

A Critical Review of Existing Probability of Success (PoS) Methods in Geothermal Exploration and Introduction of Demand Oriented, Geologically Conditioned PoS (DOGC-PoS) for Pre-Drilling Assessment: Spatial DOGC-PoS Mapping of the Rhaetian Deltaic System

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Abstract

Probability of Success (PoS) assessment supports geothermal exploration, project planning, investment, insurance, and energy-system design. Existing geothermal PoS methodologies have progressively advanced from qualitative geological judgment and static threshold criteria toward stochastic and performance-oriented assessment. Nevertheless, success is still frequently defined by geological conditions or separate thresholds for temperature, flow rate, transmissivity, permeability, or productivity. These criteria are valuable for reservoir characterization and exploration risk assessment, but they do not necessarily establish whether a geothermal system can deliver the thermal output required for its intended application.

This study critically reviews the methodological development of geothermal PoS assessment and introduces the Demand Oriented, Geologically Conditioned Probability of Success framework (DOGC-PoS). The framework defines success as the probability that a geothermal system will meet or exceed an explicitly specified thermal energy, thermal power, or other project-specific performance target over a corresponding assessment period. The resulting probability is conditional on the geological interpretation and uncertainty representation, together with the system configuration, operating assumptions, demand conditions, and performance model. Geological and hydraulic properties are therefore treated as uncertain controls on performance rather than as independent final definitions of success. DOGC-PoS further requires the probabilistic representation of these properties to remain consistent with the geological architecture and processes controlling the reservoir.

The framework is demonstrated through a spatial proof-of-concept application to the Rhaetian Deltaic System of the North German Basin. Reservoir thickness distributions are conditioned by mapped reservoir classes, while spatially varying permeability distributions are derived from mapped observations using four-nearest-neighbor inverse-distance weighting. These locally conditioned distributions are propagated through hydraulic and thermal production calculations using Monte Carlo simulation, and PoS is evaluated for monthly thermal energy targets of 1,000, 2,500, and 5,000 MWh under otherwise identical assumptions. The demonstration is intentionally restricted to permeability and reservoir thickness as spatially varying uncertain inputs and is intended to illustrate the methodological principle rather than provide a regional drilling location assessment.

The resulting PoS surfaces are strongly spatially heterogeneous and decrease systematically as the required thermal energy output increases. Locations with comparatively greater reservoir thickness and higher locally conditioned permeability generally retain their relative performance advantage across the demand scenarios, while their absolute probability of meeting the required output declines and the extent of higher-PoS areas contracts. The results show that geological heterogeneity controls the relative spatial performance potential of different locations, whereas the selected demand target determines the absolute probability that their performance constitutes success. DOGC-PoS therefore provides a methodological architecture that integrates geological conditioning, uncertainty propagation, performance modeling, and project-specific demand within a common probabilistic assessment of whether a geothermal system is likely to fulfill its intended function.

Keywords: Geothermal Energy; Probability of Success; DOGC-PoS; Uncertainty Quantification; Geological Conditioning; Demand Oriented assessment; Monte Carlo simulation; Geothermal Exploration

1. Introduction

Geothermal projects require major technical and financial decisions before subsurface conditions and long-term system behaviour can be observed directly. During exploration and early project planning, uncertainty remains about whether a suitable reservoir is present and how it is configured. Its depth, thermal and hydraulic characteristics, connectivity, fluid properties and sustainable productivity also remain uncertain. Drilling provides essential direct information but requires substantial capital investment and does not eliminate uncertainty about how the system will perform. Injectivity, pressure response, thermal decline, operational reliability and long-term heat production can remain uncertain. PoS assessment therefore has an important role in geothermal exploration and project planning, as well as in investment, insurance, public funding and energy system design. Its purpose is ultimately to support decisions about whether a proposed geothermal system is sufficiently likely to fulfill the function for which it is being developed.

The meaning of geothermal success, however, has not been defined consistently. Several established approaches originate from petroleum exploration concepts in which geological success is estimated from the probabilities assigned to necessary subsurface elements. Their geothermal adaptations commonly evaluate the likelihood of encountering targeted temperature, reservoir presence, permeability, transmissivity, sealing conditions, fluid occurrence or hydraulic connectivity. Other methodologies define exploration success through minimum temperature and flow rate or hydraulic productivity thresholds, frequently under specified drawdown conditions. These approaches have made important contributions by structuring geological reasoning and incorporating reference well information into quantitative exploration risk assessments that can support insurance and pre-drilling investment decisions (Schulz et al., 2005, 2007; Ganz, 2015; Schumacher et al., 2020).

The methodological development of geothermal PoS has progressively expanded beyond these approaches. The field has increasingly adopted stochastic methods and decision analysis to represent uncertain subsurface conditions and their consequences. Geostatistical modeling and Monte Carlo simulation are now used alongside probabilistic reservoir and performance assessment, while economic analysis and Value of Information methods extend the assessment toward project decisions. Van Wees et al. (2012), for example, propagated geological and engineering uncertainty through a geothermal doublet model and evaluated the probability of attaining minimum thermal output. Zimmermann et al. (2019) combined sedimentological reservoir mapping with Monte Carlo simulation to obtain more geologically realistic predictions of reservoir properties and hydraulic performance. Such developments represent an important transition from qualitative geological judgement and isolated parameter thresholds toward stochastic assessment focused more directly on system performance.

A fundamental conceptual distinction nevertheless remains between the probability of encountering suitable subsurface conditions and the probability that the resulting geothermal system will fulfill its intended purpose. Temperature and hydraulic properties such as permeability, transmissivity, reservoir thickness and flow rate are important controls on performance, but none represents project success independently. A reservoir can exceed conventional geological and hydraulic thresholds while still delivering insufficient thermal output for the intended consumer. Conversely, conditions below a generalized threshold may still be sufficient for a smaller heat demand or a different operating configuration, particularly where one reservoir property partly compensates for a limitation in another. Reservoir thickness and permeability, for example, interact in controlling hydraulic productivity, while flow rate and the temperature difference between production and reinjection jointly determine thermal power. Treating these quantities as separate binary success criteria can therefore conceal combinations of conditions that ultimately determine usable heat delivery.

Success must consequently be defined in relation to an explicit project objective. The same geothermal reservoir may be sufficient for one heating application and inadequate for another. A system may satisfy an annual energy requirement while failing to provide the required output during periods of high demand. System design and operation also affect performance. Well configuration and permissible drawdown constrain production, while reinjection temperature, operating duration, production strategy and plant availability influence the heat that can be delivered. The proportion of total demand that geothermal energy is expected to cover further determines whether this output is sufficient. Probability of Success should therefore not be regarded as an intrinsic or permanent characteristic of a reservoir, geological formation or geographic location. It is conditional on the selected performance target and assessment period, as well as on the geological interpretation, system configuration, operating assumptions and demand characteristics. It also depends on the modeling approach and the information available at the time of assessment.

This interpretation also makes uncertainty analysis and quantification central to PoS assessment. Before drilling, geological properties and reservoir architecture are inferred from incomplete and spatially uneven evidence. After drilling, some uncertainties are reduced, while others become better defined as information on productivity, injectivity, hydraulic communication, pressure response, fluid chemistry and long-term performance improves. A deterministic calculation using one assumed value for each uncertain parameter cannot describe the range of plausible system outcomes or the frequency with which a specified project objective might be achieved. Relevant uncertainties must therefore be identified, represented appropriately and propagated through a model that connects uncertain system conditions to the selected definition of success. At the same time, a numerical probability does

not become reliable simply because uncertainty has been represented statistically. The probability distributions and parameter relationships used in the model, together with the scenarios being assessed, must remain physically and geologically plausible.

This requirement is particularly important in heterogeneous geothermal reservoirs. Geological observations are not interchangeable numerical samples drawn from one homogeneous regional population. Reservoir properties reflect how a formation was deposited, deformed and altered during burial, together with its geometry and the degree to which its pore and fracture system is connected or compartmentalised. In the North German Basin, for example, the hydraulic quality of Mesozoic sandstone reservoirs varies strongly with depositional architecture and subsequent diagenetic modification (Franz et al., 2018; Zimmermann et al., 2019; Schumacher et al., 2020). Mapping facies, sandstone thickness and reservoir quality at high resolution therefore improves the prediction of where favourable reservoir conditions may occur. These conditions, however, do not by themselves establish whether the resulting reservoir performance is sufficient for a specified heat requirement.

This distinction creates an important link between geological conditioning and demand oriented assessment. Applying the same permeability distribution and reservoir thickness distribution throughout a spatially heterogeneous formation may preserve the regional numerical ranges of those properties while removing their geological organisation within individual reservoir bodies. The resulting probability would describe an average statistical reservoir rather than the locally varying conditions represented by the available geological information. Conversely, a reservoir quality map can identify comparatively promising locations but cannot determine whether their performance is sufficient for a particular thermal energy demand. A PoS assessment that is useful for decision making therefore requires both steps. Geological information must first constrain the uncertain system states considered plausible, after which those states must be evaluated against an explicit performance requirement.

The conceptual basis for a demand oriented interpretation of geothermal success was established by Sangin et al. (2025a), who critically reviewed more than 50 methodologies and studies relevant to geothermal PoS. They identified the lack of a consistent definition of success that is both project specific and operationally applicable as a recurring limitation. The study proposed that geothermal success should ultimately be related to useful thermal energy delivery rather than solely to the attainment of individual geological indicators. Sangin et al. (2025b) subsequently operationalised this principle in a hydrothermal assessment conducted before drilling, in which uncertainty in permeability and aquifer thickness was propagated through hydraulic and thermal calculations using Monte Carlo simulation. Simulated heat production was evaluated against seasonally distributed heat demand targets for different consumer groups. The resulting PoS changed with the magnitude and temporal distribution of

demand despite unchanged geological input distributions, demonstrating that the geological conditions required to achieve a given PoS depend on what the geothermal system is expected to supply.

The present study extends this development by introducing the Demand Oriented, Geologically Conditioned Probability of Success framework (DOGC-PoS). DOGC-PoS defines geothermal success as the probability that a system will satisfy a specified thermal energy, thermal power or other explicitly defined performance target over a corresponding assessment period. This probability is conditional on the adopted geological interpretation and available information, together with the system configuration, operating assumptions, demand conditions and performance model. Geological and hydraulic variables are therefore retained as fundamental controls on system performance, but they are no longer treated as independent final definitions of success. Instead, uncertain and geologically plausible system states are propagated through an appropriate performance model, and success is determined by whether the resulting output satisfies the specified project requirement.

DOGC-PoS is intended as a methodological architecture rather than a universally prescribed calculation algorithm. Its implementation can therefore vary with reservoir type, project stage, available data and the decision being addressed. Different applications may use different geological models and uncertainty representations, together with numerical, statistical or decision analysis methods appropriate to the problem. The defining principle lies in how these elements are connected. Geological interpretation constrains the uncertain conditions and parameter combinations considered plausible. Uncertainty quantification represents and propagates those conditions, while performance modeling translates them into possible system outputs. The demand of the project then determines which outputs constitute success. The framework therefore integrates elements that have often been treated separately within geothermal PoS assessment.

To demonstrate this principle spatially, the Rhaetian Deltaic System of the North German Basin is used as a case study and proof of concept. The Rhaetian sandstones constitute an established hydrothermal exploration target whose reservoir properties exhibit pronounced spatial heterogeneity associated with a deltaic system dominated by fluvial processes (Franz et al., 2018). Published facies and sandstone thickness maps provide the geological framework for the spatial probabilistic model, while mapped permeability observations represent local variations in hydraulic properties. Reservoir thickness distributions are conditioned by the mapped reservoir classes, and local permeability distributions reflect the spatial arrangement of these observations. The resulting distributions are propagated through hydraulic and thermal production calculations using Monte Carlo simulation. PoS is then evaluated for monthly thermal energy requirements of 1,000, 2,500 and 5,000 MWh under otherwise identical assumptions. The application is designed to illustrate the central proposition that geological heterogeneity

determines the relative performance potential of different locations, whereas the selected thermal energy requirement determines the absolute probability that their performance is sufficient to constitute success.

The spatial application is deliberately restricted and should therefore be interpreted as a methodological demonstration rather than a regional geothermal forecast or drilling location assessment. Permeability and reservoir thickness are the only spatially varying uncertain parameters represented probabilistically in the calculation. Other uncertainties related to temperature, interpolation, hydraulic connectivity and fault behaviour are not propagated through the model. Nor are injectivity, operational availability, alternative well configurations or long-term reservoir response. The purpose of the application is consequently not to provide definitive PoS values for development of the Rhaetian reservoir system, but to demonstrate how a demand oriented PoS calculation can be conditioned by mapped geological heterogeneity and how the interpretation of success depends on the required thermal output.

The paper therefore addresses four interconnected questions. First, how have geothermal PoS methodologies evolved from definitions based on geological conditions and fixed thresholds toward probabilistic assessment focused on system performance? Second, how should geothermal success be defined so that PoS is explicitly related to the function and thermal output requirement of the project? Third, how should uncertainty be identified and quantified, and how should it then be propagated without separating numerical probability distributions from their geological meaning? Fourth, how can demand orientation and geological conditioning be integrated within a common spatial probabilistic framework? The study addresses these questions through a critical review of existing methodologies and the formulation of the DOGC-PoS framework. The framework is then applied spatially to the Rhaetian Deltaic System, followed by a discussion of the implications and limitations of integrating geological conditioning and uncertainty propagation with performance modeling and project specific heat demand in geothermal PoS assessment.

2. Methods:

2.1. Existing Geothermal PoS Methodologies and the Evolution of Success

Definitions

Existing geothermal PoS methodologies differ substantially in how they define success and represent uncertainty. A recurring limitation, however, is that success is commonly defined through individual geological or technical

conditions rather than through the ability of the geothermal system to satisfy a specific project requirement. This section reviews quantitative methodologies in the available literature that explicitly provide a procedure for calculating PoS in geothermal exploration or project assessment. Studies concerned with geological risk, uncertainty, reservoir quality or project feasibility without defining a quantitative PoS calculation were not treated as separate PoS methodologies. The reviewed approaches are arranged broadly according to their methodological development to trace the progression from component based geological probabilities and static thresholds toward probabilistic assessment focused increasingly on system performance and demand, including its application to hydrothermal heat production before drilling.

Otis and Schneidermann (1997)

Otis and Schneidermann (1997) developed a widely adopted petroleum exploration framework in which geological Probability of Success is calculated by multiplying the assumed independent probabilities of five essential elements of the petroleum system: source rock, reservoir rock, trap, seal and migration pathway. Its modular structure allows each element to be assessed separately before being combined into an overall probability estimate. Similar logic was later transferred to geothermal exploration, where analogous components may represent the heat source, reservoir quality and permeability, sealing formations and hydraulic connectivity. In these geothermal applications, however, PoS generally remains focused on whether the required geological conditions are present rather than whether the system can deliver a specified thermal output. The framework therefore provides limited information on whether those conditions can satisfy the energy requirement of a particular project, leaving a conceptual gap between geological discovery and successful energy delivery.

Bartakovics (2014)

Bartakovics (2014) adapted the modular hydrocarbon risk framework of Otis and Schneidermann (1997) to evaluate the geological Probability of Success of a carbonate geothermal system in Hungary. The target consists mainly of fractured and karstified limestones and dolomites, where geothermal potential depends strongly on structural continuity, fracture development, fluid occurrence and sealing conditions.

The geological Probability of Success was defined as the product of four component probabilities:

$$P_g = P_{heat} \cdot P_{reservoir} \cdot P_{system\ closed} \cdot P_{dynamics}$$

The heat component represents the probability of encountering sufficient subsurface temperatures and was evaluated using well data and regional temperature maps. The reservoir component reflects porosity, fracture intensity, lithological continuity and reservoir thickness. The closed system component represents the presence and integrity of the sealing units, while the hydraulic dynamics component accounts for fluid occurrence, flow capacity and production test information.

The component probabilities were estimated using expert geological judgement together with spatial interpolation. Inverse distance weighting and kriging were applied to temperature, porosity and reservoir thickness. Expected reservoir temperatures were approximately 134 to 137 °C, while porosity values between 0.010 and 0.018 were interpreted together with fracture observations from seismic profiles and core samples. Seal continuity, water chemistry and hydraulic evidence were also included in the assessment.

The assigned probabilities were:

$$P_{\text{heat}} = 0.80 ; P_{\text{reservoir}} = 0.75 ; P_{\text{system}} = 0.65 ; P_{\text{dynamics}} = 0.69$$

The resulting geological Probability of Success was calculated as:

$$P_g = 0.80 \times 0.75 \times 0.65 \times 0.69 = 0.2691$$

As shown in Figure 1, the interpretation scale of Otis and Schneidermann (1997) places values below 0.30 in a range indicating one or more unfavorable elements. The resulting value therefore represents a relatively low overall geological Probability of Success and indicates substantial geological risk despite several comparatively high component probabilities. Among the four components, the closed system probability is lowest, followed by hydraulic dynamics.

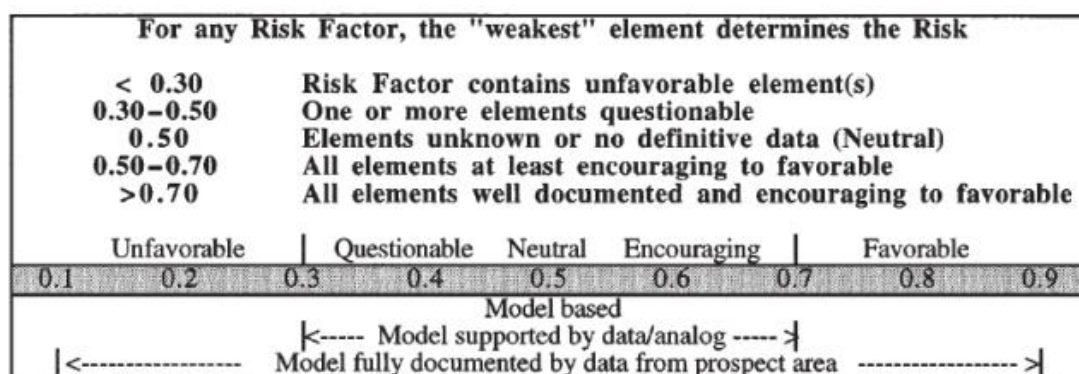


Figure 1: The ranges of the geological risk factors by Otis and Schneidermann (1997)

A major strength of the methodology is its transparency. Each geological component is clearly defined and supported by evidence from the site. The study also demonstrates how a modular framework developed for petroleum exploration can be transferred to a structurally complex carbonate geothermal reservoir. Combining expert interpretation with inverse distance weighting and kriging allows the geological conditions to be spatially constrained even where direct subsurface data are limited.

The method, however, remains restricted to geological success. It does not simulate reservoir behavior, variability in achievable flow rate, thermal decline or energy production over time. Multiplication of the four component probabilities also assumes independence, although reservoir quality, hydraulic dynamics and seal integrity may be related in fractured carbonate systems.

Despite these limitations, the study provides a useful example of an assessment that combines qualitative geological interpretation with quantitative estimation. It also shows how geostatistical methods can support geological PoS assessment in structurally complex settings where subsurface information is limited.

Schulz et al. (2007)

Building on the approach first presented by Schulz et al. (2005), Schulz et al. (2007) proposed one of the earliest structured methods for estimating the Probability of Success of deep hydrogeothermal wells in Germany. The methodology was developed in connection with geothermal exploration risk and insurance, drawing partly on experience from the Unterhaching project in the South German Molasse Basin. It therefore represents an early attempt to connect geological and hydraulic assessment with financing and risk transfer.

Exploration success is defined by whether a well reaches specified minimum values for reservoir temperature and producible flow rate under predetermined drawdown conditions. The overall Probability of Success is calculated by multiplying the probabilities of attaining the required temperature and flow rate:

$$\text{PoS} = P(T \geq T_{\min}) \cdot P(Q \geq Q_{\min})$$

Temperature and flow rate are therefore evaluated as separate threshold conditions. Although both contribute to the heat production potential of the well, the methodology does not directly calculate the probability of achieving a combined thermal power target.

The temperature probability is derived from regional borehole information and corrected bottom hole temperature measurements. Hydraulic productivity is evaluated from available well data and analytical drawdown calculations

under laminar and combined laminar-turbulent flow conditions. Greater weight is assigned to reference wells that are more representative of the prospect. Geothermal wells may, for example, receive double weight, while spatial proximity and geological similarity can further influence the weighting. This reduces the influence of reference wells that are less comparable to the target reservoir.

The method introduced transparent and empirically supported success criteria into geothermal exploration risk assessment. Its definition of success, however, remains based on fixed thresholds. Reference outcomes are classified according to whether the required temperature and flow rate are reached, without propagating uncertainty distributions through a thermal production model. The resulting PoS therefore does not describe the range of possible heat outputs arising from different combinations of geological and hydraulic conditions.

A further limitation is that multiplication of the two component probabilities assumes that attainment of the temperature and flow rate targets can be treated as independent events. This may not adequately represent settings in which thermal and hydraulic conditions are related. More importantly, exceeding both thresholds does not necessarily demonstrate that the resulting geothermal system can meet the required heat demand.

Schulz et al. (2007) recognized this limitation and argued that geothermal success could be represented more meaningfully through achievable thermal power than through separate temperature and flow rate thresholds:

$$(P_{th} \sim Q \cdot \Delta T)$$

They noted that a lower flow rate may be compensated by a greater available temperature difference and vice versa, and suggested estimating the PoS of the installed thermal capacity using methods such as Monte Carlo simulation. This observation anticipated later output-based approaches in which uncertainty is propagated through a heat production model.

Overall, Schulz et al. (2007) established a foundational framework based on empirical reference data, explicit success criteria and practical exploration risk considerations. Although limited by its binary treatment of temperature and flow rate, the approach helped integrate geothermal PoS into financial planning and exploration insurance. It also represents an important methodological step toward quantitative assessment based more directly on geothermal system performance.

Ganz (2015)

Ganz (2015) developed a quantitative Probability of Success model to support the underwriting of geothermal exploration insurance in Germany. The methodology was designed to assess the *Fündigkeitsrisiko*, or discovery

risk, of deep geothermal projects and translate geological and hydrogeological information into a form suitable for insurance risk evaluation.

The overall Probability of Success combines the probability of reaching the required reservoir temperature with the probability of achieving sufficient hydraulic productivity. Temperature probability is estimated from existing borehole data using inverse distance weighting, while hydraulic probability is derived from regional transmissivity information. In simplified form:

$$\text{PoS} = P(T \geq T_{\min}) \times P(S \geq S_{\min})$$

where $T_{\min}$ represents the required minimum temperature and ($S_{\min}$) denotes the specified transmissivity threshold.

A key contribution of the model is its use of empirically derived probabilities rather than purely qualitative expert classifications. By linking spatial geological information to explicit probability estimates, the approach provides insurers with a transparent basis for evaluating exploration risk and determining whether a project may qualify for risk transfer instruments.

Success, however, remains defined by separate temperature and transmissivity thresholds. The model does not calculate the probability that the geothermal system will deliver a specified thermal output. A prospect may therefore satisfy both thresholds even when the resulting combination of temperature and hydraulic productivity is insufficient to meet the intended heat demand.

The framework also excludes reservoir dynamics and reinjection performance, as well as operational constraints, thermal decline and surface system design. These factors can influence the amount of useful heat ultimately delivered. Multiplication of the two component probabilities also assumes independence between temperature and hydraulic productivity, which may not apply equally across all geological settings.

Overall, Ganz (2015) connected quantitative geoscientific assessment with geothermal insurance practice through a transparent and empirically grounded model for evaluating discovery risk before drilling. Its threshold based definition of success, however, limits its ability to determine whether a project can satisfy a specific thermal energy requirement.

Schumacher et al. (2020)

Schumacher et al. (2020) developed a data based Probability of Success methodology for geothermal projects in clastic reservoirs, with particular application to Rhaetian sandstones in the North German Basin. The approach

was designed to address the scarcity of hydraulic well test data by incorporating information from core measurements and borehole logs.

The methodology evaluates whether surrounding reference wells satisfy minimum requirements for temperature and hydraulic productivity defined for the planned project. For each well, hydraulic conductivity and a hypothetical flow rate are estimated using the assumed aquifer thickness, well geometry and drawdown. Thermal and hydraulic probabilities are then calculated as weighted proportions of reference wells meeting the respective thresholds and multiplied to obtain the total PoS.

A key contribution is the use of porosity data to estimate permeability. Porosity may be measured from cores or derived from sonic, density and neutron logs, while reservoir specific porosity permeability relationships are used to estimate hydraulic properties. This allows a broader range of subsurface information to contribute where direct hydraulic tests are sparse. Selection and weighting of reference wells also account for their distance and geological comparability, together with data quality, facies distribution and palaeoflow direction.

The approach extends earlier empirical threshold methods by increasing the amount of usable hydraulic information and giving greater consideration to geological setting and data quality. It is particularly applicable to porous sandstone reservoirs in which fracture flow is not dominant and where substantial legacy well and log data are available.

The PoS calculation, however, remains based on threshold classification. Each reference well is treated as successful or unsuccessful, while uncertainty in permeability, temperature, aquifer thickness and other parameters is not jointly propagated through a reservoir or thermal production model. Multiplication of the thermal and hydraulic probabilities also treats the two components as independent.

The resulting PoS is sensitive to the selection and weighting of reference wells. Schumacher et al. (2020) note that geological and data quality weights can substantially influence the calculated probability and that their numerical values are partly subjective. Diagenetic cementation, fracture controlled flow, reinjection behaviour and long-term reservoir performance are also outside the calculation.

The methodology therefore provides a useful means of integrating heterogeneous subsurface information into geological risk assessment before drilling, but it does not constitute a complete probabilistic evaluation of project performance. Success remains defined through temperature and hydraulic thresholds rather than useful thermal energy delivery. Nevertheless, the study represents an important development in empirical PoS assessment for clastic reservoirs and demonstrates the value of combining quantitative calculations with geological interpretation.

Zimmermann et al. (2019)

Zimmermann et al. (2019) developed a combined geological and probabilistic framework for geothermal reservoir risk assessment in the North German Basin, where deep sandstone formations represent important exploration targets. The approach was motivated by discrepancies between reservoir properties predicted before drilling and those subsequently measured during testing. It combines detailed subsurface reservoir mapping with Monte Carlo simulation to improve the representation of geological uncertainty.

The methodology begins with GIS based maps of reservoir facies and net sandstone thickness. These maps are constructed from sedimentological and biostratigraphic analyses of cores and outcrops, calibrated against wireline log patterns and extended using a regional database of logged wells. The resulting geological interpretation is used to estimate the probability of encountering different lithofacies associations at a hypothetical geothermal site.

The Monte Carlo model represents uncertainty in lithofacies association, effective sandstone thickness, permeability, aquifer depth and geothermal gradient, together with the relationship between depth and fluid salinity. Separate thickness and permeability distributions are assigned to distributary channels, channel belt complexes and delta plain sheetsands. The sampled values are then used to estimate flow rate, productivity index, reservoir temperature and fluid salinity.

Two exploration scenarios are compared. Ordinary Kriging produces a relatively uniform sandstone thickness distribution based on neighbouring wells. In contrast, subsurface reservoir mapping represents the discrete distribution of sandstone bodies controlled by facies and assigns different thickness and permeability distributions to the expected lithofacies associations. The Monte Carlo simulation uses 2,000 runs to generate probability distributions for the resulting reservoir performance indicators.

A major strength of the framework is the integration of geological interpretation with probabilistic uncertainty propagation. Rather than relying solely on mathematical interpolation, the method incorporates depositional setting and the relationships among lithofacies, sandstone thickness and permeability. This produces a more geologically realistic assessment of local reservoir uncertainty. The authors nevertheless acknowledge that the probabilities assigned to the different lithofacies associations remain partly subjective.

The assessment remains focused primarily on reservoir temperature and hydraulic performance. Although minimum reservoir properties associated with economically successful operation are identified, the method does not directly calculate whether the resulting thermal output would satisfy the heat demand or economic requirements

of a particular project. Reinjection conditions, operating strategy and demand profiles are also outside the assessment.

Zimmermann et al. (2019) therefore represent an important methodological transition from conventional interpolation and static reservoir assessment toward geologically informed stochastic risk analysis. The study demonstrates how sedimentological interpretation and spatial reservoir mapping can constrain the probability distributions used in Monte Carlo simulation. This treatment of geological uncertainty provides an important foundation for PoS frameworks in which simulated reservoir performance is subsequently evaluated against a specified thermal energy requirement.

Van Wees et al. (2012)

Van Wees et al. (2012) presented one of the clearest performance based approaches to geothermal Probability of Success assessment. Their methodology evaluates whether a geothermal doublet can deliver a specified minimum thermal output under uncertain geological conditions. This represents an important shift from defining success through individual geological indicators toward assessing the probability of achieving a production target. Such a target may, for example, be set at 10 MWth according to the heating demand, economic requirements or business case of the project.

The approach uses the DoubletCalc modeling tool to simulate the technical and economic performance of geothermal systems in the Netherlands. The model combines geological and hydraulic conditions with assumptions concerning well design and operation within a simplified physical representation based on mass and energy balances. Principal inputs include reservoir depth and thickness, porosity, permeability, geothermal gradient, reinjection temperature and well configuration.

Uncertainty in these parameters is propagated using Monte Carlo simulation. The resulting realizations provide probability distributions for thermal power, flow rate and pressure drop, together with pumping requirements and economic indicators such as levelized heat production cost and net present value. The model therefore connects uncertain subsurface conditions not only to hydraulic performance but also to outcomes directly relevant to project evaluation.

Results are expressed through cumulative probability curves and percentile estimates such as P10, P50 and P90. Probability of Success is defined as the probability that simulated thermal power equals or exceeds the minimum output required by the project:

$$P_r(P_{th} \geq P_{min})$$

where P_{th} is the simulated thermal power and P_{min} is the required minimum output. The resulting PoS therefore represents the proportion of simulated outcomes that satisfy the selected production criterion. The target and required confidence level may also be influenced by insurance conditions and investor risk tolerance. In the Dutch context, a PoS of at least 90% may be required for geothermal insurance coverage.

Van Wees et al. also examined how competing geological effects influence project performance. Shallower reservoirs, for example, may provide better transmissivity, while greater depth can increase reservoir temperature. The model evaluates how such trade offs affect thermal output and economic viability and can be applied both to individual projects and regional assessments. Results may also be represented spatially through maps of expected performance and cost.

A major strength of the methodology is its direct connection between geological uncertainty, thermal output and economic performance. Success is determined by whether the simulated system reaches a specified production target rather than by the presence of particular geological conditions alone.

The approach is nevertheless influenced by the regulatory, insurance and economic context in which the required target and acceptable risk level are defined. Its application in other countries may therefore require different criteria.

Van Wees et al. (2012) consequently provide an important precedent for defining geothermal PoS through targeted thermal output. By combining physical modeling, uncertainty propagation and an explicit performance criterion, the methodology demonstrates how geothermal PoS can move from geological preconditions toward probabilistic evaluation of project performance.

BVEG and DGMK (2024)

The BVEG and DGMK (2024) guideline presents a comprehensive framework for evaluating risk in deep geothermal projects, particularly where insurance or public funding is involved. Project success is divided into geological, operational and economic components that are combined to calculate the total Probability of Success:

$$PoS_{Total} = PoS_t \times PoS_{e(t)} = (PoS_g \times PoS_o) \times PoS_{e(t)}$$

where PoS_t is the technical Probability of Success, PoS_g is the geological Probability of Success, PoS_o is the operational Probability of Success, and $PoS_{e(t)}$ is the conditional economic Probability of Success.

The geological Probability of Success, (PoS_g), represents the probability of encountering a suitable geothermal reservoir and considers its presence, quality and hydraulic connectivity. These aspects are evaluated using a Chance

Adequacy Matrix adapted from Rose (2001), which combines expert judgement with structured numerical scoring (Figure 2). Although numerical values are assigned, the procedure is more accurately described as a quantified qualitative assessment because the scores are not derived from formal probability distributions.

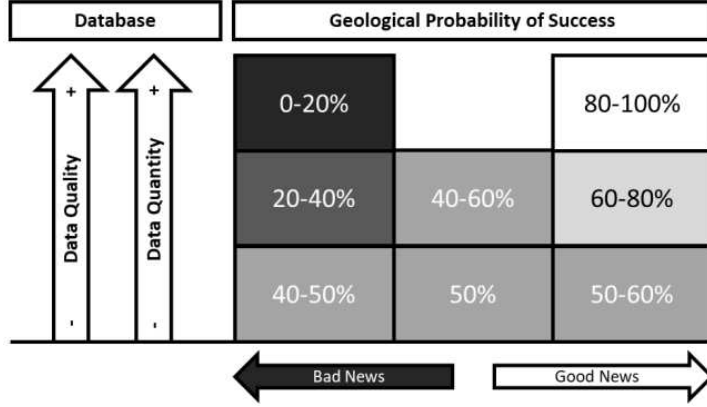


Figure 2: Chance Adequacy Matrix, modified after Rose (2001).

The operational Probability of Success, (PoS_o), represents the probability of successfully developing the geothermal target through the planned wells. It considers well design, drilling and completion complexity, construction techniques and relevant site conditions, and is estimated primarily from project experience and expert judgement. Geological and operational success are then combined as:

$$PoS_t = PoS_g \times PoS_o$$

The conditional economic Probability of Success, ($PoS_{e(t)}$) represents the probability that a technically successful project will achieve the minimum thermal output required for economic viability. It is therefore evaluated only after geological and operational success have been assumed. The total probability, PoS_{Total} , combines these components into an integrated measure of whether the project is geologically successful, technically operational and economically viable.

For the conditional economic Probability of Success, geothermal output is represented by recoverable thermal power:

$$P_{th} = \rho_f \cdot c_p \cdot Q \cdot \Delta T$$

where ρ_f is the fluid density, c_p is the specific heat capacity of the fluid, Q is the flow rate, and ΔT is the temperature difference between production and reinjection.

Because reservoir temperature and achievable flow rate remain uncertain, BVEG and DGMK (2024) recommend representing the relevant geological parameters through probability distributions and propagating them to obtain

a distribution of possible thermal power. Monte Carlo methods and tools such as DoubletCalc may be used for this calculation. Where sufficient data are unavailable, assumed distribution forms, commonly lognormal, may be applied. The simulation produces a cumulative probability curve from which an economic threshold is defined as the minimum average thermal power required for project viability.

The conditional economic Probability of Success is then calculated as the probability that simulated thermal power equals or exceeds this threshold. If, for example, 70% of the simulations produce at least 7.5 MW_{th}, as illustrated in Figure 3, then:

$$PoS_{e(t)} = 0.70$$

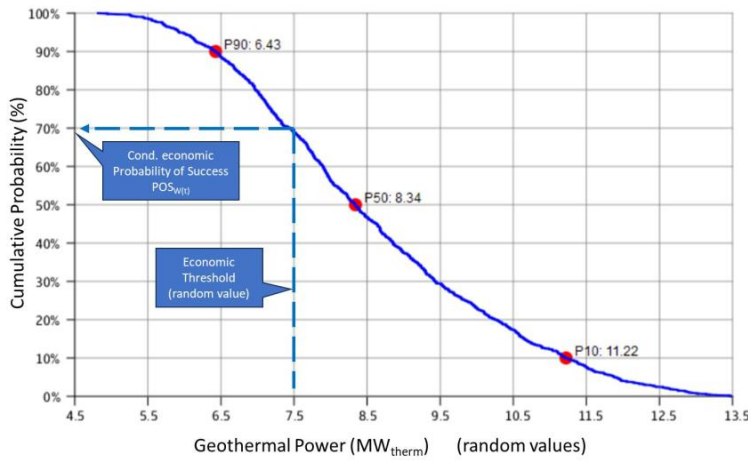


Figure 3: Probability distribution of geothermal power in MW_{therm}

A notable feature of the framework is that geological and operational failure are evaluated separately from the Monte Carlo calculation of economic performance. The distributions used to calculate $PoS_{e(t)}$ describe systems already assumed to be geologically and technically functional. Reservoir absence, inadequate reservoir quality, unsuccessful hydraulic connectivity or operational failure are instead represented through PoS_g and PoS_o .

The framework therefore combines discrete failure probabilities with continuous uncertainty in thermal performance, but these uncertainties are not propagated through one integrated simulation. Geological interpretation introduces an additional limitation because the value of PoS_g depends partly on expert judgement. Different interpretations of the same subsurface evidence may consequently produce different probability estimates. Peer review can reduce this uncertainty, but retaining alternative geological scenarios would allow their effects on thermal output and project success to be evaluated explicitly. Consequently, $PoS_{e(t)}$ should be

interpreted as a conditional probability of economic performance, not as the total Probability of Success. The complete BVEG and DGMK (2024) framework accounts separately for geological and operational failure through PoS_g , and PoS_o , but its modular structure does not propagate geological, operational and interpretive uncertainty together with the performance requirement through one unified probabilistic simulation.

Gambini et al. (2025)

Gambini et al. (2025) proposed the Reverse Enthalpy Methodology (REM) as an integrated framework for assessing geological, threshold related and commercial success in geothermal projects. The approach adapts established risk assessment principles from the oil and gas industry to the technical and economic characteristics of geothermal development.

The framework distinguishes three main components. The geological Probability of Success, P_g , represents the probability that the geothermal conceptual model is valid and that the geological elements required for development are present. Threshold probabilities evaluate whether critical fluid properties, particularly temperature and potentially adverse fluid composition, satisfy the requirements of the selected development concept. These probabilities are obtained by locating the relevant thresholds within cumulative distribution functions representing parameter uncertainty.

The commercial Probability of Success, P_c , represents the probability that the project achieves a net present value equal to or greater than zero. Well deliverability is incorporated into this assessment by relating uncertain flow rate to the drilling program, facility capacity, investment requirements and expected revenues. The method therefore connects subsurface uncertainty with project economics rather than evaluating geological conditions independently.

REM provides two procedures for estimating P_c . In the first, facility type and installed capacity are specified in advance, and the maximum drilling expenditure compatible with $NPV = 0$ is calculated. Its position within the drilling cost distribution determines the commercial Probability of Success. In the second, the number of wells and drilling expenditure are fixed, and the minimum facility capacity required to reach $NPV = 0$ is calculated. Its position within the corresponding capacity distribution is then used to estimate P_c . Both procedures can be applied iteratively as the development concept is adjusted. The methodology also introduces Dry Hole Tolerance for projects where well productivity is strongly affected by local geological variability, particularly in fractured or heterogeneous reservoirs. It represents the maximum number of unsuccessful wells that project management is prepared to accept before terminating development. This concept supports appraisal planning by evaluating the

probability of obtaining at least one successful well within an economically acceptable drilling sequence. Combined with the drilling cost analysis, it also accounts for the effect of unsuccessful wells on commercial viability.

A major strength of REM is its transparent treatment of geological, technical and economic uncertainty. Cumulative distribution functions translate uncertain parameter ranges into explicit probabilities of exceeding development specific thresholds, while the commercial analysis connects well performance and drilling expenditure directly to project value.

The methodology nevertheless continues to determine success largely through threshold exceedance. Geological conditions, fluid properties and commercial performance are ultimately evaluated against predefined limits. Although these thresholds are specific to the development concept, REM does not directly assess the probability of delivering a specified amount of useful thermal energy over a defined operating period and demand profile.

Sangin et al. (2025b)

Sangin et al. (2025b) developed a quantitative methodology for estimating the Probability of Success of hydrothermal geothermal projects before drilling using a demand oriented definition of success. Rather than treating reservoir properties such as permeability, temperature or flow rate as independent indicators of success, the method evaluates whether uncertain subsurface conditions are likely to produce sufficient thermal energy to satisfy a predefined heat demand. Success is therefore defined by the required thermal output of the intended application.

The methodology combines Monte Carlo simulation with a deterministic heat production model. Geological properties that cannot be known precisely before drilling are represented by probability distributions. Values are sampled from these distributions in each realization and propagated through the model to calculate the corresponding thermal energy output.

Thermal power and energy are calculated as:

$$P_{th} = \rho_f \cdot c_f \cdot Q \cdot \Delta T$$

$$E_{th} = P_{th} \cdot \Delta t$$

Where E_{th} is the thermal energy, P_{th} is thermal power, ρ_f is the geothermal-fluid density, c_f is the specific heat capacity of the geothermal fluid, Q is the volumetric flow rate, ΔT is the temperature difference between production

and reinjection, and Δt is the assessment period. Flow rate is estimated analytically from the hydraulic properties of the reservoir and the assumed pumping conditions:

$$Q = 2\pi \cdot K_f \cdot H \cdot \left(\frac{s}{\ln\left(\frac{R}{r}\right)} \right)$$

$$K_f = k \cdot \frac{\rho_f}{\mu_f} \cdot g$$

$$R = 3000 \cdot s \cdot \sqrt{K_f}$$

where k is intrinsic permeability, K_f is hydraulic conductivity, H is aquifer thickness, s is drawdown, R is the radius of influence of the pumping well, r is the well radius, μ_f is fluid's dynamic viscosity, and g is gravitational acceleration.

In the demonstrated application, permeability and aquifer thickness were treated as uncertain variables. One value of each was sampled in every realization and used to calculate hydraulic conductivity, flow rate, thermal power and thermal energy.

The simulated thermal energy was then compared with the heat demand for the same assessment period. A realization was classified as successful when:

$$E_{simulated} \geq E_{target}$$

and the Probability of Success was calculated as:

$$POS = \frac{N(E_{simulated} \geq E_{target})}{N_{Total}}$$

where N_{total} is the total number of Monte Carlo realizations and the numerator is the number that satisfies the selected heat demand.

This formulation produces a conditional performance probability rather than a universal measure of reservoir quality. PoS depends on the assumed geological distributions and operating conditions, together with the assessment period, system configuration and heat demand. The same reservoir can therefore produce different PoS values for different consumers, seasons or development concepts.

Sangin et al. (2025b) demonstrated the method using a hydrothermal sandstone reservoir in Güstrow, northeastern Germany. Heat demand was evaluated monthly rather than through one constant annual threshold. Five consumer

categories were considered: municipal buildings, trade and non-manufacturing activities, industry, residential buildings and all buildings combined. Annual demand was distributed across the twelve months using a normalized seasonal profile, and a monthly PoS was calculated for each category.

The same geological input distributions produced different PoS values as the magnitude and seasonal distribution of demand changed. Municipal, trade and industrial demand generally resulted in high probabilities, whereas residential demand and the combined demand of all buildings produced lower and more strongly seasonal values.

The simulation results were also used to relate individual uncertain parameters to the resulting success and failure outcomes. Where a sufficiently clear relationship exists between a parameter and system performance, a selected PoS level can be used to identify the parameter value associated with that probability of meeting the heat production target.

The same principle can be extended to other geological or operational parameters where their uncertainty is represented probabilistically and their relationship with the success criterion can be evaluated from the simulation results.

2.2. Demand-Oriented, Geologically Conditioned Probability of Success Framework

2.2.1. Conceptual Basis of DOGC-PoS

The review of existing Probability of Success methodologies demonstrates that geological conditions, reservoir quality classes and individual threshold values do not independently establish whether a geothermal project will fulfill its intended function. Permeability, reservoir thickness, temperature, transmissivity and productivity influence performance, but their significance depends on the required thermal output, operating conditions and assessment period. The Demand Oriented, Geologically Conditioned Probability of Success framework (DOGC-PoS) therefore defines success as the probability that a geothermal system will equal or exceed a specified thermal energy, thermal power or other explicitly defined performance target under stated geological, operational, demand and modeling conditions.

For a thermal energy target, the general definition is:

$$PoS(E_{target}) = Pr(E_{simulated} \geq E_{target} | \mathcal{G}, \mathcal{O}, \mathcal{D}, \mathcal{M}, \mathcal{I})$$

Where $\mathbf{G}$ represents the adopted geological interpretation and geological uncertainty, $\mathbf{O}$ represents the system configuration and operational assumptions, $\mathbf{D}$ represents the magnitude and temporal structure of heat demand, $\mathbf{M}$ represents the selected hydraulic and thermal-performance model, and $\mathbf{J}$ represents the information available at the time of assessment.

This definition treats PoS as a conditional probability specific to the project rather than as a permanent characteristic of a reservoir, formation or geographic location. The same reservoir may consequently produce different PoS values under different heat demands and assessment periods or when system configuration and operating assumptions change. Geological and hydraulic thresholds remain relevant, but they are treated as uncertain controls on system performance rather than as final definitions of success.

Geological conditioning forms the second defining component of the framework. Probability distributions should reflect the geological processes and spatial architecture controlling reservoir properties. Depositional and structural setting, diagenetic alteration and reservoir geometry influence which parameter values and combinations are plausible, while hydraulic connectivity and the comparability of reference observations further constrain their interpretation. Applying one basin wide permeability distribution or one reservoir thickness distribution to a heterogeneous formation may preserve the overall numerical range of the observations while concealing their spatial organisation within individual reservoir bodies.

DOGC-PoS is therefore formulated as a transferable methodological architecture rather than as one universally prescribed numerical algorithm. Its implementation requires an explicit project output target and a geological model that constrains the uncertain system states considered plausible. These uncertainties are then propagated through an appropriate performance model to determine the probability that the specified target will be achieved. The numerical methods used for these steps may vary with reservoir type, project stage, data availability and the purpose of the assessment.

2.2.2. Geological Basis of the Spatial Demonstration

To demonstrate the spatial implementation of DOGC-PoS, the Rhaetian Deltaic System of the North German Basin presented by Franz et al. (2018) was selected as the geological case study (Figure 4). The Rhaetian sandstones represent an established hydrothermal exploration target, but their reservoir properties vary considerably across the basin because of the depositional architecture of the deltaic system. Franz et al. (2018) addressed this heterogeneity by integrating sedimentological and palaeontological interpretation with petrographic and

petrophysical analyses, core information and wireline logs. The resulting geological model provided high resolution maps of subsurface facies, sandstone thickness and reservoir quality.

The Rhaetian Deltaic System is described as a high constructive, fluvial dominated delta comprising upper and lower delta plains together with delta front and prodelta environments. Within the lower delta plain, distributary channels are associated with levees, crevasse splays, sheet sands and interdistributary bay deposits. Towards the distal part of the system, the channels terminate in distributary and mouth bar complexes. Franz et al. (2018) identify distributary channels and their associated levee and crevasse splay deposits as particularly important for hydrothermal exploration because they form laterally extensive sandy reservoir bodies. The proportion of sandstone decreases towards the more distal delta front and prodelta environments.

This depositional control is important for probabilistic reservoir assessment because reservoir properties are not distributed uniformly throughout the Rhaetian succession. Franz et al. (2018) distinguish reservoir thickness classes of <10 m, 10 to 20 m and >20 m, and permeability classes of <250 mD, 250 to 500 mD and >500 mD. Their reservoir quality map combines the spatial reservoir thickness classes with permeability information from available wells. The resulting pattern shows that conditions relevant to geothermal production are concentrated within particular reservoir bodies rather than distributed homogeneously across the Rhaetian formation.

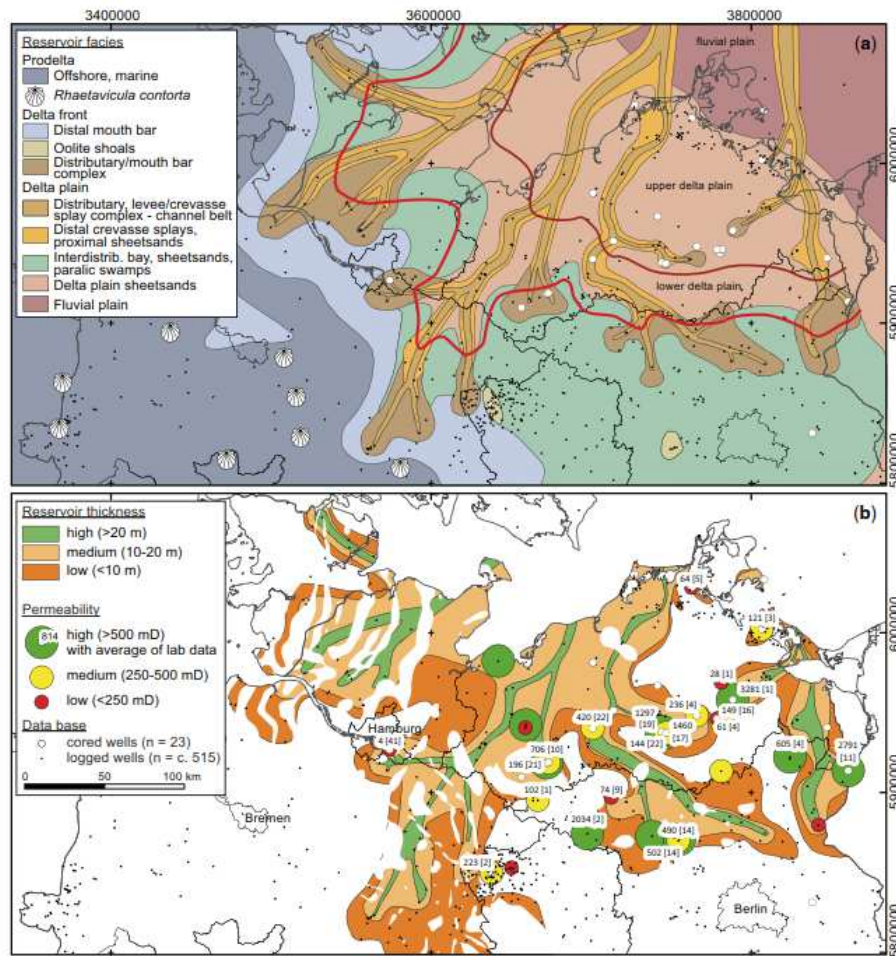


Figure 4. Spatial geological framework used for the DOGC-PoS application to the Rhaetian Deltaic System of the North German Basin. (a) Subsurface facies distribution of the high-constructive, fluvial-dominated deltaic system, with red lines indicating the margins of the upper and lower delta plains. (b) Reservoir-quality distribution represented by reservoir thickness and permeability information from mapping and geothermal wells. Reproduced from Franz et al. (2018), Figure 12.

2.2.3. Digital Extraction and Spatial Parameterization of the Geological Inputs

The published subsurface facies and reservoir-quality maps of Franz et al. (2018) were transferred into a common raster-based computational framework for spatial PoS modeling. Because the original georeferenced GIS datasets were not available for the present analysis, the published map images were aligned in image-coordinate space using their common map boundaries, coordinate information, scale, and relative geometry. The subsurface facies map was retained unchanged as the geological background for interpretation of the resulting PoS maps, whereas the reservoir-quality map was used to derive the spatially variable reservoir thickness and permeability inputs.

A semi-automated image-analysis workflow was applied to digitize the mapped reservoir thickness classes from the reservoir-quality map. The characteristic colors representing the low, medium, and high reservoir-thickness classes were defined as reference color vectors. Each raster pixel was compared with these reference values in RGB color space and assigned to the closest class when the specified color-distance criterion was satisfied.

Small disconnected components associated with text, symbols, polygon boundaries, well markers, and graphical noise were removed through connected-component filtering. Morphological opening and closing operations were subsequently applied to suppress isolated pixels and fill small interruptions caused by labels and map symbols. The procedure produced a categorical reservoir thickness raster and a spatial reservoir mask while preserving the geometry of the reservoir bodies mapped by Franz et al. (2018).

The reservoir thickness and permeability classes used for spatial conditioning were adopted directly from the reservoir-quality legend of Franz et al. (2018), Figure 4b. The source map distinguishes reservoir thickness as low (<10 m), medium (10 to 20 m), and high (>20 m), and permeability as low (<250 mD), medium (250 to 500 mD), and high (>500 mD). To enable stochastic sampling within these categorical classes, the mapped classes were represented by triangular probability distributions. The finite class boundaries shown in the source map were retained as distribution limits where applicable. For the open-ended classes, finite sampling bounds were required for the triangular distributions. The bounds adopted in the preceding demand-oriented hydrothermal application were retained because that model was parameterised for the same Rhaetian Deltaic System and therefore provides a geologically consistent uncertainty range for the present spatial application. For reservoir thickness, the adopted range of 7 to 56 m also corresponds to the range reported by Franz et al. (2018) for compound channel-belt reservoirs. Retaining the previously defined bounds additionally preserves consistency between the location-specific and spatial implementations of the demand-oriented PoS approach, rather than introducing new arbitrary truncation limits. Where no separate most-likely value was available within a bounded class, the midpoint of the class interval was used as the modal value. For the upper reservoir-thickness and permeability classes, the modal values of 30 m and 610.5 mD, respectively, were retained from the preceding demand-oriented model. The three reservoir thickness classes were therefore represented as:

$$H_{low} \sim \text{Triangular}(7, 8.5, 10)$$

$$H_{medium} \sim \text{Triangular}(10, 15, 20)$$

$$H_{high} \sim \text{Triangular}(20, 30, 56)$$

where the three values represent the minimum, modal, and maximum reservoir thickness, respectively.

Permeability information was represented by discrete colored observation symbols on the reservoir-quality map, with green, yellow, and red symbols corresponding to the high (>500 mD), medium (250 to 500 mD), and low (<250 mD) permeability classes defined by Franz et al. (2018), respectively. Color-based segmentation and connected-component analysis were used to separate these symbols from labels and other graphical elements. The centroid of each detected symbol was adopted as the spatial position of the corresponding observation.

The permeability classes were numerically encoded as:

$$C_i = \begin{cases} 1, & k_i < 250 \text{ md} \\ 2, & 250 \leq k_i \leq 500 \text{ md} \\ 3, & k_i > 500 \text{ md} \end{cases}$$

where C_i where C_i is the class assigned to observation i , and k_i is its represented permeability. The corresponding triangular permeability distributions were defined as:

$$k_{low} \sim \text{Triangular}(0.2, 125.1, 250)$$

$$k_{medium} \sim \text{Triangular}(250, 375, 500)$$

$$k_{high} \sim \text{Triangular}(500, 610.5, 5814)$$

Table 1. Triangular probability distributions assigned to the mapped reservoir thickness and permeability classes. Triangular distributions are reported as minimum, mode, and maximum values.

Reservoir-quality class	Reservoir thickness, (m)	Permeability, (mD)
Low	Triangular (7, 8.5, 10)	Triangular (0.2, 125.1, 250)
Medium	Triangular (10, 15, 20)	Triangular (250, 375, 500)
High	Triangular (20, 30, 56)	Triangular (500, 610.5, 5814)

2.2.4. Spatial Conditioning of Permeability

Because permeability information was available only at discrete observation locations, a spatial interpolation step was required before a local permeability distribution could be assigned to every raster cell. Permeability-class scores were interpolated using a four-nearest-neighbour inverse-distance-weighting algorithm.

For each raster cell within the mapped reservoir area, the four nearest permeability observations were identified. The interpolated class score was calculated as:

$$C(x) = \sum_{i \in N_4(x)} w_i(x) C_i / \sum_{i \in N_4(x)} w_i(x) \quad (1)$$

$$w_i(x) = \frac{1}{\max[d_i(x), d_{\min}]^2} \quad (2)$$

where $N_4(x)$ denotes the set of four observations nearest to cell x , $d_i(x)$ is the distance between the cell and observation i , and $d_{\min}$ is a small lower distance limit introduced to avoid singular weighting at or immediately adjacent to an observation. The inverse-square weighting exponent gives greater influence to nearby observations while allowing the surrounding observations to contribute to the local estimate.

The procedure represents a deterministic, local, non-parametric spatial interpolation. Each raster cell is estimated from its own neighbourhood rather than from a single global function fitted across the study area. It therefore retains local changes in the mapped permeability classes more effectively than assigning one permeability distribution to the entire Rhaetian system. However, the interpolation remains controlled by geometric distance and does not independently reproduce palaeoflow direction, anisotropy, facies boundaries, or hydraulic connectivity.

The interpolated score was allowed to vary continuously between 1 and 3. To avoid abrupt changes in permeability distributions at class boundaries, the minimum, modal, and maximum parameters of the local triangular distribution were linearly interpolated between adjacent classes. For a cell with $1 \leq C(x) \leq 2$, the interpolation factor was defined as:

$$\alpha = C(x) - 1 \quad (3)$$

and the local parameter vector was calculated as:

$$\theta_k(x) = (1 - \alpha)\theta_{k,low} + \alpha\theta_{k,medium} \quad (4)$$

where:

$$\theta_k = (k_{min}, k_{mode}, k_{max}) \quad (5)$$

For cells with $2 \leq C(x) \leq 3$, the same procedure was applied between the medium- and high-permeability distributions. This generated a spatially continuous field of local probability distributions while retaining the class information contained in the source map.

The method does not assume that all locations belonging to one named facies possess identical permeability or reservoir thickness. Instead, the facies interpretation constrains the geological context, the mapped sandstone bodies define the spatial reservoir geometry, and the interpolated observations determine the local permeability distributions.

2.2.5. Cell-Based Monte Carlo Calculation

Each raster cell within the digitized reservoir mask was treated as an individual probabilistic assessment location. Here, " $\mathbf{x}$ " denotes the spatial location of an individual raster cell within the model domain. The cell was assigned the triangular reservoir thickness distribution corresponding to its mapped thickness class and the locally interpolated triangular permeability distribution derived from the four-nearest-neighbour interpolation.

For each cell, 1,000 paired realizations of reservoir thickness and permeability were generated, with the two parameters sampled independently from their respective local distributions. The number of realizations was selected to provide stable Monte Carlo estimates while maintaining a manageable computational demand for cell-by-cell simulation across the spatial raster. With 1,000 realizations, the maximum Monte Carlo standard error of the estimated PoS is approximately 0.016, which was considered sufficient for distinguishing the regional spatial and demand-dependent patterns investigated in this study.

Permeability values were converted from millidarcies to square metres before being introduced into the hydraulic calculation. For each realization j , hydraulic conductivity in the spatial location of " $\mathbf{x}$ " was calculated as:

$$K_{f,j}(\mathbf{x}) = k_j(\mathbf{x}) \cdot \frac{\rho_f}{\mu_f} \cdot g \quad (6)$$

where $k_j(\mathbf{x})$ is the sampled permeability for realization j , ρ_f is fluid density, μ_f is the dynamic fluid-viscosity parameter, and g is gravitational acceleration. The radius of influence was estimated as:

$$R_j(\mathbf{x}) = 3000 \cdot s \cdot \sqrt{K_{f,j}(\mathbf{x})} \quad (7)$$

The corresponding volumetric flow rate was calculated as:

$$Q_j(x) = 2\pi \cdot K_{f,j}(x) \cdot H_j(x) \cdot \left(\frac{s}{\ln\left(\frac{R_j(x)}{r}\right)} \right) \quad (8)$$

where $H_j(x)$ is the sampled reservoir thickness, s is drawdown, and r is well radius.

Thermal power and thermal energy were then calculated using the equations adopted from the preceding demand-oriented PoS model:

$$P_{th,j}(x) = \rho_f \cdot c_f \cdot Q_j(x) \cdot \Delta T \quad (9)$$

$$E_j(x) = P_{th,j}(x) \cdot \Delta t \quad (10)$$

where c_f is the specific heat capacity of the geothermal fluid, ΔT is the temperature difference between produced and reinjected fluid, and Δt is the operating period. A 30-day operating period was adopted as a standardized monthly assessment interval. All parameters listed in Table 2 were held constant across the spatial domain and thermal-energy target scenarios, while permeability and reservoir thickness were treated as spatially varying uncertain inputs.

Table 2. Fixed hydraulic, thermal, operational, and simulation parameters used in the cell-based Monte Carlo DOGC-PoS calculations.

Parameter	Symbol	Value
Fluid density	ρ_f	1100 kg.m ⁻³
Dynamic viscosity of the geothermal fluid	μ_f	7.5*10 ⁻⁴ Pa.s
Specific heat capacity of the geothermal fluid	c_f	3750 J.kg ⁻¹ .K ⁻¹
Production-to-reinjection temperature difference	ΔT	30 K
Drawdown	s	300 m
Well radius	r	0.216 m
Gravitational acceleration	g	9.8 m.s ⁻²
Operating period	Δt	30 days

Parameter	Symbol	Value
Monte Carlo realizations per cell	N	1000

The calculated thermal power is obtained in watts. Multiplication by the operating period in seconds gives thermal energy in joules. The monthly heat-demand targets expressed in MWh were therefore converted to joules before comparison with the simulated thermal-energy output.

All parameters other than permeability and reservoir thickness were held constant. Consequently, spatial variation in the resulting PoS maps was generated exclusively by the mapped geometry and uncertainty of these two reservoir properties. This controlled implementation isolates the effect of geological reservoir-quality variation on the probability of satisfying alternative heat-output targets.

Each realization was classified as successful when:

$$E_j(x) \geq E_{target} \quad (11)$$

The cell-specific Probability of Success was calculated as:

$$PoS(x, E_{target}) = \frac{1}{N} \sum_{j=1}^N I[E_j(x) \geq E_{target}] \quad (12)$$

Where $I[E_j(x) \geq E_{target}]$ is an indicator function that equals one when the simulated thermal energy meets or exceeds the target and zero otherwise.

2.2.6. Demand Scenarios and Construction of the PoS Maps

The calculation was repeated for **three** monthly thermal-energy targets:

$$E_{target} = 1,000; 2,500; \text{ and } 5,000 \text{ MWh per month}$$

The selected targets were intended to represent progressively increasing heat-production requirements while remaining within a practically relevant range for the hydraulic and thermal configuration considered in the present proof-of-concept assessment. Over the adopted 30-day assessment period, targets of 1,000, 2,500, and 5,000 MWh correspond to continuous average thermal outputs of approximately 1.4, 3.5, and 6.9 MW, respectively. These values are comparable in magnitude to reported thermal capacities of medium-deep geothermal developments in northern Germany. Käsbohrer et al. (2025), for example, report approximately 4.3 MW of heat production for the

Potsdam development and a design capacity of up to 7.5 MW for the Rhaetian geothermal system at Schwerin, supplied by a production rate of 150 m³/h. If these thermal capacities were maintained continuously over a 30-day period, they would correspond to approximately 3,100 and 5,400 MWh, respectively. The selected scenarios therefore represent a lower, intermediate, and comparatively demanding monthly thermal-energy requirement within a range consistent with the scale of existing or recently developed geothermal heat-production systems.

The targets were applied uniformly across the mapped area. Consequently, the geological framework, spatial reservoir **parameterization**, operational assumptions, and assessment period remained unchanged among the scenarios, while only the thermal-energy criterion defining success was varied. This allowed the effect of increasing the required output on the spatial Probability of Success to be evaluated independently of changes in the underlying geological model.

The cell-specific probabilities were assembled into three raster PoS surfaces. Cells outside the digitized reservoir mask were excluded from the calculation and were not assigned zero probabilities, because a zero PoS would incorrectly imply that a probabilistic reservoir assessment had been performed at those locations.

A limited mask-constrained smoothing operation was applied after raster assembly to reduce pixel-scale discontinuities introduced by image segmentation and image-derived raster digitization. Smoothing was restricted to the interpreted reservoir bodies and was not permitted to create probability values outside their mapped boundaries. Identical smoothing parameters, raster extent, map geometry, and **color** scale were used for all three scenarios to preserve direct comparability.

A final monotonicity control was applied because, under identical geological and operational assumptions, satisfying a higher thermal-energy target must be a subset of satisfying a lower target. For any spatial location x within the evaluated reservoir mask, the resulting probabilities were therefore required to satisfy:

$$PoS_{5000}(x) \leq PoS_{2500}(x) \leq PoS_{1000}(x) \quad (13)$$

This control prevented small local reversals caused by finite Monte Carlo sampling, raster resampling, interpolation, or smoothing from being interpreted as physically meaningful differences among the scenarios.

The resulting maps are presented and compared in the Results section. They represent demand-conditioned transformations of the spatial reservoir-quality information rather than direct reproductions of the original reservoir-quality map.

3. Results: Spatial Demand-Oriented Probability of Success in the Rhaetian Deltaic System

Application of the DOGC-PoS framework produced spatially heterogeneous Probability of Success distributions for monthly thermal-energy targets of 1,000, 2,500, and 5,000 MWh (Figure 5). The geological framework and operational assumptions were identical in all three scenarios, while the thermal-energy target defining success was varied.

At 1,000 MWh/month, large parts of the mapped reservoir bodies exhibit moderate to high PoS, with extensive yellow, orange, and red zones (Figure 5a). Lower probabilities occur mainly along the margins of the reservoir bodies and in areas represented by less productive combinations of reservoir thickness and permeability. The spatial pattern is strongly heterogeneous, with elongated and discontinuous high-PoS zones reflecting the mapped reservoir architecture.

Increasing the target to 2,500 MWh/month reduces the magnitude and spatial extent of the higher probabilities (Figure 5b). The principal high-PoS zones remain spatially recognizable, but some areas shift toward intermediate probabilities and the lower-probability margins expand. At 5,000 MWh/month, this reduction becomes more pronounced (Figure 5c). High probabilities become increasingly concentrated within a smaller number of reservoir bodies, while larger portions of the mapped system exhibit low to moderate PoS.

As required by the monotonicity control described in Section 2.2.6, the resulting PoS values satisfy:

$$PoS_{5000}(x) \leq PoS_{2500}(x) \leq PoS_{1000}(x)$$

Despite the decline in absolute probability with increasing target, the relative spatial pattern remains broadly consistent. Locations associated with greater reservoir thickness and higher locally interpolated permeability generally retain higher PoS than surrounding areas across all three scenarios. **The represented geological heterogeneity** therefore controls the relative spatial performance of the reservoir system, while the selected thermal-energy requirement controls the absolute probability that a given location satisfies the definition of success.

Because permeability and reservoir thickness were the only spatially varying uncertain parameters in the present implementation, the resulting differences should be interpreted specifically as the effect of spatial reservoir-quality heterogeneity under otherwise identical assumptions. The maps therefore demonstrate how the same geological

system can produce different spatial PoS distributions when evaluated against different project-specific thermal-energy requirements.

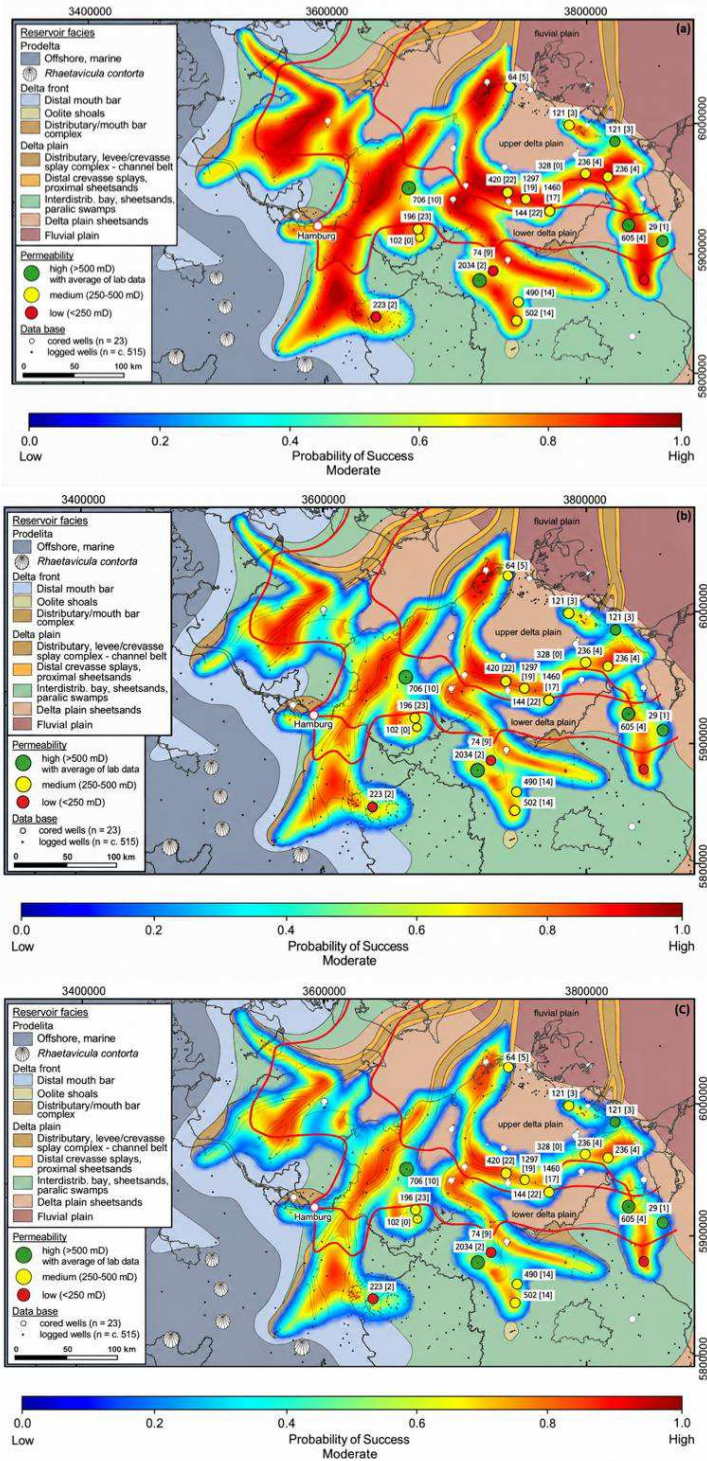


Figure 5. Demand-Oriented, Geologically Conditioned Probability of Success (DOGC-PoS) maps for the Rhaetian Deltaic System of the North German Basin for monthly thermal-energy targets of (a) 1,000 MWh, (b) 2,500 MWh, and (c) 5,000 MWh. Geological background and reservoir-quality information are based on Franz et al. (2018).

4. Discussion

The review of existing geothermal Probability of Success methodologies shows a progressive development from qualitative geological judgment and component-based probability assessment toward stochastic, performance-oriented modeling. Important advances have been made using reference-well statistics, geostatistical interpolation, Monte Carlo simulation, reservoir-performance modeling, geological mapping, and economic assessment. Nevertheless, these developments have not always been integrated within a common definition of what geothermal success means. Four requirements emerge as particularly important for a decision-relevant PoS assessment: success should not be defined only by static geological or hydraulic thresholds; it should be evaluated against a project-specific thermal-output target; uncertainty should be explicitly represented and propagated; and the probabilistic model should remain conditioned by geological understanding.

DOGC-PoS combines these requirements within one methodological architecture. Geological and operational parameters are treated as controls on performance rather than independent definitions of success, simulated performance is compared with an explicit thermal energy or thermal power requirement, uncertain conditions are propagated probabilistically, and the numerical representation is conditioned by the geological architecture and processes controlling the reservoir. The spatial application to the Rhaetian Deltaic System provides a controlled demonstration of how these principles interact. The same geological framework produces different absolute probabilities when evaluated against different thermal-energy requirements, while spatial differences in reservoir quality determine which locations retain comparatively higher performance as demand increases. The following discussion evaluates these four characteristics and their integration within DOGC-PoS.

4.1. Scope and Limitations of Static Success Definitions

The use of geological and hydraulic thresholds is particularly appropriate when PoS is intended to quantify exploration risk or support insurance. Temperature, flow rate, transmissivity, and related parameters can be defined before drilling and evaluated directly through measurements and hydraulic testing after well completion. They therefore provide transparent and verifiable criteria for determining whether the drilled well has achieved the

conditions specified for exploration success. This practical requirement is central to approaches such as Schulz et al. (2007), Ganz (2015), and Schumacher et al. (2020), which were developed partly in the context of geothermal exploration-risk assessment and insurance. In this setting, linking success directly to delivered heat would be problematic because the final thermal output also depends on the surface installation, operating strategy, and consumer, which extend beyond the geological performance of the drilled well.

The limitation of threshold-based approaches therefore concerns their scope rather than their validity. Temperature, permeability, transmissivity, aquifer thickness, and flow rate provide measurable indicators of subsurface and well performance, but they do not by themselves determine whether the complete geothermal system will satisfy a particular heat requirement. A reservoir may meet the specified exploration thresholds while remaining insufficient for one application, yet be adequate for another with a lower demand or different system configuration. Conversely, a demand-oriented PoS should not be interpreted as a more permanent measure of success. Heat demand may change substantially during the operating life of a geothermal project, so the corresponding PoS is conditional on the demand scenario adopted at the time of assessment and should be recalculated when that requirement changes. DOGC-PoS therefore complements rather than replaces threshold-based exploration PoS by addressing a different decision question: whether the expected performance of the geothermal system is sufficient for a specified use.

This distinction is especially important when PoS is extended from exploration or well-performance assessment to the performance of the complete geothermal system. Reservoir thickness and permeability jointly influence hydraulic productivity, while flow rate and the temperature difference between production and reinjection control thermal power. The amount of thermal energy produced further depends on operating duration and system configuration. Evaluating these variables through separate thresholds may therefore not capture combinations in which one property partly compensates for another when system output is considered. Schulz et al. (2007) already recognized this distinction by noting that geothermal performance could ultimately be expressed through thermal power rather than through independent temperature and flow-rate conditions.

Reservoir-quality mapping illustrates a related distinction at the spatial scale. Franz et al. (2018) integrated facies interpretation, sandstone thickness, porosity, permeability, and reservoir characterization to identify promising parts of the Rhaetian reservoir system. Such maps provide an essential basis for predicting where productive reservoir conditions may occur. Franz et al. (2018), however, distinguish reservoir-quality assessment from the probability of commercial success. A high-quality reservoir body therefore indicates geological potential, but does not by itself determine whether a particular thermal-energy requirement will be satisfied.

DOGC-PoS builds on this geological and hydraulic information by using it within a system-performance assessment. Geological and hydraulic parameters remain fundamental controls on performance and may also retain their established role as measurable criteria for exploration-risk assessment. Within DOGC-PoS, however, they are propagated as uncertain variables or operational constraints through the performance model rather than serving as the final definition of system-level success. The resulting thermal output is then evaluated against the specified project requirement.

The present spatial results illustrate the consequence of this distinction. Locations characterized by greater reservoir thickness and higher permeability repeatedly achieve higher PoS than neighbouring lower-quality areas, confirming the importance of the underlying reservoir properties. However, the calculated system-level PoS changes when the required thermal output changes. Geological reservoir quality therefore controls the relative performance potential of a location, while the selected output requirement determines whether that performance satisfies the specified project objective.

Static geological and hydraulic thresholds therefore remain appropriate for reservoir screening, well-performance evaluation, exploration-risk assessment, and insurance where clearly measurable completion criteria are required. DOGC-PoS addresses a complementary question by evaluating whether the resulting geothermal system is likely to meet a specified thermal requirement under defined geological, operational, and demand assumptions. The two approaches should therefore not be regarded as competing definitions of PoS, but as assessments directed at different stages and decision objectives within geothermal project development.

4.2. Success Should Be Redefined as a Targeted Heat Output

If geological and hydraulic parameters are controls on performance rather than final success criteria, the next question is what quantity should define success. For heat-producing geothermal systems, the most direct project-relevant criterion is whether the system can provide the required thermal output over the relevant assessment period. This may be expressed as thermal energy, thermal power, or another explicitly defined performance requirement appropriate to the project.

Output-oriented approaches already represent an important transition in geothermal PoS methodology. Van Wees et al. (2012), for example, propagated geological and engineering uncertainty through a geothermal doublet model and assessed the probability of achieving a minimum thermal-power requirement. Such approaches move the assessment closer to the actual function of the geothermal project because they evaluate the combined consequences of uncertain subsurface and engineering conditions rather than requiring each parameter to exceed an isolated threshold.

A further step is required, however, to make the output criterion fully project-specific. A thermal-output value has decision meaning only in relation to what the system is expected to supply. A reservoir capable of supplying one consumer may be inadequate for another. The same system may also satisfy demand during part of the year while failing during periods of higher load. Consequently, success cannot be defined independently of the magnitude, temporal structure, and required coverage of heat demand.

This principle is explicitly incorporated within DOGC-PoS. Demand is not applied after calculation of an already established geological probability. It forms part of the definition of the successful event itself. A realization is successful when the simulated thermal output equals or exceeds the thermal-energy or thermal-power requirement selected for the same assessment period. The resulting PoS is therefore conditional on both the possible performance of the geothermal system and the output expected from it.

The earlier demand-oriented application at Güstrow demonstrated this relationship temporally. Identical geological input distributions produced different monthly PoS values for different consumer categories and seasons because the amount of required heat changed. The permeability associated with a selected PoS also changed between months, demonstrating that even a geological threshold can become demand-dependent when interpreted through a performance objective rather than treated as a universal value.

The spatial application presented in this study extends the same principle across a heterogeneous reservoir system. The geological framework, reservoir geometry, operational assumptions, and modeling procedure were kept constant, while the monthly thermal-energy requirement was increased from 1,000 to 2,500 and 5,000 MWh. The resulting PoS declined systematically with increasing demand. Areas with moderate or high probabilities at 1,000 MWh/month contracted as the target increased, with higher probabilities becoming progressively concentrated within fewer reservoir bodies at 5,000 MWh/month.

This result illustrates, by construction, that PoS is not an intrinsic characteristic of a reservoir body or geographic location. The subsurface did not change between the three scenarios. What changed was the criterion against which the same uncertain geological conditions were judged. A location that is highly likely to supply 1,000 MWh/month may have a substantially lower probability of supplying 2,500 or 5,000 MWh/month. The meaning of success is therefore conditional on the intended application.

At the same time, increasing demand did not randomly reorganize the spatial ranking of the reservoir system. Locations associated with more favorable combinations of reservoir thickness and permeability generally retained higher PoS than surrounding locations as the output requirement increased. This reveals an important separation

between two controls. Geology governs the relative capacity of various locations to perform, while demand governs the absolute probability that the performance of any location is sufficient. DOGC-PoS connects these controls by evaluating geologically and operationally plausible performance against an explicit project requirement.

This interpretation also clarifies why a demand-oriented PoS should not be understood as replacing geological assessment with energy-system analysis. The output target determines which simulated states count as successful, but the distribution of simulated output remains controlled by the geological, hydraulic, operational, and modeling assumptions supplied to the calculation. The demand criterion therefore provides the decision boundary, while geological and technical conditions determine how likely the system is to cross that boundary.

Defining success at the level of targeted heat output consequently improves both interpretation and transferability. A PoS value can be reported together with the demand target, assessment period, operating assumptions, and system configuration under which it was obtained. Alternative consumers, development concepts, seasonal requirements, well configurations, or required fractions of demand coverage can then be evaluated consistently without redefining the underlying geological system. In this sense, DOGC-PoS changes PoS from a generalized rating of reservoir favorability into a conditional probability that the geothermal system will fulfill its intended function.

4.3 Uncertainty Analysis and Quantification in PoS Assessment Is Essential

At a fundamental level, probability becomes relevant only when the outcome being assessed is uncertain. If an outcome were known with certainty, there would be no meaningful probability to estimate. Probability of Success therefore presupposes uncertainty. This is particularly relevant to geothermal projects, where major decisions must be made before reservoir conditions and future system performance can be observed completely. Before drilling, reservoir presence, geometry, depth, temperature, hydraulic properties, connectivity, fluid composition, and spatial heterogeneity remain uncertain, while drilling and operation introduce or reveal additional uncertainties concerning productivity, injectivity, pressure response, thermal decline, equipment reliability, and long-term heat delivery.

Uncertainty should also be distinguished from risk. Uncertainty arises from incomplete knowledge, measurement limitations, interpretation, natural variability, and imperfect prediction, whereas risk emerges when uncertain outcomes are considered together with their probability and consequences for a defined objective (Ross, 2004; Trainor-Guitton et al., 2016; Witter et al., 2018; BVEG and DGMK, 2024). An uncertain permeability value, for

example, becomes a project risk when it creates the possibility that the required production rate or thermal output cannot be achieved. The relevance of uncertainty is therefore inseparable from the project objective.

Uncertainty analysis and uncertainty quantification serve related but different purposes. Uncertainty analysis identifies the uncertain variables, assumptions, dependencies, geological interpretations, and processes that may influence the outcome. Uncertainty quantification represents selected uncertainties mathematically and propagates them through the model. Merely identifying permeability, reservoir thickness, temperature, or demand as uncertain does not reveal their effect on project performance. Conversely, assigning probability distributions without considering their physical meaning, geological relationships, or spatial structure may provide numerical precision without adequately representing the underlying system.

A useful distinction is commonly made between epistemic uncertainty and aleatory variability. Epistemic uncertainty results from incomplete knowledge and may be reduced through additional drilling, seismic investigation, hydraulic testing, monitoring, model calibration, geological reinterpretation, and data assimilation (Bond, 2015; Witter et al., 2018). Aleatory variability reflects heterogeneity or variability that cannot necessarily be eliminated through additional observations. At reservoir scale, this may include small-scale variations in grain size, cementation, pore structure, fractures, and permeability, while comparable variability occurs on the demand side through short-term consumption and behavioral variation (Witter et al., 2018; Kim and Park, 2025). Distinguishing between these uncertainty types is important because epistemic uncertainty may justify additional data acquisition or Value of Information analysis, whereas aleatory variability generally needs to be accommodated within probabilistic assessment and system design (Dowd, 2018; Witter et al., 2018).

Uncertainty also evolves throughout the geothermal project. During exploration, uncertainty is dominated by geological interpretation and the predicted presence, geometry, temperature, quality, and connectivity of the reservoir. Drilling and appraisal reduce some of these uncertainties while providing new information on productivity, injectivity, fluid chemistry, pressure response, and hydraulic communication. During operation, uncertainty increasingly concerns dynamic reservoir response, scaling, corrosion, reinjection effects, thermal depletion, equipment availability, and changing demand (Yin et al., 2020; BVEG and DGMK, 2024; Hoteit et al., 2023; Shoeibi Omrani et al., 2025; Opgenoort et al., 2025; Kumar and Yelam, 2025). PoS should therefore be considered updateable as new geological, drilling, testing, production, monitoring, and demand information becomes available.

Geological uncertainty forms the foundation of geothermal PoS because subsurface conditions control fluid circulation and heat extraction. Relevant uncertainties concern reservoir geometry, thermal and hydraulic

properties, lithofacies and structural architecture, fluid properties, and the connectivity and continuity of productive intervals (BVEG and DGMK, 2024; Szklarz et al., 2024). Their uncertainty reflects spatial heterogeneity as well as incomplete observations and geological interpretation. Reservoir properties may vary with depositional environment, grain size, burial history, compaction, diagenesis, faulting, and stratigraphic continuity (Kristensen et al., 2016; Weibel et al., 2020; Yin et al., 2020).

These parameters should not automatically be treated as statistically independent. Porosity, permeability, grain size, facies, mineralogy, burial depth, and diagenetic alteration may be physically related, while structural architecture influences reservoir continuity and connectivity (Kristensen et al., 2016; Yin et al., 2020). Independent sampling of dependent parameters can therefore create combinations that are statistically permissible but geologically implausible. Conditional distributions, facies-specific parameterization, explicit correlation structures, or alternative geological scenarios may be required where such relationships materially influence the calculated performance (Yin et al., 2020; Gambini et al., 2025).

Operational uncertainty influences how effectively the geological resource can be converted into useful heat. Well operation, system configuration, pumping conditions, reinjection temperature, and operational availability can all affect achievable thermal output (Szklarz et al., 2024). Geological and operational conditions are also coupled. An operating strategy suitable for one realization of permeability or reservoir connectivity may perform differently under another, while changes in pressure difference or well spacing can modify production and long-term thermal response (Wang et al., 2025). PoS should therefore represent the performance of the reservoir together with the operating conditions under which it is intended to function.

Demand introduces an additional source of uncertainty and, within a demand-oriented PoS framework, also defines the performance requirement. Heat demand varies with season, weather, occupancy, user behavior, building characteristics, network development, and other technical and socio-economic factors (Shamsi et al., 2020; Sporleder, 2024). Uncertainty in demand influences system sizing, operating strategy, thermal storage, auxiliary heat requirements, supply reliability, and cost (Sporleder, 2024; Opgenoort et al., 2025). A geological realization that is sufficient for one consumer or season may therefore be insufficient for another. Geological conditions, operating strategy, and demand should be evaluated together when their interaction determines whether the project objective is achieved (Hoteit et al., 2023).

Model-related uncertainty must likewise be recognized. Conceptual models, governing equations, boundary conditions, parameterization, spatial interpolation, numerical resolution, input distributions, and omitted processes all influence probabilistic predictions (Witter et al., 2018; Yin et al., 2020; Bao et al., 2025; Gambini et al., 2025).

Simplifying assumptions such as homogeneous properties, constant parameters, steady-state conditions, or fixed operating conditions may be necessary, particularly during early project stages, but the resulting PoS remains conditional on those assumptions. Increasing the number of Monte Carlo realizations can reduce sampling variability but cannot compensate for an inadequate geological model, inappropriate distributions, unrealistic parameter relationships, or omitted physical processes (Witter et al., 2018; Bao et al., 2025).

Deterministic calculations remain useful for reference cases and model evaluation, but one combination of permeability, thickness, temperature, drawdown, reinjection conditions, and demand provides only one possible performance estimate. It does not show the range of plausible outcomes or the frequency with which the required project target would be satisfied. Probabilistic methods address this limitation by propagating uncertain conditions through the performance model and producing a distribution of possible outcomes. Monte Carlo simulation has therefore been applied increasingly in geothermal assessment to represent uncertainty in reservoir properties, hydraulic response, heat production, resource estimates, and economic performance (Trainor-Guitton et al., 2016; Witter et al., 2018; Zimmermann et al., 2019; Wang et al., 2023).

Sensitivity analysis and Value of Information analysis can further identify which uncertainties have the greatest influence on performance and where reducing uncertainty would provide the greatest decision value (Dowd, 2018; Witter et al., 2018; Shoeibi Omrani et al., 2025). This is important because not every uncertain parameter needs to receive the same level of investigation or probabilistic detail. The uncertainty representation should reflect the decision being made, the available information, and the relative influence of the uncertain variables on the probability of achieving the project objective.

The present DOGC-PoS application demonstrates this principle in a deliberately restricted form. Reservoir thickness and permeability are treated as spatially varying uncertain parameters and propagated through the hydraulic and thermal-production model using Monte Carlo simulation. The resulting PoS therefore represents uncertainty associated specifically with these two reservoir properties under otherwise fixed assumptions. Temperature variation, reservoir connectivity, fault behavior, compartmentalization, injectivity, operational availability, long-term thermal decline, and other sources of uncertainty are not represented probabilistically in the present proof-of-concept application.

This limitation illustrates an important principle of PoS assessment: a calculated probability represents only the uncertainty space included in the model. A numerically precise PoS should therefore not be interpreted as a complete probability of project success unless the relevant geological, operational, demand-side, and model-

related uncertainties have been represented accordingly. Transparent reporting of which uncertainties are included, which are held constant, and which assumptions condition the calculation is essential.

Uncertainty analysis and quantification are therefore not optional additions to PoS assessment. They provide the mechanism through which incomplete knowledge and variability are translated into a probability of meeting the defined project objective. PoS should consequently be interpreted as a conditional and updateable probability based on the information available, the geological interpretation, the uncertainty representation, the operating assumptions, the assessment period, and the selected definition of success.

4.4. Quantitative Models Cannot Fully Capture Geological Complexity

Uncertainty quantification is essential for Probability of Success assessment, but mathematical treatment of uncertainty does not by itself ensure geological realism. Reservoir properties are structured by depositional architecture, burial history, structural development, diagenesis, cementation, dissolution, compaction, and fracturing. Probability distributions may therefore contain individually plausible values while still producing combinations or spatial patterns that are inconsistent with the geological system.

This is particularly important in sedimentary hydrothermal reservoirs. Franz et al. (2018) demonstrated for the Rhaetian Deltaic System of the North German Basin that high-quality sandstone reservoirs are concentrated within specific depositional environments, particularly distributary-channel belts and related sandstone bodies, while adjacent facies may contain thinner sediments or poorer hydraulic properties. Their facies, sandstone-thickness, and reservoir-quality maps were constructed by integrating sedimentological and paleontological interpretation with core and wireline data, petrography, diagenetic analysis, geochemistry, and hydraulic characterization. The resulting numerical reservoir representation is therefore not merely an interpolation of measurements, but an expression of the underlying geological model.

Zimmermann et al. (2019) demonstrated the consequences of this relationship directly for geothermal risk assessment. By combining subsurface reservoir mapping with Monte Carlo simulation, they showed that facies-informed representation of sandstone thickness can produce different predictions from conventional spatial interpolation and consequently alter stochastic estimates of flow rate and productivity. Treating the entire formation as one statistical population could instead combine observations from productive channel sandstones, marginal deposits, and poorer reservoir facies. Although such a distribution might reproduce the overall numerical range of reservoir properties, its realizations would not necessarily represent geologically coherent reservoir conditions.

Schumacher et al. (2020) provide an important example of incorporating geological conditioning directly into a quantitative PoS methodology. Their approach for clastic reservoirs in the North German Basin combines hydraulic well tests, core measurements of porosity and permeability, and porosity estimates derived from sonic, density, and neutron logs. Where direct permeability information is unavailable, reservoir-specific porosity-permeability relationships are used to infer hydraulic properties. Importantly, the reference data are not selected solely according to geometric distance. For the Rhaetian fluvial sandstone reservoir, an elliptical hydraulic-data search area is aligned with the interpreted paleoflow direction and expected channel geometry, while temperature observations are evaluated in relation to geological influences such as nearby salt structures. The statistical population entering the PoS calculation is therefore conditioned by geological comparability as well as spatial proximity.

The importance of Schumacher et al. (2020) extends beyond increasing the amount of usable hydraulic information. Their study demonstrates that geological interpretation influences which observations are considered representative and which empirical relationships can reasonably be used. This also exposes a limitation: a porosity-permeability relationship developed for a particular clastic reservoir reflects its depositional setting, pore structure, and diagenetic history and cannot automatically be transferred to geologically different reservoirs.

The carbonate examples of Käsbohrer et al. (2025) make this limitation particularly clear. As illustrated in Figure 6, the Rüdersdorf Schaumkalk can contain substantial moldic porosity produced by dissolution while retaining very low permeability and transmissivity because much of the pore space is poorly connected. The Korallenoolith Formation similarly shows how sparry calcite cementation can occlude primary pore space and how fractures may themselves become mineralized. These examples demonstrate that neither porosity nor visible fracturing can be translated directly into hydraulic productivity without considering pore geometry, connectivity, lithology, and diagenetic history. A porosity-permeability relationship applicable to interconnected fluvial sandstones could therefore substantially overestimate the hydraulic performance of a carbonate reservoir dominated by isolated moldic pores.

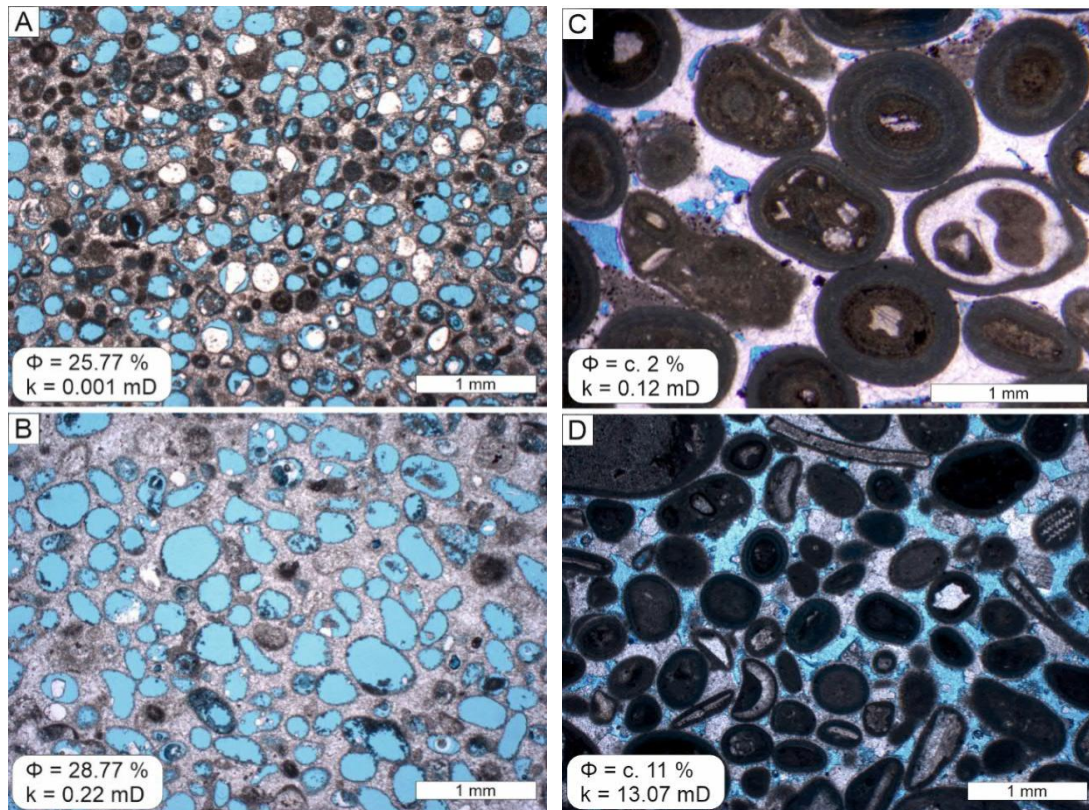


Figure 6. Petrographic examples illustrating the geological dependence of porosity-permeability relationships in Mesozoic carbonate reservoirs of the North German Basin. Panels A and B show mouldic porosity in the Rüdersdorf Schaumkalk, where comparatively high porosity is associated with very low permeability because much of the pore space is poorly connected. Panels C and D show oolitic facies of the Korallenoolith Formation with differing degrees of calcite cementation and pore connectivity. The examples demonstrate that porosity cannot be translated directly into hydraulic performance without considering pore geometry, connectivity, and diagenetic history. Reproduced from Käsbohrer et al. (2025), Figure 3.

The same geological dependence remains relevant even when more advanced methods are used. Käsbohrer et al. (2025) describe how high-resolution three-dimensional seismic data and machine-learning-assisted interpretation can improve the identification of fluvial sandstone bodies and reduce uncertainty in reservoir prediction. Such methods can substantially improve spatial characterization, but their geological meaning must still be evaluated against cores, wireline logs, depositional models, petrophysical measurements, and appropriate analogs. Quantitative and data-driven methods can therefore strengthen geological interpretation, but they cannot replace it.

The combined lessons from Franz et al. (2018), Zimmermann et al. (2019), Schumacher et al. (2020), and Käsbohrer et al. (2025) establish why geological conditioning is a necessary component of DOGC-PoS. Geological information should not enter a probabilistic model merely as a collection of numerical observations from which

regional distributions are constructed. Instead, geological interpretation should constrain the selection and spatial transfer of observations, the applicability of parameter relationships and probability distributions, and the plausibility of resulting reservoir configurations. Geological setting and data quality therefore become integral to the construction of the probabilistic model rather than serving only as background information.

The spatial application presented in this study provides a controlled demonstration of geological conditioning in DOGC-PoS. If one common permeability distribution and one common reservoir-thickness distribution had been applied throughout the Rhaetian reservoir system, the formation would effectively have been represented as a homogeneous statistical population. Although such an approach could preserve the regional numerical ranges of both parameters, it would remove their spatial organization within individual reservoir bodies and produce a PoS representative of an average statistical reservoir rather than the locally varying geological conditions.

DOGC-PoS instead introduces geological conditioning before the probabilistic performance calculation. Reservoir thickness distributions are assigned according to mapped reservoir classes, while local permeability distributions reflect the spatial arrangement of permeability observations. The resulting PoS surfaces are therefore spatially heterogeneous rather than representing one uniform regional probability field.

The results also show that geological conditioning and demand orientation have complementary roles. Geological heterogeneity controls the relative ranking of locations, whereas the thermal-energy target determines the absolute probability that a location is classified as successful. Consequently, reservoir bodies that perform comparatively well at 1,000 MWh/month generally retain their relative ranking as demand increases, although their PoS declines at higher targets. The resulting maps are therefore not direct reproductions of the geological input maps, but demand-conditioned transformations of geological information through the hydraulic, thermal, and probabilistic model.

The present geological conditioning nevertheless remains a proof of concept. The four-nearest-neighbor inverse-distance-weighting procedure does not explicitly represent paleoflow direction, anisotropy, hydraulic connectivity, compartmentalization, fault effects, or uncertainty in the interpolation itself, while the mapped reservoir geometry is treated as fixed. Future applications could incorporate original georeferenced well and seismic data, facies-constrained geostatistics, alternative geological realizations, or Bayesian approaches to represent these uncertainties more explicitly.

These limitations illustrate why uncertainty quantification and geological conditioning must be used together. Monte Carlo simulation can propagate the distributions supplied to it, but it cannot determine whether those

distributions or spatial relationships are geologically appropriate. Geological interpretation, conversely, can constrain plausible reservoir states but cannot by itself quantify the probability that the required heat output will be achieved.

This complementarity is a defining characteristic of DOGC-PoS. Geological interpretation constrains plausible probabilistic inputs, uncertainty quantification propagates them through the system-performance model, and the resulting outputs are evaluated against a project-specific thermal requirement. The contribution of DOGC-PoS therefore lies not in any individual numerical technique, but in integrating geological conditioning, uncertainty propagation, performance modeling, and a demand-oriented definition of success within one assessment framework.

Within the methodologies reviewed in this study, this integration provides a more comprehensive basis for geothermal PoS assessment because characteristics that are often treated separately are connected within a common logic. The Rhaetian application illustrates this directly: geological heterogeneity controls the spatial distribution of reservoir quality, probabilistic modeling represents the range of possible performance, and the selected thermal-energy target determines whether that performance is sufficient to constitute success.

5. Conclusion

The review of existing geothermal Probability of Success methodologies shows a clear methodological progression from qualitative geological judgment and component-based exploration probabilities toward quantitative, stochastic, and performance-oriented assessment. Reference-well statistics, geostatistical modeling, Monte Carlo simulation, reservoir-performance modeling, and geological mapping have substantially improved the representation of subsurface uncertainty and exploration risk. Nevertheless, a recurring conceptual limitation remains: suitable geological conditions or the attainment of individual thresholds for temperature, permeability, transmissivity, productivity, or flow rate do not necessarily establish whether a geothermal system will fulfill the function for which it is being developed.

This study therefore proposes the Demand Oriented, Geologically Conditioned Probability of Success framework (DOGC-PoS), in which success is defined as the probability that a geothermal system will meet or exceed an explicitly defined thermal-energy, thermal-power, or other project-specific performance target over a corresponding assessment period. Geological and hydraulic parameters remain fundamental because they control the range of possible system performance, but they are treated as uncertain inputs and constraints rather than as

independent final definitions of success. PoS consequently becomes a conditional measure that depends on the geological interpretation, uncertainty representation, system configuration, operating assumptions, assessment period, and performance requirement against which the system is evaluated.

The framework also establishes that uncertainty quantification and geological conditioning cannot be separated. Probabilistic simulation can propagate uncertainty through a performance model, but it cannot determine whether the distributions, parameter relationships, or spatial structures supplied to that model are geologically plausible. Geological interpretation provides this constraint by determining which observations are representative, which parameter relationships are transferable, how reservoir properties are spatially organized, and which combinations of conditions constitute plausible reservoir states. DOGC-PoS therefore connects geological interpretation, uncertainty representation, performance modeling, and the definition of success within one assessment logic rather than treating them as independent components.

The spatial application to the Rhaetian Deltaic System demonstrates the consequences of this integration. Reservoir thickness distributions were conditioned by mapped reservoir classes, while local permeability distributions reflected the spatial arrangement of permeability observations. Propagating these locally varying geological conditions through the same hydraulic and thermal model produced strongly heterogeneous PoS surfaces. Under otherwise identical assumptions, increasing the monthly thermal-energy target from 1,000 to 2,500 and 5,000 MWh progressively reduced PoS and contracted the spatial extent of higher-PoS areas. Locations associated with greater reservoir thickness and higher permeability generally retained their relative advantage as demand increased, but their absolute probability of satisfying the required output declined.

The results therefore demonstrate the complementary roles of geology and demand. Geological heterogeneity determines the relative performance potential of different locations, whereas the selected performance requirement determines whether that potential is sufficient to constitute success. A reservoir body consequently does not possess one permanent Probability of Success. The same geological conditions can correspond to a high PoS for one heat requirement and a substantially lower PoS for another. In this sense, PoS should be interpreted not as an intrinsic property of a reservoir or geographic location, but as the probability of fulfilling a specified project objective under explicitly stated conditions.

The Rhaetian application remains a controlled proof of concept rather than a regional drilling-location forecast. Only permeability and reservoir thickness were treated as spatially varying uncertain parameters, while temperature variation, geological-model uncertainty, hydraulic connectivity, classification, fault behavior, injectivity, operational availability, well configuration, thermal decline, and long-term reservoir response were not

propagated probabilistically. Future implementations should incorporate these uncertainties where appropriate and use original georeferenced geological, well, seismic, operational, and demand data. Alternative geological realizations, facies-constrained geostatistical methods, sensitivity analysis, Bayesian updating, and Value of Information analysis could further strengthen the framework and support its application throughout successive stages of geothermal development.

DOGC-PoS is therefore not proposed as a universal numerical algorithm or as a replacement for geological, technical, economic, environmental, regulatory, or social assessment. Its contribution is the methodological relationship it establishes among these elements relevant to performance assessment: geological understanding constrains the plausible system states, uncertainty analysis represents what is not known, probabilistic modeling propagates those uncertainties into possible system outcomes, and the project-specific requirement determines which outcomes constitute success. By making this relationship explicit, geothermal Probability of Success can move from a generalized rating of reservoir quality toward a transparent, adaptable, and decision-relevant assessment of whether a geothermal system is likely to fulfill its intended function.

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List of abbreviations and symbols

Abbreviations and methodological labels

Abbreviation / symbol	Definition
PoS	Probability of Success
DOGC-PoS	Demand Oriented, Geologically Conditioned Probability of Success
BVEG	Bundesverband Erdgas, Erdöl und Geoenergie e.V.
DGMK	Deutsche Wissenschaftliche Gesellschaft für nachhaltige Energieträger, Mobilität und Kohlenstoffkreisläufe e.V.
REM	Reverse Enthalpy Methodology
GIS	Geographic information system
RGB	Red-green-blue color space
LLM	Large language model
NPV	Net present value

Symbols and indices

Abbreviation / symbol	Definition
Pr	Probability operator; Pr(A) denotes the probability of event A
P _g	Geological Probability of Success in component-based methodologies
P _{heat}	Probability assigned to the heat component in the Bartakovics (2014) geological PoS formulation
P _{reservoir}	Probability assigned to the reservoir component in the Bartakovics (2014) geological PoS formulation
P _{system closed}	Probability assigned to the closed-system component in the Bartakovics (2014) geological PoS formulation

Abbreviation / symbol	Definition
P_{dynamics}	Probability assigned to the hydraulic-dynamics component in the Bartakovics (2014) geological PoS formulation
T	Reservoir temperature
T_{min}	Required minimum reservoir temperature
Q	Volumetric flow rate
Q_{min}	Required minimum volumetric flow rate
S	Transmissivity
S_{min}	Required minimum transmissivity threshold
P_{th}	Thermal power
P_{min}	Required minimum thermal-power target
$\text{PoS}_{\text{Total}}$	Total Probability of Success in the BVEG and DGMK (2024) framework
PoS_{t}	Technical Probability of Success
PoS_{g}	Geological Probability of Success
PoS_{o}	Operational Probability of Success
$\text{PoS}_{\text{e}}(t)$	Conditional economic Probability of Success
P_{c}	Commercial Probability of Success in the Reverse Enthalpy Methodology
E_{th}	Thermal energy
ρ_{f}	Density of the geothermal fluid
c_{p}	Specific heat capacity of the fluid in the reviewed BVEG and DGMK formulation
c_{f}	Specific heat capacity of the geothermal fluid in the DOGC-PoS calculation
ΔT	Temperature difference between produced and reinjected geothermal fluid
Δt	Operating or assessment period
k	Intrinsic permeability
K_{f}	Hydraulic conductivity
H	Aquifer or reservoir thickness in the hydraulic flow equation; in the present DOGC-PoS application, H denotes reservoir thickness
s	Drawdown
R	Radius of influence of the pumping well
r	Well radius
μ_{f}	Dynamic viscosity of the geothermal fluid
g	Gravitational acceleration
$E_{\text{simulated}}$	Simulated thermal-energy output
E_{target}	Specified thermal-energy target used to define success
N_{Total}	Total number of Monte Carlo realizations in the preceding demand-oriented PoS formulation
$\mathcal{G}$	Adopted geological interpretation and geological uncertainty in the general DOGC-PoS definition

Abbreviation / symbol	Definition
$\mathcal{O}$	System configuration and operational assumptions in the general DOGC-PoS definition
$\mathcal{D}$	Magnitude and temporal structure of heat demand in the general DOGC-PoS definition
$\mathcal{M}$	Selected hydraulic and thermal-performance model in the general DOGC-PoS definition
$\mathcal{I}$	Information available at the time of assessment in the general DOGC-PoS definition
$H_{\text{low}}, H_{\text{medium}}, H_{\text{high}}$	Triangular reservoir-thickness distributions assigned to the low, medium, and high mapped reservoir classes
$k_{\text{low}}, k_{\text{medium}}, k_{\text{high}}$	Triangular permeability distributions assigned to the low, medium, and high permeability classes
C_i	Numerical permeability-class score assigned to observation i
k_i	Permeability represented by observation i
$C(x)$	Interpolated permeability-class score at spatial location x
$N_4(x)$	Set of the four permeability observations nearest to spatial location x
$w_i(x)$	Inverse-distance weight assigned to observation i at spatial location x
$d_i(x)$	Distance between spatial location x and observation i
d_{min}	Small lower distance limit used to avoid singular inverse-distance weighting
α	Linear interpolation factor between adjacent permeability-class distributions
$\theta_k(x)$	Parameter vector of the local triangular permeability distribution at spatial location x
θ_k	Triangular permeability parameter vector ($k_{\text{min}}, k_{\text{mode}}, k_{\text{max}}$)
$k_{\text{min}}, k_{\text{mode}}, k_{\text{max}}$	Minimum, modal, and maximum permeability values of a triangular distribution
x	Spatial location of an individual raster cell
i	Permeability-observation index
j	Monte Carlo realization index
N	Number of Monte Carlo realizations per raster cell
$k_j(x)$	Sampled permeability for realization j at spatial location x
$K_{f,j}(x)$	Hydraulic conductivity for realization j at spatial location x
$R_j(x)$	Radius of influence for realization j at spatial location x
$Q_j(x)$	Volumetric flow rate for realization j at spatial location x
$H_j(x)$	Sampled reservoir thickness for realization j at spatial location x
$P_{\text{th},j}(x)$	Thermal power for realization j at spatial location x
$E_j(x)$	Thermal energy for realization j at spatial location x
$I[\cdot]$	Indicator function equal to one when the specified success condition is satisfied and zero otherwise
$\text{PoS}(x, E_{\text{target}})$	Cell-specific Probability of Success at spatial location x for the specified thermal-energy target

Abbreviation / symbol	Definition
PoS ₁₀₀₀ (x), PoS ₂₅₀₀ (x), PoS ₅₀₀₀ (x)	Cell-specific PoS for monthly thermal-energy targets of 1,000, 2,500, and 5,000 MWh, respectively
P10, P50, P90	Percentile estimates used to summarize simulated outcome distributions in the reviewed literature

Units

Abbreviation / symbol	Definition
MW	Megawatt
MWth	Megawatt thermal
MWh	Megawatt-hour
W	Watt
J	Joule
mD	Millidarcy
m	Meter
m ²	Square meter
m ³ h ⁻¹	Cubic meters per hour
kg m ⁻³	Kilograms per cubic meter
Pa s	Pascal-second
J kg ⁻¹ K ⁻¹	Joules per kilogram per kelvin
m s ⁻²	Meters per second squared
K	Kelvin, used for temperature differences
°C	Degrees Celsius

Availability of data and materials

The data used in this study were derived from publicly available published sources cited in the manuscript. The spatial geological inputs used for the DOGC-PoS demonstration were reconstructed from the published facies and reservoir-quality maps of Franz et al. (2018). Derived data and computational materials used for the analysis are available from the corresponding author upon reasonable request.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

Se.S. conceived the study, conducted the literature review, developed the DOGC-PoS framework, prepared and processed the spatial geological inputs, implemented the spatial interpolation and Monte Carlo workflow, performed the probabilistic analyses, prepared the figures and visualizations, interpreted the results, and wrote and revised the manuscript. U.K. provided scientific supervision, contributed to the methodological interpretation, and critically reviewed and revised the manuscript. All authors read and approved the final manuscript.

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Declaration of LLM technologies in the writing process

During the preparation and revision of this manuscript, the corresponding first author used large language models to assist with grammar and vocabulary correction, language refinement of author-written text, and occasional identification and correction of errors in Python code. All resulting text and code were reviewed and verified by the authors, who take full responsibility for the content of the manuscript.

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