

METHODOLOGY

Open Access



Toward standardized protocols for geothermal potential assessment: a multi-scale, multi-physics workflow for deep resources

Gianluca Gola^{1*} , Racine Basant², Valentina Cortassa², Antonio Galgaro³, Thomas Nanni^{1,3}, Pawel Slupski³, Magdala Tesaro² and Adele Manzella⁴

*Correspondence:

Gianluca Gola

gianluca.gola@cnr.it

¹Institute of Geoscience and Earth Resources, Consiglio Nazionale Delle Ricerche, Turin, Italy

²University of Trieste, Trieste, Italy

³University of Padua, Padua, Italy

⁴Institute of Geoscience and Earth Resources, Consiglio Nazionale Delle Ricerche, Pisa, Italy

Abstract

Assessing geothermal systems requires a standardized approach, which actually remains underdeveloped. This study aims to overcome this lack, starting to review and discuss the most widely utilized methods and open-source tools for underground characterization and geothermal potential assessment at regional to continental scales, establishing a workflow applicable everywhere, whether with extensive subsurface data (brownfield) or less-explored or unexplored regions (greenfield). By integrating multi-scale geological, petrophysical, and geophysical constraints with robust thermal modelling strategies, this workflow offers a consistent framework for estimating geothermal potential and facilitating comparative analysis across different regions, in order to facilitate the geothermal exploitation feasibility analyses.

Keywords Geothermal energy, Resource assessment, Geothermal potential, Multi-scale protocol

Introduction

The global push for sustainable and low-carbon energy sources has boosted interest in geothermal energy as a reliable and continuous energy supply. The estimation of the energy potential of any energy source is a pillar for business development and energy planning and affects global and national energy policy. Unfortunately, assessing geothermal potential, especially at depths of kilometres (deep geothermal potential), varies widely across regions and research teams, mainly because there are no standardized, reproducible procedures. Existing studies often rely on disparate datasets, variable modelling assumptions, and discipline-specific methodologies, making it hard to compare findings and share best practices. As geothermal exploration moves into areas with complex geology and limited data, the importance of adopting common integrated, multi-scale, and multi-physics approaches becomes increasingly clear. Moreover, geothermal systems are expanding to include new concepts beyond hydrothermal systems. While the potential of EGS systems may rely on methods similar to those used

© The Author(s) 2026. **Open Access** This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

for hydrothermal systems, and accommodation is only required to consider permeability enhancements and estimate total costs for economic viability, demonstrations of deep heat exchangers and underground heat storage require updating the methods used for potential assessment.

Geothermal systems are inherently complex, shaped by the interplay among geological structures, crustal-scale physical properties, and the subsurface thermal regime. A robust assessment, therefore, requires the integration of information spanning several spatial scales, namely from shallow sedimentary basins to deep crustal and lithospheric domains, as well as multiple physical processes, including heat conduction, fluid flow, and rock rheology. Recent advances in open-access geological and geophysical datasets, together with the availability of open-source modelling tools, now offer unprecedented opportunities to build comprehensive and reproducible workflows that combine structural, thermal, and petrophysical information.

In this study, we propose a standardized workflow for regional deep geothermal potential assessment that integrates three complementary modelling domains (Fig. 1). The framework is organized around three pillars that collectively ensure a robust, data-driven evaluation of geothermal resources. The two evidence pillars comprise the external observational constraints: geophysical evidence, which delineates crustal and subcrustal architecture and defines the physical boundaries for subsurface modelling, and petrophysical–thermal evidence, derived from laboratory and in situ measurements, which provides the quantitative parameters required for accurate model parameterization. They are the pillars built on direct evidence, as opposed to modelling assumptions, and they define the empirical framework within which the central integrated model must operate. These constraints anchor the workflow to physical properties and reduce the uncertainty inherent in subsurface interpretation.

The central pillar is the integrated model, which synthesizes all available datasets into a coherent 3D representation of the subsurface. This modelling framework encompasses the reconstruction of crustal geometries, the thermal modelling based on petrophysical parameters and corrected temperature/heat flow data, and the geothermal potential assessment through approaches ranging from heat-in-place calculations to advanced thermo-hydraulic simulations. Beyond these established components, the workflow

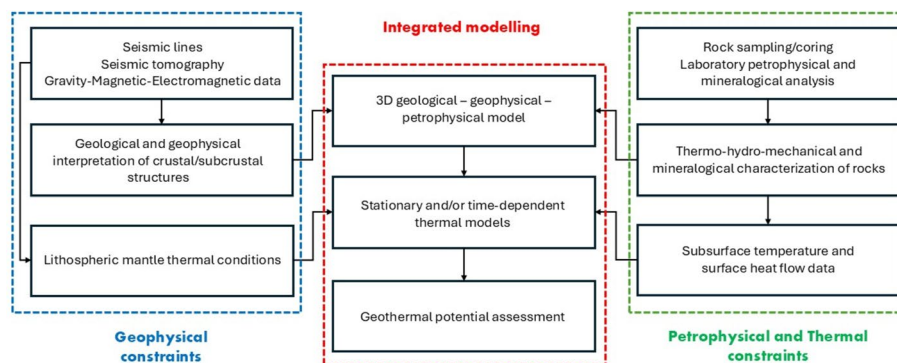


Fig. 1 Workflow for geothermal potential assessment. The central pillar depicts the core methodological sequence: 3D geological–geophysical–petrophysical modelling, thermal simulations, and geothermal potential evaluation. The evidence pillars summarize the geophysical constraints (left) that define crustal and subcrustal architecture and deep thermal boundary conditions, and the direct subsurface constraints (right), that include rock sampling, laboratory analyses, and temperature/heat-flow measurements, supporting the petrophysical and thermal parameterization

incorporates two innovative elements: a coupled well–reservoir modelling scheme, and a thermodynamic module for simulating surface-plant performance. Together, these additions create a continuous chain from subsurface characterization to surface energy conversion, enabling a realistic and internally consistent techno-economic assessment of geothermal resources.

Reconstruction of the crustal structures

The deep geothermal potential assessment is possible only upon a detailed characterization of the underground conditions. Indeed, the knowledge of the structure and thermophysical properties is fundamental to determine the thermal and thermodynamic behaviour of heat and mass transfer processes in rock formations. Such knowledge also plays a key role in reducing exploration risk and optimizing the design of energy production systems. Reconstructing the depth of the main sedimentary units covering the crystalline crust is essential for implementing a geological model. Given the strong heterogeneity of the shallowest part of the crust, geophysical data (e.g., seismic and gravity) may lack sufficient resolution to achieve this aim. Direct information on the outcropping geological units and subsurface lithology, acquired by stratigraphic analyses and core sampling, supports and constrains geophysical data analysis. In the following sections, we outline the data and the key steps to analyse and integrate them into a consistent geological model that extends downward to the crystalline basement.

Data collection

Geological modelling for geothermal assessment typically relies on the integration of heterogeneous subsurface datasets, including seismic reflection profiles, borehole information, and associated cartographic material (Fig. 2). In many sedimentary basins worldwide, a significant proportion of these data are *vintage datasets* acquired during earlier hydrocarbon exploration phases. Increasingly, such data are becoming publicly accessible through national or regional data repositories, following legislation that mandates the release of exploration data after a defined confidentiality period.

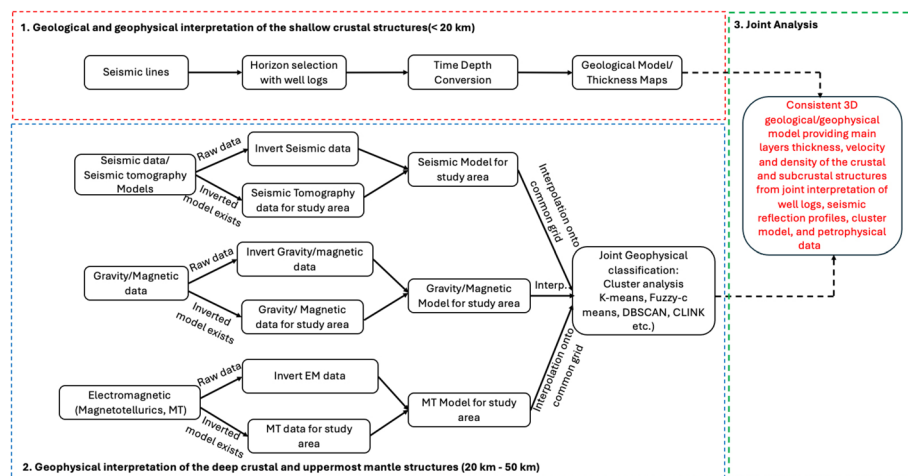


Fig. 2 Workflow to get a consistent geological and geophysical model interpreting the main crustal and subcrustal structures. Top: geological and geophysical workflow for crustal investigation down to 20 km depth. Bottom: geophysical workflow for deep crustal investigation

Public databases commonly provide a combination of seismic reflection profiles, borehole reports and logs, and location maps in various digital or scanned formats. Although these datasets are often heterogeneous in quality, resolution, and format, they represent a valuable and cost-effective data source for regional geothermal assessments. The workflow described below is designed to be applicable to any geological context, where legacy or mixed-format subsurface data are available, and is illustrated using examples from publicly accessible datasets.

Map digitalization and spatial referencing

A critical first step in any subsurface workflow is the consistent spatial referencing of all available data. Seismic lines, boreholes, and auxiliary cartographic information are often provided in different coordinate systems and file formats, including vector formats (e.g., KML, shapefiles) and scanned raster maps (e.g., PDF or TIFF).

Raster maps must be converted into suitable image formats and georeferenced using identifiable control points. Coordinate systems must be transformed into a single, consistent spatial reference system appropriate for the study area. Once georeferenced, the locations of seismic profiles and boreholes can be digitized into vector datasets, forming the spatial framework for subsequent interpretation and modelling steps.

This harmonization of spatial data is essential to ensure geometric consistency between surface maps, borehole locations, and subsurface interpretations, particularly when integrating datasets acquired at different times and for different purposes.

Borehole data and stratigraphic definition

Borehole data provide the most direct and reliable information on subsurface geology and represent the primary calibration points for geological and geophysical models. Well reports typically include well location, elevation, total depth, deviation data, lithological descriptions, and, where available, geophysical logs.

The first step in borehole integration is to ensure correct spatial positioning, including coordinate system transformation and correction of depth references to absolute elevations or depths. While many wells are vertical, deviated or horizontal wells require trajectory corrections to accurately represent their subsurface geometry.

Once correctly positioned, boreholes are used to define stratigraphic boundaries and vertical resolution for the geological model. The level of stratigraphic detail should be adapted to the scale of the study area and the density of available data. Regional-scale studies generally require coarser stratigraphic subdivision, whereas local studies with dense data coverage can justify higher resolution. In data-poor areas, lower resolution stratigraphic schemes help reduce uncertainty and avoid over-interpretation.

Because borehole data directly sample the subsurface, they are generally considered to have the lowest geological uncertainty and therefore provide the primary reference for lithological interpretation and petrophysical characterization, particularly where surface outcrops are absent or distant.

Seismic reflection data and well–seismic integration

Seismic reflection data are essential for extrapolating borehole information away from well control and for constructing three-dimensional geological models. In many legacy

datasets, seismic profiles are available only as scanned paper sections, requiring conversion into digital seismic formats (e.g., SEG-Y) before interpretation.

This conversion typically involves: 1) image preprocessing (cropping, straightening, and cleaning), 2) extraction of acquisition and display parameters from profile annotations (e.g., trace spacing, time range, datum, elevation corrections), and 3) transformation of raster images into seismic trace data. Several open-source and commercial tools are available for this purpose, and the choice of software depends on data quality, format, and project constraints. The workflow itself is software-agnostic and can be implemented with different tools.

Prior to interpretation, scanned seismic profiles require image pre-processing to isolate the seismic signal, including cropping and straightening to remove headers and non-data elements and to ensure consistent orientation. This step can be performed using open-source image editing software such as GIMP. Raster seismic images are then converted into SEG-Y format using dedicated conversion tools for vintage seismic data, including open-source or academic solutions such as the Kogeo Seismic Toolkit (2026) and WIGGLE2SEG-Y (Sopher 2018; WIGGLE2SEG-Y. 2026), as well as commercial software (e.g. IMAGE2SEG-Y 2026). Tool performance depends strongly on scan quality, and different solutions may be required for different datasets. Once converted, seismic data are imported into a seismic interpretation platform together with spatial metadata, using either commercial software (e.g., IHS Kingdom Suite 2026; Schlumberger Petrel 2026) or open-source alternatives (e.g., OpenTect 2026), to enable integrated well–seismic interpretation within a consistent geographic reference frame.

Since seismic data are recorded in the time domain, while borehole data are measured with respect to depth, a time–depth relationship must be established. Interpretation is preferably carried out in the time domain to preserve seismic reflector geometry. Borehole stratigraphy can be converted from depth to two-way travel time using velocity information derived from sonic logs, check-shot or vertical seismic profile data, stacking velocities, or lithology-based velocity models (e.g., Sheriff and Geldart 1995; Benetatos et al. 2019). Where possible, multiple velocity approaches should be compared and integrated to improve robustness.

Seismic interpretation enables the correlation of stratigraphic horizons and faults between wells, providing the structural and stratigraphic framework for three-dimensional geological modelling. The level of interpretation detail should be aligned with the study objectives and data resolution, typically focusing on major lithological contrasts that also control petrophysical, thermal, and hydraulic properties relevant for geothermal assessment.

In Fig. 3, the main steps to follow and the software options for each step are displayed, along with an example of an interpreted seismic profile and borehole data. In this example, the interpreted seismic horizons correspond to the main lithologic changes, which can be detected by variations in reflector amplitude, induced by impedance changes associated with the predominant lithology. The well tops, converted to two-way time, are used to calibrate the position of unit tops.

After interpretation, seismic horizons are commonly converted back to depth using the same velocity models applied during the well–seismic tie. These data can then be interpolated at a uniform grid, in order to obtain geological surfaces, such as depths of the stratigraphic units, using appropriate algorithms (e.g., kriging, conformal gridding,

Seismic data workflow

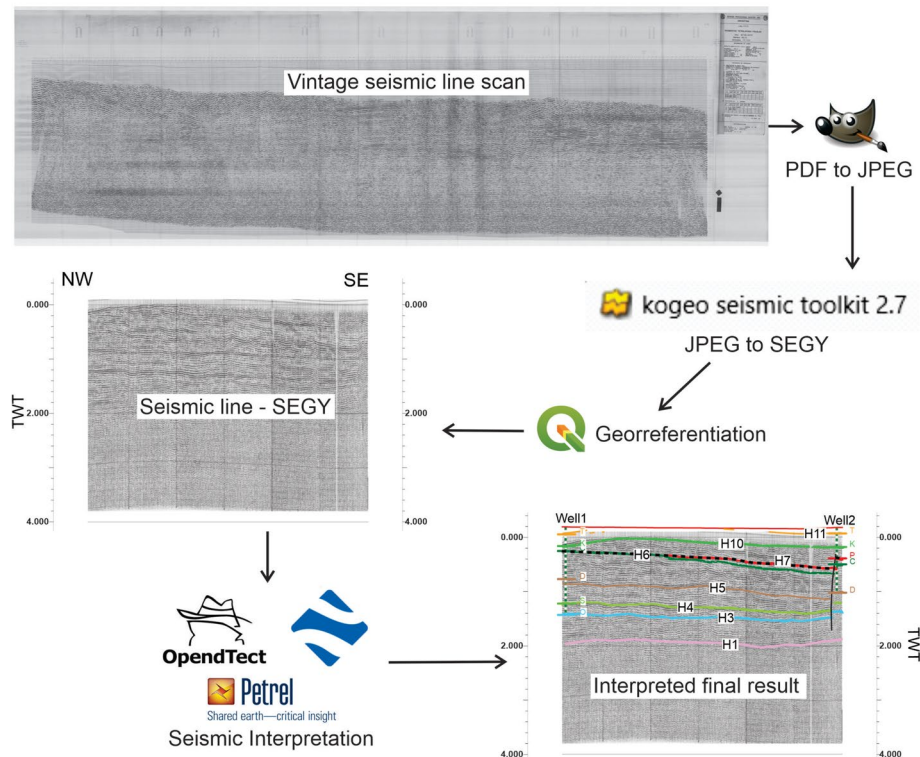


Fig. 3 Workflow to process vintage seismic reflection data. A seismic scan in PDF format is transformed to JPEG (GIMP software), converted into SEGY (Koge Seismic Toolkit), and then georeferenced (QGIS) to have a SEGY file that can be interpreted by identifying seismic horizons (OpendTect, IHS Kingdom Suite, Schlumberger Petrel), to determine the main discontinuities

or convergent interpolation, depending on the data distribution). In case significant lateral lithological variations occur within stratigraphic units, facies maps can be incorporated to capture their heterogeneity.

The resulting three-dimensional geological model provides the structural and stratigraphic foundation for subsequent thermal, petrophysical, and geothermal potential analyses.

Uncertainty assessment

Uncertainty is inherent to subsurface geological modelling, particularly when integrating heterogeneous and legacy datasets, and should be explicitly addressed in geothermal assessment workflows. A way to evaluate the uncertainty related to the depths of the seismic horizons is provided by the data-driven approach of Kint et al. (2020) and applied in the study of Livani et al. (2023), in which confidence levels are assigned to data types and interpreted surfaces based on data origin, quality, resolution, and spatial distribution. Borehole data generally have the lowest uncertainty, while seismic interpretations are associated with higher uncertainty, due to data quality limitations, velocity value assumptions, and interpretational ambiguity, especially when derived from digitized vintage profiles. These uncertainty classes can be propagated through the modelling workflow and visualized as confidence ranges or maps, allowing identification of well-constrained vs poorly constrained areas and improving the robustness of the geothermal potential assessment.

Laboratory analysis of petrophysical properties

The laboratory analysis of petrophysical properties is crucial for the correct interpretation of results from geological and geophysical studies, for correlating drilling logs, building a geological model, and populating thermal numerical models with the most realistic values. Characterization of thermal and hydro-mechanical properties, including density, porosity, and permeability, together with a petrographic study of reservoir rocks, provide additional data to improve the accuracy and reliability of geothermal models (Gola et al. 2022; Facci et al. 2024). A petrophysical analysis can be directly correlated with the target rocks through the acquisition of cores or indirectly associated by sampling analogues of the target rocks outcropping at the surface, or by importing and comparing target rocks data from a recently systematized database (P³) by Dalla Santa et al. (2020). Bär et al. (2020). This comprehensive approach enables the integration of laboratory measurements with numerical simulations and enhances the accuracy of geothermal models.

Petrological study

A detailed petrographic description of rocks, covering their structure, texture, mineral assemblage, chemical composition, and proper lithological classification, is essential for developing an efficient and accurate laboratory analysis workflow. The selection of analytical methods is highly dependent on the characteristics of the rock. Petrography is also crucial for accurate rock classification and provides insights into the true heterogeneity and anisotropy of the subsurface by identifying features such as foliation, bedding, grain size, cementation, alteration, and fracture-related fabrics, which frequently influence permeability pathways and thermal behaviour at the reservoir scale. Mineralogical and chemical composition provide the basis for assigning realistic physical properties and rock-physics relationships, since thermal conductivity, heat capacity, density, and mechanical response can vary strongly with mineral content, porosity type, and alteration state. Accurate and consistent rock classification ensures that units in the geological model correspond to meaningful material domains instead of merely geometric layers. This reduces parameter ambiguity, enhances upscaling decisions, and results in more reliable geothermal model predictions of temperature distribution, fluid flow connectivity, and long-term resource performance.

Petrophysical properties

Several key properties are used in workflows to evaluate geothermal potential, as described below.

Density and seismic velocities (V_p , V_s) connect remotely measurable data, like geophysical studies, to underground geological materials and structures. Density influences gravity anomalies and acoustic impedance, aiding in distinguishing lithologies, estimating porosity, and assessing mass distribution beneath the surface. Seismic velocities reveal mineral composition, porosity, fluid content, pressure, temperature, and fracturing, crucial for converting seismic travel times into depth, calibrating reflection amplitudes, and detecting boundaries such as faults, contacts, and stratigraphic changes. When combined, density and velocity data reduce ambiguity in inversion, support consistent rock-physics relationships, and offer the quantitative constraints necessary to

integrate seismic, gravity, and well or laboratory data into a unified 3D geological model, enhancing confidence in both structural and property predictions.

Thermal properties, namely thermal conductivity, thermal diffusivity, heat capacity, and radiogenic heat production, control how geothermal models predict subsurface temperatures and recoverable heat. Thermal conductivity governs steady-state conductive transfer and therefore exerts first-order control on simulated geothermal gradients, reservoir temperatures at depth, and the spatial distribution of heat flow used to rank prospects. Heat capacity and thermal diffusivity regulate transient behaviour, which is essential for modelling time-dependent processes, such as production-induced cooling, reinjection plumes, and thermal breakthrough at wells. Radiogenic heat production provides an internal volumetric heat source, particularly relevant in felsic crustal rocks, and can significantly modify the vertical distribution of heat flow and the curvature of the geothermal gradient. Spatial variations in radiogenic heat production, which are mainly linked to lithology, crustal composition, and depth-dependent decay, can generate lateral contrasts in heat flow comparable to those produced by conductivity variations, and therefore must be incorporated when assessing geothermal potential and interpreting temperature logs. Constraining all these parameters through laboratory measurements, well-log calibration, and uncertainty ranges reduces non-uniqueness in model inversion, improves the consistency between simulated and observed temperature profiles, and ultimately yields more robust forecasts of long-term temperature sustainability and thermal power potential.

Hydraulic properties, especially porosity and permeability, largely determine whether heat in the subsurface is practically accessible and sustainable under production. Porosity sets the available pore volume for storing and circulating fluids and influences bulk thermal behaviour through fluid–rock heat exchange, which affects predicted reservoir heat-in-place and reinjection mixing. Permeability controls how easily fluids can move through the formation, so it governs achievable flow rates, pressure drawdown, required pumping power, and the evolution of the temperature field during production. Together, porosity and permeability define advective heat transport and strongly shape model forecasts of thermal breakthrough timing, production temperature decline, and long-term deliverability, which are central outputs used to assess and compare geothermal prospects.

Laboratory analysis

Since measurement methods have different sample preparation requirements, it is advisable to first select the necessary parameters for further investigation and determine the appropriate analytical method for sample preparation. The workflow should be tailored to each sample based on its parameters, including size, shape (such as core plug, cube, or irregular shape), cohesion, and overall porosity.

Bulk density and hydraulic properties can be measured in the laboratory, using the Archimedes method in accordance with the EU 1936:2007 standard. Alternative methods can be used depending on the required accuracy, sample shape and size, and instrument availability. Alternative approaches include the mass and geometric volume determinations (for regular samples) or photogrammetry (for irregular samples), the liquid displacement method (water, helium), pycnometer, and mercury intrusion

porosimeter (MIP). Most methods listed above allow fast and accurate measurement of porosity, permeability, and density.

P- and S-wave velocities on core plugs or cubic samples can be measured using an ultrasonic pulse transmission analyser. The measurement should be performed under conditions that reflect the presumed *in situ* environment, e.g., controlled confining pressure, temperature and water saturation.

Thermal property measurements are typically carried out in laboratory under controlled environmental conditions (pressure, temperature, and fluid saturation) on reasonable-sized rock samples. Ambient conditions (room temperature and atmospheric pressure) are typically adopted to determine experimental data. These values are successively adjusted accounting for crustal and sub-crustal pressure and temperature conditions (Norden et al. 2020). Numerous experimental techniques have been developed to investigate the thermal conductivity and diffusivity of rocks and their dependences on chemical and physical variables. They fall into one of two categories: steady-state or transient methods (Beck 1988). Only thermal conductivity is provided by steady-state methods; on the other hand, depending on the experimental design, transient methods may provide either conductivity, or diffusivity or both. The standard steady-state techniques such as the divided bar method (Pribnow and Sass 1995) are accurate but suffer from long measurement times. In comparison, transient methods, such as the transient line source (Von Herzen and Maxwell 1959), the transient divided bar (Pasquale et al. 2015), the transient plane source (Zheng et al. 2020), the laser flash method (Parker et al. 1961), the 3- ω method (Cahill 1990) and the optical scanning method (Popov et al. 1999) provide higher throughput with several advantages, for example a simpler sample preparation and a shorter measurement time. Among all, the optical scanning method performs fast, contactless-based, high-resolution conductivity profiles along the scanning line and capture variability, due to mineralogical heterogeneity.

The rock heat capacity can be investigated by direct measurements adopting Differential Scanning Calorimeters (DSC) or the Drop calorimetry technique. During a DSC test, the sample and a reference material are subjected both to the same temperature program (heating, cooling, or holding isothermally) and the difference in heat flow required to maintain both the samples at nearly the same temperature throughout the experiment is measured. The Drop calorimetry is a classic, cost-effective method, where a rock sample is heated to a high, stable temperature and then, quickly dropped into an insulated calorimeter containing a known mass of water. The final equilibrium temperature of the water is measured to calculate the heat lost by the rock, using the principle of energy conservation. Alternatively, the heat capacity can be derived from thermal diffusivity if density and thermal conductivity are known.

Radiogenic heat production is quantified by determining the concentrations of U (ppm), Th (ppm) and K (%), whose radioactive decay provides a significant internal heat source in the continental crust. These concentrations are typically measured through high-precision laboratory techniques such as Inductively Coupled Plasma–Mass Spectrometry (ICP-MS) and Inductively Coupled Plasma–Optical Emission Spectroscopy (ICP-OES), which yield accurate U and Th abundances, and X-ray fluorescence, which is particularly effective for K and major elements. Laboratory gamma-ray spectrometry offers a non-destructive alternative by directly detecting the characteristic gamma emissions of the U- and Th-decay chains and of ^{40}K . *In situ* estimates can also be obtained

from downhole total gamma-ray (GR) logs, which measure the total natural gamma radiation of the formation, or spectral GR logs, which provide U, Th and K concentrations. Finally, radiogenic heat production is computed from the concentrations of Uranium, Thorium and Potassium or from total GR logs in API units using standard relations (Rybach 1986; Hasterok and Chapman 2011).

Several laboratory methods can be used to find out about the petrographic and mineralogical features of rocks. The foundation for identifying mineral assemblages, textures, and alteration features remains conventional optical petrography on thin sections. Scanning Electron Microscopy coupled with Energy-Dispersive Spectroscopy (SEM-EDS) provides high-resolution imaging and semi-quantitative chemical data, enabling precise mineral identification and microtextural analysis. Quantitative mineral maps and modal mineralogy can be made with automated systems like QEMSCAN or Mineral Liberation Analysis (MLA). These systems use SEM imaging and spectral classification. While micro-X-ray fluorescence (XRF) provides spatially resolved elemental maps to supplement petrographic observations, X-ray diffraction (XRD) is extensively used to identify crystalline phases and quantify bulk mineral composition. Grain fabrics, pore networks, and fractures can be seen using non-destructive 3D imaging methods like micro-X-ray computed tomography (CT). Although micro-CT isn't mineral-specific, it can be used with XRD, SEM-EDS, or micro-XRF to link mineralogy and microstructure. All together, these methods give a full picture of the mineralogy, texture, and petrophysical features of rock sample.

The properties listed and described here are essential inputs for numerical modelling, but in some cases, other properties may be required for correct computation and a realistic assessment of geothermal potential, e.g., uniaxial compressive strength, tensile strength, Young's modulus, or Poisson's ratio. These properties can be measured directly or calculated from the parameters described here using theoretical correlation curves (Rahman and Sarkar 2023). Table 1 summarizes the key properties, the analytical techniques employed to measure them, and their applications.

Properties uncertainties

In heterogeneous stratigraphic units, parameterization for geothermal numerical simulations should be approached as an upscaling and representativeness problem, rather than the selection of a single "best" laboratory value. Laboratory measurements should be stratified by coherent geological domains (e.g., facies, alteration grade, or fracture-intensity class) and summarized using robust statistics that capture both central tendency and dispersion.

Uncertainty quantification, driven by measurement error propagation and the intrinsic variability of rock properties, should be treated as an integral part of the laboratory workflow to ensure that representative values are correctly used during the geothermal modelling phase.

Geophysical modelling

Developing a geological model, encompassing the main boundary locations and the physical parameters of the crystalline crust and sub-crustal structures, can be achieved through the integration of geophysical datasets. The combination of multi-disciplinary data can help reduce and examine the uncertainties associated with interpreting deeper

Table 1 Summary of key rock properties, analytical methods, and primary applications in geothermal reservoir characterization

Name (property group)	Method(s)	Application
Density (ρ bulk / grain)	Archimedes method (EU 1936:2007); mass–volume determination; photogrammetry, liquid displacement (water, helium); He-pycnometry; mercury intrusion porosimetry (MIP); micro-CT	Constraints on lithology, porosity, and impedance; calibration of rock-physics models; input for thermal and hydraulic parameterization
Porosity (ϕ)	Combined bulk and grain density (Archimedes + He-pycno); saturation methods; MIP; micro-CT	Estimation of pore volume and fluid storage; linkage to V_p , V_s and thermal properties; heat-in-place assessment
Permeability (K)	Steady-state Darcy flow; pulse-decay; measurements under controlled effective stress and saturation, micro-CT assisted pore-scale flow modelling	Fluid and heat transport modelling; prediction of drawdown and breakthrough; assessment of reservoir productivity
Seismic velocities (V_p , V_s)	Ultrasonic pulse transmission on core plugs or cubes; measurements under controlled confining pressure, temperature, and saturation	Time–depth conversion; sensitivity to fractures, fluids, and stress; reduction of inversion non-uniqueness
Thermal conductivity (k)	Steady-state divided bar; transient line source; transient divided bar; transient plane source (TPS); 3- ω method; optical scanning	Determination of heat flow and geothermal gradient; strong control on temperature-depth estimates; detection of mineralogical heterogeneity
Thermal diffusivity (α)	Laser flash analysis (LFA); TPS/hot-disk; indirect derivation from k, ρ -and C_p	Transient heat propagation; breakthrough timing; calibration of time-dependent thermal models
Heat capacity (C_p) and volumetric heat capacity (ρC_p)	Differential Scanning Calorimetry (DSC); drop calorimetry; indirect derivation from k, ρ , and α	Thermal energy storage; temperature draw-down behaviour; estimation of recoverable heat
Radiogenic heat production (A)	ICP-MS/ICP-OES (U, Th); XRF (K, major elements); laboratory gamma-ray spectrometry; downhole total and spectral GR logs	Quantification of internal heat sources; crustal thermal modelling; correction of temperature-depth profiles
Petrography / mineralogy / chemistry	Thin-section petrography; SEM-EDS; QEMSCAN/MLA; micro-XRF; XRD; ICP-MS/ICP-OES; micro-CT	Chemical, mineralogical and textural characterization; assessment of anisotropy and heterogeneity; support for rock classification and petrophysical parameter assignment
Mechanical properties	Uniaxial/triaxial compression; Brazilian tensile tests; elastic moduli from strain gauges or ultrasonics	Wellbore stability and stimulation design; thermo-hydro-mechanical (THM) modelling; stress-dependent permeability and damage analysis

structural features. In this section, we first outline the useful geophysical datasets for constraining structural features up to the upper mantle with an emphasis on seismic tomography and gravity datasets. We next describe the use of joint geophysical interpretation techniques to quantitatively classify geophysical datasets and to develop a more robust understanding of deep structural features within the geothermal system.

Geophysical data

The use of existing Seismic Tomography models helps lower the computational time and costs of inversions, examine uncertainties and reduce the non-uniqueness associated with geophysical inversions. For example, in Europe, passive techniques have been widely used for developing seismic tomography models, due to the recent evolution of the AlpArray (Hetényi et al. 2018) and AdriaArray (Kolínský et al. 2025) seismic networks. As a result, there are several open-source seismic tomography models, mostly focusing on the Alpine chain and surrounding regions (Diehl et al. 2009; Lu et al. 2018; Paffrath et al. 2021; Magrini et al. 2022; Bagagli et al. 2025; Braszus et al. 2025; Kästle et

al. 2025; Roisenberg et al. 2025) or extending to the entire Italy (Magnoni et al. 2022). The models, originally used to investigate and understand the geodynamics of the area, are suitable for investigating the extent and spatial constraints of deep geological structures, including the possible upper crust/lower crust boundary and the consistency of Moho depths. Access to the tomography models is provided in the respective articles and are downloadable in netCDF, ASCII grids, or binary formats. Along with these models, open-source global seismic tomography datasets are available through the IRIS Earth Product Model Query (IRIS Dmc 2026). Alternatively, raw seismic data from the earlier-cited tomography studies can be re-analysed. A list of open-source global seismic tomography data and codes can be accessed at the Seismolink website.

Existing gravity dataset can also be used to investigate the extent and spatial constraints of geological features. Examples of open-source gravity data include those composing the first pan-Alpine surface gravity database (Zahorec et al. 2021). The data, compiled from national gravity databases and shipborne data of the Service Hydrographique et Océanographique de la Marine and of the Bureau Gravimétrique International, spans from 2 to 23°E and from 41 to 51°N and is available on a 4 km × 4 km grid. A 2 km × 2 km grid is also available, but upon request. The compilation follows the most recent gravity processing standard that included mass, bathymetric, lake and atmospheric corrections, resulting in Free Air anomaly and Complete Bouguer anomaly dataset (Zahorec et al. 2021). Other open-source global gravity models are downloadable at the International Centre for Global Earth models (ICGEM 2026) or the Bureau Gravimétrique International (BGI - Bureau Gravimétrique International 2026). Overall, gravity data are used to image density anomalies that can be related to the size and location of different geological structures. For example, low- and high-density anomalies have been identified in geothermal settings, as low-density clay cap rocks or alteration zones and intrusive regions, respectively (Nigussie et al. 2023; Soekarno et al. 2025).

To model crustal density variations, it is first necessary to isolate the gravity effects of the mantle from the crust. This regional-residual gravity separation is applied using wavelength-based filtering techniques, such as polynomial trend surface fitting, upward continuation, and frequency-domain filtering, or forward modelling the gravity response below the mantle and subtracting from the Complete Bouguer Anomaly (Telford et al. 1990). To calculate the gravity effect of the mantle, open-source tools can be used. For example, *Perple_X* (2026), a thermodynamic calculation package (Conolly 2005), computes equilibrium mineral assemblages, as well as values of physical parameters, such as velocities and densities, as functions of pressure, temperature, and bulk composition (see Sect. "Thermal structure from seismic velocity inversion" for further use of this tool).

Residual data can then be inverted using open-source inversion modelling tools. Examples of these tools include GROWTH-23, which features a GUI interface and allows the recovery of general 3D structures for anomalous density as a free aggregation of small parallelepiped cells, each filled with an adjusted density contrast (Camacho et al. 2024). Another example is *jif3D*, which is a framework for single- and joint-inversion of various types of geophysical data. It comprises forward solvers for first arrival travel times, scalar and tensor gravity data, magnetics, magnetotellurics, electrical resistivity tomography and surface waves in 3D (Moorkamp et al. 2011) and can be used within the Python Jupyter notebook environment IGMAS+ (Interactive Gravity and Magnetic Application System Plus), developed at GFZ German Research Centre for Geosciences,

which allows interactive construction of polyhedral bodies and constrained forward and inverse modelling based on geological and seismic information (Anikiev et al. 2023; Götze and Lahmeyer 1988; Schmidt et al. 2010). Another useful tool is SimPEG (Simulation and Parameter Estimation in Geophysics), a Python package for simulation and gradient-based parameter estimation in geophysics (Cockett et al. 2015). It is based on a finite-volume method for forward modelling and a gradient method for inversion modelling. Gravity inversions can also be constrained with a priori data. For example, available seismic tomography models can be converted into density using velocity-density relationships. First, the S- waves are converted into P- wave velocity using the polynomial relation described in Brocher (2005). Then, the P-waves are converted into density using the polynomial relation to the fourth order defined by Brocher (2005) based on the “Nafe-Drake” curve.

Joint geophysical interpretation

Extracting robust geological interpretations of a geothermal system from a single geophysical model is inherently challenging because geophysical inversions are non-unique and ill-conditioned. Moreover, model parameters may be weakly constrained in regions affected by the spatial distribution of the geophysical network or by fundamental limitations of the geophysical method. Given the availability of several geophysical datasets, as mentioned in Sect. “Data collection”, the integration of multiple geophysical methods can help overcome these challenges and ultimately reduce uncertainties in geophysical interpretations. Recent advancements in machine learning and geosciences have enabled geoscientists to effectively integrate and utilize physical properties from multidisciplinary geophysical datasets.

Machine learning, subdivided into supervised and unsupervised methods, has been applied to quantitatively integrate geophysical data. Supervised techniques, which require labelled data, have been applied mostly in brownfield exploration. For supervised techniques, the labelled data, or a priori information, are used to train datasets and improve geophysical models. However, successful training of datasets requires large datasets. In the absence or scarcity of a priori information, as in greenfield exploration, unsupervised methods provide an automated labelled process to classify datasets. Table 2 provides an overview of some unsupervised clustering techniques for classifying the similarities amongst datasets. Centroid-based techniques, such as k-means and Fuzzy c-means, utilize the sum of squares of the Euclidean distance to group similar classes or clusters. The k-means is described as a hard clustering method, where datapoints are assigned exclusively to a single cluster, while the Fuzzy c-means is a soft clustering technique, in which each data point can belong to multiple clusters with varying degrees of membership. The distribution-based method utilizes a probability distribution to group datapoints. Meanwhile, density-based clustering focuses on the formation of high-density regions, treating points in low-density areas as noise, while connectivity-based clustering relies on a linkage mechanism to group datapoints.

Joint interpretation of geophysical datasets first involves ensuring that all models are spatially coincident. This can be achieved by interpolating the geophysical models onto a common grid. The datasets are then normalized and clustered into 2 to 10 clusters or any desired number. Scikit-learn (2026) is an open-source machine learning library for the Python programming language and is equipped with various clustering algorithms

Table 2 Overview of some unsupervised clustering techniques for classifying the similarities amongst datasets

Method	Objective	Measure of similarity	Method	References
Centroid based	Clusters are modelled as spherical structures defined by centroids, with hard assignments placing each data point into exactly one cluster based on distance minimization	Euclidean distance (typically squared Euclidean distance)	k-means	MacQueen (1967)
	Clusters are defined as spherical distributions of data points, where each point may partially belong to multiple clusters through fuzzy membership values	Weighted Euclidean distance with membership degrees	Fuzzy c-means	Bezdek et al. (Bezdek et al. 1984)
Distribution based	Clusters are defined as components of a mixture model, where each component represents a distinct probability distribution generating the data	Probability density / likelihood (Gaussian probability)	Expectation–maximization using Gaussian Mixture Models	Dempster et al. (1977)
Density based	Clusters are defined as sets of density-connected points forming high-density regions, while points in low-density regions are treated as noise	ϵ -neighborhood density (distance $\leq \epsilon$, MinPts)	DBSCAN (Density-based spatial clustering of applications with noise)	Ester et al. (1996)
Connectivity based	Objects are grouped based on proximity and linkage criteria	Maximum pairwise distance between clusters (complete linkage)	CLINK (complete linkage clustering)	Defays (1977)

(Pedregosa et al. 2011). The optimum number of clusters can be determined using 1) the elbow method i.e., the point at which the calculated within-cluster sum of squares decreases could indicate the best number of clusters (MacQueen 1967); 2) the partitioning coefficient and the partitioning entropy (Bezdek et al. 1984). A high value of the normalized partitioning coefficient suggests that there is little overlap between clusters. Entropy is a measure of the degree of disorder or randomness in a system. Well-sorted clusters will display low partitioning entropy and high partitioning coefficient; and 3) the Bayesian Information Criterion (BIC), a statistical method that computes the likelihood of data (Neath and Cavanaugh 2012). The lowest BIC represents the best number of clusters. Lastly, any available a priori geological data can be used to further constrain the number of clusters.

The simultaneous interpretation of multiple geophysical parameters of each class is then examined to differentiate geological features, and petrophysical or well log databases are used for validation. For example, a low resistivity coupled with a low seismic velocity perturbation and low density helped constrain the 3D architecture of the conductive clay cap of the volcanic geothermal system of Montserrat, West Indies (Basant et al. 2021). In this case, a Fuzzy c-means clustering algorithm integrated magnetotellurics, seismic tomography and gravity datasets to jointly interpret physical properties such as resistivity, velocity perturbation and density contrasts. The geological logs from wells drilled in the area confirmed the presence of smectite clays within the clay cap domain identified by cluster analysis. Another way to validate integrated geophysical modeling is by laboratory experiments on high pressure and temperature measurements, obtained on upper crustal, lower crustal and mantle rocks (Kern 1982, 1994, 2011; Kern and Schenk 1985; Burke and Fountain 1990; Mengel and Kern 1992; Christensen and

Mooney 1995), since they are useful for differentiating rocks, on the base of their physical parameters (e.g., density and velocity).

Handling geophysical uncertainty

Uncertainty in the geophysical domain is primarily related to the resolution and heterogeneity of geophysical datasets, as well as the non-uniqueness of clustering results. The workflow handles this by first understanding the uncertainties within the individual geophysical datasets. For example, exploring the resolution tests of seismic tomography models can highlight which areas are best resolved. Understanding and testing the effect of interpolating the datasets onto a common grid spacing can also help determine if oversampling or downsampling occurred. Furthermore, normalizing datasets prior to clustering helps ensure clustering is unbiased. More importantly, evaluating cluster stability using metrics, such as the elbow method, normalized partitioning coefficient and normalized partitioning entropy or BIC, supports the decision on the optimal number of clusters chosen. Overall, by comparing alternative clustering outcomes and assessing their geological plausibility, the workflow explicitly quantifies uncertainty in the definition of deep crustal domains.

Reconstructing the subsurface natural thermal state

A reliable geothermal assessment involves the reconstruction of the subsurface natural thermal state. This aspect requires the integration of a quality-checked temperature dataset together with a geometrically consistent subsurface model, which also encompasses the petrophysical model. To evaluate the subsurface thermal structure, thermal and hydraulic numerical simulations are often employed. Numerical methods can resolve the thermal regime at different investigation scales, from reservoir to crustal scale, accounting for different heat sources, namely groundwater convection, radiogenic decay, magma injection and frictional heat. The proposed workflow is displayed in Fig. 4.

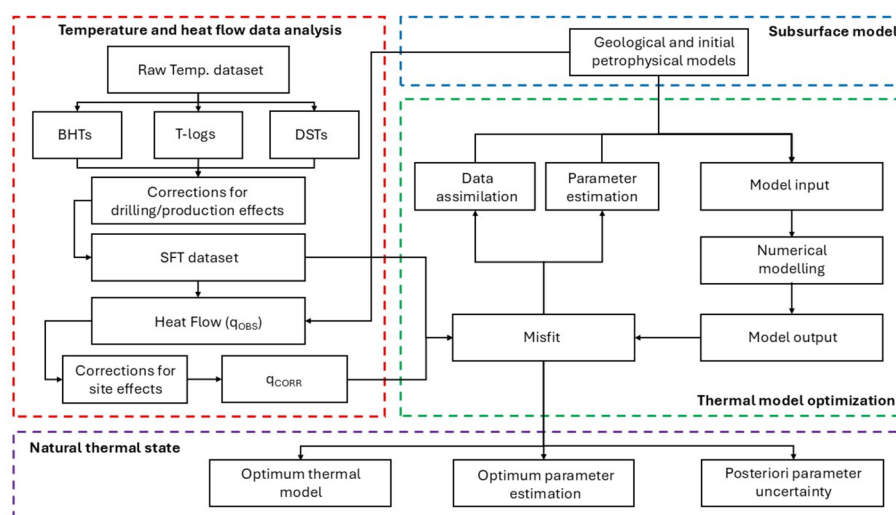


Fig. 4 Workflow for subsurface thermal modelling and parameter estimation. The diagram illustrates the combined use of corrected temperature and heat flow data together with geological–petrophysical models within a numerical simulation framework. Observed and simulated temperature/heat flow are compared through a misfit function, which drives either parameter estimation or data assimilation procedures. This iterative process yields the optimum thermal model, the best-fit parameter set, and the associated posterior uncertainty

Temperature data

Temperature data represent both a basic input parameter for site-specific heat flow determination and a fundamental constraint for the calibration of thermal numerical models. Typically, these data derive from exploratory geothermal and petroleum wells and consist of Bottom Hole Temperatures (BHTs), continuous high-resolution thermal logs and Drill Stem Tests (DSTs) temperatures. Raw BHTs consistently underestimate the static formation temperatures (SFTs) because of the circulation of the cooler drilling mud (Pasquale et al. 2008). Only measurements recorded after the borehole thermal regime has attained pre-drilling conditions are indicative of the static formation temperature. Nevertheless, thermal recovery may require several months. Such a long time can only be expected in experimental geothermal boreholes, which are thermally logged to obtain the undisturbed geothermal gradient. Therefore, to achieve reliable SFT estimates, both the DST and BHT datasets need to be carefully analysed and eventually adjusted. The principal methods are summarized in Table 3.

Several BHT correction methods exist, differing in complexity, data requirements, and underlying assumptions (Deming 1989; Goutorbe et al. 2007; Pasquale et al. 2008, 2012; Rangel-Arista et al. 2024). When time–temperature series are recorded during geophysical logging operations at increasing shut-in time (Δt), the SFT can be extrapolated by the application of analytical and semi-analytical or graphical methods. Analytical methods rely on the solution of the thermal diffusion equation under the assumption that circulating drilling mud acts as a heat sink or source. These methods can be classified based on their inherent boundary conditions, namely linear, spherical, and cylindrical source.

The chief practical difficulty in applying the linear source method (Horner 1951), also known as the Horner plot correction, is that information on the duration of mud circulation after the end of drilling operations (t_c) is often unavailable. Various investigators circumvented this difficulty by adopting reasonable values in the range 4 – 8 h, although t_c values as great as 30 – 40 h are reported (Deming 1989 and references therein). Otherwise, t_c can be inferred as a function of bottom hole depth using empirical formulas (Hermanrud et al. 1990; Pasquale et al. 2008). Rigorous theoretical investigations revealed that when $(t_c/\Delta t) > 1/3$ for all Horner data points, straight-line extrapolations underestimate the SFT. For such situations, Roux et al. (1980) proposed an additional correction as a function of rock thermal diffusivity, mud circulation time and borehole radius.

The spherical source model (Ascencio et al. 1994) assumes that heat transfer during the thermal recovery follows a spherical-radial heat flow pattern. For $\Delta t > (2R^2/\alpha)$, where R is the thermal influence radius and α the rock thermal diffusivity, the behaviour of T versus $1/\sqrt{t}$ is linear. When the recording instrument is not at the bottom of the well, models based upon linear or cylindrical sources should be used (Ascencio et al. 2006).

The cylindrical source models explicitly incorporate borehole geometry, but to obtain tractable analytical expressions they typically assume zero circulation time. Their complexity ranges from the simplest formulation based on a single medium with average thermal properties (Middleton 1979), similar to the assumptions underlying linear and spherical source models, to more realistic two-component representations that distinguish between the thermal properties of drilling mud and surrounding rocks (Cooper and Jones 1959). Pasquale et al. (2008) applied both the linear model and the

Table 3 Overview of some methods for downhole temperature correction

Method	Principle	Equation	Requirements
<i>BHT—analytical</i>			
Horner (1951)	Linear source	$BHT(t_c, \Delta t) = SFT_H + m_H \ln(1 + t_c / \Delta t)$	BHTs, t_c , Δt
Roux et al. (1982)	Linear source	$SFT_R = SFT_H - (2.303 \cdot m_H \cdot t_D)$	BHTs, t_c , Δt , k_{rock} , $\rho_{C_{rock}}$, r_{well}
Ascencio (1994)	Spherical source	$BHT(\Delta t) = SFT_A + m_A (1 / \sqrt{\Delta t})$	BHTs, Δt
Middleton (1982)	Cylindrical source	$BHT(\Delta t) = SFT_M - (SFT - T_{mud}) [1 - e^{-r^2 / 4\alpha\Delta t}]$	BHTs, Δt , $k_{rock-mud}$, $\rho_{C_{rock-mud}}$, r_{well}
Cooper & Jones (1959)	Cylindrical source	$BHT(\Delta t) = T_{mud} + (SFT - T_{mud}) [1 - F(\alpha, \tau)]$	BHTs, Δt , k_{rock} , $\rho_{C_{rock}}$, $\rho_{C_{mud}}$, r_{well}
<i>BHT—empirical</i>			
Förster et al. (1997)	BHT comparison with SFT/DST	$SFT = BHT + (A + Bz)$	BHT, z
Waples & Ramly (2001)	BHT comparison with SFT/DST	$SFT = T_o + \left[\frac{(A \cdot \ln(\Delta t) + B)}{z^C} \right] \cdot (BHT - T_o)$	BHT, Δt , z
Schulz a& Werner (1987)	Initial temperature deviation	$SFT = BHT + \left[\frac{1 + \exp(-r^2 / 4\alpha\Delta t)}{1 - \exp(-r^2 / 4\alpha\Delta t)} \right] \cdot (BHT - T_o)$	BHT, Δt , k_{rock} , $\rho_{C_{rock}}$, r_{well}
Agemar (2022)	Initial temperature deviation	$SFT = \frac{BHT \cdot Ar + T_o (\exp(-r^2 / 4\alpha\Delta t) - 1)}{Ar + (\exp(-r^2 / 4\alpha\Delta t) - 1)}$	BHT, Δt , k_{rock} , $\rho_{C_{rock}}$, r_{well}
Pasquale et al. (2008)	Horner slope vs depth	$SFT = BHT + (az + bz^2) \cdot \ln(1 + t_c / \Delta t)$	BHT, t_c , Δt , z
<i>DST temperature</i>			
Two-phase Joule–thomson correction	Isenthalpic energy balance	$SFT = T_{DST} + \frac{\dot{m}_{Cp,g} \cdot \mu_{JT,g} \cdot \Delta P}{\dot{m}_{Cp,g} + \dot{m}_{Cp,f}}$	T_{DST} , ΔP , $\dot{m}_g$, $\dot{m}_f$, $C_{p,g}$, $C_{p,f}$, $\mu_{JT,g}$

two-component cylindrical model to a dataset of 29 time–temperature series and compared the resulting SFTs. On average, the Horner method yielded SFT values approximately 1 °C lower, with maximum differences of about 7°C. The discrepancy between temperatures predicted by the Horner method and those obtained using the Cooper and Jones model becomes negligible for $\Delta t > 10$ h. The authors therefore recommend avoiding the Horner method when the borehole radius is large or, equivalently, when Δt is too short.

Widely used in industry are the graphical, semi-analytical methods. One of the most common in the Oil and Gas sector is the method proposed by Fertl and Wichmann (1977). Although it resembles a Horner-type plot, it does not rely on an explicit physical formulation. A different approach, originally developed for geothermal exploration in Italy, is that of Barelli and Palamà (1981), which introduced a semi-empirical graphical method explicitly grounded in the physics of the cylindrical source. Both methods employ semi-logarithmic charts in which BHT data are plotted as a function of a dimensionless time on the ordinate axis; the SFT is then obtained by extrapolating the resulting straight line to the right and reading the intercept on the abscissa.

When BHT records have only one shut-in time available, several empirical relations have been proposed (Förster et al. 1997; Waples and Ramly 2001; Pasquale et al. 2008; Agemar 2022). These empirical approaches rely on the assumption that systematic and predictable trends, controlled by factors such as bottom-hole depth, shut-in duration, borehole radius, borehole heating rate, and regional thermal regime, can be statistically identified. Calibration of the empirical coefficients is typically performed through comparative analysis with DST temperatures and/or static formation temperatures derived from time–temperature series, sometimes including their regression slopes. Although such methods should be applied cautiously outside the calibration domain, it is important to emphasize that uncorrected BHTs are unusable for quantitative thermal studies; applying an empirical correction therefore provides the best available estimate of subsurface temperature when more rigorous transient data are lacking.

During production tests, if the flowing fluid is dominated by liquid phase, the DST temperatures offer accurate estimates of the SFTs (Beardsmore and Cull 2001). Nevertheless, in gas-bearing formations (e.g., CH₄, CO₂) the temperatures may systematically underestimate the true SFT. This bias arises from the cooling associated with isenthalpic expansion of the reservoir fluid as it passes through the downhole choke or valve, a process governed by the Joule–Thomson (J-T) effect. In single-phase gas systems, the J-T cooling can be substantial, leading to significant temperature depression relative to the undisturbed conditions. Several correction schemes have been proposed within the petroleum engineering literature (Hermanrud et al. 1991; Zhang et al. 2017; Yang et al. 2019), but their applicability is often limited by the scarcity of detailed pressure and temperature profiles, which are typically unavailable due to the industrial and confidential nature of production test data. A practical and physically grounded alternative is to adopt a standard isenthalpic energy balance for a two-phase water–gas mixture, if the total enthalpy of the flowing system remains constant during the throttling process. In this framework, the liquid water behaves as an effective thermal ballast: owing to its high heat capacity relative to gas, it attenuates the temperature drop associated with gas expansion. This approach yields a more conservative and realistic estimate of SFT during DST operations.

Heat flow data

Conductive surface heat-flow estimates derived from static formation temperature (SFT) data provide a fundamental constraint for reconstructing lithospheric geotherms. Three principal approaches are commonly employed. The interval method computes heat flow within a defined depth interval as the product of thermal conductivity and the temperature gradient, following Fourier's law. The Bullard method (Bullard 1939) expresses heat flow as the slope of the linear relation between temperature and cumulative thermal resistance in a layered medium under 1D steady-state conduction. A third approach, the boot-strapping method (Chapman 1986), iteratively solves the 1D steady-state heat-conduction equation from the surface downward, incorporating radiogenic heat production.

The interval method is preferable when thermal conductivity is well constrained and the geothermal gradient is relatively noise-free, whereas the Bullard method is advantageous because it operates directly on temperatures, facilitating the identification of intervals that deviate from steady-state conduction. Since both temperature and thermal resistance carry uncertainty, Bullard plots require Bivariate Least Squares or Orthogonal Distance Regression to avoid biased heat-flow estimates. Regarding the boot-strapping method, its main source of uncertainty arises from the cumulative propagation of errors in thermal conductivity, radiogenic heat-production estimates, and shallow temperature data. Because the method integrates downward from the surface, small errors introduced in the upper part of the model can amplify with depth, leading to increasingly uncertain temperature and heat-flow estimates. For this reason, the boot-strapping approach is most reliable when high-quality conductivity and heat-production data are available and when the near-surface thermal structure is well constrained.

The measured heat flow (q_{obs}) rarely matches the long-term, steady-state regional value (q_{corr}) because several transient or geometric processes perturb the upper crustal thermal structure. The most significant are topography, paleoclimate, and sedimentation/erosion. Applying these corrections in order of decreasing spatial wavelength ensures that short-wavelength, near-surface disturbances are removed before deeper, long-wavelength effects, thereby avoiding systematic over- or under-correction. Neglecting these processes can bias both heat-flow estimates and temperature extrapolations at large depths.

Topography induces lateral heat refraction: elevated areas act as thermal sinks, producing $q_{\text{obs}} < q_{\text{corr}}$, whereas depressions act as thermal sources, yielding $q_{\text{obs}} > q_{\text{corr}}$. The magnitude of the anomaly depends on relief amplitude, wavelength, and it decays with horizontal distance and depth. Corrections may be obtained using analytical formulations (Lee 1991), which express the terrain effect as an additive perturbation to the temperature field satisfying Laplace's equation, or through 2D/3D finite-element models (e.g., Pauselli et al. 2019; Colgan et al. 2021). Numerical conduction models quantify the topographic perturbation and express it as a multiplicative correction factor that can be applied either to the geothermal gradient or directly to the heat-flow density, consistently accounting for the depth intervals considered.

Paleoclimate correction removes the transient thermal signal produced by past surface-temperature variations, which diffuse into the upper crust and perturb present-day subsurface temperature field. In practice, paleoclimate diffusion models represent surface-temperature history as a sequence of step functions, each defined by a duration and an amplitude (positive or negative) relative to a reference temperature. The present-day

anomaly is the superposition of all past steps. Mean annual temperatures from 1900 or 1950 are commonly used as baselines; among these, 1950 is often preferred because it precedes the onset of rapid modern warming and aligns with long, high-quality instrumental records. Because the penetration depth of each anomaly scales with $\sqrt{\alpha t}$, Quaternary climate cycles affect the upper 2–3 km of the crust, and the resulting correction can reach several degrees Celsius (Pasquale et al. 2012; Pauselli et al. 2019), depending on the magnitude and timing of past temperature changes.

Time-dependent changes driven by either sedimentation or tectonic uplift and erosion further complicate the thermal regime. Rapid sediment accumulation produces thermal blanketing, reducing the near-surface geothermal gradient because part of the thermal energy is spent in warming newly deposited, cooler sediments. Conversely, crustal uplift and erosion induce thermal rejuvenation, steepening the geothermal gradient because hotter material moves upward. These processes are described by the transient advection–diffusion equation, often based on a semi-infinite half-space with a constant basal flow and a moving upper boundary, whose vertical velocity term represents the rate of sedimentation (negative) or erosion (positive). The magnitude correction depends on two primary factors: the sedimentation/erosion rate and the rock thermal diffusivity. Correction methods solve this equation using either stepwise or continuous surface-elevation histories to remove the transient component and recover the steady-state heat flow (e.g., Von Herzen and Uyeda 1963).

Thermal modelling

A steady-state 1-D conductive geotherm can be reconstructed directly from the surface heat flow corrected for static and transient effects by integrating the heat-conduction equation with internal heat production:

$$T(z) = T_o + \frac{q_o}{k_r} z - \frac{A}{2k_r} z^2 \quad (1)$$

where T is the temperature profile as function of depth z , T_o and q_o are the mean annual temperature and the corrected heat flow at the surface, k_r the porous rock thermal conductivity, and A the radiogenic heat-production rate. Alternatively, the subsurface temperature field can be obtained by solving numerical heat-transport models that couple conduction and convection in porous and/or fractured media. The transient temperature distribution governed by the advection–diffusion equation accounting for internal heat sources is:

$$(\rho c_p)_r \frac{\partial T}{\partial t} + (\rho c_p)_f \mathbf{v} \nabla T = \nabla \cdot (k_r \nabla T) + A \quad (2)$$

where ρ is density, c_p the specific heat capacity, k the thermal conductivity, $\mathbf{v}$ the Darcy velocity of the fluid, and A the radiogenic heat-production rate. The subscripts r and f refer to the porous rock and the circulating fluid, respectively. When fluid flow is explicitly modelled, Darcy's law links velocity to pressure gradients:

$$\mathbf{v} = -\frac{K_r}{\mu_f} (\nabla p - \rho_f \mathbf{g} \nabla z) \quad (3)$$

with K_r the rock permeability, μ_f the fluid dynamic viscosity, p the pressure and $\mathbf{g}$ the gravitational acceleration. These equations form a coupled nonlinear system whose solution provides the time-dependent thermal structure of the reservoir.

There are several numerical simulation codes that can be applied for scientific investigations of hydrothermal flows. The most popular codes are the TOUGH suite (Pruess 2004; Jung et al. 2017), the SHEMAT suite (Keller et al. 2020), CSMP+ + (Matthäi et al. 2007), MUFITS (Afanasyev 2013) and MODFLOW (Morway et al. 2025). A review of other simulators examining their applicability and limitations can be found in Ingebritsen et al. (2010) and Scheidegger and Tamayo-Mas (2019). A list of selected open source and proprietary numerical simulation codes employed in geothermal reservoir simulation is in Table 4.

Specific geothermal reservoir simulators solve the heat-transport equation using enthalpy rather than temperature as the primary variable. This formulation is particularly advantageous in multiphase and multispecies systems, where fluid properties change abruptly across phase boundaries or near the critical point. By expressing energy conservation in terms of enthalpy, the numerical scheme can naturally accommodate latent heat effects, phase transitions, and strongly non-linear equations of state. As a result, enthalpy-based solvers offer stability and accuracy when modelling supercritical

Table 4 Overview of some numerical simulation codes for geothermal reservoir modelling

Software	Principle	Method	Repository/licensing
<i>Open-source</i>			
SHEMAT-suite	Coupled flow, heat and species transport in porous media under sub- and supercritical conditions; parameter estimation by stochastic and deterministic Bayesian approaches	FDM	https://github.com/ElsevierSoftwareX/SOFTX_2020_135
MUFITS	Multiphase multicomponent flows in porous media under sub- and supercritical conditions; inverse modelling capabilities	FDM/FVM	http://mufits.org
OpengeoSys	Thermo-hydro-mechanical-chemical processes in porous and fractured media	FEM	https://gitlab.opengeosys.org/ogs/ogs
FEHM	Multiphase multicomponent flows in porous and fractured media under sub- and supercritical conditions	FEM	https://github.com/lanl/FEHM
MODFLOW	Multiphase multicomponent flows in porous media under sub- and supercritical conditions; inverse modelling capabilities	FDM	https://www.usgs.gov/software/modflow-6-usgs-modular-hydrologic-model
<i>Proprietary</i>			
TOUGH suite	Multiphase multicomponent flow in porous and fractured media under sub- and supercritical conditions; inverse modelling capabilities and uncertainty propagation analysis	IFDM	Berkeley Lab
Comsol multiphysics	Coupled thermo-hydro and thermo-hydro-mechanical under subcritical conditions, provide parameter optimization capabilities and sensibility analysis	FEM	Comsol
CSMP+ +	Multi-physics thermal–hydrological–mechanical–chemical processes under sub- and supercritical conditions	FEM/FVM	ETH Zuerich, Switzerland Montanuniversitaet Leoben, Austria Heriot Watt University, Edinburgh, UK University of Melbourne, Australia

conditions, boiling and condensation fronts, or reservoirs containing mixtures of water, steam, and non-condensable gases (Magnusdottir and Finsterle 2015; Scott et al. 2015).

Stochastic approaches in 3D temperature modelling provide a powerful framework for representing the spatial variability and uncertainty inherent in subsurface thermal fields (Vogt et al. 2010; Degen et al. 2022). Unlike deterministic models, which yield a single best-estimate temperature distribution, stochastic methods explicitly account for the uncertainties and spatially sparse nature of geological, petrophysical, and thermal data. Advanced inverse-modelling algorithms, most notably the Gauss-Marquardt–Levenberg method, and null-space Monte Carlo analysis, can be managed through the PEST Suite (Doherty 2025). PEST is a collection of model-independent parameter estimation and uncertainty-analysis tools designed to calibrate numerical models through automated optimization. Because PEST communicates with external simulators through input/output files, it can be coupled with virtually any numerical simulation code.

Thermal structure from seismic velocity inversion

Another approach to estimate lateral and vertical temperature variations in the lithosphere and the sub-lithospheric mantle is to use forward models of seismic velocities, as functions of pressure (P) and temperature (T), with one or more chemical bulk compositions as inputs. The match between the velocities of the seismic tomography and those obtained from the models allows temperature estimation at the defined pressure conditions. In recent decades, a few open-source software packages have been developed to perform the thermodynamic modelling useful for this aim (Conolly, 2005; Hacker and Abers 2004; Abers and Hacker 2016). Among others, the software *Perple_X* (Conolly, 2005) is very well-known to the geological and geophysical community. It includes a collection of Fortran77 programs suitable for different types of modelling and calculations, aimed to define the Earth's physical properties and mineralogic phase diagrams, and is periodically updated. In particular, the software performs a Gibbs free energy minimization to determine the mineral phase relations at each (P , T) point in the model and computes the bulk elastic properties of the mineral assemblage via an equation of state. *Perple_X* includes several thermodynamic databases (e.g., Holland and Powell 1998 and 2011; Stixrude and Lithgow-Bertelloni 2011), allowing the chemical bulk compositions of the crust/mantle layer to be expressed with a variable number of oxides. These databases are based on equations of state valid across different pressure ranges, corresponding to the depth of the crust and mantle. The main challenge of this approach is selecting the input chemical bulk composition that best represents the crust/mantle conditions characterizing the study area. As discussed in previous studies (e.g., Kaban et al. 2014; Tesauro et al. 2014, 2020, 2026), this requires a deep a-priori knowledge of the crustal/mantle rock composition (e.g., based on xenolith samples) or the use of additional geophysical data, such as gravity, sensitive to other physical parameters (e.g., density).

Furthermore, the seismic tomography models provide velocities lower than those estimated by *Perple_X*, because the software does not account for factors, such as viscoelastic effects occurring at high temperatures, as well as the presence of sediments, fractures, pores, melt, and fluids. Therefore, the synthetic velocities have to be corrected for these effects, named anelastic effects, using models available in the literature (e.g., Cammarano et al. 2003; Cobden et al. 2018) or empirical corrections that model the impact of the sediments (Roisenberg et al., 2025). Other uncertainties, affecting the

method described, depend on the specific seismic tomography model used (e.g., types of algorithms used to derive the velocities, number and distribution of the seismic stations needed to record the arrival times) and are difficult to quantify.

Other studies (Fomin et al. 2026; Fulla et al. 2021 and references therein) use different types of seismic data (e.g., receiver function and surface-wave dispersion curves), together with other geophysical data (geoid and gravity anomalies, elevation, surface heat flow, and gravity gradients) to infer the composition and temperature, following a probabilistic joint inversion method. Other recent studies follow this approach including in the input crustal thermal parameters, such as radiogenic heat and thermal conductivity (Chambers et al. 2025 and reference therein). All the described approaches, despite the possible uncertainties, have the strong advantage of estimating the temperatures, also in transient conditions, over large areas, with a small computational time and uniform resolution (according to the seismic model used). They can also easily identify the location of thermal anomalies and thus, they can be suggested for a preliminary evaluation of the thermal state conditions of the region of interest and its deep structures, for which direct data are very often unavailable or few and unevenly distributed (e.g., deep wells and xenoliths).

Geothermal potential assessment: methods, codes and reporting

The potential for geothermal development and the economic value of geothermal projects are described by various terms. The evaluation of geothermal potential represents a critical step in the development of a geothermal project, as it provides the quantitative basis for resource screening, technology selection, and economic feasibility assessment. Geothermal systems are strongly site-specific, and their exploitability depends on a complex interplay between geological, thermal, hydraulic, and technological factors. Consequently, geothermal potential assessment requires an integrated, multidisciplinary approach capable of progressively refining estimates as data availability and model complexity increase. Geothermal potential assessment methods evolved from simplified static estimations toward integrated, physics-based and techno-economic workflows capable of representing the full geothermal system, from the subsurface heat source to the surface energy conversion and economic performance. Depending on the nature of input parameters, the various methods can be categorized into two groups, namely the static and the dynamic methods (Ciriaco et al. 2020). Static methods provide first-order estimates of geothermal potential without relying on production history. They are particularly useful during early exploration phases when subsurface data are limited. One of the most relevant static approaches is the surface heat flux method (Muffler and Cataldi 1978), which estimates the potential as the sum of the convective heat flow, namely the heat discharged at the surface by hot springs and fumaroles, and the conductive heat flow integrated over a surface. While conceptually simple, this method suffers from large uncertainties and often the natural heat loss underestimates the installed capacity by up to an order of magnitude (Wisian et al. 2001; Williams 2005; Ciriaco et al. 2020). Then, its use is limited to qualitatively confirming the geothermal potential of convective hydrothermal systems with surface manifestations. Moreover, its suitability for blind systems, namely geothermal resources without surface manifestations, such as those covering most geothermal plays in Europe and possibly worldwide, is questioned (Aghemar et al. 2018). By contrast, dynamic methods incorporate production history from

wells and reservoir response, providing more realistic estimates of sustainable capacity, but they can be used only in areas where underground characterization is advanced, and therefore, in brownfields. In hydrothermal systems, this implies the robust definition of the geothermal reservoir geometry, including its areal extent, thickness, structural controls, and the spatial relationships between reservoir units, cap rocks, and potential heat sources. Such characterization relies on borehole measurements, geophysical interpretations, and numerical thermal models that account for both conductive and convective heat transfer as stated in Sect. "Thermal modelling".

Modern approaches recognize that geothermal potential is not a single quantity but a sequence of progressively refined metrics (Trumpy et al. 2016; Limberger et al. 2018), which involve: 1) heat in place estimates, 2) recoverable heat estimates, 3) energy capacity estimates obtained by conversion, and 4) economically viable output. Accordingly, the state of the art is structured around those four tightly connected domains. Despite their different physical–mathematical formulations and specialized computational tools, coupling them is crucial for maintaining internal consistency and providing reliable decision support. Monte Carlo simulations are typically employed to derive probabilistic estimates of recoverable heat and energy potential (e.g., P10, P50, and P90 values) by explicitly propagating uncertainty in key geological, thermal, and petrophysical parameters. The combined effect of these uncertainties is sampled through repeated realizations, yielding probability distributions that quantitatively reflect the range of likely resource and power estimates rather than a single deterministic outcome. The proposed workflow is displayed in Fig. 5.

Static resource estimation

Nowadays, early-stage geothermal potential assessment commonly relies on the volumetric method, which calculates the recoverable thermal energy in porous and permeable rock volumes, adjusted by recovery factors, conversion efficiency, and plant life. Since the early 1970s, the volumetric method has represented a cornerstone of geothermal resource assessment in hydrothermal systems (Bolton 1973; Nathenson 1975). This

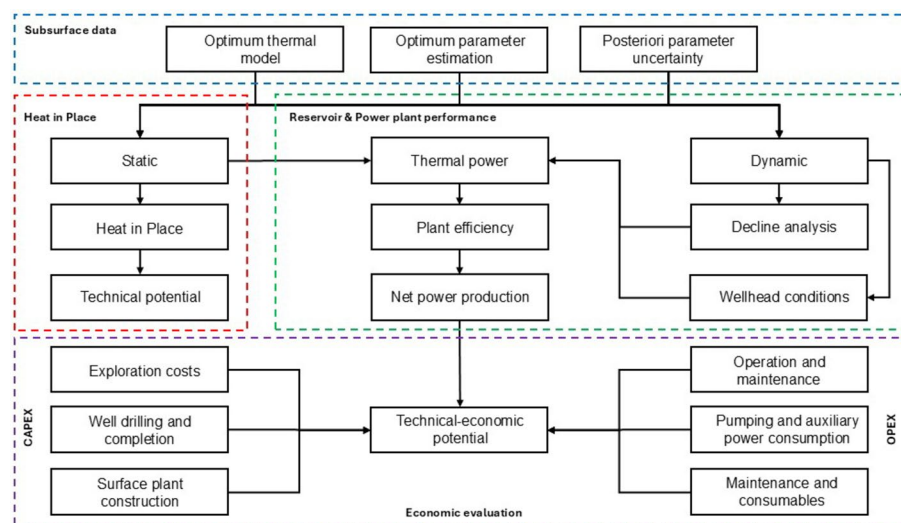


Fig. 5 Workflow for geothermal project assessment, illustrating how subsurface characterization, heat-in-place estimation, reservoir and power-plant performance analysis, and CAPEX/OPEX evaluation jointly contribute to determining the technical–economic potential of a geothermal resource

method, based on subsurface volume discretization, temperature and thermophysical properties estimation, is often referred to as the heat in place (HIP) approach. The HIP method is primarily intended for regional screening and preliminary assessment, rather than for detailed project design or production forecasting. The original formulation to estimate the total thermal energy in place (J) is:

$$Q = V \left[(1 - \phi) (\rho c_p)_r + \phi (\rho c_p)_f \right] (T - T_{ref}) \quad (4)$$

where V is the reservoir volume (m^3), ϕ the porosity (dimensionless), ρ the density ($kg\ m^{-3}$), c the specific heat ($J\ kg^{-1}\ K^{-1}$), T the reservoir temperature (K or $^{\circ}C$) and T_{ref} the reference temperature (K or $^{\circ}C$), namely the lowest temperature to which the produced geothermal fluids are assumed to be cooled when extracting energy from the underground. T_{ref} may be taken as the mean annual surface temperature or the base temperature, e.g., the rejection temperature from a power plant condenser. The subscripts r and f refer to the rock and geothermal fluid properties, respectively.

The HIP method has been refined and adapted by various institutions and research groups, leading to several methodological variants. Among the most influential developments are the U.S. Geological Survey (USGS) methodology (Colin et al. 2008; Williams et al. 2008) and the approaches codified within national reporting frameworks such as the Australian and Canadian Geothermal Reporting Codes (Committee and (AGRCC) 2010; CGCC 2010). Accounting for two-phase-bearing geothermal reservoirs (liquid and steam), the Eq. 4 becomes:

$$Q = V \left\{ (1 - \phi) (\rho c_p)_r (T - T_{ref}) + \phi [(1 - s_w) \rho_s (h_s - h_w) + s_w \rho_w (h_w - h_{wo})] \right\} \quad (5)$$

where s_w (dimensionless) is the relative water saturation and h the fluid enthalpy ($J\ kg^{-1}$) at reservoir pressure and temperature conditions. The subscripts r , s , and w refer to rock, steam, and water, respectively, and h_{wo} represents the water enthalpy at the cut-off temperature. A first filtering step at this stage is to identify the reservoir volume that effectively contributes to the potential estimate. This “effective reservoir” concept (Trumpy et al. 2015; Santilano et al. 2019) implies that only the reservoir volume with temperatures above the cut-off temperature, defined as the minimum economic reservoir fluid temperature for commercial energy extraction, is considered.

While HIP calculations provide an upper bound to the available resource, only a fraction of this thermal energy can be technically recovered and converted into useful energy. Depending on the surface technology, this useful energy may be delivered either as electric power (MW_e) or as thermal power (MW_{th}). The power potential over plant life can be calculated as:

$$P_{e,th} = \frac{Q \cdot R \cdot \eta}{3.6 \cdot 10^9 \cdot LT \cdot 8760} \quad (6)$$

where Q is the recoverable heat, R the recovery factor (dimensionless), η the overall plant efficiency (dimensionless), and LT the economic lifetime of the project (yrs). At denominator, the coefficients are the conversion factor to MWh ($1\ MWh = 3.6 \times 10^9\ J$) and the hours per year (8760 h). A crucial aspect of Eq. 6 is therefore the estimation of both the recovery factor R and plant efficiency η , which determines whether the resulting power is expressed in MW_e or MW_{th} , depending on the final use of geothermal heat.

The recovery factor indicates the proportion of stored heat that can be economically retrieved. Its estimate is inherently speculative, and the common approach involves underground numerical simulations to determine the amount of heat that can be extracted, accounting for the optimal number of wells, their spacing, water yield per well, and admissible drawdown (Fan et al. 2022). To reduce errors, predicted results are validated with field data when available. This type of “history matching” is commonly used in reservoir analysis, and R can be as high as 25% for hydrothermal systems (Tester et al. 2006). In geothermal fields in operation in the United States, such as The Geysers, Coso, and Dixie Valley, recovery factors range from approximately 5% to 20% (Williams 2007). In EGS reservoirs, R is generally lower due to lower permeability. Grant (2016) reported recovery factors of only 0.2–2% for the EGS research sites of Fenton Hill (USA), Rosemanowes (UK), Hijori (Japan), and Cooper Basin (Australia).

The estimation of useful power is strongly dependent on the efficiency of the surface system. For electricity generation, a universal metric based on the Second Law is commonly employed to compare the performance of geothermal power plants. The utilization efficiency, or exergetic efficiency, measures how effectively a plant converts the available exergy into useful work. Based on exergy considerations, the technological quality of geothermal power plants typically ranges between 30 and 65% (DiPippo 2007, 2015). In practical assessments, however, it is often more convenient to adopt the net thermal efficiency, a First-Law metric defined as the ratio between the net electricity produced and the total thermal energy input. Due to the Carnot limit, parasitic loads, and system losses, net thermal efficiencies generally range from 8 to 20%, with a global mean of about 12% (Zarrouk and Moon 2014). For geothermal potential assessment, this efficiency can be estimated using empirical relationships, that express η as a function of the geothermal fluid temperature or enthalpy (Zarrouk and Moon 2014). Alternatively, the plant's efficiency can be modelled accounting for all stages of the system, from the turbine (or heat exchanger, in case of direct uses) to the injection well, as discussed in Sect. “Modelling of surface utilization systems”.

When considering direct thermal uses, the same formulation applies, but η represents the efficiency of the heat-transfer process rather than a thermodynamic conversion efficiency. In such cases, η is typically much higher (70–90%), and the resulting power corresponds to thermal power (MW_{th}) rather than electrical power.

Dynamic methods

A time-dependent geothermal potential assessment relies on the available thermal power defined as:

$$P_{th}(t) = q_m(t) c_p (T(t) - T_{ref}) \quad (7)$$

with $q_m(t)$ and $T(t)$ the mass flow rate and the production temperature, respectively, as function of time. Although geothermal reservoirs are quite different from petroleum reservoirs in many ways, their natural response to exploitation can be assessed employing the decline analysis method, which has long been available and tested in Oil & Gas fields. The generalized decline model is (Arps 1945).

$$q_m(t) = \frac{q_{m,i}}{(1 + bD_it)^{1/b}} \quad (8)$$

with q_{mi} and D_i the initial mass flow rate and decline rate, respectively, and b the decline exponent. From Eq. 8, three equations are derived for analysing flow rate decline and they are the so-called exponential ($b=0$), hyperbolic ($0 < b < 1$), and harmonic equations ($b=1$) (Aragón-Aguilar et al. 2013). The choice of the most appropriate equation and the coefficient D and b are solved by fitting the available production data over time. The equation to obtain the initial mass flow rate is:

$$q_{m,i} = \frac{Kh(p_i - p_f)}{\mu B_o [\ln(r_e/r_w) + S]} \quad (9)$$

with K the permeability, h the production thickness, p_i the initial pressure, p_f the flowing pressure, μ the fluid viscosity, B_o the fluid volume factor, r_e the reservoir drainage radius, r_w the well radius, and S the skin factor.

In high-temperature geothermal reservoirs, a decline in pressure caused by exploitation may initiate boiling in part or all of the reservoir. In this case the changes in the reservoir caused by exploitation will include changes in the steam/water ratio, as well as pressure and temperature changes. More advanced reservoir-scale assessments employ solutions to the heat transport equation, incorporating production and injection wells together with the geometry of borehole field. The numerical reservoir simulations represent the most advanced dynamic approach, solving coupled mass and energy balance equations in discretized reservoir models. This approach accounts for heterogeneity, recharge, and thermal decline. Numerical simulations are computationally intensive but provide the most reliable forecasts of reservoir performance under different production scenarios.

In addition to conventional reservoir-scale simulations, transient modelling of deep closed-loop heat exchangers (DCHE) and deep thermal energy storage (TES) systems has become increasingly relevant for assessing the time-dependent behaviour of engineered geothermal systems. Unlike open-loop reservoirs, DCHEs rely exclusively on conductive heat transfer through the surrounding formations, making their performance highly sensitive to the temporal evolution of the subsurface temperature field, the thermal depletion around the wellbore, and the operational strategy adopted at the surface. Numerical simulations such as those presented in recent DCHE studies (e.g., Gola et al. 2022; Magaji et al. 2024), solve the coupled heat transport and fluid flow equations along the entire closed-loop circuit, capturing variations in production temperature, thermal breakthrough, and the propagation of thermal perturbations in the host rock. Similarly, transient modelling is essential for TES systems, where cyclic injection and extraction operations induce periodic thermal waves. These dynamic approaches provide a physically consistent framework to evaluate system sustainability, optimise operating schedules, and quantify recoverable heat over time, and complementing decline-curve analysis.

Wellhead conditions

Wellbore simulations represent a critical intermediate step between reservoir and surface utilization modelling. Borehole-reservoir coupling introduces an effective estimation of the available thermal power available at the wellhead. It requires the evaluation of pressure and heat losses of the geothermal fluid along the well path up to the surface.

Analytical and semi-analytical formulations for wellbore pressure and heat losses (Ramey 1962; Hasan et al. 1996) are widely used, particularly for long-term production analysis. In this context, solutions for a coupled P–T framework and multiphase flow are proposed (Zheng et al. 2022; Jing et al. 2025). Beside the analytical solutions based on energy balance equations, the geothermal well can be modelled numerically solving for mass, momentum, and energy balance equations. A comprehensive overview of the physical and mathematical approaches for geothermal wellbore simulation is provided in Tonkin et al. (2021). For high-enthalpy systems, two-phase flow correlations and slip models are required to represent flashing and steam-water mixtures. These models account for pressure losses due to gravity, friction, acceleration due to phase transitions, and heat exchange between the fluid and surrounding formations.

Modelling of surface utilization systems

From the wellhead conditions, thermodynamic modelling of the geothermal power plant or heat utilization system becomes possible. Detailed plant models simulate the performance of different conversion technologies, such as dry steam, flash, or binary cycles, and quantify net power output, conversion efficiency, and auxiliary power consumption. For thermal applications, system-level models assess heat delivery rates and seasonal performance. This stage marks the transition from theoretical resource potential to technically exploitable energy production. Plant models are based on mass and energy balances across turbines, separators, heat exchangers, condensers, pumps, and cooling systems. Accurate thermophysical property models, such as IAPWS formulations for water and steam (Wagner and Pruss, 2002) and dedicated correlations for organic working fluids (Badr et al. 1985), are critical to quantify conversion efficiency and parasitic losses. Binary cycle modelling requires a detailed representation of heat exchanger performance using effectiveness–NTU (Number of Transfer Units) or logarithmic mean temperature difference approaches. These models provide estimates of net electrical power output and thermal utilization efficiency.

For district heating systems, the thermal power is defined by the portion of the geothermal production that remains above the minimum supply temperature required by the network. The effective thermal potential is further constrained by hydraulic and thermal losses along the distribution network. Pressure losses are estimated using standard pipe-flow formulations (e.g., Darcy–Weisbach), accounting for the hierarchical structure of branched distribution networks, where the most distant users experience the highest cumulative head losses. In parallel, temperature decay along the network is evaluated through one-dimensional heat-loss models, typically expressed as an exponential attenuation form. These hydraulic and thermal constraints jointly determine the maximum number of users that can be reliably supplied while maintaining adequate supply temperature and pressure at the network periphery.

Technical–economic evaluation

A meaningful economic evaluation can be conducted only after geothermal production potential has been quantified through physically consistent reservoir, wellbore, and plant modelling. Techno-economic models translate technical performance into financial indicators using discounted cash-flow analysis. Techno-economic models combine capital and operational expenditures with projected energy production to calculate key

economic indicators. In this context, the reliability of economic metrics is inherently dependent on the accuracy and consistency of the preceding physical and thermodynamic assessments. Key outputs include levelized cost of energy (LCOE), net present value (NPV), internal rate of return (IRR), and payback time. Capital expenditures typically include drilling, wellfield development, and surface plant construction, while operational expenditures account for maintenance, auxiliary power consumption, and reinjection costs.

Code comparison

Numerous analytical and numerical models are available to simulate specific components of geothermal systems; however, only a limited number are open-source tools and can conduct comprehensive techno-economic potential assessments.

The most comprehensive open-source tools for geothermal potential assessment at the concession scale are GEOPHIRES and genGEO. GEOPHIRES (Beckers and McCabe 2019) is a well-established tool, now available both as an open-source Python code and as a web application. It was originally developed to estimate the techno-economic potential of power plants in Hot-Dry-Rock and Enhanced-Geothermal-System environments. Over time, it has been expanded to incorporate thermal and combined heat and power (cogeneration) end uses beyond electricity production, and to update the cost, reservoir, and wellbore models (Beckers et al. 2014; Beckers and McCabe 2019). GEOPHIRES is particularly powerful for subsurface assessment, as it can either employ one of its built-in analytical models to estimate reservoir production temperature or import performance results generated with external simulators such as TOUGH2 and FEFLOW.

genGEO is another open-source Python code that integrates reservoir, well, and power-plant models to estimate electricity generation and LCOE and is available on the GitHub platform (Adams et al. 2021). Although developed specifically for power-generation applications, its strength lies in the versatility and detail with which it simulates the thermodynamic cycle of the surface plant.

GEOPHIRES and genGEO differ substantially in scope, modelling philosophy, and level of physical detail. GEOPHIRES is designed as an integrated, reduced-complexity simulator that couples reservoir performance, surface-plant behaviour, and economic evaluation within a computationally efficient framework. It is particularly suited for scenario screening, sensitivity analysis, and rapid evaluation of geothermal heating, cooling, and power-generation concepts. GEOPHIRES incorporates simplified but robust representations of reservoir temperature decline, flow-rate evolution, and plant efficiency, making it ideal for preliminary feasibility studies and policy-oriented assessments.

In contrast, genGEO adopts a more detailed, engineering-grade approach, with modular thermodynamic models for surface power cycles, flexible representation of working fluids, and explicit optimisation of plant design parameters. genGEO is therefore better suited for high-fidelity analysis of system performance, technology comparison, and regional or national-scale resource assessments. While GEOPHIRES excels in transparency and computational speed, genGEO provides greater physical detail and design flexibility. Together, the two tools offer complementary capabilities: GEOPHIRES supports rapid techno-economic exploration, whereas genGEO enables deeper engineering analysis and optimisation of geothermal systems across both electricity-generation and direct-use applications.

Table 5 Comparison between the UNFC classification axes and the proposed workflow for deep geothermal potential assessment, highlighting how geological, technical, and techno-economic components of the workflow map onto the G, F, and E dimensions of the UNFC framework

UNFC			Workflow
Axis	Description	Elements	Domain
Geological knowledge	G-axis quantifies the degree of geological confidence in the resource estimate	It includes the level of certainty regarding subsurface temperature distribution, reservoir geometry, permeability structure, and fluid properties	Geological modelling Geophysical modelling Petrophysical characterization Thermal modelling (natural state)
Field project feasibility	F-axis assesses the technical maturity of the project, from conceptual exploration to fully developed and producing operations	It captures the progression of engineering design, project planning, drilling strategies, reservoir management, and operational readiness	Thermal modelling (dynamic production) Well–reservoir coupling Surface-plant thermodynamic modelling
Environmental and socio-economic viability	E-axis reflects the degree to which a project is aligned with societal priorities, including climate goals, environmental protection, and economic feasibility	It incorporates factors such as policy frameworks, environmental constraints, social acceptance, market conditions, and long-term sustainability	Technical–economic evaluation

Reporting protocols

The United Nations Framework Classification for Resources (UNFC [2026](#)) represents one of the most comprehensive and internationally harmonized systems for classifying and reporting energy and mineral resources. The UNFC accommodates in a universal, resource-agnostic framework the fossil fuels, minerals, renewables, anthropogenic resources, and, crucially, geothermal energy. The 2019 update consolidates the system into a robust, multidimensional structure that enables transparent communication of resource maturity, uncertainty, and socio-economic viability across diverse stakeholders, including governments, industry, investors, and regulatory bodies.

At its core, the UNFC is built upon three independent axes: Geological Knowledge (G), Field Project Feasibility (F), and Environmental-Socioeconomic Viability (E). Each axis captures a distinct dimension of resource maturity. The classification along one axis does not predetermine the classification along the others. This independence is essential for geothermal systems, where geological knowledge, technical feasibility, and socio-economic viability often evolve at different rates and may be constrained by different types of uncertainty. Together, these axes form a three-dimensional classification matrix that allows any resource to be positioned according to its maturity, uncertainty, and viability.

The [Table 5](#) compares the UNFC classification axes with the proposed workflow for geothermal potential assessment, illustrating how each axis corresponds to specific technical activities within the evaluation process. The G-axis aligns with subsurface characterization tasks, namely geological and geophysical modelling, petrophysical analysis, and natural-state thermal modelling, that determine the level of confidence in the resource estimate. The F-axis reflects the technical maturity of the project and is linked to dynamic production modelling, well–reservoir coupling, and surface-plant thermodynamic simulations. The E-axis encompasses the full spectrum of environmental, social, regulatory, and economic conditions that influence project viability. Within this broader UNFC dimension, our workflow contributes specifically to the techno-economic

evaluation, providing the quantitative basis for assessing project feasibility. Integrating our workflow with the UNFC axes therefore supports a transparent, consistent, and comparable classification of deep geothermal projects, while acknowledging that a complete E-axis evaluation extends beyond the technical domain addressed here.

Discussion

Determining the extent of heat extractable from the subsurface and its utilization for thermal applications or conversion to electricity is essential for energy planning and evaluating opportunities. For the purpose of developing and comparing energy system decarbonization scenarios across various geographic regions, end uses, and technologies, it is imperative to employ and disseminate standardized tools. In the sectors of industry and power markets, this objective has been approached through the creation of reporting protocols that establish consistent assessment criteria. Some protocols, e.g., the Geothermal Resource Portfolio Optimization and Reporting Technique (GeoRePORT 2026) system in the U.S, are based on geological, technical, and socio-economic assessment tools and use geothermal resource or technology attributes to compare the potential for geothermal development, without a quantitative estimate of producible energy. The AGRCC and CGCC protocols, on the other hand, which were developed for the Australian and Canadian power markets, incorporate the volume method for evaluating geothermal power potential (Australian Geothermal Reporting Code Committee (AGRCC) 2010; Canadian Geothermal Code Committee (CGCC) 2010). However, reporting protocols provide rules, not tools or codes, and the computation is left to the users. In Sects. "Reconstruction of the crustal structures" and "Geophysical modelling", we propose a workflow to develop a consistent geological and geophysical model of a geothermal reservoir, leveraging the extensive open-source geological and geophysical data available. This data can be used to accurately define the main boundaries of crustal structures and to assign physical parameter values to the identified layers. We suggest performing an initial detailed analysis of these data to identify their suitable application. This helps avoid organizing expensive field campaigns for similar data collection or enhances the planning of field campaigns if more data are required. Furthermore, various open-source numerical codes are accessible, offering valuable tools for processing, interpreting, and integrating geological and geophysical data, and we described their potential uses.

We should notice that for reconstructing shallow structures, we recommend a deterministic approach (Sect. "Reconstruction of the crustal structures"). This is because surface proximity provides more direct information and requires higher model resolution, especially given the expected greater variability in thermal gradient. In contrast, deep crustal structures are usually modelled more consistently using a statistical approach (e.g., machine learning algorithms), due to the greater number of geophysical datasets available and the limited direct information, such as those from deep wells (Sect. "Geophysical modelling"). However, direct measurements (e.g., petrophysical analyses from collected samples, as described in Sect. "Laboratory analysis of petrophysical properties") are also helpful for constraining geophysical models and ensuring consistency between the reconstructed shallow and deep structures. Finally, we would like to emphasize that the reconstruction of the crustal and uppermost mantle structures, as we described, is essential for the evaluation of the geothermal potential, as of any other type

of georesources. To reconstruct the thermal state of the subsurface at shallow depths, we suggested to use bottom hole temperatures (BHT) data and explained the corrections that are needed to apply, in order to increase the data robustness (Sect. "[Reconstructing the subsurface natural thermal state](#)"). We also proposed several numerical approaches for calculating the temperature distribution, in absence of BHT data, both in steady state and transient conditions. We described their advantages and disadvantages, as well as their range of applicability, according to the technique used. In most cases, we need to solve the heat transfer equation, for which the values of the thermal parameters are used as input. The last ones, if direct measurements are not available, can be derived from the crustal model implemented using geological, petrophysical and geophysical data (Sects. "[Reconstruction of the crustal structures](#)", "[Laboratory analysis of petrophysical properties](#)" and "[Geophysical modelling](#)"). Alternatively, the temperature distribution can be derived using a statistical approach or other geophysical data (e.g., seismic velocities can be converted into temperatures). We can predict that with the continuous increase of open-source data and algorithms, new ways to geothermally characterise a target area will soon open. The choice of the approach to follow will mostly depend on the purpose of the geothermal investigation, besides the data availability.

Thanks to the codes mentioned in Sect. "[Geothermal potential assessment: methods, codes and reporting](#)", it is now possible to compute the geothermal potential not only in accordance with existing reporting protocols, but also for other applications beyond electricity generation from hydrothermal and EGS systems. Nonetheless, this still isn't sufficient. As outlined in the preceding section, there exists a family of methodologies designated for calculating geothermal potential, each of which has been developed to suit specific datasets. Existing geothermal potential codes are consistently tailored to a particular method, irrespective of the volume of data employed. This constitutes a limitation, as certain methods are optimal for specific datasets, while alternative methods are more appropriate for others.

Another limitation is the availability and handling of large and comparable datasets. Moreover, as highlighted by Franzmann et al. (2025) who considered EGS power plants, factors like land eligibility and a country's energy demand, besides reservoir model selection and national electricity costs, are crucial in shaping the role of geothermal plants, beyond just their technical energy potential. To evaluate the global geothermal potential for the report titled 'The Future of Geothermal Energy', the International Energy Agency engaged the Project InnerSpace (2026) to assess the geothermal potential for various end-uses (International Energy Agency (IEA) (2024)). The volume method again serves as the basis for this assessment, and reference parameters are provided in the report. However, while the Project InnerSpace provides a framework for data sharing and the computation of geothermal favourability and potential, only the resulting maps are freely accessible; the computational models themselves are not available for public and online use. This limits cross-checking and continuous updating of the resulting maps. A further limitation of existing geothermal estimation codes is their failure to consider uncertainty in underground data. This is especially vital in greenfield areas, where exploration risk influences resource classification, investment choices, and long-term performance predictions. Therefore, a specialized and geo-scientifically rigorous assessment framework—such as the one suggested in Gambini et al. (2025)—should be integrated into geothermal assessment codes.

The objective of resource classification under the UNFC is to provide a standardized, consistent, and multidimensional framework for describing and comparing resource development projects, including geothermal systems. In contrast, the workflow for geothermal resource assessment represents the technical and methodological implementation of these classification principles. The workflow aligns with the range of technical studies required by UNFC for defining a project, including geological, geophysical, petrophysical, and reservoir modelling investigations aimed at estimating producible geothermal energy. A comparison between the two approaches highlights their strong complementarity. The UNFC provides a high-level classification and decision-support framework, integrating technical, economic, environmental, and uncertainty-related aspects into a unified system. The workflow, instead, constitutes the scientific and technical pathway through which the data necessary for such classification are generated. Geological, geophysical, and natural-state thermal modelling, together with petrophysical analysis, primarily constrain resource characterization (G-axis). Dynamic well–reservoir coupled simulations and surface-plant thermodynamic modelling contribute to defining technical feasibility (F-axis). Finally, integrating economic aspects positions the project along the E-axis, completing the classification process. Environmental, social, and regulatory factors, although explicitly required by the UNFC, are not developed here, as they require dedicated protocols.

Conclusions

By reviewing the most widely used tools and methods for characterizing geothermal reservoirs across different scales and datasets, we derived a comprehensive workflow for evaluating geothermal potential. This framework is structured around three main pillars.

Two evidence pillars comprise the external constraints that anchor the modelling process to measurable physical evidence. Geophysical constraints include the suite of seismic, potential-field, and electromagnetic observations that delineate crustal and subcrustal architecture and define the physical boundaries within which geological and thermal models must remain consistent. Petrophysical and thermal characterization encompasses the acquisition, measurement, processing and interpretation of the physical properties of rocks, subsurface temperature and terrestrial heat flow data. These measurements provide the physically meaningful parameters required for robust geological, petrophysical, and thermal modelling. Without them, simulations would rely on generic or weakly constrained assumptions, significantly increasing uncertainty.

The central pillar is the integrated geological–geophysical–petrophysical modelling, which synthesizes all available datasets into a single, coherent 3D representation of the subsurface. This step transforms heterogeneous information into a quantitative model, ensures that thermal simulations are geologically realistic and physically constrained, and reduces uncertainty by combining independent data sources. The workflow also incorporates two innovative components: a coupled well–reservoir modelling strategy applicable at regional scale, and a thermodynamic modelling module for the surface geothermal plant. These additions enable a seamless connection between subsurface processes and surface energy conversion, allowing for a realistic and internally consistent techno-economic assessment of geothermal resources.

Together, these three pillars and their innovative extensions provide a rigorous and reliable basis for geothermal potential evaluation, including temperature prediction, heat-in-place estimation, and reservoir performance assessment.

The proposed workflow is designed to be adaptable and scalable, enabling its implementation in both data-rich and data-poor environments. It underscores the importance of reproducibility, transparency, and the utilization of open-source tools whenever feasible. Ultimately, it seeks to support decision-making processes in geothermal exploration, mitigate uncertainties in initial assessments, and foster the development of standardized protocols and reporting methods within the geothermal community.

Acknowledgements

Not applicable.

Author contributions

GG designed the paper, drafted the Introduction and Sects. "Laboratory analysis of petrophysical properties", "Reconstructing the subsurface natural thermal state" and "Geothermal potential assessment: methods, codes and reporting", contributed to Discussion and Conclusions, critically revised and finalised the work. VC drafted Sect. "Reconstruction of the crustal structures". PS and AG drafted Sects. "Laboratory analysis of petrophysical properties". RB drafted Sect. "Geophysical modelling". MT critically revised Sects. "Reconstruction of the crustal structures" and "Geophysical modelling" and contributed to drafting Sects. "Reconstructing the subsurface natural thermal state" and "Discussion". TN contributed to drafting Sect. "Reconstructing the subsurface natural thermal state". AM contributed to the design of the work, drafted the abstract, Sects. "Discussion" and "Conclusions", revised the first version of the manuscript and formatted its final version. All authors approved the final version and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

Funding

The content of this paper has been prepared in the frame of the InGEO project, a PRIN 2022 PNRR Project that received funding from the European Union, Next Generation EU.

Data availability

No datasets were generated or analysed during the current study.

Declarations

Competing interests

The authors declare no competing interests.

Received: 13 March 2026 / Accepted: 17 June 2026

Published online: 06 July 2026

References

- Abers GA, Hacker BR. A MATLAB toolbox and Excel workbook for calculating the densities, seismic wave speeds, and major element composition of minerals and rocks at pressure and temperature. *Geochem Geophys Geosyst*. 2016. <https://doi.org/10.1002/2015GC006171>.
- Adams BM, Ogland-Hand J, Bielicki J, Schädle P, Saar MO. Estimating the geothermal electricity generation potential of sedimentary basins using genGEO (the generalizable geothermal techno-economic simulator). *ChemRxiv*. 2021. <https://doi.org/10.26434/chemrxiv-13514440-v1>.
- Afanasyev AA. Application of the reservoir simulator MUFITS for 3D modelling of CO₂ storage in geological formations. *Energy Procedia*. 2013;40:365–74. <https://doi.org/10.1016/j.egypro.2013.08.042>.
- Agemar T. Bottom hole temperature correction based on empirical correlation. *Geothermics*. 2022;99:102296. <https://doi.org/10.1016/j.geothermics.2021.102296>.
- Agemar T, Weber J, Moeck IS. Assessment and public reporting of geothermal resources in Germany: review and outlook. *Energies*. 2018;11:332. <https://doi.org/10.3390/en11020332>.
- Anikiev D, Götze HJ, Plonka C, Scheck-Wenderoth M, Schmidt S. IGMAS+: interactive gravity and magnetic application system. GFZ Data Services. 2023. <https://doi.org/10.5880/GFZ.4.5.IGMAS>.
- Aragón-Aguilar A, Barragán-Reyes RM, Arellano-Gómez VM. Methodologies for analysis of productivity decline: a review and application. *Geothermics*. 2013;48:69–79. <https://doi.org/10.1016/j.geothermics.2013.04.002>.
- Arps JJ. Analysis of decline curves. *Trans Am Inst Min Metall Pet Eng*. 1945;160:228–47.
- Ascencio F, García A, Rivera J, Arellano V. Estimation of undisturbed formation temperatures under spherical–radial heat flow conditions. *Geothermics*. 1994;23(4):317–26.
- Ascencio F, Samaniego F, Rivera J. Application of a spherical–radial heat transfer model to calculate geothermal gradients from measurements in deep boreholes. *Geothermics*. 2006;35:70–8.
- Badr O, O'Callaghan PW, Probert SD. Thermodynamic and thermophysical properties of organic working fluids for Rankine-cycle engines. *Appl Energy*. 1985;19(1):1–40. [https://doi.org/10.1016/0306-2619\(85\)90037-6](https://doi.org/10.1016/0306-2619(85)90037-6).

- Bagagli M, Molinari I, Diehl T, Kissling E. Local earthquake tomography of the Alpine region from 24 years of data. *Geophys J Int*. 2025;241(1):454–73. <https://doi.org/10.1093/gji/ggae412>.
- Bär K, Reinsch T, Bott J. The PetroPhysical property database (P3): a global compilation of lab-measured rock properties. *Earth Syst Sci Data*. 2020;12:2485–507. <https://doi.org/10.5194/essd-12-2485-2020>.
- Barelli A, Palamà A. A new method for evaluating formation equilibrium temperature in holes during drilling. *Geothermics*. 1981;10(2):95–102.
- Basant RA, Ryan GA, Peacock JR, Camacho AG, Blake OO, Hautmann S, et al. Multi-geophysical parameter classification of the Montserrat geothermal system. *Geothermics*. 2021;90:102006. <https://doi.org/10.1016/j.geothermics.2020.102006>.
- Beardsmore GR, Cull JP. *Crustal heat flow: a guide to measurement and modelling*. Cambridge: Cambridge University Press; 2001.
- Beck AE. Methods for determining thermal conductivity and thermal diffusivity. In: Haenel R, Rybach L, Stegena L, editors. *Handbook of terrestrial heat-flow density determination*. Dordrecht: Kluwer Academic Publishers; 1988. p. 87–124.
- Beckers KF, McCabe K. GEOPHIRES v2.0: updated geothermal techno-economic simulation tool. *Geotherm Energy*. 2019;7:5. <https://doi.org/10.1186/s40517-019-0119-6>.
- Beckers KF, Lukawski MZ, Anderson BJ, Moore MC, Tester JW. Levelized costs of electricity and direct-use heat from enhanced geothermal systems. *J Renew Sustain Energy*. 2014;6(1):013141. <https://doi.org/10.1063/1.4865575>.
- Benetatos C, Codegone G, Marzano F, Peter C, Verga F. Calculation of lithology-specific P-wave velocity relations from sonic well logs for the Po Plain area and the northern Adriatic Sea. In: *Offshore Mediterranean Conference and Exhibition*. Ravenna, Italy. -2019; 2019-OMC.
- Bezdek JC, Ehrlich R, Full W. FCM: the fuzzy c-means clustering algorithm. *Comput Geosci*. 1984;10(2–3):191–203. [https://doi.org/10.1016/0098-3004\(84\)90020-7](https://doi.org/10.1016/0098-3004(84)90020-7).
- BGI - Bureau Gravimétrique International. <https://bgi.obs-mip.fr/grids-and-models-2>. Accessed 2026.
- Bolton RS. Management of a geothermal field. In: Armstead HCH, editor. *Geothermal energy—review of research and development*. Paris: UNESCO; 1973. p. 175–84.
- Braszus B, Rietbrock A, Haberland C. A 3D velocity model for the European Alps: new insights into the crustal structure. *J Geophys Res Solid Earth*. 2025;130(10):e2025JB031877. <https://doi.org/10.1029/2025JB031877>.
- Brocher TM. Empirical relations between elastic wave speeds and density in the earth's crust. *Bull Seismol Soc Am*. 2005;95(6):2081–92. <https://doi.org/10.1785/0120050077>.
- Bullard EC. Heat flow in South Africa. *Proc R Soc Lond A*. 1939;173(955):474–502. <https://doi.org/10.1098/rspa.1939.0159>.
- Burke MM, Fountain DM. Seismic properties of rocks from an exposure of extended continental crust: new laboratory measurements from the Ivrea zone. *Tectonophysics*. 1990;182(1–2):119–46. [https://doi.org/10.1016/0040-1951\(90\)90465-S](https://doi.org/10.1016/0040-1951(90)90465-S).
- Cahill DG. Thermal conductivity measurement from 30 to 750 K: the 3 ω method. *Rev Sci Instrum*. 1990;61:802–8. <https://doi.org/10.1063/1.1141498>.
- Camacho AG, Vajda P, Fernández J. GROWTH-23: an integrated code for inversion of complete bouguer gravity anomaly or temporal gravity changes. *Comput Geosci*. 2024;182:105495. <https://doi.org/10.1016/j.cageo.2024.105495>.
- Cammarano F, Goes S, Vacher P, Giardini D. Inferring upper-mantle temperatures from seismic velocities. *Phys Earth Planet Inter*. 2003;138:197–222. [https://doi.org/10.1016/S0031-9201\(03\)00156-0](https://doi.org/10.1016/S0031-9201(03)00156-0).
- Canadian Geothermal Code Committee (CGCC). *Canadian geothermal code for public reporting*. Vancouver: Canadian Geothermal Energy Association. 2010.
- Chambers EL, Fullea J, Kiyan D, Lebedev S, et al. A new subsurface temperature model for Ireland from joint geophysical–petrological inversion of seismic, surface heat flow and petrophysical data. *Geophys J Int*. 2025;243:1–25. <https://doi.org/10.1093/gji/ggaf281>.
- Chapman DS. Thermal gradients in the continental crust. In: Dawson JB, Carswell DA, Hall J, Wedepohl KH, editors. *The nature of the lower continental crust*. Geol Soc Spec Publ. London: Geological Society; 1986.24. P. 63–70.
- Christensen NI, Mooney WD. Seismic velocity structure and composition of the continental crust: a global view. *J Geophys Res Solid Earth*. 1995;100(B6):9761–88. <https://doi.org/10.1029/95JB00259>.
- Ciriaco AE, Zarrouk SJ, Zakeri G. Geothermal resource and reserve assessment methodology: overview, analysis and future directions. *Renew Sustain Energy Rev*. 2020;119:109515. <https://doi.org/10.1016/j.rser.2019.109515>.
- Cobden L, Trampert J, Fichtner A. Insights on upper mantle melting, rheology, and anelastic behavior from seismic shear wave tomography. *Geochem Geophys Geosyst*. 2018;19:3892–916. <https://doi.org/10.1029/2017GC007370>.
- Cockett R, Kang S, Heagy LJ, Pidlisecky A, Oldenburg DW. SimPEG: an open source framework for simulation and gradient based parameter estimation in geophysical applications. *Comput Geosci*. 2015;85:142–54. <https://doi.org/10.1016/j.cageo.2015.09.015>.
- Colgan W, MacGregor JA, Mankoff KD, Haagensohn R, Rajaram H, Martos YM, et al. Topographic correction of geothermal heat flux in Greenland and Antarctica. *J Geophys Res Earth Surf*. 2021;126:e2020JF005598. <https://doi.org/10.1029/2020JF005598>.
- Colin FW, Marshall JR, Mariner RH. A review of methods applied by the US geological survey in the assessment of identified geothermal resources. *US Geol Surv Open-File Rep*. 2008. <https://doi.org/10.3133/ofr20081296>.
- Australian Geothermal Reporting Code Committee (AGRCC). *The Australian geothermal reporting code*. Canberra: Australian Geothermal Energy Group 2010.
- Connolly JAD. Computation of phase equilibria by linear programming: a tool for geodynamic modeling and its application to subduction zone decarbonation. *Earth Planet Sci Lett*. 2005;236:524–41. <https://doi.org/10.1016/j.epsl.2005.04.033>.
- Cooper LR, Jones C. The determination of virgin strata temperatures from observations in deep survey boreholes. *Geophys J Int*. 1959;2:116–31.
- Dalla Santa G, Galgaro A, Sassi R, Cultrera M, et al. An updated ground thermal properties database for GSHP applications. *Geothermics*. 2020;82:101758. <https://doi.org/10.1016/j.geothermics.2019.101758>.
- Defays D. An efficient algorithm for a complete link method. *Comput J*. 1977;20(4):364–6. <https://doi.org/10.1093/comjnl/20.4.364>.
- Degen D, Veroy K, Wellmann F. Uncertainty quantification for basin-scale geothermal conduction models. *Sci Rep*. 2022;12:4246. <https://doi.org/10.1038/s41598-022-08017-2>.
- Deming D. Application of bottom-hole temperature corrections in geothermal studies. *Geothermics*. 1989;18(5–6):775–86. [https://doi.org/10.1016/0375-6505\(89\)90006-5](https://doi.org/10.1016/0375-6505(89)90006-5).

- Dempster AP, Laird NM, Rubin DB. Maximum likelihood from incomplete data via the EM algorithm. *J R Stat Soc Series B Stat Methodol.* 1977;39(1):1–38.
- Diehl T, Husen S, Kissling E, Deichmann N. High-resolution 3-D P-wave model of the alpine crust. *Geophys J Int.* 2009;179(2):1133–47.
- DiPippo R. Ideal thermal efficiency for geothermal binary plants. *Geothermics.* 2007;36(3):276–85. <https://doi.org/10.1016/j.geothermics.2007.03.002>.
- DiPippo R. Geothermal power plants: evolution and performance assessments. *Geothermics.* 2015;53:291–307. <https://doi.org/10.1016/j.geothermics.2014.07.005>.
- IRIS DMC - Earth Model Query. <https://ds.iris.edu/spud/earthmodel>. Accessed 2026.
- Doherty J. Calibration and uncertainty analysis for complex environmental models. 2nd ed. Brisbane: Watermark Numerical Computing; 2025.
- Ester M, Kriegel HP, Sander J, Xu X. A density-based algorithm for discovering clusters in large spatial databases with noise. In: *Proc 2nd Int Conf Knowledge Discovery and Data Mining Portland OR*; 1996. p 226–231.
- Facci M, Di Sipio E, Gola G, Montegrossi G, Galgaro A. Sustainable reuse of oil and gas wells for geothermal energy production: numerical analysis of deep closed loop solutions in Italy. *Energy Convers Manag X.* 2024. <https://doi.org/10.1016/j.ecmx.2024.100743>.
- Fan Y, Zhang S, Huang Y, Pang Z, Li H. Determining the recoverable geothermal resources using a numerical thermo-hydraulic coupled modeling in geothermal reservoirs. *Front Earth Sci.* 2022;9:787133. <https://doi.org/10.3389/feart.2021.787133>.
- Fertl WH, Wichmann PA. How to determine static BHT from well log data. *World Oil.* 1977;184:105–6.
- Fomin I, Afonso JC, Gorbato A, Salajegheh F, Dave R, Darbyshire FA, et al. Multi-observable thermochemical tomography: new advances and applications to the Superior and North Australian cratons. *J Geophys Res Solid Earth.* 2026;131:e2025J-B031939. <https://doi.org/10.1029/2025JB031939>.
- Förster A, Merriam DF, Davis JC. Spatial analysis of temperature (BHT/DST) data and consequences for heat-flow determination in sedimentary basins. *Geol Rundsch.* 1997;86:252–61. <https://doi.org/10.1007/s005310050135>.
- Franzmann D, Heinrichs H, Stolten D. Global geothermal electricity potentials: a technical, economic, and thermal renewability assessment. *Renew Energy.* 2025;250:123199. <https://doi.org/10.1016/j.renene.2025.123199>.
- Fullea J, Lebedev S, Martinez Z, Celli NL. WINTERC-G: mapping the upper mantle thermochemical heterogeneity from coupled geophysical–petrological inversion of seismic waveforms, heat flow, surface elevation and gravity satellite data. *Geophys J Int.* 2021;226:146–91. <https://doi.org/10.1093/gji/ggab148>.
- Gambini R, Waters DW, Sansone F, Memmo V. Risk and uncertainty in geothermal projects: characteristics, challenges and application of the novel reverse enthalpy methodology. *Energies.* 2025;18:4157. <https://doi.org/10.3390/en18154157>.
- GeoRePORT - Geothermal Resource Portfolio Optimization and Reporting Technique. <https://openet.org/wiki/GeoRePORT/Overview>. Accessed 2026.
- Gola G, Di Sipio E, Facci M, Galgaro A, Manzella A. Geothermal deep closed-loop heat exchangers: a novel technical potential evaluation to answer the power and heat demands. *Renew Energy.* 2022;191:1201–15. <https://doi.org/10.1016/j.renene.2022.08.071>.
- Götze HJ, Lahmeyer B. Application of three-dimensional interactive modeling in gravity and magnetics. *Geophysics.* 1988;53(8):1096–108. <https://doi.org/10.1190/1.1442546>.
- Goutorbe B, Lucazeau F, Bonneville A. Comparison of several BHT correction methods: a case study on an Australian data set. *Geophys J Int.* 2007;170(2):913–22.
- Grant MA. Physical performance indicators for HDR/EGS projects. *Geothermics.* 2016;63:2–4. <https://doi.org/10.1016/j.geothermics.2015.01.004>.
- Hacker BR, Abers GA. Subduction Factory 3: an Excel worksheet and macro for calculating the densities, seismic wave speeds, and H₂O contents of minerals and rocks at pressure and temperature. *Geochem Geophys Geosyst.* 2004;5:Q01005. <https://doi.org/10.1029/2003GC000614>.
- Hasan AR, Kabir CS, Ameen MM. A mechanistic model for circulating fluid temperature. *SPE J.* 1996;1(2):133–44. <https://doi.org/10.2118/27890-PA>.
- Hasterok D, Chapman DS. Heat production and geotherms for the continental lithosphere. *Earth Planet Sci Lett.* 2011;307(1–2):59–70. <https://doi.org/10.1016/j.epsl.2011.04.034>.
- Hermanrud C, Cao S, Lerche I. Estimates of virgin rock temperature derived from BHT measurements: bias and error. *Geophysics.* 1990;55(7):924–31. <https://doi.org/10.1190/1.1442906>.
- Hermanrud C, Lerche I, Meisinger KK. Determination of virgin rock temperature from drillstem tests. *J Pet Technol.* 1991;43(9):1126–31. <https://doi.org/10.2118/19464-PA>.
- Hetényi G, Molinari I, Clinton J, et al. The AlpArray seismic network: a large-scale European experiment to image the Alpine orogen. *Surv Geophys.* 2018;39:1009–33. <https://doi.org/10.1007/s10712-018-9472-4>.
- Holland TJB, Powell R. An internally consistent thermodynamic data set for phases of petrological interest. *J Metamorph Geol.* 1998;16:309–43.
- Holland TJB, Powell R. An improved and extended internally consistent thermodynamic dataset for phases of petrological interest, involving a new equation of state for solids. *J Metamorph Geol.* 2011;29:333–83.
- Horner DR. Pressure build-up in wells. In: *Proc 3rd World Petroleum Congress The Hague.* 1951;924–931.
- ICGEM - International Centre for Global Earth Models. <https://icgem.gfz.de>. Accessed 2026.
- IHS Kingdom Suite. <https://kingdom.ihs.com>. Accessed 15 May 2026.
- IMAGE2SEGY. <https://chesapeake-tech.com/products/imagetosegy>. Accessed 2026.
- Ingebritsen SE, Geiger S, Hurwitz S, Driesner T. Numerical simulation of magmatic hydrothermal systems. *Rev Geophys.* 2010;48(1):RG1002. <https://doi.org/10.1029/2009RG000287>.
- The future of geothermal energy. Paris: IEA; 2024. Available from: <https://www.iea.org/reports/the-future-of-geothermal-energy>.
- Jing D, Wang J, Xia C. Evaluating the temperature profile and pressure drops in gas-lift wells via coupled temperature–pressure analysis. *Sci Rep.* 2025;15:22868. <https://doi.org/10.1038/s41598-025-05362-w>.
- Jung Y, Pau GSH, Finsterle S, Pollyea RM. TOUGH3: a new efficient version of the TOUGH suite of multiphase flow and transport simulators. *Comput Geosci.* 2017;108:2–7. <https://doi.org/10.1016/j.cageo.2016.09.009>.

- Kaban MK, Tesauro M, Mooney WD, Cloetingh SAPL. Density temperature and composition of the North American lithosphere new insights from a joint analysis of seismic gravity and mineral physics data 1 density structure of the crust and upper mantle. *J Geophys Res Solid Earth*. 2014. <https://doi.org/10.1002/2014GC005483>.
- Kästle ED, Paffrath M, El-Sharkawy A. Alpine crust and mantle structure from 3D Monte Carlo surface- and body-wave tomography. *J Geophys Res Solid Earth*. 2025;130(2):e2024JB030101. <https://doi.org/10.1029/2024JB030101>.
- Keller J, Rath V, Bruckmann J, Mottaghy D, Clauser C, Wolf A, et al. SHEMAT-Suite: an open-source code for simulating flow, heat and species transport in porous media. *SoftwareX*. 2020;12:100533. <https://doi.org/10.1016/j.softx.2020.100533>.
- Kern H. Elastic-wave velocity in crustal and mantle rocks at high pressure and temperature: the role of the high–low quartz transition and dehydration reactions. *Phys Earth Planet Inter*. 1982;29(1):12–23. [https://doi.org/10.1016/0031-9201\(82\)90034-0](https://doi.org/10.1016/0031-9201(82)90034-0).
- Kern H. The influence of dry and water-saturated cracks on seismic velocities of crustal rocks: a comparison of experimental data with theoretical model. *Surv Geophys*. 1994;15:543–72. <https://doi.org/10.1007/BF00665986>.
- Kern H, Schenk V. Elastic wave velocities in rocks from a lower crustal section in southern Calabria (Italy). *Phys Earth Planet Inter*. 1985;40(3):147–60. [https://doi.org/10.1016/0031-9201\(85\)90035-7](https://doi.org/10.1016/0031-9201(85)90035-7).
- Kern H. Measuring and modeling of P and S-wave velocities on crustal rocks: a key for the interpretation of seismic reflection and refraction data. *Int J Geophys*. 2011. <https://doi.org/10.1155/2011/530728>.
- Kint L, Hademenos V, De Mol R, Stafleu J, Van Heteren S, Van Lancker V. Uncertainty assessment applied to marine subsurface datasets. *Q J Eng Geol Hydrogeol*. 2020. <https://doi.org/10.1144/qjgegh2020-028>.
- Kogeo Seismic Toolkit. <http://www.kogeo.de>. Accessed 2026.
- Kolinský P, Meier T, Agius M, et al. AdriaArray a passive seismic experiment to study structure, geodynamics and geohazards of the adriatic plate. *Ann Geophys*. 2025. <https://doi.org/10.4401/ag-9284>.
- Lee TC. On terrain corrections in terrestrial heat flow. *Pure Appl Geophys*. 1991;135:1–13. <https://doi.org/10.1007/BF00877005>.
- Limberger J, Boxem T, Pluymaekers M, Bruhn D, Manzella A, Calcagno P, et al. Geothermal energy in deep aquifers: a global assessment of the resource base for direct heat utilization. *Renew Sustain Energy Rev*. 2018;82:961–75. <https://doi.org/10.1016/j.rser.2017.09.084>.
- Livani M, Petracchini L, Benetatos C, Marzano F, Billi A, Carminati E, et al. Subsurface geological and geophysical data from the Po Plain and the northern adriatic sea (north Italy). *Earth Syst Sci Data*. 2023;15:4261–88. <https://doi.org/10.5194/essd-15-4261-2023>.
- Lu Y, Stehly L, Paul A, AlpArray Working Group. High-resolution surface wave tomography of the European crust and uppermost mantle from ambient seismic noise. *Geophys J Int*. 2018;214(2):1136–50. <https://doi.org/10.1093/gji/ggy188>.
- MacQueen JB. Some methods for classification and analysis of multivariate observations. In: *Proc 5th Berkeley Symp Math Stat Probab Berkeley, CA*. 1967;281–297.
- Magaji A, Dou B, Gola G, Ali S, Al-Wesabi I. Transforming abandoned petroleum wells in the Nigerian sector of the Chad Basin into triplet borehole heat exchangers for sustainable power generation. *Int J Hydrogen Energy*. 2024;71:1056–69. <https://doi.org/10.1016/j.ijhydene.2024.05.275>.
- Magnoni F, Casarotti E, Komatitsch D, Di Stefano R, Ciaccio MG, Tape C, et al. Adjoint tomography of the Italian lithosphere. *Commun Earth Environ*. 2022. <https://doi.org/10.1038/s43247-022-00397-7>.
- Magnusdottir L, Finsterle S. An iTOUGH2 equation-of-state module for modeling supercritical conditions in geothermal reservoirs. *Geothermics*. 2015;57:8–17. <https://doi.org/10.1016/j.geothermics.2015.05.003>.
- Magrini F, Lauro S, Kästle E, Boschi L. Surface-wave tomography using SeisLib: a Python package for multiscale seismic imaging. *Geophys J Int*. 2022;231(2):1011–30. <https://doi.org/10.1093/gji/ggac248>.
- Matthäi SK, Geiger S, Roberts SG, Paluszny A, et al. Numerical simulation of multi-phase fluid flow in structurally complex reservoirs. *Geol Soc Lond Spec Publ*. 2007. <https://doi.org/10.1144/SP292.22>.
- Mengel K, Kern H. Evolution of the petrological and seismic moho implications for the continental crust–mantle boundary. *Terra Nova*. 1992;4(1):109–16. <https://doi.org/10.1111/j.1365-3121.1992.tb00472.x>.
- Middleton MF. A model for bottom-hole temperature stabilization. *Geophysics*. 1979;44:1458–62. <https://doi.org/10.1190/1.1441000>.
- Moorkamp M, Heincke B, Jegen M, Roberts AW, Hobbs RW. A framework for 3-D joint inversion of MT, gravity and seismic refraction data. *Geophys J Int*. 2011;184:477–93.
- Morway ED, Provost AM, Langevin CD, Hughes JD, et al. A new groundwater energy transport model for the MODFLOW hydrologic simulator. *Groundwater*. 2025;63(3):409–21. <https://doi.org/10.1111/gwat.13470>.
- Muffler LJP, Cataldi R. Methods for regional assessment of geothermal resources. *Geothermics*. 1978;7:53–89. [https://doi.org/10.1016/0375-6505\(78\)90002-0](https://doi.org/10.1016/0375-6505(78)90002-0).
- Nathenson M. Physical factors determining the fraction of stored energy recoverable from hydrothermal convection systems and conduction-dominated areas. *US. Geol Surv Open-File Rep*. 1975;75-525.
- Neath AA, Cavanaugh JE. The Bayesian information criterion: background, derivation, and applications. *Wiley Interdiscip Rev Comput Stat*. 2012;4(2):199–203. <https://doi.org/10.1002/wics.199>.
- Nigussie W, Alemu A, Mickus K, Keir D, Demissie Z, Muhabaw Y, et al. Subsurface structural control of geothermal resources in a magmatic rift: gravity and magnetic study of the tulu moye geothermal prospect, main ethiopian rift. *Front Earth Sci*. 2023. <https://doi.org/10.3389/feart.2023.1181533>.
- Norden B, Förster A, Förster HJ, Fuchs S. Temperature and pressure corrections applied to rock thermal conductivity: impact on subsurface temperature prognosis and heat-flow determination in geothermal exploration. *Geotherm Energy*. 2020;8:1–19. <https://doi.org/10.1186/s40517-020-0157-0>.
- OpendTect. <https://dgbes.com/software/opendtect>. Accessed 2026.
- Paffrath M, Friederich W, Schmid SM, Handy MR, AlpArray Working Group. Imaging structure and geometry of slabs in the greater Alpine area: a P-wave travel-time tomography using AlpArray seismic network data. *Solid Earth*. 2021;12:2671–93. <https://doi.org/10.5194/se-12-2671-2021>.
- Parker WJ, Jenkins RJ, Butler CP, Abbott GL. Flash method of determining thermal diffusivity, heat capacity, and thermal conductivity. *J Appl Phys*. 1961;32:1679–84. <https://doi.org/10.1063/1.1728417>.
- Pasquale V, Chiozzi P, Gola G, Verdoya M. Depth-time correction of petroleum bottom hole temperatures in the Po Plain. Italy. *Geophysics*. 2008;73(6):E187–97. <https://doi.org/10.1190/1.2980363>.
- Pasquale V, Chiozzi P, Verdoya M, Gola G. Heat flow in the western po basin and surrounding orogenic belts. *Geophys J Int*. 2012;190:8–22.

- Pasquale V, Verdoya M, Chiozzi P. Measurements of rock thermal conductivity with a transient divided bar. *Geothermics*. 2015;53:183–9. <https://doi.org/10.1016/j.geothermics.2014.05.008>.
- Pauselli C, Gola G, Mancinelli P, Trumpy E, Saccone M, Manzella A, et al. A new surface heat flow map of the northern apennines between latitudes 42.5 and 44.5°N. *Geothermics*. 2019;81:39–52. <https://doi.org/10.1016/j.geothermics.2019.04.002>.
- Pedregosa F, Varoquaux G, Gramfort A, Michel V, Thirion B, Grisel O, et al. Scikit-learn: machine learning in python. *J Mach Learn Res*. 2011;12:2825–30.
- Perple_X. <https://www.perplex.ethz.ch>. Accessed 2026.
- Schlumberger Petrel. <https://www.slb.com/products-and-services/delivering-digital-at-scale/software/petrel-subsurface-software/petrel>. Accessed 2026.
- Popov YA, Pribnow DFC, Sass JH, Williams CF, Burkhardt H. Characterization of rock thermal conductivity by high-resolution optical scanning. *Geothermics*. 1999;28:253–76. [https://doi.org/10.1016/S0375-6505\(99\)00007-3](https://doi.org/10.1016/S0375-6505(99)00007-3).
- Pribnow DFC, Sass JH. Determination of thermal conductivity for deep boreholes. *J Geophys Res Solid Earth*. 1995;100:9981–94. <https://doi.org/10.1029/95JB00960>.
- Project InnerSpace. <https://projectinnerspace.org>. Accessed 2026.
- Pruess K. The TOUGH codes: a family of simulation tools for multiphase flow and transport processes in permeable media. *Vadose Zone J*. 2004;3:738–46. <https://doi.org/10.2113/3.3.738>.
- Rahman T, Sarkar K. Correlations between uniaxial compressive strength and dynamic elastic properties for six rock types. *Int J Geomech*. 2023. <https://doi.org/10.1061/JGNALGMENG-7854>.
- Ramey HJ. Wellbore heat transmission. *J Pet Technol*. 1962;14:427–35. <https://doi.org/10.2118/96-PA>.
- Rangel-Arista JA, Zarrouk SJ, Kaya E. Temperature transient analysis: static formation temperature test (SFTT) an overview. *Geothermics*. 2024;122:103058. <https://doi.org/10.1016/j.geothermics.2024.103058>.
- Roisenberg HB, Boschi L, Cammarano F. Thermal and compositional characterization of the greater Alpine crust using seismic observables. *J Geophys Res Solid Earth*. 2025. <https://doi.org/10.22541/essoar.174982553.37362364/v1>.
- Roux B, Sanyal SK, Brown SL. An improved approach to estimating true reservoir temperature from transient temperature data. In: SPE California Regional Meeting Stanford, CA. 1980; <https://doi.org/10.2118/8888-MS>.
- Rybach L. Amount and significance of radioactive heat sources in sediments. In: *Thermal modelling in sedimentary basins*. 1986. p 311–322.
- Santilano A, Trumpy E, Gola G, Donato A, Scrocca D, Ferrarini F, et al. A methodology for assessing the favourability of geopressured-geothermal systems in sedimentary basin plays: a case study in Abruzzo (Italy). *Geofluids*. 2019. <https://doi.org/10.1155/2019/4503943>.
- Scheidegger J, Tamayo-Mas E. Review of saturated groundwater model codes for Hydro-JULES. Nottingham: British Geological Survey; 2019.
- Schmidt S, Götz HJ, Fichler C, Alvers M. IGMAS+—a new 3D gravity, FTG and magnetic modeling software. In: Zipf A, Behncke K, Hillen F, Scheffermeyer J, editors. *GEO-INFORMATIK 2010*. Heidelberg: AKA GmbH; 2010. p. 57–63.
- Scikit-learn. <https://scikit-learn.org>. Accessed 2026.
- Scott S, Driesner T, Weis P. Geologic controls on supercritical geothermal resources above magmatic intrusions. *Nat Commun*. 2015;6:7837. <https://doi.org/10.1038/ncomms8837>.
- Seismolink. <https://seismo-learn.org/links/codes>. Accessed 2026.
- Sheriff RE, Geldart LP. *Exploration seismology*. 2nd ed. Cambridge: Cambridge University Press; 1995. <https://doi.org/10.1017/CBO9781139168359>.
- Soekarno H, Pranoto B, Restiana A, Martha A, Setiadi T, Hudayat N, et al. Identifying geological fault structures using GGMplus satellite data and derivative methods to characterize Mount Endut geothermal systems via 3D inversion gravity modeling. *Geomat Environ Eng*. 2025;19:31–62.
- Sopher D. Converting scanned images of seismic reflection data into SEG-Y format. *Earth Sci Inform*. 2018. <https://doi.org/10.1007/s12145-017-0329-z>.
- Stixrude L, Lithgow-Bertelloni C. Thermodynamics of mantle minerals II. Phase equilibria. *Geophys J Int*. 2011;184:1180–213. <https://doi.org/10.1111/j.1365-246X.2010.04890.x>.
- Telford WM, Geldart LP, Sheriff RE. *Applied geophysics*. 2nd ed. Cambridge: Cambridge University Press; 1990.
- Tesauro M, Kaban MK, Mooney WD, Cloetingh SAPL. Density, temperature, and composition of the North American lithosphere new insights from a joint analysis of seismic, gravity, and mineral physics data: 2. Thermal and compositional model of the upper mantle. *Geochem Geophys Geosyst*. 2014. <https://doi.org/10.1002/2014GC005484>.
- Tesauro M, Kaban MK, Aitken ARA. Thermal and compositional anomalies of the Australian upper mantle from seismic and gravity data. *Geochem Geophys Geosyst*. 2020;21:e2020GC009305. <https://doi.org/10.1029/2020GC009305>.
- Tesauro M, Kaban MK, Youssef M. Thermal and compositional state of the South African cratonic region from seismic and gravity models. *Glob Planet Change*. 2026;259:105360. <https://doi.org/10.1016/j.gloplacha.2026.105360>.
- Tester JW, Anderson BJ, Batchelor AS, Blackwell DD, DiPippo R, Drake EM, et al. The future of geothermal energy impact of enhanced geothermal systems on the United States in the 21st century. Cambridge (MA) Massachusetts Institute of Technology. Report No. INL/EXT. 2006;06–11746. <https://doi.org/10.2172/911903>.
- Tonkin RA, O'Sullivan MJ, O'Sullivan JP. A review of mathematical models for geothermal wellbore simulation. *Geothermics*. 2021;97:102255. <https://doi.org/10.1016/j.geothermics.2021.102255>.
- Trumpy E, Donato A, Gianelli G, Gola G, Minissale A, Montanari D, et al. Data integration and favourability maps for exploring geothermal systems in Sicily, southern Italy. *Geothermics*. 2015;56:1–16. <https://doi.org/10.1016/j.geothermics.2015.03.004>.
- Trumpy E, Botteghi S, Caiozzi F, Donato A, Gola G, Montanari D, et al. Geothermal potential assessment for a low carbon strategy: a new systematic approach applied in southern Italy. *Energy*. 2016;103:167–81. <https://doi.org/10.1016/j.energy.2016.02.144>.
- UNFC - United Nations Framework Classification for Resources. <https://unece.org/sustainable-energy/united-nations-framework-k-classification-resources-unfc>. Accessed (2026).
- Vogt C, Mottaghy D, Wolf A, Rath V, et al. Reducing temperature uncertainties by stochastic geothermal reservoir modelling. *Geophys J Int*. 2010;181(1):321–33.
- Von Herzen R, Maxwell AE. The measurement of thermal conductivity of deep-sea sediments by a needle-probe method. *J Geophys Res*. 1959;64:1557–63. <https://doi.org/10.1029/JZ064i010p01557>.

- Von Herzen RP, Uyeda S. Heat flow through the eastern Pacific Ocean floor. *J Geophys Res.* 1963;68:4219–50. <https://doi.org/10.1029/JZ068i014p04219>.
- Wagner W, Pruss A. The IAPWS formulation 1995 for the thermodynamic properties of ordinary water substance for general and scientific use. *J Phys Chem Ref Data.* 1995;31:387–535. <https://doi.org/10.1063/1.1461829>.
- Waples DW, Ramly M. A statistical method for correcting log-derived temperatures. *Pet Geol.* 2001;7:231–40. <https://doi.org/10.1144/petgeo.7.3.231>.
- WIGGLE2SEGY. <https://github.com/DSOPHER/WIGGLE2SEGY>. Accessed 15 May 2026.
- Williams CF, Reed MJ, Anderson AF. Updating the classification of geothermal resources. *Geotherm Resour Counc Trans.* 2008;32:431–6.
- Williams CF. Evaluating heat flow as a tool for assessing geothermal resources. In: *Proc 30th Workshop Geothermal Reservoir Engineering* Stanford, CA. Stanford: Stanford University. SGP-TR-2005;176.
- Williams CF. Updated methods for estimating recovery factors for geothermal resources. In: *Proc 32nd Workshop Geothermal Reservoir Engineering*; Stanford, CA. Stanford: Stanford University; SGP-TR-183. 2007 22–24.
- Wisian KW, Blackwell DD, Richards M. Correlation of surface heat loss and total energy production for geothermal systems. *Geotherm Resour Counc Trans.* 2001;25:331–6.
- Yang B, Zhang H, Wu B, Lv K, Zhou Y, Li X, et al. Joule–Thomson effect on bottom hole temperature in ultra-high-temperature and high-pressure gas wells. *ACS Omega.* 2019;4(2):3700–10. <https://doi.org/10.1021/acsomega.4c09926>.
- Zahorec P, Papco J, Pašteka R, et al. The first pan-Alpine surface-gravity database: a modern compilation that crosses frontiers. *Earth Syst Sci Data.* 2021;13(5):2165–209. <https://doi.org/10.5194/essd-13-2165-2021>.
- Zarrouk SJ, Moon H. Efficiency of geothermal power plants: a worldwide review. *Geothermics.* 2014;51:142–53. <https://doi.org/10.1016/j.geothermics.2013.11.001>.
- Zhang Y, Zheng S, Wang Q. Improved analysis of transient temperature data from permanent down-hole gauges (PDGs). *J Geophys Eng.* 2017;14(4):739–50. <https://doi.org/10.1088/1742-2140/aa66da>.
- Zheng Q, Kaur S, Dames C, Prasher RS. Analysis and improvement of the hot disk transient plane source method for low thermal conductivity materials. *Int J Heat Mass Transf.* 2020;151:119331. <https://doi.org/10.1016/j.jijheatmasstransfer.2020.119331>.
- Zheng J, Dou Y, Li Z, et al. Investigation and application of wellbore temperature and pressure field coupling with gas–liquid two-phase flowing. *J Pet Explor Prod Technol.* 2022;12:753–62. <https://doi.org/10.1007/s13202-021-01324-w>.

Publisher's Note

Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.