CHIST-ERA-19

SEEDS Project

Deliverable 2.3

Quantification of uncertainty associated with each scenario across multiple dimensions.

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3 Executive summary

Post-normal science acknowledges the limitations of existing knowledge and the existence of values and stakes and highlights the importance of embracing uncertainty in modelling and decision-making. The SEEDS project's objective is to engage citizens in the debate of possible futures of the energy system. Therefore, it is coherent with the framework of post-normal science since it acknowledges the existence of values and stakes and aims to foster public participation.

This deliverable addresses the second limitation of existent knowledge: its uncertainty. We disclose the three methods used in the project (participatory process, energy modelling Calliope and ENBIOS assessment of environmental impacts) and their possible uncertainties through the NUSAP pedigree matrix and sensitivity auditing. This assessment of uncertainty is also summarized to ensure the maximum information for the participants in preference statement in the webapp. We include this at the end of the deliverable (section 88). Also, a quantitative assessment of sensitivity is done for the ENBIOS part through Monte Carlo method.

Monte Carlo simulation suggests a variability of results of spore 0 similar to the dispersion of impacts in the option space of the 270 alternatives, being the highest for Freshwater Eutrophication and lowest for Global Warming. Additionally, our results show that the deterministic calculation is at the lower sections of the stochastic distribution of environmental impacts. This discrepancy underscores the importance of incorporating different techniques to account for uncertainty and variability in impact assessments.

4 Introduction

Energy transition is not a “*puzzle solving*” task, where we can find a completely deterministic optimum solution through scientific information. Instead, it is an inherently social challenge that requires both scientific information with different degrees of uncertainty and other kinds of knowledge and social debate in order to take decisions and make policy.

Public agreement and participation are decisive for the assessment of issues and acceptance of the costs. Over the last decades, an ambience of declining trust and increasing problems with the reliability of scientific knowledge in the public sphere has raised debate. In that context, transparency must be adopted when models are used as a basis for policy assessment (Saltelli & Funtowicz, 2014). It involves engaging multiple stakeholders, including experts, policymakers, and the public, in decision-making processes.

Post-normal science (PNS) (Funtowicz & Ravetz, 1994) is a mode of scientific inquiry suitable for addressing complex, uncertain and controversial issues. Post-normal science acknowledges the limitations of existing knowledge and the existence of values and stakes and highlights the importance of embracing uncertainty in decision-making.

The SEEDS project aims to address the disconnection between the modelling of pathways for the energy transition and stakeholder participation which is informed about the consequences of those pathways. It uses a PNS approach as it includes a human-computer loop to integrate in the assessment multiple points of view and values (expert and non-expert) and acknowledges the uncertainty of the modelling workflows.

In this report, we introduce the assessment of uncertainty, whose results will complement the energy and socio-ecological modeling results in the webapp. As proposed by Funtowicz & Ravetz (1994) and Saltelli (2019), we questioned to what extent, if any, our models are fit to represent the real world. Some tools can be used to make models more transparent and undercover unspoken beliefs underlying a model. In the methods section, we explain their characteristics. Afterwards, we apply them to each of the steps of the human-computer loop.

5 The SEEDS workflow

The workflow is consistent with PNS methods; featuring narrative assessment (Lisbon), modelling (Delft and Barcelona), and return and feedback (Tallin). The human-computer loop has started with an action-research-guided engagement process to identify key parameters to be included in energy and environmental modelling. Then, we calculated scenarios of energy transition for Portugal with the Calliope framework, considering suboptimal options for techno-economic factors. This analysis resulted in 261 pathways that were assessed with the ENBIOS tool to calculate their socio-environmental impacts. The results are to be shown in a webapp that is the project's flagship, and which is designed as a tool to support public decision-making. There are two rounds of webapp engagement. After the first round of selection of preferent scenarios by the webapp users, Calliope will be adapted to those preferences.

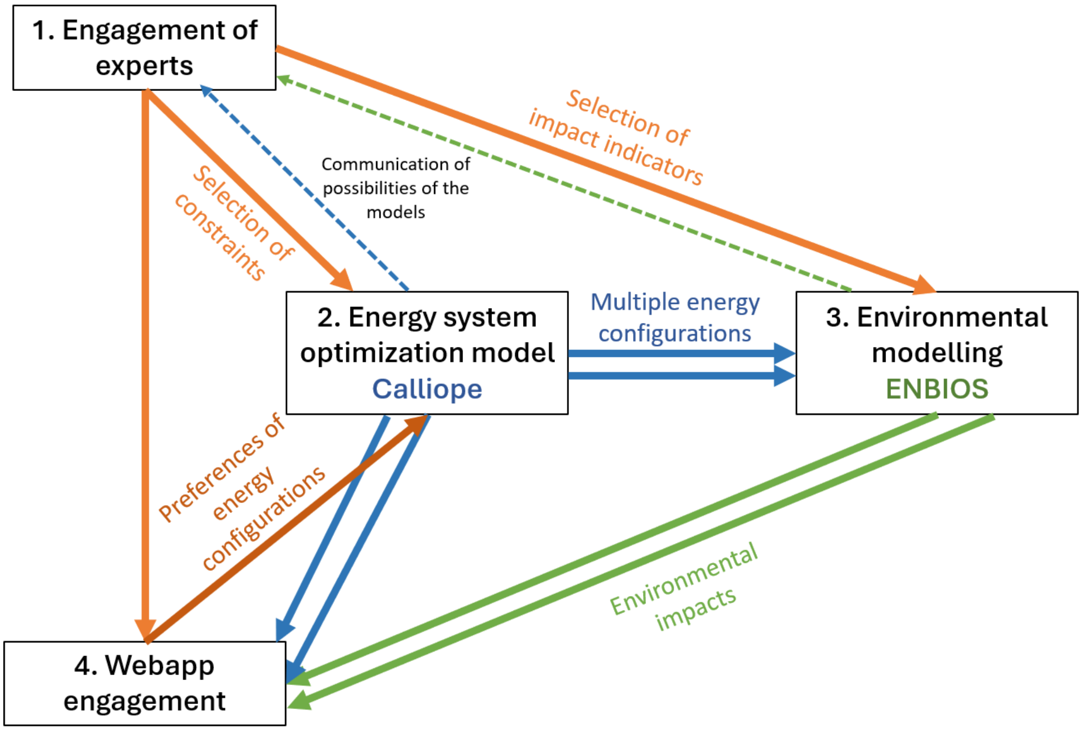

***Figure 1**: Integrated models and participatory processes in SEEDS with information flows linking them*

6 Methods

6.1 NUSAP

The NUSAP (*Numerical, Unit, Spread, Assessment, Pedigree)* is a notation system proposed by Funtowicz & Ravetz (1990), to address uncertainty in science for policy both quantitatively and qualitatively. The core function of this framework is to communicate uncertainty in a more structured and comprehensible way, making it particularly useful when dealing with complex, contentious, or policy-relevant issues.

The qualitative assessment is the characterization of the model's "*Pedigree*", which evaluates uncertainties operating at a deeper level of the model, by presenting the mode of production of quantitative information. The pedigree evaluation is done following a rubric-like pedigree matrix, which allows the user to make informal judgements of reliability, quality, and available knowledge (Funtowicz & Ravetz, 1990) . It also offers high flexibility and it can be adapted to the different models under study.

The analysis of the different models involved could be approached from different perspectives and resolutions, ranging from the evaluation of each input source to a more general view of the model. Pedigree matrixes have been used for models (Funtowicz & Ravetz, 1990), LCA inventories (Muller et al., 2016; Weidema & Wesnæs, 1996), and assumptions in models (Kloprogge et al., 2011; Pye et al., 2018; Vaughan & Gough, 2016). We propose a general overview of each model for various reasons: Firstly, the different models use a large number of inputs. Secondly, all that information could be overwhelming for the user to understand. Lastly, synthesizing all this information would be a highly time-consuming activity beyond this project's scope.

The Pedigree tries to acknowledge several dimensions of uncertainty the modelling process, and it is based on a structured scoring system. The proposed *Pedigree* matrix is shown in **Error! Reference source not found.**:

Score	Theoretical Structure	Data Input	Testing	Peer Acceptance	Model Independence
4	Established theory	Review-Database	Corroborated (peer tested)	Total	Total
3	Theory-Based Model	Historic field	Comparison	High	Very high
2	Computational Model	Experimental	Uncertainty analysis	Medium	Medium
1	Statistical Processing	Calculated	Sensitivity Analysis	Low	Low
0	Definitions	Expert-Guess	None	None	None

Table 1*: Pedigree matrix for SEEDS. Example for the Environmental Model*

This matrix aims to grasp the quality of the models/methods used in the project. Some of the levels might be currently unattainable, for example a model that is considered an "established theory" for forecasting future energy systems. The phases evaluated in the pedigree matrix we use here range from general scientific classifications, such as *theoretical structure* or *peer acceptance,* which are common for all the models involved, to more specific and model-related concepts (*Data Input* or *Testing). By analyzing the different phases:*

- **Theoretical structures:** This category is extracted from the *Scientific Pedigree Matrix* (Funtowicz & Ravetz, 1990). It tries to qualify the scientific method. This category ranges from "*Established Theory*", such as Einstein's relativity equations (corroborated and accepted with other theories), to *Definitions*, where the data is treated and collected following a routine.
- **Data Input:** This category is strongly dependent on the model under assessment. The best category for the energy model might not be the best for the environmental model.

The pedigree matrix from Table **1** follows the values proposed in the *pedigree matrix for environmental models* (Funtowicz & Ravetz, 1990). In these cases, since the data is not usually produced in the same project, the "*review*" is the best option. *Experimental* is lower than *historic/field* given that laboratory data could not reflect the field conditions of the model.

- **Testing:** This phase refers to the validation of the models, a process focused on determining whether the model accurately represents the behaviour of the system (Kerr& Goethel, 2014). Models can be validated by comparing the output to independent field or experimental data sets that align with the simulated scenario. However, operational validation using field data might not be possible when the simulated scenario extends outside the realm of observed conditions (such as climate forecast). The truth is that any particular testing procedure might be ideal for one modelling approach, but inappropriate for others (Kirchner et al., 1996). However, modelers should be requested to disclosure the tests that they have conducted or the fact that the model has not been tested at all.
- **Peer acceptance:** This category tries to catch the state of the art of the model employed among other experts in the field.
- **Model Independence:** Also regarded as "*relation with other models*", this category tries to capture the accumulated error (either coming from assumptions or data input). For instance, if a model is dependent on the output of 3 other models, each of them with different data sources, the accumulated error would be higher than each of these three models.

6.2 Sensitivity auditing (SAUD)

The pedigree matrix gives a qualitative indication of the uncertainty underlying the different models, data and assumptions. However, enhanced vigilance is needed in drawing model-based inferences for policy (Saltelli & Funtowicz,2014). It is based on a checklist covering the following points:

- **Check against rhetorical use of mathematical modelling:** This rule prescribes avoiding overelaborated models that allow hiding assumptions and even inferring the desired results (models used ritually and to confirm preexistent views), and establish a disguise of objectivity behind complex formal structures: ***"****Are large models being used where simpler ones would suffice?"*(Lo Piano et al., 2023)
- **Assumption hunting:** The auditing process should aim to identify all the assumptions (both implicit and explicit) underlying the model.

- **Detect garbage in garbage out (GIGO):** This refers to some bad practices in science that try to constrain the uncertainties in the inputs to boost the model's certainty. For example, the use of one-size-fits-all probability distributions that do not reflect real knowledge of uncertainty (Lo Piano & Benini, 2022). It also works in the opposite direction; some modelers could bloat models' inputs to prevent regulators from making decisions. For example, how tobacco companies and climate deniers have created uncertainty by denying the scientific evidence (Oreskes & Conway, 2010).
- **Anticipate criticism:** The modeler should find sensitive assumptions by doing state-of-the-art sensitivity and uncertainty analysis before publishing it.
- **Perform Uncertainty Analysis and Sensitivity Analysis**
- **Do the right sums:** Sensitivity and uncertainty analyses are of no use if the model is not capturing well the system or not assessing the "correct" problem, for example excluding perspectives from stakeholders, or relevant dimensions.
- **Aim for transparency:** The modelers should avoid black box models. There must be an exercise for communicating model assumptions and uncertainties and allowing third parties to replicate the results.

Hence, a list of questions addressing SAUD rules has been proposed for each modelling group involved in this project. The questions range from a brief description of the model to the identification of the assumptions made, including the testing and validation procedures.

7 Analysis of uncertainty

7.1 Participatory process

7.1.1 Model explanation

Using the energy transition in Portugal as a pilot case, we began by identifying three critical branching points which guided the analysis of criteria, considering political, economic, technological, social, and environmental factors, towards fostering more democratic and socially engaging energy transition scenarios and policies. We engaged both expert stakeholders and citizens, by taking stock of the results of a Delphi study and a workshop with 19 stakeholder experts, to collect insights into the sociopolitical acceptance of citizens regarding different renewable energy technologies.

The Delphi method was implemented between May and November 2022, to enable the identification and selection of criteria (Belton et al., 2019; Flostrand et al., 2020a). The Delphi was complemented by a workshop exercise in which participants were asked to critically assess extreme scenarios that reflected the critical branching points (McGookin et al., 2021).

The Delphi approach supports the identification and/or valuation of criteria to inform new policy pathways (Förster & von der Gracht, 2014). It is usually described as a foresight methodology, as it is often applied in studies seeking to gain insights into different possibilities for the future (Aengenheyster et al., 2017). The key principles of the methodology include the anonymity of experts, repetitiveness, and feedback, presenting the results in the form of statistical analysis, and offering participants the possibility of reviewing and reconsidering their answers(Hirschhorn, 2019). These principles were upheld throughout this study, and all panel participants provided informed consent and were duly informed about the process, following strict ethical guidelines.

The Delphi involved ten energy and climate experts, including policy (2 experts), technology and market (5 experts), and civil society (3 experts). The Delphi involves successive rounds of questionnaires until consensual decisions are achieved. In our case, this resulted in three rounds of questioning, consisting of: i) a set of open questions for the first-round questionnaire; ii) 43 closed questions, in which panel participants were asked to evaluate from 1 (not important) to 9 (extremely important) each of the criteria related to the key topics identified in the first round; iii) an attempt to reach a consensus among respondents; in this last round, only the questions for which there was no consensus in the previous round were included.

Afterwards, a workshop involved a second panel of stakeholders, invited to participate in an online event, in which an exercise was implemented to foster a discussion around three pairs of extreme scenarios. The participatory exercise introduced a wider reflection on stakeholder concerns regarding the dynamics of the energy system being modelled. A total of 19 participants attended the participatory exercise, which took place in November 2022, representing market (5 participants), policy (2), civil society and academia (7) and community stakeholder groups (5).

7.1.2 Sources of uncertainty

Participatory and co-production approaches are critical to addressing complex problems, as citizens, stakeholders and policymakers are faced with a wide range of solutions. These dynamics are particularly relevant in energy transition studies since the interconnectedness of energy systems calls for decision-making methods capable of integrating diverse criteria (Bhardwaj et al., 2019). The integration of stakeholder preferences with technologically rich energy systems modelling is thus a crucial pathway towards describing viable and desirable energy futures. Such integration can include a wide range of participatory approaches for supporting decision-making processes about different modelled scenarios and outputs.

In this context, one common framework is participatory multi-criteria decision-making (MCDM), which has been applied to support decision-making, and to enable evaluating and deciding between conflicting ideas for determining the best alternative when weighting different criteria (Siksnelyte-Butkiene et al., 2021). More specifically, we followed a methodological strategy based on a participatory enquiry for selecting and weighting criteria (Wang et al., 2009) by taking stock of a Delphi method for criteria selection and of a pairwise comparison with a wider group of participants for weighting the different criteria.

Within this methodology (see upcoming article, Campos et al., 2023), a series of questions were arrived at, for which a consensus between participants of the different workshops was attempted. Regarding the questions for which no consensus was reached, the pairwise methodology was utilized, following the method described in (Shaaban et al., 2018). This method offers a ranking of the different criteria and was performed by asking 55 participants how they rated one criterion compared to another, in terms of relevance, on a scale of 1 to 9.

In each step of this methodology, we followed the best practices in terms of convergence of opinions and consistency checks, thus minimizing the overall uncertainty of the results. In choosing the participants for the workshops we aimed for a high degree of representativeness, in terms of stakeholders engaged with the energy transition in Portugal. We thus have a high level of confidence in the results (preferences) that were obtained. However, we cannot be entirely sure that a completely different set of stakeholders might not have produced slightly different results. This level of uncertainty can be quantified by looking at our results more carefully (see upcoming article, Campos et al., 2023).

7.1.3 Sources of uncertainty

We list below all the main assumptions underlying our participatory process approach.

- *Problem framing*: The definition of the open questions for the first-round questionnaire (in the Delphi methodology) was informed by the previously identified branching points, resulting from a regulatory and policy documentary review, and by the input provided by energy system modelling experts (Madrid-Lopez et al., 2021; Pfenninger & Pickering, 2018a).
- *Choice of participants*: Participants were selected from among those who had participated in the first project webinar and a SEEDS survey carried out in 2021, which involved academics, policymakers, industry representatives and civil society representatives (Campos et al., 2022)
- *Definition of consensus in the Delphi methodology*: Although there is no universal agreement on what is considered a consensus, it is generally accepted that recommendations are positive when they vary between 51% and 100% (von der Gracht, 2012). Thus, the assumption for reaching consensus was achieving a value for the interquartile range of the different replies lower or equal to 1.

7.1.4 Testing

As this is not a numerical model (but theory-based), the issue of testing does not come up in a straightforward manner. However, the validation of the procedure included the different steps in the Delphi approach. Thus, in the third round of the Delphi, a total of 77% consensus was reached (i.e. percentage results from the number of consensuses divided by the number of questions in the round). This included a consensus (i.e., the interquartile range for each question is lower or equal to 1) of 100% on all the questions related to the new technologies and decarbonization issues, 88% on new policies, 83% consensus on aspects related to a sustainable transition, 67% regarding land use management, lithium mining, and environmental and resource information, and, finally, 50% on public acceptance issues (Campos et al., 2024, forthcoming).

7.1.5 Alternatives

There is a wide range of alternative related methods There are diverse types of Delphi approaches (e.g., policy, classical, decision-making) (Flostrand et al., 2020b). The Delphi applied in this study was a policy Delphi study, which primarily seeks to explore and discuss different policy directions for the future (Linstone & Turoff, 2011). It was chosen due to the group's familiarity with this methodology and the fact that it is a very well-established method, used in a wide variety of multiple-criteria decision-making studies in different areas of governance.

The main strengths of the method employed include the iterative nature of the Delphi process, the possibility for the stakeholders to refine their opinions and the friendly atmosphere of the events, which encouraged frank exchange of points of view. The main weakness is the relatively low number of participants in the first Delphi process (10), although still in line with many related studies and within the limits of the validity of the method. The impact of the weakness was partially mitigated by the following workshop (for which a "world café" technique was chosen, with 19 participants) which further validated the criteria resulting from the Delphi analysis.

7.1.6 Pedigree Matrix

The underlined terms (below) reflect the self-assessment made for our participatory process. The output vector is (3,2,2,3,3), according to this assessment.

Score	Theoretical structure	Data Input	Testing	Peer Acceptance	Model Independence
4	Established theory	Review-Database	Corroborated (peer tested)	Total	Total
3	Theory-based model	Historic field	Comparison	High	Very high
2	Computational model	Experimental	Uncertainty analysis	Medium	Medium
1	Statistical Processing	Calculated	Sensitivity analysis	Low	Low

0	Definitions	Expert-Guess	None	None	None

Table 2: *Pedigree matrix for the participatory process*

7.2 Energy modelling

7.2.1 Model explanation

We model the energy system of Portugal based on the open-source modelling framework Calliope (Pfenninger & Pickering, 2018b). In particular, we build on the existing Sector-Coupled Euro-Calliope (SC-EC) model generator (Pickering et al., 2022) that allows to create Calliope-interpretable model datasets for any European country, including all energy sectors and several sub-national regions for renewables deployment. More information on the SC-EC model generator and the underlying data sources and assumptions are available as part of the associated publication (Pickering et al., 2022).

7.2.2 Sources of uncertainty

Calliope is affected by two macro-categories of uncertainties: *parametric* and *structural*. Parametric uncertainty is associated with the uncertainty of input parameters, such as costs, weather data and demand time series. Structural uncertainty, instead, refers to the irreducible gap between the model formulation and the real world, particularly as regards the model's capacity to approximate the complexity of real-world decision-making processes.

In the SEEDS project, we address structural uncertainty explicitly, by acknowledging the impossibility of conventional model optimisation methods to resolve the plurality and complexity of views of real-world stakeholders. In fact, rather than using the model to search for a single, deceptively "optimal" solution influenced by uncertainty, we generate a broad range of equally feasible and economically comparable system design alternatives near the mathematical optimum via our in-house SPORES algorithm. The idea is that those shall facilitate, thanks to the interface developed by TLU's project partners, stakeholder's appraisal of the trade-offs between the many possible options and, ultimately, the identification of a consensus solution within the extended peer community of stakeholders and scientists, in line with PNS principles. Furthermore, the SEEDS project foresees, the first of its kind, a second iteration in the process that generates the alternatives for stakeholders' appraisal. Such a second iteration builds automatically on stakeholder preferences collected through the interface during a first interactive stakeholder engagement and uses these preferences to guide the SPORES search more effectively towards the discovery of feasible options that match stakeholder needs on their way to the identification of a consensus solution. This human-in-the-loop (HIL) approach to the generation of alternatives makes stakeholders part of the computational workflow itself and allows addressing structural uncertainty even further.

Parametric uncertainty is, instead, something we do not focus on within the SEEDS project. Based on recent work of our team using the same model version but expanded to the whole European system (Tröndle, 2020) we have found the variations in the model's results brought about by parametric uncertainty (in terms of weather, demand, and cost assumptions) to be largely incorporated by the range of results generated via the above SPORES approach. What is more, the testing of a different parametric assumption would lead to the generation of a whole new set of system design alternatives, which would be difficult to resolve in a user-friendly way within the interface for stakeholders' navigation of the option space. We deem therefore sensible not to overload stakeholders with such information and to focus solely on the exploration of system design possibilities opened by our addressing of structural uncertainty.

7.2.3 Assumptions

We list below all the main assumptions underlying the above model of the Portuguese energy system, dividing them into three macro-categories: narratives, model structure, and parameters.

Narratives.

- *Problem framing*: Techno-economic problem, relaxed to account for unmodelled objectives. Identification of broad ranges of carbon-neutral and energy-self-sufficient system designs for the entire Portuguese energy system.
- *Scenarios*: No scenarios but an exploration of 260 maximally different feasible system designs within 10% of the lowest feasible system cost.
- *Policy targets and boundary conditions*: no net CO2 emissions (bioenergy is considered carbon-neutral), in line with European targets for 2050. Limited imports of energy from outside Portugal, to avoid optimistic assumptions about the availability of energy from other countries.

Model structure.

- *Mathematical formulation*: linear programming (LP) generation of alternative feasible system designs starting from the least-cost feasible solution. The generation of alternatives is based on the SPORES algorithm, an original advancement of MGA methods.
- *Key decision variables*: which technologies to deploy and where. This includes end-use conversion technologies, which means the model decides whether to electrify a given use of energy or rely on carbon-neutral fuels.
- *Explored solution space*: 260 feasible system designs within 10% of the lowest feasible system cost (near-optimal solutions).
- *Geographical scope*: Portugal, 2 main nodes (North and South) for demand and non-electric sectors (heat, transport, industry) and 18 sub-nodes for finer detail on renewables deployment

potentials and decisions. No single sub-node can install more than 30 GW of capacity to avoid unrealistic over-concentration of capacity in the model. Limited imports or exports of energy from outside the country.

- *Temporal scope*: one representative year, 3-hour resolution. The system is designed considering the lifetime of technologies and their annualized cost. There is no analysis of system evolution through time to reach the end-state design.

Parameters and conventions.

- *Costs*: projections considering 2050 as the desired end state. Detailed sources are provided for each technology as comments in the associated input files, available on Zenodo (Pickering, 2022) for the parent model.
- *Interest rates*: uniform interest rate of 0.073 based on the average wind onshore WACC, under the assumption that wind onshore is one of the most deployed technologies. The source is reported in the associated input file.
- *Weather conditions*: 2016 reference weather year as the most recent available year of full model data.
- *Demand*: all existing demand for energy in the considered country, including electricity, heat, mobility and industry demands. Industry demand comprises both energy and fuel feedstock demands. Demand values and time series are always linked to the chosen weather year for consistency.
- *Technologies*: only existing or commercially mature generation, storage, conversion and transmission technologies, with a few unavoidable exceptions (for instance, in the production of some synthetic fuels).
- Exogenous factors: the use of energy in industrial processes that can be electrified based on today's technology is electrified by default, assuming this is the most desirable option. The rest must be met via fuels.

Other relevant aspects beyond the model scope.

- *Technologies*:
  - No carbon capture and storage not deemed technically and economically mature.
  - No direct use of hydrogen for road transport or building heat due to the need for an overhaul of transmission networks as well as end-use technologies to enable distributed hydrogen use and the emerging market dominance of electrification, for instance, in passenger and freight vehicles.

7.2.4 Testing

The Calliope software internal code is tested with a comprehensive suite of automated software tests and has been used in a large range of peer-reviewed publications (Research | Calliope, 2023.). Furthermore, being completely freely and openly available, Calliope ensures transparency and reproducibility. The SC-EC model generator, which we use to structure and populate with Calliope-interpretable data our model of the Portuguese energy system, is also openly available on GitHub and has been published in a peer-reviewed study. Sense-checks of the results generated by the model have been carried out internally for the project.

7.2.5 Alternatives

A Similar high-resolution, cross-sectoral energy system model of Portugal could be built with a variety of open or commercial modelling frameworks. However, there are fewer alternatives when open-source is required. Nevertheless, the bottleneck on the way to this type of modelling is represented by data availability, more than by model capabilities. The above SC-EC model generator allows us to deal with data generation for all sectors and desired sub-national regions in a rigorous and reproducible way. The only model generator with comparable capabilities that we are aware of is PyPSA-Eur (Hoersch et al., 2018).

7.2.6 Pedigree matrix

The underlined terms reflect the self-assessment made.

Score	Theoretical structure	Data Input	Testing	Peer Acceptance	Model Independence
4	Established theory	Review-Database	Corroborated (peer tested)	Total	Total
3	Theory-based model	Historic field	Comparison	High	Very high
2	Computational model	Experimental	Uncertainty analysis	Medium	Medium
1	Statistical Processing	Calculated	Sensitivity analysis	Low	Low
0	Definitions	Expert-Guess	None	None	None

Table 3: *Pedigree matrix for the energy system model*

7.3 ENBIOS assessment – LCA part

7.3.1 What is this model doing?

For the calculation of the environmental impacts an open-source tool ENBIOS (Enbios · PyPI, 2023) was used. It combines Life Cycle Assessment (LCA) with Multi-Scale Integrated Analysis of Societal and Ecosystem Metabolism (MuSIASEM) methodologies.

According to the definition provided by the European Environmental Agency (Life Cycle Assessment — European Environment Agency, 2023.) "*life cycle assessment is a process of evaluating the effects that a product has on the environment over the entire period of its life thereby increasing resource-use efficiency and decreasing liabilities. It can be used to study the environmental impact of either a product or the function the product is designed to perform*". LCA aims to consider all the inputs and outputs (elementary biosphere and technosphere flows) of a process during all the stages of its life cycle. The enormous number of impacts and resource uses from the environment are translated into more grouped categories of environmental impacts (midpoint and endpoint indicators). The amount of each relevant biosphere flow is multiplied by a characterization factor according to the indicator.

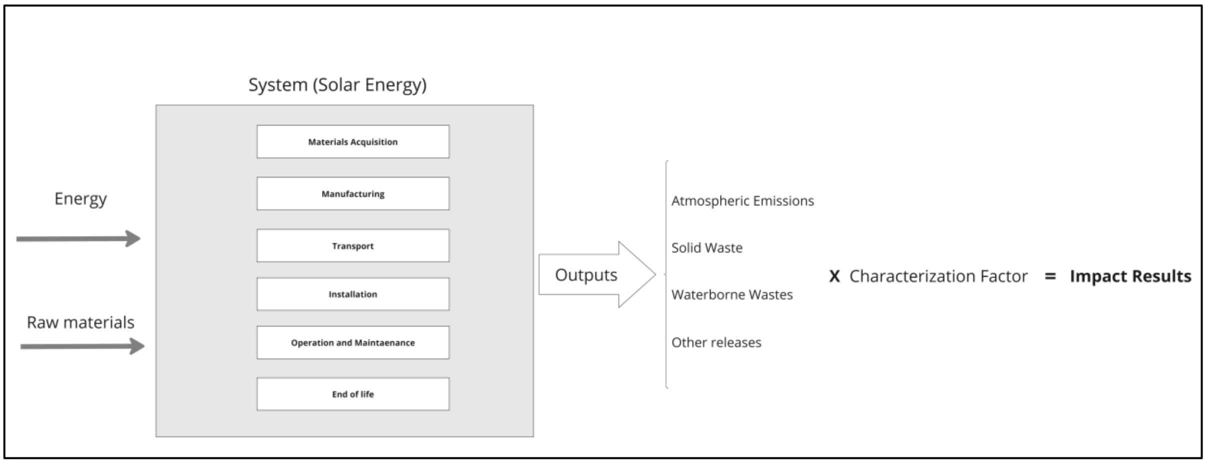

Figure 2*: Conceptual representation of LCA.*

A conventional LCA study (such as this case), uses goal and scope criteria and foreground data as inputs (International Organization for Standardization, 2006). For more information regarding the LCA configuration of this study, see (de Tomás-Pascual et al., 2024)

For the generation of results shared with the users, MuSIASEM was only used for functional hierarchical grouping and classification purposes and for framing the definition of the LCA.

7.3.2 Sources of Uncertainty in LCA

According to Walker et al. (2003), the use of LCA as a decision support can be hampered by numerous uncertainties embedded in the calculation. He identified three different dimensions of uncertainty: (i) location; (ii) level; (iii) nature. Level refers to the degree of uncertainty. Nature refers to the relation of uncertainty with reality and can be divided into two types: epistemic (due to the lack of knowledge), and ontic (inherent variability of the system) (Igos et al., 2019).

Location refers to the position of uncertainty within the modelling framework. Igos et al., (2019) proposes the following categories:

- **Quantity**: Refers to the uncertainty present in the input data (*inventory data),* and the impact assessment methods (*characterization factors*). In this study, the quantitative is restricted to the inherent uncertainty present in the databases used (ecoinvent 3.9.1 cutoff) (Wernet et al., 2016), and the characterization factors coming from the ReCiPe methods (M. Huijbregts et al., 2016).
- **Model structure:** This category represents the mismatch between the mathematical model and the real structure of the system. This includes some assumptions of linearity in the input-output response or the application of generic characterization factors for specific local conditions. Check section 6.3.3 for more information regarding the assumptions.
- **Context:** It refers to the fact that the modeler makes methodological choices related to the definition and construction of the model (e.g, definition of goal and scope, end-of-life rules, allocation rules, among many others). The decisions taken are listed in Table 2. Additional information regarding the setup can be found in (de Tomás-Pascual et al., 2024).

Table 4: Context uncertainty items. Decisions taken by the modeler.

Source	Decision
Goal and Scope	Limited scope due to availability in the data and methodological limitations. Only *generation, storage, conversions,* and *imports* were studied.
Technological representativeness	Dependent from the database Ecoinvent 3.9.1. Check annex from (de Tomás-Pascual et al., 2024)
Geographical representativeness	National Level. Activity with location "PT" selected in the inventory database when available. If not, the closest geographical activity was selected as a proxy. Regionalization of the impacts has not been applied.
Variability of performance characteristics	Only the modification of the local electricity mix was considered.
Temporal representativeness	*Business as usual* approach. No prospective adaptation of the inventories.

Representativeness of the environmental impacts	Indicators were selected based on the Delphi analysis. Midpoint indicators were chosen in order to get a more comprehensible result. For more information regarding the methods, check M. Huijbregts et al., (2016). However, some of the indicators chosen in the Delphi analysis do not exist in LCIA methods as they would have been expected in the Delphi (e.g. land use (Milà I Canals et al., 2007)).
Multifunctionality	Allocation presented in the inventory database

Furthermore, this type of analysis suffers from a particular source of epistemological uncertainty. When trying to assess future impacts, the inherent uncertainty of the future arises (Björklund, 2002; Mendoza Beltran et al., 2020). This case is common among prospective LCA studies.

7.3.3 Assumptions

In the setup of the model different assumptions (implicit and explicit) were introduced.

Inherent to LCA studies:

- **Linearity in technology scalation**: In LCA the product systems scale up linearly. This means that the impact of demanding 1000 units will be 1000 times bigger than demanding 1 unit. However, as pointed out by Pizzol et al., (2020) real-world systems are more complex and do not follow such a linear trend. With emerging technologies, for instance, a massive increase in production volume leads to a reduction in the environmental burden thanks to economies of scale and technological learning. Nevertheless, a particular study of non-linear trends in emerging technologies was out of the scope of this study. This might affect the results of technologies such as hydrogen, batteries, and thermal storage.
- **Linearity in dose-response**: In LCA it is assumed that the impact of the first unit remains the same as the impact of the last unit emitted. This means that the impact increases following a linear trend. However, in other fields such as biology, it is well known that the dose response of a chemical over a biological component does not follow a linear behavior.
- **Deterministic values for the characterization factors:** Although some studies are recognizing the inherent uncertainty in characterization factors, such as (M. A. J. Huijbregts et al., 2003), most of them focus only on a few impact categories or do not present an easy methodology for integrating this uncertainty in LCA (Santos et al., 2022). This author has proposed a methodology for including stochastic calculations for the LCA characterization factors.

Specific assumptions in the case study:

- **Business as usual approach:** It has been considered that the efficiency of technologies will remain the same in 2050. In other words, no inventory modifications were considered. Although it could seem a notable assumption, the value of the calculation is not the amount of the final impact itself, but the comparison among different configurations.
- **Inventory representativity:** the modeler chooses the most similar technologies in ecoinvent for those in the model. Therefore, the inventory data corresponds to existing technology, and this will capture represent only broadly the actual behavior of the system in the future. This assumption carries multiple uncertainties (quantitative, context, and ontic).
- **Scope:** Due to some methodological issues, we did not include end-use activities modeled in the Calliope framework. Besides, some others were not included:
    - Hydrogen imports and exports
    - Conversion of hydrogen (hydrogen to methanol/methane/liquids).
    - DAC

  Furthermore, the transport of electricity is not explicitly modeled. This means that the scope of the environmental analysis is not covering the energy system fully.

7.3.4 Sensitivity and Uncertainty Analysis

Spearman correlation was used as a sampling technique to analyze the correlation between the demand for different technologies considered and the total impact related to that spore. This technique has been applied by several authors to analyse the uncertainty regarding different inventories (Chen & Corson, 2014; Geisler et al., 2005; Groen et al., 2017; Heijungs & Lenzen, 2014; Mattila et al., 2012; Mattinen et al., 2014). In our case, we analyse quantitative uncertainty related to the different coherent configurations according to the constraints defined in Calliope. These are the inventories for the foreground LCA in Enbios. The fact that we are dealing with 261 and 271 systems, each with different energy configurations, already distributes the input for the analysis.

Monte Carlo simulations are used to calculate the uncertainty related to a single configuration by allowing for stochastic variations in LCA modeling. This provides insights into uncertainty propagation.

7.3.4.1 Spearman correlation

Spearman rank correlation coefficients determine the influence of the input data (here, the energy mix at level n-3) on the output distribution (environmental impacts) (Groen et al. 2017; Saltelli and Marivoet 1990). The relations between the input values (energy mix) and the environmental impacts for each indicator help in understanding what technologies are correlated to impacts and looking for alternative inventories if it is considered that their uncertainty might be a key influencing factor.

In (de Tomás-Pascual et al., 2024) we presented Spearman correlation figures to analyse the results. These same values can be read from a sensitivity analysis perspective. Values with the highest absolute index tend to drive the model.

7.3.4.2 Monte Carlo simulations

In order to assess the accumulated uncertainty in LCA, we conducted Monte Carlo simulations consisting of 200 iterations for spore 0. When comparing the results obtained from the Monte Carlo simulation to the static analysis, we find that the variability of the Monte Carlo simulation generally lies within the variability of the option space of spores. The largest dispersion is for freshwater eutrophication and the smallest, for global warming. The static impact is located towards the lower end of the standard error distribution. This suggests that the static calculation might underestimate the environmental impacts of the configurations, according to the uncertainty distributions in ecoinvent.

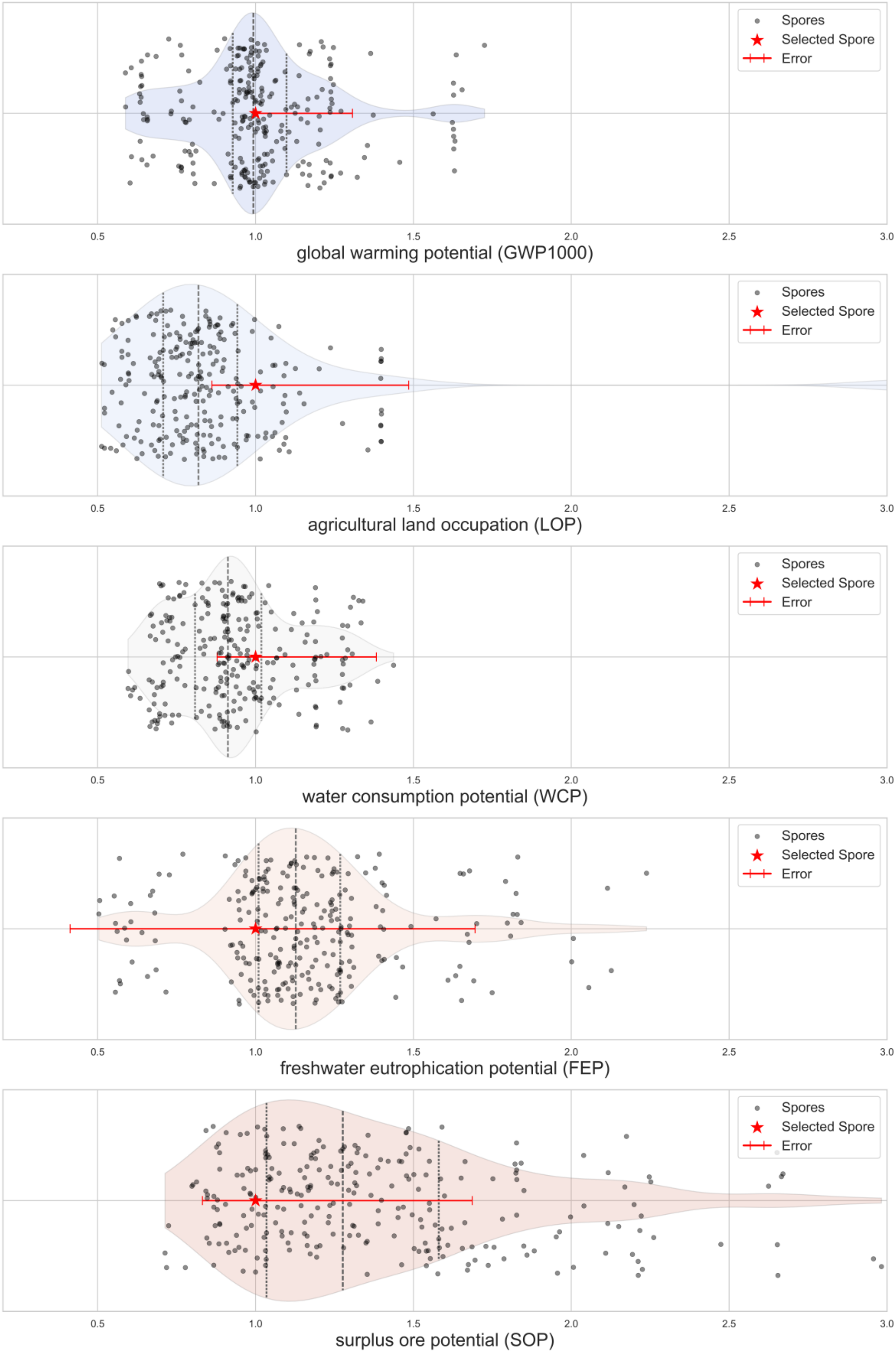

Figure 3: *Environmental impacts of 261 energy system configurations (spores). Results are normalized by the selected spore (0). The red line highlights the standard deviation of the stochastic values of the spore 0 using Monte Carlo.*

7.3.5 Alternatives

Based on the first criteria mentioned in the Sensitivity Auditing process *"check against the rhetorical use of mathematical modelling",* Life Cycle Assessment is a simple and powerful option. According to the European Commission (European Commission, 2023), Life Cycle Assessment is the best methodological tool currently available for assessing the environmental impact of a system's life cycle. However, some other tools are available:

- Ecological Footprint Analysis
- Input-Output analysis

7.3.6 Pedigree matrix

The underlined terms reflect the self-assessment made for the environmental analysis.

Score	**Theoretical Structure**	**Data Input**	**Testing**	**Peer Acceptance**	**Model Independence**
4	Established theory	Review-Database	Corroborated (peer tested)	Total	Total
3	Theory-Based Model	Historic field	Comparison	High	Very high
2	Computational Model	Experimental	Uncertainty analysis	Medium	Medium
1	Statistical Processing	Calculated	Sensitivity Analysis	Low	Low
0	Definitions	Expert-Guess	None	None	None

***Table 5**: Pedigree matrix for the environmental model*

8 Text for the web

In this section, there is the text that we included in the webapp for transparency with its users.

8.1 Models as tools to explore possible futures

Models do not predict the future since forecasting social systems is an impossible task. Our model has generated **261 possible future energy systems** in Portugal within the objectives of carbon neutrality and close to cost minimization, called spores. These scenarios have different configurations (energy mix and regional distribution) with a concomitant diversity of costs and impacts: investment, employment, income, landscape, etc. The impacts shown here are *climate change*, *agricultural land occupation*, *natural land transformation*, *metal depletion* and *water depletion*, which were selected during a participatory process. Different stakeholders will evaluate differently the importance of these dimensions according to their values, stakes and knowledge, which will make those possible futures more or less attractive. One of the reasons why social systems are not forecastable or controllable is that they depend on decisions at different scales where these different values, knowledge and interests are put into practice: companies' decisions and interests, market dynamics, individuals' choices, and political decisions that aim to reach different visions of the future. Policy-making therefore cannot be simply based on "scientific evidence", but on a political debate and compromise of visions and interests of the different stakeholders.

Since models cannot be expected to be "prediction tools", we use models as tools for broad and diverse audiences to state their preferences but also for learning and social debate. Through this webapp, the general public can **explore** these possible futures and **express their preferent spores.**

To ensure a totally informed opinion, we are presenting how the methods and models in this app work and how they might be not exact. This inexactitude is not a matter of this work only, but it is inherent in any model and exploration of plausible futures. So what we are doing here is only exposing it transparently. In the following sections, we present the general structure of the model in this app and its uncertainty is qualitatively described.

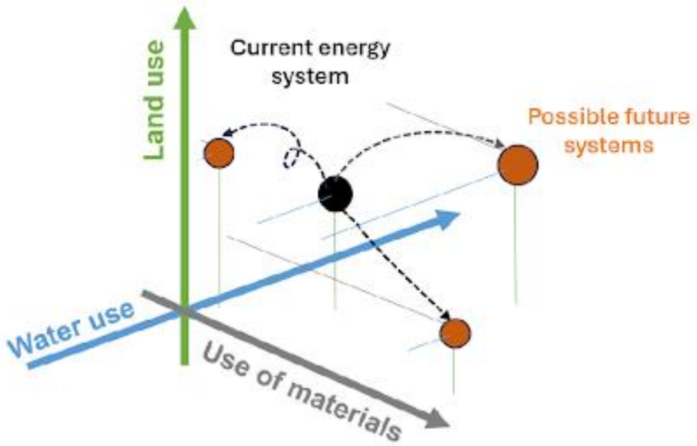

Figure 4: *Energy systems and environmental implications*

8.2 The uncertainty of models

Some of the reasons models cannot predict the future are the uncertainty in data, model assumptions and structure. Models are by definition **representations and simplifications of reality**. Nowadays, there are hundreds of models of energy systems, which focus on specific subsectors or aim to address the whole energy system, include more or less dimensions, and currently available or expected technologies or have different spatial and temporal resolutions.

Each type of model could address issues such as the scale of centralisation and regional distribution of renewables, storage or demand response requirements, or the speed of transition. We cannot model every aspect at the same time for computing power limitations. Results are affected by **modelling** choices: possible underrepresentation of certain aspects (choice of boundary of the system and resolution), the way processes and relationships are represented (equations and algorithms), etc.

Moreover, the **data** used to build models is difficult to be exact: older data, non-geographically specific, problems with measurement equipment, estimation of characteristics and cost of future technologies (e.g., technologies in development phase not in use yet or future improvements in current technologies), estimation of availability of materials, etc. In general, the analysis of future configurations of the energy system involves a high level of uncertainty due to the unknown characteristics and even the existence of future technologies. These go from the efficiency of wind turbines to the feasibility of large-scale carbon capture and storage.

8.3 General structure of the model

The model in this app is made of two different models that are ensembled: Calliope and ENBIOS. This means simply that the outputs of the model generating low-carbon scenarios are the inputs for the model calculating the rest of impacts.

The conditions for the energy model and the environmental impact indicators were selected through a participatory process. Then, the energy model (Calliope) generates 260 possible energy system configurations following conditions of low cost and net-zero direct CO2 emissions. Finally, the environmental model (ENBIOS) calculates the environmental impacts of those 260 configurations. The scope of the model is the whole energy system of Portugal in 2050. Therefore, we are not analysing the transition pathway but only the possible final configuration of the system.

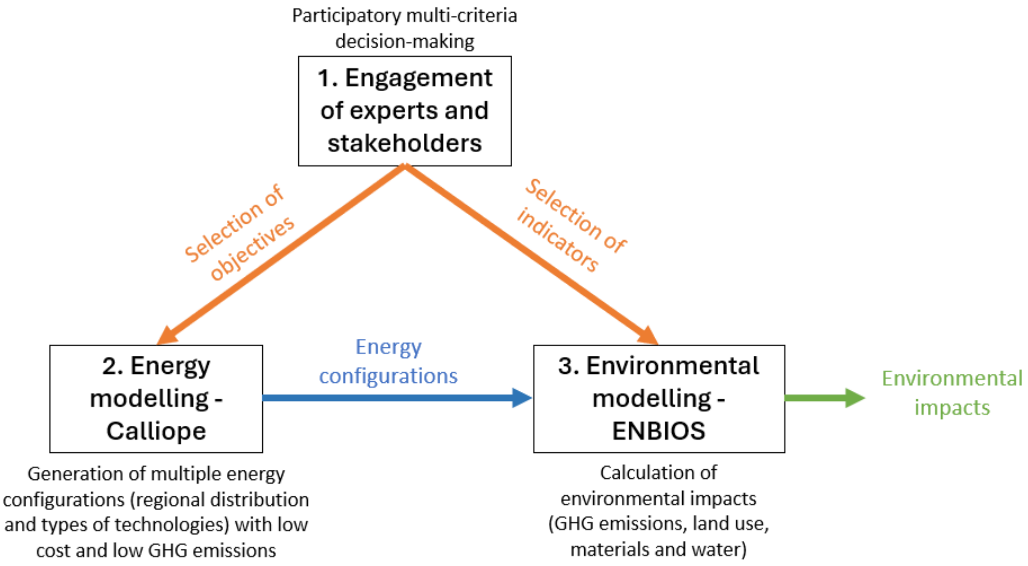

Figure 5: *Workflow in SEEDS*

8.4 Part 1: participatory process

8.4.1 Why?

Energy models generate possible future configurations of the energy system or calculate the impacts of given energy scenarios. However, these mathematical assessments are full of assumptions and modelling choices and some inevitably contain different political and economic perspectives. In the SEEDS project, instead of generating a set of scenarios or conditions according to the modelers’ choices, we conducted participatory processes to select the conditions from which the energy model will generate scenarios (e.g., subregions, technology sectors) and the environmental impacts that will be shown to the participants of the scenario selection process.

8.4.2 How?

These participatory processes were a Delphi survey (10 expert stakeholders), and a workshop (19 stakeholders). The analysis builds on an overview of the Portuguese energy and climate policy regulatory frameworks. This way, we want to understand the most relevant criteria for renewable energy-modelled scenarios such as the acceptance of energy technologies.

Figure 6: *Detailed workflow in SEEDS*

8.4.2.1 Policy Delphi study:

The policy Delphi study allows the discussion and valuation of possible directions and policies for the future. The Delphi involves three rounds of questionnaires until consensual decisions are achieved. The first part consisted of open-ended questionnaire, whose responses built a structured questionnaire for the second and third rounds with close-ended responses. The final questionnaire aimed to reach consensus, and an average of 77% was reached. Maximum consensus was reached for questions related to new technologies and decarbonisation issues, whereas only 50% was reached on public acceptance.

This involved 10 diverse energy and climate experts: two related to policy, five to technology and market, and three to civil society. The number of participants is small but considered to be enough. Calliope and ENBIOS modellers also participated in order to match the selection of the participants to the possibilities given by the models. Because they were not measurable, 14 criteria were left out of the assessment.

8.4.2.2 World café workshop:

This online workshop took place in November 2022 involved market (5 participants), policy (2), civil society and academia (7) and community stakeholder groups (5). This consisted of a discussion around three pairs of extreme scenarios. The topics were: fast vs slow transition, government vs community-driven, national self-sufficiency (storage) vs import-based. This introduced a wider reflection on stakeholder concerns.

8.5 Part 2: Calliope model – generation of low-carbon energy scenarios

8.5.1 How does it work?

Calliope calculates the need for different energy power plants, storage systems, etc. It provides the amount of energy provided by each type of technology in a given year. Unlike other models that only address electricity production, Calliope also includes heat and fuels. Its objective here is to generate 260 maximally different system designs that are within 10% of the lowest feasible system cost with no net CO2 emissions and limited imports from other countries.

8.5.1.1 Special features:

Computational power is a limit for modelling. Therefore, each model focus on some scales and resolutions, addressing different issues. For example, a very detailed technical assessment of the operation of one year of electricity production, storage and distribution in a country would require a very high spatial and hourly (or less) resolution with different assumptions on climate conditions and electricity demand. On the other hand, assessments of the transition to renewables to 2050 estimating the global use of materials might not reach that spatial and time resolution.

One of the main challenges of renewable electricity production is the inherent **variability** related to weather conditions. Until now, the electricity power system adapted to the instantaneous demand of electricity since some types of power plants such as gas combined cycles can be switched on and off very quickly to adapt to rapid changes in demand. This variability of renewables has temporal and regional implications.

In terms of **time**, both demand and wind and solar resources change depending on the seasons (e.g., more or less heating or cooling demand, holidays, etc.) and on an hourly basis (e.g., less activity at night, more activity when everyone is cooking dinner at home, etc.). This model includes this kind of small-scale temporal variability, which is key for the analysis of storage and the shares of wind and solar in the electricity mix. More specifically, the temporal scope is the analysis of one year and it is disaggregated for electricity at 3-hour resolution. 2016 is taken as reference year for the variability of demand and weather. Diverse demand and weather time series could be used for decreasing uncertainty of results.

The variability of renewables also depends largely on the **location**. Therefore, the model also addresses different spatial resolutions. Weather conditions (input) and electricity production (output) are available for 18 sub-regions for finer detail on renewables deployment. Finer spatial resolution could provide more exact results and specific distribution of infrastructure. On the other hand, there are only two regions for demand and non-electric sectors.

8.6 Part 3: ENBIOS – environmental impacts

8.6.1 How does it work?

Not only GHG emissions and cost are important for assessing energy systems. There are lots of variables that are important: land use, materials, etc. ENBIOS calculates the requirements and impacts of the energy system generated by Calliope from a life-cycle perspective.

The impacts for the generation of 1 unit of energy for each technology are stored in Ecoinvent databases of processes. These are data inventories of very detailed inputs and outputs for the production of one unit of energy of each type, including both direct and indirect impacts. For example, we could analyze the production of heat in a boiler. The combustion of biomass in a boiler generates **direct impacts**, for example, the generation of different gases (carbon dioxide, carbon monoxide, etc.), ashes and pollutants. **Indirect impacts** refer to those due to the production of the inputs necessary to that process, for example, the production of biomass in agriculture and forestry and the manufacturing of the boiler. We will allocate the impact of the production of the boiler (industry, materials extraction, etc.) proportional to the expected production in the whole lifetime of the boiler. Each unit of heat produced by the boiler will include a share of the impacts for the manufacturing of the boiler. These indirect impacts can be further detailed and branched, for example, with the production of fertilizers for agriculture.

Here, we can see already some **assumptions** that involve uncertainties, for example, the lifetime and overall production of devices and machinery, the detail of the production chains (boundaries of the system), the type of boiler (this might refer to a similar technology of what we are expecting or to old, outdated data). These are set for each process in Ecoinvent. The modeller selects the processes that are most similar to those in the analysed system and can also make adaptations. However, there is another inherent uncertainty of exploration of possible futures: we do not really know how technology will be in the future. Here, we are using data from existing technologies and we have adapted the electricity mix to those expected in the future.

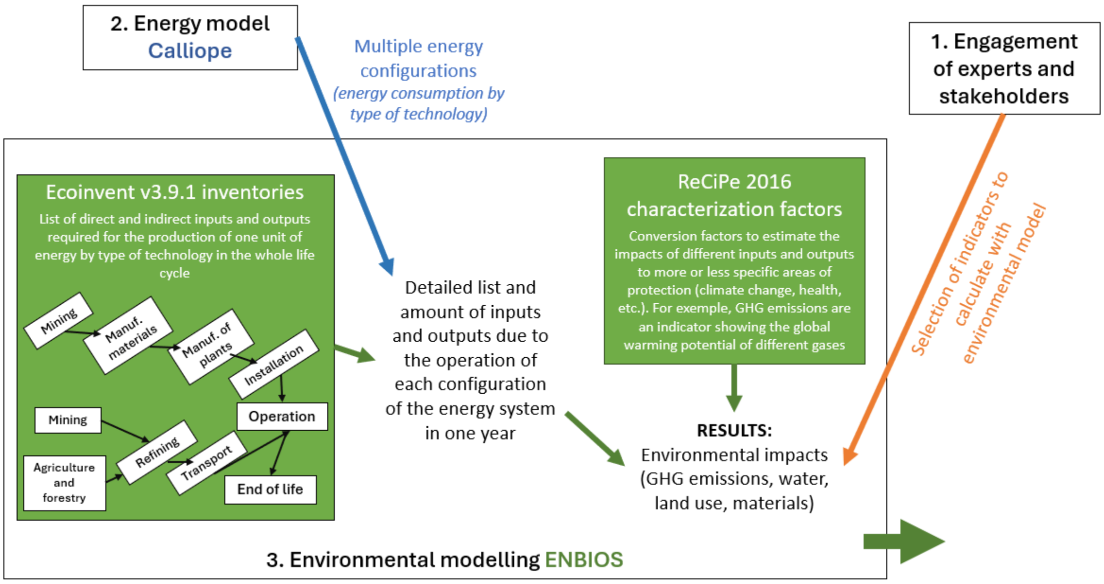

***Figure** 7: Simplified environmental modeling explanation*

These inventories in Ecoinvent are very detailed lists of inputs and outputs related to the production of one unit of energy. However, the environmental impacts considered refer to impacts which are generated by more than one of those inputs or outputs. For example, climate change impacts (GWP100) are the weighted addition of different greenhouse gases: carbon dioxide, methane, etc. To achieve those final indicators of environmental impacts, we use **characterization factors** that are set by established Life-Cycle Impact assessment methodologies. Despite this standardization, there are assumptions affecting those results. For example, this impact calculation assumes linearity, which means that the impact of the first unit is considered the same as the last unit. For example, is considered the same as the last unit, or in the case of climate change, we are assessing the impacts in a 100-year timeframe, when the different greenhouse gases have different warming potentials and residence times in the atmosphere, that are affected by the increasing concentration of GHG in the atmosphere.

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