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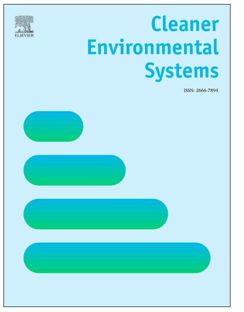

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Simplified models for predicting the environmental impacts of geothermal power generation

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Abstract

Geothermal energy is a renewable source of base-load power that could facilitate decarbonising the power generation sector. This work proposes novel simplified models based on Life Cycle Assessment (LCA) that enable rapid but accurate estimates of the environmental impacts of geothermal power. The proposed approach not only reduces the variability of LCA estimates due to methodological choices, but also substantially facilitates data collection by identifying the most important input parameters. These parameters are selected using Sobol' total order indices from Global Sensitivity Analysis to a general parametric model. The models are applicable to both conventional and enhanced geothermal technologies, and cover numerous environmental impact categories. We determine the level of correlation between the simplified models and the general model. Our analysis shows that the simplified models correlate well with the general model, with correlation coefficients above 0.75 for both types of geothermal technologies and for all environmental categories. We also evaluate the performance of the simplified models by comparison with literature data. The results are positive, especially for conventional technologies where the relative difference with literature data on climate change impacts averages 14%. Finally, we identify the most appropriate model for each technology archetype and environmental category.

Word count: 7977

Keywords

renewable energy; enhanced geothermal systems; carbon footprint; meta models; model validation

Highlights

- Simplified geothermal models rely on 1-5 influential parameters
- Influential parameters are obtained from Sobol' total order indices
- Models cover conventional/enhanced technologies and multiple environmental categories
- Carbon footprint estimates are validated against literature data
- Open-source python script for easy updates or customisation.

1 Introduction

Geothermal energy embodies the natural heat content of the Earth. It is a renewable source adequate for providing base-load power that is continuously replenished by decay of radioactive elements such as uranium, thorium and potassium at a rate that is comparable with current human consumption (Gando et al., 2011). Unlike solar and wind, geothermal energy can generate base-load power because it is independent of seasonal and climatic conditions. These features make it a key energy source that could help the decarbonisation of the power generation sector, and thus the transition to a low-carbon economy needed to mitigate long-term and possibly irreversible consequences of global warming (Masson-Delmotte et al., 2018).

Life Cycle Assessment (LCA) is the prevailing tool for the quantification of environmental impacts of technologies. The LCA methodology (ISO, 2006a, 2006b), has two important features: it covers the whole life-cycle, and considers a number of environmental issues that include but are not limited to climate change (Hauschild et al., 2018). These features enable identification of trade-offs (i.e. burden-shifting between environmental categories and between life cycle phases), making LCA a widely-adopted tool for facilitating decisions-making. However, LCA studies on geothermal power exhibit a significant variability; for instance, the carbon footprint of electricity from geothermal spans over two orders of magnitude, from ~5 and up to ~800 gCO_2-eq./kWh (Paulillo et al., 2019a, 2019b). This variability is only in part due to LCA methodological choices like the definition of the system boundary, but it is also due to differing site-specific conditions such as the composition of the geothermal fluid or the depth of the geothermal reservoir (Bayer et al., 2013; Tomasini-Montenegro et al., 2017). Notably, the latter emphasizes the importance of collecting high-quality field data, which arguably is the most time-consuming phase of the LCA methodology for any application.

Meta-analysis of LCA studies offers an approach to handle variability (Brandão et al., 2012; Warner et al., 2010). It aims at harmonizing methodological choices and identifying most commonly observed parameter values to provide a reduced range of possible environmental impacts (Farrell et al., 2006). An alternative approach hinges on the development of simplified LCA models based on a small set of influential parameters that are responsible for most of the variability of the LCA results (Padey et al., 2013); these parameters are typically identified by means of Global Sensitivity Analysis (GSA) (Saltelli et al., 2008). Because simplified LCA models require relatively small site-specific data, they enable quick estimations of the environmental impacts. They can be used by policy makers to support the development of energy policies using simple, yet reliable approximations, and by geothermal companies lacking LCA expertise or accurate datasets to quantify the environmental performance of their plants. Early simplified LCA models in the energy sector were developed for wind power (Padey et al., 2013) and for enhanced geothermal systems - an emerging technology for geothermal power generation (Lacirignola et al., 2014). A notable limitation of these early models is that they focus on a single environmental impact category: climate change. More recently, simplified models covering additional categories have been developed by Douziech and colleagues for several geothermal technology archetypes (Douziech et al., 2021, 2020).

In this study we introduce novel simplified LCA models based on previously published GSA results (Paulillo et al., 2021) that enable quick estimations of the environmental impact of electricity generation from geothermal energy. Similar to Douziech et al., our models cover multiple environmental categories; but unlike their models, ours encompass two generic archetypes: conventional and enhanced geothermal technologies. Conventional geothermal technologies represent most of the geothermal installed capacity (Bertani, 2016; IGA, 2015), and harness high-enthalpy hydrothermal reservoirs by means of well-known conversion technologies such as dry-steam and flash plants. By contrast, Enhanced Geothermal Systems (EGS) were developed to harness unconventional geothermal reservoirs that lack either water or sufficient permeability; the technology uses hydraulic stimulation to create an "engineered" reservoir, and generates electricity typically by means of binary cycle plants (MIT, 2006; Sanchez-Roa et al., 2021). This work builds upon a previous study in which we identified the most influential parameters for the quantification of the environmental impacts associated with both conventional and enhanced geothermal technologies (Paulillo et al., 2021). In that study, we developed a complex model based on multiple parameters (termed "general model"), and then applied GSA to quantify the contribution of the variance of each input parameter to the model output. Those results are used here to develop the simplified models.

The remainder of this article is organised as follows: in Section 2 we present the proposed simplified models and their parameters; in Section 3 we validate the simplified models first against the general model, and then against literature data; finally, we discuss the results of our analyses in Section 4, and summarise the key conclusions in Section 5.

2 Methods: generation of simplified LCA models

In Paulillo et al. (2021), we developed a general parametric LCA model for estimating the environmental impacts of conventional and enhanced geothermal power technologies. Notably, we assumed that the former covers dry steam and single/multiple flash plants but not binary cycle ones, which only make up a small portion of global installed capacity (Bertani, 2016). By contrast, we only considered binary cycle plants for enhanced geothermal systems. The general model relies on the ecoinvent database (v3.6, cutoff) (Wernet et al., 2016) and the Environmental Footprint 2.0 (EF2.0) (Fazio et al., 2018) method to quantify environmental impacts (Fazio et al., 2018). It adopts a functional unit of 1 kWh of electricity and cradle-to-grave system boundaries, covering all activities from the construction of wells/plant to their decommissioning; all other assumptions are presented and discussed in Paulillo et al. (2021). The model relies on 25 input parameters, which describe aspects of both the geothermal reservoir and the power plant. Paulillo et al. (2021) applied GSA to 21 of the 25 parameters – i.e., those for which a range of variability was determined – to identify parameters that affect the most the variability of the model output, and by extension that of LCA results on geothermal power generation. We used the variance-based methodology developed by Sobol' (2001) to quantify the importance of each parameter, which was expressed in terms of first and total order indices using estimators based on Monte Carlo simulations (Jansen, 1999; Saltelli et al., 2010).

Unlike first-order indices, total-order indices account for interaction effects between parameters. Low total-order indices identify non influential parameters which can be fixed anywhere within their range of variability without significantly affecting the model output (Saltelli et al., 2008). Thus, using total order indices we can identify those parameters that can be assigned a pre-compiled value, within a range of acceptable values, as this choice will not strongly affect the model prediction. Using fewer parameters, the model will be simpler in the sense that fewer data will be needed to make predictions. However, the selection of the value of total order index that distinguishes between influential and non-influential parameters is arbitrary and consequential. The higher the threshold, the higher the number of non-influential parameters; therefore, the resulting simplified model is simpler but less accurate. On the contrary, the lower the threshold, the higher the number of influential parameters, ultimately recovering the original model. In this study we present several simplified models developed using four thresholds of the total order index; these correspond to 0.2, 0.15, 0.1, 0.05. For instance, a threshold of 0.2 means that all parameters having contributions, including interaction effects, lower or equal to 20% of the variance of the model output are considered non-influential.

From the general model, we developed the simplified models for each environmental category or group of environmental categories featuring the same influential parameters, by fixing all non-influential parameters to their median values (Table S19 in the Supporting Information). The non-influential parameters are lumped together alongside other coefficients of the general model to generate numerical coefficients (namely α, β, χ and δ, as defined in Section 2.1 and 2.2), which are reported in Section S1 of the Supporting Information. The simplified models and their parameters for conventional and enhanced geothermal technologies are reported in Sections 2.1 and 2.2, respectively. The models were developed using Brightway2 (Mutel, 2017); the Python code is available at https://github.com/a-pau/gsa_geothermal.

2.1 Conventional geothermal technologies

Equations 1-4 report the proposed simplified LCA models for conventional geothermal technologies; the parameters of the simplified models for each threshold of the total order index are given in Table 1. In the climate change category, the parameter "operational CO_2 emissions" (which features the highest total order index) explains nearly 100% of the variance of the general model's output. The remaining parameters of the general model present negligible total order indices (Paulillo et al., 2021). However, an additional parameter must be considered: operational emissions of CH_4. This was not covered by the general model because a range of variability could not be determined; but it can significantly affect the carbon footprint of conventional geothermal technologies when methane is present in above-average concentration in the geothermal fluid, for instance in the region of Tuscany, Italy (Basosi et al., 2020; Bravi and Basosi, 2014). Therefore, for the climate change category the general model can be simplified to a two-parameter equation, which is shown in Equation 1. We assume that this simplified model applies to all thresholds, even though a total order index was not calculated for the parameter "operational CH_4 emissions". In Equation 1, α_1 and α_2 respectively represent the characterisation factors for CO_2 and CH_4 using Global Warming Potentials for a 100-year time frame (Fazio et al., 2018; IPCC, 2013), whilst α_3 corresponds to the impacts of the other terms of the general model obtained using median values for the non-influential parameters and the Ecoinvent database (v3.6). The numerical values for α_1, α_2 and α_3 are reported in Table S1 in the Supporting Information.

The remaining categories in the EF2.0 method feature the same influential parameters for each threshold. This is because these parameters either affect the overall amount of electricity generated (e.g. producers capacity) or they determine the number of wells to be drilled; in both cases, all categories are affected in a similar manner. Two parameters contribute to more than 15% of the variance of the general model's results; these parameters are: producers' capacity CW_{ne}, i.e. the maximum electric energy that each production well is capable of generating, and the average depth of wells W_d. Therefore, for these categories and for both 15 and 20% thresholds, a two-parameter simplified model can be developed from the general model; this is shown in Equation 2, where the impact for each environmental category *k* is obtained as a combination of W_d, CW_{ne} and four numerical coefficients $\beta_{1 \ldots 4,k}$ that are specific to each environmental category. Note that the capacity of the production wells is used in the general parametric model to predict the number of production wells that are required to meet the installed capacity of the plant.

When the total order index threshold is reduced to 10%, one additional parameter needs to be included in the simplified model: the initial harmonic decline rate of the production wells (Sanyal, 2004), which is used in the general model to estimate the number of make-up wells required during the lifetime of the plant. The simplified model at 10% is reported in Equation 3.

Finally, for a threshold of the total order index of 5%, the simplified model employs one additional parameter, the success rate of primary wells SR_p: the general model assumes that some wells may be unsuccessful (e.g. due to unexpected mechanical problems encountered during drilling) and thus considers that the number of wells drilled is higher than that required to meet the installed capacity of the plant. (The success rate is defined as the percentage of successful exploration, primary and make-up wells.) The simplified model for a threshold of 5% is reported in Equation 4. The numerical coefficients $\beta_{1\dots6,k}$ for each threshold and each environmental category are reported in Tables S2 to S4 in the Supporting Information.

Climate change	All thresholds	$Impact = E_{CO_2} \cdot \alpha_1 + E_{CH_4} \cdot \alpha_2 + \alpha_3$	(1)
Remaining categories	20/15%	$Impact_k = \frac{W_d \cdot \beta_{1,k} + \beta_{2,k}}{CW_{ne}} + W_d \cdot \beta_{3,k} + \beta_{4,k}$	(2)
	10%	$Impact_k = \frac{D_i \cdot W_d \cdot \beta_{1,k} + D_i \cdot \beta_{2,k} + W_d \cdot \beta_{3,k} + \beta_{4,k}}{CW_{ne}} + W_d \cdot \beta_{5,k} + \beta_{6,k}$	(3)
	5%	$Impact_k = \frac{SR_p \cdot D_i \cdot W_d \cdot \beta_{1,k} + D_i \cdot SR_p \cdot \beta_{2,k} + SR_p \cdot \beta_{3,k} + W_d \cdot \beta_{4,k}}{SR_p \cdot CW_{ne}} + W_d \cdot \beta_{5,k} + \beta_{6,k}$	(4)

Table 1 – Parameters of the simplified models for conventional geothermal technologies.

Acronym	Parameter	Unit	Threshold
E_{CO_2}	Operational CO_2 emissions	kg CO_2/kWh	20%,15%,10%, 5%
E_{CH_4}	Operational CH_4 emissions	kg CH_4/kWh	20%,15%,10%, 5%
CW_{ne}	Producers' capacity	MW/well	20%,15%,10%, 5%
W_d	Average depth of wells	m/well	20%,15%,10%, 5%
D_i	Initial harmonic decline rate	-	10%, 5%
SR_p	Success rate, primary wells	%	5%

2.2 Enhanced geothermal technologies

The simplified models for enhanced geothermal technologies are reported in Equation 5-8, whilst Table 2 includes the relevant parameters for each threshold. Like for conventional technologies, we grouped together the environmental categories that feature the same influential parameters and thus can be described by the same equations. We note that the grouping of categories is only intended to facilitate their description: it does not represent any specific relation between categories. Equation 5 and 6 apply to the environmental categories included in Group 1, whilst Equation 7 and 8 apply to the categories included in Group 2. The categories that belong to Group 1 and 2 differ according to the specific threshold considered, as detailed in Table 3. In essence, the simplified models for Group 2 categories differ from those for Group 1 in that they include an additional parameter: the average diesel consumption for drilling one meter of well, D; this is because the categories in Group 2 (e.g. marine and terrestrial eutrophication) are those that are most affected by impacts associated with diesel production and burning in a diesel-electric generator set. (It must be noted that our model does not account for the possibility of using electricity directly from the grid. Although this is a reasonable assumption because most wells are drilled in this way, future model improvements should consider this aspect.)The parameter "installed capacity" (P_{ne}) represents the maximum gross electric power output of the power plant without considering auxiliary power requirements. This is the most influential parameter for enhanced geothermal technologies, and the only one that contributes to more than 20% of the variance of the general model output in all environmental categories (see Paulillo et al., 2021). Therefore, for a threshold of 20% the simplified model for all environmental categories is represented by Equation 5. (Note that, as shown in Table 3, at 20% all environmental categories are included in Group 1.) At 15% and 10% thresholds, the same simplified model (Equation 5) can be used for the categories in Group 1 (see Table 3). As noted above, for Group 2 categories the simplified model needs the specific diesel consumption for drilling wells D; therefore, for 15% and 10% thresholds the general model can be simplified to Equation 7. Finally, at the 5% threshold, two additional parameters are required for both Group 1 and Group 2 categories, these are the average depth of wells W_d and the success rate of primary wells SR_p; the simplified models for Group 1 and Group 2 categories at 5% threshold are reported in Equation 6 and 8, respectively. The numerical values of the coefficients χ and δ for each environmental category are reported in Table S5 to S11 in the Supporting Information.

Group 1

20/15/10%

$$Impact_k = \frac{\chi_{1,k}}{P_{ne}} + \chi_{2,k} \tag{5}$$

5%

$$Impact_k = \frac{SR_p \cdot W_d \cdot \chi_{1,k} + SR_p \cdot \chi_{2,k} + W_d \cdot \chi_{3,k}}{SR_p \cdot P_{ne}} + \chi_{4,k} \tag{6}$$

Group2

15/10%

$$Impact_k = \frac{D \cdot \delta_{1,k} + \delta_{2,k}}{P_{ne}} + \delta_{3,k} \tag{7}$$

5%

$$Impact_k = \frac{D \cdot W_d \cdot SR_p \cdot \delta_{1,k} + D \cdot W_d \cdot \delta_{2,k} + SR_p \cdot W_d \cdot \delta_{3,k} + SR_p \cdot \delta_{4,k} + W_d \cdot \delta_{5,k}}{SR_p \cdot P_{ne}} + \delta_{6,k} \tag{8}$$

Table 2 - Parameters of the simplified models for enhanced geothermal technologies

Acronym	**Parameter**	**Unit**	**Threshold**
P_{ne}	Installed capacity	MW	20%,15%,10%, 5%
D	Diesel consumption	MJ/m	15%,10%, 5%
W_d	Average depth of wells	m/well	5%
SR_p	Success rate, primary wells	%	5%

Table 3 – Environmental categories belonging to Group 1 (green) and Group 2 (orange), according to the thresholds considered in the simplified models for enhanced geothermal technologies.

	20%	15%	10%	5%
climate change	green	green	green	orange
human toxicity: carcinogenic	green	green	green	green
ionising radiation: human health	green	green	orange	orange
human toxicity: non-carcinogenic	green	green	green	green
ozone depletion	green	green	orange	orange
photochemical ozone formation: human health	green	green	orange	orange
particulate matter formation	green	green	green	green
acidification	green	green	orange	orange
ecotoxicity: freshwater	green	green	green	green
eutrophication: freshwater	green	green	green	green
eutrophication: marine	green	orange	orange	orange
eutrophication: terrestrial	green	orange	orange	orange
material resources: metals/minerals	green	green	green	green
water use	green	green	green	green
energy resources: non-renewable	green	green	green	orange
land use	green	green	green	green

3 Results: Validation of the simplified models

3.1 Comparison with the general model

We use two statistical measures to validate the simplified models against the general model: the Pearson correlation coefficient (r) and the Spearman rank correlation coefficient (ρ). The former measures the level of linear correlation between two variables (in this case the results of the general model and those of the simplified models); the latter quantifies the level of correlation between the ranking of two variables. Both coefficients vary between 1 and -1. Values of 1 and -1 indicate respectively perfect positive and negative correlation between the results (for Pearson) and the ranking of the results (for Spearman) of the general model and of the simplified models. Values close to 0 indicate negligible correlation. Evaluating both Pearson and Spearman correlation coefficients is useful because it enables understanding how well the relationship between the general and the simplified model can be described by linear and/or monotonic relationships, respectively. For example, a low value of the Pearson coefficient combined with a high value for Spearman suggests the existence of a monotonic, non-linear relationship.

Figure 1 and Figure S1 (in the Supporting Information) report the Pearson and Spearman coefficients for conventional and enhanced geothermal technologies, respectively. The coefficients were calculated from results of Monte Carlo simulations with 10,000 iterations using the same ranges of variability and distributions of the parameters of the general model that were used for GSA purposes (Paulillo et al., 2021). For this analysis we disregard the parameter operational CH_4 emissions (which applies to the climate change category and conventional technologies) because this was not included in the general model (Section 2.1). In Figure S3 and Figure S4 in the Supporting Information, we also compare the results of the general model and those of the simplified models for each threshold, for conventional and enhanced geothermal technologies, respectively. Notably, for enhanced technologies, Figure S4 shows the presence of a small number of outliers where the general model predicts significantly higher environmental impact than the simplified models. Because the Spearman correlation coefficients is highly sensitive to the presence of outliers, the coefficient in Figure 1 is calculated disregarding the highest 0.1% values from the general model. For completeness, the Pearson coefficient including outliers is reported in Figure S2 in the Supporting Information.

Figure 1 shows that the simplified models correlate well with the general model for both conventional and enhanced geothermal technologies. The level of correlation increases with decreasing thresholds, i.e. from 20% to 5%. Overlapping data points entail that the simplified models at different thresholds use the same equation (see Section 2). For conventional technologies, a near perfect correlation exists between the simplified model and the general model for the climate change category. For the remaining category, the simplified models at 20%/15% yield Pearson correlation coefficients of ~0.87, which increases above 0.9 for a threshold of 10% and above 0.95 for a threshold of 5%. For enhanced technologies, the simplified models yield comparable, albeit smaller, correlation coefficients, which are in the 0.8-0.9 range for 20%/15%/10% thresholds, and above 0.9 for 5%. Figure S2 in the Supporting Information shows that the Pearson correlation coefficient for enhanced plants including outliers is on average 0.05 smaller, but still high enough to indicate good correlation.

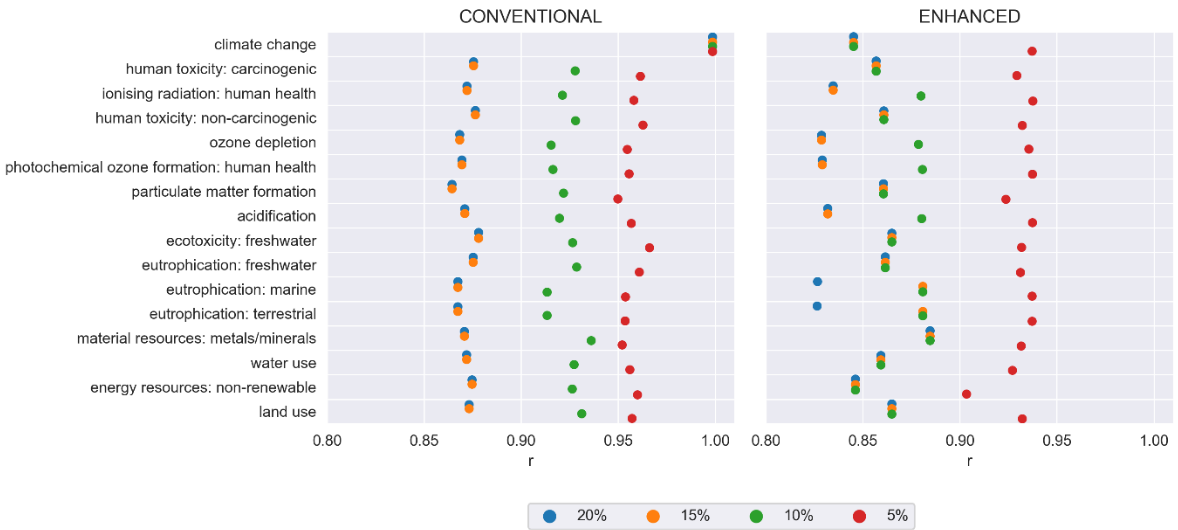

Figure 1 – Pearson correlation coefficient (r) between the general model and the simplified model for 20%, 15%, 10% and 5% thresholds, for the categories included in the EF2.0 method.

Similar results are obtained for the Spearman rank correlation coefficient (ρ); these are reported in Figure S1. Our results demonstrate the presence of a good level of correlation of the ranking of results between general and simplified models, and that this correlation increases with decreasing the threshold of simplified models. As for the Pearson correlation coefficient, the simplified models and the general model for conventional geothermal technologies exhibit near perfect correlation for the climate change category. For the remaining categories, ρ increases from 0.84-0.88 at 20/15% to 0.91-0.94 at 10% and above 0.95 at 5%. For enhanced technologies, ρ is included in the 0.83-0.88 range for 20%, 15% and 10%, and it is above 0.9 for 5%.

3.2 Comparison with carbon footprint estimates from literature

To validate the simplified models, in Figure 2 we compare carbon footprints obtained from literature studies with results from the simplified models. The latter are calculated using values of the relevant parameters obtained from the literature. Numerical values of the carbon footprints and of the simplified models' parameters are reported in Table S20 and S21. In Figure 2 we also include the overall variability of the general model (Paulillo et al., 2021). The comparison is limited to a single environmental category – climate change – because i) most LCA studies focus on this category, and ii) when other environmental impact categories were considered, impact assessment models different than EF2.0 were used to quantify the environmental impacts, and therefore no systematic comparison was possible. The comparison encompasses six studies and ten scenarios for conventional geothermal technologies (Basosi et al., 2020; Bravi and Basosi, 2014; Buonocore et al., 2015; Marchand et al., 2015; Paulillo et al., 2019a; Sullivan et al., 2010), and eight studies and fifteen scenarios for enhanced geothermal technologies (Bauer et al., 2017; De Rose et al., 2020; Frick et al., 2010; Lacirignola and Blanc, 2013; Menberg et al., 2021; Paulillo et al., 2020a; Pratiwi et al., 2018; Treyer et al., 2015).

For conventional geothermal technologies only one point estimate is provided for the simplified models; this is because for the climate change category the simplified models use the same equation for all thresholds (Section 2.1). The chart shows that the simplified model yields estimates that are close to literature data; notably, our model estimates do not differ from literature data by more than 18% for all scenarios considered. The relative difference is lowest (<2%) for Marchand et al. (2015) and Sullivan et al. (2010) data, and highest for Bravi and Basosi (2014) (scenarios PC4 and PC5) and Buonocore et al. (2015). The simplified model is more accurate when operational CH_4 emissions are low (i.e. below 1 g/kWh[1], like in Buonocore et al., 2015; Marchand et al., 2015; Paulillo et al., 2019a; Sullivan et al., 2010) with an average discrepancy of 8%. The relative difference for case studies with high CH_4 emissions (Basosi et al., 2020; Bravi and Basosi, 2014) is larger, averaging 14%. The general model does not include CH_4 emissions. This explains why case studies with high CH_4 emissions are well above the median value of the general model, with those with very high emission values (Bravi and Basosi, 2014) being even above 99th percentile.

To demonstrate the importance of operational CH_4 emissions, in Figure S5 we report the same comparison when the simplified model does not include CH_4 emissions as an input parameter. Notably, this is accomplished by setting $\alpha_2 = 0$. The chart shows that the "modified" simplified model performs well when CH_4 emissions are low, which is expected; however, it significantly underestimates the carbon footprint when operational CH_4 emissions are large, thus justifying their inclusion as an additional parameter.

For enhanced geothermal technologies, the simplified models at 20%, 15% and 10% thresholds coincide, and are therefore shown as one data point in the chart. The comparison shows that the

[1] Note that the values of CH_4 emissions are reported in Table S18.

simplified model at 5% generally yield estimates closer to literature data, and lower than that estimated by the simplified model derived using 20/15/10% thresholds. The simplified models at 5% are more accurate because they employ four parameters, compared to only one for thresholds higher than 10%. They yield lower estimates because of the success rate parameter: at thresholds higher than 5%, this parameter is fixed to a value of ~72%, whilst the selected studies report no unsuccessful wells (i.e. success rate of 100%).

The simplified models for enhanced technologies are less accurate than those for conventional technologies. The relative differences between literature data and our model's estimates average 77% and 48% for thresholds higher than 10% and for a threshold of 5%, respectively. The largest discrepancies are found for Paulillo et al. (2020a) estimates, which differ by more than 100%, and for Lacirignola and Blanc (2013) (S2), where the estimates of the simplified model are 150 and 69% lower. The largest discrepancy in absolute terms is found for the case study of Frick et al. (2010) (D1), where the simplified models underestimate literature data by more than 400 gCO_2-eq./kWh; notably, this is the only case where the literature data is above the 99th percentile of the general model. The reasons for some of these discrepancies are discussed in Section 4.3.

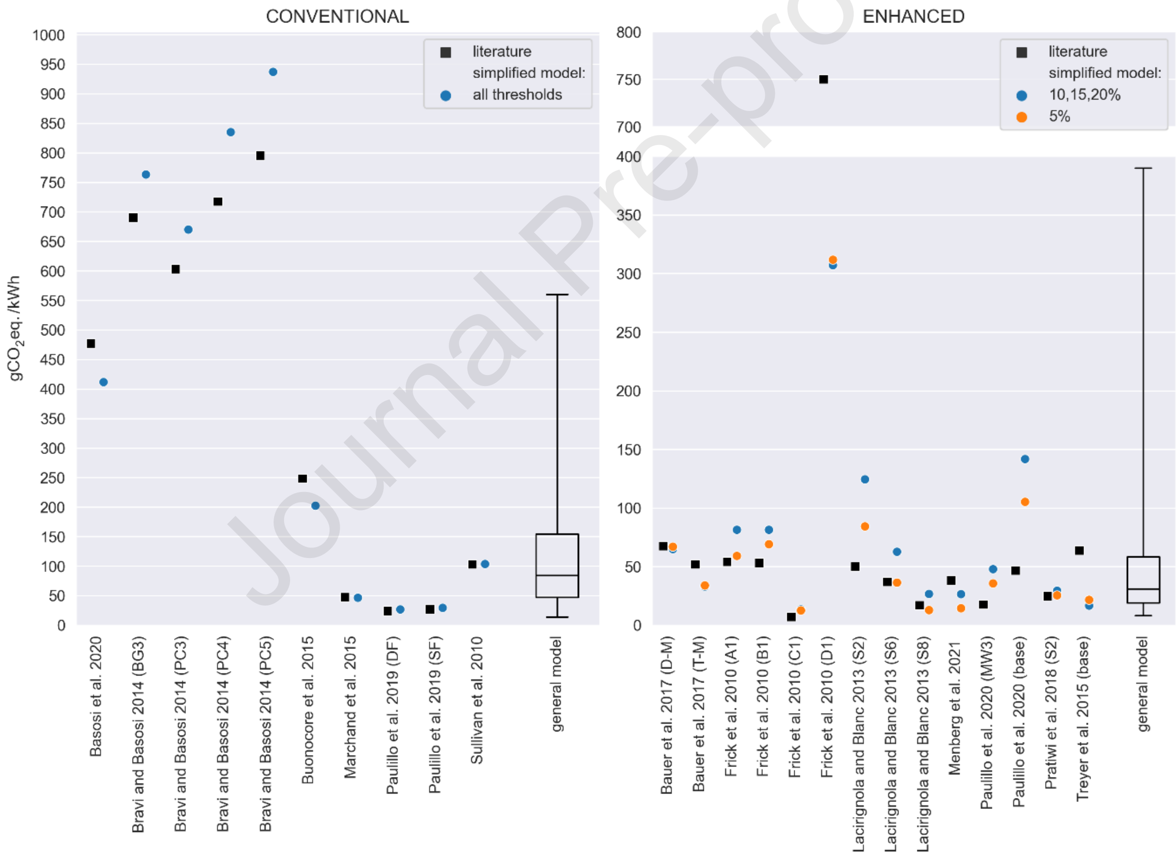

Figure 2 – Comparison between estimates from the simplified model, literature data and variability of the general model for the climate change category, and for conventional (left) and enhanced (right) geothermal technologies. The y-axis of the right chart is broken for better visualisation of deviations at low impacts. For each literature study, the acronym reported within brackets represents a specific scenario.

3.3 Extended comparison across multiple environmental categories

We expand the comparison reported in Section 3.2 to the remaining categories in the EF2.0 method, to investigate whether the simplified model (and indeed the general model) performs well for categories other than climate change. Specifically, we compare the simplified models with literature data from two case studies for which we had access to the underlying models. One study focused on

Hellisheiði, a conventional double-flash geothermal power plant in Iceland (Paulillo et al., 2019a), and the other on the United Down Deep Geothermal Power (UDDGP) project, an enhanced plant under construction in Cornwall, United Kingdom (Paulillo et al., 2020a). The results from these studies (Paulillo et al., 2020b, 2019b) have been re-calculated using the EF2.0 method. The comparison, which also includes the variability of the general model, is reported in Figure 3 and Figure 4.

Figure 3 shows that discrepancies between literature data and results predicted from the simplified models are minimal across all environmental categories. The estimates from literature are below the 25th percentile in all categories, implying that the Hellisheidi plant yields lower environmental impacts that the median value estimated by the general model. The simplified models report similar (albeit slightly higher) estimates, which decrease with reducing the threshold from 20% to 5%. This is expected, as reducing the threshold increases the accuracy of the simplified models (Section 2.2).

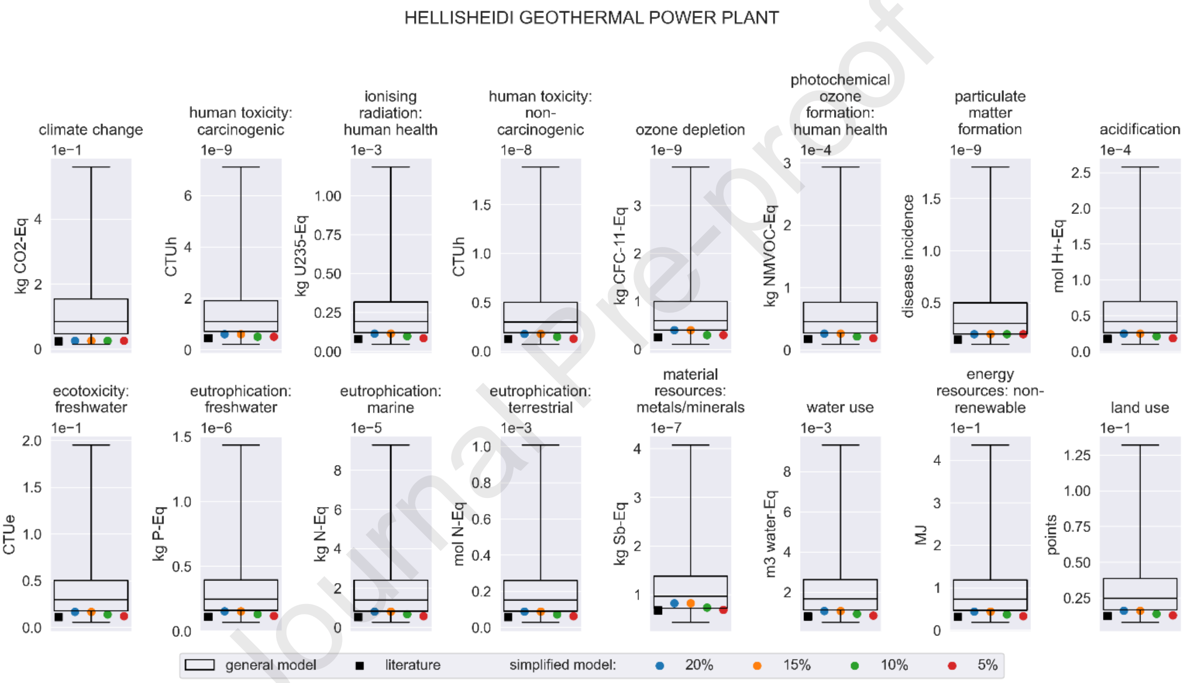

Figure 3 – Comparison between the variability of the general model, results from the simplified models and literature data for the Hellisheiði geothermal power plant. In the box-and-whisker plot, the horizontal lines represent median values, the boxes correspond to 25th and 75th percentiles, and the whiskers indicate 1st and 99th percentiles

For the United Downs geothermal plant (see Figure 4), the comparison is less positive. The estimates from literature are higher than the median value of the general model but lie within the 25-75th percentile range with the sole exception of the category minerals and metals (which is higher than the 75th percentile). The simplified models systematically overestimate the literature data by a factor of 2-3 for models at 20%, 15% and 10%, and by a factor of 1.5-2 for a threshold of 5%. However, all estimates from the simplified models are within the same order of magnitude as those from the literature. The results obtained from the model derived from the 5% threshold are substantially closer than those at higher thresholds; this indicates the importance of the additional parameters used by the model at 5%, which include the average depth of the wells and their success rate (Section 2.2). The comparison also highlights the importance of the parameter diesel consumption, which is evident for those environmental categories (see Table 3) where the estimates at 15% and/or 10% thresholds differ from those at 20%.

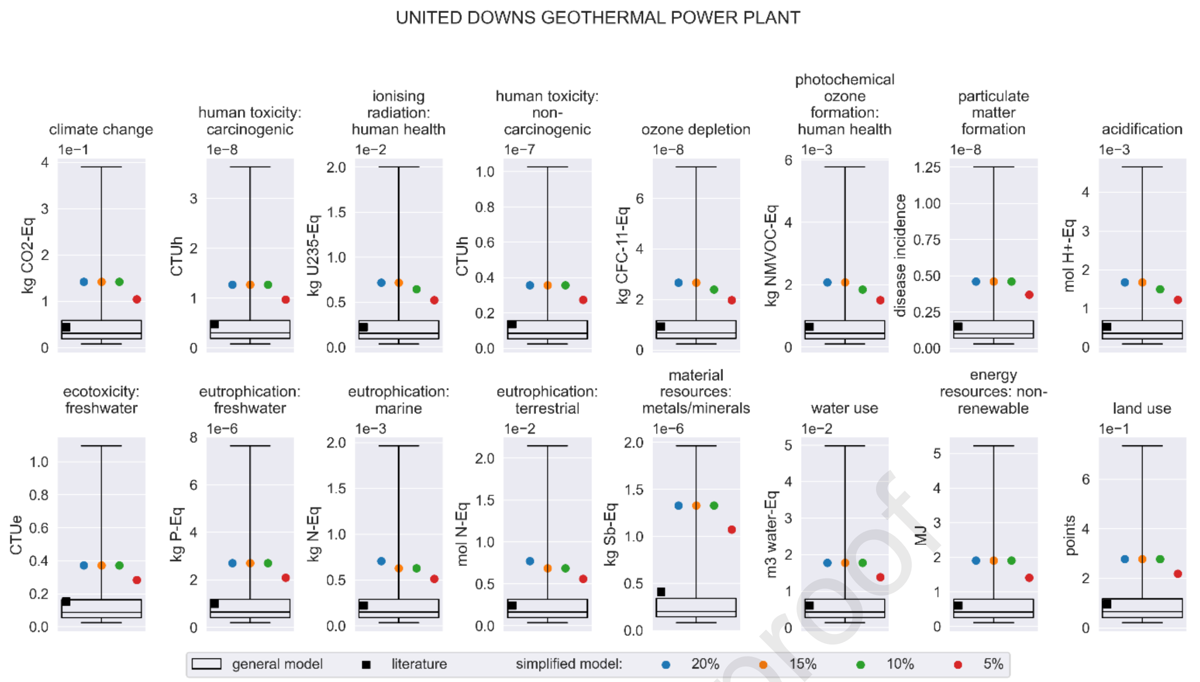

Figure 4 - Comparison between the variability of the general model, results from the simplified model and literature data for the united downs deep geothermal power project (UDDGP). In the box-and-whisker plot, the horizontal lines represent median values, the boxes correspond to 25th and 75th percentiles, and the whiskers indicate 1st and 99th percentiles.

The systematic overestimation of environmental impacts by the simplified models in comparison to literature data is due to the exploratory wells. Although the number of exploratory wells that is estimated by the simplified models corresponds to the actual number drilled at the United Downs site (Paulillo et al., 2020a, 2020b), the models also make the simplifying assumption that these wells have the same depth of primary wells. By contrast, at United Downs the exploratory wells were drilled to a depth of only 200m, thus being practically negligible when compared to primary wells with an average depth of 4000m. When both the general and the simplified models are modified to exclude the construction of exploratory wells, the results from the simplified models decrease, approaching the estimates from the literature. This comparison, which is reported in Figure S6 in the Supporting Information, shows that the simplified models yield results approximately twice those from literature data for thresholds of 20%, 15% and 10%, whilst the results at 5% are not higher than 100% of the literature data.

4 Discussion

4.1 Correlation between general model and simplified models

All simplified models proposed correlate well with the general model derived previously. As expected, the level of correlation (for both Pearson and Spearman coefficients) increases with decreasing the threshold of the total order indices that is used for developing the simplified models, and thus with increasing the number of parameters. However, even with the highest threshold of 20% (which translates to only 1-2 parameters used by the simplified models as opposed to 25 in the original model) the correlation coefficients are above 0.75 for all categories.

The comparison between simplified and general models reported in the Supporting Information (Figure S4) highlight the existence of a small number of outliers (below 0.1% of all data points) for enhanced geothermal technologies where the results from the general model are significantly higher than those from the simplified ones. These outliers represent worst case (and unlikely) scenarios, described by parameters that are not included in the simplified models. These scenarios include very low values of the success rate for exploratory wells (i.e. below 10%), and high values of material requirements for the construction of wells, primarily steel for casing (e.g. above 130 kg/m). (The importance of exploratory wells for enhanced geothermal technologies is discussed in Section 4.2.) These outliers are shown to affect the Pearson correlation coefficient but not to an extent that invalidates the correlation between the simplified models and the general model. The Pearson correlation coefficient including outliers is above 0.7 for all environmental categories considered.

4.2 Importance of exploratory wells for enhanced geothermal technologies

The exploratory wells play an important role in the simplified models for enhanced geothermal technologies. As noted in Section 4.1, very low values of the success rate of exploratory wells cause significant discrepancies between the general model and the simplified models. The importance of the exploratory wells is also shown when the simplified models are compared with literature data for the United Downs geothermal plant (Figure 4). In this case, the simplified models yield estimates substantially higher (up to a factor of 3) than literature data; but when the models are modified to exclude exploratory wells (Figure S6), the results approach those from literature data. Interestingly, for the Hellisheiði geothermal plant (Figure 3) the estimates for the simplified models are close to literature data even though no exploratory wells were considered in the study (Paulillo et al., 2019a).

The environmental impacts associated with geothermal technologies – including both conventional and enhanced ones – are primarily attributed to the construction of wells, with the only exception of climate change impacts for conventional technologies, which are driven by discharges of CO_2 and CH_4 occurring during the operation of the power plant. The general model assumes for both conventional and enhanced plants that three exploratory wells are required (DiPippo, 2016); these wells, which are assumed to have the same depth of the “operational” (i.e. production, injection and/or make-up) wells, are scaled by a factor of 0.3 to account for a lower diameter (Marchand et al., 2015). Therefore, three exploratory wells are equivalent to 0.9 operational wells; this represents a significant proportion of the number of wells drilled for enhanced geothermal technologies, but only a small fraction of the wells that are on average drilled for conventional ones. In fact, the general model assumes that enhanced geothermal plants feature either a single doublet or a single triplet configuration (i.e. two or three wells including producers and injectors), whereas the median number of wells estimated by the general model for conventional plants is 36.

Because of the importance of exploratory wells for enhanced geothermal operations, we include in the Supporting Information numerical coefficients for the simplified models that include the scenario of no exploratory wells being built. We recommend using these coefficients when it is known that no exploratory wells were built for the specific plant under investigation, and to use the original coefficients if the number of equivalent exploratory wells is either unknown or close to that assumed by the general model (i.e., 0.9).

4.3 Selection of the appropriate simplified model

As noted in Section 2, in general the choice of the simplified model at different thresholds entails a trade-off between accuracy and simplicity. Our analysis shows that the carbon footprint of conventional geothermal technologies can be accurately predicted by a two-parameters model, relying on operational emissions of CO_2 and CH_4 as parameters (Equation 1). When operational emissions of methane are not substantial, the carbon footprint can be predicted using only the amount of CO_2 released during operations of the plant (Equation S1). This represents the conditions of most conventional power plants considered in published LCA studies. Notable exceptions are geothermal plants in Tuscany, Italy, which feature methane emissions from 2 and up to 12 g/kWh (corresponding to ~74 and ~444 gCO_2-eq) (Bravi and Basosi, 2014; Buonocore et al., 2015).

For enhanced geothermal technologies, the comparison with climate change estimates from literature studies suggests that the simplified model at 5% threshold yields on average estimates closer to literature data. This is expected as at 5% the model employs a higher number of parameters, specifically diesel consumption, success rate of primary wells and depth of wells. Amongst these, the success rate of primary wells plays a more important role given that most studies report success rates of 100%, whilst the median value used in the simplified model equates to ~72% (Table S19). This means that when the simplified models do no not use such parameter, the number of drilled wells that the model estimates is higher by a factor of ~39% (i.e. 1/0.72). The simplified models yield estimates only in few cases significantly different from literature data. Notable examples are the case studies by Paulillo et al. (2020a), where the discrepancies are due to the number of depth of exploratory wells, as discussed in Section 4.2. Another example is scenario D1 by Frick et al. (2010); in this case the authors considered a worst case scenario where parameters relating to geothermal conditions of the site (i.e. temperature of the geothermal fluid and geothermal gradient) and to the power plant (e.g. lifetime, capacity factor, etc) are considerably below average. In addition to differences in technical/field data, it must also be noted that the comparative analysis is affected by differences in the underlying databases; for example, Lacirignola and Blanc (2013) used version 2.2 of the ecoinvent database, as opposed to version 3.6 that we used for our study.

For the remaining categories in the EF2.0 method, the comparison reported in Figure 3 for conventional geothermal technologies shows that there is little difference between all simplified models. This comparison suggests that there is no reason for using a lower threshold, and therefore a higher number of parameters model. However, for enhanced geothermal technologies Figure 4 shows a clear advantage in using lower thresholds models (in particular that at 5%), and that when no exploratory wells are built, the appropriate coefficients need to be employed (see Section 4.2).

4.4 Limitations

The simplified models proposed in this study for estimating the environmental impacts of conventional and enhanced geothermal technologies were developed from the general model and the results from a Global Sensitivity Analysis carried out by Paulillo et al. (2021). Therefore, the simplified models carry the same limitations of the study on which they are based; these limitations include assumptions on the distributions of some parameters, lack of distributions for a small number of parameters, and lack of data for few parameters (primarily operational emissions of non-condensable gases other than CO_2, e.g. SO_2, NH_3).

In this study, we performed a comprehensive validation of the simplified models for the climate change category; the comparison could only be extended to other environmental categories for two specific case studies because i) most studies do not report categories other than climate change, ii) because, even when they do, impact assessment methods other than EF2.0 are employed, and iii) we had access to the underlying LCA models of the two case studies. The extended comparison leads to generally positive results, but it should be extended to a larger number of studies to comprehensively assess the reliability of the models proposed. In addition, future studies should compare our simplified models with those developed by Douziech et al. (2021, 2020), to investigate the relative advantages and disadvantages of our approaches. Notably, their models differ from ours in two key aspects: first, they apply to specific geothermal plant archetypes (e.g. "geothermal flash power plants producing electricity and limited amount of heat from a geothermal source with moderate to high content of NCGs"); second, they were developed from first (rather than total) order indices. We could not perform this comparison because Douziech et al.'s models use a different impact assessment method (i.e. ILCD 2018).

Finally, we identify two additional limitations pertaining to the simplified models. First, the simplified models (and the general model from which the simplified models are derived) are based on the ecoinvent database (v3.6 cut-off) for calculating the impacts of processes in the system boundary. This means that the numerical coefficients require constant updating unless the relevant processes are known not to have been affected by updates of the database. A similar limitation applies to the impact assessment method: the numerical coefficients require updating each time a new version of the Environmental Footprint method is released. However, updating the simplified models and the numerical coefficients is straightforward and can be carried out with the openly available Python scripts at https://github.com/a-pau/gsa_geothermal.

5 Conclusions

This article presented novel simplified models for the rapid estimation of the environmental impacts of geothermal power generation. The models are "simplified" because they rely on a small set of influential parameters, thus significantly facilitating data collection. The parameters were identified via Global Sensitivity Analysis (GSA) applied to a complex general parametric model developed in a previous study by the same authors. Our simplified models cover both conventional and enhanced geothermal technologies, and include all environmental categories in the Environmental Footprint 2.0 (EF2.0) method. The models are represented by algebraic equations that can be easily (and quickly) resolved, even by hand. For each technology archetype, we developed two sets of models to account for the fact that influential parameters differ across categories. In addition, we developed several simplified models according to different thresholds of Sobol' total order indices.

We validated the simplified models via determination of the correlation with the general model, and comparison with literature data. We quantified the level of correlation via Pearson and Spearman correlation coefficients; our results show that the simplified models correlate well with the general model, with both coefficients being above 0.75 even for the high Sobol' total order index threshold of 20%. We compared the simplified models estimates with literature data for the climate change category, and we performed an extended comparison across multiple categories for two specific case studies. The results of the comparison, which are generally positive, highlight two criticalities. First, operational emissions of methane for conventional technologies (which were not included in the general model due to lack of data) can play an important role in the climate change category; but when CH_4 emissions are not substantial, one parameter – operational CO_2 emissions – is sufficient to estimate the carbon footprint of conventional technologies. Second, the number of exploratory wells, which is set to a pre-compiled value due to lack of data, can substantially affect the estimations for enhanced technologies because they account for a large portion of the total number of wells; for this reason, we have developed a modified version of the simplified models that assume no construction of exploratory wells. The results of the comparative analysis also show that i) there is little difference between thresholds for conventional technologies, and ii) the models at 5% thresholds are the most appropriate for enhanced technologies. A minor limitation of our simplified models is that they require constant updates of the underlying LCA database and EF2.0 factors; however, updating the models in the future can be straightforward, and the Python code is openly available on GitHub. The method proposed in this article for the development of simplified models is not restricted to geothermal applications, rather it can be applied to any product system upon appropriate parametrization.

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