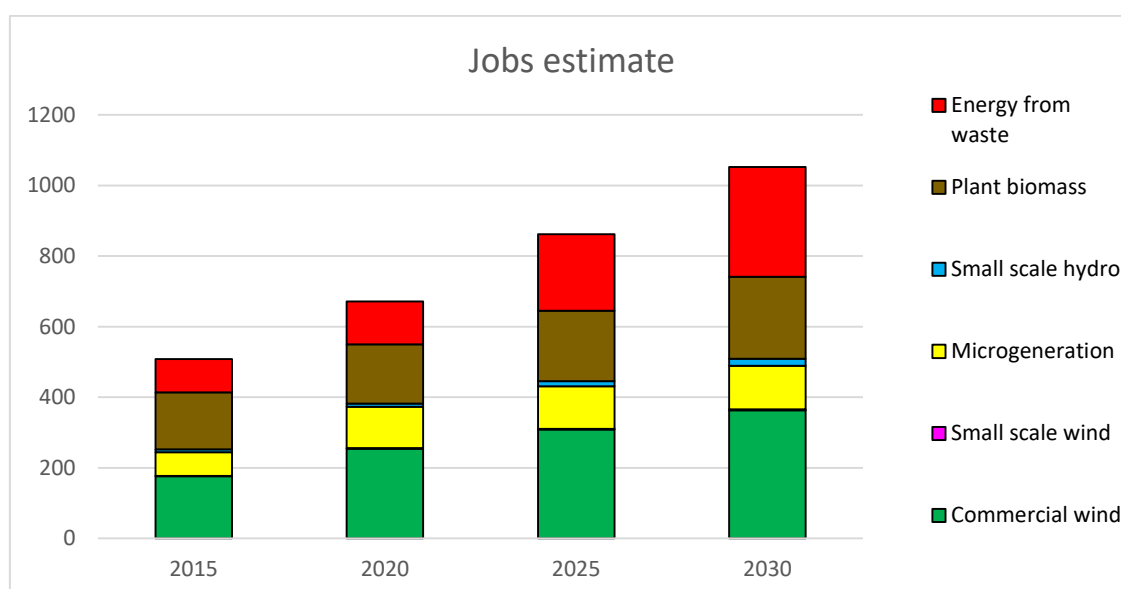


Figure 45: Scenario 1 - Job estimate

The data from Table 23 and Figure 45 present that jobs are increasing over the years, starting at a low point of 508 in 2015 and reaching 1,050 by 2030. In 2015, the total number of jobs is 508, with commercial wind contributing the most with 176 jobs, followed by plant biomass with 161 jobs and energy from waste with 94. Microgeneration has also a significant impact providing 67 jobs. Small scale wind and hydro offer 1 and 7 jobs respectively. In 2020, Commercial wind remains on the top providing 254 jobs, while a significant impact has also the plant biomass, energy from waste and microgeneration with 167, 122 and 117 jobs, respectively. Small scale hydro

and wind have lower contributions with 9 and 1 jobs each. By 2025, commercial wind offers 308 jobs. Energy from waste climbs to 217 jobs, while plant biomass and microgeneration contribute with 199 and 121 jobs, respectively. By 2030, commercial wind is expected to provide 363 jobs, followed by energy from waste with 312 jobs and plant biomass with 232 jobs. The other sectors also increase. Microgeneration offers 124 jobs, while small scale hydro provides 19 jobs and small scale wind also provides 2 jobs.

4.2 Outcomes of scenario 2: UK renewable strategy mix

The results of scenario 2 are shown at the following tables and figures:

Table 24: Scenario 2 - Global Warming Potential (GWP)

Global Warming Potential (GWP) [kg CO ₂ -Equiv.]	2015	2020	2025	2030
Total	5,73E+07	7,55E+07	1,96E+08	3,16E+08
Commercial wind	4,85E+06	6,98E+06	7,13E+06	7,28E+06
Small scale wind	1,20E+05	1,73E+05	3,29E+05	4,84E+05
Microgeneration	7,66E+06	1,34E+07	1,47E+07	1,60E+07
Small scale hydro	1,58E+05	1,92E+05	3,16E+05	4,40E+05
Plant biomass	9,91E+06	1,03E+07	1,20E+07	1,37E+07
Energy from waste	3,46E+07	4,44E+07	1,61E+08	2,78E+08

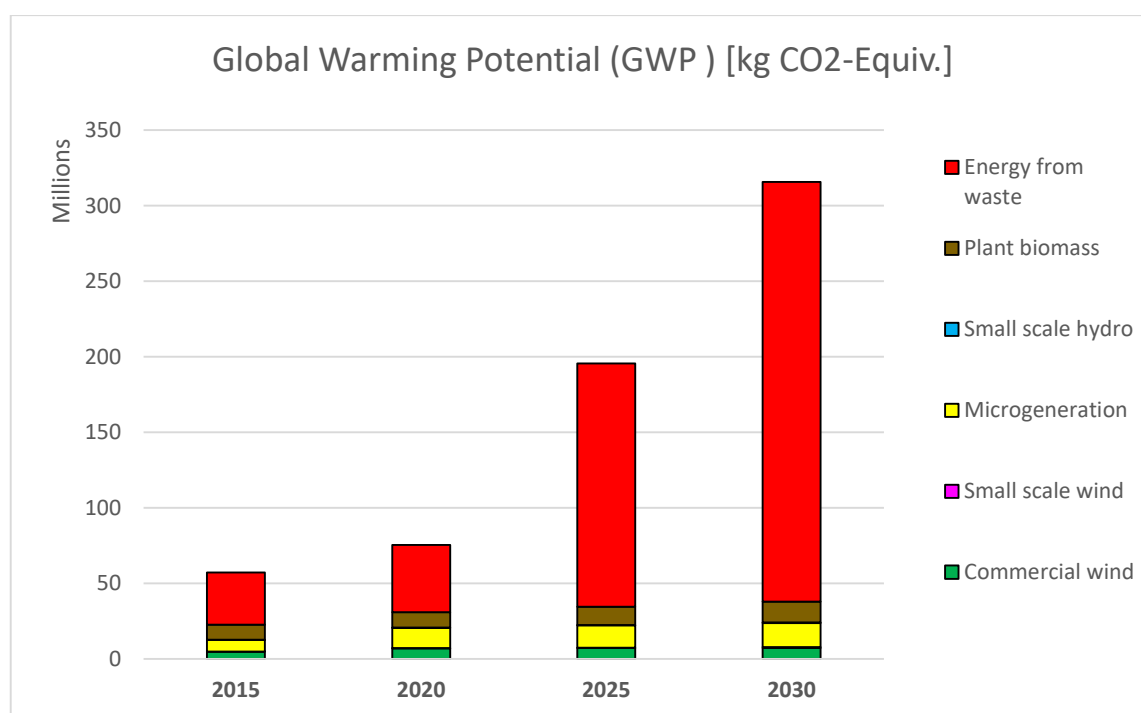


Figure 46: Scenario 2 - Global Warming Potential (GWP)

The data from

Table 24 and Figure 46 present that over the analyzed period from 2015 to 2030, the Global Warming Potential (GWP) exhibits a consistent upward trend, escalating from 5.73E+07 kg CO₂e in 2015 to 3.16E+08 kg CO₂e by 2030. Notably, energy from waste emerges as the predominant contributor throughout each year, peaking at 2.78E+08 kg CO₂e in 2030. Plant biomass and microgeneration also play substantial roles,

maintaining consistent contributions across the years. Microgeneration emits 7.66E+06 kg CO₂e in 2015, reaching 1.6E+07 kg CO₂e by 2030. Relatively, plant biomass starts with a 9.91E+06 kg CO₂e and reaches 1.37E+07 kg CO₂e by 2030. Commercial wind, small scale hydro, and small scale wind exhibit comparatively lower GWP values. The overall hierarchy of contributions remains stable at most of the parts, with each energy source contributing progressively more to the total GWP.

Table 25: Scenario 2 - Abiotic Depletion Potential (ADP elements)

Abiotic Depletion Potential (ADP elements) [kg Sb-Equiv.]	2015	2020	2025	2030
Total	1,20E+03	1,82E+03	1,93E+03	2,03E+03
Commercial wind	8,18E+02	1,18E+03	1,20E+03	1,23E+03
Small scale wind	2,68E+00	3,86E+00	7,34E+00	1,08E+01
Microgeneration	3,49E+02	6,11E+02	6,70E+02	7,29E+02
Small scale hydro	8,18E-01	9,92E-01	1,63E+00	2,28E+00
Plant biomass	2,51E+01	2,60E+01	3,04E+01	3,47E+01
Energy from waste	2,96E+00	3,80E+00	1,38E+01	2,38E+01

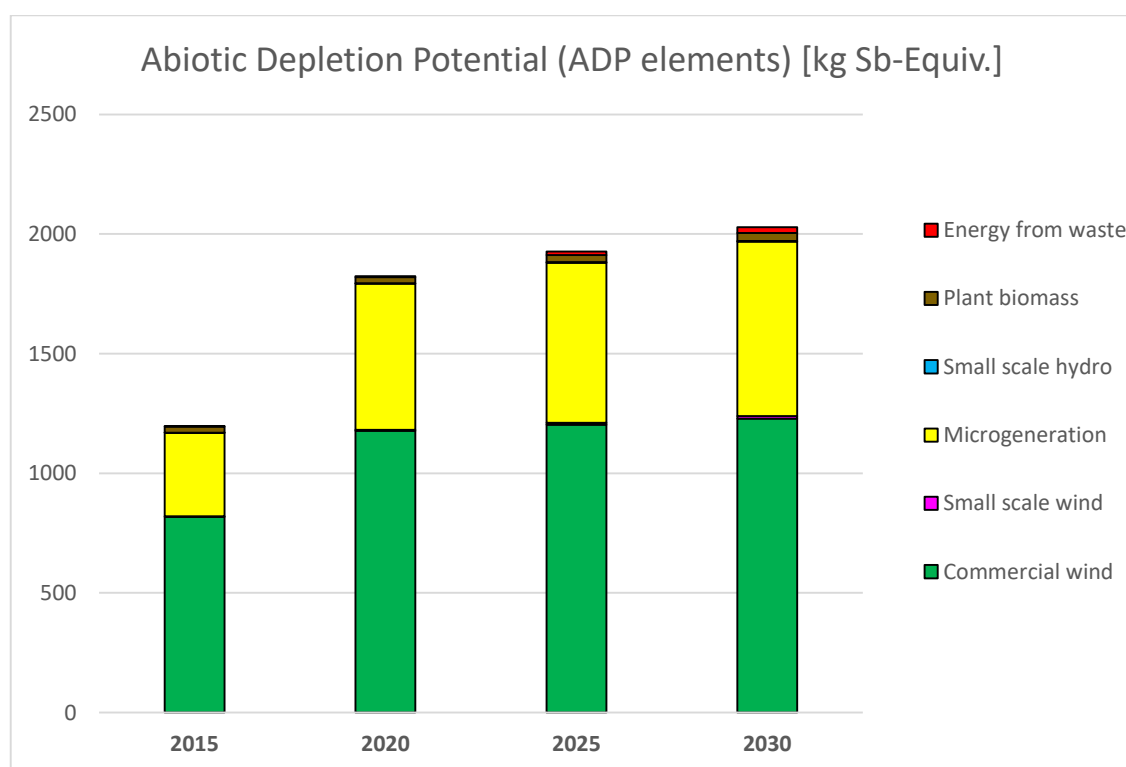


Figure 47: Scenario 2 - Abiotic Depletion Potential (ADP elements)

The data from Table 25 and Figure 47 present that across the evaluated period spanning from 2015 to 2030, there is a consistent increase in Abiotic Depletion Potential (ADP) elements, rising from 1.20E+03 kg SbE in 2015 to 2.03E+03 kg SbE in 2030. In this

context, commercial wind consistently holds a prominent position, escalating from 8.18E+02 kg SbE in 2015 to 1.23E+03 kg SbE in 2030. The second highest emitting contributor is microgeneration, starting with 3,49E+02 kg SbE in 2015 and reaching 7.29E+02 kg SbE by 2030. Interestingly, the ADP contribution from plant biomass has a substantial surge, jumping from 2.51E+01 kg SbE in 2015 to 3.47E+01 kg SbE in 2030. Last but not least, small scale wind, small scale hydro, and energy from waste also contribute to ADP, with increasing values over the years. The outcome of this comparison should be focused on the two main contributors here, commercial wind and microgeneration.

Table 26: Scenario 2 - Abiotic Depletion Potential (ADP fossil)

Abiotic Depletion Potential (ADP fossil) [MJ]	2015	2020	2025	2030
Total	2,72E+08	3,86E+08	5,45E+08	7,04E+08
Commercial wind	6,46E+07	9,31E+07	9,51E+07	9,71E+07
Small scale wind	1,63E+06	2,35E+06	4,46E+06	6,58E+06
Microgeneration	9,56E+07	1,67E+08	1,84E+08	2,00E+08
Small scale hydro	1,53E+06	1,86E+06	3,06E+06	4,26E+06
Plant biomass	7,12E+07	7,38E+07	8,61E+07	9,84E+07
Energy from waste	3,72E+07	4,77E+07	1,73E+08	2,98E+08

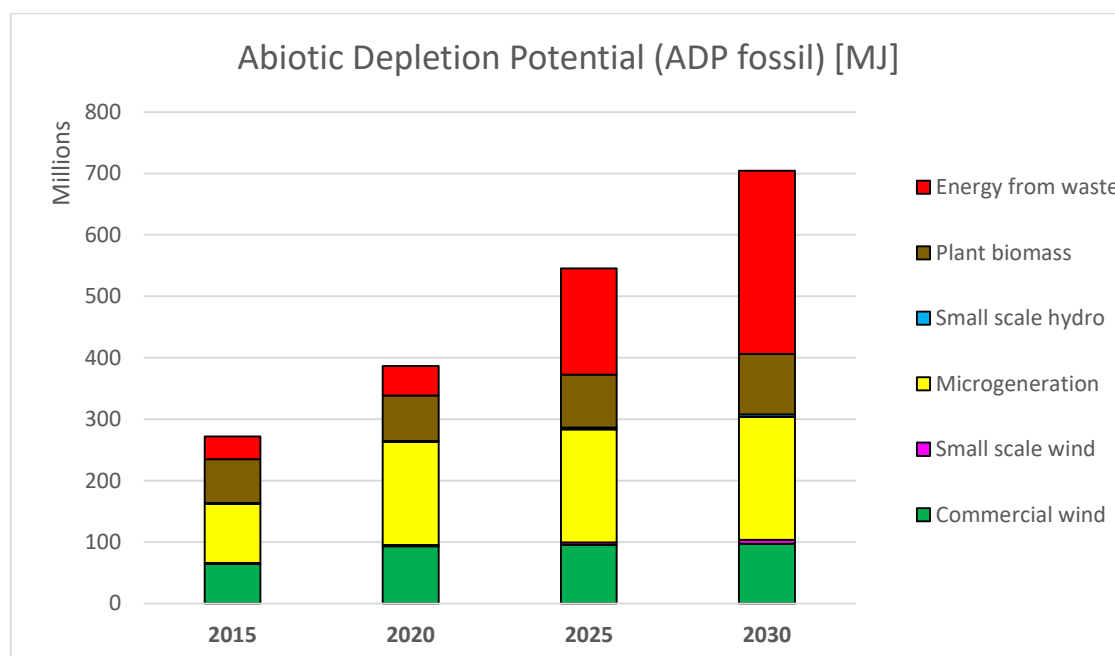


Figure 48: Scenario 2 - Abiotic Depletion Potential (ADP fossil)

The data from Table 26 and Figure 48 present that over the analyzed period from 2015 to 2030, the Abiotic Depletion Potential (ADP) in terms of fossil resources demonstrates a

substantial increase, surging from 2.72E+08 MJ in 2015 to 7.04E+08 MJ in 2030. Among the energy sources, commercial wind consistently emerges as a major contributor, with its share rising from 6.46E+07 MJ in 2015 to 9.71E+07 MJ in 2030. Microgeneration significantly contributes to ADP fossil, experiencing an increase from 9.56E+07 MJ in 2015 to 2.00E+08 MJ in 2030. Energy from waste catches the attention, especially in the significant increase in 2030, contributing the most with 2.98E+08 MJ. Plant biomass has a small steady increase over the years, starting from 7.12E+07 MJ in 2015 to 9.84E+07 MJ. Meanwhile, small scale hydro and wind also showcase increasing trends in their contributions. The top three contributors, energy from waste, microgeneration, and commercial wind, highlight the evolving environmental impact of various energy sources.

Table 27: Scenario 2 - Acidification Potential (AP)

Acidification Potential (AP) [kg SO₂-Equiv.]	2015	2020	2025	2030
Total	2,53E+05	3,12E+05	5,43E+05	7,73E+05
Commercial wind	2,56E+04	3,69E+04	3,76E+04	3,84E+04
Small scale wind	6,36E+02	9,16E+02	1,74E+03	2,56E+03
Microgeneration	3,47E+04	6,08E+04	6,67E+04	7,25E+04
Small scale hydro	6,28E+02	7,62E+02	1,25E+03	1,75E+03
Plant biomass	1,32E+05	1,37E+05	1,60E+05	1,82E+05
Energy from waste	5,93E+04	7,61E+04	2,76E+05	4,76E+05

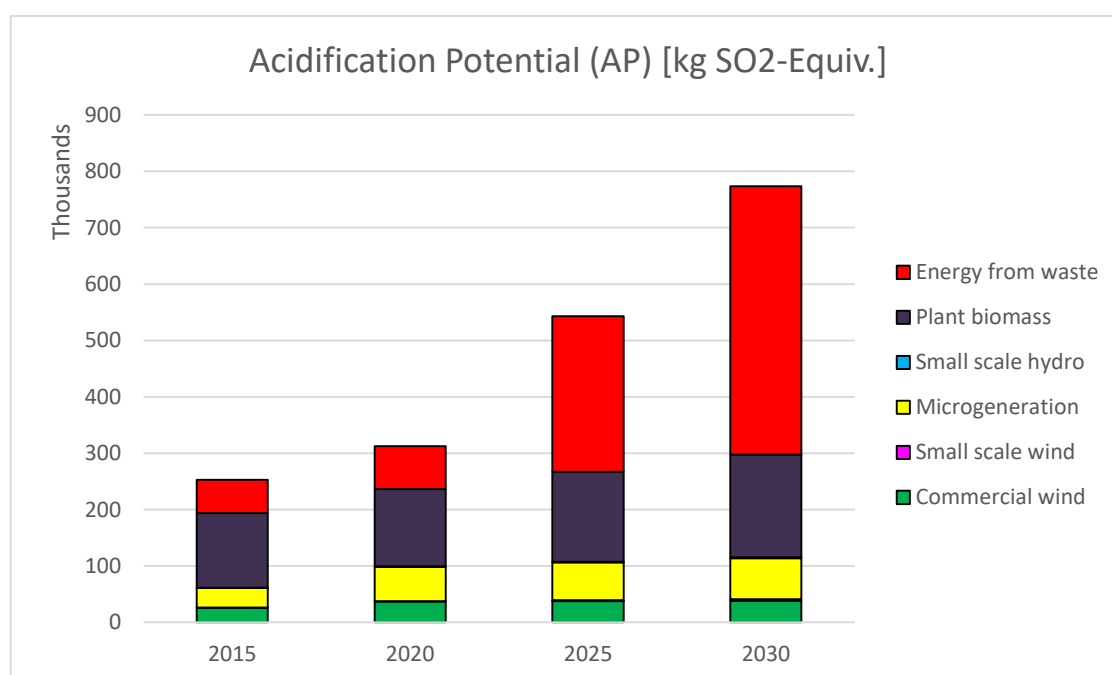


Figure 49: Scenario 2 - Acidification Potential (AP)

The data from Table 27 and Figure 49 present that over the period from 2015 to 2030, the Acidification Potential (AP) in terms of sulfur dioxide equivalents reveals a substantial increase, escalating from 2.53E+05 kg SO₂e in 2015 to 7.73E+05 kg SO₂e in 2030. Notably, energy from waste displays a significant surge, starting with 5.93E+04 kg SO₂e in 2015 and reaching 4.76E+05 kg SO₂e in 2030, emphasizing its noteworthy contribution to acidification and underscoring the importance of sustainable waste management practices. Plant biomass follows an increasing trend, contributing 1.32E+05 kg SO₂e in 2015, reaching 1.82E+05 kg SO₂e in 2030. Microgeneration, as a third contributor, shows a steady rise, from 3.47E+04 kg SO₂e in 2015 to 7.25E+04 kg SO₂e in 2030, while commercial wind exhibits a comparatively moderate increase, from 2.56E+04 kg SO₂e in 2015 to 3.84E+04 kg SO₂e in 2030. Small scale wind and hydro have increasing values too, but they remain comparatively low. These analyses highlight the diverse acidification potentials of different energy sources and emphasize the need for strategic environmental considerations in the adoption and development of sustainable energy solutions.

Table 28: Scenario 2 - Eutrophication Potential (EP)

Eutrophication Potential (EP) [kg Phosphate-Equiv.]	2015	2020	2025	2030
Total	9,56E+04	1,25E+05	1,59E+05	1,94E+05
Commercial wind	1,87E+04	2,69E+04	2,75E+04	2,81E+04
Small scale wind	4,17E+02	6,00E+02	1,14E+03	1,68E+03
Microgeneration	2,31E+04	4,05E+04	4,44E+04	4,83E+04
Small scale hydro	2,38E+02	2,89E+02	4,75E+02	6,62E+02
Plant biomass	4,69E+04	4,86E+04	5,67E+04	6,47E+04
Energy from waste	6,30E+03	8,08E+03	2,93E+04	5,05E+04

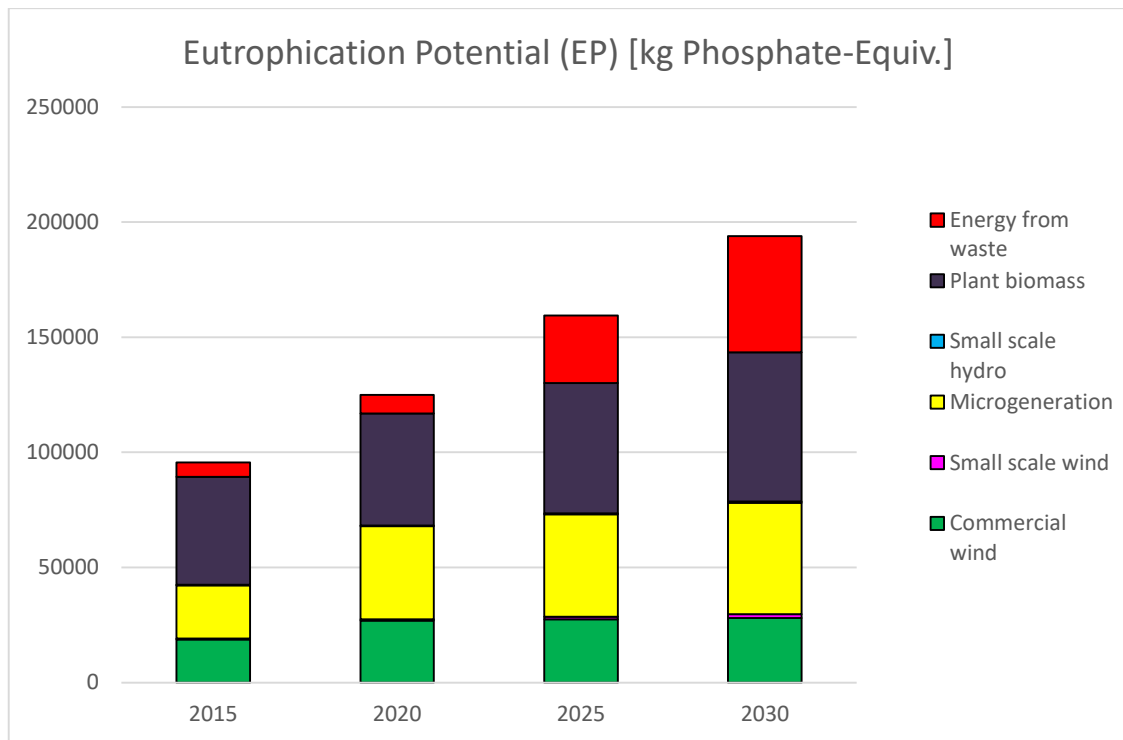


Figure 50: Scenario 2 - Eutrophication Potential (EP)

The data from Table 28 and Figure 50 present that over the evaluated period from 2015 to 2030, the Eutrophication Potential (EP) in terms of phosphate equivalents exhibits an overall increase, ascending from 9.56×10^4 kg Phosphate-Equiv. in 2015 to 1.94×10^5 kg Phosphate-Equiv. in 2030. Focusing on specific energy sources, energy from waste displays a noticeable rise, starting at 6.30×10^3 kg Phosphate-Equiv. in 2015 and reaching 5.05×10^4 kg Phosphate-Equiv. in 2030, emphasizing its growing contribution to eutrophication. Although, the most significant contributor is plant biomass that follows a similar increasing trend, contributing 4.69×10^4 kg Phosphate-Equiv. in 2015 and reaching 6.47×10^4 kg Phosphate-Equiv. in 2030. Microgeneration shows an increase, from 2.31×10^4 kg Phosphate-Equiv. in 2015 to 4.83×10^4 kg Phosphate-Equiv. in 2030, while commercial wind contributes with 1.87×10^4 kg Phosphate-Equiv. in 2015, reaching 2.81×10^4 kg Phosphate-Equiv. Small scale wind and hydro contribute with comparatively lower values.

Table 29: Scenario 2 - Fresh Aquatic Ecotoxicity Potential (FAETP)

Freshwater Aquatic Ecotoxicity Potential (FAETP) [kg DCB-Equiv.]	2015	2020	2025	2030
Total	7,12E+07	1,06E+08	1,11E+08	1,16E+08
Commercial wind	5,26E+07	7,57E+07	7,73E+07	7,90E+07
Small scale wind	1,70E+05	2,45E+05	4,64E+05	6,84E+05
Microgeneration	1,52E+07	2,65E+07	2,91E+07	3,17E+07
Small scale hydro	1,27E+05	1,54E+05	2,54E+05	3,54E+05
Plant biomass	3,13E+06	3,24E+06	3,78E+06	4,32E+06
Energy from waste	1,24E+04	1,59E+04	5,76E+04	9,93E+04

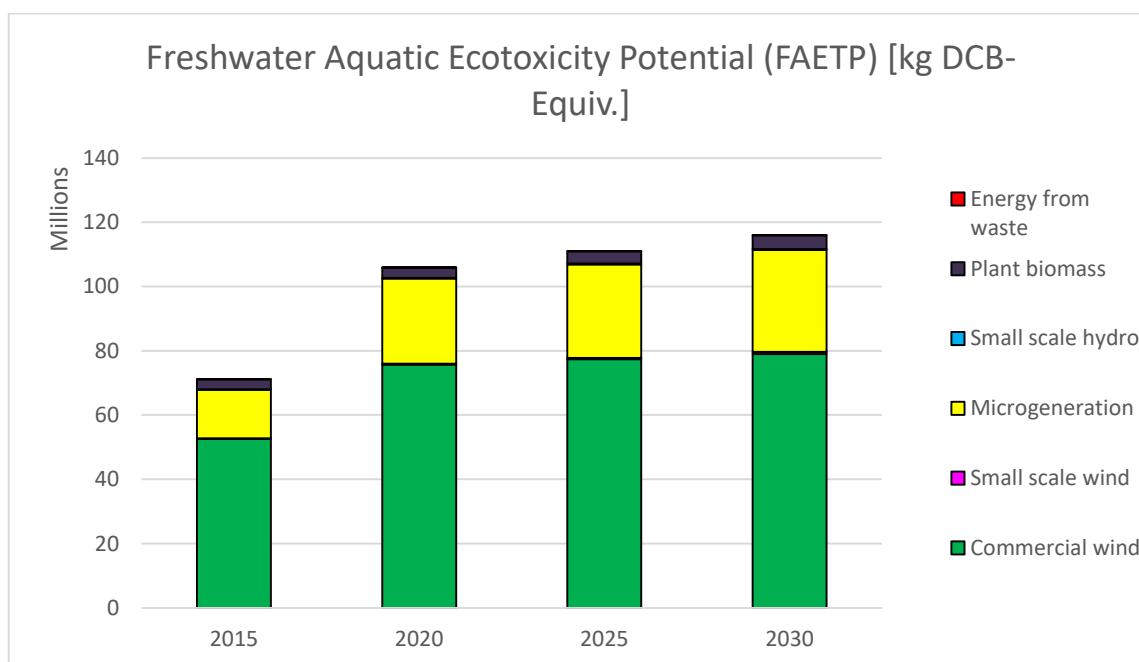


Figure 51: Scenario 2 - Fresh Aquatic Ecotoxicity Potential (FAETP)

The data from Table 29 and Figure 51 present that across the timeframe from 2015 to 2030, the Freshwater Aquatic Ecotoxicity Potential (FAETP) measured in kilograms of DCBe witnesses a notable increase, surging from 7.12E+07 kg DCBe in 2015 to 1.16E+08 kg DCBe in 2030. Focusing on specific contributors, commercial wind stands out with the higher values, starting at 5.26E+07 kg DCBe in 2015 and reaching 7.90E+07 kg DCBe in 2030, emphasising its considerable impact on freshwater aquatic ecotoxicity. Microgeneration also shows a steady increase, contributing 1.52E+07 kg DCBe in 2015 and reaching 3.17E+07 kg DCBe in 2030, underlining its growing contribution. Plant biomass follows a similar trend, with a rise from 3.13E+06 kg DCBe in 2015 to 4.32E+06

kg DCBe in 2030. The rest of the energy sources like energy from waste, small scale hydro and small scale wind have relatively small values, although they are increasing over the years. These analyses highlight the varying levels of freshwater aquatic ecotoxicity potential associated with different energy sources, underscoring the need for strategic environmental considerations and the exploration of alternatives, less ecotoxic solutions in the pursuit of sustainable energy generation.

Table 30: Scenario 2 - Human Toxicity Potential (HTP)

Human Toxicity Potential (HTP) [kg DCB-Equiv.]	2015	2020	2025	2030
Total	5,69E+07	8,05E+07	8,88E+07	9,70E+07
Commercial wind	3,04E+07	4,38E+07	4,48E+07	4,57E+07
Small scale wind	6,36E+05	9,16E+05	1,74E+06	2,56E+06
Microgeneration	1,23E+07	2,16E+07	2,37E+07	2,58E+07
Small scale hydro	2,01E+05	2,44E+05	4,02E+05	5,60E+05
Plant biomass	1,26E+07	1,31E+07	1,53E+07	1,75E+07
Energy from waste	6,23E+05	8,00E+05	2,90E+06	5,00E+06

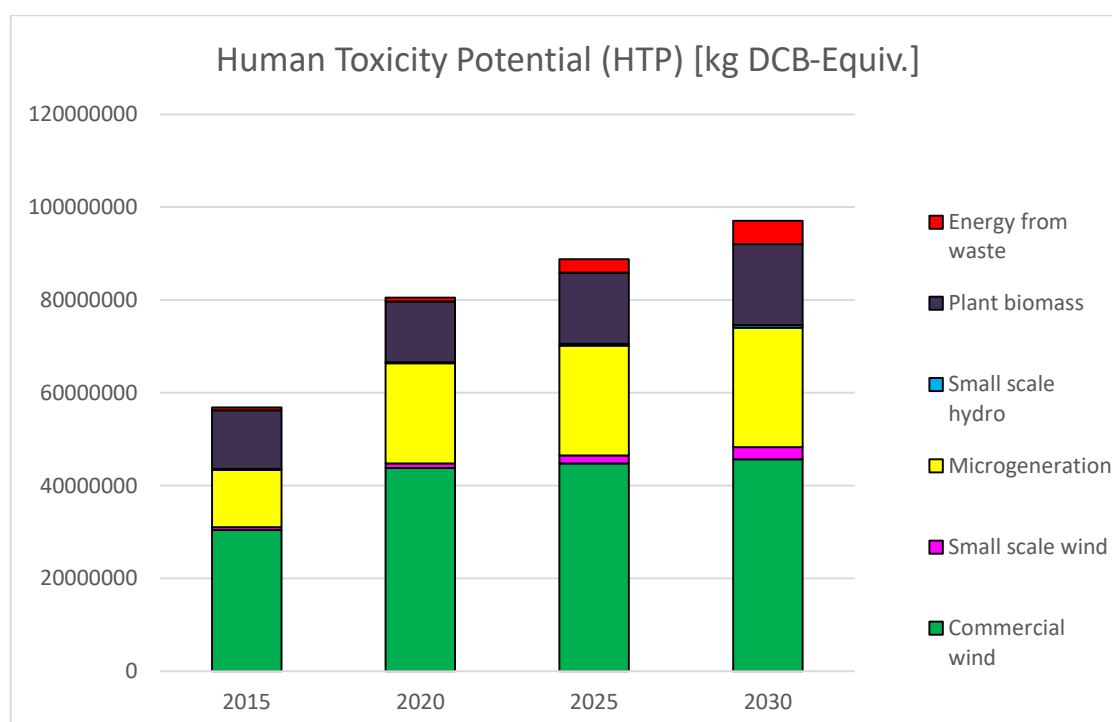


Figure 52: Scenario 2 - Human Toxicity Potential (HTP)

The data from Table 30 and Figure 52 present that over the period from 2015 to 2030, the Human Toxicity Potential (HTP) measured in kilograms of DCBe demonstrates an overall increase, rising from 5.69E+07 kg DCBe in 2015 to 9.70E+07 kg DCBe in 2030.

Examining various energy sources, commercial wind stands out as the most significant contributor, with its HTP increasing from 3.04E+07 kg DCBe in 2015 to 4.57E+07 kg DCBe in 2030. Microgeneration, with a rise from 1.23E+07 kg DCBe in 2015 to 2.58E+07 kg DCBe in 2030, takes the second place and plant biomass, increases from 1.26E+07 kg DCBe in 2015 to 1.75E+07 kg DCBe in 2030, emerge as noteworthy contributors. Energy from waste and small scale wind have small, but notable increase over the years, starting from 6.23E+05 kg DCBe and 6.36E+05 kg DCBe and reaching 5.00E+06 kg DCBe and 2.56E+06 kg DCBe, respectively. These findings underscore the varying levels of human toxicity potential associated with different energy sources, emphasizing the importance of comprehensive assessments for sustainable energy choices and strategies to minimize adverse human health impacts.

Table 31: Scenario 2 - Marine Aquatic Ecotoxicity Potential (MAETP)

Marine Aquatic Ecotoxicity Potential (MAETP) [kg DCB-Equiv.]	2015	2020	2025	2030
Total	5,78E+10	8,71E+10	1,03E+11	1,19E+11
Commercial wind	3,02E+10	4,35E+10	4,44E+10	4,54E+10
Small scale wind	3,10E+08	4,47E+08	8,49E+08	1,25E+09
Microgeneration	1,97E+10	3,45E+10	3,79E+10	4,12E+10
Small scale hydro	1,75E+08	2,13E+08	3,51E+08	4,88E+08
Plant biomass	4,29E+09	4,45E+09	5,18E+09	5,92E+09
Energy from waste	3,09E+09	3,96E+09	1,44E+10	2,48E+10

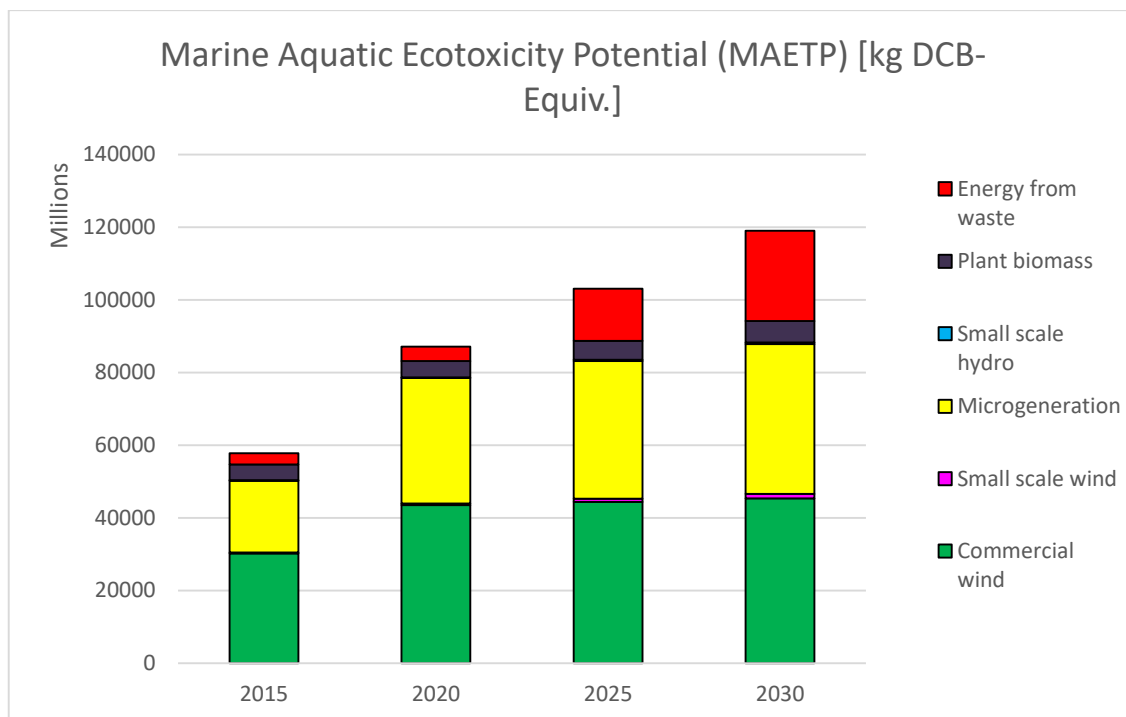
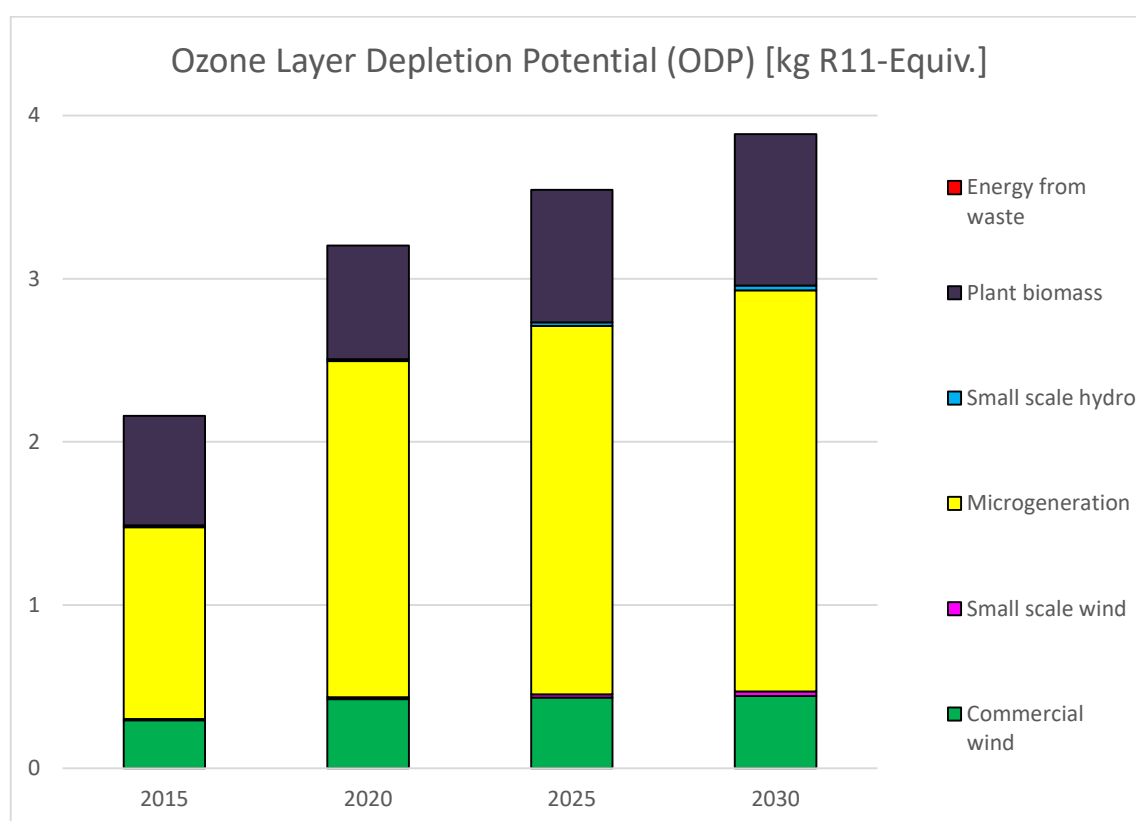


Figure 53: Scenario 2 - Marine Aquatic Ecotoxicity Potential (MAETP)

The data from Table 31 and Figure 53 present that Marine Aquatic Ecotoxicity Potential (MAETP) increases over the years, reaching 1.19×10^{11} kg DCBe, by 2030, with commercial wind being consistently the energy source with the highest contribution. In 2015, the total MAETP is 5.78×10^{10} kg DCBe. Commercial wind has the highest impact with 3.02×10^{10} kg DCBe, followed by microgeneration with 1.97×10^{10} kg DCBe. Plant biomass and energy from waste play a significant role emitting 4.29×10^9 and 3.09×10^9 kg DCBe, respectively. Commercial wind emerges as one of the dominant contributors over the next years, with its MAETP increasing to 4.54×10^{10} kg DCBe in 2030. Microgeneration and plant biomass stand out as significant contributors. The first one emits 1.97×10^{10} kg DCBe and in 2015 to 4.12×10^{10} kg DCBe in 2030, and the second rises from 4.29×10^9 kg DCBe in 2015 to 5.92×10^9 kg DCBe in 2030. Energy from waste starts with 3.09×10^9 in 2015, increasing to 3.96×10^9 , 1.44×10^{10} and 2.48×10^{10} kg DCBe over 2020, 2025 and 2030, respectively. Small scale wind and small scale hydro display escalating trends in their contributions to MAETP over the years.

Table 32: Scenario 2 - Ozone Layer Depletion Potential (ODP)

Ozone Layer Depletion Potential (ODP) [kg R11-Equiv.]	2015	2020	2025	2030
Total	2,16E+00	3,20E+00	3,54E+00	3,89E+00
Commercial wind	2,95E-01	4,24E-01	4,33E-01	4,42E-01
Small scale wind	6,98E-03	1,01E-02	1,91E-02	2,81E-02
Microgeneration	1,18E+00	2,06E+00	2,26E+00	2,46E+00
Small scale hydro	1,08E-02	1,31E-02	2,15E-02	3,00E-02
Plant biomass	6,71E-01	6,95E-01	8,11E-01	9,27E-01
Energy from waste	3,57E-08	4,59E-08	1,66E-07	2,87E-07

**Figure 54: Scenario 2 - Ozone Layer Depletion Potential (ODP)**

The data from Table 32 and Figure 54 present that Ozone Layer Depletion Potential (ODP) increases over the years, with the most significant energy source in terms of emissions is microgeneration. In 2015, the total ODP is 2.16E+00 kg R11e. Microgeneration has the highest ODP with 1.18E+00 kg R11e, followed by plant biomass with 6.71E-01 kg R11e. Commercial wind emits 2.95E-01 kg R11e. Small scale hydro, small scale wind and energy from waste contribute the least with 1.08E-02, 6.98E-03 and 3.57E-08 kg R11e, respectively. In 2020, the total ODP increases to 3.20E+00 kg R11e, with microgeneration remaining the highest contributor with 2.06E+00 kg R11e. Plant

biomass and commercial wind emit 6.95E-01 and 4.24E-01 kg R11e, respectively. Small scale hydro and wind contributes with 1.31E-02 and 1.01E-02 kg R11e, while energy from waste with 4.59E-08 kg R11e. During 2025, the ranking remains the same: microgeneration, plant biomass and commercial wind emit 2.26E+00, 8.11E-01 and 4.33E-01 kg R11e. Small scale hydro, wind and energy from waste increase but not significantly. In 2030, the total ODP reaches 3.89E+00 kg R11e. Microgeneration emits 2.46E+00 kg R11e, while plant biomass and commercial wind increase to 9.27E-01 and 4.42E-01kg R11e, respectively. Small scale hydro increases to 3.00E-02 kg R11. Small scale wind and energy from waste emit 2.81E-02 and 2.87E-07, respectively.

Table 33: Scenario 2 - Photochemical Ozone Creation Potential (POCP)

Photochemical Ozone Creation Potential (POCP) [kg Ethene-Equiv.]	2015	2020	2025	2030
Total	2,15E+04	2,57E+04	3,62E+04	4,66E+04
Commercial wind	2,72E+03	3,92E+03	4,00E+03	4,09E+03
Small scale wind	6,38E+01	9,19E+01	1,75E+02	2,57E+02
Microgeneration	2,46E+03	4,30E+03	4,72E+03	5,14E+03
Small scale hydro	6,56E+01	7,97E+01	1,31E+02	1,83E+02
Plant biomass	1,40E+04	1,45E+04	1,69E+04	1,93E+04
Energy from waste	2,20E+03	2,82E+03	1,02E+04	1,76E+04

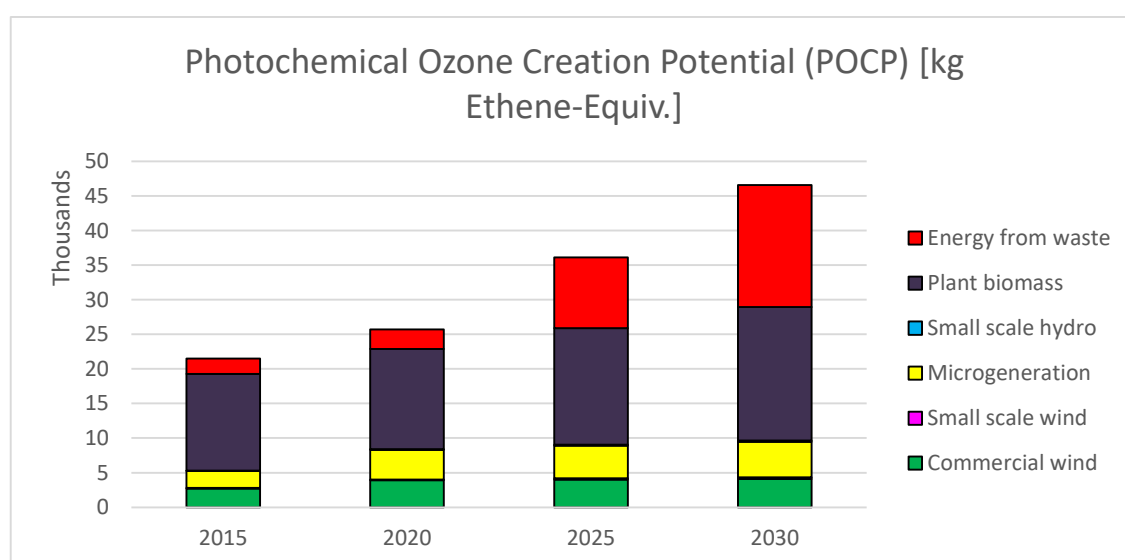


Figure 55: Scenario 2 - Photochemical Ozone Creation Potential (POCP)

The data from Table 33 and Figure 55 present that Photochemical Ozone Creation Potential (POCP) increases over the years, while plant biomass is the hot-spot every year. In 2015, the total POCP is 2.15E+04 kg Ethene Eq. Plant biomass has the highest

impact with 1.40E+04 kg Ethene Eq, followed by microgeneration with 2.46E+03 kg Ethene Eq. Commercial wind comes in the third place and energy from waste in the fourth emitting 2.72E+03 and 2.20E+03 kg Ethene Eq, respectively. Small scale hydro and small scale wind contribute to 6.56E+01 and 6.38E+01 kg Ethene Eq, respectively. In 2020, the total POCP increases to 2.57E+04 kg Ethene Eq. Plant biomass remains on the top with 1.45E+04 kg Ethene Eq, followed by microgeneration with 4.30E+03 and commercial wind 3.92E+03 kg Ethene Eq. The lowest contributions are pointed to energy from waste, small scale hydro and wind with 2.82E+03, 7.97E+01 and 9.19E+01 kg Ethene Eq., respectively. By 2025, the ranking does not changes with plant biomass emits 1.69E+04 kg Ethene Eq, while energy from waste takes the second place and microgeneration the third place with emissions of 1.02E+04 and 4.72E+03 kg Ehtene Eq. Commercial wind is also significant with 4.00E+03 kg Ethene Eq. Small scale wind and small scale hydro, still have the lowest emissions above all and they contribute to 1.75E+02 and 1.31E+02 kg Ethelene Eq. In 2030, the total POCP reaches 4.66E+04 kg Ethene Eq. Plant biomass emits 1.93E+04 kg Ethene Eq, while energy from waste 1.76E+04 kg Ethene Eq. Commercial wind, microgeneration, small scale wind and hydro contribute with 4.09E+03, 5.14E+03, 2.57E+02 and 1.83E+02 kg Ethene Eq, respectively.

Table 34: Scenario 2 - Terrestrial Ecotoxicity Potential (TETP)

Terrestrial Ecotoxicity Potential (TETP) [kg DCB-Equiv.]	2015	2020	2025	2030
Total	9,05E+05	1,10E+06	1,30E+06	1,50E+06
Commercial wind	2,61E+05	3,77E+05	3,85E+05	3,93E+05
Small scale wind	1,56E+04	2,25E+04	4,27E+04	6,29E+04
Microgeneration	6,51E+04	1,14E+05	1,25E+05	1,36E+05
Small scale hydro	3,93E+03	4,78E+03	7,86E+03	1,10E+04
Plant biomass	5,39E+05	5,59E+05	6,52E+05	7,45E+05
Energy from waste	1.93E+04	2.47E+04	4.40E+04	6.33E+04

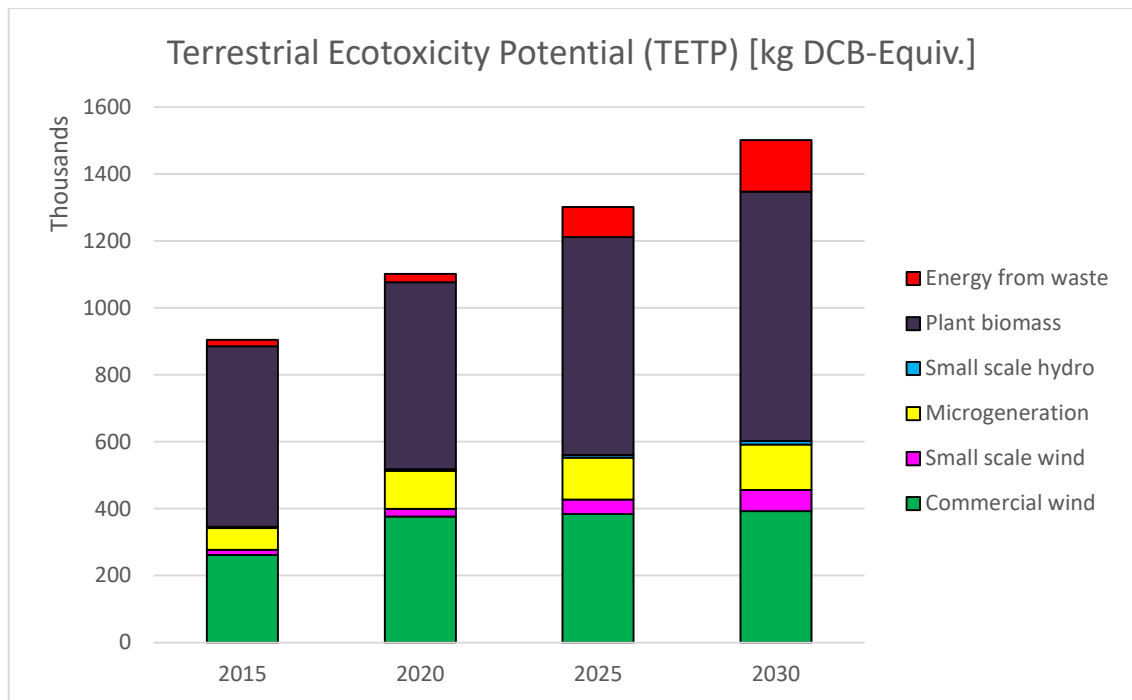
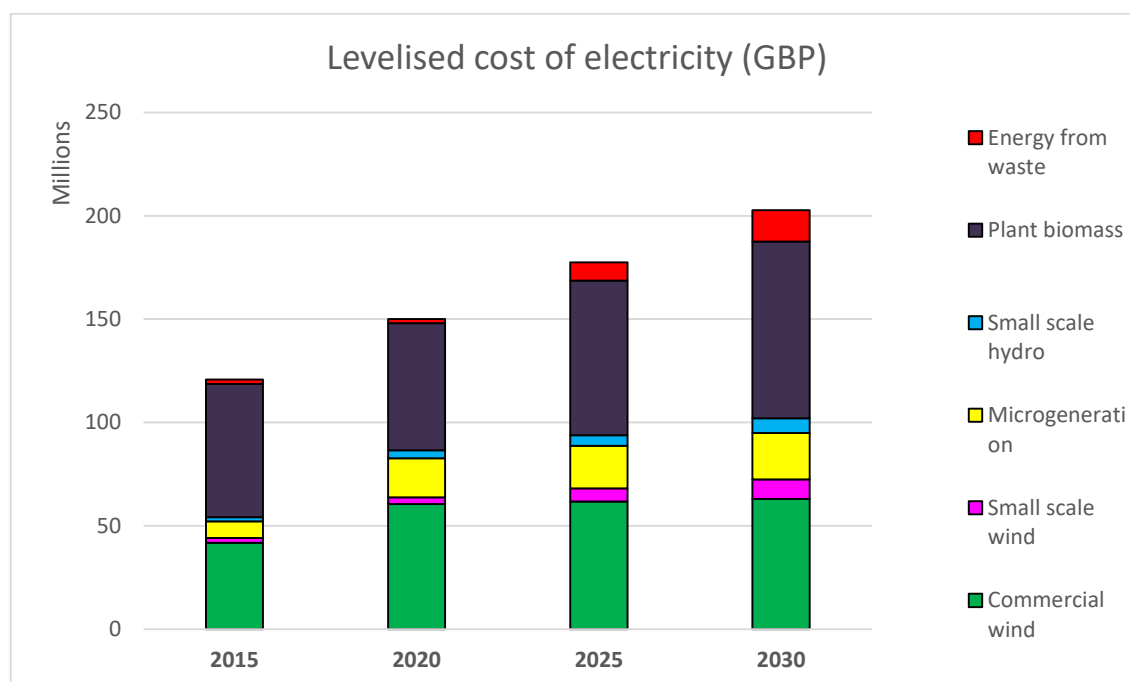


Figure 56: Scenario 2 - Terrestrial Ecotoxicity Potential (TETP)

The data from Table 34 and Figure 56 present that Terrestrial Ecotoxicity Potential (TETP) increases over the years, reaching $1.50\text{E}+06$ kg DCBe by 2030. In 2015, the total TETP is $9.05\text{E}+05$ kg DCBe. Plant biomass contributes to $5.39\text{E}+05$ kg DCBe, followed by commercial wind to $2.61\text{E}+05$ kg DCBe and microgeneration to $6.51\text{E}+04$ kg DCBe. Energy from waste, small scale wind and hydro contribute with $6.51\text{E}+04$, $1.56\text{E}+04$, $3.93\text{E}+03$ kg DCBe, respectively. In 2020, the total TETP increases to $1.10\text{E}+06$ kg DCBe. Plant biomass emits $5.59\text{E}+05$ kg DCBe, while commercial wind contributes with $3.77\text{E}+05$ kg DCBe. The rest of the energy sources have lower contributions compared to the sources above. By 2025, plant biomass is still on the top emitting $6.52\text{E}+05$ kg DCBe. Commercial wind and microgeneration keep rising until $3.85\text{E}+05$ and $1.14\text{E}+05$ kg DCBe, respectively. In 2030, the ranking remains the same: plant biomass, commercial wind, microgeneration, energy from waste, small scale wind and small scale hydro reach $7.45\text{E}+05$, $3.93\text{E}+05$, $1.36\text{E}+05$, $6.33\text{E}+04$, $3.93\text{E}+04$ and $1.10\text{E}+04$ kg DCBe, respectively. These findings emphasize the varying levels of terrestrial ecotoxicity potential associated with different energy sources. It underscores the need for comprehensive assessments and sustainable practices to minimize adverse impacts on terrestrial ecosystems as the demand for energy continues to grow.

Table 35: Scenario 2 - Levelised Cost of Electricity (GBP)

Levelised cost of electricity (GBP)	2015	2020	2025	2030
Total	1,21E+08	1,50E+08	1,77E+08	2,02E+08
Commercial wind	4,18E+07	6,05E+07	6,18E+07	6,31E+07
Small scale wind	2,30E+06	3,33E+06	6,32E+06	9,31E+06
Microgeneration	8,09E+06	1,88E+07	2,06E+07	2,24E+07
Small scale hydro	1,90E+06	3,91E+06	5,12E+06	7,13E+06
Plant biomass	6,44E+07	6,16E+07	7,48E+07	8,55E+07
Energy from waste	2,23E+06	1,98E+06	8,78E+06	1,51E+07

**Figure 57: Scenario 2 - Levelised Cost of Electricity (GBP)**

The data from Table 35 and Figure 57 present that levelised cost of electricity increases over the years and by 2030 reaches the value of 2.02E+08 GBP. In 2015, the total Levelised cost of electricity reaches 1.21E+08 GBP. Plant biomass and commercial wind are the most significant contributors with 6.44E+07 and 4.18E+07 GBP respectively, while the lowest values are pointed to microgeneration, energy from waste, small scale wind and hydro with 8.09E+06, 2.23E+06, 2.30E+06 and 1.90E+06 GBP, respectively. In 2020, the total LCOE increases to 1.50E+08 GBP and the ranking remains the same. Although, microgeneration climbs to 1.88E+07 GBP. By 2025, the total LCOE further increases to 1.77E+08 GBP, with plant biomass continuing to be the top contributor, with 7.48E+07 GBP. Commercial wind and microgeneration contribute with 6.185E+07 and 2.06E+07 GBP, respectively. Energy from waste, small scale wind and hydro have a

small steady increase. In 2030, the ranking for the highest contributors remains the same: plant biomass, commercial wind, microgeneration with 8.55E+07, 6.31E+07 and 1.51E+07 GBP. Small scale hydro, energy from waste and small scale wind follow and energy from waste significantly climbs to 1.51E+07 GBP.

Table 36: Scenario 2 - Deaths estimate

Deaths estimate	2015	2020	2025	2030
Total	1,01E+00	1,12E+00	2,07E+00	3,03E+00
Commercial wind	1,17E-02	1,69E-02	1,72E-02	1,76E-02
Small scale wind	7,76E-05	1,12E-04	2,12E-04	3,13E-04
Microgeneration	2,41E-03	4,23E-03	4,64E-03	5,04E-03
Small scale hydro	5,37E-02	6,52E-02	1,07E-01	1,49E-01
Plant biomass	7,09E-01	7,35E-01	8,57E-01	9,79E-01
Energy from waste	2,33E-01	3,00E-01	1,09E+00	1,87E+00

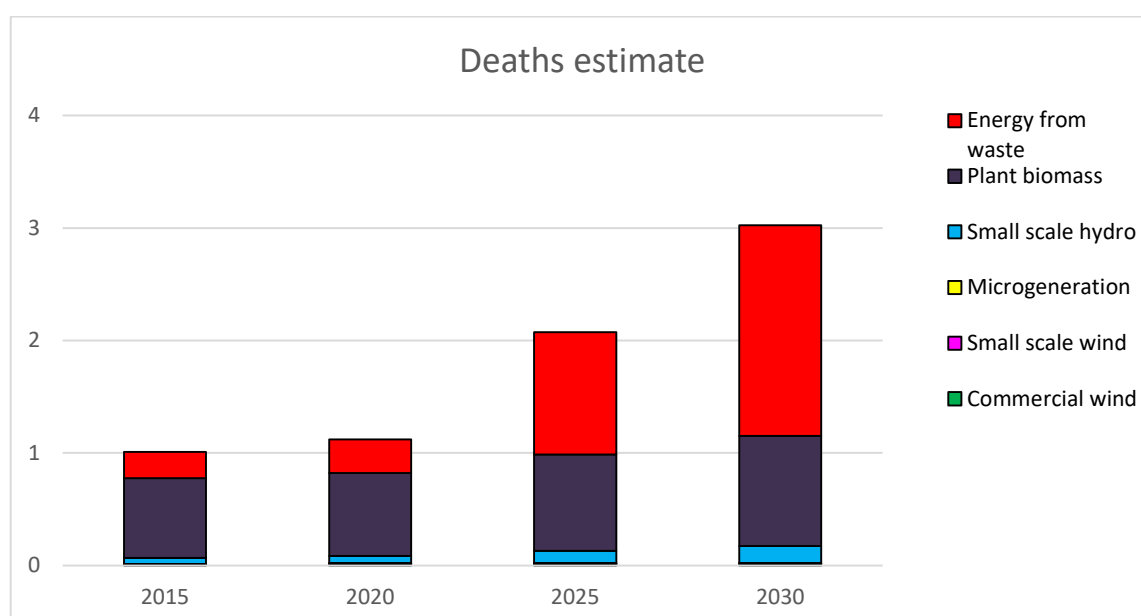


Figure 58: Scenario 2 - Deaths estimate

The data from Table 36 and Figure 58 present that deaths estimate is a number increasing over the years. In 2015, the total estimated deaths are 1.01E+00 people. Plant biomass has the highest death estimate with 7.09E-01, followed by energy from waste with 2.33E-01 people. Small scale hydro plays also a significant role with 5.37E-02 and commercial wind 1.17E-02 deaths estimate. Microgeneration and small scale wind have the lowest death estimates with 2.41E-03 and 7.76E-05, respectively. In 2020, the total estimated deaths increase to 1.12E+00. Plant biomass remains on the top with 7.35E-01, followed by energy from waste at 3.00E-01. Small scale hydro, commercial wind and

microgeneration contribute with 6.52E-02, 1.69E-02 and 4.23E-03, respectively. Small scale wind has the lowest risk with 1.12E-04 deaths estimate. By 2025, the total estimated deaths climb to 2.07E+00. The ranking does not remain the same, with plant biomass being in the second place with 8.57E-01. Energy from waste comes first with 1.09E+00. In 2030, the total estimated deaths reach 3.03E+00, almost two people. Energy from waste is the hot spot here with a relatively significant increase reaching 1.87E+00. Plant biomass comes in the second place with 7.67E-01 deaths estimated, while small scale hydro and commercial wind contribute with 9.79E-01 and 1.76E-02, respectively. Microgeneration and small scale wind have also increased to 5.04E-03 and 3.13E-04, respectively.

Table 37: Scenario 2 - Jobs estimate

Jobs estimate	2015	2020	2025	2030
Total	5,08E+02	6,71E+02	1,04E+03	1,42E+03
Commercial wind	1,76E+02	2,54E+02	2,59E+02	2,64E+02
Small scale wind	1,17E+00	1,68E+00	3,19E+00	4,70E+00
Microgeneration	6,70E+01	1,17E+02	1,29E+02	1,40E+02
Small scale hydro	7,83E+00	9,50E+00	1,56E+01	2,18E+01
Plant biomass	1,61E+02	1,67E+02	1,95E+02	2,23E+02
Energy from waste	9,49E+01	1,22E+02	4,42E+02	7,61E+02

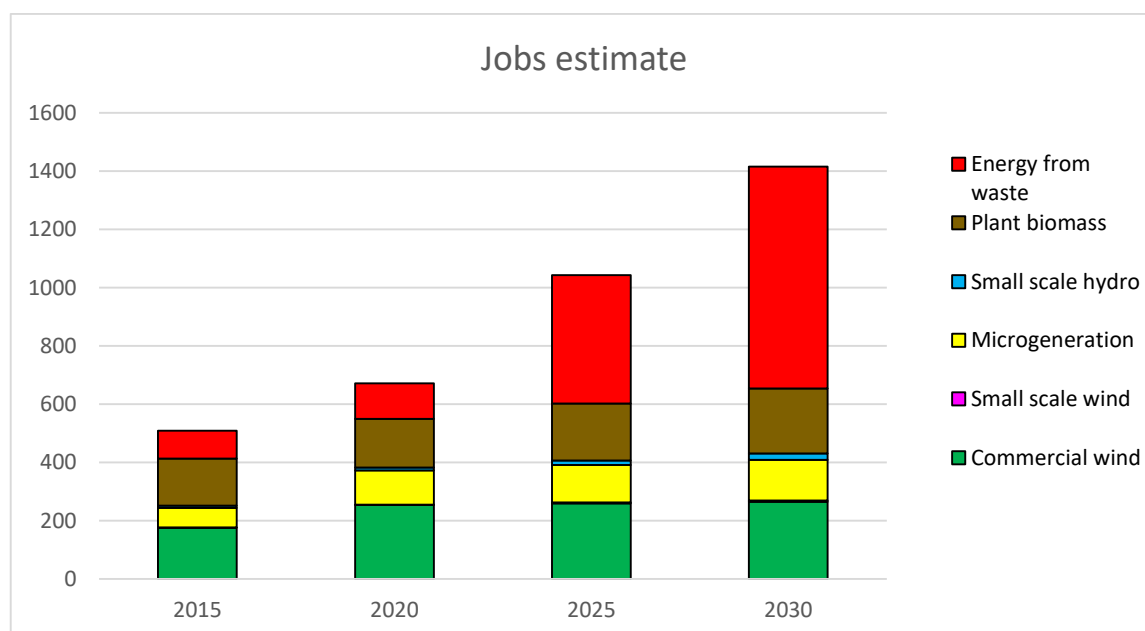


Figure 59: Scenario 2 - Jobs estimate

The data from Table 37 and Figure 59 present that jobs are increasing over the years, starting at a low point of 508 in 2015 and reaching 1,420 by 2030. In 2015, the total

number of jobs is 508, with commercial wind contributing the most with 176 jobs, followed by plant biomass with 161 jobs and energy from waste with 94. Microgeneration has also a significant impact providing 67 jobs. Small scale wind and hydro offer 1 and 7 jobs respectively. In 2020, commercial wind remains on the top providing 254 jobs, while a significant impact has also the plant biomass, energy from waste and microgeneration with 167, 122 and 117 jobs, respectively. Small scale hydro and wind have lower contributions with 9 and 1 jobs each. By 2025, commercial wind offers 259 jobs. However, energy from waste climbs to 442 jobs, while plant biomass and microgeneration contribute with 195 and 129 jobs, respectively. By 2030, commercial wind is expected to provide 264 jobs. Energy from waste still offers the most of the jobs with 761 jobs and plant biomass with 223 jobs. Microgeneration offers 140 jobs, while small scale hydro provides 21 jobs and small scale wind also provides 2 jobs. These findings highlight the employment potential associated with different energy sources, emphasizing the importance of considering socio-economic factors alongside environmental impacts when evaluating and planning for the adoption of diverse energy generation methods.

4.3 Outcomes of scenario 3: No new development of new commercial wind

The results of scenario 3 are shown at the following tables and figures:

Table 38: Scenario 3 - Global Warming Potential (GWP)

Global Warming Potential (GWP) [kg CO₂-Equiv.]	2015	2020	2025	2030
Total	5,73E+07	7,55E+07	1,42E+08	2,09E+08
Commercial wind	4,85E+06	6,98E+06	6,98E+06	6,98E+06
Small scale wind	1,20E+05	1,73E+05	1,73E+05	1,74E+05
Microgeneration	7,66E+06	1,34E+07	1,68E+07	2,02E+07
Small scale hydro	1,58E+05	1,92E+05	4,08E+05	6,25E+05
Plant biomass	9,91E+06	1,03E+07	1,38E+07	1,73E+07
Energy from waste	3,46E+07	4,44E+07	1,04E+08	1,64E+08

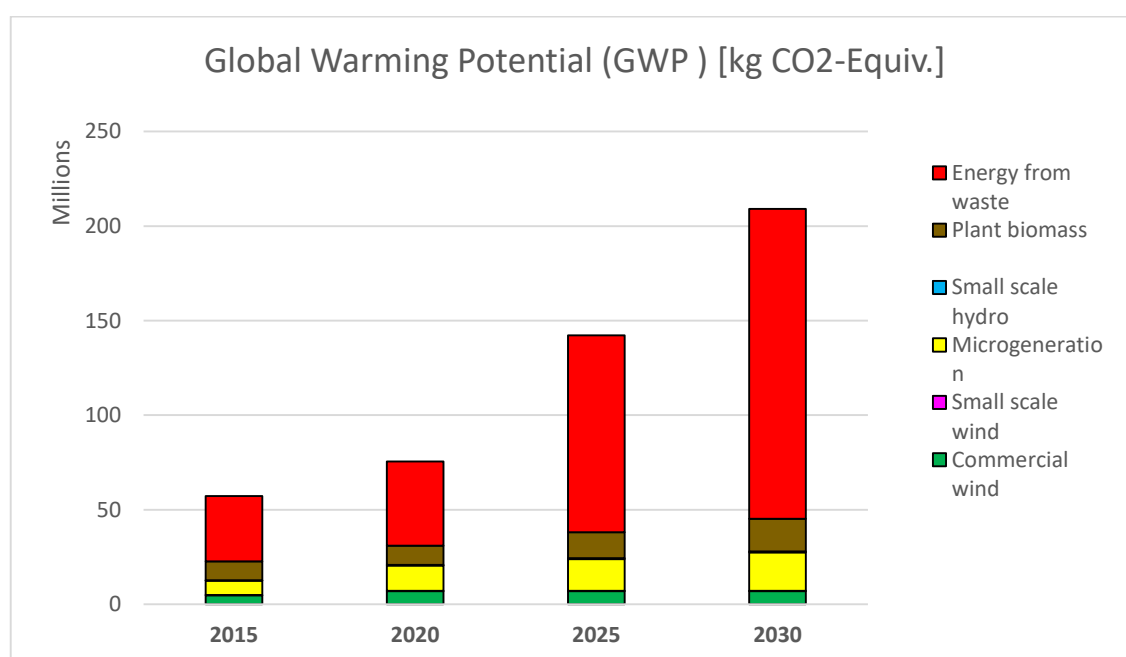


Figure 60: Scenario 3 - Global Warming Potential (GWP)

The data from Table 38 and Figure 60 present that over the analyzed period from 2015 to 2030, the Global Warming Potential (GWP) exhibits a consistent upward trend, escalating from 5.73E+07 kg CO₂e in 2015 to 2.09E+08 kg CO₂e by 2030. Notably, energy from waste emerges as the predominant contributor throughout each year, peaking at 1.64E+08 kg CO₂e in 2030. Plant biomass and microgeneration also play substantial roles, maintaining consistent contributions across the years. Microgeneration emits 7.66E+06 kg CO₂e in 2015, reaching 2.02E+07 kg CO₂e by 2030. Relatively, plant biomass

starts with a 9.91E+06 kg CO₂e and reaches 1.73E+07 kg CO₂e by 2030. Commercial wind emits 4.85E+06 kg CO₂e in 2015 and reaches 6.98E+06 kg CO₂e by 2030. Small scale hydro, and small scale wind exhibit comparatively lower GWP values. The overall hierarchy of contributions remains stable at most of the parts, with each energy source contributing progressively more to the total GWP.

Table 39: Scenario 3 - Abiotic Depletion Potential (ADP elements)

Abiotic Depletion Potential (ADP elements) [kg Sb-Equiv.]	2015	2020	2025	2030
Total	1,20E+03	1,82E+03	1,99E+03	2,16E+03
Commercial wind	8,18E+02	1,18E+03	1,18E+03	1,18E+03
Small scale wind	2,68E+00	3,86E+00	3,87E+00	3,87E+00
Microgeneration	3,49E+02	6,11E+02	7,66E+02	9,20E+02
Small scale hydro	8,18E-01	9,92E-01	2,11E+00	3,23E+00
Plant biomass	2,51E+01	2,60E+01	3,49E+01	4,38E+01
Energy from waste	2,96E+00	3,80E+00	8,90E+00	1,40E+01

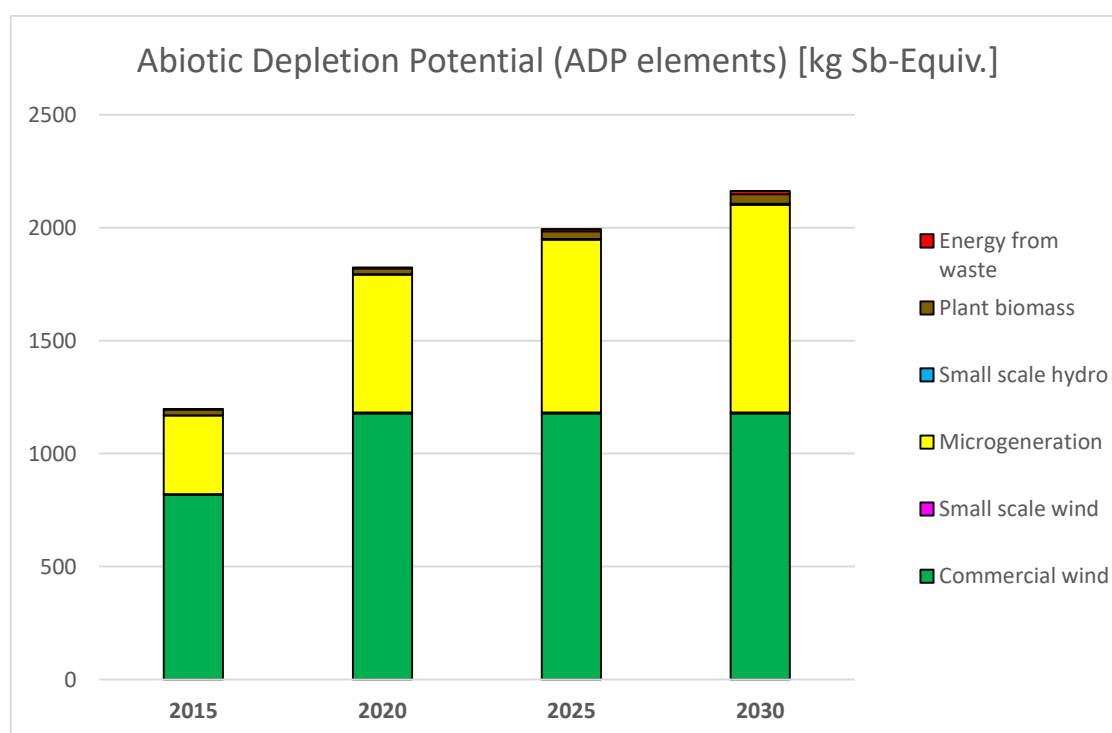


Figure 61: Scenario 3 - Abiotic Depletion Potential (ADP elements)

The data from Table 39 and Figure 61 present that across the evaluated period spanning from 2015 to 2030, there is a consistent increase in Abiotic Depletion Potential (ADP) elements, rising from 1.20E+03 kg SbE in 2015 to 2.16E+03 kg SbE in 2030. In this context, commercial wind consistently holds a prominent position, escalating from

8.18E+02 kg SbE in 2015 to 1.18E+03 kg SbE in 2030. The second highest emitting contributor is microgeneration, starting with 3,49E+02 kg SbE in 2015 and reaching 9.20E+02 kg SbE by 2030. Interestingly, the ADP contribution from plant biomass has a substantial surge, jumping from 2.51E+01 kg SbE in 2015 to 4.38E+01 kg SbE in 2030. Last but not least, small scale wind, small scale hydro, and energy from waste also contribute to ADP, with increasing values over the years. The outcome of this comparison should be focused on the two main contributors here, commercial wind and microgeneration.

Table 40: Scenario 3 - Abiotic Depletion Potential (ADP fossil)

Abiotic Depletion Potential (ADP fossil) [MJ]	2015	2020	2025	2030
Total	2,72E+08	3,86E+08	5,20E+08	6,54E+08
Commercial wind	6,46E+07	9,31E+07	9,31E+07	9,31E+07
Small scale wind	1,63E+06	2,35E+06	2,35E+06	2,36E+06
Microgeneration	9,56E+07	1,67E+08	2,10E+08	2,52E+08
Small scale hydro	1,53E+06	1,86E+06	3,95E+06	6,05E+06
Plant biomass	7,12E+07	7,38E+07	9,90E+07	1,24E+08
Energy from waste	3,72E+07	4,77E+07	1,12E+08	1,76E+08

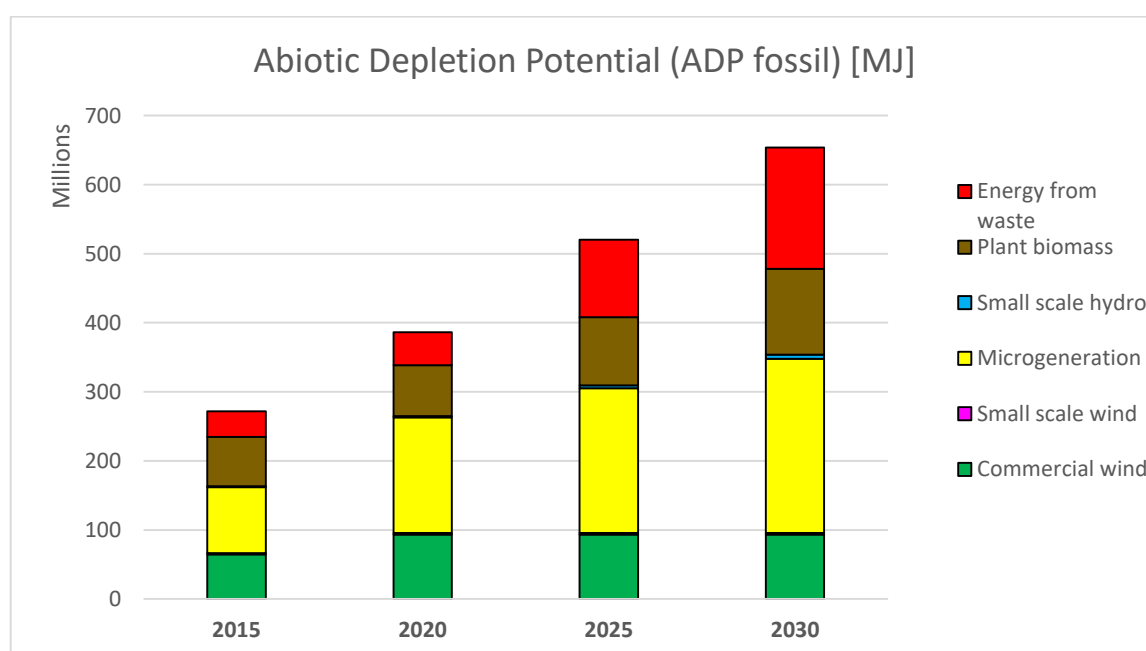


Figure 62: Scenario 3 - Abiotic Depletion Potential (ADP fossil)

The data from Table 40 and Figure 62 present that over the analyzed period from 2015 to 2030, the Abiotic Depletion Potential (ADP) in terms of fossil resources demonstrates a substantial increase, surging from 2.72E+08 MJ in 2015 to 6.54E+08 MJ in 2030. Among

the energy sources, commercial wind consistently emerges as a major contributor, with its share rising from 6.46E+07 MJ in 2015 to 9.31E+07 MJ in 2030. Microgeneration significantly contributes to ADP fossil, experiencing an increase from 9.56E+07 MJ in 2015 to 2.52E+08 MJ in 2030. Energy from waste catches the attention, especially in the significant increase in 2030, contributing the most with 1.76E+08 MJ. Plant biomass has a small steady increase over the years, starting from 7.12E+07 MJ in 2015 to 1.24E+08 MJ. Meanwhile, small scale hydro and wind also showcase increasing trends in their contributions. The top three contributors, energy from waste, microgeneration, and commercial wind, highlight the evolving environmental impact of various energy sources.

Table 41: Scenario 3 - Acidification Potential (AP)

Acidification Potential (AP) [kg SO₂-Equiv.]	2015	2020	2025	2030
Total	2,53E+05	3,12E+05	4,77E+05	6,42E+05
Commercial wind	2,56E+04	3,69E+04	3,69E+04	3,69E+04
Small scale wind	6,36E+02	9,16E+02	9,18E+02	9,19E+02
Microgeneration	3,47E+04	6,08E+04	7,62E+04	9,15E+04
Small scale hydro	6,28E+02	7,62E+02	1,62E+03	2,48E+03
Plant biomass	1,32E+05	1,37E+05	1,84E+05	2,30E+05
Energy from waste	5,93E+04	7,61E+04	1,78E+05	2,80E+05

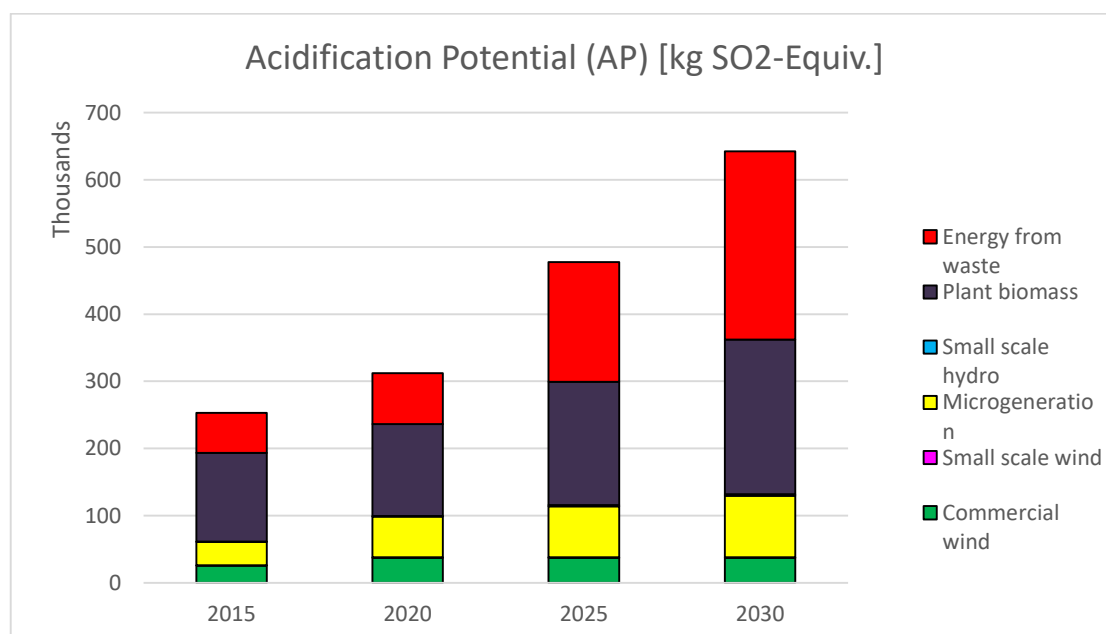


Figure 63: Scenario 3 - Acidification Potential (AP)

The data from Table 41 and Figure 63 present that over the period from 2015 to 2030, the Acidification Potential (AP) in terms of sulfur dioxide equivalents reveals a substantial increase, escalating from 2.53E+05 kg SO₂e in 2015 to 6.42E+05 kg SO₂e in 2030. Notably, energy from waste displays a significant surge, starting with 5.93E+04 kg SO₂e in 2015 and reaching 2.80E+05 kg SO₂e in 2030, emphasizing its noteworthy contribution to acidification and underscoring the importance of sustainable waste management practices. Plant biomass follows an increasing trend, contributing 1.32E+05 kg SO₂e in 2015, reaching 2.30E+05 kg SO₂e in 2030. Microgeneration, as a third contributor, shows a steady rise, from 3.47E+04 kg SO₂e in 2015 to 9.15E+04 kg SO₂e in 2030, while commercial wind exhibits a comparatively moderate increase, from 2.56E+04 kg SO₂e in 2015 to 3.69E+04 kg SO₂e in 2030. Small scale wind and hydro have increasing values too, but they remain comparatively low. These analyses highlight the diverse acidification potentials of different energy sources and emphasize the need for strategic environmental considerations in the adoption and development of sustainable energy solutions.

Table 42: Scenario 3 - Eutrophication Potential (EP)

Eutrophication Potential (EP) [kg Phosphate-Equiv.]	2015	2020	2025	2030
Total	9,56E+04	1,25E+05	1,63E+05	2,01E+05
Commercial wind	1,87E+04	2,69E+04	2,69E+04	2,69E+04
Small scale wind	4,17E+02	6,00E+02	6,01E+02	6,02E+02
Microgeneration	2,31E+04	4,05E+04	5,07E+04	6,10E+04
Small scale hydro	2,38E+02	2,89E+02	6,14E+02	9,39E+02
Plant biomass	4,69E+04	4,86E+04	6,52E+04	8,17E+04
Energy from waste	6,30E+03	8,08E+03	1,89E+04	2,98E+04

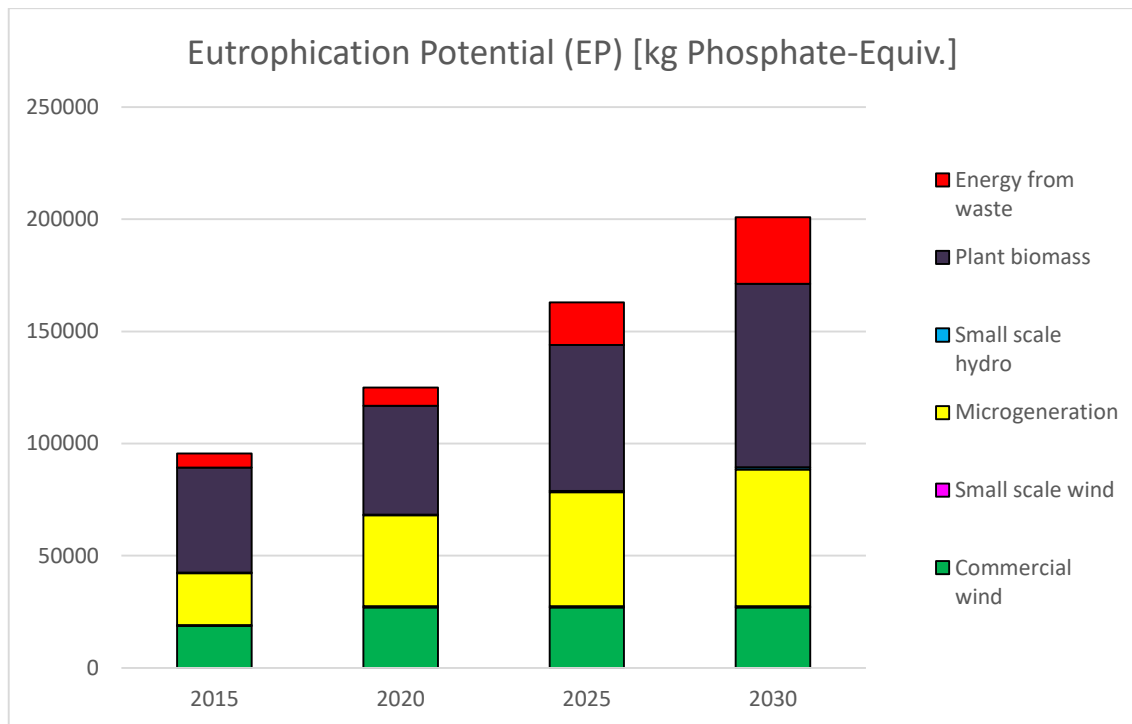


Figure 64: Scenario 3 - Eutrophication Potential (EP)

The data from Table 42 and Figure 64 present that over the evaluated period from 2015 to 2030, the Eutrophication Potential (EP) in terms of phosphate equivalents exhibits an overall increase, ascending from 9.56×10^4 kg Phosphate-Equiv. in 2015 to 2.01×10^5 kg Phosphate-Equiv. in 2030. Focusing on specific energy sources, energy from waste displays a noticeable rise, starting at 6.30×10^3 kg Phosphate-Equiv. in 2015 and reaching 2.98×10^4 kg Phosphate-Equiv. in 2030, emphasizing its growing contribution to eutrophication. Although, the most significant contributor is plant biomass that follows a similar increasing trend, contributing 4.69×10^4 kg Phosphate-Equiv. in 2015 and reaching 8.17×10^4 kg Phosphate-Equiv. in 2030. Microgeneration shows an increase, from 2.31×10^4 kg Phosphate-Equiv. in 2015 to 6.10×10^4 kg Phosphate-Equiv. in 2030, while commercial wind contributes with 1.87×10^4 kg Phosphate-Equiv. in 2015, reaching 2.69×10^4 kg Phosphate-Equiv. Small scale wind and hydro contribute with comparatively lower values.

Table 43: Scenario 3 - Fresh Aquatic Ecotoxicity Potential (FAETP)

Freshwater Aquatic Ecotoxicity Potential (FAETP) [kg DCB-Equiv.]	2015	2020	2025	2030
Total	7,12E+07	1,06E+08	1,14E+08	1,22E+08
Commercial wind	5,26E+07	7,57E+07	7,57E+07	7,57E+07
Small scale wind	1,70E+05	2,45E+05	2,45E+05	2,45E+05
Microgeneration	1,52E+07	2,65E+07	3,33E+07	4,00E+07
Small scale hydro	1,27E+05	1,54E+05	3,28E+05	5,02E+05
Plant biomass	3,13E+06	3,24E+06	4,34E+06	5,45E+06
Energy from waste	1,24E+04	1,59E+04	3,72E+04	5,86E+04

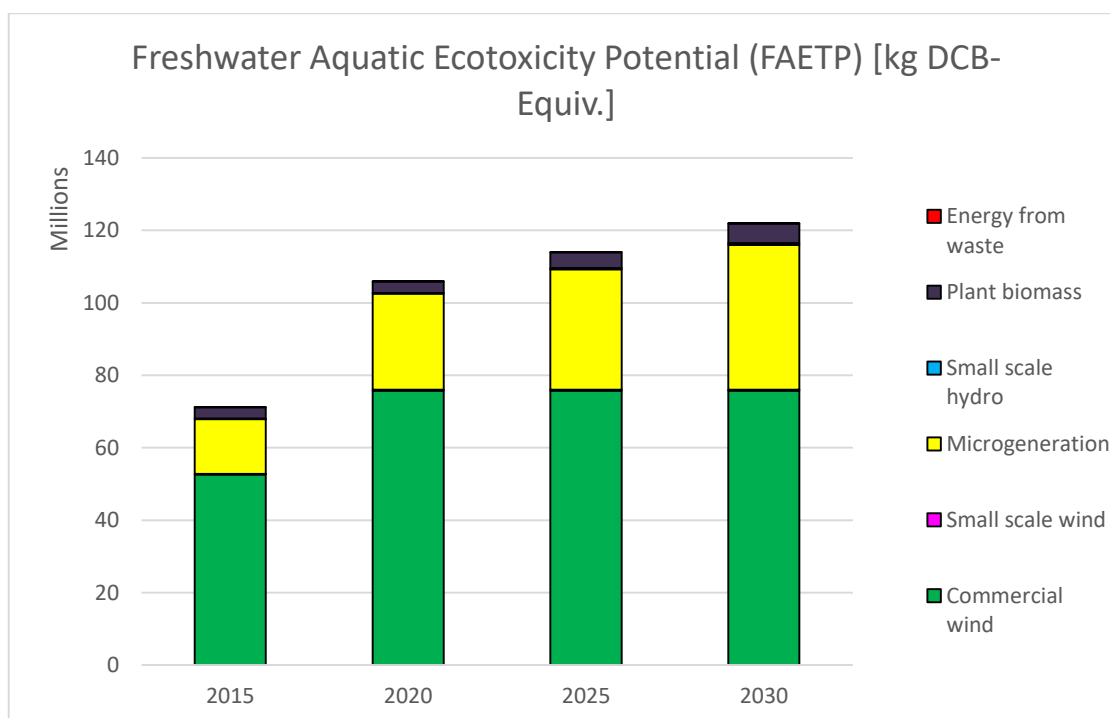


Figure 65: Scenario 3 - Fresh Aquatic Ecotoxicity Potential (FAETP)

The data from Table 43 and Figure 65 present that across the timeframe from 2015 to 2030, the Freshwater Aquatic Ecotoxicity Potential (FAETP) measured in kilograms of DCBe witnesses a notable increase, surging from 7.12E+07 kg DCBe in 2015 to 1.22E+08 kg DCBe in 2030. Focusing on specific contributors, commercial wind stands out with the higher values, starting at 5.26E+07 kg DCBe in 2015 and reaching 7.57E+07 kg DCBe in 2030, emphasizing its considerable impact on freshwater aquatic ecotoxicity. Microgeneration also shows a steady increase, contributing 1.52E+07 kg DCBe in 2015 and reaching 4.00E+07 kg DCBe in 2030, underlining its growing contribution. Plant biomass follows a similar trend, with a rise from 3.13E+06 kg DCBe in 2015 to 5.45E+06

kg DCBe in 2030. The rest of the energy sources like energy from waste, small scale hydro and small scale wind have relatively small values, although they are increasing over the years. These analyses highlight the varying levels of freshwater aquatic ecotoxicity potential associated with different energy sources, underscoring the need for strategic environmental considerations and the exploration of alternative, less ecotoxic solutions in the pursuit of sustainable energy generation.

Table 44: Scenario 3 - Human Toxicity Potential (HTP)

Human Toxicity Potential (HTP) [kg DCB-Equiv.]	2015	2020	2025	2030
Total	5,69E+07	8,05E+07	9,18E+07	1,03E+08
Commercial wind	3,04E+07	4,38E+07	4,38E+07	4,38E+07
Small scale wind	6,36E+05	9,16E+05	9,18E+05	9,19E+05
Microgeneration	1,23E+07	2,16E+07	2,71E+07	3,25E+07
Small scale hydro	2,01E+05	2,44E+05	5,19E+05	7,94E+05
Plant biomass	1,26E+07	1,31E+07	1,76E+07	2,20E+07
Energy from waste	6,23E+05	8,00E+05	1,87E+06	2,95E+06

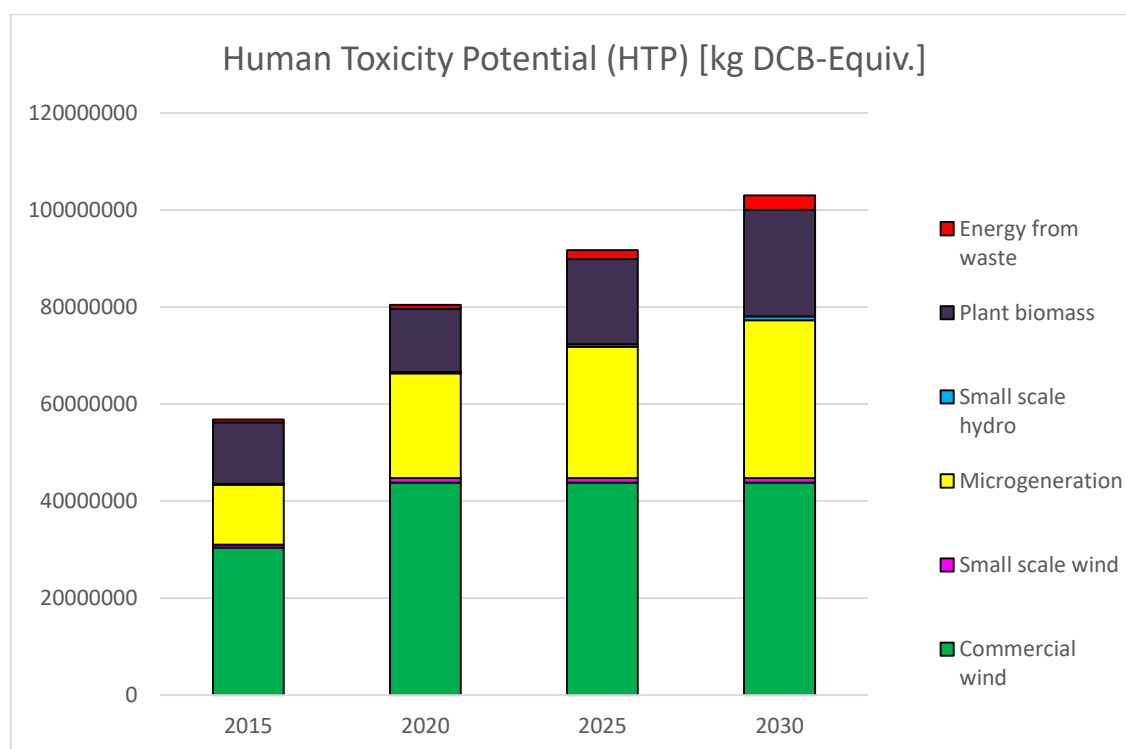


Figure 66: Scenario 3 - Human Toxicity Potential (HTP)

The data from Table 44 and Figure 66 present that over the period from 2015 to 2030, the Human Toxicity Potential (HTP) measured in kilograms of DCBe demonstrates an overall increase, rising from 5.69E+07 kg DCBe in 2015 to 1.03E+08 kg DCBe in 2030.

Examining various energy sources, commercial wind stands out as the most significant contributor, with its HTP increasing from 3.04E+07 kg DCBe in 2015 to 4.38E+07 kg DCBe in 2030. Microgeneration, with a rise from 1.23E+07 kg DCBe in 2015 to 3.25E+07 kg DCBe in 2030, takes the second place and plant biomass, increases from 1.26E+07 kg DCBe in 2015 to 2.20E+07 kg DCBe in 2030, emerge as noteworthy contributors. Energy from waste and small scale wind have small, but notable increase over the years, starting from 6.23E+05 kg DCBe and 6.36E+05 kg DCBe and reaching 2.95E+06 kg DCBe and 9.19E+06 kg DCBe, respectively. These findings underscore the varying levels of human toxicity potential associated with different energy sources, emphasizing the importance of comprehensive assessments for sustainable energy choices and strategies to minimize adverse human health impacts.

Table 45: Scenario 3 - Marine Aquatic Ecotoxicity Potential (MAETP)

Marine Aquatic Ecotoxicity Potential (MAETP) [kg DCB-Equiv.]	2015	2020	2025	2030
Total	5,78E+10	8,71E+10	1,03E+11	1,19E+11
Commercial wind	3,02E+10	4,35E+10	4,35E+10	4,35E+10
Small scale wind	3,10E+08	4,47E+08	4,48E+08	4,48E+08
Microgeneration	1,97E+10	3,45E+10	4,33E+10	5,20E+10
Small scale hydro	1,75E+08	2,13E+08	4,53E+08	6,93E+08
Plant biomass	4,29E+09	4,45E+09	5,96E+09	7,48E+09
Energy from waste	3,09E+09	3,96E+09	9,29E+09	1,46E+10

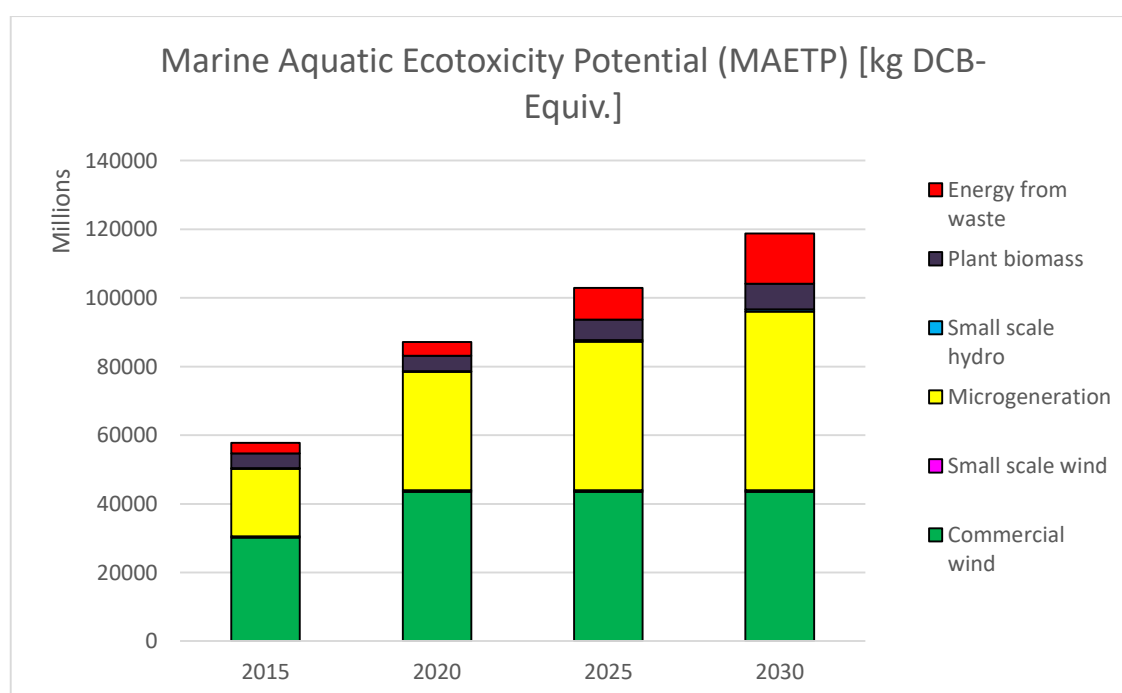


Figure 67: Scenario 3 - Marine Aquatic Ecotoxicity Potential (MAETP)

The data from Table 45 and Figure 67 present that Marine Aquatic Ecotoxicity Potential (MAETP) increases over the years, reaching 1.19E+11 kg DCBe, by 2030, with commercial wind being consistently the energy source with the highest contribution. In 2015, the total MAETP is 5.78E+10 kg DCBe. Commercial wind has the highest impact with 3.02E+10 kg DCBe, followed by microgeneration with 1.97E+10 kg DCBe. Plant biomass and energy from waste play a significant role emitting 4.29E+09 and 3.09E+09 kg DCBe, respectively. Commercial wind emerges as one of the dominant contributors over the next years, with its MAETP increasing to 4.35E+10 kg DCBe in 2030. Microgeneration and plant biomass stand out as significant contributors. The first one emits 1.97E+10 kg DCBe and in 2015 to 5.20E+10 kg DCBe in 2030, and the second rises from 4.29E+09 kg DCBe in 2015 to 7.48E+09 kg DCBe in 2030. Energy from waste starts with 3.09E+09 in 2015, increasing to 3.96E+09, 9.29E+09 and 1.46E+10 kg DCBe over 2020, 2025 and 2030, respectively. Small scale wind and small scale hydro display escalating trends in their contributions to MAETP over the years.

Table 46: Scenario 3 - Ozone Layer Depletion Potential (ODP)

Ozone Layer Depletion Potential (ODP) [kg R11-Equiv.]	2015	2020	2025	2030
Total	2,16E+00	3,20E+00	3,98E+00	4,75E+00
Commercial wind	2,95E-01	4,24E-01	4,24E-01	4,24E-01
Small scale wind	6,98E-03	1,01E-02	1,01E-02	1,01E-02
Microgeneration	1,18E+00	2,06E+00	2,58E+00	3,10E+00
Small scale hydro	1,08E-02	1,31E-02	2,78E-02	4,26E-02
Plant biomass	6,71E-01	6,95E-01	9,33E-01	1,17E+00
Energy from waste	3,57E-08	4,59E-08	1,07E-07	1,69E-07

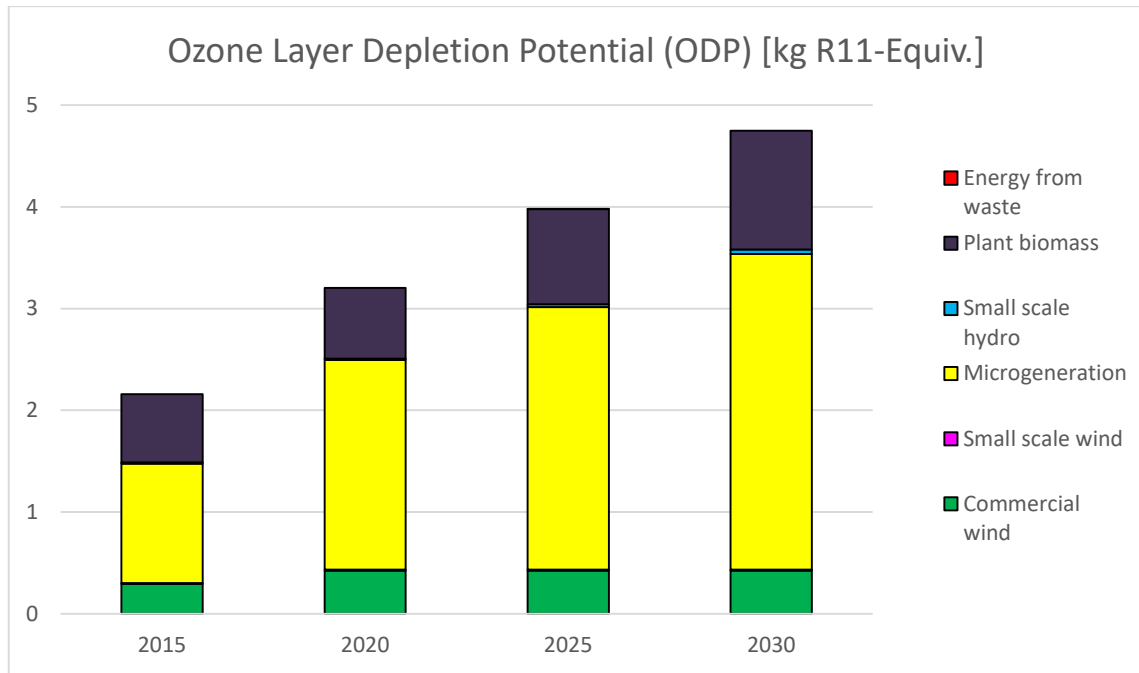
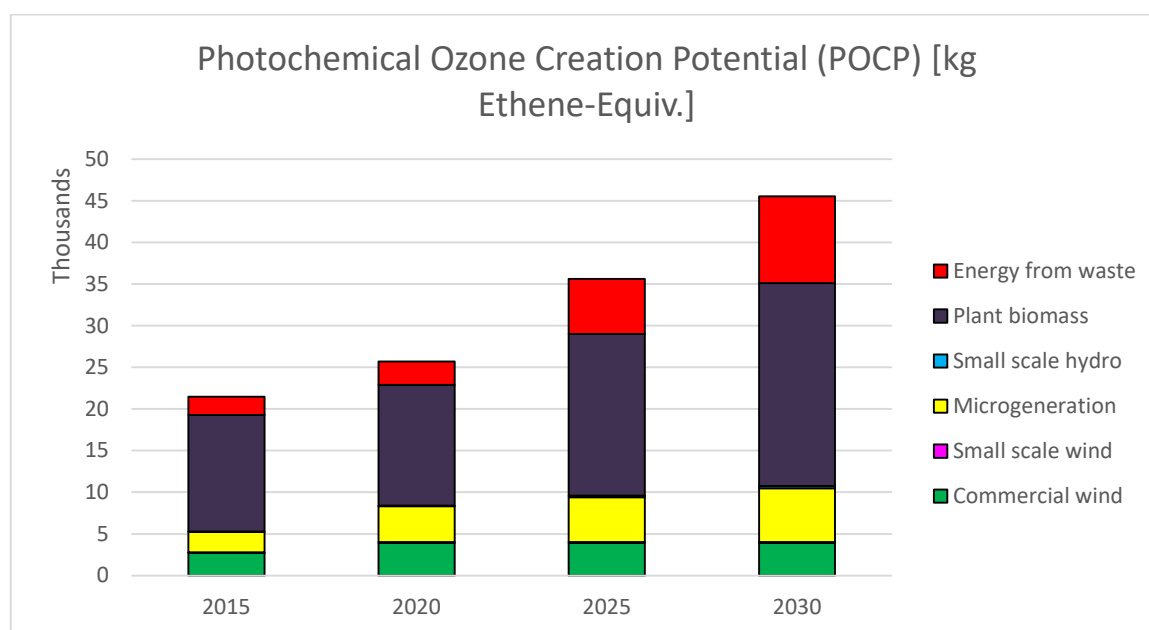


Figure 68: Scenario 3 - Ozone Layer Depletion Potential (ODP)

The data from Table 46 and Figure 68 present that Ozone Layer Depletion Potential (ODP) increases over the years, with the most significant energy source in terms of emissions is microgeneration. In 2015, the total ODP is 2.16E+00 kg R11e. Microgeneration has the highest ODP with 1.18E+00 kg R11e, followed by plant biomass with 6.71E-01 kg R11e. Commercial wind emits 2.95E-01 kg R11e. Small scale hydro, small scale wind and energy from waste contribute the least with 1.08E-02, 6.98E-03 and 3.57E-08 kg R11e, respectively. In 2020, the total ODP increases to 3.20E+00 kg R11e, with microgeneration remaining the highest contributor with 2.06E+00 kg R11e. Plant biomass and commercial wind emit 6.95E-01 and 4.24E-01 kg R11e, respectively. Small scale hydro and wind contributes with 1.31E-02 and 1.01E-02 kg R11e, while energy from waste with 4.59E-08 kg R11e. During 2025, the ranking remains the same: microgeneration, plant biomass and commercial wind emit 2.58E+00, 9.33E-01 and 4.24E-01 kg R11e. Small scale hydro, wind and energy from waste increase but not significantly. In 2030, the total ODP reaches 4.75E+00 kg R11e. Microgeneration emits 3.10E+00 kg R11e, while plant biomass and commercial wind increase to 1.17E+00 and 4.24E-01kg R11e, respectively. Small scale hydro increases to 4.26E-02 kg R11. Small scale wind and energy from waste emit 1.01E-02 and 1.69E-07, respectively.

Table 47: Scenario 3 - Photochemical Ozone Creation Potential (POCP)

Photochemical Ozone Creation Potential (POCP) [kg Ethene-Equiv.]	2015	2020	2025	2030
Total	2,15E+04	2,57E+04	3,56E+04	4,55E+04
Commercial wind	2,72E+03	3,92E+03	3,92E+03	3,92E+03
Small scale wind	6,38E+01	9,19E+01	9,21E+01	9,22E+01
Microgeneration	2,46E+03	4,30E+03	5,39E+03	6,48E+03
Small scale hydro	6,56E+01	7,97E+01	1,69E+02	2,59E+02
Plant biomass	1,40E+04	1,45E+04	1,94E+04	2,44E+04
Energy from waste	2,20E+03	2,82E+03	6,61E+03	1,04E+04

**Figure 69: Scenario 3 - Photochemical Ozone Creation Potential (POCP)**

The data from Table 47 and Figure 69 present that Photochemical Ozone Creation Potential (POCP) increases over the years, while plant biomass is the hot-spot every year. In 2015, the total POCP is 2.15E+04 kg Ethene Eq. Plant biomass has the highest impact with 1.40E+04 kg Ethene Eq, followed by microgeneration with 2.46E+03 kg Ethene Eq. Commercial wind comes in the third place and energy from waste in the fourth emitting 2.72E+03 and 2.20E+03 kg Ethene Eq., respectively. Small scale hydro and small scale wind contribute to 6.56E+01 and 6.38E+01 kg Ethene Eq., respectively. In 2020, the total POCP increases to 2.57E+04 kg Ethene Eq. Plant biomass remains on the top with 1.45E+04 kg Ethene Eq, followed by microgeneration with 4.30E+03 and commercial wind 3.92E+03 kg Ethene Eq. The lowest contributions are pointed to energy from waste, small scale hydro and wind with 2.82E+03, 7.97E+01 and 9.19E+01 kg Ethene Eq., respectively. By 2025, the ranking does not changes with plant biomass

emits 1.94E+04 kg Ethene Eq., while energy from waste takes the second place and microgeneration the third place with emissions of 1.04E+04 and 6.48E+03 kg Ehtene Eq. Commercial wind is also significant with 3.92E+03 kg Ethene Eq. Small scale wind and small scale hydro, still have the lowest emissions above all and they contribute to 9.22E+01 and 2.59E+02 kg Ethelene Eq. In 2030, the total POCP reaches 4.55E+04 kg Ethene Eq. Plant biomass emits 2.44E+04 kg Ethene Eq, while energy from waste 1.04E+04 kg Ethene Eq. Commercial wind, microgeneration, small scale wind and hydro contribute with 3.92E+03, 6.48E+03, 9.22E+01 and 2.59E+02 kg Ethene Eq, respectively.

Table 48: Scenario 3 - Terrestrial Ecotoxicity Potential (TETP)

Terrestrial Ecotoxicity Potential (TETP) [kg DCB-Equiv.]	2015	2020	2025	2030
Total	9,05E+05	1,10E+06	1,36E+06	1,62E+06
Commercial wind	2,61E+05	3,77E+05	3,77E+05	3,77E+05
Small scale wind	1,56E+04	2,25E+04	2,25E+04	2,25E+04
Microgeneration	6,51E+04	1,14E+05	1,43E+05	1,72E+05
Small scale hydro	3,93E+03	4,78E+03	1,02E+04	1,55E+04
Plant biomass	5,39E+05	5,59E+05	7,49E+05	9,40E+05
Energy from waste	1,93E+04	2,47E+04	5,79E+04	9,11E+04

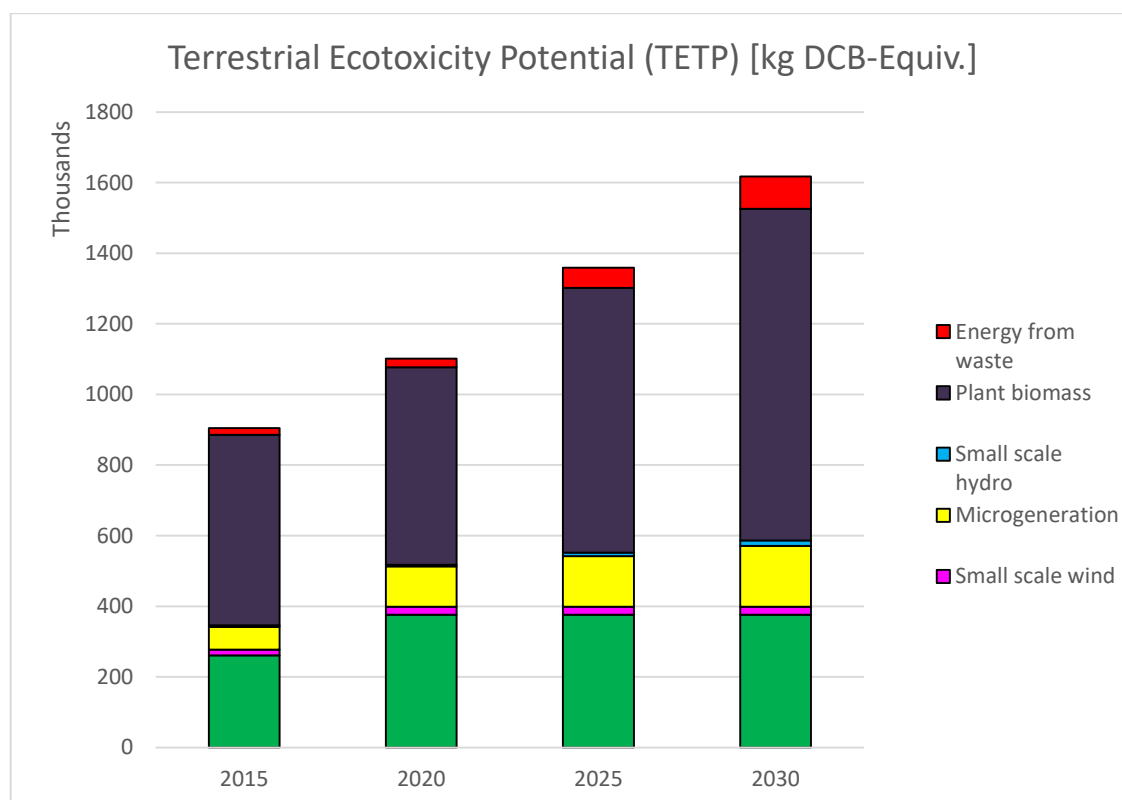


Figure 70: Scenario 3 - Terrestrial Ecotoxicity Potential (TETP)

The data from Table 48 and Figure 70 present that Terrestrial Ecotoxicity Potential (TETP) increases over the years, reaching 1.62E+06 kg DCBe by 2030. In 2015, the total TETP is 9.05E+05 kg DCBe. Plant biomass contributes to 5.39E+05 kg DCBe, followed by commercial wind to 2.61E+05 kg DCBe and microgeneration to 6.51E+04 kg DCBe. Energy from waste, small scale wind and hydro contribute with 6.51E+04, 1.56E+04, 3.93E+03 kg DCBe, respectively. In 2020, the total TETP increases to 1.10E+06 kg DCBe. Plant biomass emits 5.59E+05 kg DCBe, while commercial wind contributes with 3.77E+05 kg DCBe. The rest of the energy sources have lower contributions compared to the sources above. By 2025, plant biomass is still on the top emitting 7.49E+05 kg DCBe. Commercial wind and microgeneration keep rising until 3.77E+05 and 1.43E+05 kg DCBe, respectively. In 2030, the ranking remains the same: plant biomass, commercial wind, microgeneration, energy from waste, small scale wind and small scale hydro reach 9.40E+05, 3.77E+05, 1.72E+05, 9.11E+04, 2.25E+04 and 1.55E+04 kg DCBe, respectively. These findings emphasize the varying levels of terrestrial ecotoxicity potential associated with different energy sources. It underscores the need for comprehensive assessments and sustainable practices to minimize adverse impacts on terrestrial ecosystems as the demand for energy continues to grow.

Table 49: Scenario 3 - Levelised Cost of Electricity (GBP)

Levelised cost of electricity (GBP)	2015	2020	2025	2030
Total	1,21E+08	1,50E+08	1,86E+08	2,19E+08
Commercial wind	4,18E+07	6,05E+07	6,05E+07	6,05E+07
Small scale wind	2,34E+06	3,38E+06	3,38E+06	3,39E+06
Microgeneration	8,09E+06	1,88E+07	2,35E+07	2,83E+07
Small scale hydro	1,90E+06	3,91E+06	6,61E+06	1,01E+07
Plant biomass	6,44E+07	6,16E+07	8,60E+07	1,08E+08
Energy from waste	2,23E+06	1,98E+06	5,68E+06	8,93E+06

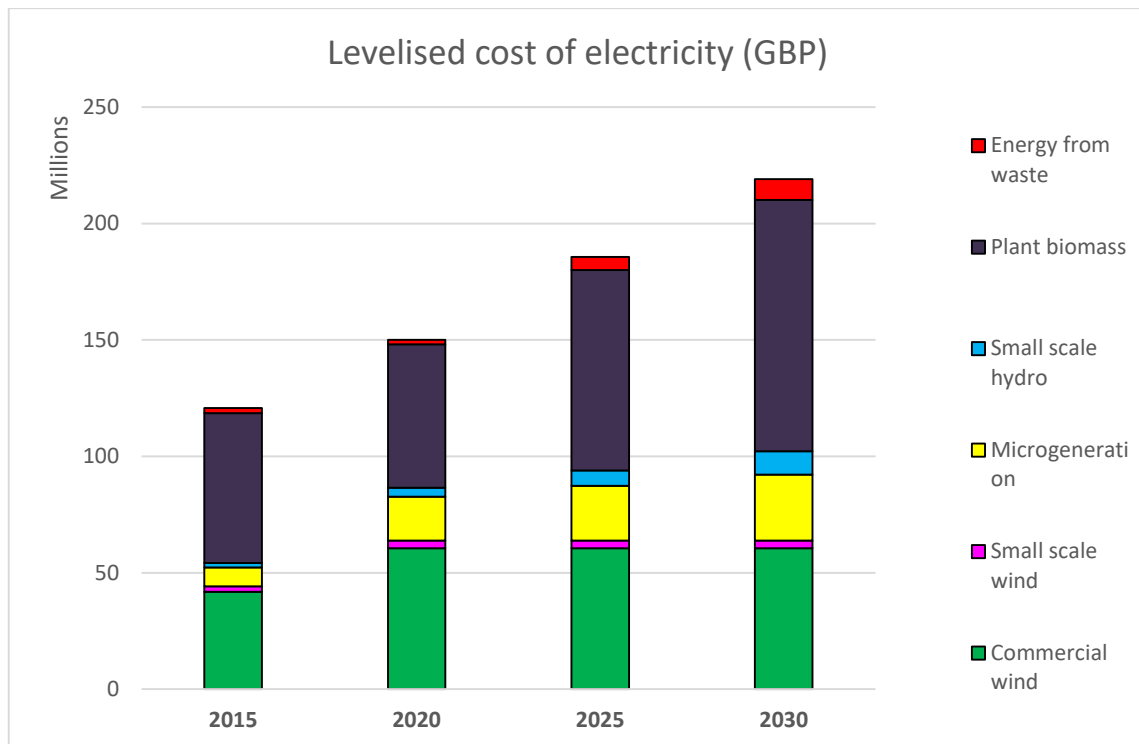
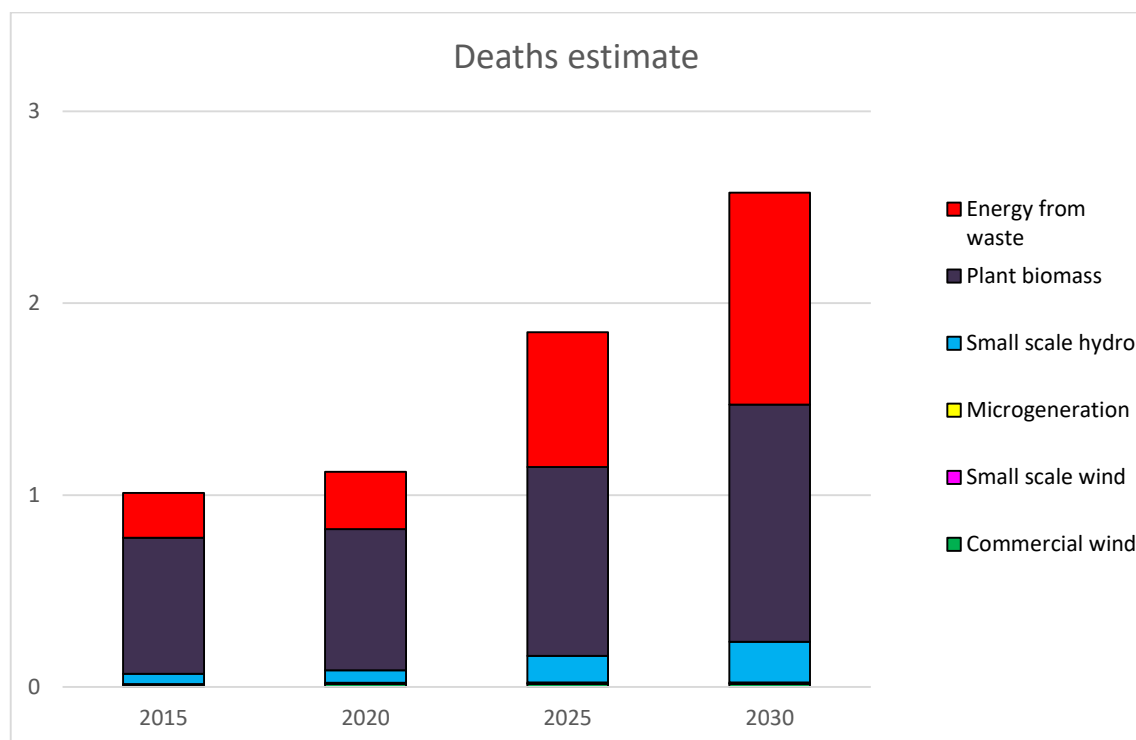


Figure 71: Scenario 3 - Levelised Cost of Electricity (GBP)

The data from Table 49 and Figure 71 present that levelised cost of electricity increases over the years and by 2030 reaches the value of $2.03\text{E}+08$ GBP. In 2015, the total Levelised cost of electricity reaches $1.21\text{E}+08$ GBP. Plant biomass and commercial wind are the most significant contributors with $6.44\text{E}+07$ and $4.18\text{E}+07$ GBP respectively, while the lowest values are pointed to microgeneration, energy from waste, small scale wind and hydro with $8.09\text{E}+06$, $2.23\text{E}+06$, $2.34\text{E}+06$ and $1.90\text{E}+06$ GBP, respectively. In 2020, the total LCOE increases to $1.50\text{E}+08$ GBP and the ranking remains the same. Although, microgeneration climbs to $1.88\text{E}+07$ GBP. By 2025, the total LCOE further increases to $1.86\text{E}+08$ GBP, with plant biomass continuing to be the top contributor, with $8.60\text{E}+07$ GBP. Commercial wind and microgeneration contribute with $6.05\text{E}+07$ and $2.35\text{E}+07$ GBP, respectively. Energy from waste, small scale wind and hydro have a small steady increase. In 2030, the ranking for the highest contributors remains the same: plant biomass, commercial wind, microgeneration with $8.93\text{E}+07$, $6.05\text{E}+07$ and $2.83\text{E}+07$ GBP. Small scale hydro, energy from waste and small scale wind follow.

Table 50: Scenario 3 - Deaths estimate

Deaths estimate	2015	2020	2025	2030
Total	1,01E+00	1,12E+00	1,85E+00	2,58E+00
Commercial wind	1,17E-02	1,69E-02	1,69E-02	1,69E-02
Small scale wind	7,76E-05	1,12E-04	1,12E-04	1,12E-04
Microgeneration	2,41E-03	4,23E-03	5,30E-03	6,37E-03
Small scale hydro	5,37E-02	6,52E-02	1,39E-01	2,12E-01
Plant biomass	7,09E-01	7,35E-01	9,86E-01	1,24E+00
Energy from waste	2,33E-01	3,00E-01	7,02E-01	1,10E+00

**Figure 72: Scenario 3 - Deaths estimate**

The data from Table 50 and Figure 72 present that deaths estimate is a number increasing over the years. In 2015, the total estimated deaths are 1.01E+00 people. Plant biomass has the highest death estimate with 7.09E-01, followed by energy from waste with 2.33E-01 people. Small scale hydro also plays a significant role with 5.37E-02 and commercial wind 1.17E-02 deaths estimate. Microgeneration and small scale wind have the lowest death estimates with 2.41E-03 and 7.76E-05, respectively. In 2020, the total estimated deaths increase to 1.12E+00. Plant biomass remains on the top with 7.35E-01, followed by energy from waste at 3.00E-01. Small scale hydro, commercial wind and microgeneration contribute with 6.52E-02, 1.69E-02 and 4.23E-03, respectively. Small scale wind has the lowest risk with 1.12E-04 deaths estimate. By 2025, the total

estimated deaths climb to 1.85E+00. The ranking remains the same, with plant biomass being in the first place with 9.86E-01. Energy from waste follows with 7.02E-01 deaths. In 2030, the total estimated deaths reach 2.58E+00, almost two people. Energy from waste is the hot spot here with a relatively significant increase reaching 1.10E+00. Although, plant biomass is still in the first place with 1.24E+00 deaths estimated, while small scale hydro and commercial wind contribute with 2.12E-01 and 1.69E-02, respectively. Microgeneration and small scale wind have also increased to 6.37E-03 and 1.12E-04, respectively.

Table 51: Scenario 3 - Jobs estimate

Jobs estimate	2015	2020	2025	2030
Total	5,08E+02	6,71E+02	9,32E+02	1,19E+03
Commercial wind	1,76E+02	2,54E+02	2,54E+02	2,54E+02
Small scale wind	1,17E+00	1,68E+00	1,68E+00	1,68E+00
Microgeneration	6,70E+01	1,17E+02	1,47E+02	1,77E+02
Small scale hydro	7,83E+00	9,50E+00	2,02E+01	3,09E+01
Plant biomass	1,61E+02	1,67E+02	2,24E+02	2,81E+02
Energy from waste	9,49E+01	1,22E+02	2,85E+02	4,49E+02

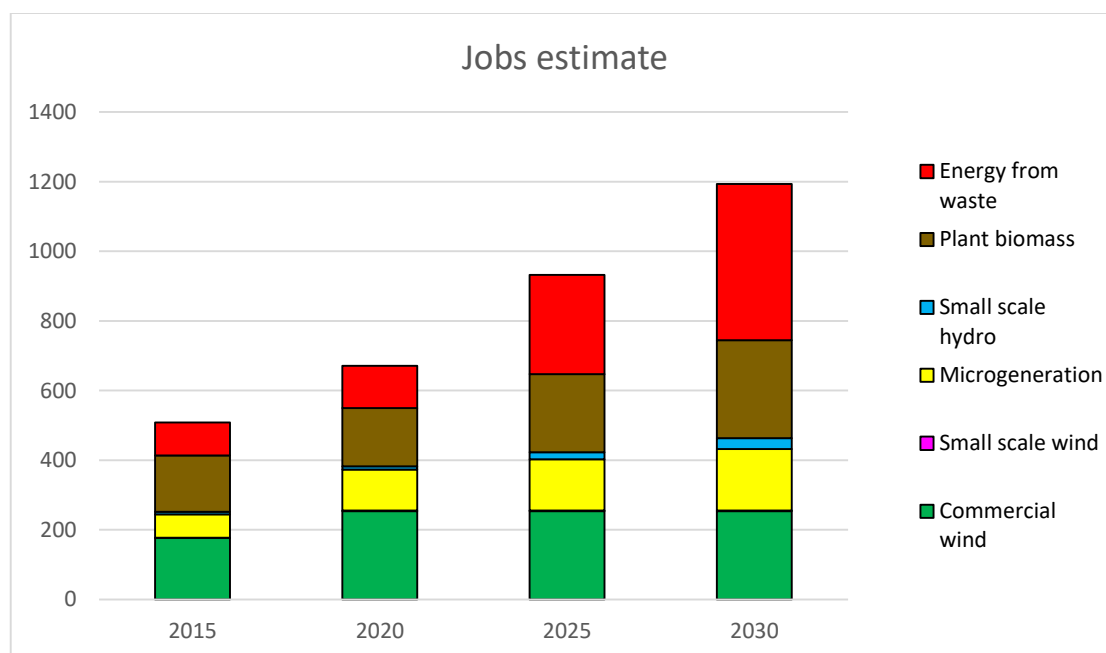


Figure 73: Scenario 3 - Jobs estimate

The data from Table 51 and Figure 73 present that Jobs are increasing over the years, starting at a low point of 508 in 2015 and reaching 1,190 by 2030. In 2015, the total number of jobs is 508, with commercial wind contributing the most with 176 jobs,

followed by plant biomass with 161 jobs and energy from waste with 94. Microgeneration has also a significant impact providing 67 jobs. Small scale wind and hydro offer 1 and 7 jobs respectively. In 2020, commercial wind remains on the top providing 254 jobs, while a significant impact has also the plant biomass, energy from waste and microgeneration with 167, 122 and 117 jobs, respectively. Small scale hydro and wind have lower contributions with 9 and 1 jobs each. By 2025, commercial wind offers 254 jobs. However, energy from waste climbs to 285 jobs, while plant biomass and microgeneration contribute with 224 and 147 jobs, respectively. By 2030, commercial wind is expected to provide 254 jobs. Energy from waste still offers most of the jobs with 449 jobs and plant biomass with 281 jobs. Microgeneration offers 177 jobs, while small scale hydro provides 30 jobs and small scale wind also provides 1 job. These findings highlight the employment potential associated with different energy sources, emphasizing the importance of considering socio-economic factors alongside environmental impacts when evaluating and planning for the adoption of diverse energy generation methods.

4.4 Comparative assessment of all scenario outcomes

To be able to come up to the final conclusion of the thesis a comparative scenarios analysis is necessary as follows.

Table 52: Comparative Global Warming Potential (GWP)

Global Warming Potential (GWP) [kg CO ₂ -Equiv.]	2015	2020	2025	2030
Scenario 1	5,73E+07	7,55E+07	1,14E+08	1,53E+08
Scenario 2	5,73E+07	7,55E+07	1,96E+08	3,16E+08
Scenario 3	5,73E+07	7,55E+07	1,42E+08	2,09E+08

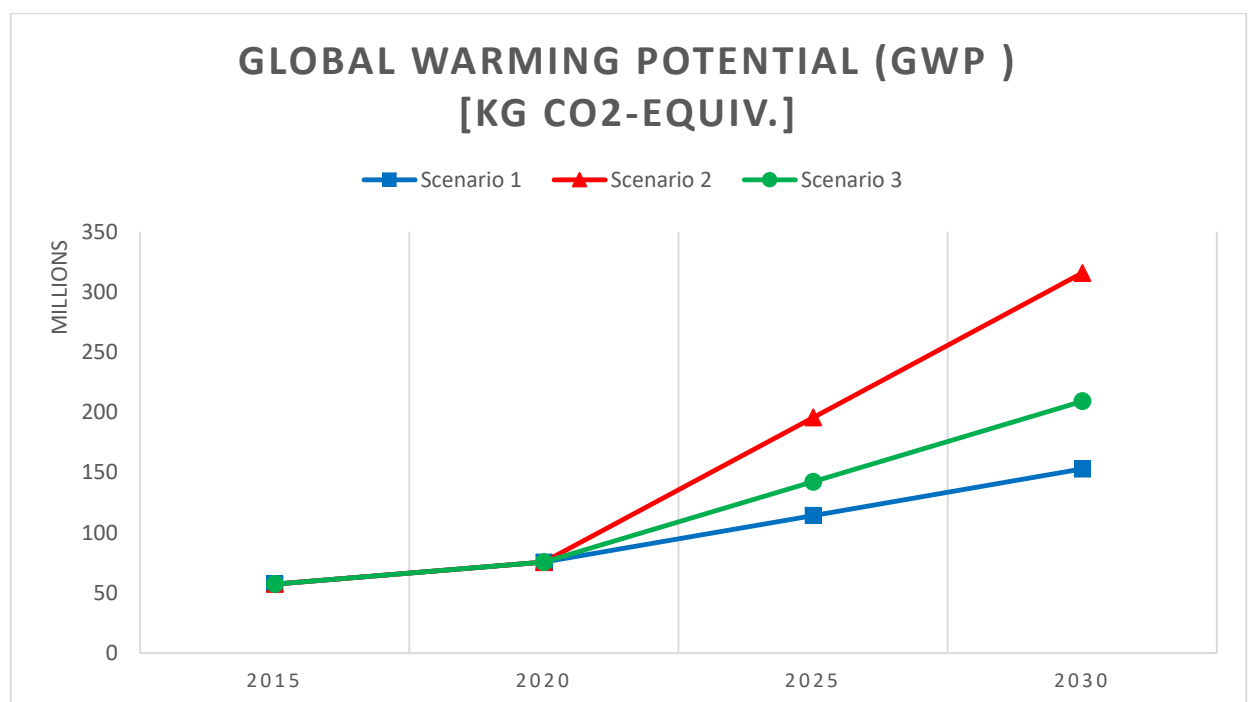


Figure 74: Comparative Global Warming Potential (GWP)

The data from Table 52 and Figure 74 present that by analyzing the Global Warming Potential (GWP) values for the given scenarios across different years reveals interesting trends. In 2015, all scenarios have identical GWP values, standing at 5.73E+07 kg CO₂-Equiv. However, by 2020, Scenario 1, Scenario 2 and Scenario 3 show an increase to 7.55E+07 kg CO₂-Equiv. By 2025, Scenario 2 exhibits a significant surge to 1.96E+08 kg CO₂-Equiv., surpassing both Scenario 1 and Scenario 3, with values 1.14E+08 and 1.42E+08 kg CO₂-Equiv, respectively. By 2030, Scenario 2 continues to escalate, reaching 3.16E+08 kg CO₂-Equiv., making it the highest among all scenarios. Scenario 3 follows with 2.09E+08 kg CO₂-Equiv., and Scenario 1 trails behind at 1.53E+08 kg CO₂-Equiv.

Consequently, in 2030, Scenario 2 emerges as the scenario with the highest Global Warming Potential, Scenario 1 with the lowest, and Scenario 2's GWP is notably higher than the other scenarios, indicating a substantial difference in environmental impact.

Table 53: Comparative Abiotic Depletion Potential (ADP elements)

Abiotic Depletion Potential (ADP elements) [kg Sb-Equiv.]	2015	2020	2025	2030
Scenario 1	1,20E+03	1,82E+03	2,10E+03	2,38E+03
Scenario 2	1,20E+03	1,82E+03	1,93E+03	2,03E+03
Scenario 3	1,20E+03	1,82E+03	1,99E+03	2,16E+03

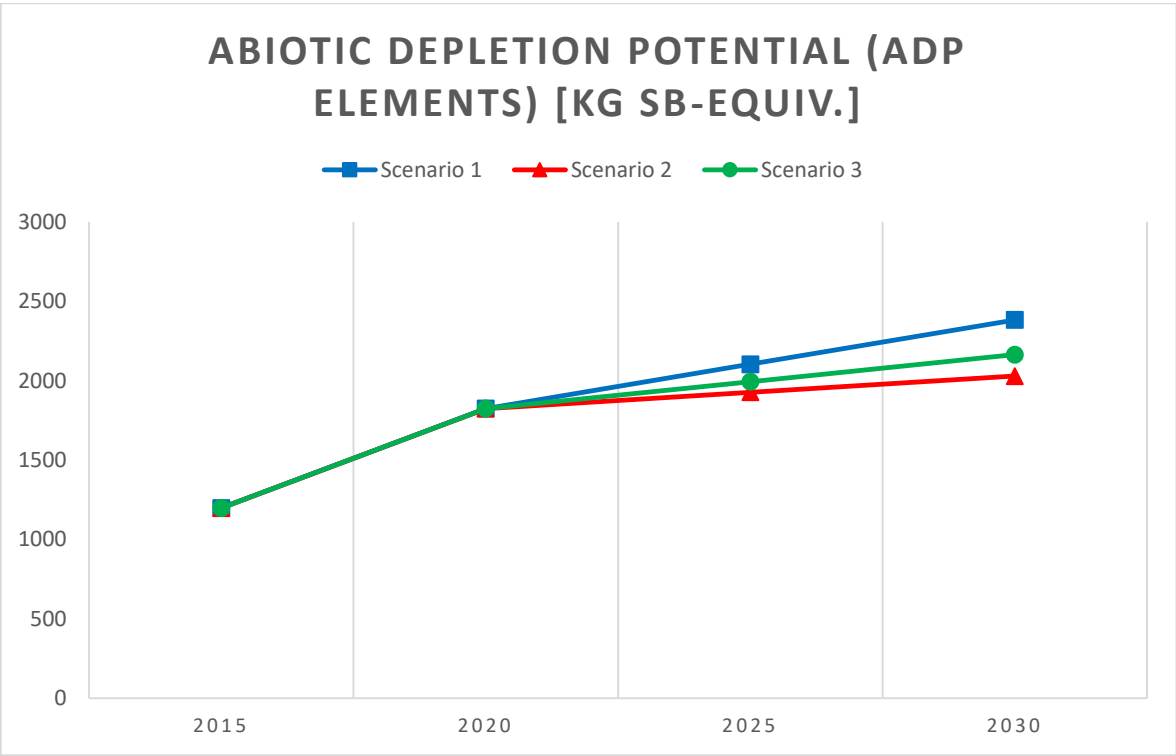


Figure 75: Comparative Abiotic Depletion Potential (ADP elements)

The data from Table 53 and Figure 75 show that by examining the Abiotic Depletion Potential (ADP) values for different scenarios and years, noteworthy patterns are exposed. In 2015, all scenarios begin with identical ADP values of 1.20E+03 kg Sb-Equiv. For 2020, the ADP values across all scenarios increase to 1.82E+03 kg Sb-Equiv. By 2025, Scenario 1 reaches 2.10E+03 kg Sb-Equiv., becoming the scenario with the highest ADP, while Scenario 2 and Scenario 3 both exhibits slightly lower values, with 1.93E+03 and 1.99E+03 kg Sb-Equiv. However, by 2030, Scenario 1 continues to rise to 2.38E+03 kg Sb-Equiv., maintaining its position as the scenario with the highest ADP. Scenario 3 follows with 2.16E+03 kg Sb-Equiv., surpassing Scenario 2 with 2.03E+03 kg Sb-Equiv. In

conclusion, for the year 2030, Scenario 1 has the highest Abiotic Depletion Potential, Scenario 3 follows, and Scenario 2 has the lowest. The difference in ADP values highlights the varying impacts of these scenarios on abiotic resource depletion.

Table 54: Comparative Abiotic Depletion Potential (ADP fossil)

Abiotic Depletion Potential (ADP fossil) [MJ]	2015	2020	2025	2030
Scenario 1	2,72E+08	3,86E+08	4,64E+08	5,42E+08
Scenario 2	2,72E+08	3,86E+08	5,45E+08	7,04E+08
Scenario 3	2,72E+08	3,86E+08	5,20E+08	6,54E+08

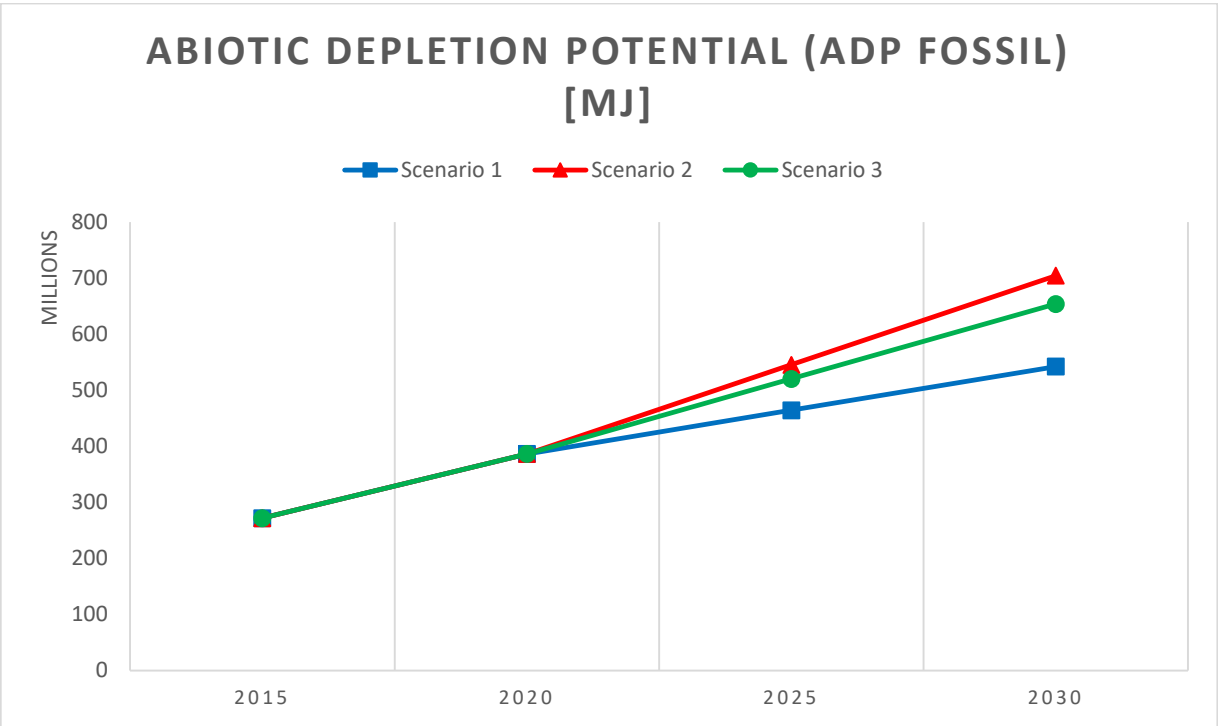


Figure 76: Comparative Abiotic Depletion Potential (ADP fossil)

The data from Table 54 and Figure 76 present that by analyzing the Abiotic Depletion Potential (ADP) values for fossil resources in different scenarios and years reveals interesting trends. In 2015, all scenarios start with identical ADP values of 2.72E+08 MJ. Moving to 2020, the ADP values across all scenarios increase to 3.86E+08 MJ. By 2025, Scenario 2 exhibits a significant rise to 5.45E+08 MJ, surpassing both Scenario 1 and Scenario 3, with 4.64E+08 and 5.20E+08 MJ, respectively. However, by 2030, Scenario 2 continues to escalate, reaching 7.04E+08 MJ, making it the scenario with the highest ADP for fossil resources. Scenario 3 follows with 6.54E+08 MJ, and Scenario 1 trails behind at 5.42E+08 MJ. Consequently, in 2030, Scenario 2 emerges as the scenario with the highest Abiotic Depletion Potential for fossil resources, Scenario 3 follows, and

Scenario 1 has the lowest. The substantial difference in ADP values signifies the varying impacts of these scenarios on the depletion of fossil resources.

Table 55: Comparative Acidification Potential (AP)

Acidification Potential (AP) [kg SO ₂ -Equiv.]	2015	2020	2025	2030
Scenario 1	2,53E+05	3,12E+05	4,08E+05	5,04E+05
Scenario 2	2,53E+05	3,12E+05	5,43E+05	7,73E+05
Scenario 3	2,53E+05	3,12E+05	4,77E+05	6,42E+05

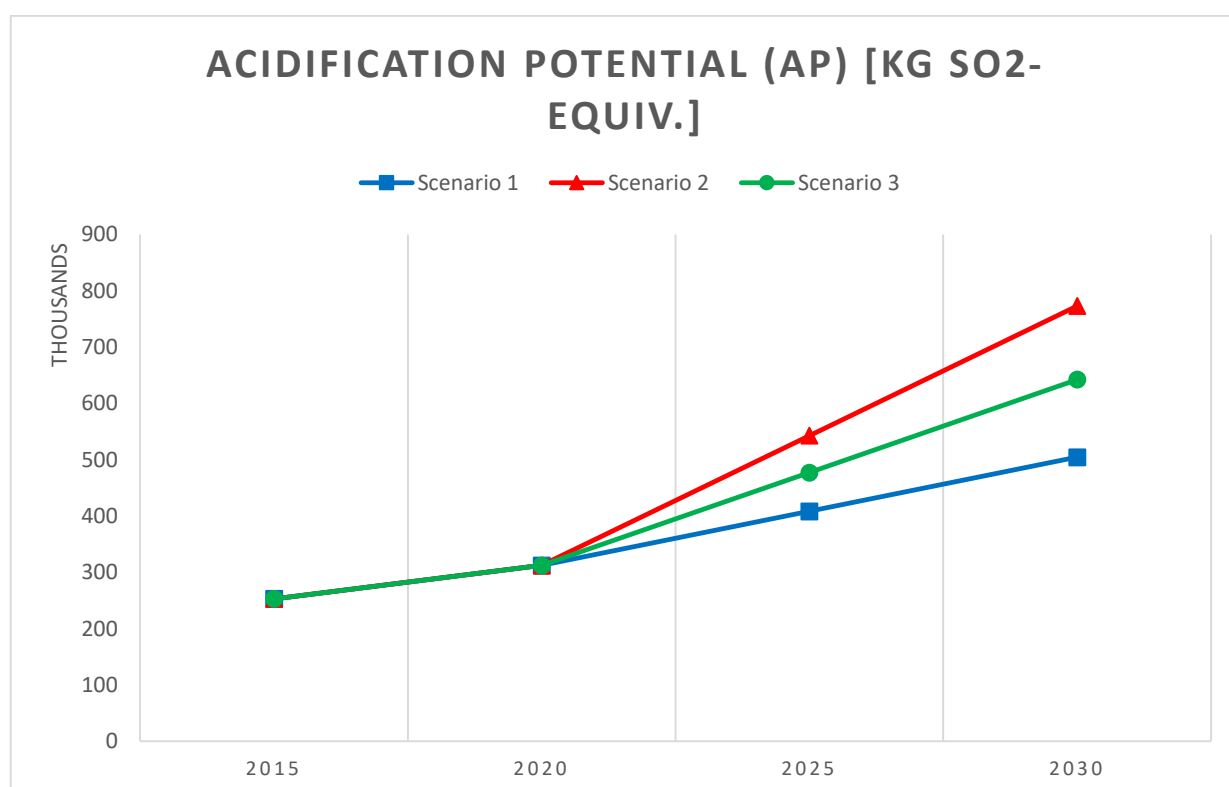


Figure 77: Comparative Acidification Potential (AP)

The data from Table 55 and Figure 77 show that by examining the Acidification Potential (AP) values for different scenarios and years sheds light on notable trends. In 2015, all scenarios begin with identical AP values of 2.53E+05 kg SO₂-Equiv. Moving to 2020, the AP values across all scenarios increase to 3.12E+05 kg SO₂-Equiv. By 2025, Scenario 2 exhibits a substantial rise to 5.43E+05 kg SO₂-Equiv., surpassing both Scenario 1 and Scenario 3, with 4.08E+05 and 4.77E+05 kg SO₂-Equiv, respectively. Continuing to 2030, Scenario 2 further escalates to 7.73E+05 kg SO₂-Equiv., making it the scenario with the highest Acidification Potential. Scenario 3 follows with 6.42E+05 kg SO₂-Equiv., surpassing Scenario 1 with 5.04E+05 kg SO₂-Equiv. In conclusion, for the year 2030, Scenario 2 has the highest Acidification Potential, Scenario 3 follows, and Scenario 1 has

the lowest. The considerable differences in AP values highlight the varying impacts of these scenarios on acidification potential in the environment.

Table 56: Comparative Eutrophication Potential (EP)

Eutrophication Potential (EP) [kg Phosphate-Equiv.]	2015	2020	2025	2030
Scenario 1	9,56E+04	1,25E+05	1,48E+05	1,71E+05
Scenario 2	9,56E+04	1,25E+05	1,59E+05	1,94E+05
Scenario 3	9,56E+04	1,25E+05	1,63E+05	2,01E+05

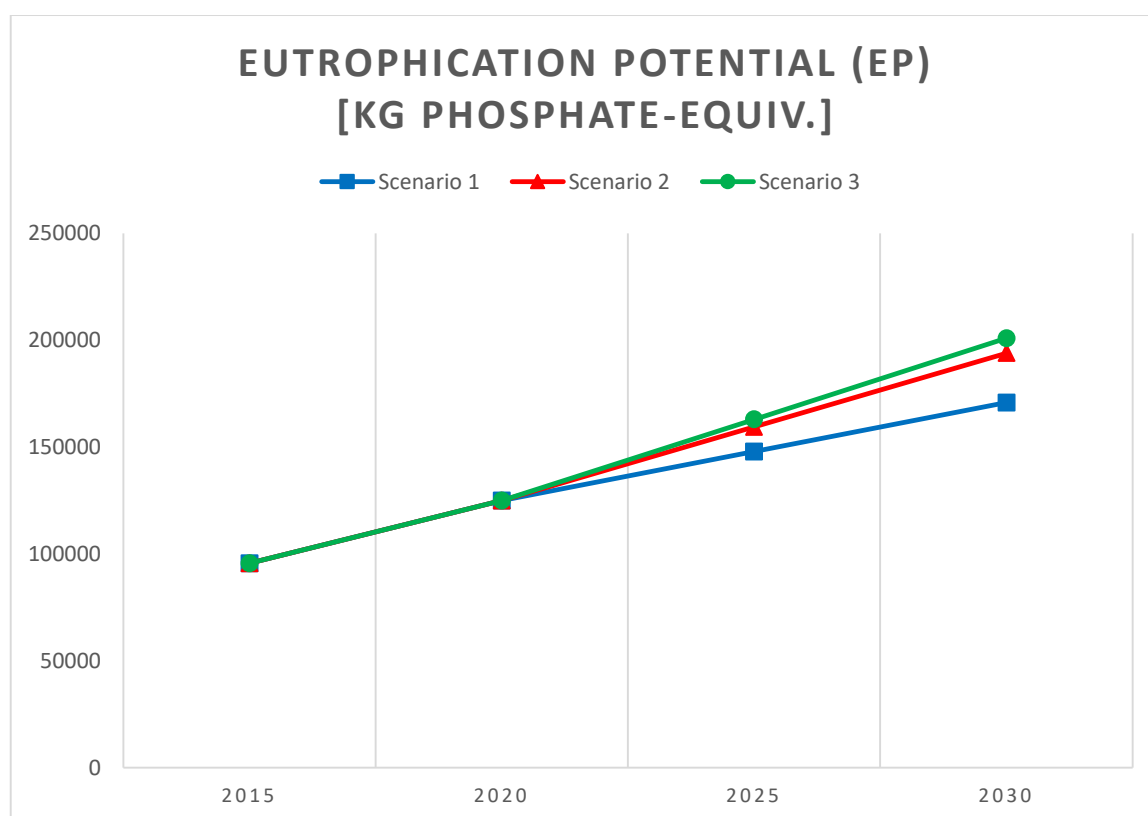


Figure 78: Comparative Eutrophication Potential (EP)

The data from Table 56 and Figure 78 show that by analyzing the Eutrophication Potential (EP) values for different scenarios and years reveals distinctive patterns. In 2015, all scenarios commence with identical EP values of 9.56E+04 kg Phosphate-Equiv. Progressing to 2020, the EP values across all scenarios increase to 1.25E+05 kg Phosphate-Equiv. By 2025, Scenario 3 exhibits the highest rise to 1.63E+05 kg Phosphate-Equiv., surpassing both Scenario 1 and Scenario 2, with 1.48E+05 and 1.59E+05 kg Phosphate-Equiv, respectively. However, by 2030, Scenario 3 continues to escalate, reaching 2.01E+05 kg Phosphate-Equiv., making it the scenario with the highest Eutrophication Potential. Scenario 2 follows with 1.94E+05 kg Phosphate-Equiv.,

surpassing Scenario 1 with 1.71E+05 kg Phosphate-Equiv. In conclusion, for the year 2030, Scenario 3 has the highest Eutrophication Potential, Scenario 2 follows, and Scenario 1 has the lowest. The substantial differences in EP values underscore the varying impacts of these scenarios on eutrophication potential in the environment.

Table 57: Comparative Fresh Aquatic Ecotoxicity Potential (FAETP)

Freshwater Aquatic Ecotoxicity Potential (FAETP) [kg DCB-Equiv.]	2015	2020	2025	2030
Scenario 1	7,12E+07	1,06E+08	1,24E+08	1,42E+08
Scenario 2	7,12E+07	1,06E+08	1,11E+08	1,16E+08
Scenario 3	7,12E+07	1,06E+08	1,14E+08	1,22E+08

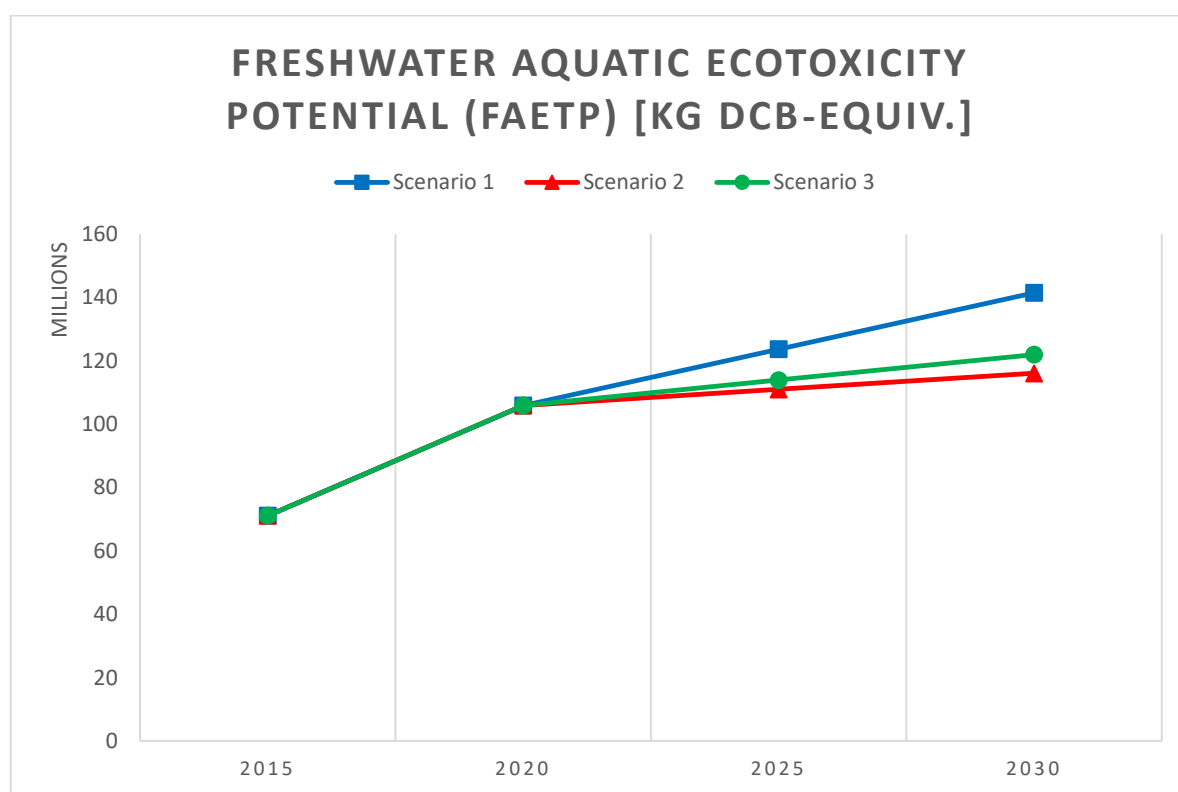


Figure 79: Comparative Fresh Aquatic Ecotoxicity Potential (FAETP)

The data from Table 57 and Figure 79 present that by examining the Freshwater Aquatic Ecotoxicity Potential (FAETP) values for different scenarios and years reveals discernible trends. In 2015, all scenarios initiate with identical FAETP values of 7.12E+07 kg DCB-Equiv. Advancing to 2020, the FAETP values across all scenarios increase to 1.06E+08 kg DCB-Equiv. By 2025, Scenario 1 exhibits the highest rise to 1.24E+08 kg DCB-Equiv., surpassing both Scenario 2 and Scenario 3, with 1.11E+08 and 1.14E+08 kg DCB-Equiv., respectively. However, by 2030, Scenario 1 continues to escalate, reaching 1.42E+08 kg

DCB-Equiv., making it the scenario with the highest Freshwater Aquatic Ecotoxicity Potential. Scenario 3 follows closely with $1.22\text{E}+08$ kg DCB-Equiv., surpassing Scenario 2 with $1.16\text{E}+08$ kg DCB-Equiv. In conclusion, for the year 2030, Scenario 1 has the highest Freshwater Aquatic Ecotoxicity Potential, Scenario 3 follows, and Scenario 2 has the lowest. The significant differences in FAETP values underscore the varying impacts of these scenarios on freshwater aquatic ecosystems.

Table 58: Comparative Human Toxicity Potential (HTP)

Human Toxicity Potential (HTP) [kg DCB-Equiv.]	2015	2020	2025	2030
Scenario 1	$5,69\text{E}+07$	$8,05\text{E}+07$	$9,41\text{E}+07$	$1,08\text{E}+08$
Scenario 2	$5,69\text{E}+07$	$8,05\text{E}+07$	$8,88\text{E}+07$	$9,70\text{E}+07$
Scenario 3	$5,69\text{E}+07$	$8,05\text{E}+07$	$9,18\text{E}+07$	$1,03\text{E}+08$

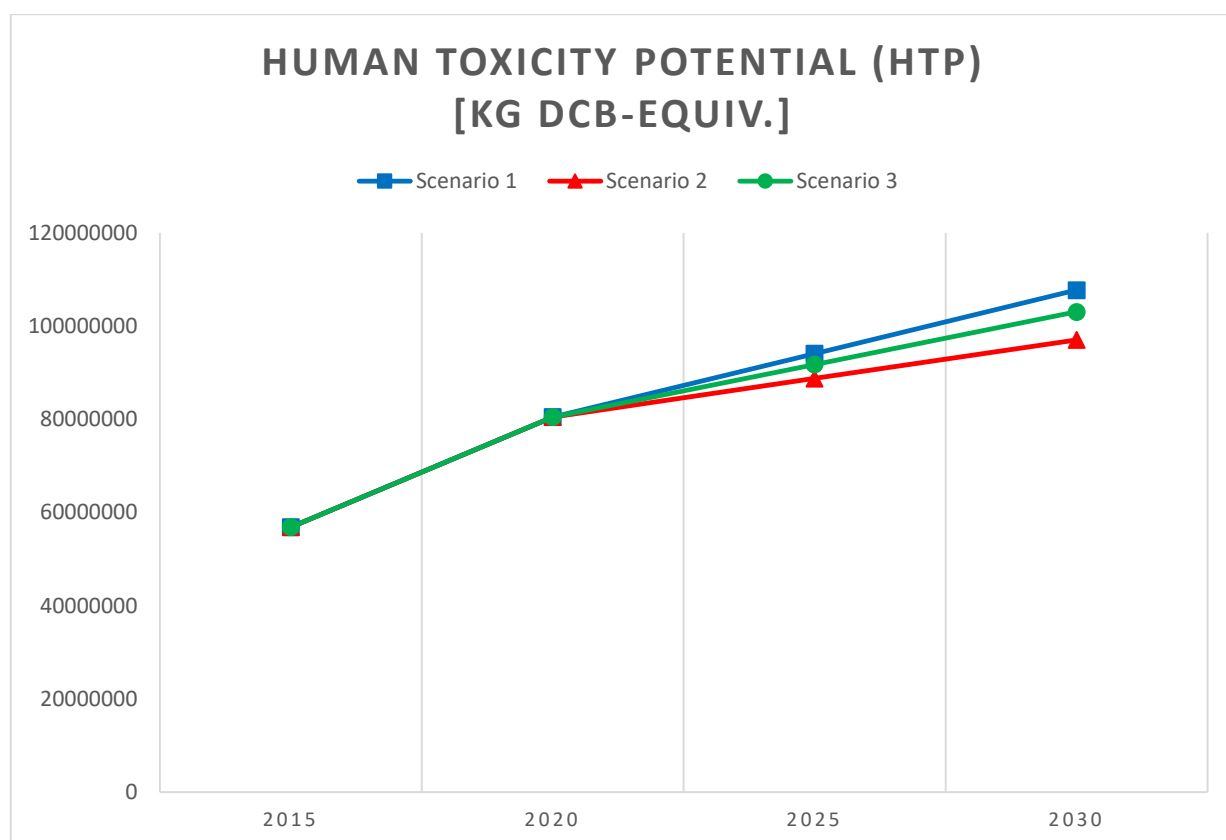


Figure 80: Comparative Human Toxicity Potential (HTP)

The data from Table 58 and Figure 80 show that by analyzing the Human Toxicity Potential (HTP) values for different scenarios and years reveals discernible trends. In 2015, all scenarios start with identical HTP values of $5.69\text{E}+07$ kg DCB-Equiv. Progressing to 2020, the HTP values across all scenarios increase to $8.05\text{E}+07$ kg DCB-Equiv. By 2025, Scenario

1 exhibits the highest rise to 9.41E+07 kg DCB-Equiv., surpassing both Scenario 2 and Scenario 3, with 8.88E+07 and 9.18E+07 kg DCB-Equiv., respectively. However, by 2030, Scenario 1 continues to escalate, reaching 1.08E+08 kg DCB-Equiv., making it the scenario with the highest Human Toxicity Potential. Scenario 3 follows closely with 1.03E+08 kg DCB-Equiv., surpassing Scenario 2 with 9.70E+07 kg DCB-Equiv. In conclusion, for the year 2030, Scenario 1 has the highest Human Toxicity Potential, Scenario 3 follows, and Scenario 2 has the lowest. The considerable differences in HTP values underscore the varying impacts of these scenarios on human toxicity potential.

Table 59: Comparative Marine Aquatic Ecotoxicity Potential (MAETP)

Marine Aquatic Ecotoxicity Potential (MAETP) [kg DCB-Equiv.]	2015	2020	2025	2030
Scenario 1	5,78E+10	8,71E+10	1,02E+11	1,16E+11
Scenario 2	5,78E+10	8,71E+10	1,03E+11	1,19E+11
Scenario 3	5,78E+10	8,71E+10	1,03E+11	1,19E+11

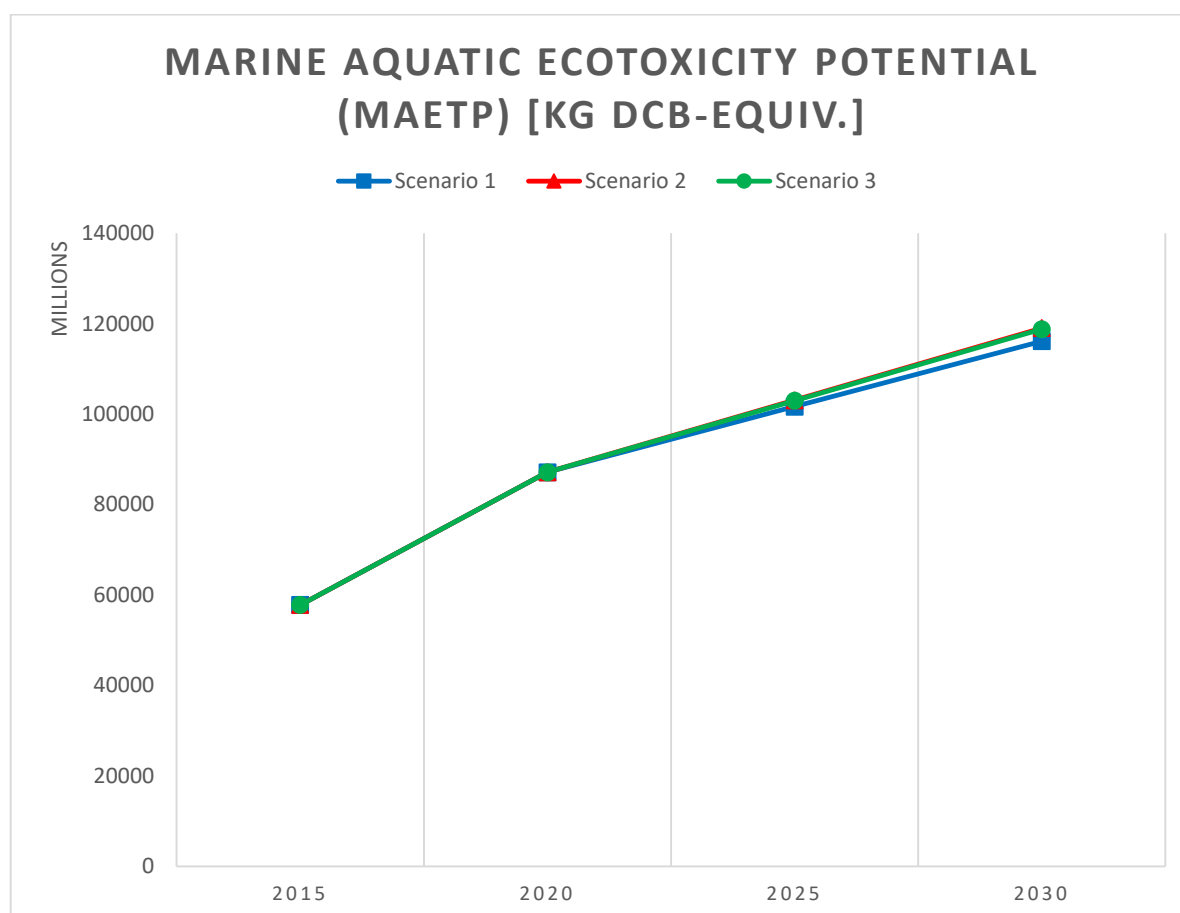


Figure 81: Comparative Marine Aquatic Ecotoxicity Potential (MAETP)

The data from Table 59 and Figure 81 show that by Examining the Marine Aquatic Ecotoxicity Potential (MAETP) values for different scenarios and years reveals consistent trends. In 2015, all scenarios commence with identical MAETP values of 5.78E+10 kg DCB-Equiv. Advancing to 2020, the MAETP values across all scenarios increase to 8.71E+10 kg DCB-Equiv. By 2025, Scenario 1 exhibits a rise to 1.02E+11 kg DCB-Equiv., closely behind from Scenarios 2 and 3, with a higher value reaching 1.03E+11 kg DCB-Equiv. However, by 2030, all scenarios show a further increase, with Scenario 1 reaching 1.16E+11 kg DCB-Equiv., Scenario 2 at 1.19E+11 kg DCB-Equiv., and Scenario 3 also at 1.19E+11 kg DCB-Equiv. In conclusion, for the year 2030, all scenarios have almost the same Marine Aquatic Ecotoxicity Potential. The consistent values highlight the parallel impacts of these scenarios on marine aquatic ecosystems.

Table 60: Comparative Ozone Layer Depletion Potential (ODP)

Ozone Layer Depletion Potential (ODP) [kg R11-Equiv.]	2015	2020	2025	2030
Scenario 1	2,16E+00	3,20E+00	3,50E+00	3,79E+00
Scenario 2	2,16E+00	3,20E+00	3,54E+00	3,89E+00
Scenario 3	2,16E+00	3,20E+00	3,98E+00	4,75E+00

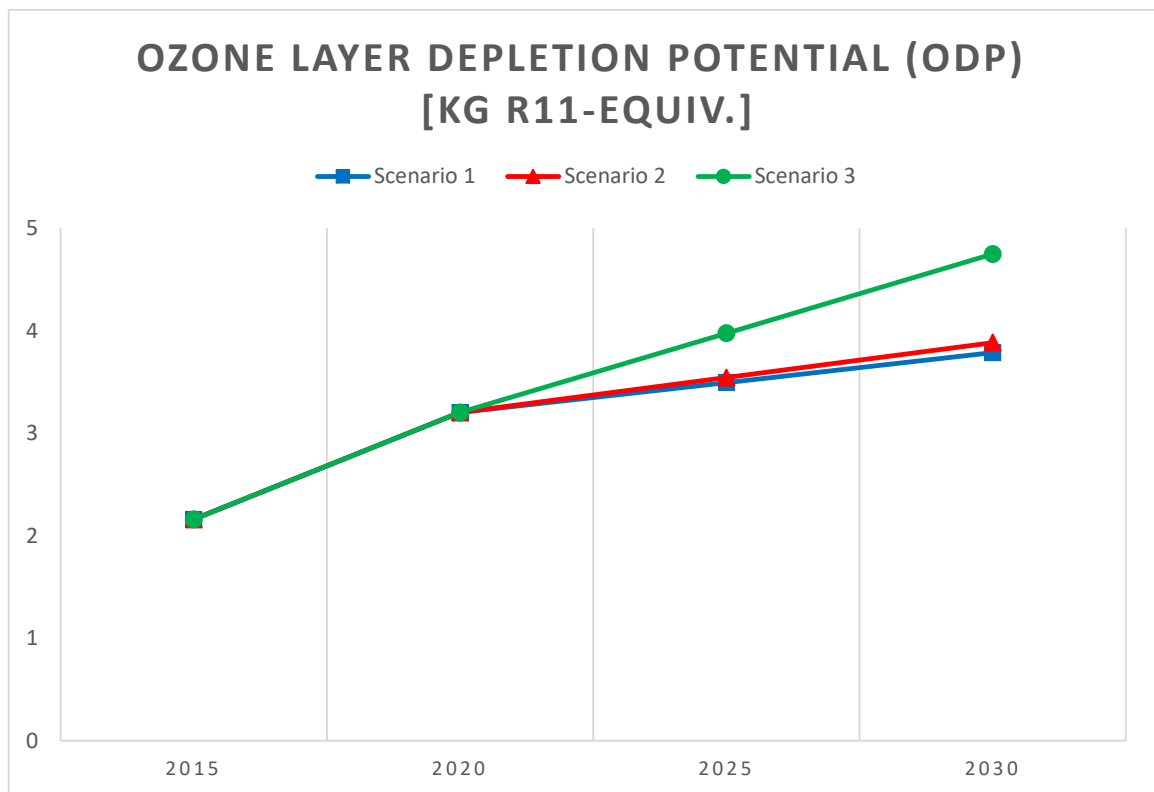


Figure 82: Comparative Ozone Layer Depletion Potential (ODP)

The data from Table 60 and Figure 82 present that by analyzing the Ozone Layer Depletion Potential (ODP) values for different scenarios and years reveals distinct trends. In 2015, all scenarios commence with identical ODP values of 2.16E+00 kg R11-Equiv. Progressing to 2020, the ODP values across all scenarios increase to 3.20E+00 kg R11-Equiv. By 2025, Scenario 3 exhibits the highest rise to 3.98E+00 kg R11-Equiv., surpassing both Scenario 1 and Scenario 2, with 3.50E+00 and 3.54E+00 kg R11-Equiv, respectively. However, by 2030, Scenario 3 continues to escalate, reaching 4.75E+00 kg R11-Equiv., making it the scenario with the highest Ozone Layer Depletion Potential. Scenario 2 follows closely with 3.89E+00 kg R11-Equiv., surpassing Scenario 1 with 3.79E+00 kg R11-Equiv. In conclusion, for the year 2030, Scenario 3 has the highest Ozone Layer Depletion Potential, Scenario 2 follows, and Scenario 1 has the lowest. The substantial differences in ODP values underscore the varying impacts of these scenarios on ozone layer depletion potential.

Table 61: Comparative Photochemical Ozone Creation Potential (POCP)

Photochemical Ozone Creation Potential (POCP) [kg Ethene-Equiv.]	2015	2020	2025	2030
Scenario 1	2,15E+04	2,57E+04	3,17E+04	3,78E+04
Scenario 2	2,15E+04	2,57E+04	3,62E+04	4,66E+04
Scenario 3	2,15E+04	2,57E+04	3,56E+04	4,55E+04

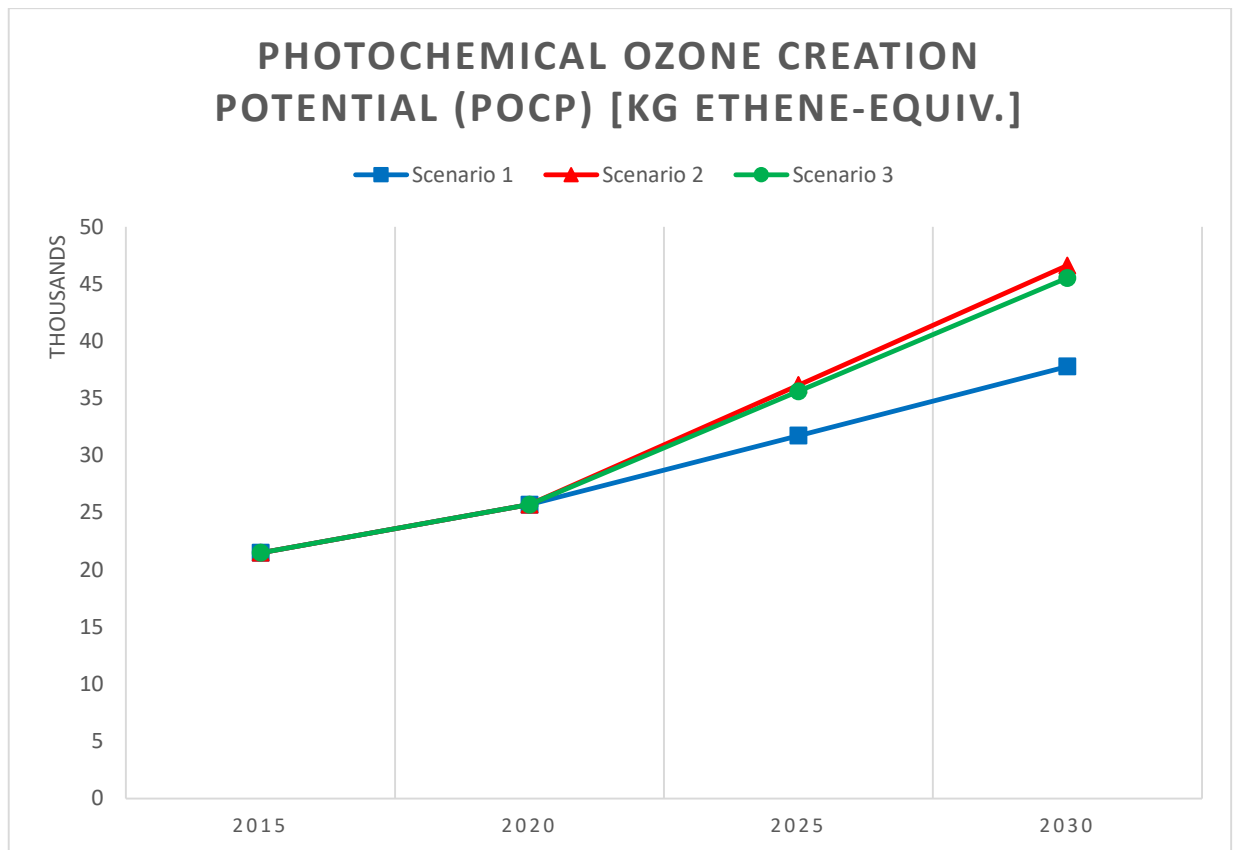
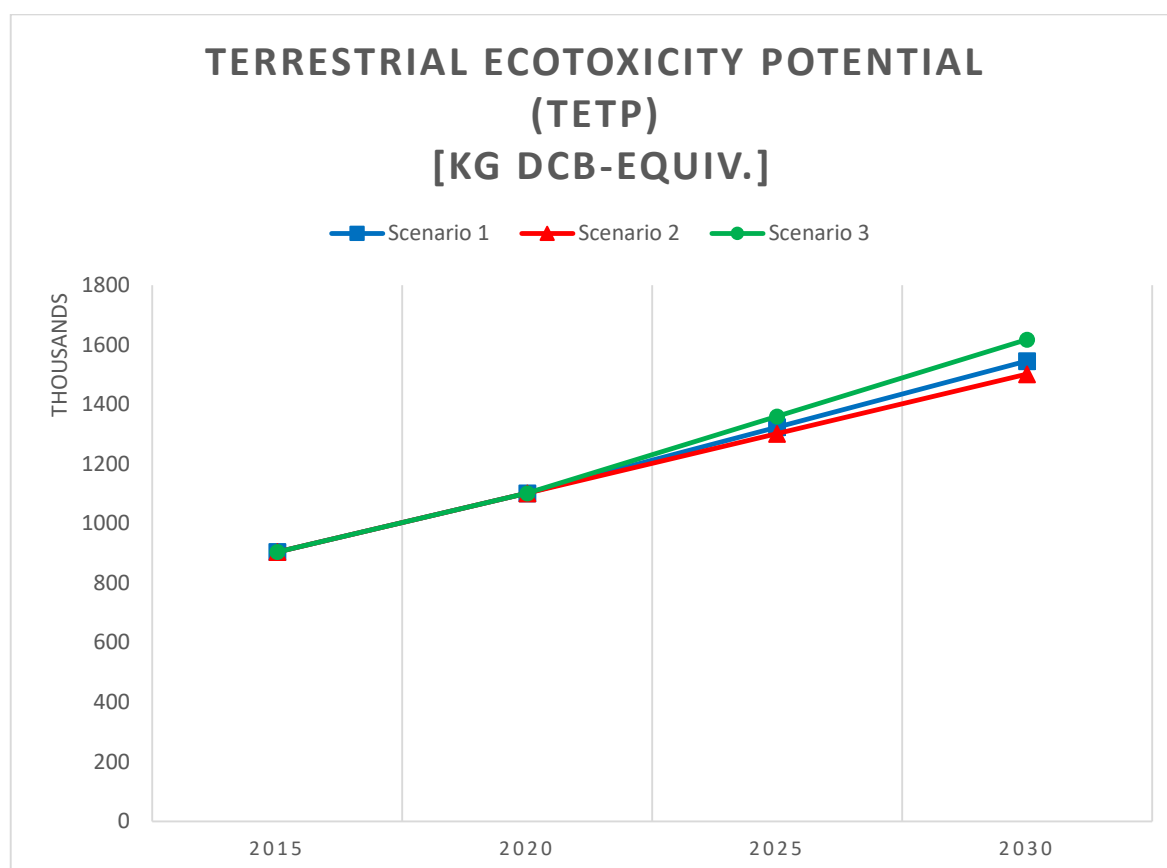


Figure 83: Comparative Photochemical Ozone Creation Potential (POCP)

The data from Table 61 and Figure 83 show that by Analyzing the Photochemical Ozone Creation Potential (POCP) values for different scenarios and years reveals interesting trends. In 2015, all scenarios start with identical POCP values of 2.15E+04 kg Ethene-Equiv. Progressing to 2020, the POCP values across all scenarios increase to 2.57E+04 kg Ethene-Equiv. By 2025, Scenario 2 exhibits a significant rise to 3.62E+04 kg Ethene-Equiv., surpassing both Scenario 1 and Scenario 3, with 3.17E+04 and 3.56E+04 kg Ethene-Equiv., respectively. By 2030, Scenario 2 continues to escalate, reaching 4.66E+04 kg Ethene-Equiv., making it the scenario with the highest Photochemical Ozone Creation Potential. Scenario 3 follows closely with 4.55E+04 kg Ethene-Equiv., surpassing Scenario 1 with 3.78E+04 kg Ethene-Equiv. In conclusion, for the year 2030, Scenario 2 has the highest Photochemical Ozone Creation Potential, Scenario 3 follows, and Scenario 1 has the lowest. The considerable differences in POCP values underscore the varying impacts of these scenarios on photochemical ozone creation potential.

Table 62: Comparative Terrestrial Ecotoxicity Potential (TETP)

Terrestrial Ecotoxicity Potential (TETP) [kg DCB-Equiv.]	2015	2020	2025	2030
Scenario 1	9,05E+05	1,10E+06	1,32E+06	1,55E+06
Scenario 2	9,05E+05	1,10E+06	1,30E+06	1,50E+06
Scenario 3	9,05E+05	1,10E+06	1,36E+06	1,62E+06

**Figure 84: Comparative Terrestrial Ecotoxicity Potential (TETP)**

The data from Table 62 and Figure 84 present that by analyzing the Terrestrial Ecotoxicity Potential (TETP) values for different scenarios and years reveals consistent trends. In 2015, all scenarios begin with identical TETP values of 9.05E+05 kg DCB-Equiv. Advancing to 2020, the TETP values across all scenarios increase to 1.10E+06 kg DCB-Equiv. By 2025, Scenario 3 exhibits the highest rise to 1.36E+06 kg DCB-Equiv., surpassing both Scenario 1 and Scenario 2, with 1.32E+06 and 1.30E+06 kg DCB-Equiv., respectively. However, by 2030, Scenario 3 continues to escalate, reaching 1.62E+06 kg DCB-Equiv., making it the scenario with the highest Terrestrial Ecotoxicity Potential. Scenario 1 follows closely with 1.55E+06 kg DCB-Equiv., surpassing Scenario 2 with 1.50E+06 kg DCB-Equiv. In conclusion, for the year 2030, Scenario 3 has the highest Terrestrial Ecotoxicity Potential, Scenario 1 follows, and Scenario 2 has the lowest. The

considerable differences in TETP values underscore the varying impacts of these scenarios on terrestrial ecosystems.

Table 63: Comparative Levelised Cost of Electricity (GBP)

Levelised cost of electricity (GBP)	2015	2020	2025	2030
Scenario 1	1,21E+08	1,501E+08	1,83E+08	2,14E+08
Scenario 2	1,21E+08	1,5007E+08	1,77E+08	2,02E+08
Scenario 3	1,21E+08	1,5007E+08	1,86E+08	2,19E+08

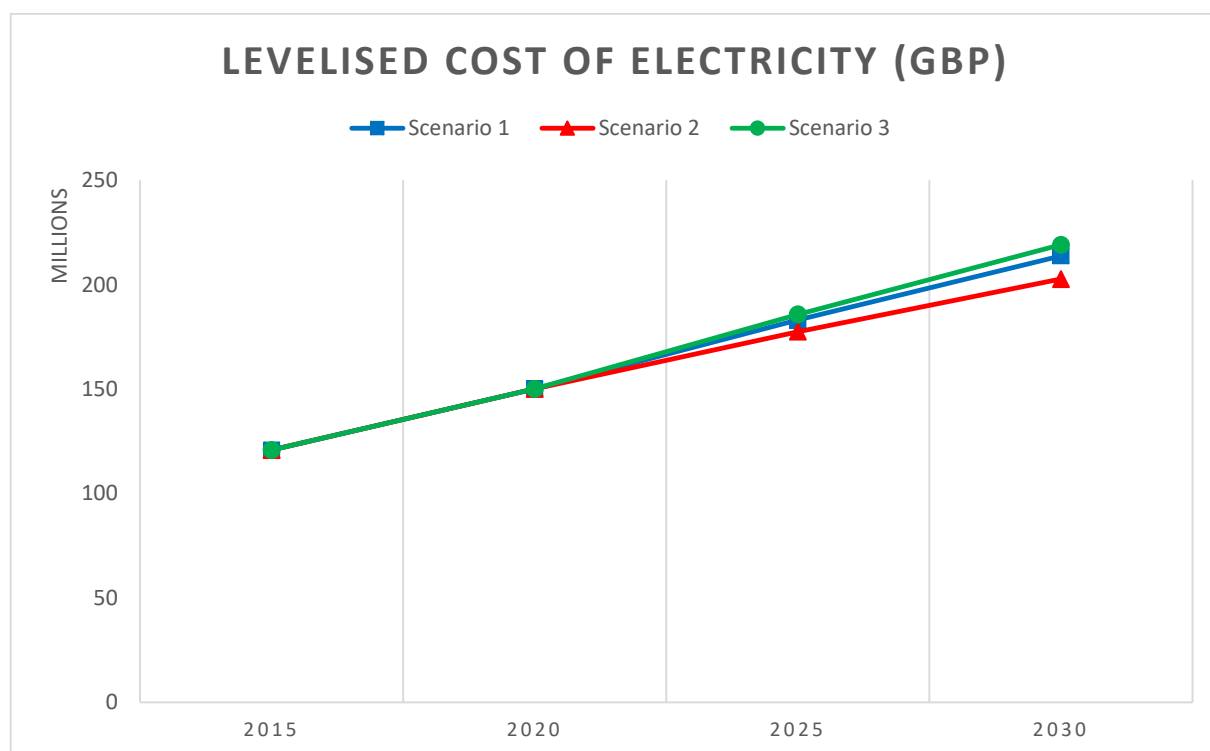


Figure 85: Comparative Levelised Cost of Electricity (GBP)

The data from Table 63 and Figure 85 illustrate that by analyzing the Levelised Cost of Electricity (GBP) values for different scenarios and years reveals distinct trends. In 2015, all scenarios start with identical Levelised Cost values of 1.21E+08 GBP. Progressing to 2020, the Levelised Cost values across all scenarios increase, with Scenario 1 at 1.501E+08 GBP, Scenario 2 at 1.5007E+08 GBP, and Scenario 3 at 1.5007E+08 GBP. By 2025, Scenario 3 exhibits a rise to 1.86E+08 GBP, surpassing both Scenario 1 and Scenario 2, with 1.83E+08 and 1.77E+08E+08 GBP, respectively. However, by 2030, Scenario 3 has the highest Levelised Cost of Energy at 2.19E+08 GBP, followed by Scenario 1 with 2.14E+08 GBP, and Scenario 2 with 2.02E+08 GBP. In conclusion, for the year 2030, Scenario 3 has the highest Levelised Cost of Electricity, Scenario 1 follows,

and Scenario 2 has the lowest. The differences in Levelised Cost values underscore the varying economic impacts of these scenarios on electricity generation.

Table 64: Comparative Deaths estimate

Deaths estimate	2015	2020	2025	2030
Scenario 1	1,01E+00	1,12E+00	1,54E+00	1,95E+00
Scenario 2	1,01E+00	1,12E+00	2,07E+00	3,03E+00
Scenario 3	1,01E+00	1,12E+00	1,85E+00	2,58E+00

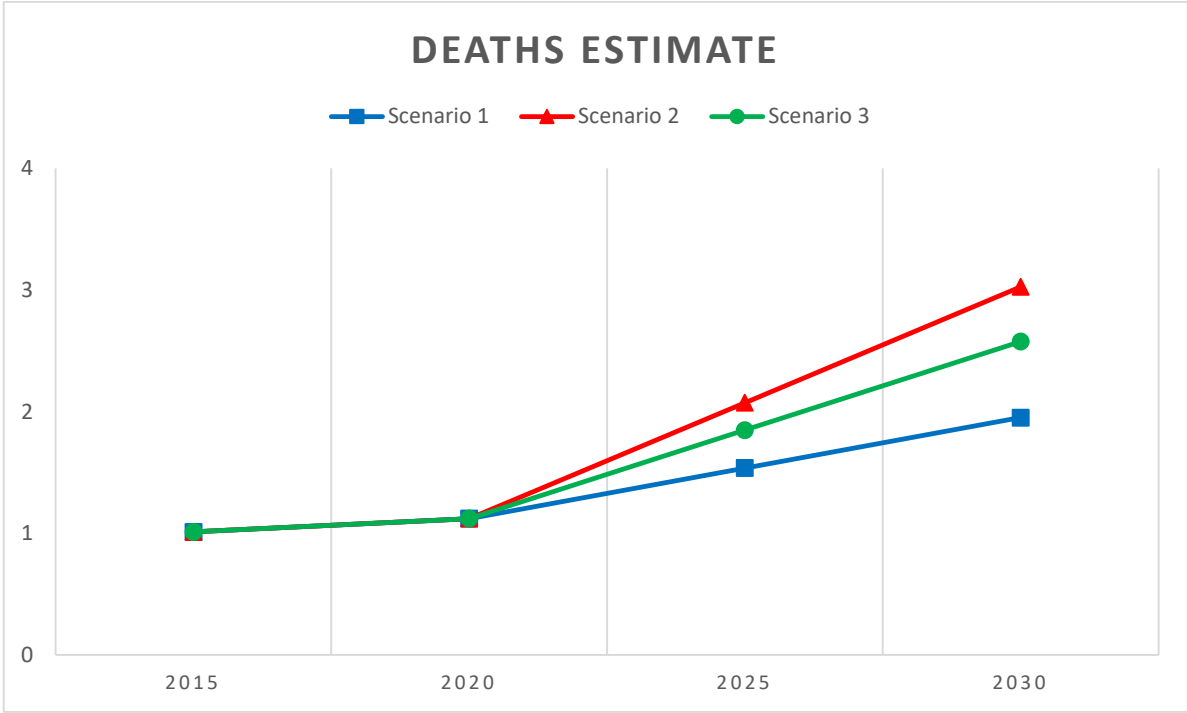
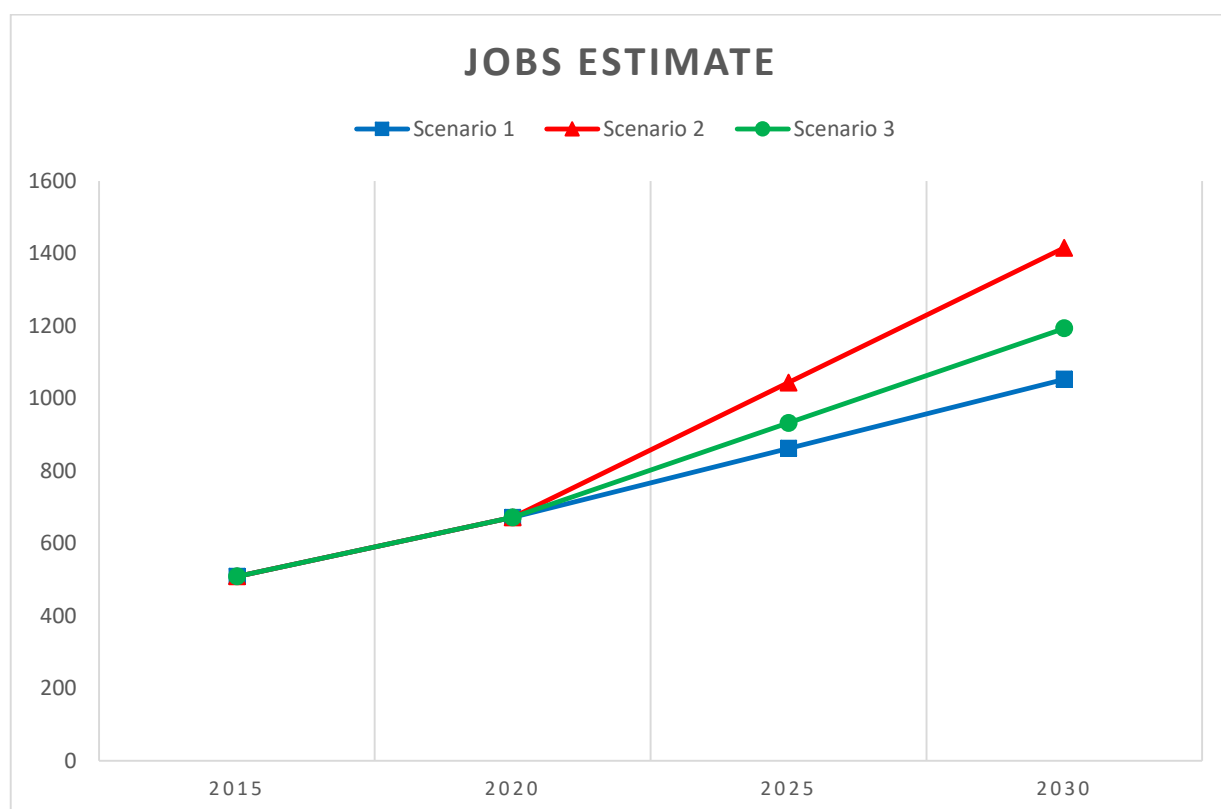


Figure 86: Comparative Deaths estimate

The data from Table 64 and Figure 86 present that by analyzing the Deaths Estimate for different scenarios and years reveals notable trends. In 2015, all scenarios start with identical estimates of 1.01 death. Progressing to 2020, the estimates across all scenarios increase to 1.12 deaths. By 2025, Scenario 2 exhibits a significant rise to 2.07 deaths, surpassing both Scenario 1 and Scenario 3, with 1.54 and 1.85, respectively. By 2030, Scenario 2 continues to escalate, reaching 3.03 deaths, making it the scenario with the highest death estimate. Scenario 3 follows with 2.58 deaths, surpassing Scenario 1 with 1.95 deaths. In conclusion, for the year 2030, Scenario 2 has the highest death estimate, Scenario 3 follows, and Scenario 1 has the lowest. The substantial differences in death estimates underscore the varying impacts of these scenarios on mortality rates.

Table 65: Comparative Job estimate

Jobs estimate	2015	2020	2025	2030
Scenario 1	5,08E+02	6,71E+02	8,62E+02	1,05E+03
Scenario 2	5,08E+02	6,71E+02	1,04E+03	1,42E+03
Scenario 3	5,08E+02	6,71E+02	9,32E+02	1,19E+03

**Figure 87: Comparative Job estimate**

The data from Table 65 and Figure 87 illustrate that by Analyzing the Jobs Estimate for different scenarios and years reveals significant trends. In 2015, all scenarios start with identical estimates of 508 jobs. Progressing to 2020, the estimates across all scenarios increase to 671 jobs. By 2025, Scenario 2 exhibits a substantial rise to 1040 jobs, surpassing both Scenario 1 and Scenario 3, with 862 and 932, respectively. By 2030, Scenario 2 continues to escalate, reaching 1420 jobs, making it the scenario with the highest job estimate. Scenario 3 follows with 1190 jobs, surpassing Scenario 1 with 1050 jobs. In conclusion, for the year 2030, Scenario 2 has the highest job estimate, Scenario 3 follows, and Scenario 1 has the lowest. The considerable differences in job estimates underscore the varying impacts of these scenarios on employment opportunities.

4.5 Outcomes of the life cycle sustainability assessment by using fuzzy logic evaluation based on the three scenarios

4.5.1 Normalisation results

4.5.1.1 Normalisation results for environmental LCA

For the environment, which is based on indicators that express a 'pressure' to the ecological and human system, the target is the minimization, so Equation 1 (subchapter 3.4.4.1) was used and the results are presented at Table 66, for each scenario.

Table 66: Normalised values for environmental LCA

Global Warming Potential (GWP) [kg CO ₂ -Equiv.]	2030	NORMALISED
Scenario 1	1.53E+08	1.00
Scenario 2	3.16E+08	0.00
Scenario 3	2.09E+08	0.65
Abiotic Depletion Potential (ADP elements) [kg Sb-Equiv.]	2030	NORMALISED
Scenario 1	2.38E+03	0.00
Scenario 2	2.03E+03	1.00
Scenario 3	2.16E+03	0.62
Abiotic Depletion Potential (ADP fossil) [MJ]	2030	NORMALISED
Scenario 1	5.42E+08	1.00
Scenario 2	7.04E+08	0.00
Scenario 3	6.54E+08	0.31
Acidification Potential (AP) [kg SO ₂ -Equiv.]	2030	NORMALISED
Scenario 1	5.04E+05	1.00
Scenario 2	7.73E+05	0.00
Scenario 3	6.42E+05	0.49
Eutrophication Potential (EP) [kg Phosphate-Equiv.]	2030	NORMALISED
Scenario 1	1.71E+05	1.00
Scenario 2	1.94E+05	0.23
Scenario 3	2.01E+05	0.00
Freshwater Aquatic Ecotoxicity Potential (FAETP) [kg DCB-Equiv.]	2030	NORMALISED
Scenario 1	1.42E+08	0.00
Scenario 2	1.16E+08	1.00
Scenario 3	1.22E+08	0.77

Human Toxicity Potential (HTP) [kg DCB-Equiv.]	2030	NORMALISED
Scenario 1	1.08E+08	0.00
Scenario 2	9.70E+07	1.00
Scenario 3	1.03E+08	0.44
Marine Aquatic Ecotoxicity Potential (MAETP) [kg DCB-Equiv.]	2030	NORMALISED
Scenario 1	1.161E+11	1.00
Scenario 2	1.190E+11	0.00
Scenario 3	1.188E+11	0.09
Ozone Layer Depletion Potential (ODP) [kg R11-Equiv.]	2030	NORMALISED
Scenario 1	3.79E+00	1.00
Scenario 2	3.89E+00	0.90
Scenario 3	4.75E+00	0.00
Photochemical Ozone Creation Potential (POCP) [kg Ethene-Equiv.]	2030	NORMALISED
Scenario 1	3.78E+04	1.00
Scenario 2	4.66E+04	0.00
Scenario 3	4.55E+04	0.12
Terrestrial Ecotoxicity Potential (TETP) [kg DCB-Equiv.]	2030	NORMALISED
Scenario 1	1.55E+06	0.62
Scenario 2	1.50E+06	1.00
Scenario 3	1.62E+06	0.00

4.5.1.2 Normalisation for economic LCA

For the costing, which is based on the Levelised Cost of Electricity (LCoE), the target is the minimisation and Table 67 is giving the following results for each scenario.

Table 67: Normalised values for economic LCA

Levelised cost of electricity (GBP)	2030	NORMALISED
Scenario 1	2.14E+08	0.32
Scenario 2	2.03E+08	1.00
Scenario 3	2.19E+08	0.00

4.5.1.3 Normalisation for social LCA

For the social LCA, for the 'Deaths estimation' indicator that express a negative 'pressure', the target is the minimisation, while for the 'Job creation estimation' that

express a positive influence to society, the target is the maximisation. Both results are presented in the Table 68.

Table 68: Normalised values for social LCA

Deaths estimate	2030	NORMALISED
Scenario 1	1.95	1.00
Scenario 2	3.03	0.00
Scenario 3	2.58	0.42
Jobs estimate	2030	NORMALISED
Scenario 1	1052.62	0.00
Scenario 2	1415.10	1.00
Scenario 3	1193.12	0.39

4.5.2 Fuzzy inference system results

4.5.2.1 Fuzzy Results for Land

The results for all 3 scenarios are presented at the Table 69:

Table 69: Fuzzy inference for land

Abiotic Depletion Potential (ADP elements) [kg Sb-Equiv.]	NORMALISED	Abiotic Depletion Potential (ADP fossil) [MJ]	NORMALISED	Terrestrial Ecotoxicity Potential (TETP) [kg DCB-Equiv.]	NORMALISED	Acidification Potential (AP) [kg SO ₂ -Equiv.]	NORMALISED	Global Warming Potential (GWP) [kg CO ₂ -Equiv.]	NORMALISED	Eutrophication Potential (EP) [kg Phosphate-Equiv.]	NORMALISED	DEFUZZIFIED RESULT
Scenario 1	0.00	Scenario 1	1.00	Scenario 1	0.62	Scenario 1	1.00	Scenario 1	1.00	Scenario 1	1.00	0.5
Scenario 2	1.00	Scenario 2	0.00	Scenario 2	1.00	Scenario 2	0.00	Scenario 2	0.00	Scenario 2	0.23	0.25
Scenario 3	0.62	Scenario 3	0.31	Scenario 3	0.00	Scenario 3	0.49	Scenario 3	0.65	Scenario 3	0.00	0.347

Scenario 1 exhibits the highest impact across various indicators, including Abiotic Depletion Potential (ADP fossil), Acidification Potential (AP), Global Warming Potential (GWP), and Eutrophication Potential (EP). Notably, Scenario 1 ranks the highest in most indicators, verifying its significant environmental footprint. Scenario 2 has the highest

impacts on Abiotic Depletion Potential (ADP elements) and in Terrestrial Ecotoxicity (TETP). Scenario 3 generally falls between Scenarios 1 and 2 in terms of impact, showing moderate environmental effects. The FIS output, represented by the 'LAND' variable, aligns with these patterns, ranking Scenario 1 with the highest impact, followed by Scenario 3 and Scenario 2 with moderate and minimal impacts, with defuzzified values of 0.5, 0.347 and 0.25, respectively.

4.5.2.1.1 Fuzzy Results for Water

The concentrated results for all 3 scenarios are shown at the Table 70:

Table 70: Fuzzy inference for water

Eutrophication Potential (EP) [kg Phosphate-Equiv.]	NORMAL SED	Freshwater Aquatic Ecotoxicity Potential (FAETP) [kg DCB-Equiv.]	NORMAL SED	Marine Aquatic Ecotoxicity Potential (MAETP) [kg DCB-Equiv.]	NORMAL SED	Acidification Potential (AP) [kg SO ₂ -Equiv.]	NORMAL SED	Global Warming Potential (GWP) [kg CO ₂ -Equiv.]	NORMAL SED	DEFUZZIFIED RESULT
Scenario 1	1.00	Scenario 1	0.00	Scenario 1	1.00	Scenario 1	1.00	Scenario 1	1.00	0.5
Scenario 2	0.23	Scenario 2	1.00	Scenario 2	0.00	Scenario 2	0.00	Scenario 2	0.00	0.25
Scenario 3	0.00	Scenario 3	0.77	Scenario 3	0.09	Scenario 3	0.49	Scenario 3	0.65	0.489

Scenario 1 has the highest impact across the following indicators: Eutrophication Potential (EP), Marine Aquatic Ecotoxicity Potential (MAETP), Acidification Potential (AP) and Global Warming Potential (GWP). These findings suggest that Scenario 1 has the highest impact on water-related environmental aspects. Scenario 2 exhibits the least impact across the indicators, indicating a more favourable environmental profile, with a high impact only on Freshwater Aquatic Ecotoxicity Potential (FAETP). Scenario 3 falls between the extremes, showing a moderate environmental impact compared to Scenarios 1 and 2, with the highest on Freshwater Aquatic Ecotoxicity Potential (FAETP) with 0.77. The FIS output variable 'WATER' aligns with these trends, ranking Scenario 1 with the highest impact, followed by Scenario 3 and Scenario 2 with moderate and minimal impacts, with defuzzified values of 0.5, 0.489 and 0.25, respectively.

4.5.2.1.2 Fuzzy Results for Air

The results for all 3 scenarios are shown as follows at the Table 71:

Table 71: Fuzzy inference for air

Ozone Layer Depletion Potential (ODP) [kg R11-Equiv.]	NORMALISED	Photochemical Ozone Creation Potential (POCP) [kg Ethene-Equiv.]	NORMALISED	Global Warming Potential (GWP) [kg CO ₂ -Equiv.]	NORMALISED	DEFUZZIFIED RESULT
Scenario 1	1.00	Scenario 1	1.00	Scenario 1	1.00	0.917
Scenario 2	0.90	Scenario 2	0.00	Scenario 2	0.00	0.5
Scenario 3	0.00	Scenario 3	0.12	Scenario 3	0.65	0.358

Scenario 1 exhibits the highest impact across the assessed indicators, including Ozone Layer Depletion Potential (ODP), Photochemical Ozone Creation Potential (POCP), and Global Warming Potential (GWP), with normalised factor 1.00. These results suggest that Scenario 1 has the highest impact on air quality and climate-related aspects. Scenario 2 portrays the lowest normalized values for POCP and GWP. Scenario 3 falls between the extremes, presenting a moderate environmental impact compared to Scenarios 1 and 2. For Scenario 3 normalized values for POCP and GWP are 0.12 and 0.65, respectively. The FIS output variable 'AIR' aligns with these trends, ranking Scenario 1 with the highest impact, followed by Scenario 2 and Scenario 3 with moderate and minimal impacts, with defuzzified values of 0.917, 0.5 and 0.358, respectively.

4.5.2.1.3 Fuzzy Results for Human

The results for all 3 scenarios are shown as follows at the Table 72:

Table 72: Fuzzy inference for human

Human Toxicity Potential (HTP) [kg DCB-Equiv.]	NORMALISED	Global Warming Potential (GWP) [kg CO ₂ -Equiv.]	NORMALISED	DEFUZZIFIED RESULT
Scenario 1	0.00	Scenario 1	1.00	0.5
Scenario 2	1.00	Scenario 2	0.00	0.5
Scenario 3	0.44	Scenario 3	0.65	0.514

Scenario 1 exhibits a minimal Human Toxicity Potential (HTP) and the highest Global Warming Potential (GWP), resulting in a defuzzified aggregated 'HUMAN' value of 0.5. This suggests that while Scenario 1 has a low impact on human toxicity, it contributes significantly to climate-related concerns. Scenario 2, on the other hand, demonstrates the opposite trend with high HTP and low GWP, leading to an equal defuzzified 'HUMAN' value of 0.5. This implies that while Scenario 2 presents a significant risk to human toxicity, while its contribution to climate change is relatively low. Scenario 3 has impacts to both HTP and GWP, resulting in the highest defuzzified 'HUMAN' value of 0.514.

4.5.2.1.4 Fuzzy Results for Environment

The results for all 3 scenarios are shown as follows at the Table 73:

Table 73: Fuzzy inference for environment

LAND	Defuzzified value	WATER	Defuzzified value	HUMAN	Defuzzified value	AIR	Defuzzified value	DEFUZZIFIED RESULT
Scenario 1	0.500	Scenario 1	0.500	Scenario 1	0.500	Scenario 1	0.917	0.5
Scenario 2	0.250	Scenario 2	0.250	Scenario 2	0.500	Scenario 2	0.500	0.25
Scenario 3	0.347	Scenario 3	0.489	Scenario 3	0.514	Scenario 3	0.358	0.394

Scenario 1 presents the highest impacts across land, water, human-related factors, and air indicators with defuzzified value of 0.5 for the first three and 0.917 for the air indicator. Scenario 2, marked by minimal impacts on land and water, with defuzzified values of 0.25, but elevated impacts on human health and air quality, with value of 0.5. Scenario 3 moderates impacts across all indicators, generates a defuzzified value of 0.394. The FIS output variable 'ENVIRONMENT' aligns with these trends, ranking Scenario 1 with the highest impact, followed by Scenario 3 and Scenario 2 with moderate and minimal impacts, with defuzzified values of 0.5, 0.394 and 0.25, respectively.

4.5.2.1.5 Fuzzy Results for Social

The results for all 3 scenarios are shown as follows at the Table 74:

Table 74: Fuzzy inference for social

Deaths_estimate	NORMALISED	Jobs_estimate	NORMALISED	DEFUZZIFIED RESULT
Scenario 1	1.000	Scenario 1	0.000	0.500
Scenario 2	0.000	Scenario 2	1.000	0.500
Scenario 3	0.418	Scenario 3	0.388	0.419

Based on the fuzzy logic system with the provided rules and configurations, when deaths estimate is very high (1.000) and jobs estimate is very low (0.000), the system outputs a defuzzified result of 0.500. This corresponds to the 'AVERAGE' linguistic variable for 'Socialoutput.' In scenario 2, with deaths estimate being very low (0.000) and jobs estimate being very high (1.000), the system outputs a defuzzified result of 0.500. Again, this corresponds to the 'AVERAGE' linguistic variable for 'Socialoutput.' For Scenario 3, with normalized deaths estimate and jobs estimate values, the FIS produces a defuzzified result of approximately 0.419.

4.5.2.2 Results and discussion for fuzzy composite indicators

The results for all 3 scenarios are shown as follows at the Table 75:

Table 75: Final aggregation LCSA

ENVIRONMENT	DEFUZZIFIED RESULT	SOCIAL	DEFUZZIFIED RESULT	ECONOMIC	NORMALISED	
Scenario 1	0.938	Scenario 1	0.5	Scenario 1	0.32	0.359
Scenario 2	0.25	Scenario 2	0.5	Scenario 2	1	0.250
Scenario 3	0.25	Scenario 3	0.412	Scenario 3	0	0.244

Scenario 1 presents high environmental impact on environmental aspect with defuzzified value of 0.938, while social aspect has a value of 0.5, and a relatively low economic impact of 0.32. Scenario 2 is characterized by low environmental and social impacts 0.25 and 0.5 defuzzified value, respectively and a high economic impact with 1.00 value. Scenario 3 presents the lowest impacts for all the three categories of

environmental, social and economic aspects with 0.25, 0.412 and 0.00 values, respectively. The FIS output variable 'LCSA' aligns with these trends, ranking Scenario 1 with the highest impact, followed by Scenario 2 and Scenario 3 with moderate and minimal impacts, with defuzzified values of 0.359, 0.250 and 0.244 respectively.

5. Conclusion

5.1 Novelty of the proposed method

The novelty of the methods used in this thesis is focused on the combination of the following three main points:

- Thorough investigation of the current situation of the renewables in Cumbria, utilizing many sources and analysing a lot of data. Detailed analysis on electricity generation and focusing on more decentralized smaller scale renewable energy technologies – not only higher technologies and national level.
- Integrated assessment for environmental, economic and social aspects of smaller scale renewables. The decentralized nature and the considerable low scale mean that some of these assessments of such a mix for their independence as well as for their overall sustainability will be carried out for the first time.
- Using capacity oriented (MW installed) rather than electricity generation oriented (MWh produced) puts the focus on the building/supply side of the decision-making process rather than the use/demand side.

5.2 Outcomes by confronting the research questions

The novelty features of this research illustrated above supported the answer to the research questions set in the beginning of this doctoral research. It is important to add a note, which refers to all the research questions that the central point of this thesis is focusing on small scale technologies at a local scale explicitly for Cumbria as a case study. Therefore, whenever the terms “renewable energy technologies” and “renewable energy scenarios” are used, these refer to the small-scale technologies for electricity generation.

a) How the current renewable energy technologies in Cumbria are assessed in terms of their environmental, economic and social impacts?

Based on the impacts calculated for each renewable energy technology independently,

Small scale hydro seems to be the less impactful, having the lowest impact per kWh of electricity generated followed by Commercial wind which has the highest per kWh impacts for FAETP and Plant Biomass, which has the highest per kWh impact for POCP and EP. Small scale wind and Energy from Waste follow with having the highest per kWh impact for HTP, TETP and GWP, AP respectively. Microgeneration seems to be the most impactful having the highest per kWh impact for ADP (elements and fossils), MAETP and ODP.

For the economic impacts the lowest per kWh is attributed to the Energy from Waste followed by Commercial wind. Microgeneration, Small scale hydro and Plant biomass seem to be in the middle and small scale wind to be the most expensive technology.

On the contrary, for the social impacts small scale wind, Commercial wind and Microgeneration seem to have the per kWh generated lowest estimate for deaths but at the same time lowest estimate for job creation, followed by small scale hydro. Plant biomass and Energy from waste seem to have the highest number of estimated deaths and jobs per kWh created.

b) Is it possible to identify realistic short-term, mid-term and long-term renewable energy scenarios for the Cumbria county?

Based on the analysis provided in chapter 3 and the tables presented in subsection 3.3 on the data collection for scenarios, it has been possible to identify three short-term, mid-term and long-term renewable energy scenarios for the Cumbria county based on: i) Existing Deployment projections, ii) UK Renewable Strategy mix and iii) No new commercial wind cases. These scenarios have been configured based on data and restrictions described in various reports and official sites and they can be considered representative especially since the actual values for 2020 were used. Whether the projections to 2030 will be materialized depends on the policies to be developed further and implemented in a very volatile and uncertain environment. So far, the covid 19 pandemic as well as the war in Ukraine have changed the demand and supply of energy and along with the deepening of the climate crisis it becomes obvious that they can act as higher-level pressures that could change a national energy planning pathway. On top of that there are several the advances in the field of specific technologies that should be

considered such as the energy storage that can further support decentralization as well as a smaller scale modular nuclear reactors that could present a very low carbon electricity generation alternative.

c) How these renewable energy scenarios can be assessed for their overall performance taking into account a life cycle approach?

Based on the results presented and analysed in chapter 4, it is shown that looking at each life cycle environmental impact indicator separately, these scenarios can be assessed for their individual environmental, economic and social indicators as well as for their overall sustainability indicators. Scenario 1 seems to be the best for GWP, ADP fossils, AP, EP, MAETP, ODP, POCP, average for TETP and the worst for ADP elements, FAETP and HTP. It also has the average LCoE and lowest death and jobs estimate. Scenario 2 seems to be the best for ADP elements, FAETP, HTP and TETP, average for EP and ODP and the worst for GWP, ADP fossils, AP, MAETP and POCP. It also has lowest LCoE and highest death and jobs estimate. Scenario 3 seems to be the worst for EP, ODP and TETP and average for all the rest. It also has highest LCoE and average death and jobs estimate.

The use of fuzzy inference made it possible to aggregate the indicators and provide an overall environmental performance ranking Scenario 1 as the best and the other two sharing the lowest position. It also provided a score for the overall social performance with Scenarios 1 and 2 sharing the best position and followed very closely by Scenario 3, although all of their scores seem to classify their performance close to average. The main benefit from the use of fuzzy inference is that it made possible to assess the three scenarios for their overall performance ranking highest Scenario 1, followed by Scenario 2 and Scenario 3 with very close scores.

5.3 Discussion on the philosophical underpinning of the iCumbRIA

At its core, the iCumbRIA model – and by extension, this entire thesis – is driven by a philosophical commitment in addressing the urgent and deeply interconnected global

challenges of: the climate crisis, the environmental degradation, the need for sustainable energy and energy democracy. These are not concepts that exist only in the scientific or policy discussions. They are actual cases of real life with immediate and long-term effects on communities, ecosystems, economies and future generations. This thesis responds to those realities by developing a practical, integrated model, the iCumbRIA, for assessing energy scenarios – that places emphasis on environment, economy and society simultaneously.

5.3.1 Climate crisis and sustainable energy as driving forces of iCumbRIA

The roots of scientific research on climate crisis can be traced back through over a century of analyses, beginning with early observations, such as those made by (Arrhenius, 1897). Since the end of 19th century until present, the field of climate science has been developed enormously, with recent studies like (Callahan and Mankin, 2025) confirming the accelerating impacts of human activity and particularly the energy production by fossil fuels. Furthermore, it is important to consider multiple kinds of environmental degradation – not only the ones related to climate crisis (Kouloumpis et al., 2015).

Central to the iCumbRIA model is the inclusion of a set of well-established environmental indicators – within the model – which are used to assess the broader sustainability of various energy technologies. These include a number of factors, which address climate crisis, environmental degradation and sustainable energy from multiple views:

- Global Warming Potential (GWP) – which assesses the impact of greenhouse gases, including releases during energy production and use.
- Abiotic Depletion Potential (ADP) – focusing on the exhaustion of fossil fuels and minerals, as well.
- Acidification Potential and Eutrophication Potential – which respectively examine the impacts of emissions from energy processes, too, on soil acidity and nutrient overloading in water bodies.

- Freshwater Aquatic, Marine Aquatic, and Terrestrial Ecotoxicity Potentials – addressing the risks posed by toxic substances to different ecosystems, involving, also, the extraction, processing and burning of fossil fuels.
- Human Toxicity Potential – which evaluates health risks from long-term exposure to harmful emissions, caused by the energy production and use, too.
- Ozone Layer Depletion Potential – concerning substances, such as from energy-related activities that break down stratospheric ozone, increasing UV radiation exposure.
- Photochemical Ozone Creation Potential – related to ground-level ozone formation, from numerous emission sources, like the ones produced at the energy sector, contributing to smog and respiratory illness.

Each one of these indicators captures a specific environmental consequence of energy production, transport and use. The challenge is for a full view of the entire life cycle to be given, not just a limited focus on carbon numbers. Behind them is a philosophical belief: that real environmental sustainability needs to be based on a clear, data-based understanding of all effects – both visible and hidden, short-term and long-term.

The energy in order to be sustainable has to take into account not only the environmental indicators, as noted above, but also the economic and the social indicators. A comprehensive economic indicator that has been analyzed in this thesis (subchapters 2.1 and 3.4.2) is the Levelised Cost of Electricity (LCoE). LCoE provides a comparable metric for assessing the affordability of different energy options. Alongside this, the iCumbRIA also integrates social indicators: “Human Deaths” and “Jobs”, which are associated with each energy scenario. These are not symbolic additions – they are key to understanding the real-world.

Taken as a whole, the model embodies a LCSA approach, one that seeks to overcome traditional analysis in sustainability thinking. The inclusion of environmental, economic, and social indicators within a unified, fuzzy logic based tool reflects a philosophical orientation towards the idea that sustainability is not the result of isolated improvements in one domain, but rather the outcome of balancing multiple, sometimes competing, goals. This integrated view is also supported in recent literature, such as the work of (Ee et al., 2024), who promotes the implementation of green technologies as part of a broader framework that reflects the priorities, which are mentioned in the United Nations Sustainable Development Goals (SDGs).

5.3.2 Energy democracy as foundational motivator of iCumbRIA

The second philosophical foundation of the iCumbRIA model has its grounding in the principles of energy democracy. Whereas the climate crisis and the environmental degradation demand urgent action for the planet, energy democracy also requires attention and rethinking of how and by whom the actions concerning environment and especially energy are carried out. This needs deeper participation, shared decision-making and a reconfiguration of the energy systems.

In most cases, changes in how the energy is produced has been forced on communities rather than developed together. It has been observed worldwide that renewable energy installations – particularly wind farms – have frequently been developed by large-sized companies in ways that overlook or bypass the community concerns. However, the role of citizen engagement in sustainable energy transitions is important as many studies – for example: (Nolden et al., 2020), (Braunholtz-Speight et al., 2021) and (Depeng et al., 2024) – have demonstrated that community energy initiatives, which are locally rooted and democratically governed can deliver significant environmental and social benefits, while also cultivating collective responsibility.

The iCumbRIA model is deliberately designed to support and enhance this kind of citizen-led engagement. It is not an academic model meant only for researchers or policymakers. It has been specifically adapted to be user-friendly, allowing communities and local energy groups to input their own data, assess potential scenarios, and visualize outcomes in a meaningful way. In regions such as Cumbria, where solid energy communities already exist (Gormally et al., 2012) and (Gormally et al., 2014), such tools can empower local actors to make more informed, democratic decisions about their energy future. Moreover, the inclusion of indicators such as “Jobs” and “Human Deaths” ensures that communities can clearly see the social consequences – both positive and negative – of various energy pathways. The goal is to make sustainability understandable, actionable, and relevant at the local level.

5.3.3 Conceptual basis of iCumbRIA

This research is carried out to contribute to an area where further study is needed in both academic literature and practical application, as numerous models exist for environmental assessment (presented in chapter 2), but what is missing is the specifically tailored, locally oriented, integrated, life-cycle-sustainability-based approach, which iCumbRIA provides with fuzzy logic. Moreover, the iCumbRIA was developed with accessibility in mind – capable of being used not only by experts, but also by citizens, municipalities, cooperatives, and other local actors without the need of a specialized software.

Furthermore, what is even more important is that this thesis addresses the following issue: how to balance environmental respect with social justice and economic realities. By embedding LCSA into a framework that is both reliable and inclusive, the iCumbRIA offers a tool for participatory sustainability – one that acknowledges complexity without becoming inaccessible or too much technocratic.

This thesis developed the iCumbRIA model that helps assess energy choices in a way that is easy to use and considers environmental, economic and social values. It is based on the ideas of climate responsibility and sustainability offering the flexibility for community use during the decision-making process. The goal is to support both academic and real-world use, helping to connect ideas with action, during the energy transition period and beyond it.

5.3.4 Concluding reflections on the philosophical framework of iCumbRIA

In summary, the philosophical foundation of the iCumbRIA model is based on two pillars: a) the recognition of the climate crisis, as well as the environmental degradation and the need for sustainable energy in total, as crucial challenges for humanity, requiring life-cycle environmental, economic, and social assessment and b) the commitment to energy democracy as a pathway to fairer, more inclusive decision-making. By integrating these principles into iCumbRIA, this thesis offers a practical contribution to both academic research and real-world energy planning.

Through its emphasis on fuzzy logic, inclusive indicators, and local adaptability, the iCumbRIA model aims to help communities visualize, understand, and ultimately shape energy futures that are not only sustainable, but also just and democratic. In doing so, iCumbRIA demonstrates that science and communities can work together in an efficient way to meet the challenges for a sustainable future.

5.4 Limitations and future uses of the thesis

Despite the strengths of this thesis, several limitations should be acknowledged:

- a) **Standardization challenges in LCC and SLCA:** One major limitation lies in the absence of widely accepted standards for LCC and SLCA. While the United Nations and other bodies have made significant contributions to the field, the methodologies remain subject to debate and lack uniform implementation. Unlike LCA, which has seen considerable harmonization, LCC and SLCA are still implemented inconsistently, with practitioners often relying on individual judgment in the absence of standardized frameworks. In the case of LCC, the LCoE is currently regarded as one of the most practical approaches, offering a common reference point, though it too has its limitations.
- b) **Data availability and variability:** Another limitation concerns the accessibility and consistency of data. In many cases, proxy data or the best available estimates had to be used due to limited or outdated information. This is particularly relevant in assessing the embodied impacts of technologies like wind turbines, where the environmental cost of electricity used in manufacturing varies widely between countries and over time. Ideally, a more dynamic and localized data model would enhance accuracy, especially in accounting for the changing carbon intensity of national grids.
- c) **Complexity and practicality of LCSA:** The application of LCSA presents practical challenges as well. It is inherently time-intensive, requires specialized expertise, and is often designed for evaluating specific products. These factors can make it less adaptable for broader policy analysis, where flexibility is essential. Nonetheless, LCSA is gaining traction – particularly following the integration of the Product Environmental Footprint (PEF) methodology into policy frameworks – positioning it

as an increasingly influential tool in both research and regulatory environments (Sala et al., 2021).

To build upon the foundations of this thesis, future studies could revisit and refine the limitations outlined above. This could involve updating the underlying data in light of recent technological advances, and re-evaluating scenarios to reflect the evolving geopolitical and energy landscapes both globally and nationally. A key area for development lies in further enhancing and expanding the iCumbRIA model. Thanks to its modular and adaptable design, the model is well-suited for application not only within Cumbria, but also across the broader UK context and potentially on a global scale. With additional refinement, iCumbRIA could serve as a robust and versatile decision-support tool for scientists, policymakers, stakeholders, energy communities and citizens working at the intersection of sustainability, energy planning and regional development.

5.5 Epilogue and remarks

The outcomes by including the final conclusions of subchapter 5.1, too, suggest that from all the scenarios that came from Cumbria County Council documents (Cumbria County Council, 2011) and were used in this thesis, the Scenario 1 is the most advantageous, with Scenarios 2 and 3 following in terms of preference. Despite not securing the highest scores in all intermediate life cycle assessments, Scenario 1 has the actual potential to improve the decision-making process for local renewable energy planning within this framework.

The iCumbRIA model, as a development of this PhD, together with the data acquired, the novel method described and the results presented in this thesis could contribute to a more reliable and innovative holistic approach for the sustainable use of renewable energy technologies.

Reference List

- Akhtar, S., Reza, B., Hewage, K., Shahriar, A., Zargar, A., Sadiq, R., 2014. Life cycle sustainability assessment (LCSA) for selection of sewer pipe materials. *Clean Technol. Environ. Policy* 7, 1–32. <https://doi.org/10.1007/s10098-014-0849-x>
- Alejandrino, C., Mercante, I., Bovea, M.D., 2021. Life cycle sustainability assessment: Lessons learned from case studies. *Environ. Impact Assess. Rev.* 87, 106517. <https://doi.org/10.1016/j.eiar.2020.106517>
- Al-Kuwari, A., Kucukvar, M., Onat, N.C., 2024. Uncovering the role of sustainable value chain and life cycle management toward sustainable operations in electricity production technologies. *Oper. Manag. Res.* 17, 1360–1379. <https://doi.org/10.1007/s12063-024-00510-3>
- Arpke, A., Hutzler, N., 2005. Operational Life-Cycle Assessment and Life-Cycle Cost Analysis for Water Use in Multioccupant Buildings. *J. Archit. Eng.* 11, 99–109. [https://doi.org/10.1061/\(ASCE\)1076-0431\(2005\)11:3\(99\)](https://doi.org/10.1061/(ASCE)1076-0431(2005)11:3(99))
- Arrhenius, S., 1897. On the Influence of Carbonic Acid in the Air upon the Temperature of the Earth. *Publ. Astron. Soc. Pac.* 9, 14. <https://doi.org/10.1086/121158>
- Baumann, H., Tillman, A.-M., 2004. The Hitch Hiker's Guide to LCA, Studentlitteratur Lund. <https://doi.org/10.1065/lca2006.02.008>
- Benoît, C., Norris, G.A., Valdivia, S., Citroth, A., Moberg, A., Bos, U., Prakash, S., Ugaya, C., Beck, T., 2010. The guidelines for social life cycle assessment of products: just in time! *Int. J. Life Cycle Assess.* 15, 156–163. <https://doi.org/10.1007/s11367-009-0147-8>
- Bhunja, S., Tehranipoor, M., 2019. Chapter 2 - A Quick Overview of Electronic Hardware, in: Bhunja, S., Tehranipoor, M. (Eds.), *Hardware Security*. Morgan Kaufmann, pp. 23–45. <https://doi.org/10.1016/B978-0-12-812477-2.00007-1>
- BIZCAT, 2013. The West Cumbria Energy Compass.
- Bonilla-Alicea, R.J., Fu, K., 2022. Social life-cycle assessment (S-LCA) of residential rooftop solar panels using challenge-derived framework. *Energy Sustain. Soc.* 12, 7. <https://doi.org/10.1186/s13705-022-00332-w>
- Braunholtz-Speight, T., McLachlan, C., Mander, S., Hannon, M., Hardy, J., Cairns, I., Sharmina, M., Manderson, E., 2021. The long term future for community energy in Great Britain: A co-created vision of a thriving sector and steps towards realising it. *Energy Res. Soc. Sci.* 78, 102044. <https://doi.org/10.1016/j.erss.2021.102044>
- Britain's Energy Coast, 2008. Britain's energy coast / a Masterplan for West Cumbria - executive summary 48.
- Brown, K.L., Greer, D.C., Schwegler, B., 2011. Life Cycle Management Approach to the Design of Large-Scale Resorts. *Life Cycle Sustain. Manag.* https://doi.org/10.1007/978-94-007-1899-9_22
- Brundtland, G., Khalid, M., Agnelli, S., Al-Athel, S., Chidzero, B., Fadika, L., Hauff, V., Lang, I., Shijun, M., Morino de Botero, M., Singh, M., Okita, S., Others, A., 1987. Our Common Future ('Brundtland report'), Oxford Paperback Reference. <https://doi.org/10.1002/jid.3380010208>
- Bucher, R., Jeffrey, H., Bryden, I.G., Harrison, G.P., 2016. Creation of investor confidence: The top-level drivers for reaching maturity in marine energy. *Renew. Energy* 88, 120–129. <https://doi.org/10.1016/j.renene.2015.11.033>
- Callahan, C.W., Mankin, J.S., 2025. Carbon majors and the scientific case for climate liability. *Nature* 640, 893–901. <https://doi.org/10.1038/s41586-025-08751-3>
- CFI [WWW Document], 2022. . Corp. Finance Inst. URL <https://corporatefinanceinstitute.com/resources/valuation/levelized-cost-of-energy-lcoe/> (accessed 1.15.24).

- Chong, Y.T., Teo, K.M., Tang, L.C., 2016. A lifecycle-based sustainability indicator framework for waste-to-energy systems and a proposed metric of sustainability. *Renew. Sustain. Energy Rev.* 56, 797–809. <https://doi.org/10.1016/j.rser.2015.11.036>
- Cumbria Clean Energy Strategy, 2022.
- Cumbria County Council, 2011. Cumbria Renewable Energy Capacity and Deployment Study Final report to Cumbria County Council.
- Dantas, T., Soares, S., 2022. Systematic literature review on the application of life cycle sustainability assessment in the energy sector. *Environ. Dev. Sustain.* 24. <https://doi.org/10.1007/s10668-021-01559-x>
- Depeng, H., Lacarcel, F.J.S., Simón-Moya, V., 2024. The dynamics of energy communities and innovative cooperatives: Mapping current knowledge and future trends. *J. Innov. Knowl.* 9, 100626. <https://doi.org/10.1016/j.jik.2024.100626>
- Ee, A.W.L., Lee, J.T.E., Tian, H., Lim, E.Y., Yan, M., Tong, Y.W., Zhang, J., Ng, A.T.S., Ok, Y.S., Kua, H.W., 2024. Current status on utilizing a life cycle system perspective to evaluate renewable energy production systems for achieving UN SDGs. *Resour. Conserv. Recycl.* 203, 107381. <https://doi.org/10.1016/j.resconrec.2023.107381>
- Environmental Footprint methods - European Commission [WWW Document], 2022. URL https://green-business.ec.europa.eu/environmental-footprint-methods_en (accessed 1.17.24).
- Fetanat, A., Tayebi, M., Mofid, H., 2022. Combining life cycle sustainability assessment and fuzzy multicriteria decision making method for prioritizing the flare technologies in the oil, gas, and chemical plants. *Environ. Prog. Sustain. Energy* 41, e13837. <https://doi.org/10.1002/ep.13837>
- FuzzyLite Limited, 2015. Fuzzylite™.
- Gangadharan, P., Zanwar, A., Zheng, K., Gossage, J., Lou, H.H., 2012. Sustainability assessment of polygeneration processes based on syngas derived from coal and natural gas. *Comput. Chem. Eng.* 39, 105–117. <https://doi.org/10.1016/j.compchemeng.2011.10.006>
- Gormally, A.M., Pooley, C.G., Whyatt, J.D., Timmis, R.J., 2014. “They made gunpowder ... yes down by the river there, that’s your energy source”: attitudes towards community renewable energy in Cumbria. *Local Environ.* 19, 915–932. <https://doi.org/10.1080/13549839.2013.810206>
- Gormally, A.M., Whyatt, J.D., Timmis, R.J., Pooley, C.G., 2012. A regional-scale assessment of local renewable energy resources in Cumbria, UK. *Energy Policy* 50, 283–293. <https://doi.org/10.1016/j.enpol.2012.07.015>
- Graedel, T.E., Barr, R., Chandler, C., Chase, T., Choi, J., Christoffersen, L., Friedlander, E., Henly, C., Jun, C., Nassar, N.T., Schechner, D., Warren, S., Yang, M.Y., Zhu, C., 2012. Methodology of metal criticality determination. *Environ. Sci. Technol.* 46, 1063–1070. <https://doi.org/10.1021/es203534z>
- Grießhammer, R., Buchert, M., Gensch, C.-O., Hochfeld, C., Manhart, A., Rüdener, I., 2007. PROSA—Product Sustainability Assessment. Freiburg.
- Gu, L., Lin, B., Zhu, Y., Gu, D., Huang, M., Gai, J., 2008. Integrated assessment method for building life cycle environmental and economic performance. *Build. Simul.* 1, 169–177. <https://doi.org/10.1007/s12273-008-8414-3>
- Guinée, J. (Ed.), 2002. Handbook on Life Cycle Assessment: Operational Guide to the ISO Standards, Eco-Efficiency in Industry and Science. Springer Netherlands.
- Guinée, J.B., Heijungs, R., Huppes, G., Zamagni, A., Masoni, P., Buonamici, R., Ekvall, T., Rydberg, T., 2011. Life cycle assessment: past, present, and future. *Environ. Sci. Technol.* 45, 90–96. <https://doi.org/10.1021/es101316v>
- Hacking, T., Guthrie, P., 2008. A framework for clarifying the meaning of Triple Bottom-Line, Integrated, and Sustainability Assessment. *Environ. Impact Assess. Rev.* 28, 73–89. <https://doi.org/10.1016/j.eiar.2007.03.002>

- Hallste Pérez, T., Rodríguez-Chueca, J., Pérez Rodríguez, J., 2023. Inclusion of key social indices for a comparative assessment of the sustainability of the life cycle of current and future electricity generation in Spain: A proposed methodology. *Sci. Total Environ.* 899, 165541. <https://doi.org/10.1016/j.scitotenv.2023.165541>
- Hayatina, I., Auckaili, A., Farid, M., 2023. Review on the Life Cycle Assessment of Thermal Energy Storage Used in Building Applications. *Energies* 16, 1170. <https://doi.org/10.3390/en16031170>
- Heijungs, R., Huppes, G., Guinée, J.B., 2010. Life cycle assessment and sustainability analysis of products, materials and technologies. Toward a scientific framework for sustainability life cycle analysis. *Polym. Degrad. Stab.* 95, 422–428. <https://doi.org/10.1016/j.polymdegradstab.2009.11.010>
- Hemmati, M., Bayati, N., Ebel, T., 2024. Integrated life cycle sustainability assessment with future energy mix: A review of methodologies for evaluating the sustainability of multiple power generation technologies development. *Renew. Energy Focus* 49, 100581. <https://doi.org/10.1016/j.ref.2024.100581>
- Holdgate, M., 2009. The scope for renewable energy in Cumbria.
- International Standard Organization, 2006. ISO 14040:1997 - Environmental management - Life Cycle Assessment - Principles and Framework. *Int. Organ. Stand.*
- IRENA, ILO, 2022. Renewable energy and Jobs: Annual review 2022.
- Kabeyi, M.J.B., Olanrewaju, O.A., 2023. The levelized cost of energy and modifications for use in electricity generation planning. *Energy Rep., Technologies and Materials for Renewable Energy, Environment and Sustainability* 9, 495–534. <https://doi.org/10.1016/j.egyr.2023.06.036>
- Keller, H., Rettenmaier, N., Reinhardt, G.A., 2015. Integrated life cycle sustainability assessment - A practical approach applied to biorefineries. *Appl. Energy* 154, 1072–1081. <https://doi.org/10.1016/j.apenergy.2015.01.095>
- Klöpffer, W., 2008. Life Cycle Sustainability Assessment of Products (with Comments by Helias A. Udo de Haes, p. 95). *Int. J. Life Cycle Assess.* 13, 89–95. <http://dx.doi.org/10.1065/lca2008.02.376>
- Kosareo, L., Ries, R., 2007. Comparative environmental life cycle assessment of green roofs. *Build. Environ.* 42, 2606–2613. <https://doi.org/10.1016/j.buildenv.2006.06.019>
- Kouloumpis, V., Azapagic, A., 2022. A model for estimating life cycle environmental impacts of offshore wind electricity considering specific characteristics of wind farms. *Sustain. Prod. Consum.* 29, 495–506. <https://doi.org/10.1016/j.spc.2021.10.024>
- Kouloumpis, V., Azapagic, A., 2018. Integrated life cycle sustainability assessment using fuzzy inference: A novel FELICITA model. *Sustain. Prod. Consum.* 15. <https://doi.org/10.1016/j.spc.2018.03.002>
- Kouloumpis, V., Kouikoglou, V., Phillis, Y., 2008. Sustainability Assessment of Nations and Related Decision Making Using Fuzzy Logic. *Syst. J. IEEE* 2, 224–236. <https://doi.org/10.1109/JSYST.2008.925256>
- Kouloumpis, V., Stamford, L., Azapagic, A., 2015. Decarbonising electricity supply: Is climate change mitigation going to be carried out at the expense of other environmental impacts? *Sustain. Prod. Consum.* 1, 1–21. <https://doi.org/10.1016/j.spc.2015.04.001>
- Kouloumpis, V., Yan, X., 2021. Sustainable energy planning for remote islands and the waste legacy from renewable energy infrastructure deployment. *J. Clean. Prod.* 307, 127198. <https://doi.org/10.1016/j.jclepro.2021.127198>
- Kvarnström, E., Schönning, C., Carlsson-Reich, M., Gustafsson, M., Enocksson, E., 2003. Recycling of wastewater-derived phosphorus in Swedish agriculture - A proposal. *Water Sci. Technol.* 48, 19–25.
- Lassio, J.G., Magrini, A., Castelo Branco, D., 2021. Life cycle-based sustainability indicators for electricity generation: A systematic review and a proposal for assessments in Brazil. *J. Clean. Prod.* 311, 127568. <https://doi.org/10.1016/j.jclepro.2021.127568>

- Leroy-Parmentier, N., Valdivia, S., Loubet, P., Sonnemann, G., 2023. Alignment of the life cycle initiative's "principles for the application of life cycle sustainability assessment" with the LCSA practice: A case study review. *Int. J. Life Cycle Assess.* 28, 1–37. <https://doi.org/10.1007/s11367-023-02162-0>
- Liu, G., 2014. Development of a general sustainability indicator for renewable energy systems: A review. *Renew. Sustain. Energy Rev.* 31, 611–621. <https://doi.org/10.1016/j.rser.2013.12.038>
- Mamdani, 1977. Application of Fuzzy Logic to Approximate Reasoning Using Linguistic Synthesis. *IEEE Trans. Comput.* C-26, 1182–1191. <https://doi.org/10.1109/TC.1977.1674779>
- Markandya, A., Wilkinson, P., 2007. Electricity generation and health. *Lancet Lond. Engl.* 370, 979–990. [https://doi.org/10.1016/s0140-6736\(07\)61253-7](https://doi.org/10.1016/s0140-6736(07)61253-7)
- Marshall, A., Quinlan, P., Berry, J., 2013. Supporting regional growth from the higher education community : the Energy Coast Campus Programme in West Cumbria. *J. Innov. Impact* 5, 104–115.
- Myhr, A., Bjerkseter, C., Ågotnes, A., Nygaard, T.A., 2014. Levelised cost of energy for offshore floating wind turbines in a life cycle perspective. *Renew. Energy* 66, 714–728. <https://doi.org/10.1016/j.renene.2014.01.017>
- Neugebauer, S., Martinez-Blanco, J., Scheumann, R., Finkbeiner, M., 2015. Enhancing the practical implementation of life cycle sustainability assessment – proposal of a Tiered approach. *J. Clean. Prod.* 102. <https://doi.org/10.1016/j.jclepro.2015.04.053>
- Niemeijer, D., de Groot, R.S., 2008. A conceptual framework for selecting environmental indicator sets. *Ecol. Indic.* 8, 14–25. <https://doi.org/10.1016/j.ecolind.2006.11.012>
- Nolden, C., Barnes, J., Nicholls, J., 2020. Community energy business model evolution: A review of solar photovoltaic developments in England. *Renew. Sustain. Energy Rev.* 122, 109722. <https://doi.org/10.1016/j.rser.2020.109722>
- Nzila, C., Dewulf, J., Spanjers, H., Tuigong, D., Kiriamiti, H., van Langenhove, H., 2012. Multi criteria sustainability assessment of biogas production in Kenya. *Appl. Energy* 93, 496–506. <https://doi.org/10.1016/j.apenergy.2011.12.020>
- Ostermeyer, Y., Wallbaum, H., Reuter, F., 2013. Multidimensional Pareto optimization as an approach for site-specific building refurbishment solutions applicable for life cycle sustainability assessment. *Int. J. Life Cycle Assess.* 18, 1762–1779. <https://doi.org/10.1007/s11367-013-0548-6>
- Parent, J., Cucuzzella, C., Revéret, J.P., 2013. Revisiting the role of LCA and SLCA in the transition towards sustainable production and consumption. *Int. J. Life Cycle Assess.* 18, 1642–1652. <https://doi.org/10.1007/s11367-012-0485-9>
- Pesonen, H.L., Horn, S., 2013. Evaluating the Sustainability SWOT as a streamlined tool for life cycle sustainability assessment. *Int. J. Life Cycle Assess.* 18, 1780–1792. <https://doi.org/10.1007/s11367-012-0456-1>
- Pham, D.T., Castellani, M., 2002. Action aggregation and defuzzification in Mamdani-type fuzzy systems. *Proc. Inst. Mech. Eng. Part C J. Mech. Eng. Sci.* 216, 747–759. <https://doi.org/10.1243/09544060260128797>
- Piluso, C., Huang, J., Liu, Z., Huang, Y., 2010. Sustainability assessment of industrial systems under uncertainty: A fuzzy logic based approach to short-term to midterm predictions. *Ind. Eng. Chem. Res.* 49. <https://doi.org/10.1021/ie100164r>
- Rashid, E., Majed, N., 2023. Integrated life cycle sustainability assessment of the electricity generation sector in Bangladesh: Towards sustainable electricity generation. *Energy Rep.* 10, 3993–4012. <https://doi.org/10.1016/j.egyr.2023.10.041>
- REF [WWW Document], 2024. URL <https://ref.org.uk/> (accessed 1.15.24).
- Ren, J., Manzardo, A., Mazzi, A., Zuliani, F., Scipioni, A., 2015a. The Environmental Impacts and Allocation Methods Used in LCA Studies of Vegetable Oil-Based Bio-diesels. *Waste Biomass Valorization* 20, 579–603. <https://doi.org/10.1007/s11367-015-0877-8>

- Ren, J., Manzardo, A., Mazzi, A., Zuliani, F., Scipioni, A., 2015b. Prioritization of bioethanol production pathways in China based on life cycle sustainability assessment and multicriteria decision-making. *Int. J. Life Cycle Assess.* 20, 842–853. <https://doi.org/10.1007/s11367-015-0877-8>
- Reza, B., Sadiq, R., Hewage, K., 2013. A fuzzy-based approach for characterization of uncertainties in emergy synthesis: an example of paved road system. *J. Clean. Prod.* 59, 99–110. <https://doi.org/10.1016/j.jclepro.2013.06.061>
- Ristimäki, M., Säynäjoki, A., Heinonen, J., Junnila, S., 2013. Combining life cycle costing and life cycle assessment for an analysis of a new residential district energy system design. *Energy* 63, 168–179. <https://doi.org/10.1016/j.energy.2013.10.030>
- Rob Hoogmartens, , Steven Van Passel, , Karel Van Acker, , Maarten Dubois, 2014. Life Cycle Sustainability Assessment: Bridging the Gap Between LCA, LCC, and S-LCA.
- Saaty, T., 1980. *The Analytic Hierarchy Process*, McGraw-Hill Inc. McGraw-Hill, New York. <https://doi.org/0070543712>
- Sala, S., Amadei, A.M., Beylot, A., Ardente, F., 2021. The evolution of life cycle assessment in European policies over three decades. *Int. J. Life Cycle Assess.* 26, 2295–2314. <https://doi.org/10.1007/s11367-021-01893-2>
- Santoyo-Castelazo, E., Azapagic, A., 2014. Sustainability assessment of energy systems: Integrating environmental, economic and social aspects. *J. Clean. Prod.* 80. <https://doi.org/10.1016/j.jclepro.2014.05.061>
- Schlör, H., Fischer, W., Hake, J.F., 2015. The system boundaries of sustainability. *J. Clean. Prod.* 88, 52–60. <https://doi.org/10.1016/j.jclepro.2014.04.023>
- Schlör, H., Fischer, W., Hake, J.F., 2012. The meaning of energy systems for the genesis of the concept of sustainable development. *Appl. Energy* 97, 192–200. <https://doi.org/10.1016/j.apenergy.2012.03.009>
- Schlör, H., Hake, J.F., 2015. Sustainability Assessment Circle. *Energy Procedia* 75, 2641–2648. <https://doi.org/10.1016/j.egypro.2015.07.361>
- Simões, C.L., Costa Pinto, L.M., Simoes, R., Bernardo, C.A., 2013. Integrating environmental and economic life cycle analysis in product development: a material selection case study. *Int. J. Life Cycle Assess.* 18, 1734–1746. <https://doi.org/10.1007/s11367-013-0561-9>
- Singh, A., Olsen, S.I., 2011. A critical review of biochemical conversion, sustainability and life cycle assessment of algal biofuels. *Appl. Energy* 88, 3548–3555. <https://doi.org/10.1016/j.apenergy.2010.12.012>
- Sonnemann, G., Gemechu, E.D., Adibi, N., De Bruille, V., Bulle, C., 2015. From a critical review to a conceptual framework for integrating the criticality of resources into Life Cycle Sustainability Assessment. *J. Clean. Prod.* 94, 20–34. <https://doi.org/10.1016/j.jclepro.2015.01.082>
- Sovacool, B.K., Andersen, R., Sorensen, S., Sorensen, K., Tienda, V., Vainorius, A., Schirach, O.M., Bjørn-Thygesen, F., 2016. Balancing safety with sustainability: assessing the risk of accidents for modern low-carbon energy systems. *J. Clean. Prod.* 112, 3952–3965. <https://doi.org/10.1016/j.jclepro.2015.07.059>
- Subhadra, B., Edwards, M., 2010. An integrated renewable energy park approach for algal biofuel production in United States. *Energy Policy* 38, 4897–4902. <https://doi.org/10.1016/j.enpol.2010.04.036>
- Sugeno, M., 1985. An introductory survey of fuzzy control. *Inf. Sci.* 36, 59–83. [https://doi.org/10.1016/0020-0255\(85\)90026-X](https://doi.org/10.1016/0020-0255(85)90026-X)
- Thinkstep A.G., 2019. GaBi.
- Traverso, M., Finkbeiner, M., Jørgensen, A., Schneider, L., 2012. Life Cycle Sustainability Dashboard. *J. Ind. Ecol.* 16, 680–688. <https://doi.org/10.1111/j.1530-9290.2012.00497.x>
- Vadlivia, S., Ugaya, C.M.L., Sonnemann, G., Hildenbrand, J. (Eds.), 2011. *Towards a Life Cycle Sustainability Assessment - Making Informed choices on products*. UNEP-DTIE, Paris.

- Wernet, G., Bauer, C., Steubing, B., Reinhard, J., Moreno-Ruiz, E., Weidema, B., 2016. The ecoinvent database version 3 (part I): overview and methodology. *Int. J. Life Cycle Assess.* 21, 1218–1230. <https://doi.org/10.1007/s11367-016-1087-8>
- Woodward, D.G., 1997. Life cycle costing—Theory, information acquisition and application. *Int. J. Proj. Manag.* 15, 335–344. [https://doi.org/10.1016/S0263-7863\(96\)00089-0](https://doi.org/10.1016/S0263-7863(96)00089-0)
- Yang, S., Ma, K., Liu, Z., Ren, J., Man, Y., 2020. Chapter 5 - Development and applicability of life cycle impact assessment methodologies, in: Ren, J., Toniolo, S. (Eds.), *Life Cycle Sustainability Assessment for Decision-Making*. Elsevier, pp. 95–124. <https://doi.org/10.1016/B978-0-12-818355-7.00005-1>
- Zamagni, A., 2012. Life cycle sustainability assessment. *Int. J. Life Cycle Assess.* 17, 373–376. <https://doi.org/10.1007/s11367-012-0389-8>
- Zamagni, A., Pesonen, H.-L., Swarr, T., 2013. From LCA to Life Cycle Sustainability Assessment: concept, practice and future directions. *Int. J. Life Cycle Assess.* 18, 1637–1641. <https://doi.org/10.1007/s11367-013-0648-3>
- Zimmermann, H.-J., 2001. *Fuzzy Set Theory—and Its Applications*. Springer Netherlands, Dordrecht. <https://doi.org/10.1007/978-94-010-0646-0>

Appendices

- A. Rulebase for 6 inputs LAND composite indicator
- B. Rulebase for 5 inputs WATER composite indicator
- C. Rulebase for 3 inputs AIR composite indicator
- D. Rulebase for 2 inputs HUMAN composite indicator
- E. Rulebase for 4 inputs ENVIRONMENT composite indicator
- F. Rulebase for 3 inputs LCSA composite indicator

A. Rulebase for 6 inputs LAND composite indicator

[illegible]

[illegible]

[illegible]

[illegible]

726	if GWP is GOOD and ADP_elements is GOOD and ADP_fossils is GOOD and TETP is GOOD and Acidification is AVERAGE and Eutrophication is GOOD then LAND is GOOD	0.000
727	if GWP is GOOD and ADP_elements is GOOD and ADP_fossils is GOOD and TETP is GOOD and Acidification is GOOD and Eutrophication is BAD then LAND is AVERAGE	0.000
728	if GWP is GOOD and ADP_elements is GOOD and ADP_fossils is GOOD and TETP is GOOD and Acidification is GOOD and Eutrophication is AVERAGE then LAND is GOOD	0.000
729	if GWP is GOOD and ADP_elements is GOOD and ADP_fossils is GOOD and TETP is GOOD and Acidification is GOOD and Eutrophication is GOOD then LAND is VERY_GOOD	0.000

B. Rulebase for 5 inputs WATER composite indicator

[illegible]

[illegible]

[illegible]

[illegible]

231 if GWP is GOOD and Eutrophication is GOOD and FAETP is AVERAGE and MAETP is AVERAGE and Acidification is GOOD
 then WATER is GOOD
 232 if GWP is GOOD and Eutrophication is GOOD and FAETP is AVERAGE and MAETP is GOOD and Acidification is BAD then
 WATER is GOOD
 233 if GWP is GOOD and Eutrophication is GOOD and FAETP is AVERAGE and MAETP is GOOD and Acidification is AVERAGE
 then WATER is GOOD
 234 if GWP is GOOD and Eutrophication is GOOD and FAETP is AVERAGE and MAETP is GOOD and Acidification is GOOD
 then WATER is VERY_GOOD
 235 if GWP is GOOD and Eutrophication is GOOD and FAETP is GOOD and MAETP is BAD and Acidification is BAD then
 WATER is AVERAGE
 236 if GWP is GOOD and Eutrophication is GOOD and FAETP is GOOD and MAETP is BAD and Acidification is AVERAGE then
 WATER is GOOD
 237 if GWP is GOOD and Eutrophication is GOOD and FAETP is GOOD and MAETP is BAD and Acidification is GOOD then
 WATER is GOOD
 238 if GWP is GOOD and Eutrophication is GOOD and FAETP is GOOD and MAETP is AVERAGE and Acidification is BAD then
 WATER is GOOD
 239 if GWP is GOOD and Eutrophication is GOOD and FAETP is GOOD and MAETP is AVERAGE and Acidification is AVERAGE
 then WATER is GOOD
 240 if GWP is GOOD and Eutrophication is GOOD and FAETP is GOOD and MAETP is AVERAGE and Acidification is GOOD
 then WATER is VERY_GOOD
 241 if GWP is GOOD and Eutrophication is GOOD and FAETP is GOOD and MAETP is GOOD and Acidification is BAD then
 WATER is GOOD
 242 if GWP is GOOD and Eutrophication is GOOD and FAETP is GOOD and MAETP is GOOD and Acidification is AVERAGE
 then WATER is VERY_GOOD
 243 if GWP is GOOD and Eutrophication is GOOD and FAETP is GOOD and MAETP is GOOD and Acidification is GOOD then
 WATER is VERY_GOOD

C. Rulebase for 3 inputs AIR composite indicator

- 1 if GWP is BAD and POCP is BAD and Ozone_depletion is BAD then AIR is VERY_BAD
- 2 if GWP is BAD and POCP is BAD and Ozone_depletion is AVERAGE then AIR is BAD
- 3 if GWP is BAD and POCP is BAD and Ozone_depletion is GOOD then AIR is AVERAGE
- 4 if GWP is BAD and POCP is AVERAGE and Ozone_depletion is BAD then AIR is BAD
- 5 if GWP is BAD and POCP is AVERAGE and Ozone_depletion is AVERAGE then AIR is AVERAGE
- 6 if GWP is BAD and POCP is AVERAGE and Ozone_depletion is GOOD then AIR is AVERAGE
- 7 if GWP is BAD and POCP is GOOD and Ozone_depletion is BAD then AIR is AVERAGE
- 8 if GWP is BAD and POCP is GOOD and Ozone_depletion is AVERAGE then AIR is AVERAGE
- 9 if GWP is BAD and POCP is GOOD and Ozone_depletion is GOOD then AIR is AVERAGE
- 10 if GWP is AVERAGE and POCP is BAD and Ozone_depletion is BAD then AIR is BAD
- 11 if GWP is AVERAGE and POCP is BAD and Ozone_depletion is AVERAGE then AIR is AVERAGE
- 12 if GWP is AVERAGE and POCP is BAD and Ozone_depletion is GOOD then AIR is AVERAGE
- 13 if GWP is AVERAGE and POCP is AVERAGE and Ozone_depletion is BAD then AIR is AVERAGE
- 14 if GWP is AVERAGE and POCP is AVERAGE and Ozone_depletion is AVERAGE then AIR is AVERAGE
- 15 if GWP is AVERAGE and POCP is AVERAGE and Ozone_depletion is GOOD then AIR is AVERAGE
- 16 if GWP is AVERAGE and POCP is GOOD and Ozone_depletion is BAD then AIR is AVERAGE
- 17 if GWP is AVERAGE and POCP is GOOD and Ozone_depletion is AVERAGE then AIR is AVERAGE
- 18 if GWP is AVERAGE and POCP is GOOD and Ozone_depletion is GOOD then AIR is GOOD
- 19 if GWP is GOOD and POCP is BAD and Ozone_depletion is BAD then AIR is AVERAGE
- 20 if GWP is GOOD and POCP is BAD and Ozone_depletion is AVERAGE then AIR is AVERAGE
- 21 if GWP is GOOD and POCP is BAD and Ozone_depletion is GOOD then AIR is AVERAGE
- 22 if GWP is GOOD and POCP is AVERAGE and Ozone_depletion is BAD then AIR is AVERAGE
- 23 if GWP is GOOD and POCP is AVERAGE and Ozone_depletion is AVERAGE then AIR is AVERAGE
- 24 if GWP is GOOD and POCP is AVERAGE and Ozone_depletion is GOOD then AIR is GOOD
- 25 if GWP is GOOD and POCP is GOOD and Ozone_depletion is BAD then AIR is AVERAGE
- 26 if GWP is GOOD and POCP is GOOD and Ozone_depletion is AVERAGE then AIR is GOOD
- 27 if GWP is GOOD and POCP is GOOD and Ozone_depletion is GOOD then AIR is VERY_GOOD

D. Rulebase for 2 inputs HUMAN composite indicator

- 1 if GWP is BAD and HTP is BAD then HUMAN is VERY_BAD
- 2 if GWP is BAD and HTP is AVERAGE then HUMAN is BAD
- 3 if GWP is BAD and HTP is GOOD then HUMAN is AVERAGE
- 4 if GWP is AVERAGE and HTP is BAD then HUMAN is BAD
- 5 if GWP is AVERAGE and HTP is AVERAGE then HUMAN is AVERAGE
- 6 if GWP is AVERAGE and HTP is GOOD then HUMAN is GOOD
- 7 if GWP is GOOD and HTP is BAD then HUMAN is AVERAGE
- 8 if GWP is GOOD and HTP is AVERAGE then HUMAN is GOOD
- 9 if GWP is GOOD and HTP is GOOD then HUMAN is VERY_GOOD

E. Rulebase for 4 inputs ENVIRONMENT composite indicator

- [illegible]

63 if LAND is GOOD and WATER is BAD and AIR is GOOD and HUMAN is GOOD then ENVIRONMENT is GOOD
64 if LAND is GOOD and WATER is AVERAGE and AIR is BAD and HUMAN is BAD then ENVIRONMENT is AVERAGE
65 if LAND is GOOD and WATER is AVERAGE and AIR is BAD and HUMAN is AVERAGE then ENVIRONMENT is AVERAGE
66 if LAND is GOOD and WATER is AVERAGE and AIR is BAD and HUMAN is GOOD then ENVIRONMENT is AVERAGE
67 if LAND is GOOD and WATER is AVERAGE and AIR is AVERAGE and HUMAN is BAD then ENVIRONMENT is AVERAGE
68 if LAND is GOOD and WATER is AVERAGE and AIR is AVERAGE and HUMAN is AVERAGE then ENVIRONMENT is AVERAGE
69 if LAND is GOOD and WATER is AVERAGE and AIR is AVERAGE and HUMAN is GOOD then ENVIRONMENT is GOOD
70 if LAND is GOOD and WATER is AVERAGE and AIR is GOOD and HUMAN is BAD then ENVIRONMENT is AVERAGE
71 if LAND is GOOD and WATER is AVERAGE and AIR is GOOD and HUMAN is AVERAGE then ENVIRONMENT is GOOD
72 if LAND is GOOD and WATER is AVERAGE and AIR is GOOD and HUMAN is GOOD then ENVIRONMENT is VERY_GOOD
73 if LAND is GOOD and WATER is GOOD and AIR is BAD and HUMAN is BAD then ENVIRONMENT is AVERAGE
74 if LAND is GOOD and WATER is GOOD and AIR is BAD and HUMAN is AVERAGE then ENVIRONMENT is AVERAGE
75 if LAND is GOOD and WATER is GOOD and AIR is BAD and HUMAN is GOOD then ENVIRONMENT is GOOD
76 if LAND is GOOD and WATER is GOOD and AIR is AVERAGE and HUMAN is BAD then ENVIRONMENT is AVERAGE
77 if LAND is GOOD and WATER is GOOD and AIR is AVERAGE and HUMAN is AVERAGE then ENVIRONMENT is GOOD
78 if LAND is GOOD and WATER is GOOD and AIR is AVERAGE and HUMAN is GOOD then ENVIRONMENT is VERY_GOOD
79 if LAND is GOOD and WATER is GOOD and AIR is GOOD and HUMAN is BAD then ENVIRONMENT is GOOD
80 if LAND is GOOD and WATER is GOOD and AIR is GOOD and HUMAN is AVERAGE then ENVIRONMENT is VERY_GOOD
81 if LAND is GOOD and WATER is GOOD and AIR is GOOD and HUMAN is GOOD then ENVIRONMENT is VERY_GOOD

F. Rulebase for 3 inputs LCSA composite indicator

1. if ENVIRONMENT is BAD and LCC is BAD and SOCIAL is BAD then LCSA is VERY_BAD
2. if ENVIRONMENT is BAD and LCC is BAD and SOCIAL is AVERAGE then LCSA is VERY_BAD
3. if ENVIRONMENT is BAD and LCC is BAD and SOCIAL is GOOD then LCSA is VERY_BAD
4. if ENVIRONMENT is BAD and LCC is AVERAGE and SOCIAL is BAD then LCSA is VERY_BAD
5. if ENVIRONMENT is BAD and LCC is AVERAGE and SOCIAL is AVERAGE then LCSA is BAD
6. if ENVIRONMENT is BAD and LCC is AVERAGE and SOCIAL is GOOD then LCSA is BAD
7. if ENVIRONMENT is BAD and LCC is GOOD and SOCIAL is BAD then LCSA is VERY_BAD
8. if ENVIRONMENT is BAD and LCC is GOOD and SOCIAL is AVERAGE then LCSA is BAD
9. if ENVIRONMENT is BAD and LCC is GOOD and SOCIAL is GOOD then LCSA is BAD
10. if ENVIRONMENT is AVERAGE and LCC is BAD and SOCIAL is BAD then LCSA is VERY_BAD
11. if ENVIRONMENT is AVERAGE and LCC is BAD and SOCIAL is AVERAGE then LCSA is BAD
12. if ENVIRONMENT is AVERAGE and LCC is BAD and SOCIAL is GOOD then LCSA is BAD
13. if ENVIRONMENT is AVERAGE and LCC is AVERAGE and SOCIAL is BAD then LCSA is BAD
14. if ENVIRONMENT is AVERAGE and LCC is AVERAGE and SOCIAL is AVERAGE then LCSA is AVERAGE
15. if ENVIRONMENT is AVERAGE and LCC is AVERAGE and SOCIAL is GOOD then LCSA is AVERAGE
16. if ENVIRONMENT is AVERAGE and LCC is GOOD and SOCIAL is BAD then LCSA is BAD
17. if ENVIRONMENT is AVERAGE and LCC is GOOD and SOCIAL is AVERAGE then LCSA is AVERAGE
18. if ENVIRONMENT is AVERAGE and LCC is GOOD and SOCIAL is GOOD then LCSA is GOOD
19. if ENVIRONMENT is GOOD and LCC is BAD and SOCIAL is BAD then LCSA is VERY_BAD
20. if ENVIRONMENT is GOOD and LCC is BAD and SOCIAL is AVERAGE then LCSA is BAD
21. if ENVIRONMENT is GOOD and LCC is BAD and SOCIAL is GOOD then LCSA is BAD
22. if ENVIRONMENT is GOOD and LCC is AVERAGE and SOCIAL is BAD then LCSA is BAD
23. if ENVIRONMENT is GOOD and LCC is AVERAGE and SOCIAL is AVERAGE then LCSA is AVERAGE
24. if ENVIRONMENT is GOOD and LCC is AVERAGE and SOCIAL is GOOD then LCSA is GOOD
25. if ENVIRONMENT is GOOD and LCC is GOOD and SOCIAL is BAD then LCSA is BAD
26. if ENVIRONMENT is GOOD and LCC is GOOD and SOCIAL is AVERAGE then LCSA is GOOD
27. if ENVIRONMENT is GOOD and LCC is GOOD and SOCIAL is GOOD then LCSA is VERY_GOOD