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Resource Assessment: Estimating the Potential of a Geothermal Reservoir

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ABSTRACT

Geothermal reservoirs are a valuable source of sustainable energy. The economic viability of harnessing geothermal energy is dependent on the size of the energy resource. However, determining the energy potential of a geothermal reservoir is generally complicated and uncertain due to a low availability of data. The estimation of the energy resource is often done by calculating the stored heat capacity of the reservoir, using temperature measurements and information on the rock properties. However, these estimations of the geothermal energy resource are approximate and uncertain, relying on a poorly defined recovery factor.

Advances in numerical modelling and uncertainty quantification allow us to give a better estimate of the energy resource of a geothermal field. In this paper we illustrate this method using a synthetic model of a geothermal system. By allowing for uncertainty in the model parameters (rock permeability, and the magnitude and location of the deep upflow sources) we generate 2000 sample models based on the geological model of the system. These sample models are each run to steady state using the Waiwera geothermal simulator. The models are then conditioned on the location and temperature of the base of the clay cap using approximate Bayesian computation (ABC). Finally, an innovative method is applied to estimate and run maximum potential production scenarios for each of the conditioned sample models. The forecasts from these scenarios combine to give an assessment of the geothermal resource including uncertainty. The resource assessment uses the same data that are available for a traditional stored heat calculation but also includes reservoir physics, wellbore physics and realistic energy extraction scenarios to provide a more accurate forecast. Our method can be applied in less than a month using widely available computational resources.

1. INTRODUCTION

1.1 Geothermal energy

Hot geothermal reservoirs generally consist of a heat source, permeable media and convecting fluid. The heat source (magma), which is located deep under the ground, heats up the fluid. The hot fluid, mostly water, then flows towards the surface through the porous and permeable subsurface. Wells can be drilled into the reservoir to extract the hot fluid which can be used to generate electricity. In warm water systems there is no fluid convection, and the lower enthalpy fluid is generally used for direct use of heat (e.g., Lund & Toth, 2020) rather than electricity generation.

1.2 The status quo

When investigating a new geothermal field and its potential to generate electricity, the first step is to estimate the power output. However, these power estimations are difficult because of a low availability of data, and the difficulty and expense of gathering data deep underground. Traditionally, power output estimations are made by calculating the stored heat, applying a recovery factor and then using a very simple Monte Carlo approach to estimate uncertainty (e.g., Garg and Combs, 2015; Grant, 2015; Sanyal and Butler, 2005; Williams et al., 2008; Williams, 2014; Zarrouk and Simiyu, 2013). This approach is approximate and uncertain and ignores much of the physics that takes place in geothermal reservoirs. Regardless, multi-million-dollar decisions are based on them.

Grant (2015) notes that the Australian Code Lexicon is somewhat negative about the early use of computer modeling for resource assessment. It states: *"At the exploration stage, when limited data are available, numerical simulation is unlikely to give a more realistic estimate of long-term capacity than simpler volumetric methods".* Grant comments that *"This sweeping claim is at variance with industry practice and experience".*

The authors agree with Grant and suggest that, even at an early stage of data collection, computer modeling should be preferred to a stored heat estimate. The rest of the paper discusses our methodology for using numerical modelling for resources estimation.

1.3 A new method

Numerical modelling for geothermal reservoirs has been carried out since the 1970s (Stanford Geothermal Program, 1980; O'Sullivan, 1985; O'Sullivan et al., 2001; O'Sullivan and O'Sullivan 2016). In this paper we propose a new method for assessing the geothermal power output potential based on using numerical models, available data and innovative algorithms. This method requires simulating a large number of sample models, which makes it highly dependent on computational speed. Fortunately, recently developed, highly parallelised geothermal simulators like Waiwera, developed by the University of Auckland and GNS Science (Croucher et al., 2020), are much faster and make this new method feasible. Waiwera can simulate geothermal models in parallel on multiple cores, which massively speeds up the simulation, especially when high performance computers are used.

The advantage of this method is that the geothermal power estimations are based on simulations which accurately include reservoir physics, wellbore physics and realistic energy extraction scenarios. The method also produces robust estimates of the uncertainty in the resource assessment using well-established uncertainty quantification techniques.

2. METHODOLOGY

2.1 Steady state models

The first step for our resource assessment is to use the 3D geological model to set up a numerical model where the geology, alteration, structural setting and potential deep upflow locations define a large set of model parameters. We then generate a prior (unconditioned) ensemble of sample models by randomly sampling model parameters from realistic ranges. These sample models are simulated to a steady state before any production simulations are carried out. For this paper we generated 2000 sample models to estimate the power output of our synthetic geothermal system. Each of these 2000 sample models have a set of randomly selected values for the 325 parameters defined for the base model which is described in detail by Renaud et al. (2021). We next discuss how the prior distributions of these randomly selected parameter values are constructed.

2.1.1 Uncertain parameters

Generally, when we develop a new numerical model, we start with an initial guess based on expert knowledge for rock permeabilities and upflow rates. These parameters are then manually calibrated using the available data. At the exploration stage of a geothermal field there are little data available and we can skip the calibration process and instead create an ensemble of sample models by randomly sampling model parameters from realistic prior distributions and then use an algorithm (discussed below) to choose the acceptable geothermal models.

Below in Table 1 the prior mean and standard deviations for the prior distributions of the uncertain model parameters are shown. The prior mean rock permeability varies due to the location of the rock types, e.g., surface rocks, clay-cap rocks or rocks at large depths. Furthermore, we assume a correlation between permeabilities in directions 1, 2 and 3. The horizontal permeability directions (1-2) have a correlation of 0.8 and horizontal with vertical permeability (1-3 and 2-3) have a correlation of 0.5. These correlations assure that, when samples are generated, the horizontal permeability of a single rock type are of the same order of magnitude, in most cases also the same order of magnitude as the vertical permeability. As an example, Figure 1 shows the probability density function of the permeability of rock type A0002 which assumes the log permeability is normally distributed. The mean is set at 1e-13 m^{-2} with a standard deviation of log-permeability 1 m^{-2}.

For the upflow parameters the total deep upflow is randomly divided over potential locations in 26 blocks in the bottom layer, located on the main faults of the system. Figure 2 shows four model samples demonstrating how the total upflow rate varies as well as the distribution of the upflow.

Table 1: The initial guess for the model parameters and the uncertainty of these parameters measured in standard deviation.

Model parameter	Prior mean	Standard deviation
Rock permeability	5e-12 to 1e-16 m^{-2}	(of log-permeability) 1 m^{-2}
Rock porosity	0.05 to 0.2	25% of mean
Total upflow rate	49.0 kg/s	9.8 kg/s

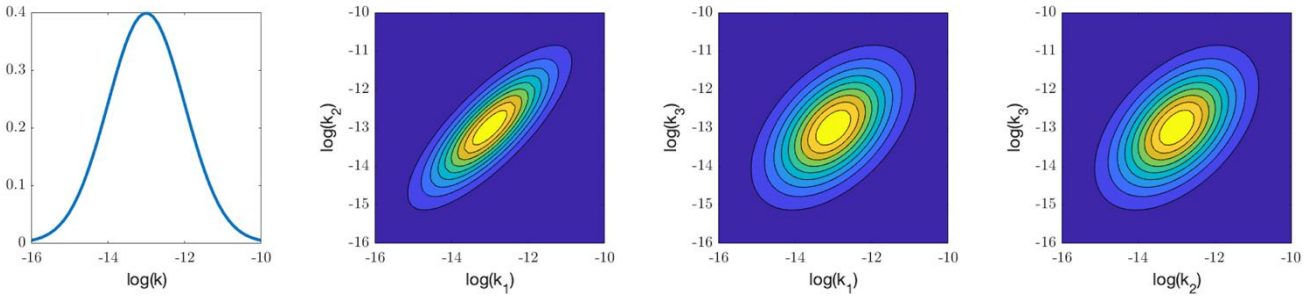

Figure 1: The probability density function for the permeability directions (1, 2 and 3) of rock type A0002 assuming the log permeability is normally distributed. The most left plot shows the marginal (i.e., 1-dimensional) density of directions 1, 2 and 3 which are for rock type A0002, while (from left to right) the joint density of directions 1 and 2, 1 and 3, and 2 and 3 are shown.

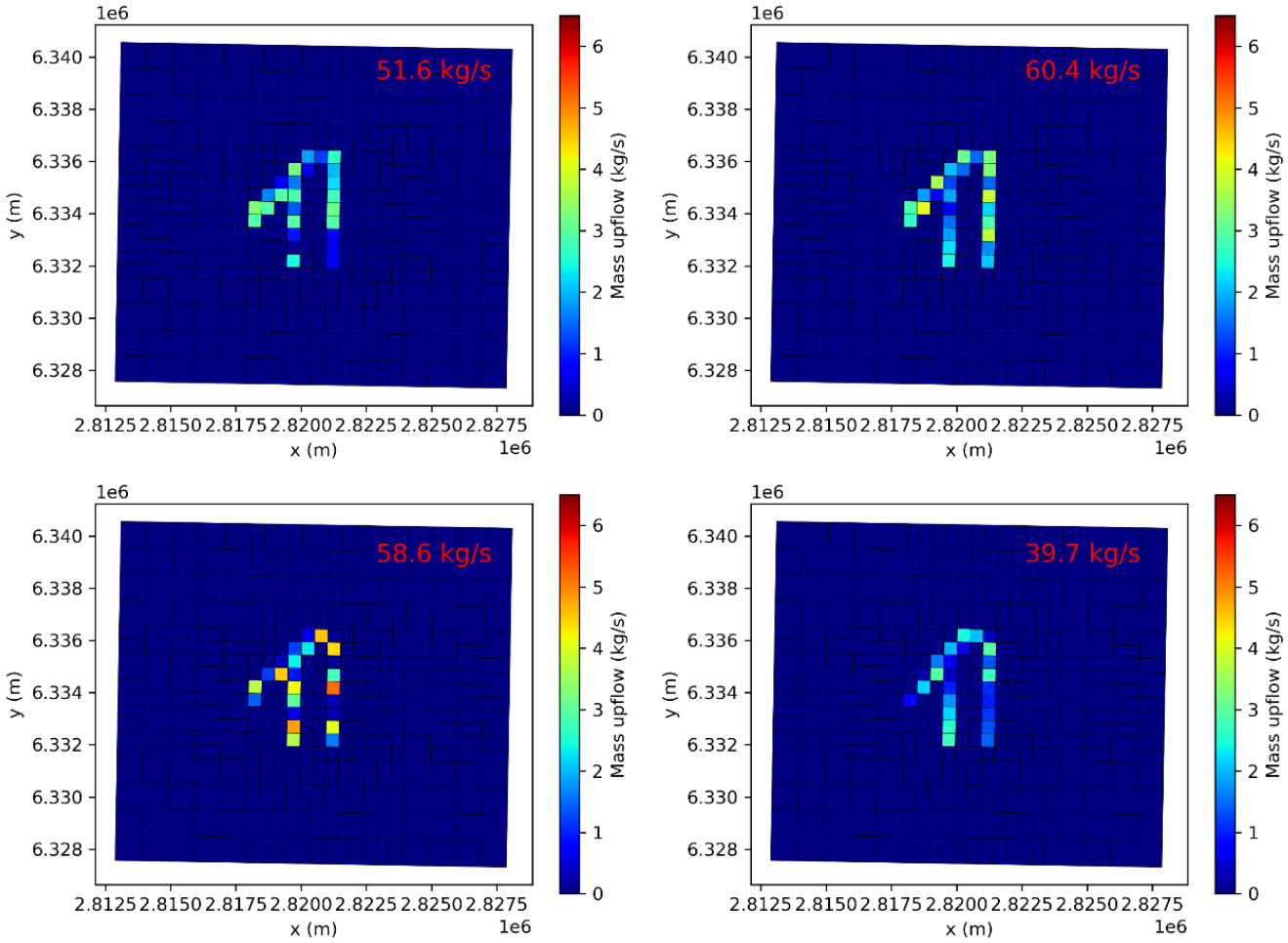

Figure 2: Four examples of the variation in total upflow (red text) and the distribution of the deep upflow sources located at the bottom of the sample models -3250 mRL (layer 69).

2.1.2 Conditioning on the clay cap

The second step of our approach is to condition the steady state models on the location and temperature of the clay cap. We do this using approximate Bayesian computation (ABC) (reviewed by Beaumont 2019; Marin et al., 2012) as described below. Thus, to apply our methodology some data giving the location of the clay cap is required e.g., MT survey data, clay mineralogy from drilling cuttings or downhole temperatures. For this study we have assumed that only the MT survey data is available for conditioning the models.

A clay cap is formed by a transformation of a rock structure due to heating. Temperatures of 200 °C are needed to form a clay cap. After the clay cap is formed, the hot fluids do not flow easily through the clay cap due to its low permeability. However, we can expect a temperature of approximately 180 °C just below the clay cap. We have identified the blocks in the model directly underneath the clay cap and divided them in two groups based on elevation. The deepest of the identified blocks, generally located on the outer areas of the clay cap, are not included when we condition our sample models. We disregard these outer blocks because of the uncertainty of the MT inversion at depth and at the edges of the clay cap. In Figure 3 the locations of the identified blocks are shown in a 2D- and 3D-map of the geothermal model.

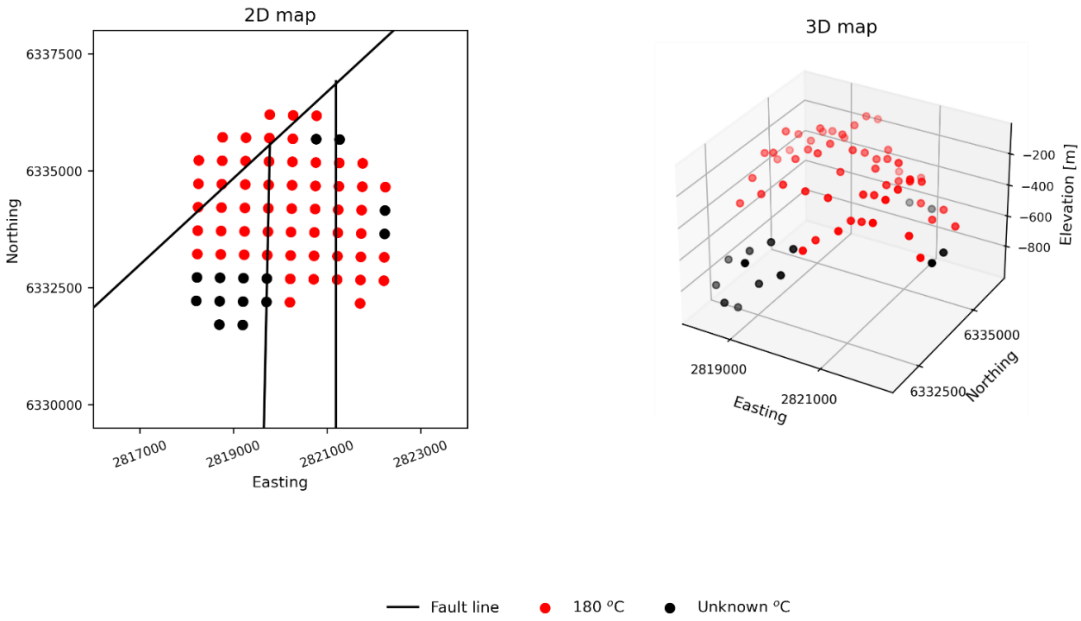

Figure 3: Blocks located right below the clay cap. The colors indicate the temperatures on which the steady state models are conditioned.

We then use the temperature distributions obtained from each of the steady state models to condition on the blocks directly under the clay cap, assumed to have a temperature of approximately 180 °C. As mentioned above, we use ABC for the conditioning, which implements an approximate form of Bayes' theorem to obtain a posterior ensemble of models given a prior ensemble of models and observed data (Beaumont, 2019; Marin et al., 2012; Vrugt and Sadegh, 2013). This is a form of *simulation-based* inference (Cranmer, 2020) which requires the ability to efficiently run a large number of models to form a prior ensemble. However, in contrast to many other optimisation or sampling-based methods, both simulation and conditioning steps are fully parallelisable. In ABC, the usual posterior based on Bayes' theorem:

$$p(k|y_o) \propto p(y_o|k)p(k),$$

where y_o represents a vector of observed data and k represents the parameter vector, is replaced by an approximate version:

$$p(k|d(y,y_o) < \varepsilon) \propto p(d(y_o,y) < \varepsilon)|k)p(k),$$

where d represents a distance measure between observed, y_o, and simulated, y, datasets and ε represents an acceptance tolerance. In our present work the data are the assumed temperatures directly under the clay clap.

The above approximate posterior is computed by direct Monte Carlo simulation: model samples are simulated from the prior, $p(k)$, and these are then simulated forward to produce simulated datasets that are accepted or rejected depending on whether they are within the distance tolerance chosen. This tolerance can be difficult to tune; a popular approach, which we use here, is to define it implicitly by accepting a fixed percentage of models with the lowest distance to the data (Marin et al., 2012). Due to the long run time of geothermal models we use a relatively coarse tolerance, retaining the 10% best fitting models. In other areas with cheaper models a more typical value is around 1%.

To implement ABC, we used the *ccandu* (*c*onditional *c*omposition *and u*ncertainty quantification) Python package being developed in-house at the University of Auckland to implement a range of uncertainty analysis methods. However, ABC itself is relatively straightforward to implement directly.

2.2 Production models

After we selected our acceptable steady state models based on the geophysical data, we applied an innovative method to estimate and run maximum potential production scenarios for each of the conditioned sample models. We used the steady state model as an initial state for the production model and for this paper we simulated 25 years of future production extracting energy, using a typical flash power plant configuration. However, the method we describe below can easily be tailored to accommodate different power plant designs and operating conditions and even to produce different resource assessments for each.

One of the challenges with using uncertainty quantification of geothermal models for resource assessment is that each model sample needs a specific optimal extraction scenario to be designed. Typically, the design of future scenarios for a geothermal model is done manually by geothermal reservoir modellers and then optimised to achieve maximum energy extraction. However, with potentially many thousands of sample models, this manual approach is clearly not viable.

The innovative method we have developed is an iterative algorithm that can select the best targets for production and reinjection for any given sample model. The iterative algorithm continues selecting targets until the additional energy produced is less than 5% of the previous iterative step indicating diminishing returns on adding new wells.

Wellbore modelling is used to represent the behaviour of each of the production wells. Before running the iterative algorithm, wellbore models are run for all possible target depths under all the likely range of thermodynamic conditions. This process can be completed within 2-3 days on a standard desktop computer. Vertical wells, with a single feed zone and typical wellbore designs are assumed in this work to demonstrate the approach. The parameters of the wellbores could easily be customised and zones for well head locations specified without affecting the application of the method.

It is important to remember that the objective of this method is to calculate the production potential for each sample model efficiently using a realistic extraction scenario. It does not aim to design the perfectly optimal extraction scenario for each sample model or the system in general. Designing an optimal extraction scenario for the system is expected to take place during the development of the production stage once exploration drilling and early production testing have taken place.

The details of the iterative algorithm of our innovative method are as follows:

2.2.1 Selection of production targets

- Pre-processing steps carried out once and applied to all samples:
    - Identify all the potential target blocks based on the resistivity boundary, geological formations and specified maximum drilling depth. For this work 1500m was used as the maximum depth.
    - Specify wellhead conditions and wellbore design, then run wellbore simulations for all potential target blocks under the likely range of thermodynamic conditions. For this work a well head pressure of 6.5 bar was used and the wells had an inner radius of 9 3/8 inches and were lined to 50m above the target feedzone.
- Pre-processing step carried out once for each sample model:
    - Calculate the productivity index for each target block using its permeability and an estimated feedzone thickness in the formula (Coats, 1997; Thomas, 1982):

$$(PI) = \frac{2\pi(\mathrm{k}\Delta\mathrm{z})}{\ln(\mathrm{r_e}/\mathrm{r_w}) + \mathrm{s} - 1/2},$$

      where PI is the productivity index, k is the permeability, Δz denotes the feedzone thickness, r_e is the grid block radius, r_w is the radius of the well and s is the skin factor. However, the grid block is not a cylindrical shape, but Cartesian, so we should use an approximate effective radius described by:

$$\mathrm{r_e} = \sqrt{\mathrm{A}/\pi},$$

      here A is the area of the grid block.
    - A feedzone thickness of 50m was used for this work.
- Iterative process carried out for every sample model:
    1. Use natural state conditions for pressure, temperature and vapour saturation at all potential target blocks to calculate an estimate of the initial flow rate and enthalpy based on the productivity index and wellbore properties.
    2. Select the block with the highest estimated steam flow rate and set up the production model with a well targeting the block.
    3. Run the new production model for 25 years.
    4. Use the final conditions from the production model for pressure, temperature and vapour saturation for all remaining target blocks to calculate estimates of the flow rate and enthalpy based on the productivity index and wellbore properties.
    5. Select the block with the highest estimated steam flow rate and add a well to the production model targeting the block.
    6. Update the wellbore pressure-enthalpy table for each production well based on the current estimates of flow rate.
    7. Run the new production model for 25 years.
    8. Return to step 4 until additional total steam production is less than 5% of previous iteration's total.
    9. Return to step 4 now only including boiling blocks as targets until additional total steam production is less than 2 kg/s

The stopping criteria in steps 8 and 9 could easily be modified if required and step 9, which allows the algorithm to tap any shallow steam caps that form, could be excluded for resource assessments where binary power plants are planned.

2.2.2 Selection of reinjection blocks

- Pre-processing steps carried out once and applied to all samples:
    - Identify all the potential target blocks based on the resistivity boundary, geological formations and specified maximum drilling depth. For this work 1500m was used as the maximum depth and blocks on the edge of the resistivity boundary were selected.
- Pre-processing step carried out once for each sample model:
    - Refine the potential target reinjection blocks based on the permeability distribution of the sample model. For this work we only included blocks with at least 50 mD permeability in one of the three directions.
- Iterative process carried out for every sample model:
    1. Begin the process at the same time as the 3rd production target is selected (see above).
    2. Use the initial and final conditions from the production model for pressure to rank the potential target reinjection blocks, from highest pressure drop to lowest pressure drop.
    3. Select the 95th percentile highest pressure drop as the target and add a reinjection well in relevant block in the production model. For this work we specified 75% of the total production as the reinjection rate and a reinjection temperature of 140°C.
    4. Run the new production model for 25 years then continue with the selection of production targets (see above) adding reinjection to the current reinjection well accordingly.
    5. After each new production run check the pressure in the reinjection block for the current reinjection well.
    6. If the reinjection pressure exceeds a specified threshold return to step 2 to add another reinjection well. For this work we used a threshold of the maximum of either the hydrostatic pressure or the natural state pressure.
    7. Once the production target selection is complete a final production run is carried out with updated reinjection rates.

The 95th percentile highest pressure drop is selected as the target because this indicates the block is well connected to the production zone and therefore likely to provide pressure support. For some sample models lower permeabilities mean that a new reinjection well cannot accommodate all the production from a single production well. In these samples additional reinjection wells are added and the production divided evenly across them. However, the number of reinjection wells is never allowed to exceed the number of production wells and in extreme cases the total reinjection is reduced to ensure realistic reinjection pressures. The fact that our algorithm has trouble achieving high rates of reinjection in sample models with lower permeability indicates it is working well. In existing geothermal developments, high rates of reinjection cannot be achieved in systems where few viable reinjection targets are available.

3. RESULTS

In total we simulated 2000 steady state models, which took 114 hours on the New Zealand eScience Infrastructure (NeSI) "Maui" supercomputer using a single node (40 cpus). The process of running the samples is completely parallelisable and so the same number of samples could have been simulated in less than a day using five nodes. Of these, 240 samples were rejected because the simulation took too long to reach a steady state solution. This was caused by combinations of extreme values for the model parameters, which is not unexpected with 325 random parameters with large standard deviations. Using ABC, as implemented in *ccandu*, to condition on the geophysical data for the clay cap we accepted just 10% of the remaining 1760 models, leaving us with 176 potential production models.

Using our new innovative method to estimate and run maximum potential production scenarios for each of the conditioned sample models required an average of 16 mins on NeSI using one node with 40 cpus. In total it required approximately 47 hours to run all 176 maximum potential production scenarios. Again, because the entire process is parallelisable, ten times as many samples could be generated and ten times as many production runs carried out within the same time frame simple by using ten nodes with 40 cpus each.

3.1 Conditioned samples

To visualise the different natural state temperature distributions for the 1760 converged sample models Figure 3 shows plots of downhole temperatures for five potential wells. The locations of the wells are also shown in the figure. Once the samples have been conditioned on the geophysical data for the clay cap the 10% that were accepted are plotted in red in the same figure. The plots show the effect of conditioning on the geophysical data, particularly for WELL-2 and WELL-3 where the range of possible downhole temperatures reduces quite significantly. Note that additional available exploration data could be used to further condition the model samples reducing the uncertainty and is discussed in detail by Power et al. (2021).

3.2 Resource Assessment

Figure 5 gives an example of the production and reinjection targets selected by our innovative algorithm for one of the sample models. As discussed above, each production and reinjection block are added iteratively and selected based on the results of the previous iteration's production simulation. For this particular sample model seven production blocks and five reinjection blocks were selected before the stopping criteria was triggered. Figure 6 shows the forecast power output for the sample using a standard conversion factor of 2.0 kg/s per MW to convert the steam flow to power for a typical flash power plant (Grant and Bixley, 2011). The figure also shows the total production mass flow rate and reinjection rate for the sample. By forecasting these quantities for all 176 samples statistics for the forecasts can be calculated. Figure 7 shows the distribution of power output forecasts. For the example geothermal system analysed in this work the mean estimate of the sustainable resource potential is 88 MW with a P90 of 37 MW and a P10 of 150 MW.

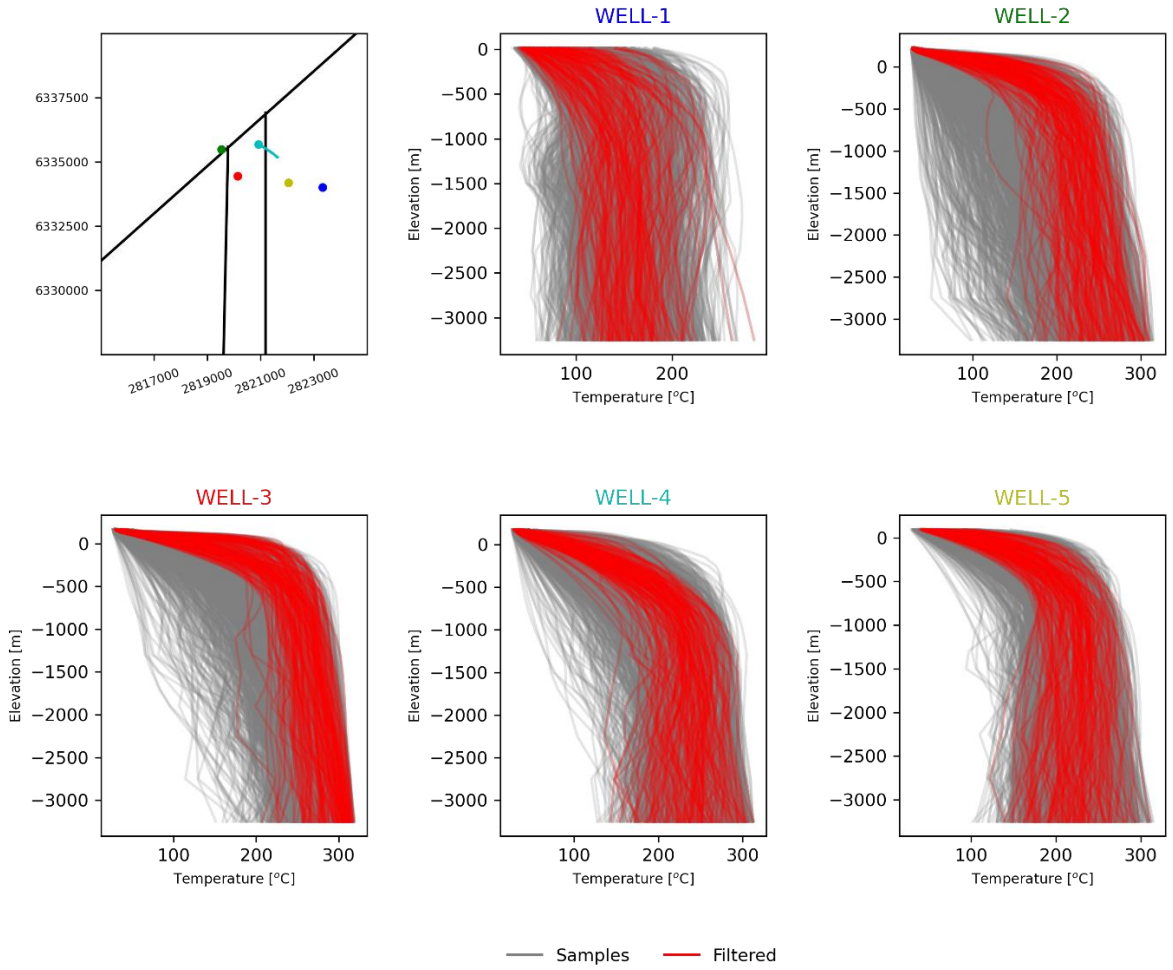

Figure 4: In the top left figure a top view of the geothermal reservoir is shown. In black lines are the fault lines and the colored dots indicate the location of five different wells. The remaining five figures show the temperature results at depth of the initial sample models (grey) and the filtered sample models (red).

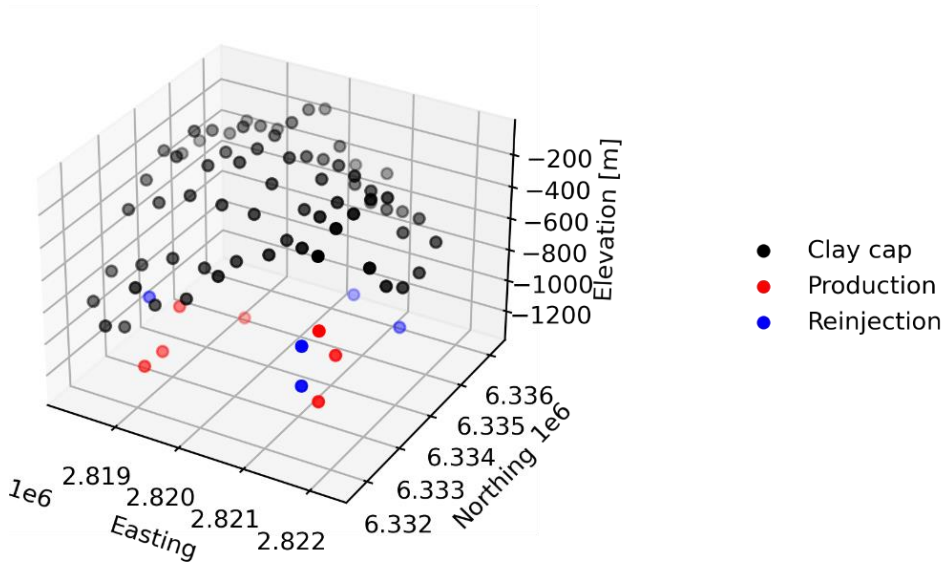

Figure 5: The selected production and reinjection blocks for an example sample model. The black dots indicate the clay cap of the reservoir for reference. The red dots and blue dots indicate the selected production and reinjection blocks, respectively.

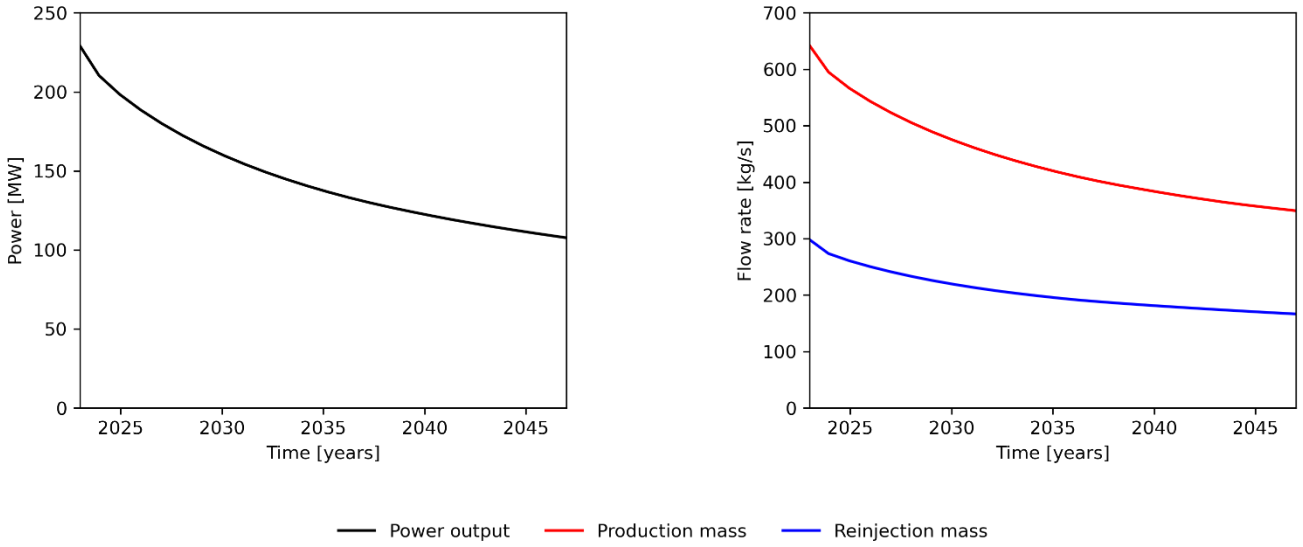

Figure 6: The power output of sample 575 is shown on the left-hand side (black). On the right-hand side the total production (red) and reinjection (blue) rates of sample 575 are shown.

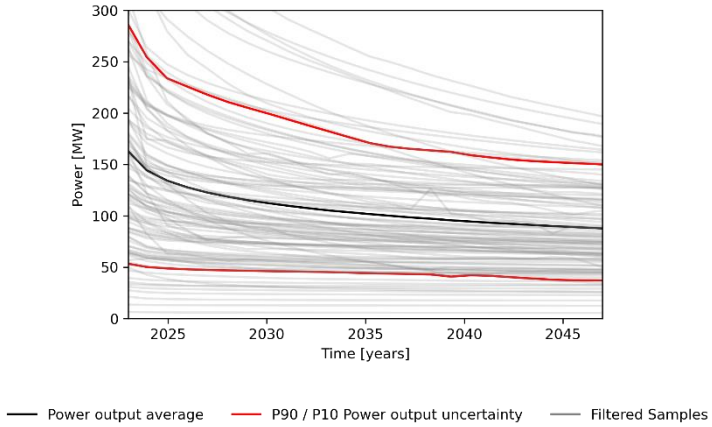

Figure 7: The average power output (black) with uncertainty bands (red) of the conditioned sample models. The uncertainty bands indicate the P90 and P10 confidence interval. Furthermore, the power output of every sample is indicated in grey.

4. CONCLUSIONS

A new method for carrying out resource assessments of geothermal systems during the exploration stage has been developed. The method uses the same available exploration field data as the traditional stored heat approach but leverages new geothermal modelling and uncertainty quantification technology to include reservoir physics, wellbore physics and realistic energy extraction scenarios. By including more accurate physics and realistic energy extraction scenarios our new method can provide a more accurate assessment of the geothermal resource including the uncertainty in the assessment. More accurate resource assessments will lead to more successful and sustainable geothermal developments.

Our new method has several other advantages over the traditional resource assessment approach:

- The resource assessment can be updated and refined, reducing uncertainty as additional exploration data is obtained.
- It is highly parallelizable and a range of possible conceptual models can be assessed within short timeframes.
- Project specific criteria can be applied to tailor the resource assessment or even to compare different above ground equipment options.
- The resource assessment model can provide the basis for ongoing reservoir modelling to support decision making throughout the development of the project.

Finally, our new method can be applied in less than a month using widely available computational resources.

5. FUTURE WORK

Currently we are working on including additional exploration data in the sample conditioning process:

- The locations, temperatures and flow rates of surface features.
- Geochemistry data such as geothermometers and surface feature chemistry.

We are also developing an approach for generating "families" of models based on the uncertainty in the 3D geological model. Another advantage of our method is that new model samples can easily be added to the ensemble and the analysis and statistics can be recalculated. Our method will also be applied to a real geothermal system soon.

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