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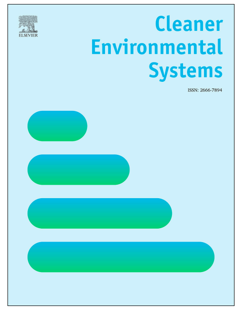

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Influential parameters for estimating the environmental impacts of geothermal power: a global sensitivity analysis study

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Abstract

The life-cycle environmental impacts of geothermal power generation are highly variable and depend on many site-specific conditions. The objective of this work is the identification of the most influential parameters for estimating the environmental impacts of geothermal electricity production. First, we developed a general model for computing the impacts of both conventional and enhanced geothermal technologies. The model is validated against selected literature studies for the climate change category. We then use Global Sensitivity Analysis (GSA) to evaluate the contribution of each parameter to the overall variance of the model's output. The results of the GSA suggest that i) the uncertainty of environmental impact estimates can be significantly reduced by obtaining more accurate values for a small number of key parameters, such as the installed capacity of the plant, operational emissions of CO_2 and the depth and capacity of wells; and ii) the majority of parameters do not affect significantly the environmental impact estimates and therefore can be fixed anywhere within their range of variability. Finally, we discuss some of the limitations of the present study and propose approaches that could be implemented to overcome such limitations.

Word count (without annexes): 7698

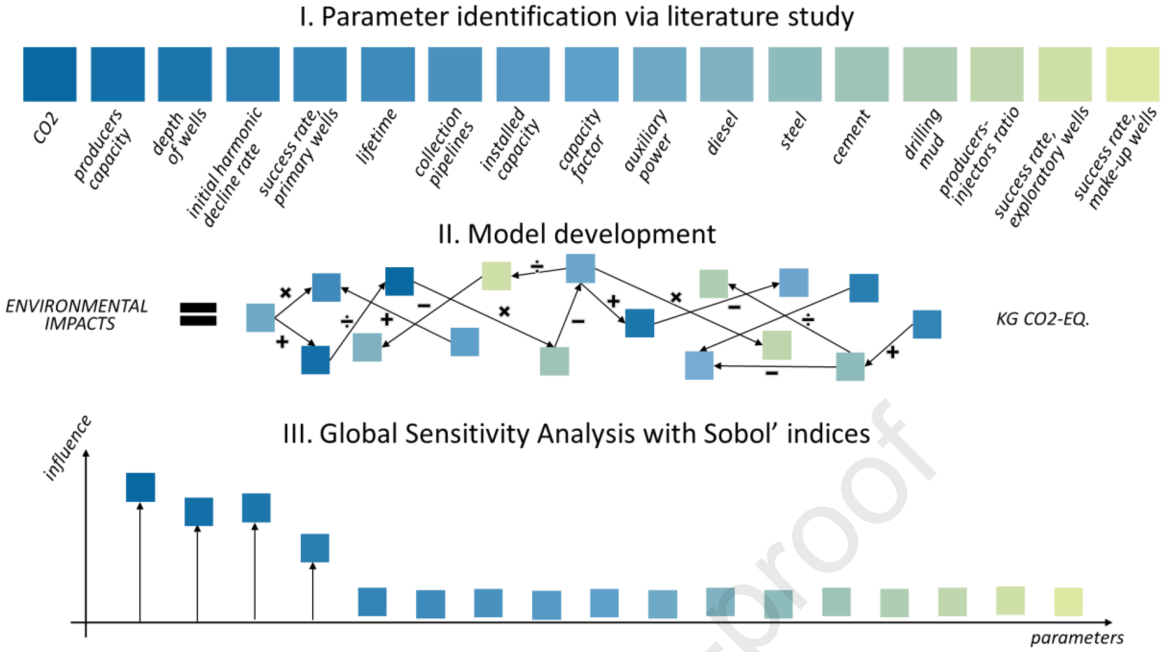
Keywords

Geothermal energy; Life Cycle Assessment; Carbon footprint; Sobol' indices; Renewable energy.

Highlights

- A novel model for estimating environmental impacts of geothermal energy is developed
- The most influential parameters are identified via Global Sensitivity Analysis
- Most parameters affect the model output only marginally
- Installed capacity and operational CO_2 emissions are among the most influential parameters

GRAPHICAL ABSTRACT



1 Introduction

The contribution of the geothermal sector to worldwide electricity production is still minuscule, although it is growing steadily. In 2019, the industry generated 92 TWh of electricity, approximately 0.3% of global electricity generation from all sources and 1.3% of that generated from renewables (IEA, 2020). The sector output is projected to grow by 5% annually to 2024; according to the International Energy Agency (IEA), this is about half of what is required to meet carbon neutrality by 2050 (IEA, 2019). As a renewable source of base-load power that is independent from seasonal and climatic conditions, geothermal energy is expected to have a significant role in the decarbonisation of the power generation sector and thus in the transition to a low-carbon economy. Of note, geothermal energy is also used for heat generation purposes, e.g. district heating; for simplicity, in this article we focus specifically on electricity generation.

Conventional geothermal systems, which make up the vast majority of geothermal installed capacity (Bertani, 2016; IGA, 2015), take advantage of high-enthalpy hydrothermal reservoirs using well-known technologies such as dry steam, and single- and double-flash plants to convert thermal energy into electricity. The Geysers Complex in California (US) is the largest geothermal field in the world with a total electric capacity of ~1.5GW (Bertani, 2016; IGA, 2015). In recent years, a novel geothermal technology, known as Enhanced Geothermal Systems (EGS), has attracted considerable interest. The technology enabled harnessing geothermal energy in locations that lack water or sufficient permeability in the rocks, by artificially creating an "engineered" reservoir using stimulation techniques (MIT, 2006). The Upper Rhine Valley - which extends across France, Germany and Switzerland - has been at the centre of the European efforts to develop EGS: the first worldwide commercial-scale power plant was commissioned at Soultz-sous-Forêts, France (Gérard et al., 2006). Other important sites for EGS development are located in Australia and in the United States (Lu, 2018). In the United Kingdom, the United Downs Deep Geothermal Power (UDDGP) project is investigating the technical and commercial viability of producing electricity from heat produced by the Cornish granites exploiting the natural permeability of a significant structural fracture zone (Ledingham et al., 2019). In Switzerland, the government's Energy Strategy 2050 (Swiss Federal Office of Energy, 2018) projects a substantial contribution from EGS in the order of 4-5 TWh; EGS has in fact been a major research topic within the past years, addressing e.g. environmental performance and costs (Hirschberg et al., 2015), risks (Trutnevyte and Wiemer, 2017), and social acceptability (Knoblauch et al., 2019).

Numerous Authors have in recent years attempted to quantify the life-cycle environmental performance of electricity from geothermal energy, focusing in particular on carbon emissions; this is primarily as part of a global effort to decarbonise the power generation sector. Life Cycle Assessment (LCA) is a standardised and widely adopted framework to quantify the environmental impacts associated with a product or service throughout its life-cycle (ISO, 2006a, 2006b). The life-cycle perspective and the consideration of a number of environmental issues enables identification of trade-offs, thus providing a robust framework for decision support (Hauschild et al., 2018). The environmental impacts of conventional geothermal energy were investigated by Bravi and Basosi (2014), Buonocore et al. (2015), Parisi et al. (2019) and Tosti et al. (2020) for plants located in Tuscany, Italy, and by Karlsdottir et al. (2020) and Paulillo et al. (2019a) for Hellisheidi, the largest combined heat-and-power geothermal plant in Iceland. For Enhanced Geothermal Systems (EGS), Frick et al. (2010) investigated multiple scenarios with the objective of quantifying a range of environmental performances. Lacirignola and Blanc (2013) and Pratiwi et al. (2018) evaluated existing or under construction EGS plants in the Soultz-sous-Forêts area, whilst Paulillo et al. (2020a) predicted the environmental performance of the United Downs Deep Geothermal Power (UDDGP) project in Cornwall, UK. Bayer et al. (2013) and Tomasini-Montenegro et al. (2017) provide comprehensive reviews of relevant LCA studies. The application of LCA on geothermal energy demonstrated that its environmental performance is dependent on site-specific conditions, such as the composition of geothermal fluid, the enthalpy of reservoir or the expected trend of long-term productivity (Bayer et al., 2013). For example, the carbon footprint of geothermal electricity generation spans over two order of magnitudes, from ~5 and up to ~800 gCO_2-eq./kWh (Paulillo et al., 2019a). Because site-specific data is not always available and data collection is time-consuming and expensive, it is useful to identify which parameters are the most important for obtaining accurate LCA estimates.

The objective of this study is to identify the most influential parameters that affect the variability of the environmental impacts of geothermal energy for the generation of electricity. To the best of our knowledge, no other article in the literature has attempted this, covering both conventional and enhanced geothermal technologies and including a wide array of environmental categories that are not limited to climate change. To this end, we first developed a novel model, based on a selected number of parameters that were obtained from an extensive critical literature analysis, for estimating (ex-ante or ex-post) the environmental impacts of both conventional and enhanced geothermal technologies. Notably, our model, unlike others available in the literature (e.g. Lacirignola et al., 2014), accounts for the possibility of failure in the drilling of wells. The model is validated by comparison with literature data for the climate change category only. We then used Global Sensitivity Analysis (GSA) to quantify the contribution of each parameter to the overall variance of the model output. Global methods take into account interaction effects among inputs and model nonlinearities (Saltelli et al., 2008), and are therefore appropriate for models with complex input dependencies (Saltelli et al., 2019). They are more computationally demanding than simpler sensitivity methods (e.g. local and screening) but, in part because of recent computational advancements, they are increasingly applied within LCA for different aims, including supporting the decision-making process (Ventura et al., 2015), prioritizing data collection for regionalization (Patouillard et al., 2019), assessing the robustness of the results (Wei et al., 2015), and calibrating or simplifying existing models - e.g. for several geothermal plant archetypes (Douziech et al., 2020), for EGS (Lacirignola et al., 2014), for wind power (Padey et al., 2013) and urban planning (Mastrucci et al., 2017). The remainder of the article is organised as follows: the model and the GSA method are introduced in Section 2. In Section 3 the model outputs are compared against literature data and the GSA results are presented. The outcomes of the study and some of its limitations are discussed in Section 4, and the key messages are summarised in Section 5.

2 Methods

2.1 The general parametric model

The general parametric model proposed here estimates the life-cycle environmental impacts per kWh of electricity generated by either conventional or enhanced geothermal power plants. Notably, we assume that only enhanced plants employ binary cycles, with conventional plants covering dry-steam and single- and multi-stage flash technologies. The model considers all activities from "cradle to grave", that is from the construction of the plant and wells up to their decommissioning. The model can be used both retrospectively, to quantify the environmental performance of an existing plant, and prospectively, to predict the environmental impacts of a future plant. In its current form, the model is not applicable to the case of heat and power co-generation. This would require allocating environmental impacts among the two functions of electricity and heat generation, to enable comparison with other energy sources. The choice of allocation strategy significantly affects the LCA results, but it is largely subjective, which makes it difficult to be considered within GSA.

In Equation (1) we illustrate the overall concept: the total impact for the environmental category *k* is obtained as the sum of the life-cycle impacts associated with geothermal wells, collection pipelines, power plant and hydraulic stimulation, each divided by the net lifetime electricity generated, plus the impact of operational emissions (which are reported per unit of electricity generated, see Table 1).

$$Impact_k\left[\frac{category\ unit}{kWh}\right] = \frac{Wells + Collection\ Pipelines + Power\ plant\ + Stimulation}{Net\ lifetime\ electricity\ generated} + Oper.emissions \quad (1)$$

The approach underlying the calculation of life-cycle environmental impacts for the relevant component of Equation (1) is exemplified in Equation (2), whilst the specific mathematical expressions for each term used in Equation (1) are presented in Section 2.2.

$$Impact_k[category\ unit] = \sum_j A_j \cdot i_{j,k} \quad (2)$$

In Equation (2), A_j represents the total amount over the life-cycle of a geothermal plant of an intermediate or an elementary flow j; and $i_{j,k}$ corresponds to the life-cycle environmental impact in the category k associated with the provision of the intermediate flow or to the characterisation factor of the elementary flow. The overall impact for the environmental category k is obtained as the sum of the product of A_i and $i_{j,k}$ over all relevant energy or material flows j. An intermediate flow is by definition a man-made product that is produced and consumed within the Technosphere (i.e., the economy or the "man-made" world), whilst an elementary flow represents an exchange between the Technosphere and the Ecosphere (or Biosphere) (Bjorn et al., 2018). For example, steel required as casing for geothermal wells is an intermediate flow whilst an emission of CO_2 during operation of the geothermal plant is an elementary flow.

The total amounts of intermediate and elementary flows A_j are obtained as functions of multiple parameters such as the installed capacity of the plant or the average depth of the wells; these parameters are described in Section 2.2. The coefficients i are reported in Annex A; they were calculated for all environmental categories in the Environmental Footprint (EF) 2.0 method (Fazio et al., 2018) using the Ecoinvent database, cut-off system model version 3.6 (Wernet et al., 2016).

2.2 Input parameters and mathematical expressions

From an extensive critical literature review of LCA studies (see references in Table 1 and Table 2), we identified 25 parameters that were deemed sufficient to develop a model capable of estimating the environmental impacts of electricity production from geothermal energy. These parameters are listed in Table 1 and Table 2, and are described in Annex B.

Table 1 reports 21 out of the 25 input parameters for which we could establish a range of variability based on literature data; these parameters are included in the Global Sensitivity Analysis (GSA). For most of these parameters, we assumed a uniform distribution because available data were not sufficient to justify the choice of an alternative distribution; when sufficient data were available, the most appropriate distribution to describe their variability was determined. Table 2 includes the remaining four parameters for which a range of variability could not be determined due to insufficient data.

Table 1 - Parameters of the proposed general parametric model, and their probability distributions that are employed in Global Sensitivity Analysis

Parameter	Unit	Acronym	Conventional			Enhanced		
			Range	Distribution	Source	Range	Distribution	Source
Power plant								
Installed capacity	MW	Pn,e	10-130*	Uniform	(Bertani, 2016, 2012)	0.4-11	Uniform	(Frick et al., 2010; Lacirignola and Blanc, 2013; Marchand et al., 2015; Paulillo et al., 2020a; Pratiwi et al., 2018; Treyer et al., 2015; Menberg et al., 2021)
Auxiliary power	-	AP	0.032-0.048	Uniform	(Karlsdóttir et al., 2015)	0.12-0.28	Uniform	(Frick et al., 2010; Lacirignola and Blanc, 2013; Pratiwi et al., 2018; Menberg et al., 2021)
Capacity factor	-	CF	0.7-0.95	Uniform	(Frick et al., 2010; Karlsdóttir et al., 2015; Lacirignola and Blanc, 2013; Marchand et al., 2015; Pratiwi et al., 2018; Rule et al., 2009; Basosi et al., 2020)	0.7-0.95	Uniform	(Frick et al., 2010; Karlsdóttir et al., 2015; Lacirignola and Blanc, 2013; Marchand et al., 2015; Pratiwi et al., 2018; Rule et al., 2009; Menberg et al., 2021)
Lifetime	years	LT	20-40	Normal. μ=30; σ=5	(Buonocore et al., 2015; Hondo, 2005; Karlsdóttir et al., 2015; Basosi et al., 2020)	20-40	Normal μ=30; σ=5	(Frick et al., 2010; Lacirignola and Blanc, 2013; Marchand et al., 2015; Pratiwi et al., 2018; Sullivan et al., 2010; Treyer et al., 2015; Menberg et al., 2021)
Collection pipelines length	m/well	CP	250-750	Uniform	(Karlsdóttir et al., 2015)	50-200	Uniform	This work**
Operational CO_2 emissions	kg CO_2/kWh	E_{CO2}	0.004-0.740	Lognormal σ=0.98; μ=0.077***	(Bertani and Thain, 2002a)			
Wells								
Primary wells number	#	WPn				2-3	Discrete uniform	(Frick et al., 2010; Lacirignola and Blanc, 2013; Marchand et al., 2015; Paulillo et al., 2020a; Pratiwi et al., 2018; Treyer et al., 2015; Menberg et al., 2021).
Producers capacity	MW/well	CWn,e	0-20	Lognormal σ=0.73; μ=5.89***	(IFC, 2013)			
Depth	m/well	Wd	660-4000	Uniform	(Bravi and Basosi, 2014; Buonocore et al., 2015; Hondo, 2005; Karlsdóttir et al., 2015; Rule et al., 2009; Basosi et al., 2020)	2500-6000	Uniform	(Frick et al., 2010; Lacirignola et al., 2014; Paulillo et al., 2020a; Pratiwi et al., 2018; Sullivan et al., 2010; Treyer et al., 2015)
Diesel	MJ/m	D	1600-2800	Uniform	(Karlsdóttir et al., 2015; Basosi et al., 2020)	3000-14000	Uniform	(Frick et al., 2010; Lacirignola and Blanc, 2013; Paulillo et al., 2020a; Pratiwi et al., 2018)
Steel	kg/m	Cs	75-125	Uniform	(Karlsdóttir et al., 2015; Basosi et al., 2020)	75-150	Uniform	(Frick et al., 2010; Lacirignola and Blanc, 2013; Paulillo et al., 2020a; Pratiwi et al., 2018; Menberg et al., 2021)
Cement	kg/m	Cc	30-50	Uniform	(Karlsdóttir et al., 2015; Basosi et al., 2020)	16-100	Uniform	(Frick et al., 2010; Lacirignola and Blanc, 2013; Paulillo et al., 2020a; Pratiwi et al., 2018)
Drilling mud	m3 water	DM	0.5-0.8	Uniform	(Frick et al., 2010; Paulillo et al., 2020a; Pratiwi et al., 2018; Treyer et al., 2015)	0.5-0.8	Uniform	(Frick et al., 2010; Paulillo et al., 2020a; Pratiwi et al., 2018; Treyer et al., 2015)
Initial harmonic decline rate	-	Di	0.01-0.10	Uniform	This work*			
Producers-injectors ratio	-	PIratio	1-3	Uniform	(IFC, 2013)			
Success rate								
Exploratory wells	%	SRe	0-100	Truncated triangular min=0; peak=100	(IFC, 2013)	0-100	Truncated triangular min=0; peak=100	(IFC, 2013)
Primary wells	%	SRp	0-100	Truncated triangular min=16.9; peak = 100	(IFC, 2013)	0-100	Truncated triangular min=16.9; peak = 100	(IFC, 2013)
Make-up wells	%	SRm	0-100	Truncated triangular min=42.1; peak = 100	(IFC, 2013)			
Stimulation								
Water	m3/well	Sw				10000-60000	Uniform	(Lacirignola and Blanc, 2013; Treyer et al., 2015)
Diesel	kWh/m3 water	Sel				10-140	Uniform	(Lacirignola and Blanc, 2013; Treyer et al., 2015)
Wells	-	SWn				0.5-1.5	Uniform	This work**

**The lower boundary is inferred from* Bertani (2012)*, who maintains that the majority of geothermal plants below 10MW use binary cycles.*

***See Annex B.*

****μ and* σ *are the mean and standard deviation of the underlying normal distribution.*

Table 2 - Fixed parameters of the proposed general parametric model.

Parameter	Unit	Acronym	Value		Source
			Conventional	Enhanced	
Exploratory wells	#	WE,n	3	3	(DiPippo, 2016a)
Organic working fluid	kg/MWel	OF	0	300	(Rogge, 2004; Treyer et al., 2015)
Cooling towers	#/MWel	CTn	0.023	0.023	(Karlsdóttir et al., 2015)
Drilling waste	kg/m of well	DW	450	450	This work*

**See Annex B.*

The specific mathematical expressions for each term of the general parametric model (see Equation (1)) are reported in Equations from (3) to (14). Some expressions are relevant to both conventional and enhanced plants, whilst others are specific to each technology; for example, the relation for hydraulic stimulation (eq. (12)) is only applicable to enhanced geothermal plants. This is how the model is made specific to either conventional or enhanced plants.

LCA studies in the literature indicate that a significant portion of the environmental impacts originate from the drilling of the wells. Therefore, the total number of wells drilled represent a critical parameter for estimating the environmental impacts. In our approach, the number of wells for conventional plants is estimated from other parameters. Explicitly, the number of production wells is estimated as the ratio between the maximum gross electric output of power plants (i.e., installed capacity) and that of individual production wells (i.e., producers capacity(Sanyal, 2004)), whilst the number of injection wells is obtained from the number of production wells and the ratio between producers and injectors. On the other hand, for enhanced geothermal technologies the model assumes either a single doublet or a single triplet configuration (i.e., with a total number of 2 or 3 respectively). We assumed that only conventional geothermal plants require make-up wells to maintain production of electricity over the lifetime; the number of make-up wells is estimated from the initial harmonic decline rate of the wells productivity (Sanyal, 2004). When the number of wells is estimated (i.e., for conventional plants), this is rounded to the least greater integer. For both conventional and enhanced technologies, we assume that the number of exploratory wells equals 3 (see Table 2), and that each of these exploratory wells has life-cycle requirements equivalent to one third of that of primary wells (i.e., producers and injectors), to account for the lower diameters of exploratory wells (Marchand et al., 2015). Finally, the model incorporates the probability that each well is successful; a well may be unsuccessful for a number of reasons, including unexpected mechanical problems encountered during drilling and inadequate conditions of the reservoir (e.g. low temperature or static pressure) (IFC, 2013). Therefore, the total number of wells drilled is usually higher than the number of wells required to sustain the plant's installed capacity; this number is also rounded to the least greater integer. The expressions for the total number of wells including ($W_{n,SR}$) and excluding success rate (W_n) for conventional and enhanced geothermal technologies are reported in Equation (5) to (6) whilst those for exploratory wells (WE_{en} and $WE_{en,SR}$) are reported in Equations (7) and (8).

$$W_n\ (conventional) = \left\lceil \frac{P_{n,e}}{CW_{n,e}} \right\rceil + \left\lceil \frac{P_{n,e}}{CW_{n,e} \cdot PI_{ratio}} \right\rceil + \left\lceil \frac{P_{n,e}}{CW_{n,e}} \cdot D_i \cdot LT \right\rceil \tag{3}$$

$$W_{n,SR}\ (conventional) = \left\lceil \frac{1}{SR_p} \cdot \left(\left\lceil {P_{n,e}}/{CW_{n,e}} \right\rceil + \left\lceil \frac{P_{n,e}}{CW_{n,e} \cdot PI_{ratio}} \right\rceil \right) \right\rceil + \left\lceil \frac{\left\lceil {P_{n,e}}/{CW_{n,e}} \cdot D_i \cdot LT \right\rceil}{SR_m} \right\rceil \tag{4}$$

$$W_n\ (enhanced) = WP_n \tag{5}$$

$$W_{n,SR}\ (enhanced) = \left\lceil \frac{WP_n}{SR_{PI}} \right\rceil \tag{6}$$

$$WE_{en} = WE_n \cdot 0.3 \tag{7}$$

$$WE_{en,SR} = \left\lceil \frac{WE_n \cdot 0.3}{SR_E} \right\rceil \tag{8}$$

The impacts associated with geothermal wells are obtained from the total number of wells including success rate, the average depth of the wells and the specific amounts per metre of well of diesel (used for powering the drilling rig), steel and cement for casing, drilling mud and drilling waste generated, according to Equation (9). We assumed that diesel engines are used to drill the wells, reflecting common practices; the amount of diesel consumed is dependent on many factors, including wells' depth and type of rock. It must be noted that recent studies have demonstrated that using electricity from the grid can yield significant reductions in environmental impacts (Karlsdottir et al., 2020; Menberg et al., 2016) .Besides the drilling phase and the treatment of drilling waste, the wells' impacts also include construction of wellheads and closure of the wells.

$$Wells = \left(W_{n,SR} + WE_{en,SR}\right) \cdot \left[i_{1,k} + W_d \cdot \left(D \cdot i_{2.1,k} + C_S \cdot i_{2.2,k} + C_C \cdot i_{2.3,k} + DM \cdot i_{2.4,k} + DW \cdot i_{2.5,k} + i_{2.6,k}\right)\right] \quad (9)$$

The impacts of collection pipelines are obtained from the number of wells (excluding success rate) and the average distance between the wells and the power plant (Equation (10)); whilst those associated with the power plant are estimated using the installed capacity and, when applicable, the amount of organic working fluid, as shown in Equation (11). It should be noted that the material requirements (and therefore the environmental impacts) of the power plant are also linked to other parameters, including the wellhead temperature and the conversion efficiency; these were not considered in our model for the sake of simplicity. We made the following additional simplifying assumptions for the power plant (see Annex B): first, both conventional and enhanced plants rely on the same life-cycle inventory for construction; second, only enhanced geothermal plants employ binary cycles (and therefore an organic working fluid, see Section 2.1) for electricity generation; third, both conventional and enhanced technology use a water-based cooling system. Of note, we could not develop the model to be specific to different conventional technologies (e.g. dry-steam or single-flash plants) because of insufficient data available in the literature; however, the potential differences among technologies are accounted for in GSA.

$$Collection\ pipelines = W_n \cdot CP \cdot i_{3,k} \quad (10)$$

$$Power\ plant = P_{n,e} \cdot \left(i_{4.1,k} + CT_n \cdot i_{4.2,k} + OF \cdot i_{4.3,k}\right) \quad (11)$$

Hydraulic stimulation is only considered for enhanced geothermal plants, in which case a fraction of the number of wells is expected to be stimulated; this is estimated as the rounded product of the number of wells and an independent parameter ranging between 0.5 and 1.5 (to ensure that at least one well is stimulated; see Annex B). The impacts are calculated considering water and diesel (for electricity production) requirements, according to Equation (12).

$$Stimulation = \left[SW_n \cdot W_n\right] \cdot S_w \cdot \left(i_{5.1,k} + S_{el} \cdot i_{5.2,k}\right) \quad (12)$$

The total electricity generated during the lifetime of the plant is calculated considering the expected lifetime of the plant, power requirements by auxiliary components and the capacity factor, according to Equation ((13). (In Equation (13), 8760 is the number of hours in a year and 1000 converts MW to kW.)

$$Lifetime\ electricity\ generated = P_{n,e} \cdot CF \cdot (1 - AP) \cdot LT \cdot 8760 \cdot 1000 \quad (13)$$

Operational emissions represent non-condensable gases that are released upon condensation of the geothermal fluid prior to reinjection. They are only significant for dry steam and flash power plants (i.e. conventional technologies), because in binary plants the geo-fluid flows in a virtual closed-cycle. Furthermore, we assume that conventional technologies only release CO_2 during standard operations; this is quantified by Equation (14). Our model does not account for discharges of other non-condensable gases (such as methane, H_2S, NH_3, and heavy metals) from conventional plants because sufficient data on their rate of emissions could not be found.

$$Operational\ emissions = E_{CO_2} \cdot i_{6,k} \quad (14)$$

We quantified the variability of the general model output via Monte Carlo simulations, using the data provided in Table 1 and a number of iterations equal to 10,000 (following Paulillo et al., 2019a).

2.3 Global Sensitivity Analysis

We use Global Sensitivity Analysis (GSA) to quantify the contribution of each input parameter to the overall variance of model output. Our analysis does not include uncertainties in the Ecoinvent database because we focus on the parameters that are specific to geothermal power plants (see Section 2.2). A plethora of GSA methods exist, including but not limited to variance-based methods (Homma and Saltelli, 1996), screening techniques to filter out non-influential inputs (Campolongo et al., 2011), computation of moment-independent indicators (Plischke et al., 2013) probabilistic methods based on Bayesian approach (Oakley and O'Hagan, 2004). Pianosi et al. (2016) presents a comprehensive literature review on GSA approaches, whilst Igos et al. (2019) provides an overview of sources, types and characterization of uncertainties, as well as sensitivity analysis methods.

Here, we first assign uncertainty distributions to model parameters, then propagate the uncertainties by means of Monte Carlo simulations, and analyse the resulting model distribution to estimate sensitivity indices for all parameters (a schematic flowchart is depicted in Figure S1 in the Supporting Information). We use the variance-based sensitivity method originally developed by Sobol' (2001) with estimators for first and total order Sobol' indices proposed by Saltelli et al. (2010). Sobol' method, which has already been deployed for LCA applications, is advantageous because it allows exploration of the whole parameter space including non-linear and interaction effects. In our nomenclature, we refer to two parameters as 'independent' when they are not related by any functional or probabilistic function, whilst they are defined as 'interacting' if the model output cannot be expressed as the sum of the effects due to each of the two parameters (Saltelli et al., 2008).

First and total order Sobol' indices are computed for each model parameter and represent the contribution of the variance of a given parameter to the variance of the model output respectively without and with consideration of interaction effects with all other parameters. When a model does not contain interaction effects (i.e., additive models), first and total order indices coincide, and each sums to one. However, if the sum of first order indices is lower than one and the sum of total order indices is higher, then interactions between the model parameters are present (Saltelli et al., 2008). A key requirement of the Sobol' methodology is that the parameters are independent from each other. We made this assumption for the parameters in Table 1; some parameters could present some degree of correlation, but this is either not obvious or not easily quantifiable.

We used quasi-random Sobol' sequences and radial sampling strategies for faster convergence of the Monte-Carlo simulations. We implemented the GSA approach in Python, using Brightway2 tool for LCA computations (Mutel, 2017), SALib Python package for sensitivity analysis (Herman and Usher, 2017), and DASK-parallel computation framework (Dask Development Team, 2016). The latter allowed to compute converged GSA indices for all methods and both conventional and enhanced technologies within 3 hours on a 2.6 GHz Intel Core i7 processor. The amount of time can be reduced to the order of tens of minutes if more computational resources are deployed, e.g. by employing a cluster.

The Sobol' indices estimator developed by Saltelli et al. requires N(k+2) model runs with all parameters varied simultaneously - where N is a constant and k is the number of parameters. We set N to 500, which resulted in 9500 and 9000 simulations for conventional and enhanced technologies, respectively, per impact category. Figures S1 and S2 in the Supporting Information show that convergence was reached after N=100 (i.e. 1900 and 1800 simulations).

3 Results

3.1 Model validation: carbon footprint of selected studies

In Figure 1 we compare the variability of the general parametric model for conventional and enhanced geothermal technologies with selected results from literature (Atilgan and Azapagic, 2016; Basosi et al., 2020; Bauer et al., 2017; Bravi and Basosi, 2014; Buonocore et al., 2015; De Rose et al., 2020; Frick et al., 2010; Hondo, 2005; Lacirignola and Blanc, 2013; Marchand et al., 2015; Menberg et al., 2021; Paulillo et al., 2020b, 2020a, 2019a, 2019b; Pratiwi et al., 2018; Sullivan et al., 2010). The comparison includes nine LCA studies on conventional and eight on enhanced geothermal technologies, respectively, and a total of 14 and 15 scenarios respectively (see Table S1 and S2 in the Supporting Information). Only some of these LCA studies use site-specific data and thus estimate the performance of actual geothermal plants. Figure 1 reports the results of Monte Carlo simulations for the climate change category; numerical results, including those for other environmental categories, are provided in Table S3 and S4 in theSupporting Information. A box-and-whisker plot is used to visualize the variability: horizontal lines represent median values, the boxes correspond to 25th and 75th percentiles, and the whiskers indicate 1st and 99th percentiles. The comparison was restricted to the climate change category (100-year time horizon) for two reasons. First, because the majority of selected LCA studies focused on this category (Tomasini-Montenegro et al., 2017); and second, because even when other environmental impact categories were considered, impact assessment methods other than EF2.0 were used to quantify the environmental impacts, and therefore no systematic comparison was possible.

Figure 1 shows that the proposed model for conventional geothermal technologies captures most of the variability in carbon footprint reported by published LCA studies. The model's median value equals 77 gCO_2-eq./kWh, whilst the 25-75 percentile range approximately corresponds to 45-150 gCO_2-eq./kWh. The comparison shows that three carbon footprint estimates (21% of all data points) fall within the 25-75 percentile range and seven estimates (50%) in the 1-25 and 75-99 percentile ranges. The four estimates developed by Bravi and Basosi (2014) are above the 99th percentile, with values ranging from ~600 to ~800 gCO_2-eq./kWh; this is chiefly caused by CH_4 emissions which are not accounted by our model (see Section 2.2).

The comparison for enhanced geothermal technologies encompasses eight estimates (53% of all data points) within the 25-75 percentile range, with a median value of ~30 gCO_2-eq./kWh, and 25-75 percentiles results in 20-60 gCO_2-eq./kWh. Two estimates (13%) are included in the 1-25 percentile range, whilst the remaining three are below and above the 1st and 99th percentile; notably, two of these represent best and worst-case estimates (Frick et al., 2010).

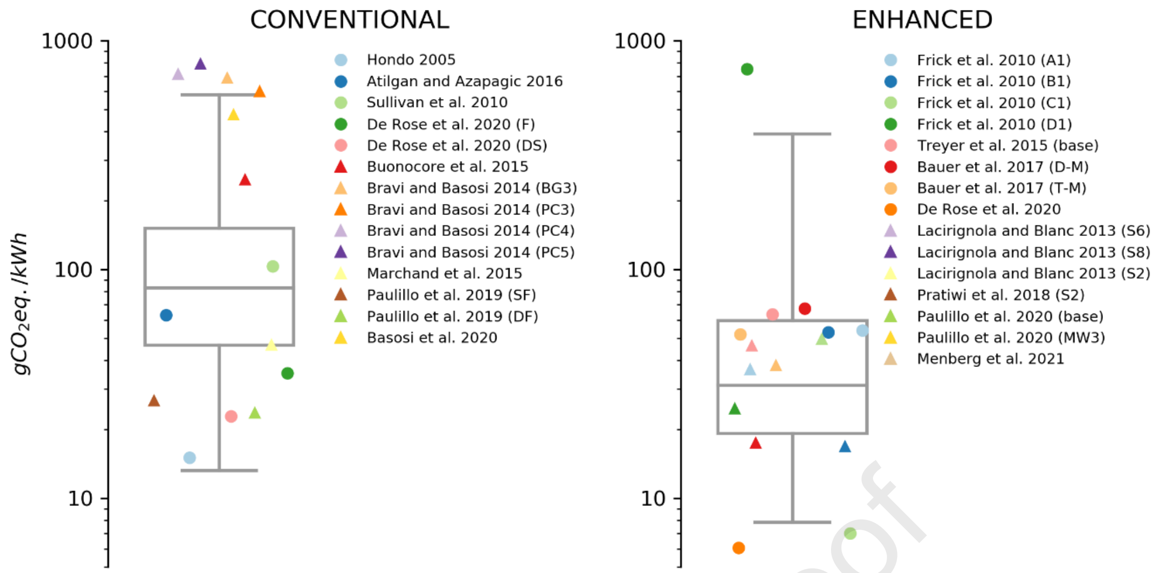


Figure 1 - Comparison of the results from the proposed general parametric model with carbon footprints from literature studies for conventional (left) and enhanced (right) geothermal technologies. The box-and-whisker plots report the 1st, 25th, 50th, 75th and 99th percentiles. Circles and triangles represent generic and site-specific studies, respectively.

3.2 Global Sensitivity Analysis: first and total order Sobol' indices

Figure 2 and Figure 3 present results of GSA (Section 0) for conventional and enhanced geothermal technologies respectively, in terms of Sobol' first and total order indices. The indices were calculated for the parameters in Table 1 for which a distribution was determined. The numerical values are reported in Tables from S4 to S7 in the Supporting Information.

With the sole exception of the climate change category for conventional technologies, the sums of first and total order indices for each environmental category are respectively slightly lower and higher than one. As noted in Section 0, this indicates the existence (albeit small) of interactions between parameters. For conventional technologies and the climate change category (Figure 2), the sums of first and total order indices are similar and close to one (0.95 and 0.98 respectively). In this case the parameter "operational CO_2 emissions" has the highest first and total order indices whilst the indices of the remaining parameters are negligible. (Note that the sum of total order indices is lower than one because we are using estimators for Sobol' indices.) In the remaining categories for conventional technologies, the two parameters with the highest index values are "producers capacity" and "depth (of wells)". The former with first and total order indices equal to 0.55-0.66 and 0.67-0.74 respectively; and the latter with values within 0.16-0.22 and 0.22-0.36 ranges for first and total order indices respectively. Amongst the remaining parameters, only "initial harmonic decline rate" features indices higher than 0.05 in both first and total order indices.

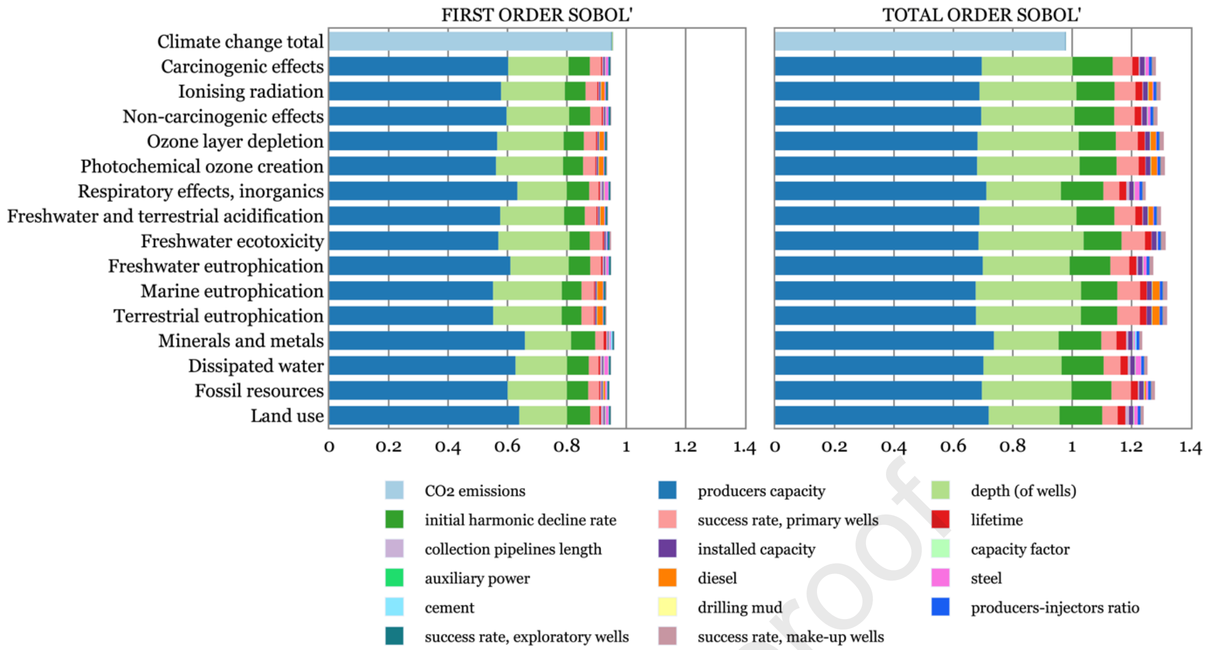


Figure 2 – Sobol' first and total order indices for conventional geothermal technologies.

For enhanced geothermal technologies (Figure 3), the parameter "installed capacity" features the highest first and total order indices in all categories, with first and total order indices included in the ranges 0.71-0.81 and 0.92-0.96, respectively. The remaining parameters feature first order indices lower than 0.05. However, for total order indices two parameters stand out. Diesel consumption for wells drilling presents the second highest values, ranging between 0.09 and 0.15, in eight environmental categories including climate change, ionising radiation, ozone layer depletion, photochemical ozone creation, freshwater and terrestrial acidification, marine eutrophication, terrestrial eutrophication and fossil resources. The "Depth (of wells)" shows the second-highest indices in the remaining categories, ranging between 0.06 and 0.08. "Success rate, primary wells" is the only one among the remaining parameters to yield values above 0.05.

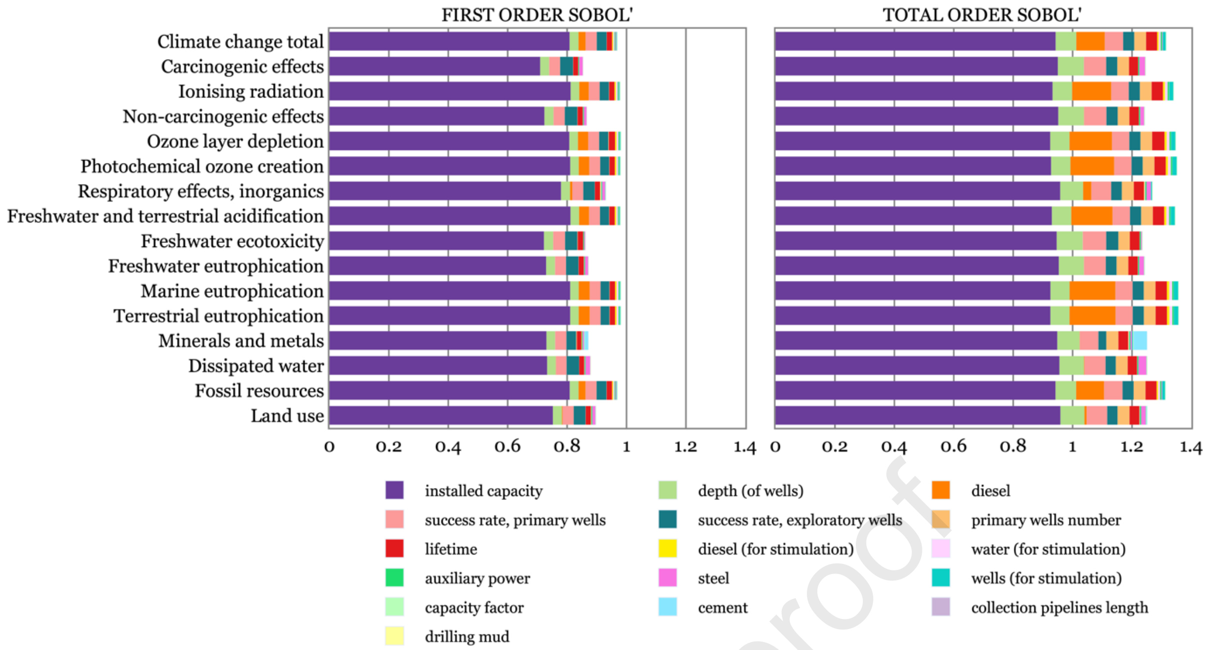


Figure 3 – Sobol' first and total order indices for enhanced geothermal technologies.

4 Discussion

4.1 Validation

The validation of the results (Section 3.1) shows that the proposed model reproduces most of the variability of the carbon footprint estimated by available literature studies. For enhanced technologies, around four fifths of all data points fall within the lower and upper quartiles (i.e., 25th and 75th), and only three data points are outside the 1-99th percentile range. However, for conventional technologies only around one fifth of the data points fall within the lower and upper quartiles (i.e., 25th and 75th); this is explained by the presence of four outliers (26% of all data points), from Bravi and Basosi. The presence of these outliers can be fully explained by either site-specific conditions or modelling assumptions, as detailed in what follows.

Bravi and Basosi (2014) quantified the carbon footprint of two conventional, dry-steam geothermal power plants in the Mount Amiata region in southern Tuscany, Italy, being over 600 gCO_2 eq./kWh generated, i.e., comparable to that of conventional natural gas and coal power plants. Emissions of methane as high as 280 gCO_2-eq./kWh drive up the carbon footprint; these are currently not accounted for by the general parametric model, primarily because we could not find sufficient data to estimate a range of variability or ascertain a median value. On the other hand, CO_2 emissions are comprehensively reported by Bertani and Thain (2002). Therefore, when the geothermal fluid presents above-average concentrations of methane, the general parametric model is likely to underestimate the carbon footprint. Notably, the general parametric model does not account for releases of other non-condensable gases like ammonia and hydrogen sulphide which can have non-negligible contributions to the acidification category.

Frick et al. (2010) developed four location-generic scenarios for EGS plants. One estimate falls below the 1st percentile, and another above the 99th percentile of the proposed model variability. These represent best- and worst-case conditions, respectively, in terms of reservoir depth, geothermal fluid temperature, auxiliary power requirements and other parameters that lead to exceptionally low and high electricity generation. The worst-case scenario in particular features a carbon footprint higher than 700 gCO_2-eq./kWh, which is considerably above the 99th percentile and comparable with fossil fuels power plants.

4.2 Global Sensitivity Analysis

The results from GSA (Section 3.2) can be interpreted in two ways, according to the two "settings" (which indicate the ultimate objective of the analysis) proposed by Saltelli et al. (2008): "Factor prioritization" and "Factor fixing". "Factor prioritization" is used to identify a parameter (or a group of parameters) which, when fixed to its true value (i.e. a value that is measured or determined for a specific site) while all other parameters vary, leads to the greatest reduction in the variance of the output. This is quantified by first order indices, which represent the contribution of the variance of a given parameter to the variance of the model output without considering interactions effects (Section 0). The chart on the left in Figure 4 shows that for enhanced geothermal technologies one parameter - "installed capacity" – can lead to an average reduction of 70% of the variance of the model output when fixed to its true value. For conventional technologies three parameters are required to reduce by an average of 70% the variance of the model; these are: "operational CO_2 emissions", "producers capacity" and "depth (of wells)". For both technologies the number of parameters increases to 4 for a reduction of 80%. These results suggest that future LCA studies should endeavour to obtain the most accurate values possible for these parameters to reduce the uncertainty of the correspondent environmental impact estimates. For instance, because the variability of the model's carbon footprint for conventional geothermal technologies can be attributed in practice only to operational emissions of CO_2 (Figure 2), it is not recommended to use values that represent the operation of another geothermal plant in a different location, or to estimate carbon emissions without appropriate knowledge and data on the geothermal plant and reservoir. Rather, our results suggest that having accurate estimates of operational CO_2 emissions for a specific operation is of paramount importance for calculating the carbon footprint of conventional geothermal technologies.

Douziech et al. (2020) applied GSA to four geothermal plant archetypes, representing EGS and ORC plants for heat production, and flash and combined heat-and-power plant for electricity generation. The underlying models share several assumptions with the models we developed, but also present notable differences; as an example, their models explicitly consider the flow rate of the geothermal fluid and the content of non-condensable gases. Douziech et al calculated first order Sobol' indices which they used as proxy (in place of total order indices) for generating simplified models (i.e. the factor fixing approach described below). The findings from Douziech et al. are in line with ours in many aspects. Two to six parameters explain 75% or more of the variance of their model's output, depending on the plant archetype and environmental category; this is compared with two to four in our study for both conventional and enhanced plants. The installed capacity (electrical and/or thermal) has among the highest first order indices across all plant archetypes. This agrees with our results for enhanced plants; however, the variability of our model for conventional plants is dominated by the producers' capacity (which determines the number of wells to be drilled). Like in our study, Douziech et al. find that the climate change category for flash/CHP plants is significantly affected by carbon emissions (including CO_2). Notably, they estimate carbon emissions based on the geo-fluid flow rate and the content of non-condensable gases and/or CO_2; whilst we use CO_2 emission values per kWh of generated obtained from a global survey of geothermal plants (Bertani and Thain, 2002b). Other parameters that are found to be influential in both studies include the number and depth of primary wells, and the number of make-up wells (which in our model are predicted via the initial harmonic decline rate). A notable difference is that Douziech et al. identify the electricity consumption of production and/or injection pumps amongst the most influential parameters for EGS/ORC plant. We hypothesise that this is because their model envisages that this electricity is (at least in part) obtained from the grid. In our study, EGS plants are assumed to generate electricity; we embedded the pumps' electricity consumption within the auxiliary power parameter, which yields low to negligible first order indices (see Figure 2 and Figure 3).

The "Factor Fixing" approach is used to identify those parameters which, left free to vary over their range of uncertainty, make no significant contribution to the variance of the output. Total order indices, which represent the fraction of the variance of the model output that is explained by a given parameter considering interaction effects, are used to this end. The parameters with the lowest total order index can then be fixed at any given value within their range of variation without affecting the output variance. The chart on the right in Figure 4 shows that this can be done for a large number of parameters. In fact, a total of 7 and 6 parameters for conventional and enhanced technologies respectively are individually responsible for less than 1% of the variance of the model output considering interactions effects (i.e. total order indices lower than 0.01). The number rises to 12 parameters for a threshold of 5% of the variance. These results suggest that, when quantitative information on any of these parameters is not immediately available, LCA practitioners can choose any value within their range of variability reported in Table 1 without altering significantly their results. Blanc et al. (2020) provide additional default parameter values.

A notable application of the Factor Fixing setting is to develop simplified models (Douziech et al., 2020; Lacirignola et al., 2014; Padey et al., 2013) that rely on a smaller subset of parameters for, e.g., estimating the environmental impacts of a technology such as geothermal power. To this end, the results for higher thresholds are particularly interesting. Figure 4 shows that only three and one parameter are individually responsible for more than 20% of the variance of the model for conventional and enhanced geothermal technologies respectively; these parameters are "operational CO_2 emissions", "producers capacity" and "depth (of wells)" for the former, and "installed capacity" for the latter. The number of parameters increases by one for a threshold of 10%; in this case the additional parameters are "initial harmonic decline rate" and "diesel consumption" for conventional and enhanced geothermal technologies respectively. Our results suggest that simplified models relying on e.g. 1-4 parameters could be developed for conventional and enhanced technologies. Such simplified models are currently being developed by the Authors.

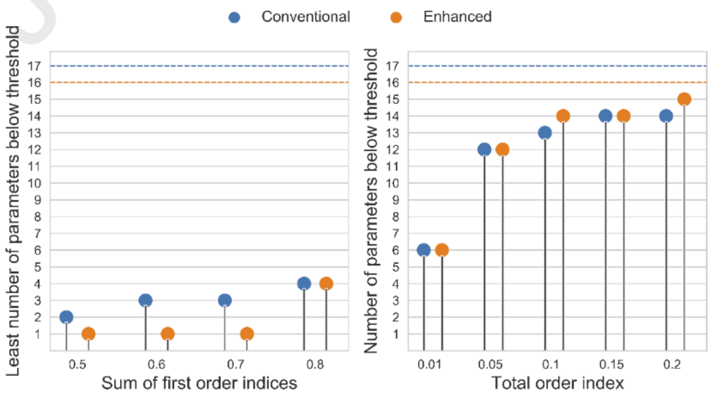


Figure 4 – Left: Least number of parameters for enhanced and conventional technologies whose sum of first order indices in all categories is below given threshold values (i.e. 0.5, 0.6, 0.7, 0.8). Right: Number of parameters for enhanced and conventional technologies whose total order indices are below given threshold values (i.e. 0.01, 0.05, 0.1, 0.15, 0.2) in all categories. The blue and orange dotted lines correspond to the number of parameters in the general model for conventional and enhanced technologies, respectively.

4.3 Limitations and recommendations for future work

The main limitation of this study concerns the distributions of the model's parameters. Whilst the parameters' variability ranges can be inferred from a few studies available in the literature, a large amount of data is required to make reasonable assumptions regarding their distribution. For most parameters (13 out of 21) we assumed uniform distributions because sufficient data was lacking to infer other distributions. This assumption is conservative because it increases the contributions to the variance output; however, it may substantially affect the GSA results especially if the parameter has a particularly skewed distribution such as that of operational CO_2 emissions. For this reason, we tested the robustness of our results by changing all uniform distributions to triangular, with peaks located at their median values. The results, which are reported in Figure S4 and S5 in the Supporting Information, show that the Sobol' indices, and therefore the ranking of the parameters, are not significantly altered compared to those reported in Section 3.2. Our model is therefore robust to this assumption. Future work should focus on investigating different distributions for other parameters too, and different combinations of these distributions as proposed by Lacirignola et al. (2017).

For some parameters used in our model we could determine neither a range of variability nor a median value. The parameters for which a range of variability could not be established (e.g. the number of exploratory wells; see Table 2) are included in the model but are not investigated by means of GSA. However, the parameters for which we could not ascertain a median value (e.g., operational emissions of non-condensable gases other than CO_2) are not considered by the model. The former represents a limitation of the GSA study whilst the latter to both the GSA analysis and the general model. Notably, the validation of the general parametric model demonstrated the importance of operational emissions of methane in conventional power plants (see Figure 1) and that our model is likely to underestimate climate change impacts when the concentration of methane in the geothermal fluid is significant (e.g. for plants in Tuscany, Italy). Future studies should quantify whether the variability on the parameters we have assumed as constant, or in the parameters that were not included in our model strongly affects the predictions of the environmental footprint of geothermal energy operations. These studies can only be completed when sufficient field data are available.

The general parametric model presented here relies on several simplifying assumptions on the plant construction; these are described in Section 2.2 and include, but are not limited to, the assumption that the material requirements for the construction of the plants only scale with the installed capacity, or that both conventional and enhanced plants use a water-based cooling system. These assumptions stem from poor data availability in the literature; future studies could develop more detailed modelling of the plant construction when more data become available. Furthermore, previous studies demonstrate that the cooling system has minor contributions to the environmental impacts (e.g., see Menberg et al., 2021; Paulillo et al., 2019a); therefore, our assumption on the type of cooling system is likely to have minor effects on the model output and the GSA results.

The model has only been validated with respect to climate change impacts obtained from literature studies. This represents an additional limitation because of two reasons. First, the model needs to be validated using site-specific data from operational plants and compared with a conventional LCA models. This cannot be done for most of the carbon footprints data points because the studies do not report many of the parameters that the general model requires. Second, the validation needs to be extended to environmental categories other than climate change; at present, our assumption that the model is valid for other environmental categories remains to be tested.

5 Conclusions

In this work we identified the most influential parameters for quantifying the environmental impacts of geothermal power generation because (i) site-specific data is not always available and (ii) data collection can be time-consuming and expensive. First, we developed a general parametric model for estimating the life-cycle environmental impacts per unit of electricity generated by both conventional and enhanced geothermal plants. We validated the general model by comparison with literature data for climate change impacts; the results show that the model is able to reproduce most of the variability of literature data. Then, we used Global Sensitivity Analysis (GSA) to quantify the contribution of each parameter to the variance of the general model output, using estimators for first and total order Sobol' indices based on Monte-Carlo simulations. We used first order indices to identify the parameters that, when fixed to their true values, lead to the greatest reduction in the variance of the output. The parameters with the highest first order indices include operational CO2 emissions", "producers capacity" and "depth (of wells)" for conventional technologies and "installed capacity" for enhanced technologies. On the other hand, we used total order indices to identify the parameters that can be fixed at any given value within their range of variation without affecting the output variance. Our analysis showed that a large number of parameters are non-influential, suggesting that (i) LCA practitioners can choose any value within the range of variability of these parameters when site-specific data is not available, and (ii) the general model could be considerably simplified by fixing all non-influential parameters. The Authors are investigating the development of such simplified models. Finally, we recommended potential future works, for example investigating different distributions and different combinations of distributions for the input parameters.

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ANNEX A - Coefficients of the Generic parametric model

The coefficients *i*, which represent either the life-cycle environmental impact (in a specific category) associated with the provision of the intermediate flow or the characterisation factor of the elementary flow, are introduced below:

i1	impact of wellhead. Material requirements are obtained from Karlsdóttir et al. (2015)
i2.1	impact per MJ of fuel burnt in a diesel-electric generating set (10MW)
i2.2	impact per kg of low-alloyed steel, for casing
i2.3	impact per kg of generic concrete, for casing
i2.4	impact per m^3 of drilling mud (water). Material requirements are obtained from Paulillo et al. (2020b) and assume 15 kg of bentonite and 20 kg of generic organic chemicals for m^3 of water
i2.5	impact of drilling waste per m of well
i2.6	impact of well closure per m of well
i3	impact per m of collection pipelines. Material requirements are based on Karlsdóttir et al. (2015)
i4.1	impact per unit of electric power of machineries and facilities, based on Karlsdóttir et al. (2015)
i4.2	impact per unit of electric power of cooling towers, obtained from Schulze et al. (2019)
i4.3	impact per unit of electric power of working fluid
i5.1	impact per m^3 of water
i5.2	impact per kWh of thermal energy (obtained from a diesel-electric generating set of 18kW)
i6	impact of carbon dioxide emissions per kWh of electricity generated

The numerical values, which are calculated using the Ecoinvent database - cut-off model, version 3.6 (Wernet et al., 2016) - are reported in Table A1 for all categories included in the Environmental Footprint (EF) 2.0 method (Fazio et al., 2018).

TABLE A1 – NUMERICAL COEFFICIENTS OF THE SPECIFIC EXPRESSIONS OF THE GENERAL PARAMETRIC MODEL (REPORTED EQUATIONS FROM (3) TO (14) IN THE MAIN ARTICLE) FOR ENVIRONMENTAL CATEGORIES IN THE EF2.0 METHOD.

	i1	**i2.1**	**i2.2**	**i2.3**	**i2.4**	**i2.5**	**i2.6**	**i3**	**i4.1**	**i4.2**	**i4.3**	**i5.1**	**i5.2**	**i6**
Climate change total	4.20E+04	8.78E-02	1.92E+00	8.72E-01	4.17E+01	7.22E-03	1.62E+00	6.19E+02	1.36E+05	2.90E+05	1.93E+01	1.10E-03	9.33E-01	1
Carcinogenic effects	9.33E-03	1.34E-10	6.01E-07	3.49E-09	5.33E-07	9.40E-08	9.24E-09	1.25E-04	1.67E-02	1.21E-02	2.08E-07	8.02E-11	4.19E-09	0
Ionising radiation	1.13E+03	5.18E-03	5.17E-02	1.28E-02	8.93E-01	6.42E-04	3.55E-02	1.57E+01	4.16E+03	2.17E+04	2.32E-01	7.55E-05	5.40E-02	0
Non-carcinogenic effects	2.21E-02	1.94E-09	1.38E-06	4.70E-08	5.49E-06	2.91E-07	1.10E-07	3.00E-04	6.10E-02	1.32E-01	1.49E-06	3.34E-10	3.05E-08	0
Ozone layer depletion	2.77E-03	1.92E-08	1.14E-07	3.16E-08	4.21E-06	2.23E-09	8.98E-08	3.89E-05	1.27E-02	1.48E-01	7.84E-04	7.16E-11	1.99E-07	0
Photochemical ozone creation	1.99E+02	1.59E-03	9.23E-03	1.97E-03	1.90E-01	6.00E-05	4.85E-03	2.82E+00	5.92E+02	8.93E+02	4.30E-02	3.30E-06	1.64E-02	0
Respiratory effects, inorganics	3.73E-03	1.57E-09	1.75E-07	1.96E-08	2.03E-06	7.92E-10	5.23E-08	5.07E-05	9.88E-03	1.36E-02	6.22E-07	5.60E-11	1.84E-08	0
Freshwater and terrestrial acidification	2.25E+02	1.24E-03	9.81E-03	2.42E-03	1.98E-01	5.60E-05	5.68E-03	3.46E+00	9.57E+02	1.77E+03	6.21E-02	5.63E-06	1.30E-02	0
Freshwater ecotoxicity	1.18E+05	1.46E-02	7.24E+00	1.63E-01	2.97E+01	5.24E+00	6.02E-01	1.59E+03	2.90E+05	3.39E+05	8.93E+00	1.30E-03	2.03E-01	0
Freshwater eutrophication	1.97E+00	1.37E-07	1.13E-04	1.09E-05	2.13E-03	1.52E-05	2.47E-05	2.87E-02	7.57E+00	3.85E+01	2.96E-04	6.68E-08	3.24E-06	0
Marine eutrophication	5.05E+01	5.55E-04	2.04E-03	6.77E-04	5.29E-02	1.85E-05	1.61E-03	6.90E-01	1.72E+02	7.23E+02	8.61E-03	9.56E-07	5.73E-03	0
Terrestrial eutrophication	5.48E+02	6.08E-03	2.18E-02	7.83E-03	4.14E-01	2.04E-04	1.86E-02	7.84E+00	1.71E+03	3.45E+03	9.59E-02	1.06E-05	6.27E-02	0
Minerals and metals	4.48E+00	8.07E-08	2.96E-05	8.63E-05	4.87E-04	2.27E-07	1.16E-04	1.38E-02	7.47E+00	8.73E+00	6.71E-04	3.23E-08	5.01E-06	0
Dissipated water	1.66E+04	1.57E-03	9.46E-01	6.29E-02	3.29E+01	7.22E-04	1.69E-01	2.37E+02	6.23E+04	3.83E+05	6.02E+00	6.00E-04	2.74E-02	0
Fossil resources	5.46E+05	1.17E+00	2.70E+01	4.38E+00	1.24E+03	1.62E-01	1.09E+01	8.01E+03	1.87E+06	4.78E+06	1.23E+02	1.72E-02	1.24E+01	0
Land use	2.68E+05	4.91E-02	1.10E+01	3.43E+00	1.48E+02	5.73E-01	1.15E+01	4.17E+03	1.05E+06	2.47E+06	3.65E+01	5.39E-03	6.69E-01	0

Annex B - Description of parameters

Power plant parameters:

Installed capacity: Maximum gross electric power output of the power plant (i.e. without considering auxiliary power requirements). The lower boundary of the installed capacity range for conventional technologies is based on Bertani (2012) who maintains that the majority of plants smaller than 10 MW employ binary cycle units.

Auxiliary power: Power requirements of auxiliary services of the power cycle and of downhole pumps (for enhanced geothermal technologies only).

Capacity factor: Unitless ratio of actual electrical energy output to maximum possible over a period of time. (Sometimes this is also referred to as Load or Availability factor.)

Lifetime: Time span over which the power plant is estimated to operate.

Collection pipelines length: Average length of collection pipelines between each primary/make-up well and power plant. A range of variability for enhanced geothermal technologies could not be determined from literature; however, based on the variability for conventional technologies, we assumed a representative range of 50-200 m.

Wells parameters:

Primary wells number: Primary wells include injection and production wells. The variability range represents a double or triple configuration.

Producers capacity: Maximum gross electrical energy that can be generated from production wells.

Wells depth: Average length of wells measured along the actual well path; this is known as "average measured depth".

Diesel: Specific consumption (as thermal energy) per metre of well of diesel burnt in a diesel-electric generating set. The generated electricity is used for powering the drilling rig.

Steel: Specific consumption per metre of well of stainless steel, used for casing.

Cement: Specific consumption per metre of well of generic Portland cement (used to hold the well's casing in position).

Drilling mud: Specific consumption per metre of well of drilling mud, which is used to remove and to bring to surface drilled cuttings, as well as for cooling the drill bit, lubricating the drill string and preventing the collapse of the well during the drilling. The drilling mud inventory assumes usage of 20 kg of generic organic chemicals and 15 kg of bentonite per m^3 of water.

Initial harmonic decline rate: Sanyal (2004) and Sanyal et al. (1989) argue that geothermal wells typically undergo a harmonic decline rate. This means that the wells productivity at any point in time can be estimated from the initial productivity and the initial harmonic decline rate. This parameter is essential in estimating the number of make-up wells that are required over a plant's lifetime to maintain electricity production. We could not determine a range of variability from the literature, but given the importance of this parameter we assumed a representative range of variability of 1 to 10% based on the work of Sanyal et al.

Production/Injection ratio: Ratio of producers to injectors.

Success rate: Percentage of successful exploration, primary and make-up wells.

Stimulation:

Water: Amount of water required for hydraulic stimulation of one well.

Diesel: Specific diesel consumption for pumping 1 m^3 of water for hydraulic stimulation. Diesel is burnt in a diesel-electric generating set to generate electricity.

Wells: We assumed that a minimum of one well in enhanced geothermal systems will undergo stimulation; the maximum number is equal to the number of primary wells. To ensure that the parameters are independent from each other (a necessary condition for Sobol' variance-based method), we calculate the number of wells that are stimulated as the rounded product of the number of primary wells and a number varying between 0.5 and 1.5 (this parameter). Note that the number varies between 0.5 and 1.5 (instead of 0 and 1) to ensure that at least one well is stimulated.

Operational CO_2 emissions: CO_2 make-up most of non-condensable gases that are present in geothermal fluids. Discharge of CO_2 occurs during cooling of geothermal fluids and prior to their reinjection into geothermal reservoirs.

Fixed parameters:

Exploratory wells: Number of exploratory wells (i.e. test wells) that are drilled at the outset of a new geothermal development to e.g. confirm the depth of the reservoir. Our assumption of three wells is based on DiPippo (2016b).

Cooling towers: For simplicity, we assume that both conventional and enhanced geothermal plants make use of cooling towers to condense the geothermal fluid prior to reinjection. The numbers of cooling tower is scaled per MW of installed capacity from Karlsdóttir et al. (2015).

Organic working fluid: Amount of organic working fluid per MW of installed capacity. The model assumes that the working fluid is perfluoropentane (the same assumption is made in the Ecoinvent database) and that there are no losses of working fluid during the lifetime of the plant. It must be noted that including leakages of working fluid and choosing a different working fluid with a higher global warming potential (GWP) - e.g. R134 or others - may lead to a higher contribution of this parameter to climate change impact as well as to the variability of the model output. However, Menberg et al. (2021) demonstrated that fluid leakages have negligible effect on the carbon footprint when low-GWP fluids are employed, which is expected as climate change mitigation strategies are tightened.

Drilling waste: Amount of drilling waste generated per metre of well. The amount of drilling waste is estimated assuming an open hole diameter of 8.5 in, a factor of 3 between the volume of the production liner to the total volume drilled, and a composition of 50% water and 50% drilling cuttings. We used a representative value for the cuttings density of 3 g/cm^3, approximately equal to that of basalt.

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