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Geophysics and Artificial Intelligence: What Revolutions?

Géophysique et intelligence artificielle : quelles révolutions ?

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Abstract. The relationship between Geophysics and Artificial Intelligence is examined through the lens of the ongoing digital transformation, driven by three major revolutions that have reshaped human interaction with the natural environment: the computer revolution, the quantum revolution, and the probabilistic revolution. Within this framework, Earth Intelligence emerges as the mathematical and conceptual bridge that reconciles Geophysics with Artificial Intelligence. By integrating physical laws, probabilistic modelling, and data-driven learning, Earth Intelligence provides a unified approach that enhances the ability of geophysics to deliver more accurate, scalable, and uncertainty-aware representations of the subsurface.

Résumé. La relation entre la géophysique et l'intelligence artificielle est analysée à travers le prisme de la transformation numérique en cours, portée par trois grandes révolutions qui ont profondément modifié l'interaction de l'être humain avec son environnement naturel : la révolution informatique, la révolution quantique et la révolution probabiliste. Dans ce cadre, l'Earth Intelligence apparaît comme le pont mathématique et conceptuel permettant de réconcilier la géophysique et l'intelligence artificielle. En intégrant les lois physiques, la modélisation probabiliste et l'apprentissage fondé sur les données, l'Earth Intelligence propose une approche unifiée qui renforce la capacité de la géophysique à produire des représentations du sous-sol plus précises, plus évolutives et explicitement conscientes des incertitudes.

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1 Introduction

The Question

The ongoing digital transformation of our globalized societies is undeniably a revolution comparable to the Industrial Revolution of 18th-century in Europe. Artificial Intelligence (AI) is to this revolution what the steam engine and the railway were in their time to the Industrial Revolution. It is therefore entirely legitimate to analyse how this revolution is transforming the practice of geophysics—that is, to reflect on the relationship between AI and geophysics.

The Reflection

While history, as the science of the past, never repeats itself by definition, the idea that "it's always the same story" challenges our perception of time. On closer inspection, the Industrial Revolution emerged from the rise of scientific thinking and the growing ability of the human mind to free itself from the "objective" constraints of the natural environment, in reaction to the religious mindset of "subjective" submission to that same environment. This "rational" evolution of Western thought reformulated our perception of the Earth's environment through the development of mathematical and physical sciences, which in turn provided the natural sciences with a language suited to an operational description of the "natural" (i.e., non-manufactured) part of that environment.

The hubris of rational thought continued until the early 20th century, with the discovery of properties of matter that defied deterministic physical models—coinciding with the revelation of the unconscious workings of the psyche. We thus witnessed the simultaneous (or, more precisely, synchronistic) emergence of statistical models in quantum physics and psychological analysis. This development gradually led, a century later, to the probabilistic revolution we are experiencing today, driven by our heightened awareness of our strong interaction with the Earth's natural environment, which is no more or less natural than we are.

To deepen this reflection, I refer to "The Interpretation of Nature and the Psyche: Synchronicity—An Acausal Connecting Principle / The Influence of Archetypal Ideas on the Scientific Theories of Kepler" by Carl Gustav Jung (1875–1961) and Wolfgang Ernst Pauli (1900–1958), originally published in 1950 and 1952.

The Answer

If we share this way of thinking, we can see the synchronistic (i.e., acausal) link between geophysics and artificial intelligence. The two are indeed connected, correlated, but not causally, meaning this connection cannot be described as a set of cause-and-effect relationships. We can only account for this synchronicity by seeking to demystify and rationalize the links between geophysics and AI. This is what we propose to do by following this plan:

After establishing the current state of each field and recalling their respective objectives:

1. First, we return to the history of the computer revolution to understand its impact on the practice of geophysics and the development of AI.
2. Second, we analyse how the quantum revolution, with its discoveries and new paradigm structuring modern physics, resonates today in the practice of geophysics and the contribution of AI.
3. Third, we explore how these links are reasonably expressed using the vocabulary and tools derived from the probabilistic revolution, initiated by theories of

randomness (geostatistics and mathematical morphology) developed in France (Fontainebleau) by Georges Matheron (1930–2000).

4. Finally, we formalize a new form of AI, specific to the geosciences, called "Earth Intelligence", which rationally combines deterministic geophysical practice with the statistical tools of AI to provide its probabilistic, "quantum" version.

2 The Subjects:

2.1 Geophysics

2.1.1 Introduction

Geophysics is a science that studies the physical properties of the Earth and its environment in order to understand its internal structure and natural phenomena (earthquakes, magnetic field, gravity, etc.). Applied geophysics, the practical branch of this discipline, uses indirect methods (seismic waves, electrical and magnetic measurements, etc.) to investigate the subsurface without drilling. It relies on solving inverse problems: from the subsurface response to external stimuli (waves, fields, etc.), it reconstructs its structural and petrophysical features.

The data, initially interpreted qualitatively, are now analysed quantitatively thanks to computing and mathematical modelling, enabling practical applications in natural resource exploration/production, environmental studies, civil engineering and archaeology.

Applied geophysics practice is generally divided into Data acquisition, processing, interpretation and modelling.

2.1.2 Geophysical Methods

Geophysical methods are grouped into major categories depending on the physical property measured and the type of wave or field used. They allow imaging, characterizing, or modelling the subsurface at different scales (from meters to kilometres). Modern geophysics is a multi-physics, multi-source and multi-scale system:

- Seismic Methods (elastic waves)

- The most widely used in oil & gas exploration, deep subsurface studies, and natural hazard assessment.

  - o Reflection Seismology

- Principle: measuring the echoes of waves reflected by geological interfaces.
- Applications: oil & gas exploration, structural geology, reservoirs, 2D/3D/4D mapping.

  - o Refraction Seismics / Surface Waves

- Principle: analysis of velocities and paths of refracted or diffracted waves.
- Applications: geotechnics, bedrock depth, weathered layer.

  - o Passive Seismics

- Principle: use of natural vibrations (ambient noise, microseisms, earthquakes).
- Applications: reservoir monitoring, seismicity, volcanism.

  - o Seismic Tomography

- Principle: 2D/3D reconstruction of the velocity field from numerous seismic ray paths.
- Applications: deep structures, crustal imaging, subduction zones.

- Gravimetric Methods (gravity field)
  - Principle: gravity varies according to rock density.
  - Applications: deep structures, salt bodies, domes, upper mantle, sedimentary basins.
- Magnetic Methods (Earth's magnetic field)
  - Principle: measurement of susceptibility and remanent magnetisation anomalies.
  - Applications: structural mapping, mining (iron, nickel), dykes, basalts.
- Electrical and Electromagnetic Methods
  - Electrical (DC currents)
    - Principle: resistivity, induced polarisation (IP).
    - Applications: hydrogeology, pollution, geotechnics, mining.
  - Electromagnetic (variable-frequency EM)
    - Principle: TEM (Transient EM), FDEM (Frequency-Domain EM).
    - Applications: groundwater, basement depth, conductive ore bodies.
  - Magnetotellurics (MT)
    - Principle: uses natural variations of the Earth's EM field.
    - Applications: geothermal studies, deep structures, subduction zones.
  - CSEM / Marine EM
    - Principle: Controlled-Source EM offshore.
    - Applications: marine oil & gas exploration, identification of resistive reservoirs (gas).
- Radar and Microwave Methods
  - GPR – Ground Penetrating Radar
    - Principle: reflection of radar waves.
    - Applications: geotechnics, archaeology, infrastructure, environment.
  - Satellite Radar (InSAR)
    - Principle: space-borne radar interferometry.
    - Applications: ground deformation, landslides, volcanism, reservoir production monitoring.
- Thermal and Geothermal Methods
  - Principle: measurement of heat flux, thermal gradients, deep temperatures.
  - Applications: geothermal energy, fluid circulation, active faults.
- Radiometric Methods
  - Principle: detection of natural radiation (uranium, thorium, potassium).
  - Applications: lithological mapping, mining.
- Modern Integration: Multi-physics Geophysics and Integrated Modelling
  - Fusion of gravity + magnetic + seismic data to constrain 2D/3D models.
  - Use of supercomputers and AI for joint inversion.
  - Development of subsurface digital twins.
  - Real-time integration with production data (4D/5D).

2.1.3 Contributions of geophysics to natural environment management

Geophysics plays a fundamental role in the sustainable management of natural resources by providing objective, quantitative, and spatially continuous knowledge of the subsurface. Through indirect measurement methods, it enables the exploration and characterization of resources without disturbing the environment, optimizes their exploitation, and reduces uncertainties.

Its main contributions include:

- Subsurface knowledge: Accurate mapping of geological structures, groundwater reservoirs, hydrocarbon accumulations, and geothermal systems.
- Risk reduction: identification of natural hazards (earthquakes, landslides, subsurface cavities, instabilities) and improved safety for engineering and industrial projects.
- Resource exploitation optimization: estimation of recoverable volumes, improved planning of wells and infrastructure, production monitoring, and 4D reservoir surveillance.
- Environmental protection: monitoring of aquifers, geological CO_2 storage, and sustainable management of mineral and energy resources.
- Decision support: integration of geophysical data into predictive models and digital twins, enabling responsible and integrated resource management.

2.1.4 Controlled Source Electromagnetic

In his contribution to the Journées Scientifiques AGAP Qualité 2024, Geoffroy Paixach reports on an interview with Richard Cooper about a new geophysical subsurface exploration tool known as CSEM (Controlled-Source Electromagnetics). This provides a good illustration of the current trend toward multi-physics geophysics and integrated modeling. We reproduce below some excerpts from the full interview.

The CSEM method makes use of a high-powered electromagnetic (EM) source which is towed behind a vessel over a 2D or 3D array of previously deployed seabed EM receivers (Figure 2.1_1).

The EM receivers log the EM field induced by the EM source; they are then recovered, and the EM responses are processed and imaged to provide a 2D or 3D resistivity map of the subsurface. Several companies were launched in the early 2000’s to exploit this method including EMGS (Norway), OHM (UK) and AGO (USA). The primary application case was to detect the presence of hydrocarbons in the subsurface.

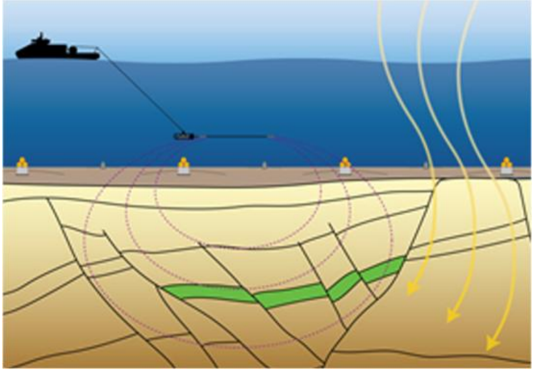


Fig. 2.1_1: The marine CSEM acquisition method

As data was acquired, it soon became clear that the industry had yet to develop the requisite processing and imaging tools needed to reliably convert the EM signals into robust resistivity maps. It was also apparent that the early marketing of CSEM data as a replacement for the seismic method was over-stated, indeed the best use of CSEM was as a complement to new or existing seismic data. By the mid-2000’s, Rock Solid Image (RSI) began to be contacted by customers, primarily in Europe, who had invested in CSEM acquisition programs but were struggling to make use of the resulting data. RSI, in partnership with OHM

(RSI and OHM later merged), began an ambitious R&D program to develop the required EM processing tools, and also, as importantly, to understand how to integrate CSEM data with seismic and borehole data (Figures 2.1_2 and 2.1_3)) to provide a more complete multiphysics representation of the sub-surface.

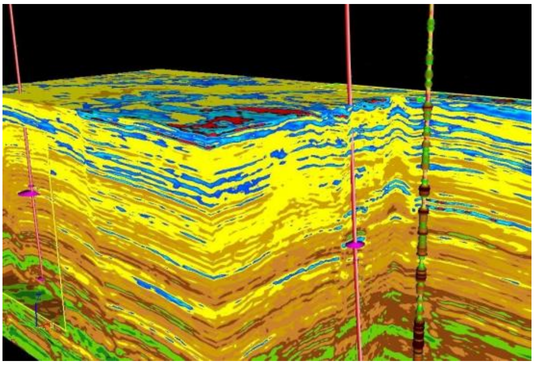


Fig. 2.1_2: Seismic and borehole data.

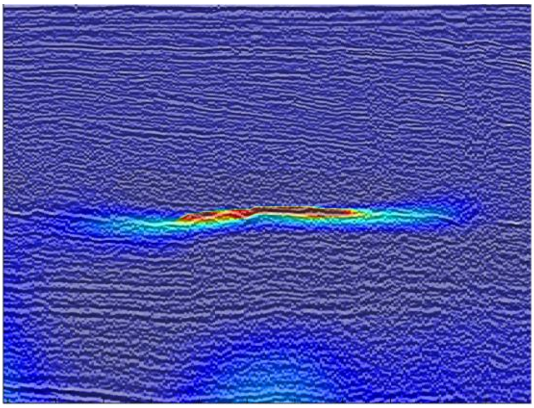


Fig. 2.1_3: Seismic and borehole data integrated with CSEM.

Despite a promising start, CSEM technology remains in only limited use today. Oil and gas companies make use of the technology in certain areas to reduce the risk of drilling expensive deep-water oil and gas wells. In addition, a number of new applications are under investigation, including the use of CSEM for monitoring carbon capture and storage systems (CCS), offshore groundwater exploration and seabed mineral exploitation.

2.2 Artificial Intelligence

2.2.1 Introduction

Artificial Intelligence (AI) is a field of computer science that aims to create systems capable of performing tasks that normally require human intelligence. These tasks include learning, reasoning, perception, natural language understanding, decision-making, problem-solving and first all computer programming.

AI relies on algorithms that enable machines to analyze data, draw conclusions, adapt to new situations, and automate complex processes.

It is generally divided into two main categories:

- Weak (or narrow) AI: designed to perform a specific task (e.g., speech recognition, content recommendation).
- Strong (or general) AI: a hypothetical form of AI capable of reasoning and learning across multiple domains, comparable to human intelligence.

Key techniques include machine learning, deep learning (neural networks), and natural language processing (LLMs). AI is the driving force behind the ongoing digital transformation, reshaping sectors such as healthcare, transportation, finance, and industry—as well as geoscience practices, including geophysics.

2.2.2 AI Methods

Artificial Intelligence encompasses a set of methods that enable a machine to perceive, reason, learn, and act. These methods fall into five major families: symbolic, statistical, connectionist, generative, and agentic.

- Symbolic AI (logic, rules, expert systems)

The first historical family of AI methods (1950–1985), based on explicit reasoning. This causal and deterministic approach is well suited to explainability but less adapted to complex or large-scale data.

  - Principles:
- Knowledge represented as logical rules (“IF… THEN”).
- Reasoning via inference, deduction, and symbolic manipulation.
  - Main methods:
- Expert systems
- Forward/backward chaining
- Knowledge representation (ontologies)
- Formal logic (LISP, PROLOG)
- Automated theorem proving
  - Applications:
- Diagnostics (medicine, chemistry)
- Structured decision support
- Industrial configurators (e.g., XCON at DEC)

- Statistical AI

AI becomes data-driven (1985–2010). This acausal approach is robust and suitable for large datasets.

  - Principles:
- Learning patterns directly from data
- Managing uncertainty using statistics
  - Main methods:
- Probabilistic models (Bayesian networks, HMMs)
- Statistical methods: (Regression, Decision trees, random forests; boosting, bagging
- SVM (Support Vector Machines)
- Clustering (k-means, DBSCAN, GMM)
  - Applications:
- Data mining, anomaly detection
- Time-series analysis
- Quantitative forecasting, classification, segmentation
- Early Big Data applications

- Connectionist AI (neural networks)

The era of deep learning (1986–present). Today this is the dominant approach due to its power, flexibility, and scalability.

- Principles:
  - Multi-layer models inspired by biological neurons
  - Learning via gradient descent and backpropagation
- Main methods:
  - Multilayer perceptrons (MLP)
  - Convolutional neural networks (CNNs): computer vision, seismic imaging 2D/3D
  - Recurrent networks (RNN, LSTM, GRU): language, time series
  - Autoencoders (AE, VAE): dimensionality reduction, latent representations
  - Generative adversarial networks (GANs)
  - Transformers (basis of LLMs such as GPT)
- Applications:
  - Vision and speech recognition
  - Signal and image analysis
  - Translation, classification, prediction
  - Geophysics: automatic seismic interpretation

- Generative AI

Generates original content (text, images, models, code). The machine no longer only predicts—it creates.

- Principles:
  - Learning data distributions
  - Generating new, plausible samples
- Main methods:
  - Diffusion models
  - GANs
  - Transformers (LLMs)
  - Variational autoencoders (VAEs)
- Applications:
  - Image, text, and video synthesis
  - Data completion, extrapolation, simulation
  - Creation of virtual geomodels
  - Geophysics: generation of synthetic seismic datasets

- Agentic AI

Acts autonomously to achieve objectives. AI no longer only responds—it performs.

- Principles:
  - Learning through interaction and sequential decision-making (Reinforcement Learning, RL)
  - Optimization of cumulative reward
- Main methods:
  - Q-learning
  - Deep Reinforcement Learning (AlphaGo, AlphaZero)
  - Actor-critic methods
  - Monte Carlo Tree Search (MCTS)
- Applications:
  - Complex games (Go, Starcraft, poker)
  - Autonomous agents

- Geophysics: Optimization of seismic acquisition, autonomous control and tuning of processing workflows

- Multi-agent, cognitive, and hybrid AI

Modern AI combines reasoning, perception, generation, and action.

  - Principles:

- Integration of symbolic, statistical, and neural approaches
- Cooperative or supervised agents
- Self-learning and explainable AI

  - Main methods:

- Autonomous agents (AutoGPT, Copilot, Gemini Agents)
- Chain-of-thought reasoning and planning
- Hybrid physics-informed/data-driven AI (PINNs, SciML)
- Multimodal architectures (text + image + code + numerical data)

  - Applications:

- Intelligent digital twins
- Assisted geoscientific interpretation
- Energy optimization, robotics, engineering
- Complex simulations and Earth system sciences

2.2.3 Contributions of AI to Geophysics

Artificial intelligence is progressively augmenting geophysics in all its components by automating, accelerating, and improving the reliability of acquisition, processing, interpretation, and modelling workflows.

- Acquisition
  - Adaptive Acquisition

- Principle: Acquisition is no longer a fixed survey plan: it evolves dynamically according to data quality and survey objectives, driven by an intelligent agent.
- Operation: After each batch of shots or measurements, an AI system evaluates:
    - achieved illumination,
    - local S/N ratio,
    - coverage vs. uncertainty,
    - fast pre-inversion indicators.

Then it automatically decides:

    - Should we densify here?
    - Should the source be moved?
    - Is acquisition sufficient to stop now?

- Expected benefits
    - 10–40% reduction in survey cost,
    - optimal coverage around critical zones,
    - reduced geological risk (fewer “blind spots”).

  - Enhanced Real-Time Quality Control

AI plays a key role in automated QC, traditionally based on manual inspection.

- Automatic anomaly detection using ML models for:
    - damaged cables,
    - faulty receivers,
    - poor coupling,
    - shot errors,
    - abnormal noise levels (wind, waves, traffic, operational noise).

- On-field Signal Enhancement (Real-Time)

- Real-time AI methods applied directly during acquisition:
    - adaptive, learning-based filtering,
    - multiple prediction,
    - missing-trace reconstruction,
    - incoherent noise suppression.
- Impact
    - immediate decisions: shoot or not, reposition, repeat,
    - reduced costs (fewer re-shoots, less downtime),
    - controlled data quality even in difficult conditions.

- Robotic Acquisition & Drones

- Autonomous drones for EM, magnetic, LiDAR, and photogrammetric surveys. AI-based navigation enables:
    - trajectory optimisation,
    - adaptive coverage depending on topography,
    - repeatable 4D measurements.
- Ground robots for seismic or light EM operations:
    - autonomous vehicles deploying/retrieving geophones,
    - self-driving lightweight vibroseis sources.
- Autonomous marine observatories:
    - self-localising OBS fleets,
    - AI-driven navigation to reduce positioning errors,
    - autonomous synchronization.

- AI Pre-Modelling & Simulation to Guide Shooting

- Real-time velocity/structural models.
  Before acquisition, AI:
    - generates plausible geological models,
    - simulates seismic response,
    - identifies poorly illuminated areas,
    - adjusts the acquisition plan.
- Fast simulation using neural networks
  Illumination or wavefront simulations can be drastically accelerated via surrogates or PINN-based models.

- Monitoring (4D / CO_2 / Geothermal)

- AI is used to:

- track microseismicity in real time,
- detect early fluid migration, leakage, or overpressure,
- correct sensor drifts,
- isolate signals related to production or saturation changes.

- In 4D seismic

- real-time alignment of vintages,
- prediction of repeatability effects,
- minimisation of non-geological perturbations.

- Processing

AI now intervenes in many processing steps. By learning the structure of the useful seismic wavefield, it enables adaptive filtering that can outperform traditional fixed filters.

- AI-Driven Denoising

- Noise types handled
    - incoherent noise (wind, swell, traffic),

    - coherent noise (ground roll, monochromatic),
    - operational artefacts (parasitic emissions, cross-talk),
    - marine streamer noise, cable noise,
    - burst noise, coupling losses.
- Techniques
    - denoising autoencoders,
    - 2D/3D CNNs learning the structure of the useful wavelet,
    - GANs for missing-signal reconstruction,
    - transformers for long-range signal structure.
- Benefits
    - more adaptive denoising than classical filters,
    - preservation of true phase and amplitude,
    - significant S/N improvement, especially in challenging (desert/offshore) environments.

o AI-Based Reconstruction & Interpolation

- Applications
    - 5D/6D interpolation (swell, irregular geometry, infill),
    - reconstruction of missing traces,
    - restoration of imperfect geometries,
    - correction of spatial aliasing.
- Methods
    - supervised deep learning (CNN, ResNets),
    - generative networks (GANs),
    - seismic super-resolution techniques.
- Impact
    - reduced need for infill acquisition,
    - improved lateral continuity,
    - enhanced frequency resolution.

o AI Wavefield Separation & Multiple Attenuation

- Applications:
    - SRME and interbed multiple attenuation,
    - up/down separation for OBS/OBC,
    - PP/PS separation,
    - removal of parasitic conversions.
- Benefits
    - reduced dependency on extremely accurate velocity models,
    - robust attenuation even in complex geology (salt, carbonates),
    - improved migration and inversion quality.

o AI-Enhanced Migration

AI can act before, during, or after migration.

- Migration optimisation
    - parameter tuning (Kirchhoff, RTM, WEM),
    - wavefield preconditioning,
    - migration artefact suppression.
- Accelerated migration
    - surrogate models approximating wave propagation,
    - drastic reduction in compute cost (HPC → GPU → AI).
- Interpretive migration
    - automatic detection of inconsistencies,
    - enhancement of weak reflectors.

- Impact
    - cleaner migrated images,
    - reduced trial-and-error cycles,
    - near-real-time migration in certain contexts.

o Inversion Preparation & Optimisation (FWI, RTM, AVO/AVA)

- Model initialisation, AI predicts:
    - initial velocity gradients,
    - deep structural trends,
    - poorly illuminated zones
    - reduces sensitivity to deterministically derived starting models (cycle-skipping).
- Hybrid inversion (PINNs)
  Networks constrained by the wave equation:
    - reduced gradient noise,
    - more stable convergence,
    - ability to incorporate statistical uncertainties.
- Parameter optimisation
  AI agents automatically analyse:
    - step length,
    - preconditioning strategies,
    - optimal smoothing,
    - frequency band selection.
- Enhanced AVO/AVA inversion
    - automatic AVO class classification,
    - estimation of Rpp/Rps gradients,
    - early detection of petrophysical anomalies.

o Specialized Processing: 4D, CO_2, Geothermal

- 4D seismic
    - automatic vintage alignment,
    - correction of acquisition variations,
    - separation of geological vs. non-geological effects,
    - early detection of saturation changes.
- CO_2 / Geothermal monitoring
    - adaptive temporal filtering,
    - microseismic event detection,
    - separation of injection-related noise,
    - probabilistic spatial analysis.

o Autonomous Processing Agents

This is the new frontier: intelligent, self-optimising seismic processing.

An AI agent can:

- test multiple denoising, migration, and inversion strategies,
- tune parameters automatically,
- determine optimal sequences,
- assess output quality using intelligent metrics.

- Interpretation

Analysis of 2D/3D/4D seismic volumes, formerly manual and time-consuming, is now performed by algorithms capable of automatically detecting:

- faults,
- horizons,
- channels,

        - canyons,
        - geobodies,
        - fracture networks,
        - seismic facies.

    - Techniques
- 2D/3D CNNs,
- transformers capturing long-range context,
- automated segmentation and supervised classification.

    - Impact
- massive time reduction: hours/days → minutes,
- improved reproducibility (reduced interpreter subjectivity),
- exhaustive mapping, including subtle/weak features.

- Modelling
    - AI-Augmented Geophysical Inversion (PINNs)

A major evolution of 2020–2025 is the convergence of physical models + learning models.

- Applications:
    - model initialisation or preconditioning (FWI, RTM),
    - fast velocity model approximation,
    - approximate solutions to physical equations via PINNs,
    - model reduction for faster simulation.
- Impact
    - significant acceleration of inversion workflows,
    - reduced non-uniqueness through statistical analysis,
    - technological foundation for subsurface Digital Twins.

    - Multi-Source & Multi-Scale Data Fusion

AI excels at combining heterogeneous datasets to produce coherent models:

    - seismic ↔ logs correlation (CNN + MLP),
    - permeability prediction from logs + seismic,
    - geostatistics + AI (co-kriging + deep learning),
    - large-scale geological pattern identification.
- Impact
    - improved vertical and lateral continuity,
    - enhanced reservoir-scale resolution.

    - Probabilistic Analysis & Uncertainty Quantification
- AI enables:
    - generation of multiple subsurface realisations (GANs, VAEs),
    - learning parameter distributions (Bayesian deep learning).
- Strategic benefit
    - more robust drilling decisions,
    - transition from deterministic to risk-oriented probabilistic modelling.

2.2.4 How good is your seismic?

When it comes to the interpretation and modeling stages, most AI contributions focus on the automatic interpretation of seismic cubes, a traditionally time-consuming step in geomodeling projects. Among the many AI and machine-learning algorithms used—most of them relying on deep learning and convolutional neural networks (CNNs), that is reproducing how human neurones work—another illustration of how AI is applied in geophysics is provided by A. Thomas and L. Lhommet at EAGE 2023, in their paper entitled “How good is your seismic? A genetic algorithm to kick-start the evaluation of CCS candidates”.

They describe “a new approach using a genetic algorithm (GA), reproducing how biologic evolution works, to automatically extract information from the 3D seismic data in an unbiased manner and in record time and show how this approach can be used to compare seismic images which have undergone different processing”.

We reproduce an excerpt from their publication below.

The artificial intelligence system is global, fully automatic, and unbiased: it only processes data, without any “a-priori”. The extraction of geological features (e.g., horizons) from seismic data can be seen as a data segmentation problem where the objective is to split the whole into the most coherent parts (Figure 2.2_1):

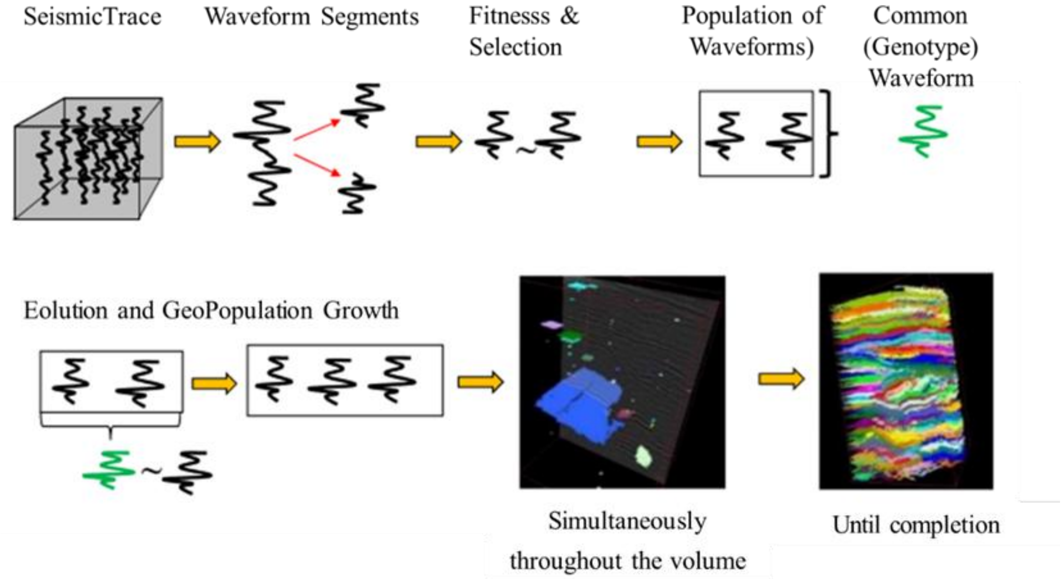


Fig.2.2_1: Principle behind the algorithm: Waveform segmentation and evolutive classification using a genetic algorithm.

The purpose of the GA is to mimic the genetic process of biological evolution based on the “survival of the fittest” principle applied to the seismic samples to produce the optimal “sub-populations” i.e. the horizons. The seismic volume is represented as a population of individuals that must be grouped into horizons throughout the process of the biological evolution. Therefore, at every generation:

– The selection - only the fittest: individuals and sub-populations that have the highest fitness (seismic similarity) are allowed to evolve. The selection is in favor of cohesion: it tends to bring together those seismic waveforms that constitute the most “balanced” horizons

– The crossover: the selected individuals and sub-populations combine their genetic information to build a new generation. The combination tends to straighten the contribution of some seismic character and therefore to maximize the intra-sub-population similarity and maximize inter subpopulation dissimilarity

– The evolution continues throughout the entire volume until all the sub-populations have been identified, characterized, and categorized into a database of horizons ready for analysis and interpretation.

The suite of attributes examined included Two Way Time (TWT), Instantaneous Amplitude (Amp) and Fitness. The “Fitness” attribute provides a measure of “genetic likeness" for each member in the population when compared to the common waveform (genotype) of the same population.

The process is very robust and repeatable allowing the user to run in parallel several volumes and compare the number of surfaces extracted as well as their characteristics (amplitude, fitness, continuity…) .

Using the fitness attribute, it is possible to scroll through large 3D seismic volumes and look for outliers, which would indicate a change of reflector geometry and geological facies, two features susceptible to draw the attention of the interpreter looking for candidates to analyse further during in the ranking process (Figure 2.2_2).

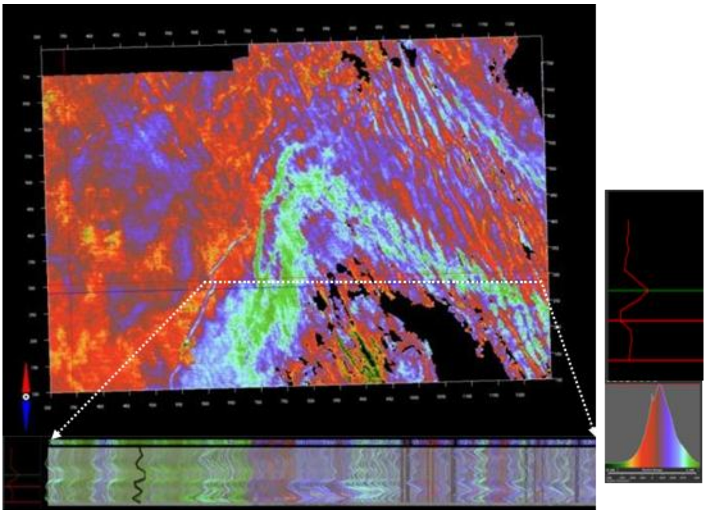


Fig.2.2_2: Example of a fitness map for a horizon (top view). High fitness between the waveform encountered and the genotype appears in green, lower fitness from blue to red. The genotype is shown at the bottom left of the picture.

Their conclusion is that with the genetic algorithm presented, it is possible to precisely compare seismic volumes which have undergone different processing and analyze in detail the variability inherent to changing imaging workflows. It also highlights the uncertainties in the final results. It remains the decision of the geoscientist to say if the presence/absence of a "hole" in a surface of interest is geological or a processing artefact.

2.3 Conclusion: A misleading picture

This overview has been written largely with the help of generative AI (ChatGPT, Mistral), both for the geophysics section and the AI section. While it appears reasonable and acceptable for the geophysics part, it becomes unrealistic, even delusional, and potentially dangerous for the AI part:

Delusional, because AI tends to take its wishes for reality: the assertive, always positive and politically correct narrative of generative AIs lacks discrimination and self-criticism. Instead of making categorical statements such as *AI predicts*, *AI enables*, *AI optimizes*, *AI identifies* (without ever providing significant quantification of these claims), it would be more appropriate to say *"AI seeks to," "AI contributes to," or "AI is used to"*.

Dangerous, because unlike geophysics—rooted in a proven scientific approach (often based on deterministic physical laws but clearly assumed and understood)—the approach of AI in geosciences presents itself as "scientific" while being based on no coherent mathematical model. This is not a neutral observation: Under the guise of scientific appearance, AI in geosciences carries a regression toward “magical thinking”, which, by definition, solves everything, if not today, certainly tomorrow.

This is a seductive narrative, but one that does not deceive practitioners and decision-makers, who remain hesitant, and rightly so, when faced in the real world with costly, high-stakes decisions in projects connected to our natural environment.

The 10 Main Criticisms Geophysicists Raise About AI:

1. Does not respect physics → leads to inconsistencies and unreliable results,
2. No quantified uncertainty → unfit for decision-making,
3. Strong dependence on the training dataset → prevents generalization,
4. Black-box behaviour and lack of quality control,
5. Smoothing / hallucinations → loss of operational value,
6. Performance still limited, with major challenges for industrial deployment,
7. Excessive automation → risk of expertise loss,
8. Non-reproducibility → unstable workflows,
9. High computational cost → practical barrier,
10. Ethical issues regarding responsibility → organizational resistance.

The risk for geophysicists when facing AI is either to “throw the baby out with the bathwater,” or, conversely, to let a form of magical thinking creep into their practice—accepting models merely because “it’s better than nothing.” This would be paradoxical, after so many years of effort and success in bringing geophysical data to a level of reliability comparable (at its own scale) to direct field measurements.

3 The Computing Revolution

3.1 The Foundation: Zero, One, many…

Since their creation after the Second World War and up to the present day, computers have operated on a binary system, i.e., using only two digits: 0 and 1. All information—whether a number, an image, or a video—is encoded in this base-2 system as bits (short for *binary digit*).

A bit is the elementary unit of information: In a classical (pre-quantum) computer memory, it can take only two states, often represented as “off/on” or “false/true.” Bits are grouped into bytes, sets of 8 bits. A byte can therefore represent 256 distinct values ($2^8 = 256$).

Examples:

- Number 1 → 00000001
- Number 2 → 00000010
- Letter ‘A’ → 01000001
- Letter ‘a’ → 01100001 (the 6th bit set to 1 distinguishes lowercase from uppercase)
- Letter ‘B’ → 01000010, letter ‘b’ → 01100010

This binary encoding enables the machine to perform both basic arithmetic operations (addition, subtraction, multiplication, division) and fundamental logical (Boolean) operations: AND, OR, and NOT.

These operations combine or invert logical states (0 or 1). From these three basic operations, more complex forms can be constructed, such as:

- XOR (exclusive OR): true if only one of the inputs is true
- NAND (NOT-AND): inverse of AND
- NOR (NOT-OR): inverse of OR

A bit is always the physical distinction between two measurable states: voltage, light, magnetisation, electric charge, radio wave, or quantum state. Bits are physically implemented in different ways depending on the technology:

Table 3.1_1: Physical expression of a Bit depending on the medium

Medium / Technology	How the bit is physically represented	State = 0	State = 1
Electric circuits (digital logic)	Electrical voltage	0 V (low level)	5 V / 3.3 V / 1.2 V (depending on technology)
CMOS transistor	Current flow (or blocking)	Transistor OFF	Transistor ON
DRAM memory	Electrical charge in a capacitor	Capacitor discharged	Capacitor charged
SRAM memory	State of a transistor latch	Internal node at 0 V	Internal node at Vdd
Magnetic storage (hard disks)	Orientation of a magnetic domain	“Down” orientation	“Up” orientation
Magnetic tape	Magnetic polarity	Polarity A	Polarity B
Optical storage (CD, DVD)	Presence or absence of a pit	Clean light reflection	Beam deformation (pit)
Flash / SSD (NAND/NOR)	Number of electrons trapped in floating gate	Few electrons → low voltage	Many electrons → high voltage
Optical fibre	Presence or absence of a light pulse	No pulse	Light pulse
Radio transmission (WiFi, 5G)	Electromagnetic signal modulation	Phase/frequency/ amplitude = 0	Phase/frequency/amplitud e = 1

Since its origins when:

- 1936: Alan Turing formalized the concept of the universal machine (the Turing machine), the theoretical foundation of modern computing.
- 1937: Claude Shannon demonstrated that electrical circuits can implement Boolean algebra, the basis of binary computation (a mathematical model).

the evolution of computing has relied on the continuous increase in computational power, with machines able to perform an ever-growing number of arithmetic and logical operations per second—far beyond the processing capabilities of the human mind.

It is useful to recall how computational power has evolved, having been multiplied by a factor of 10^{18} to 10^{20} from the ENIAC in 1946 to the AWS data centers of 2025. This figure lies beyond human comprehension, a characteristic that echoes the nature of AI itself.

A brief historical overview of the evolution of computing power and cost helps us understand the broader development of computing, its impact on geophysical data processing, interpretation, and modelling (using petroleum seismics as an example), and its role in enabling the rise of artificial intelligence algorithms.

3.2 Features

3.2.1 Evolution of Computing Power

In 80 years, computing power has grown exponentially, moving from electromechanical relays to exascale and quantum computing. Each leap in capability has expanded the scale of the phenomena that can be modelled: from ballistic missiles to global climate, from single neurons to entire neural networks.

Table 3.2_2: Evolution of computing power

Period	Dominant Technology	Order of Magnitude	Key Event
1940–1950	Relays, vacuum tubes	10^1 – 10^3 operations/s	ENIAC (1946) – birth of electronic computing
1950–1960	Transistors	10^4 – 10^5 operations/s (0.001 MIPS)	IBM 7090 – first reliable scientific computing
1960–1970	Integrated circuits	10^6 – 10^7 operations/s (10 MFLOPS)	CDC 6600 – first vector supercomputer
1970–1980	Microprocessors	10^6 – 10^8 operations/s (0.1 GFLOPS)	Cray-1, Apple II – birth of personal computing
1980–1990	UNIX workstations, RISC	10^9 – 10^{10} operations/s (1–2 GFLOPS)	Cray-2 – the gigaflop milestone
1990–2000	Parallelism / clusters	10^{12} operations/s (1 TFLOPS)	ASCI Red (1996) – first teraflop supercomputer
2000–2010	GPUs & Cloud Computing	10^{15} operations/s (1 PFLOPS)	IBM Roadrunner (2008) – the petaflop barrier
2010–2020	Deep Learning / HPC	10^{18} operations/s (exascale)	Summit, Fugaku – AI and simulation combined
2020–Present	Generative AI, quantum	$>10^{18}$ operations/s + quantum compute	Frontier (2022), IBM Condor (2023)

3.2.2 Evolution of the Cost of Computing

The cost of scientific computing has dropped even faster than its power has increased: The price per MIPS has fallen by more than 10^{11} since 1950. Computing has shifted from an industrial investment to a universal resource.

Table 3.2_3: Evolution of the Cost of Computing

Year	Power (MIPS)	Cost per MIPS (2023 USD)	Evolution
1950 UNIVAC I	0.001	$1,000,000	Computing reserved for governments and major institutions
1965 CDC 6600	3	$250,000	First scientific computing centres

Year	Power (MIPS)	Cost per MIPS (2023 USD)	Evolution
1977 Apple II	0.0003	\$6,000	Democratization of the microcomputer
1986 Cray-2	1,900	\$50	High-performance computing accessible to research
1996 ASCI Red	1,000,000	\$1	Strategic teraflop-scale computing
2010 Tesla GPU	10^9	\$0.01	Cloud & GPUs: computing on demand
2023 Exascale AI	10^{18}	$\$10^{-5}$	Cognitive computing & generative AI accessible to everyone

3.2.3 Evolution of Computing Itself

Computing has evolved from a calculation technology into a global cognitive infrastructure. It has moved from automatic processing to intelligent reasoning, connecting machines, data, and humans. From the programmable machine to cognitive computing, its progression follows:

- the miniaturisation of components,
- the collapse of computing costs,
- the rise of massive data.

Table 3.2_4: Evolution of Computing

Period	Key Stage	Major Technologies & Innovations	Impact on Power and Uses
1940–1950	Birth of automatic computation	Electromechanical relays (Z3), vacuum tubes (ENIAC), punch cards	Emergence of early "calculators," automation of military and scientific problems.
1950–1960	The transistor era	IBM 701, IBM 704, IBM 7090 (transistors), FORTRAN	Reliable electronic computing, first scientific applications (ballistics, weather).
1960–1970	Integrated circuits & minicomputers	IBM System/360, PDP-8, CDC 6600	Standardisation of computing, broader access to scientific computation.
1970–1980	Microprocessor revolution	Intel 4004/8080, Apple I/II, VAX 11/780	Democratization of personal computing, birth of micro-computing.
1980–1990	Graphical interfaces & networks	Macintosh, IBM PC, Ethernet, UNIX/X11, Sun & SGI workstations	Visual and connected computing; start of collaborative digital work.
1990–2000	Internet & the World Wide Web	HTML/HTTP, Mosaic/Netscape, Pentium	Globalization of information and digital communication.

Period	Key Stage	Major Technologies & Innovations	Impact on Power and Uses
2000–2010	Cloud & mobile computing	AWS, Azure, iPhone, Android, virtualization	Distributed computing, mobile access to data, beginnings of Big Data.
2010–2020	Big Data & cognitive computing	Hadoop, Spark, GPUs for AI, hyperscale infrastructures	Data-driven computing, explosion of Deep Learning.
2020–Present	Generative AI, quantum & Edge computing	GPT, LLMs, multimodal models, IBM/Google qubits, neuromorphic chips	Hybrid cognitive-quantum computing, autonomous agents, omnipresent intelligent systems.

3.3 Impact on Geophysics: From Analog Processing to Integrated Numerical Modelling

Digital geophysics was born from the computer revolution. Since the 1950s, geophysics has evolved from an instrumental discipline into an integrated digital geoscience. This transformation has unfolded along three major axes: signal processing, interpretation, and modelling. We illustrate this evolution using seismic exploration in the oil industry.

3.3.1 Processing: From Analog to Distributed Digital Computing

Early seismic processing in the 1950s–1960s was analog and executed on magnetic tapes. With the advent of electronic computers and later minicomputers (IBM 7090, PDP-8, CDC 6600, VAX 780…), the 1960s–1970s saw the birth of digital seismic processing: filtering, NMO correction, stacking, and migration.

The 1980s introduced UNIX workstations (SUN, SGI) and 2D/3D processing. The 1990s–2000s brought 4D processing and parallel computing (HPC). Today, cloud computing enables massive distributed processing, with automated workflows increasingly optimised by artificial intelligence.

3.3.2 Interpretation: From 2D Profiles to Cognitive Visualization

Geophysical interpretation evolved from hand-drawn 2D profiles to immersive 3D environments. The graphical interfaces of the 1980s–1990s (Sun, SGI, Landmark, GeoFrame) enabled volumetric visualization, while the tools of 2000–2010 (Petrel, OpenWorks) introduced multidisciplinary integration. Today, AI powered by computer vision and deep learning contributes to automatic recognition of facies, discontinuities, and reservoirs, supporting rapid and collaborative interpretation.

3.3.3 Modelling: From Determinism to Probabilism

Modelling has shifted from deterministic approaches—where a single model represented the subsurface—to probabilistic approaches that incorporate uncertainty and heterogeneous data. The 2010s saw the emergence of the geoscience Digital Twin, combining seismic, geology, and production into a unified dynamic model. Today, geophysical models are moving toward self-learning systems, integrated into cognitive environments capable of adjusting their parameters using new observations.

Table 3.3_1: Evolution of Geophysics (1940–Present)

Period	Key Stage	Dominant Technology	Impact on the Discipline
1940–1950	Analog measurement	Mechanical & electromechanical instruments	First field measurements; analog signals on paper or film.
1950–1960	Shift to electronics	Magnetic recorders, vacuum tubes	Amplified signal processing; beginnings of manual seismic computation.
1960–1970	Signal digitisation	Minicomputers (IBM 7090, PDP-8, CDC 6600)	Birth of digital seismic processing (filtering, NMO, stacking).
1970–1980	Automated processing	Microprocessors, FORTRAN/BASIC	Standardisation of "Digital Seismic Processing."
1980–1990	3D visualization & UNIX workstations	Sun, SGI, GeoFrame, Landmark	Transition to 3D interpretation; interactive collaboration.
1990–2000	Connected geophysics	Networks, Internet, SEG-Y databases	Data sharing and quantitative inversion.
2000–2010	HPC & Cloud	Parallel clusters, CUDA, Petrel/Eclipse	Distributed processing; integrated geology–reservoir modelling.
2010–2020	Big Data & AI	GPUs, Machine Learning, Digital Twin	Probabilistic inversion; 4D modelling; automated workflows.
2020–Present	Cognitive geoscience	AI agents, Deep Learning, hybrid cloud	Autonomous interpretation and self-learning subsurface models.

3.4 Impact on Artificial Intelligence: From Logic to Cognition

Artificial intelligence was born from the computer revolution. Its evolution is tightly linked to computing power and data availability. From symbolic and logic-based approaches, it has evolved into learning intelligence, then connected intelligence, and now generative cognition.

3.4.1 Symbolic AI (1950–1980): The Logic of Reasoning

AI emerged in the 1950s with the work of Turing, McCarthy, and Minsky. Expert systems dominated the 1970s–1980s, relying on logical rules and knowledge bases (MYCIN, DENDRAL). These approaches reached their limits due to real-world complexity and the lack of large datasets.

3.4.2 Connectionist AI (1980–2000): Neural Networks

Rediscovered in the 1980s, multilayer neural networks (backpropagation) introduced the idea of machine learning. Models such as LeNet (Yann LeCun) established the foundations of modern computer vision, but hardware capabilities remained limited.

3.4.3 Probabilistic AI and Big Data (2000–2020)

The rise of the Internet, cloud computing, and Big Data enabled modern Machine Learning. SVMs, random forests and deep neural networks transformed AI into a data science discipline. GPU architectures made large-scale training possible, and neural networks achieved human-level performance in vision and speech.

3.4.4 Generative and Cognitive AI (2020–Present)

Since 2020, large language models (LLMs) and Transformer architectures have marked the beginning of the generative AI era. These systems (GPT, Claude, Gemini, Mistral) combine text, images, and code in multimodal models capable of reasoning and creating.

AI becomes cognitive: it interacts, learns autonomously, and supports scientific research across domains.

From symbolic logic to generative cognitive intelligence: The history of AI is a shift from explicit reasoning to deep learning, and now to generative cognition—each transition driven by leaps in computing power and accessibility.

Table 3.4_1: Evolution of Artificial Intelligence (1940–Present)

Period	Dominant Paradigm	Key Technologies / Methods	Scientific & Applied Impact
1943–1956	Logical and neural foundations	Formal neuron (McCulloch & Pitts), Turing Test (1950)	Conceptualisation of machine intelligence; emergence of the “thinking system.”
1956–1970	Symbolic & logical AI	Rule systems (LISP, PROLOG), automated reasoning	Explicit reasoning; simple problem solving; early “intelligent” programs.
1970–1985	Expert systems	IF–THEN rules, knowledge bases (MYCIN, DENDRAL)	Domain-specific AI in medicine, chemistry, industry; commercial boom then stagnation.
1986–2000	Connectionist AI	Backpropagation, neural networks, LeNet, SVM	Renewal of Machine Learning; start of computer vision; rise of supervised learning.
2000–2010	Probabilistic AI & Big Data	Bayesian networks, Markov models, statistical ML, cloud computing	Data-driven AI; industrialisation of predictive models (recommendation, translation).
2010–2020	Deep Learning	CNN, RNN/LSTM, GANs, GPUs, ImageNet, TensorFlow, PyTorch	Human/superhuman performance in vision, speech, translation; explosion of AI applications.
2020–Present	Generative & cognitive AI	Transformers (GPT), LLMs, multimodal models, autonomous agents	AI capable of reasoning, generating, interacting, and planning; rise of scientific AI and agents.

3.5 Conclusion: Digital Geophysics and AI—Two Children of the Computer Revolution

Digital geophysics and artificial intelligence are two major outcomes of the computer revolution, both historically and genetically tied to the rise of computer processing power.

Their shared DNA is the processing of DATA, encoded in base-2 and handled by increasingly powerful machines.

4 The Quantum Revolution

4.1 Foundations

The quantum revolution refers to the set of discoveries made in the early 20th century (Planck, Einstein, Bohr, Schrödinger, Heisenberg, Dirac, Pauli…) that replaced the deterministic worldview of classical physics with a probabilistic, wave-based, and quantized description of matter. The term "quantum revolution" generally refers to two major periods in the history of physics and technology, each marked by fundamental advances in the discovery, understanding, and exploitation of quantum phenomena.

4.1.1 The First Quantum Revolution (Early 20th Century)

The quantum revolution introduced five key ideas:

- Energy is not continuous but emitted/absorbed in "packets" (quanta).
- Light and matter behave both as waves and particles.
- Probabilistic models apply at microscopic scales.
- Measurement modifies the system being observed.
- Non-local phenomena exist (entanglement).

4.1.2 The Second Quantum Revolution (21st Century)

Since the 1980s–2000s, a new era has emerged, centred on the control and individual manipulation of quantum systems (qubits, photons, cold atoms, etc.).

- Quantum System:

A quantum system is a physical ensemble (or a statistical ensemble: a collection of identical copies of a system, each in a different microscopic state but all compatible with the same macroscopic constraints). It is described by the laws of quantum mechanics, where properties such as energy, angular momentum, or spin are quantified, and where states are represented by vectors in a Hilbert space. Modelling a quantum system makes it possible to compute average values of observables (e.g., pressure, temperature, magnetisation) while accounting for uncertainties or incomplete knowledge of the system's exact state.

- Quantum Computing

Quantum computing uses the principles of superposition and entanglement and the fundamental laws of quantum mechanics to perform computation in a radically different way from classical computers. Unlike classical bits (0 or 1), qubits can exist in a superposition of states, enabling massive parallel computation. Quantum computing therefore uses qubits to achieve exponentially faster computation for certain classes of problems (factorisation, molecular simulation, optimisation).

4.2 Features

- Conceptual
  - A paradigm shift: from a deterministic worldview to a probabilistic one. Quantum mechanics introduced a major philosophical rupture:
  - Uncertainty is not an error but a fundamental property of matter at the subatomic scale.
- Technological
  - Rise of technologies such as the transistor, laser, MRI, and semiconductors, foundations of modern electronics.
  - Quantum computing, which strongly contributes to the evolution of computing discussed earlier.

4.3 Impact on Geophysics

- Conceptual
  - Quantum theory opened the door to recognising the limits of deterministic processing in interpretation and modelling.
- Technological
  - Thanks to new modes of data acquisition and sensors (seismometers, magnetometers, NMR, LiDAR, optical fibre…).
- Computational
  - Impact through exponentially increasing computing power enabled by transistors, integrated circuits, lasers, and semiconductor materials.

4.4 Impact on Artificial Intelligence

- Conceptual Impact: The Probabilistic World

Quantum mechanics introduced a major philosophical shift:

  - Uncertainty is not an error but a fundamental property of matter.
  - Systems are described by wave functions in multidimensional vector spaces.
  - Measurement modifies the observed state; prediction is statistical, not deterministic.

This worldview resonates with AI through:

  - machine learning,
  - neural networks,
  - Bayesian probabilistic models,
  - hybrid approaches (PINNs, probabilistic inversion).

- Technological Impact

Quantum technologies (optical fibres, transistors, lasers, high-density memory) have made possible:

  - training deep neural networks,
  - development of LLMs,
  - proliferation of seismic, logging and sensor data,
  - generative AI and hybrid physics/data-driven AI.

- Computational Impact
  - Internet, Big Data

4.5 Conclusion

The acceptance of uncertainty and of the limits of deterministic geophysical models leads naturally to a progressive adoption of AI algorithms to optimise geophysical processing, data interpretation, and modelling—ensuring the highest possible statistical consistency between models and the data used.

It is a win–win exchange in the manipulation of massive datasets.

5 The Probabilistic Revolution

“There is no such thing as a probability in itself. There are only probabilistic models.” – G. Matheron

5.1 The Basis: The Work of G. Matheron

5.1.1 Geostatistics

Georges Matheron, a young engineer from the French Corps des Mines, discovered during his posting to the Algerian Mining Board (1954–1957) Danie Krige’s thesis on the statistical regressions used by South African mining engineers to estimate ore grades in mining blocks from blast-hole data. He identified the physical effects of support and information that must be taken into account in any problem of natural resource estimation, and which are ignored by purely statistical calculations.

From there, he progressively developed (1960–1970) the theory of regionalized variables (localized in space–time), itself based on probability theory, using the formalism of random functions (stationary, intrinsic, non-stationary) to model spatial variability of data through spatial covariance functions (such as the variogram for intrinsic random functions). The reference work on the subject was published in 1970: La Théorie des variables régionalisées, et ses applications (Cahiers du Centre de Morphologie Mathématique de Fontainebleau, fascicule 5).

This formalism makes it possible to define (within the probabilistic mathematical model) the estimation error as the difference between the estimated value of the variable at a given location and its true value, which is unknown at the time of estimation. The theory shows that, under constitutive assumptions of the probabilistic model on the spatial stationarity of the mean and variance of the regionalized variable under study, it is possible to solve most problems of estimating the value of this variable at unsampled locations.

The estimation operator of the probabilistic model is called kriging (a linear estimator that guarantees a zero-mean estimation error (unbiasedness) and minimum variance (dispersion around 0) among all linear estimators). Modelling spatial covariance also makes it possible to generate conditional spatial simulations to solve estimation problems involving nonlinear transforms of the regionalized variable.

The theoretical development of these topo-probabilistic models, as well as the choice of such models to solve a given estimation problem, constitutes the discipline of geostatistics.

In 1978, G. Matheron justified the practice and operating mode of geostatistics in an essay on the practice of probability applied to unique phenomena, entitled Estimer et choisir (“To Estimate and To Choose”).

5.1.2 Mathematical Morphology

Parallel to his work on randomness represented by the ignorance of the value of a regionalized variable away from sampled locations, G. Matheron turned to another form of randomness present in the characterization of fully informed datasets in space–time (for example, an image, a simulated value grid). To address problems of shape and structure characterization, he developed a mathematical theory he claimed as original: the "Theory of Random Sets" (Cahiers du Centre de Morphologie Mathématique de Fontainebleau, 1969).

This theory is based on concepts from set theory, topology, and lattice theory, and is particularly useful for studying the shape, size, and structure of objects in a space. (Lattice formalism is a branch of mathematics, more specifically of universal algebra and partial order, which studies algebraic structures called lattices. These structures generalize notions of order and upper/lower bounds and have applications in many fields, notably theoretical computer science, logic, and algebra.)

In collaboration during the 1960s with Jean Serra, particularly for image analysis in geology and metallurgy, mathematical morphology defines two fundamental operations based on a structuring element (a simple shape such as a disk, a square, etc.) that serves as a "probe" to explore the image or the space:

- Erosion: reduces objects by eroding their boundaries.
- Dilation: enlarges objects by adding pixels or elements around their boundaries.

This work continued through to the late 1990s, notably with:

- Grayscale morphology: applied to non-binary images using local minimum and maximum operations.
- Morphology on graphs: to analyse networks (for example, fracture networks).
- Algebraic morphology: use of complete lattices to generalize operations to other types of data.

5.2 Features

5.2.1 Conceptual

The probabilistic revolution brought by G. Matheron rests on a clear distinction between the unknown reality we seek to represent and the probabilistic model we use to do so:

"There is no such thing as probability in itself. There are only probabilistic models."

In geostatistics, mathematical tools are useful constructs for solving specific questions we ask about reality, not absolute truths. During our first meeting in 1980, he told me once: "Science is not about truth."

Deterministic models that claim to represent the entirety of the spatial variations of a regionalized variable must give way to their probabilistic version, grounded in a coherent mathematical framework, which replaces a single deterministic value with a confidence interval P10–P50–P90 (10%, 50%, 90% probability that the unknown true value lies above these thresholds), established on the basis of a clearly identified and specified probabilistic model.

Mathematical morphology extends the geostatistical approach by providing a general mathematical framework for modelling uncertain geometric objects, and not only numerical variables. This is a fundamental advance because reality is not made of values, but of objects: faults, mineral grains, pores, fractures, fingerprints, cells, buildings, clouds, seismic fractures, etc. Random sets make it possible to model mathematically, and to process computationally, these geometric objects under uncertainty.

5.2.2 Technological

By defining and modelling estimation error, probabilistic geostatistical models provide a unique theoretical framework for managing spatial uncertainty, which is omnipresent in decision-making for natural resource management. Estimation error is defined in probabilistic terms by its mean and variance. It constitutes a kind of “distance” in the algebraic sense between the numerical model and its real-world target.

The resulting geostatistical (probabilistic) processing chains in geosciences are automatically optimised at each step by integrating the various heterogeneous data sources within specific probabilistic models. These guarantee the optimality (minimisation of estimation variance) of the results of successive steps, up to the construction of probabilistic numerical models expressed as confidence intervals (P10–P90) around the most probable values (P50).

Mathematical morphology extends the contribution of geostatistical models to quantifying spatial uncertainty by representing objects as random sets. It allows one to compute the membership probability p(x) of a location x to a given object by measuring morphological deformations (erosion/dilation) and deducing uncertainty maps on the position, shape, size, orientation, and topology of the object.

When used to automatically interpret geostatistical simulations, it has become one of the pillars of image processing, computer vision, biometrics, industrial inspection systems and, today, of certain hybrid AI / Deep Learning architectures.

5.2.3 Computing

Geostatistics introduced into computing the algorithmic handling of spatial uncertainty, a concept that has become central in AI, data science, robotics, computer vision, and GIS.

Geostatistical software is developed on a logic different from that of classical geomodelling software. Whereas the latter aim to offer users every possible expert operation in their domain, geostatistical software seeks instead to identify and specify, as well as possible from available data, the mathematical model best adapted to the estimation problem at hand. A useful analogy is that between visual flight (classical geomodelling software) and instrument flight (geostatistical geomodelling software) in aviation and navigation.

Mathematical morphology brings something entirely new to computing: a geometric logic of forms, operating directly on objects, independently of their pixel representation. This is a structural contribution, equivalent to what Boole was for logic, but applied to shapes in images.

5.3 Contribution to Geophysics

The potential for applying the probabilistic approach in geophysics is enormous, since it amounts to nothing less than reformulating the entire processing–interpretation–modelling chain in the spatial domain. What was unthinkable in the past due to insufficient computing power is now feasible, as we have seen with the advances of the computer revolution.

The expected benefit is supervised automation and optimisation of the entire chain through the minimisation of a single criterion—estimation variance—at each step. Working in the same space–time as the natural resource, the probabilistic approach couples the deterministic approach (for determining mean values) with a coherent handling of residual spatial variations.

Many developments have already been made in seismic signal processing (wavefield separation, noise filtering, etc.), and some steps are already operational, such as intelligent stacking, automatic interpretation by morphological segmentation, velocity field modelling, depth conversion, and inversion in exploration seismics.

5.3.1 The hybrid geophysical /geostatistical approach

A compelling illustration of the contribution of geostatistics to geophysics is provided by J.-L. Mari and A. Shtuka in "Why geostatistics can be useful in seismic processing and modelling?" presented at EAGE 2024. In the following we reproduce excerpts from the EAGE 2024 paper.

The authors introduce a hybrid geophysical–geostatistical approach, outlining a fully probabilistic workflow that spans from quantifying spatial uncertainty in the seismic data to supporting structural and petrophysical modelling with associated confidence intervals.

- Context

The workflow is demonstrated through a case study conducted at the feasibility phase of a deep geological repository for high-level radioactive waste in the eastern Paris Basin. The French National Radioactive Waste Management Agency (Andra) carried out an extensive and innovative characterization program of the Callovo-Oxfordian claystone (Cox) and the over- and underlying Oxfordian and Dogger limestones. High-resolution 3D seismic data were used to model the spatial distribution of the mechanical and hydrogeological properties of these formations.

Figure 5.3_1 shows a view of the geological model of the site and the location map of the 3D seismic survey. It also shows the flow used to build a geological model in depth.

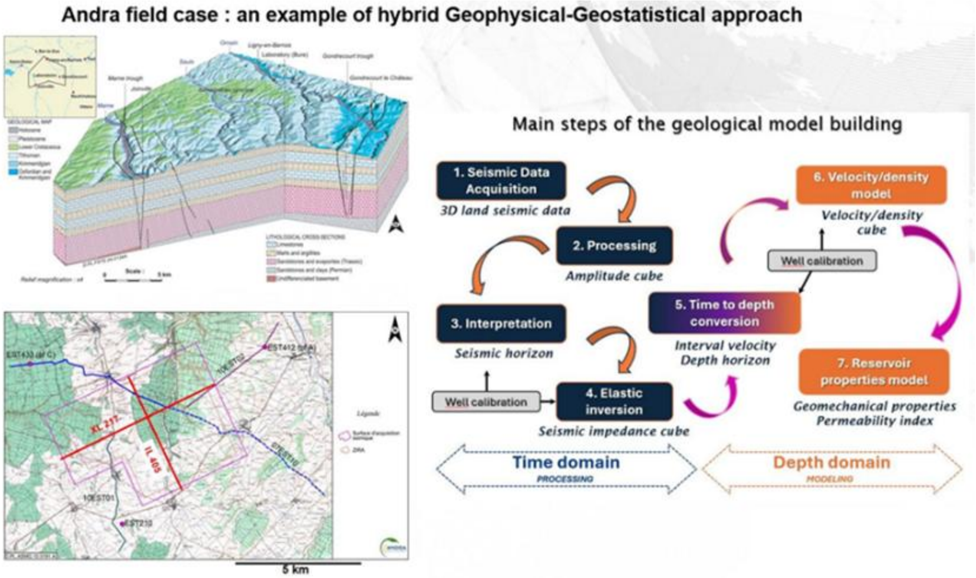


Fig.5.3_1: Location map and geomodeling workflow

- Step 1: Spatial conditioning of Pre-stack and stack seismic data (Figure 2)

Stochastic processing (spatial conditioning and factorial kriging algorithm, Shtuka et al., 2009) applied to pre-stack amplitude gathers operates within a probabilistic modelling framework to best estimate the "Signal" and "Noise" amplitude spatial components (or spaces in the frequency domain) of a Common Image Gather (CIG) from the measured amplitude traces for successive offsets.

The ratio Estimated “Noise” / Estimated “Signal” is called Spatial Quality Index (SQI). Figure 5.3_2 shows an example of stochastic processing applied to a common image gather (CIG). Figure shows the raw CIG (a), the CIG overlaid with SQI with a colour scale (b), the signal space (c) and the noise space (d). SQI confirms the zones corrupted by noise (random and coherent) of the CIG. The noisy parts of the CIG are coloured in red, while parts coloured in purple clearly show the reflected events.

The result of the stochastic processing in the spatial domain is enhancing the “Signal” to “Noise” ratio and computing the attached confidence interval as the estimation variance.

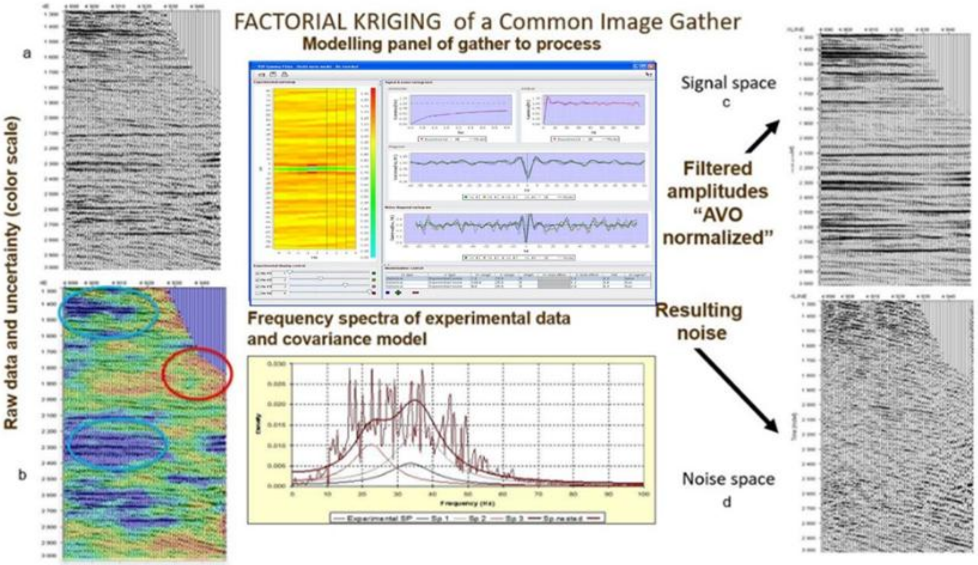


Fig.5.3_2: Hybrid Geophysical -Geostatistical processing. Factorial kriging applied to common image gather for estimating amplitude uncertainty and performing wave separation in signal space and a noise space.

- Step 2: Probabilistic multilayer depth conversion (Figure 5.3_3)

The output of Spatial Conditioning of pre stack and stack amplitude data sets is translated in terms of uncertainty attached to the seismic interpretation and input to the next Geostatistical multilayer depth conversion and velocity modelling stochastic processing step. It enables the optimisation of the parametrisation of the classical layer cake depth conversion workflow and the consistent quantification of uncertainty on the resulting interval layer velocity and horizon depth models.

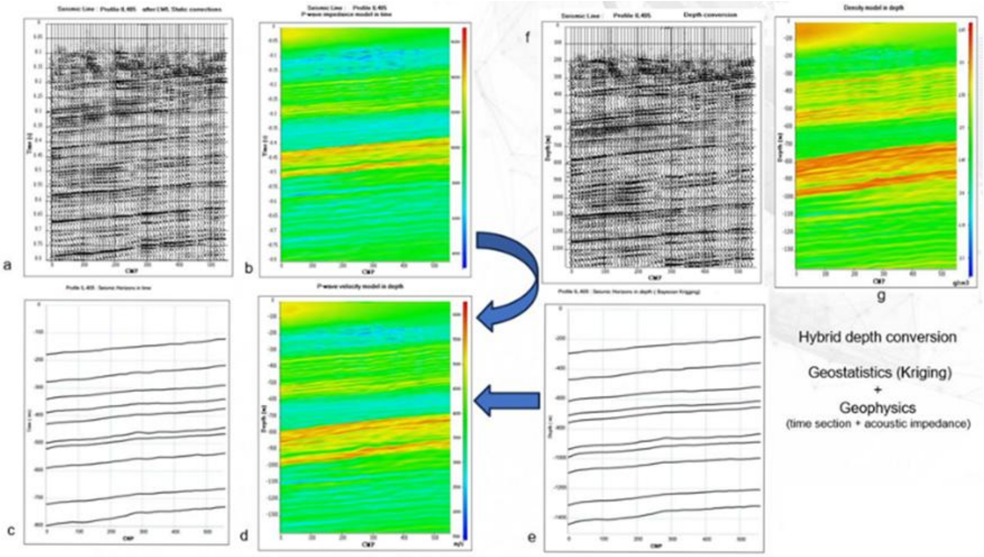


Fig.5.3_3: Hybrid Geophysical -Geostatistical processing. Time to depth conversion

- Step 3: Geomechanical property determination. (Figure 4)

Figure 5.3_4 shows successively the PSTM stacked section converted in depth using the procedure previously described (a), the spatial distribution of SQI in depth (b). SQI contribution to the geomechanical and hydrogeological model is illustrated. The PSTM section has been converted in instantaneous amplitude and then in seismic attributes used as indicators of shalyness and permeability (Mari and Yven, 2019). The low and high confidence areas (from SQI) are indicated on the depth seismic sections: instantaneous amplitude (figure 4c), shalyness (figure 4d) and permeability (figure 4e). Combination with amplitudes SQIs leads to a fully reliable uncertainty quantification attached to the seismic geomodel.

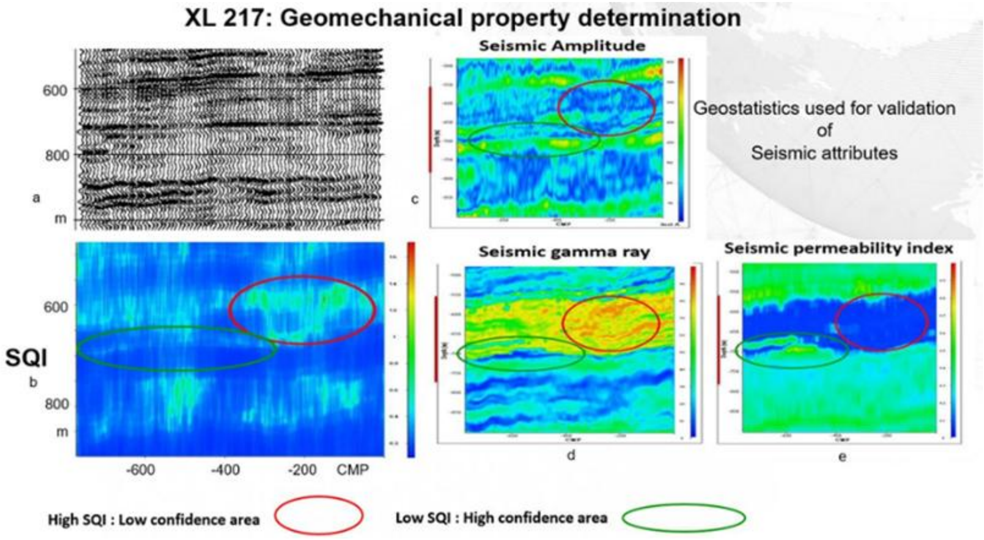


Fig.5.3_4: Hybrid Geophysical -Geostatistical processing. Geomechanical property determination

- Conclusions

The Cigeo Andra field case demonstrates how geostatistical tools have been useful in seismic processing and reservoir modelling in conditioning seismic data, providing uncertainty evaluation at each processing step, integrating different data sources and their associated uncertainties in depth conversion. Such an approach allows a hybrid geophysical-geostatistical processing for increasing confidence in seismic interpretation and limiting risks.

5.4 Contribution to Artificial Intelligence

The contribution of the theoretical framework of geostatistics and mathematical morphology to AI algorithms working on regionalised data parallels that of probability theory to statistics. It enables the calculation of probabilities attached to the object under study, and not only to the data used to study it.

In this way, we can see the usefulness of AI algorithms for automating and optimising all the statistical computations needed to select the probabilistic models best suited to the estimation or pattern-recognition problems encountered in geophysics.

5.4.1 Structural variography of seismic cubes using morphological segmentation

The PhD work Segmentation Morphologique et Topologique DE CUBES SISMIQUES of Timothée FAUCON at the Center of Mathematical Morphology, School of Mines of Paris in Fontainebleau, France) (T.Faucon. PhD Thesis. École des Mines de Paris. 2007) initiated the use of morphological tools for analyzing and interpreting seismic cubes. The first operational result of this work has been the implementation of the watershed algorithm for automatic segmentation and labeling of main spatial units inside the seismic cube.

The watershed algorithm is inspired by topography: it treats a grayscale image as a relief map, where the gray values represent elevation. Dark areas correspond to "basins," and bright areas correspond to "ridges." The idea is to simulate a gradual flooding of these basins from sources (markers) and to build barriers (watershed lines) where the waters from two different basins meet. The output of the segmentation process is a set of labeled surfaces that correspond to spatial extension of the segmented seismic attribute (local amplitude maxima in the example) as shown in Figure 5.4_1.

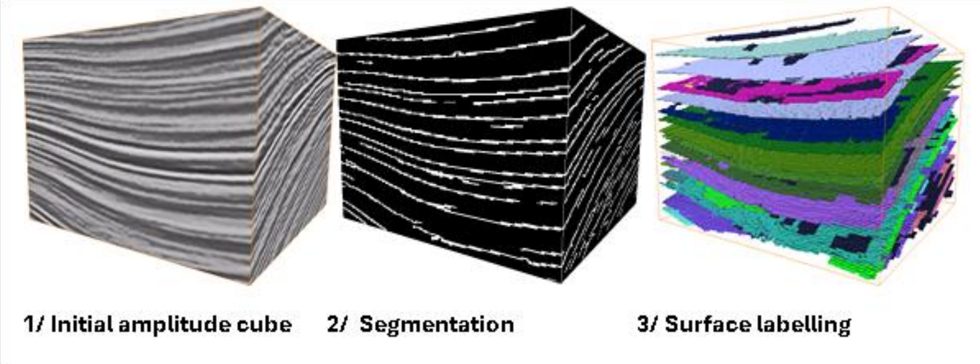


Fig.5.4_1: Morphological segmentation Flow Chart

Since 2007, mathematical morphology algorithms such as watershed or connected components are widely used in operation as shown in Figure 5.4_2 for:

- automatic spill point localisation on reservoir geostatistical structural simulations

- Horizon Segmentation: Treats seismic volumes as topographic relief, using amplitudes or attributes (e.g., similarity, envelope) to define elevations. Local minima represent layer interfaces.

- Fault Detection Applies watershed to discontinuity volumes (e.g., coherence, variance) to extract fault surfaces.

- Geological Body Segmentation: Isolates features like turbidite channels or reefs by combining watershed with interpreter-defined or pre-classified markers.

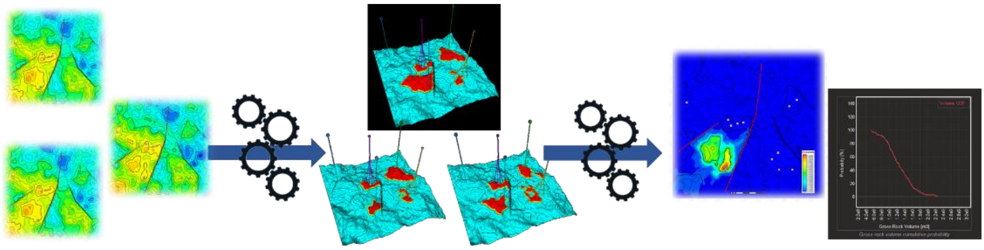


Fig.5.4_2: Ensemble based methods using mathematical morphology for managing spatial uncertainty on O&G E&P projects (from structural depth geostatistical simulations to closure probability map, spill point locations, GRV expectation curves) from UDOMORE (Seisquare) documentation

5.5 Conclusion:

The probabilistic revolution marks the transition from a deterministic view of science, which seeks a single, definitive model of reality, to an approach in which reality is described through uncertainty and multiple possible states.

In Earth sciences, and particularly in geophysics, uncertainty is not a flaw in measurement but an intrinsic property of the subsurface**.** Probabilistic modelling therefore becomes central to understanding and decision-making.

Georges Matheron gave this vision a rigorous mathematical foundation, showing how spatial uncertainty can be quantified, structured, and operationally exploited. His work remains a cornerstone of modern geosciences and of contemporary scientific AI.

6 The Emergence of Earth Intelligence

The probabilistic models of geostatistics and mathematical morphology quantify, in mathematical terms, the spatial uncertainty attached to numerical models representing the natural phenomenon under study (from estimation of the geophysical signal through to volumetric calculations and 4D monitoring in the management of sedimentary reservoirs—hydrocarbons, clay layers for nuclear waste storage, CO_2 storage, etc.).

Moreover, minimising estimation variance at each step of the processing chain leads to minimising the always negative economic impact of spatial uncertainty on the economics of exploration/production projects (loss of resource value and return on investment).

This single criterion makes it possible to:

- automate and optimise the entire geophysical processing–interpretation–modelling chain,
- drastically reduce study times,
- increase team performance,
- improve project profitability,

which are precisely the benefits attributed to artificial intelligence.

The fundamental difference is that classical AI operates on data (DATA), whereas this form of intelligence operates on the natural environment that is the object of geophysical measurements. We can therefore speak of a specific branch of AI called "Earth Intelligence (EI)".

We can gauge its relevance by revisiting the 10 main criticisms geophysicists direct at current AI:

1. Does not respect physics → inconsistencies and unreliable results
   EI treats physical laws as providing the representation of the mean value of the variable studied at a given location. They form the first-order stationarity hypothesis characterising the probabilistic model chosen to estimate the variable.
2. No quantified uncertainty → unfit for decision-making
   EI, by definition, uses quantification of spatial uncertainty as the criterion for automating and optimising processing chains, up to the mathematical computation of P10–P50–P90 confidence intervals that underlie operational decision-making.
3. Dependence on the training dataset → lack of generalisation
   EI's probabilistic models are based on the practice of probability for unique phenomena (a single realisation). It is the spatial statistics computed on the single training dataset that automatically guide the choice and parameterisation of the probabilistic model adapted to the problem. EI is therefore, by construction, generalizable to any type of regionalized dataset.
4. Black box and lack of quality control
   The probabilistic models selected by EI at each step of the EI processing chain are clearly identified, as are their parameters. Their performance is quantified statistically and presented in dashboards.
5. Smoothing / hallucinations → loss of operational value
   Strictly speaking, a numerical model must be smoother than reality because spatial uncertainty prevents identification of certain real local variations that lie beyond the model's resolution. If we seek realism in a numerical model, we must acknowledge spatial uncertainty and generate numerical simulations that correctly reproduce local unknown variations, though not necessarily at their exact real locations. One could speak of "realistic hallucinations"!
6. Performance still limited and real challenge for industrialisation
   The development of probabilistic models in geophysics has been ongoing for more than 30 years. They are available in open-source geostatistical and morphological libraries and partially industrialised in commercial software. It is now up to geophysicists to integrate them into their own software platforms.
7. Excessive automation with risk of loss of expertise
   On the contrary, EI reinforces geophysical expertise by embedding it implicitly in probabilistic models. The transfer of experience occurs through expertise in manipulating these models, much as in the video game industry.
8. Non-reproducibility → unstable workflows
   The EI workflow consists of a sequence of always identical steps, each characterised by the implementation of a clearly specified probabilistic model. These workflows are reproducible across all project types. The only potential instabilities arise from the parameterisation of the model from the available data.
9. High computational cost → practical barrier
   The issue of high computational cost for geostatistical and morphological processing has been a constant since their origins in the 1980s (Georges Matheron was programming on a small HP calculator). This significantly slowed their implementation in geophysical processing when compared at the time with other interpolation or filtering algorithms. The cost of EI in geophysics must be

compared with that of classical deterministic processing. EI optimisation can considerably reduce the number of iterations needed in processes that try to match a result (for example, migration) to the data used to construct it. Unlike classical AI, which trains on ever larger databases, EI works on the same datasets as deterministic processing, and today's computing power makes it possible to approach near real-time processing.

10. Ethical risks and responsibility → organisational resistance
EI is anything but a black box, since each step of the probabilistic processing chain and its performance are clearly documented in dashboards that can be shared among all decision-makers. On the contrary, EI workflows are traceable, scalable, and updatable, forming an objective basis on which operational decision-making can safely rely—though not without risk, which is itself quantified by probabilistic confidence intervals.

6.1 Benefits of Earth Intelligence when modeling O&G reservoirs

In the EAGE 2023 presentation on Earth Intelligence (EI), "Benefits of Earth Intelligence® when modeling O&G reservoirs: An exploration case study", L. Sandjivy and M. Collet revisit a North Sea exploration case study using the integrated UDOMORE EI software platform developed by Seisquare. The study clearly illustrates the game-changing impact of artificial intelligence on oil and gas exploration and production workflows. We reproduce below excerpts of the publication:

When addressing reservoir management and associated economic decisions, E&P decision makers and geoscientists jointly construct numerical reservoir models that:

- aim to reproduce the static and dynamic behavior of the unknown real reservoir at the time operational decisions are made;
- support the decision-making process by providing alternative low-case, best-case, and high-case numerical scenarios.

Earth Intelligence kriging-based machine learning algorithms make it possible to move beyond these often opaque "black-box" numerical models by generating explicit probabilistic scenarios ($P_s c_{enarios}$). These scenarios are traceable, easily shared, stored, retrieved, and continuously updated as new data become available.

The UDOMORE platform represents the first EI powered operational software for solving such structural challenges in O&G E&P projects.

- Stochastic workflows and P-Scenarios

Let us consider for example the structural issues faced by asset teams when deciding on implementing a new exploration well: Prospect geometry and volumetrics? Where to drill? Prognosed target depth?

Solving this structural issue using Earth Intelligence requires developing a 3-step probabilistic workflow as shown in Figure 6.1_1:

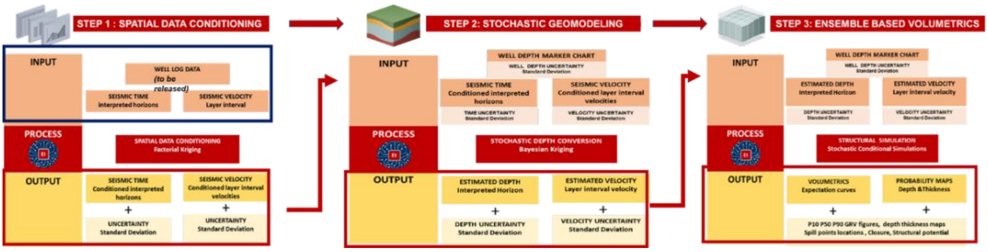


Fig. 6.1_1: The 3 steps of an EI structural modelling workflow

Notice that "EI Processes" at each step are "kriging" ML algorithms that automatically optimize the parametrization of the geophysical process involved (conditioning, velocity modeling, depth conversion, volumetrics)

- The EAGE 2016 Case study using EI: "Implementing an exploration well for targeting a North Sea prospect along major fault and below thick salt layer"

The exploration well targeted location was based on the PSDM depth interpretation of the target horizon, corresponding to a local low PSDM interval velocity inside the salt layer. (Figure 6.1_2)

The structural issue was about prognosing the depth of the target horizon H3 at the targeted well location and evaluating the GRV connected volume.

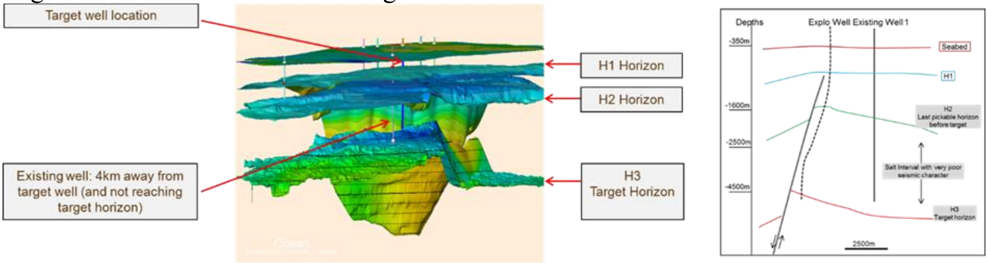


Fig.6.1_2: Location map

A North Sea exploration well was targeted after PSDM reprocessing for assessing a structural prospect sub salt and sealed by a major fault.

The data available for deciding on drilling the exploration well are:

- 3D seismic cube and 4 horizons interpretation
- 3D PSDM velocity cube
- Well marker depth chart (8 wells at H1, 1 well at H2 and H3)

The 2016 EAGE publication by describes the 3 step structural workflow that was run twice, with "raw PSDM velocity cube"(scenario 1) and with "conditioned PSDM velocity cube" (scenario 2).

As the exploration well was drilled, it allowed for validating the scenario 2 (using conditioned PSDM velocities) as it reduced the depth estimation error at the target well location from over 200m (scenario 1) to less than 40m (scenario 2) as shown in Figure 3.

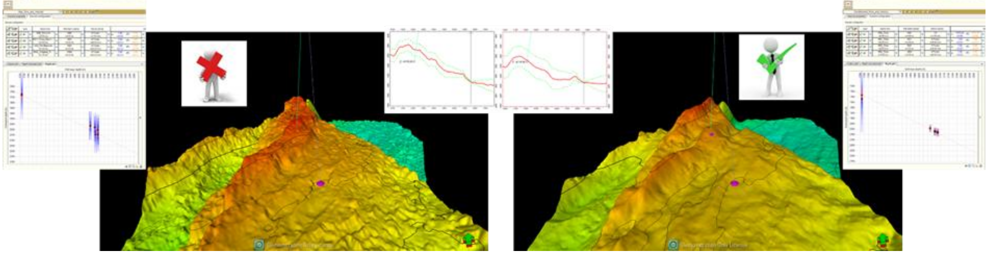


Fig.6.1_3: Depth maps at target horizon

Left Scenario 1 Raw PSDM velocities > 200m depth error at new well location Right / Scenario 2 Conditioned PSDM velocities results in < 40m depth error

- Revisiting the 2016 case study using an EI platform

In the 2016 paper "Are PSDM Depth Interpretations Reliable?", by L. Sandjivy, A. Shtuka1 and M. Collet (EAGE 2016), the stochastic structural workflow was implemented by a team of 2 people using a geostatistical toolbox (data scientists) in complement of a standard geomodelling platform (geoscientists). The turnaround time was over 5 weeks.

In 2023, in view of illustrating the present paper, the same 3 step stochastic workflow was easily implemented on the UDOMORE EI software platform (4) as 2 alternative P_scenarios (one using raw PSDM velocities and one using conditioned PSDM velocities).

Figure 6.1_4 displays the graphic interface for programming the stochastic workflow.

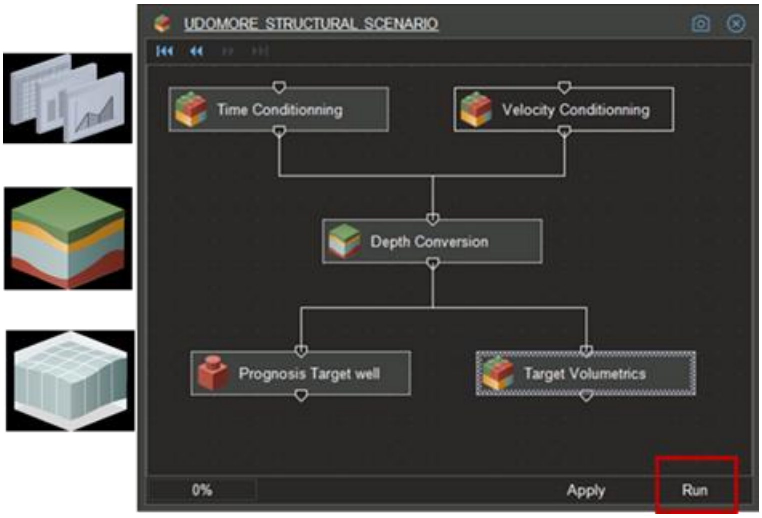
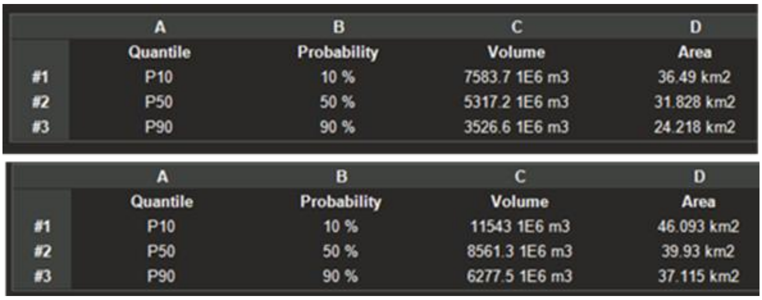


Fig.6.1_4: Graphic programming interface of the P_Scenario on the EI platform:

Each “box” contains the Input, EI process, and outputs .

By simply clicking on “Run”, any authorized user may reproduce all required outputs in real time, and possibly challenge and update the P_Scenario with new data.

Figure 6.1_5 & 6 displays some of the outputs obtained when running the EI automated workflow:



	A	B	C	D
	Quantile	Probability	Volume	Area
#1	P10	10 %	7583.7 1E6 m3	36.49 km2
#2	P50	50 %	5317.2 1E6 m3	31.828 km2
#3	P90	90 %	3526.6 1E6 m3	24.218 km2

	A	B	C	D
	Quantile	Probability	Volume	Area
#1	P10	10 %	11543 1E6 m3	46.093 km2
#2	P50	50 %	8561.3 1E6 m3	39.93 km2
#3	P90	90 %	6277.5 1E6 m3	37.115 km2

Fig.6.1_5: P10 P50 and P90 GRV figures for both scenarios Above Conditioned PSDM Below Raw PSDM

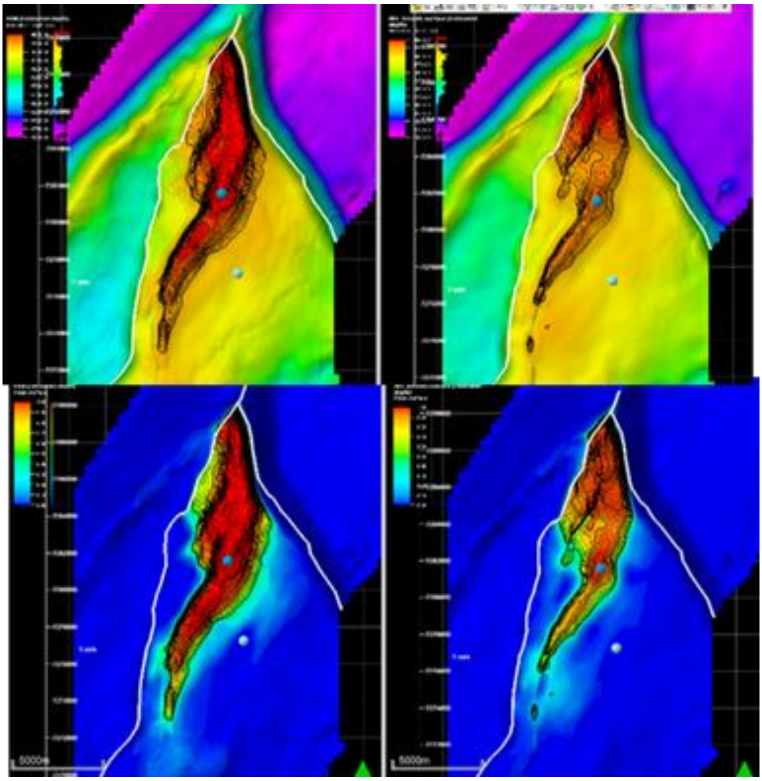


Fig.6.1_6: Depth and closure probability maps for both scenarios (Left : raw PSDM and right conditioned PSDM

- Conclusion

The same 2016 results of the case study were of course reproduced in 2023 (even better as 2023 P_scenario 2 ended up less than 10m above the actual new well depth!), but with different KPIs:

- reduced turnaround time to less than a week (over 5 time less than in 2016)
- optimized workflow performance with quantified confidence intervals.
- generation of pdf reports including input, process, output descriptions and parameters,
- sharing of smart P-scenarios instead of "black box numerical models

Revisiting the 2016 EAGE case study using an Earth Intelligent software in 2023 illustrates the main operational KPIs that must be expected from artificial intelligence when modelling O&G reservoirs.

7 Conclusion

To conclude on the proposed theme of "geophysics and AI", we can distinguish within the term geophysics:

- its object: "Applied geophysics, the practical branch of the discipline, uses indirect methods (seismic waves, electrical and magnetic measurements, etc.) to explore the subsurface without drilling."
- the means it uses to achieve this: "the acquisition of data, their processing, interpretation, and modelling."

With the digital revolution, the analog processing of geophysical data has been replaced by digital processing requiring increasingly powerful computational resources—the very same that enabled the development of artificial intelligence. Their common purpose is clear: to give meaning to data and answer the questions we ask of it, with the specific goal in geophysics of imaging and numerically modelling the physical properties of the subsurface.

This raises the question: Does scientific computing belong to AI?Scientific computing is indeed a task that normally requires human intelligence, so it belongs to AI—insofar as AI augments and extends human capabilities for calculation and reasoning.

Yet this is not the opinion of AI itself (GPT, Mistral), which argues that scientific computing relies on the explicit modelling of physical laws and on deterministic algorithms that we understand and control. It would therefore translate human intelligence into "mathematical models".This is a fundamental misunderstanding: mathematical models belong to the purely conceptual domain—a natural human resource, the "grey matter", which is fully beyond the reach of AI.

It would be more accurate to say that scientific computing translates mathematical models created by human intelligence into numerical models.Confusing mathematical models with numerical models gives artificial intelligence a "magical" aura, which is unacceptable after a century of work on the unconscious, from Sigmund Freud to C.G. Jung, exploring the relationship between consciousness and unconscious processes in the human psyche.

AI follows an empirical, statistical approach, attempting to imitate certain intelligent behaviours from numerical data (encoded in base 0–1), disregarding underlying physical equations when they exist—as they do in geophysics. It learns from experience by detecting regularities and correlations in large datasets, in order to help construct the same types of numerical models that geophysics builds using scientific computing.

It is true that these two approaches converge today in what is known as Scientific Machine Learning or Physics-Informed AI, which combines the rigour of physical models with the predictive and adaptive capabilities of AI algorithms. The question remains how this convergence will evolve.

The quantum revolution, contemporary with the work of C.G. Jung—as illustrated by his more than 20-year correspondence with Wolfgang Pauli—sheds light on the notions of rigour in the geophysical approach and flexibility in artificial intelligence.

- At the macroscopic scale of observation, deterministic physical laws apply and are sufficient to model, "objectively," the interaction between humans and their natural environment.
- At the subatomic scale, however, these laws no longer apply; a fundamental indeterminacy appears (superposition and entanglement of "quantum states"), and experimental results are conditioned by the experimental setup itself—what is called "wavefunction collapse", i.e., a single realization among all possible quantum states.

To Albert Einstein's famous statement "God does not play dice", expressing his disagreement with the probabilistic interpretation of quantum mechanics, it is relevant to juxtapose Georges Matheron's statement 50 years later:

"There is no such thing as probability in itself, there are only probabilistic models." This provides the theoretical foundation for the practice of probability in the estimation of natural phenomena (Estimer et choisir, 1978).

From a single realization of a regionalized variable, it is indeed possible to characterize and specify a probabilistic mathematical model using experimental spatial statistics, and within this model to define the random variable "estimation error", the a priori unknown difference between the estimated value of the variable at an unsampled location and its unknown true value at the time of estimation.

Applied to geophysical data processing, geostatistical or topo-probabilistic models integrate both:

- the deterministic aspects of geophysical laws (to characterize the mean spatial behaviour of the property studied), and
- the random aspects of residual spatial variability around this mean.

The minimisation of estimation error (first of the geophysical signal, then of the subsurface property)—in the probabilistic sense (zero-mean and minimum variance)—throughout the processing, interpretation, and modelling chain, makes estimation variance the unique and original cost function used by Earth Intelligence algorithms to automate and optimise each step of the workflow.

We thus see how digital geophysics and artificial intelligence were born from the digital revolution, then brought closer by the quantum revolution, before being finally united by the probabilistic revolution.

C.G. Jung demonstrated how quaternions, represented in the form of mandalas (crosses, circles…), symbolise a totality composed of apparent opposites. I propose the following one in Figure 7_1 to summarise the path travelled by the reader throughout this presentation:

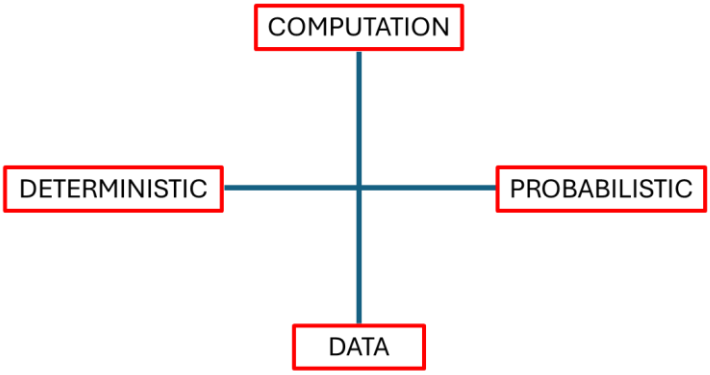


Fig 7_1: The Geophysics and Artificial Intelligence Quaternion

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