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Artificial intelligence in oil and gas exploration

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Abstract
This paper presents the development of the Digital Caspian information platform — a large-scale initiative that integrates the power of artificial intelligence (AI), geographic information systems (GIS), and digital twins. Its primary goal is to revolutionize approaches to subsurface resource management, enhance environmental safety, and optimize strategic planning for oil and gas exploration. By embedding AI at the core of the Digital Caspian, the project establishes a smart exploration system — a sophisticated combination of software and hardware tools capable of transforming the management of geological exploration processes, significantly improving their efficiency and precision. The approach relies on the principles of digital engineering, which involves the creation of virtual prototypes of real-world objects, such as hydrocarbon fields and exploration processes. Digital engineering enables rapid and effective solutions to key challenges in hydrocarbon exploration and field development. At the core of the platform is a suite of interactive geological and environmental digital maps that support high-precision forecasting and facilitate informed, science-based decision-making in critical areas such as subsurface resource use, environmental safety, and exploration planning for oil and gas.

Key words
Artificial intelligence, geographic information systems, digital twins, subsurface resource management, environmental safety, geological exploration, intelligent systems, Caspian Sea.

Introduction

The aim of this work is to develop the Digital Caspian platform—an innovative tool designed to transform approaches to the study and development of subsurface resources in the Caspian region. At the core of the platform lies a series of interactive geological and environmental digital maps that enable high-precision forecasting and informed, science-based decision-making in key areas such as subsurface resource management, environmental safety, and strategic planning of oil and gas exploration.

The relevance of this research stems from the strategic importance of the Caspian region for the development of Russia's hydrocarbon resources. This unique area, which holds vast reserves of hydrocarbons and hosts fragile, irreplaceable ecosystems, requires a balanced and scientifically grounded approach to exploration. For the first time, an innovative information platform—Digital Caspian—and a set of interactive geological and environmental digital maps have been developed specifically to address this challenge. These tools are intended to provide integrated analysis, accurate forecasting, and well-informed, science-driven decision-making in the fields of subsurface resource use, environmental protection, and forward-looking exploration planning. The multidisciplinary nature and exceptional timeliness of this initiative are particularly evident in the context of increasing anthropogenic pressure and transboundary environmental risks. In this regard, the development of digital instruments capable of enabling comprehensive monitoring, scenario modeling, and support for environmentally responsible decision-making becomes a matter of critical importance.

The integration of AI allows creating an intelligent geological exploration system "Smart oil & gas exploration" and "Smart Field" (SF) - these are software and hardware systems that combine digital technologies and engineering knowledge to optimize and transform production and logistics processes that allow managing the process of geological exploration for oil and gas and the development of hydrocarbon fields, including all stages of the life cycle of an oil and gas field. The activities of subsoil users engaged in geological exploration, production, transportation and sales are carried out within the framework of technological and business processes, coordinated by relevant projects. The main processes of companies and enterprises engaged in geological exploration, prospecting, exploration and production of hydrocarbons are determined by the life cycle of the field. The application of digital technologies to the exploration workflow primarily involves the adoption of innovative solutions for assessing and forecasting hydrocarbon potential, as well as determining optimal targets for prospecting and delineating oil and gas accumulations. To support this, digital engineering methodologies are employed—focused on the creation of virtual prototypes of real-world objects such as hydrocarbon fields and exploration processes. This enables scenario modeling, performance analysis, bottleneck identification, and process optimization without posing risks to actual operations. Digital engineering thus offers a fast and efficient means of addressing key challenges in oil and gas exploration and field development.The next evolutionary stage in digital petroleum engineering is the deployment of intelligent multi-agent systems.

Systems engineering (SE) is a scientific and applied discipline focused on the study of engineering systems and the processes, methods, and tools used for their creation and operation. SE is inherently multidisciplinary and is evolving rapidly through integration with other technologies, including ontological engineering and artificial intelligence. According to the International Council on Systems Engineering (INCOSE), systems engineering is defined as an interdisciplinary approach and a set of tools that enable the realization of successful systems.

Model-Based Engineering (MBE) is an approach to product development, manufacturing, and lifecycle support that relies on digital modeling—in this context, the modeling of the entire oil and gas exploration process. The evolution from traditional SE to MBE is illustrated in Figure 2. MBE provides a methodology for more rigorous and integrated systems engineering by combining various models across the product, production system, post-deployment support, and validation stages.

Boeing developed a framework (Figure 1) that demonstrates the application of digital twin configurations such as as-designed, as-built, and as-delivered as distinct digital product representations. The SE diamond and the Model-Based Systems Engineering (MBSE) paradigm (see Fig. 1) reflect a shift from document-centric thinking to digital design thinking, using a Digital Thread that spans the entire product lifecycle [1].

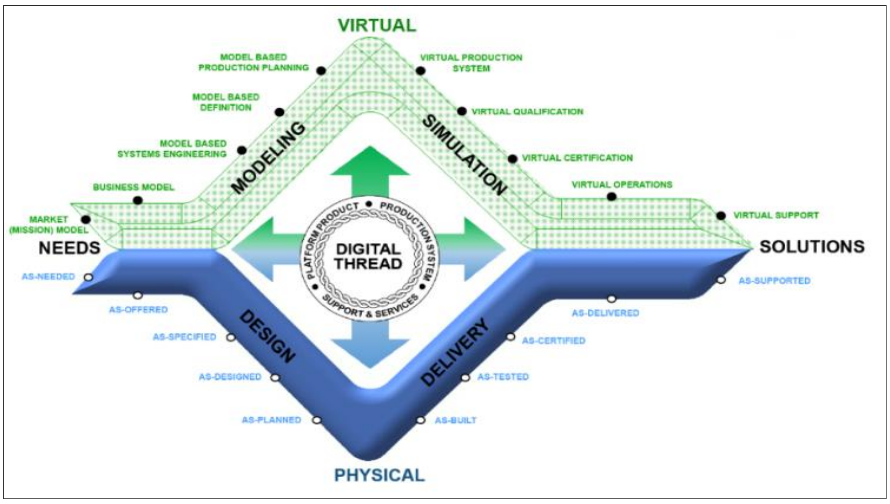

Figure 1 – Evolution of system engineering (SE) to model based engineering

(MBE) diamond symbol – a framework for MBE:

-The bottom-half of the Diamond represents Physical System (retaining traditional SE “V” flow);

-The top-half of the Diamond represents the “Virtual” Systems (i.e. the virtual representation of the physical systems);

-The interior of the Diamond represents the “Digital Thread” linking models/simulations to the physical systems design.

Gazpromneft proposed the use of digital engineering at the oil company level (Figure 2) (M. Khasanov). Considering that over 70% of research time is spent processing geodata and performing routine operations, it was proposed to delegate these tasks to artificial intelligence. The project, dubbed "Cognitive Geologist," envisions the creation of a self-learning model of a geological object that will mathematically process the initial data and produce a final result, assess the probability of correct answers, and recommend additional research to increase confidence in success. This is expected to reduce the time required to interpret geological data by approximately sixfold.

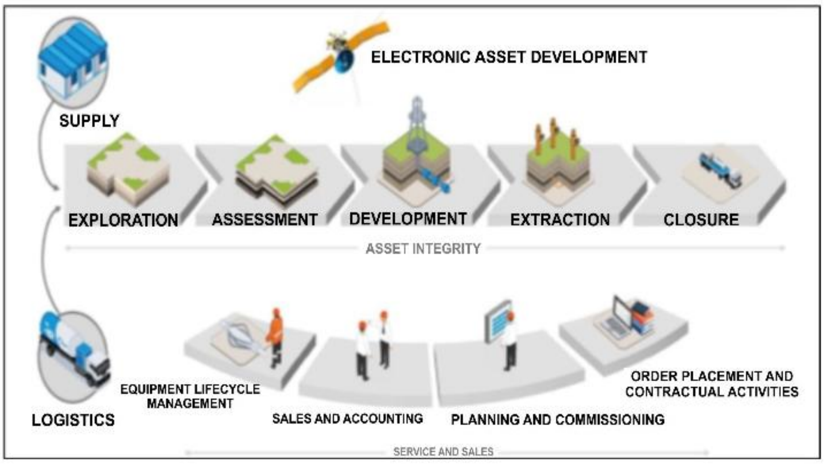

Figure 2 – Digital engineering at the oil company level

Analysis of the scientific problem and main provisions of the research

The implementation of artificial intelligence (AI) technologies is driving exponential growth in the number of artificial neural network models and their specialization for solving various target problems, such as planning and optimization of geological exploration, and the development and operation of hydrocarbon fields. To address these challenges in subsoil use, environmental safety, and oil and gas exploration planning, we need powerful, engineering-oriented artificial intelligence technologies that do not require routine human intervention and consist of both human-centric and machine-centric systems.

Modern AI systems in geological exploration are based on a synergistic combination of computational mathematics, statistics, and machine learning. Below are the key concepts and methods, grouped by their functional domains:

Fundamental mathematical concepts - the foundation without which understanding AI algorithms is impossible.

- **Linear algebra:** Core tools include vectors, matrices, tensors, linear transformations, eigenvalues, and eigenvectors, all of which are used to represent seismic data (cubes and sections) as multidimensional matrices (tensors). Any processing operation (e.g., filtering, migration) is a linear transformation applied to these matrices. In machine learning, data are represented as feature vectors, while models (e.g., linear regression) are expressed as matrix operations. Data transformation follows the formula: $Y = W * X + b$, where X — input data vector (e.g., amplitude values at a point), W — model weight matri, b — bias vector, Y — output (e.g., rock classification).

- **Mathematical analysis (Differential calculus):** Key tools include derivatives, gradients, and partial derivatives. Gradient descent is the cornerstone of training nearly all neural networks. The algorithm iteratively adjusts model parameters, moving opposite to the gradient of the loss function to minimize it: $W\_new = W\_old - \alpha * \nabla J(W)$, where W — model parameter, α — learning rate, $\nabla J(W)$ — gradient of the cost (loss) function.

- **Probability theory and mathematical statistics:** This domain underpins the concepts of probability, distributions (normal, Poisson, etc.), conditional probability, Bayes' theorem, correlation, and regression. Applications include uncertainty quantification (e.g., the probability of hydrocarbon presence in a reservoir), error analysis, Bayesian inversion of geophysical data, and statistical evaluation of core and well logging properties. The Bayes' theorem is expressed as: $P(A|B) = [P(B|A) * P(A)] / P(B)$, where A — hypothesis (e.g., "presence of a reservoir"), B — new evidence (e.g., seismic attribute). It allows updating the probability of a hypothesis given new data.

Research methods

The following methods are used to solve the assigned tasks:

1. Optimization methods: These involve tools for finding the minimum or maximum of a function under given constraints. They are used for model parameter tuning (machine learning), reservoir simulator calibration, and seismic inversion problems. The key methods of computational mathematics and AI applied in geological exploration are applied algorithms built upon the fundamental mathematical concepts described above.

2. Seismic data processing and interpretation.

- Digital signal processing (DSP): Methods include Fourier transform (frequency spectrum analysis), wavelet transform (time-frequency analysis for nonstationary signals), and filtering (low-pass, notch, and median filters for noise suppression). Application: Improving the quality of seismic data and enhancing useful signal components.

- Seismic inversion (from amplitudes to rock properties): This is a classical ill-posed inverse problem requiring the reconstruction of medium parameters (such as impedance, density, and velocity) from recorded seismic responses. Common approaches include deterministic inversion, solved via the least squares method or other regularization techniques (e.g., Tikhonov regularization): $\min \|G(m) - d\|^2 + \lambda\|Lm\|^2$, where G — forward modeling operator (seismic simulation, m — model parameters to be estimated (reservoir properties), d — observed seismic data, λ — regularization parameter, L — operator (often a derivative to enforce solution smoothness).

Statistical/Bayesian inversion provides not a single solution but a probability distribution of possible solutions, which is critical for risk assessment.

- Machine learning applications: Neural networks, especially convolutional neural networks (CNNs), are trained on synthetic or labeled real data to directly map seismic cubes into acoustic impedance cubes.
- Attribute analysis and methods: Seismic data are used to compute hundreds of mathematical attributes (amplitude-based, frequency-based, and geometric). To analyze and reduce the dimensionality of these large datasets, Principal Component Analysis (PCA) and Autoencoders are employed. The PCA formulation is based on Singular Value Decomposition (SVD) of the data matrix: $X = U\Sigma V^T$, where the columns of V represent the principal components — orthogonal directions capturing the maximum variance in the data.

3. Well logging data interpretation and rock property prediction.

Methods and formulas:

1. Linear / Logistic Regression — basic methods for regression and classification.

Logistic regression formula: $P(y=1|x) = \sigma(w^T x + b)$, where σ — is the sigmoid function $\sigma(z) = 1 / (1 + e^{-z})$. This predicts the probability of belonging to a certain class (e.g., sand or clay).

2. Support Vector Machine (SVM): finds the optimal separating hyperplane in the feature space.
3. Random Forest and Gradient Boosting (XGBoost, CatBoost): powerful ensemble methods that often achieve state-of-the-art results on tabular datasets such as well logging data.
4. Neural Networks (Fully Connected – FNN): used to model complex nonlinear relationships between geological features and measured parameters.
5. Construction and digitization of geological models.

- Interpolation and Extrapolation: for constructing and digitizing geological models. Methods include Kriging — the best linear unbiased estimator based on geostatistics and variograms, as well as splines and Radial Basis Functions (RBFs).
- Computer Vision: for automated seismic facies interpretation, texture detection, and core image analysis using Convolutional Neural Networks (CNNs) such as U-Net architectures.

6. Modeling and Risk Assessment. Statistical simulation using the Monte Carlo method is applied for estimating hydrocarbon volumes and assessing uncertainty. It involves repeated random sampling of key parameters (porosity, saturation, area) according to their probability distributions, producing a resulting distribution of possible hydrocarbon

volumes.

The outcome of this work is the development of the innovative digital, which integrates analytical modules designed to assess the hydrocarbon potential, environmental conditions, and geo-economic state of the region. Digital Caspian is a large-scale initiative that brings together the capabilities of artificial intelligence, GIS, and digital twins (Figure 3). The platform is intended to serve as the foundation for interactive geological and environmental digital maps, opening new horizons for integrated analysis, forecasting, and science-based decision-making [2-4]. Its goal is to revolutionize subsurface resource management, ensure environmental safety, and optimize the strategic planning of oil and gas exploration activities.

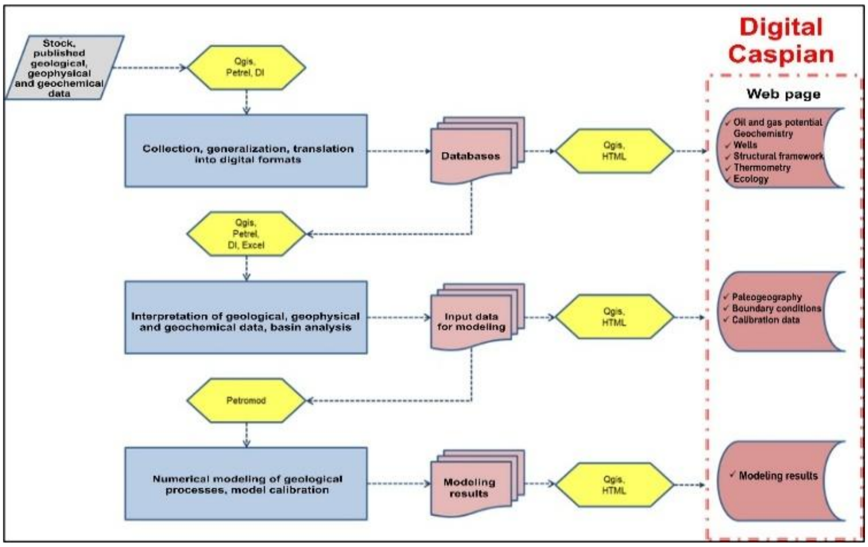

Figure 3 – Block diagram of the Digital Caspian Platform.

The diagram illustrates the structure of the Digital Caspian digital platform, where the main technological process stages are represented by blue rectangles; the software tools applied at each stage are shown in yellow diamonds; intermediate outputs used in subsequent steps appear as pink multipage documents. The outputs of each stage together form the core components (modules) of the Digital Caspian.

The platform enables forward-looking assessments of the Caspian region by predicting future changes in sea level, temperature, and salinity, leveraging the power of global climate models (CMIP6). Climate change modeling provides a window into the coming decades, allowing stakeholders to anticipate and prepare for future challenges. By utilizing advanced neural network architectures such as LSTM and Transformers, the system generates probabilistic scenarios to forecast potential crisis situations and ecological disasters—including oil spills and droughts [6-9].

Research results

The digital platform is not merely a data repository, but a knowledge system enriched with geological, geophysical, and geochemical information, enhanced by numerical modeling results that reconstruct the geological and environmental conditions and hydrocarbon systems of the Caspian region [5]. The platform enables comprehensive ecosystem monitoring—tracking pollution, forecasting degradation, and evaluating the destructive impact of oil and gas extraction on the region's fragile biodiversity.

The digital maps integrated into the platform function as an interactive database (IDB) of geological, geophysical, and geochemical data. They are designed for the visualization of structured geospatial datasets aligned with the approved architecture of the geo-information database, which is defined by the objectives of exploration activities and the outcomes of basin analysis and numerical modeling. The platform serves as a comprehensive digital environment for modeling, forecasting, and decision support in the exploration, appraisal, and development of hydrocarbon fields.

Digital Caspian combines AI, big data technologies, GIS and digital twins to enable an integrated approach to subsurface exploration and hydrocarbon development. The platform incorporates:

- Digital twins of geological systems, ecosystems, and regional infrastructure;
- Multidimensional geological and environmental models, including hydrocarbon systems and reservoir models;
- AI-based models for forecasting hydrocarbon prospectivity, environmental risks, and economic scenarios;
- GIS modules for geological data analysis, map integration, and results visualization;
- Decision support tools with built-in automated recommendations.

A key advantage of the IDB over traditional GIS-based databases is the ability to visualize its content without the need for specialized software. This accessibility allows a wide range of users—including those without training in dedicated tools or without the necessary software licenses—to engage with the curated geological information.

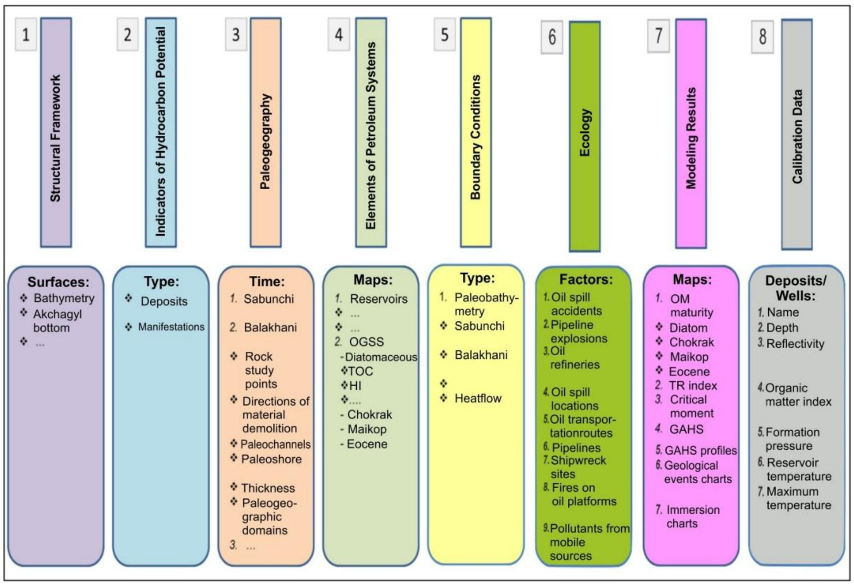

Figure 4 – Conceptual structure of the IDB.

The approaches described above were applied in the development of the IDB structure. In accordance with the project's objectives, the IDB comprises eight key modules: Structural Framework, Indicators of Hydrocarbon Potential, Paleogeography, Ecology, Elements of Petroleum Systems, Boundary Conditions, Modeling Results, and Calibration Data (Figure 4).

The first six modules contain input data for numerical modeling, including primary information and its interpretation obtained through basin analysis. The seventh module stores the results of numerical modeling of hydrocarbon generation–accumulation systems, while the eighth module includes calibration datasets [10, 11].

A core focus in the development of these modules is the modeling of hydrocarbon systems and oil and gas fields. As part of the AI-based initiative to improve the efficiency and optimization of offshore exploration processes, digital twins and digital maps have been created. The Digital Caspian platform has generated several thousand numerical models that reconstruct geological and environmental conditions, as well as hydrocarbon systems across the Caspian region.

Figure 5 presents examples of digital structural–spatial models, while Figure 6 illustrates the results of numerical modeling of hydrocarbon systems in the Caspian Sea, produced using the platform [12-14].

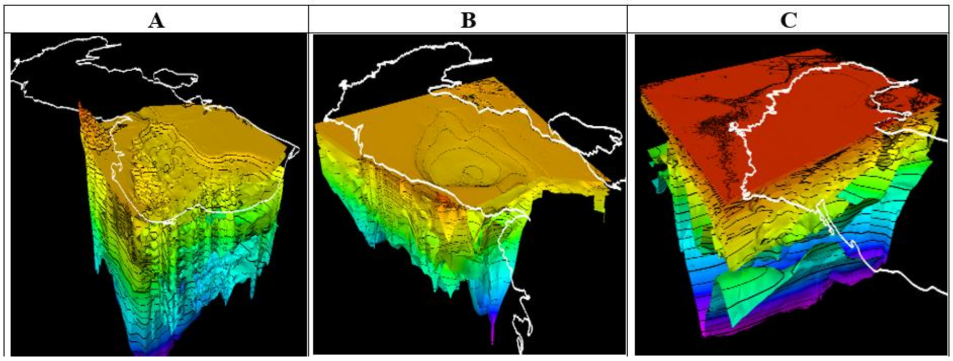

Figure 5 – Three-dimensional structural-spatial models of sedimentary basins: A – South Caspian Basin; B – Central Caspian Basin; C – North Caspian Basin.

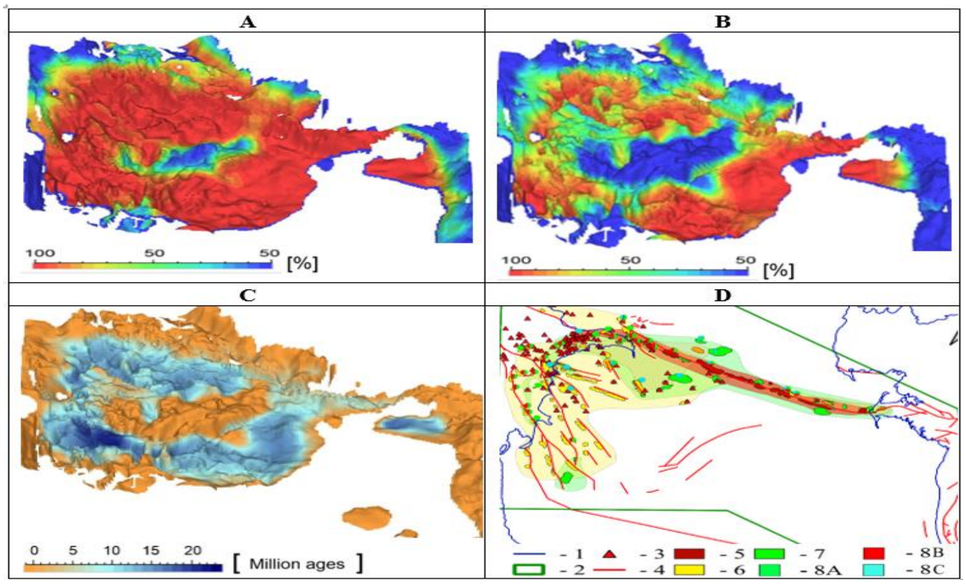

Figure 6 – Examples of digital twins and models of hydrocarbon systems in the South Caspian Basin: A – model of transformation ratio (TR) reflecting source rock generative potential;
B – model of hydrocarbon generation (catagenetic evolution); C – model of hydrocarbon migration; D – model of hydrocarbon accumulation.

Legend for Figure 6d: 1 – shoreline; 2 – study area; 3 – mud volcanoes; 4 – faults; 5 – hydrocarbon accumulation zones in the productive series of the Eocene–Pliocene petroleum system; 6 – hydrocarbon accumulation zones in the productive series of the Maikop–Pliocene petroleum system; 7 – hydrocarbon accumulation zones in the productive series of the Miocene–Pliocene petroleum system; 8 – fields: A – oil; B – gas; C – gas condensate.

The 3D and 2D models developed through numerical simulation—reconstructing geological and environmental conditions as well as the structural and functional elements of petroleum systems—have been transformed into interactive geological and environmental digital maps, including hydrocarbon system and field distribution maps (Figure 7). [15-24].

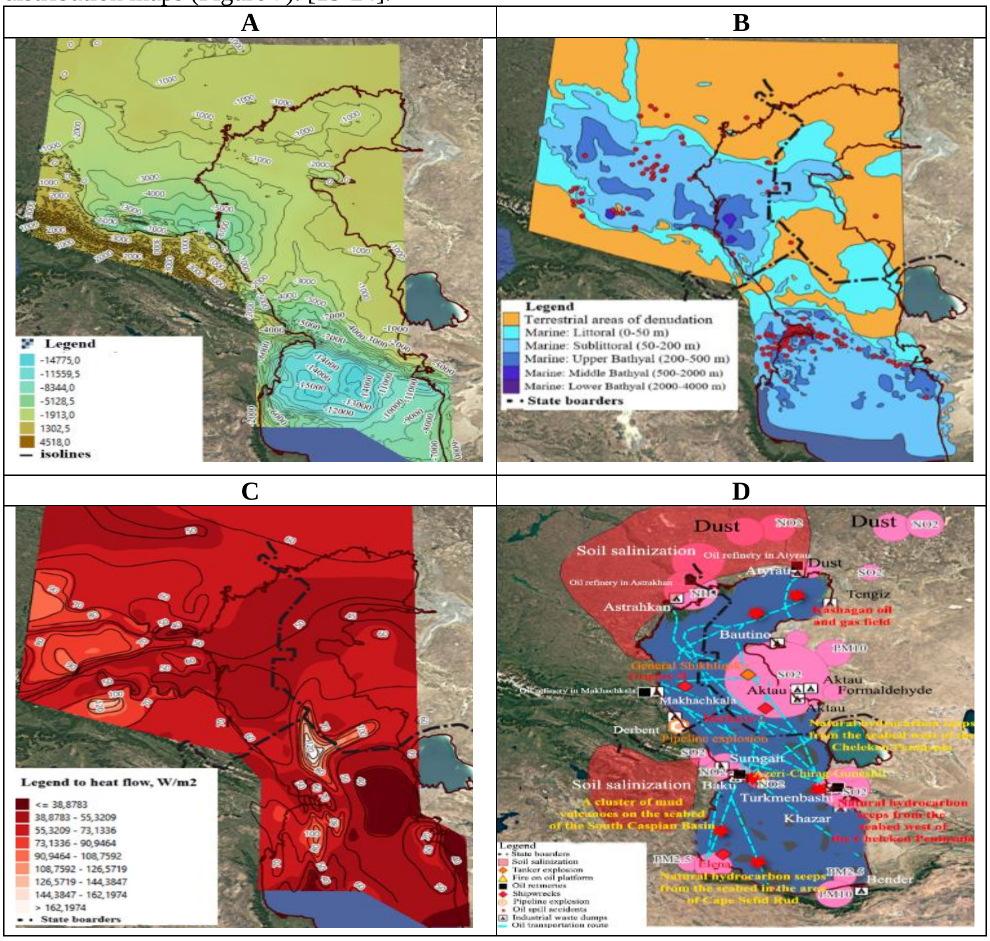

Figure 7 – Examples of digital maps derived from 3d models: A – structural–tectonic maps;
B – paleogeographic maps; C – heat flow maps; D – environmental maps.

The full workflow for transforming numerical models into digital maps includes the following steps:

1. Preparation and systematization of input data in QGIS;

2. Digitization and map construction in QGIS;
3. Construction of 3D grids in Petrel;
4. Calculation of 3D geological models in PetroMod;
5. Analysis of simulation results in QGIS;
6. Development of an interactive database using Python, incorporating artificial intelligence for the creation of a web interface, integration of resulting maps, charts, cross-sections, well and calibration data, implementation of analytical tools, and intelligent data organization.

Conclusions

The development of the Basic Modeling System (BMS) is method-oriented rather than problem-oriented, meaning that its architectural design is built not around specific problem types but around universal methodological principles.

The principles and architecture of the BMS [30] are based on the following key provisions:

1. Comprehensive support for all major technological stages of modeling.

The BMS core consists of semi-autonomous subsystems, each developed and functioning independently, yet interacting through standardized data structures—thus realizing the well-known principle by Niklaus Wirth:

Program = Algorithms + Data Structures.

2. Extensibility of implemented and supported models, algorithms, and data structures, ensuring a long lifecycle and adaptability of the BMS to advances in computational and information technologies as well as to the evolution of computing platforms.

3. Balance between universality and efficiency, meaning the system supports a wide class of problems and algorithms while maintaining high computational performance.

This is achieved through modular design, multiversion capabilities, and flexible configuration assembly for specialized applications.

4. System openness, allowing for the reuse of external software tools and fostering broad collaboration among developers through unified principles and technologies.

Implementing this level of mathematical and software integration inevitably requires large-scale coordinated technical work involving multiple teams, which brings forward system-level issues of interoperability.

Such challenges are effectively addressed through component technologies (COM – Component Object Management) [31], providing rich production interfaces, multilingual capabilities, and cross-platform compatibility for large projects.

Among the most significant results of this work are the following:

- A flexible platform architecture has been designed and implemented, built on the principles of modularity, scalability, and seamless integration with external data sources and existing industry IT solutions.
- Detailed digital twins of geological and environmental systems of the Caspian region have been developed. These virtual models—including three-

dimensional reconstructions of reservoirs, structural complexes, and ecologically stressed zones—offer deep insight into the core of natural processes.

- Advanced forecasting algorithms based on machine learning, including neural network architectures such as LSTM and Transformer, have been integrated to predict future changes with high accuracy.
- Interactive environmental maps have been developed, enabling spatial and temporal visualization of data. These tools support in-depth scientific interpretation and provide broad accessibility to information—from researchers to decision-makers.
- The platform has been successfully tested on real-world case studies covering areas of active resource extraction, biologically vulnerable zones, and regions of strategic geo-economic importance within the Caspian Basin.
- A complete set of user and methodological documentation has been prepared, ensuring the reproducibility of scientific experiments and enabling the platform's scalability for application in other regions around the world.

The scientific novelty of the presented results lies in an innovative, integrated approach to digital modeling that simultaneously incorporates geological, environmental, and anthropogenic factors. The Digital Caspian platform represents a unique tool for conducting transdisciplinary research, performing in-depth scientific analysis, and enabling sustainable resource management.

The outcomes of this work have both fundamental and applied significance for Earth sciences, digital geoecology, and the oil and gas sector.

From a scientific perspective, this research contributes to:

- Advancing methodologies for the creation of digital twins of natural systems, from geological formations to fragile biospheric oases, opening new frontiers for reality-based simulation.
- Formalizing approaches to the integration of heterogeneous geodata, environmental forecasts, and anthropogenic impact factors into a single, transparent predictive system.
- Applying advanced neural network models, such as LSTM and Transformer, to accurately assess risks amid the unpredictable dynamics of natural and geo-economic processes.
- Developing innovative forms of scientific visualization—interactive 3D maps and models of environmental conditions—which transform complex analytical outputs into intuitive and compelling representations.

From a practical standpoint, the platform offers new capabilities for:

- Subsurface resource users and oil and gas companies, who gain a powerful tool for identifying promising hydrocarbon zones and optimizing exploration activities.
- Environmental agencies, which can perform real-time monitoring, model the impacts of industrial activity, and develop effective mitigation programs.
- Scientific institutions, which benefit from a unified platform for interdisciplinary research and data exchange, bridging gaps across scientific domains.

• Policy-makers and international organizations, who can make well-founded decisions on sustainable natural resource use and environmental safety based on objective data and predictive insights.

The platform can be readily adapted to other marine and coastal regions of Russia and serves as a prototype for scaling within future national and international scientific and technological initiatives.

References

1. Ministry of Digital Development, Communications and Mass Media of the Russian Federation. (2019). Roadmap for the development of end-to-end digital technology: Neurotechnologies and artificial intelligence. [In Russian].
2. Dmitrievsky, A.N., Eremin, N.A., Filippova, D.S., & Safarova, E.A. (2020). The digital oil and gas complex of Russia. Georesursy (Georesources), Special issue, pp. 32–35. https://doi.org/10.18599/grs.2020.SI.32-35.
3. Khasanov, M.M., Prokofyev, D.O., Ushmaev, O.S., Belozerov, B.V., Gilmanov, R.R., & Margarit, A.S. (2016). Promising Big Data technologies in petroleum engineering: Gazprom Neft's experience. Neftyanoe Khozyaystvo – Oil Industry, (12), pp. 76–79. [In Russian].
4. More than just data. (2018, September). Siberian Oil. Industry 4.0 supplement. Issue 154. Retrieved from https://www.gazprom-neft.ru/press-center/sibneft-online/archive/2018-septemberprojects/1863684/
5. Mashika, A.G. (2020, December 24). Why cloud computing is needed in the oil and gas sector. Retrieved from http://neftianka.ru/zachem-nuzhny-oblachnye-vychisleniya-v-neftegazovom-sektore/ [In Russian].
6. Digital transformation. End-to-end technologies. Retrieved from https://digital.gazprom-neft.ru/technologies?page=2
7. Gazprom Neft is developing machine learning technologies. Retrieved from https://www.gazprom-neft.ru/press-center/news/gazprom-neft-razvivaet-tekhnologii-mashinnogo-obucheniya/
8. Ministry of Digital Development, Communications and Mass Media of the Russian Federation. (2019). Roadmap for the development of end-to-end digital technology: Virtual and augmented reality technologies. [In Russian].
9. Ministry of Digital Development, Communications and Mass Media of the Russian Federation. (2019). Roadmap for the development of end-to-end digital technology: New production technologies. [In Russian].
10. Varlamov, A.I., Gogonenkov, G.N., Melnikov, P.N., & Cheremisina, E.N. (2021). Current state and development prospects of digital technologies in oil and gas geology and subsurface use in Russia. Geologiya Nefti i Gaza (Geology of Oil and Gas), (3), pp. 5–20. https://doi.org/10.31087/0016-7894-2021-3-5-20.
11. Cheremisina, E.N., Kostyleva, T.V., & Muradyan, A.V. (2021). Digitalization in geological exploration: Review and analysis of the current state. Geoinformatika (Geoinformatics), (4), pp. 18–27. https://doi.org/10.47148/1609-364X-2021-4-18-27.

12. Kerimov V.Yu., Guliev I.S., Dzhavadova A.S., Kadirov F.A., Mustayev R.N., Gurbanov V.Sh., Huseynova Sh.M. (2024). Characteristics of oil and gas source strata and features of hydrocarbon systems of the South Caspian Basin, Bulletin of the National Academy of Sciences of Azerbaijan. Series: Earth Sciences, (1), pp. 77-92.
13. Kerimov, V.Y., Bondarev, A.V., Mustaev, R.N. (2017). Estimation of geological risks in searching and exploration of hydrocarbon deposits. Neftyanoe Khozyaystvo – Oil Industry, (8), pp. 36–41.
14. Kerimov, V.Yu., Shilov, G.Ya., Mustayev, R.N., Dmitrievsky, S.S. (2016). Thermobaric conditions of hydrocarbon accumulation in the low-permeability oil reservoirs of the Khadum Suite (Pre-Caucasus). Neftyanoe Khozyaystvo – Oil Industry, (2), pp. 8–11.
15. Kerimov, V.Yu., Mustaev, R.N., Etirmishli, G.D., Yusubov, N.P. (2021). Influence of modern geodynamics on the structure and tectonics of the Black Sea–Caspian region. Eurasian Mining, 35(1), pp. 3–8.
16. Kerimov, V.Yu., Serikova, U.S., Mustayev, R.N., Guliyev, I.S. (2014). Deep oil-and-gas potential of the South Caspian Basin. Neftyanoe Khozyaystvo – Oil Industry, (5), pp. 50–54.
17. Lapidus, A.L., Kerimov, V.Y., Mustaev, R.N., ...Salikhova, I.M., Zhagfarov, F.G. (2018). Natural Bitumens: Physicochemical Properties and Production Technologies Solid Fuel Chemistry, 52(6), pp. 344–355.
18. Guliev, S., Mustaev, R.N., Kerimov, V.Y., Yudin, M.N. (2018). Degassing of the earth: Scale and implications // Gornyi Zhurnal, (11), pp. 38–42.
19. Kerimov, V., Rachinsky, M., Mustaev, R., Serikova, U. (2018). Geothermal conditions of hydrocarbon formation in the South Caspian basin. Iranian Journal of Earth Sciences, 10(1), pp. 78-89.
20. Stouffer, K., Pease, M., Tang, C., et al. (2023). Guide to Operational Technology (OT) Security. National Institute of Standards and Technology (U.S.). https://doi.org/10.6028/nist.sp.800-82r3
21. Frehn, J. (2024). AI-powered identity authentication is here: What you need to know. Portnox. Retrieved from https://www.portnox.com/blog/network-security/ai-powered-identity-authentication/
22. Cheshkov, A., Zadorozhny, P., & Levichev, R. (2023). Evaluation of ChatGPT model for vulnerability detection. arXiv preprint. https://arxiv.org/abs/2304.07232
23. Steenhoek, B., Rahman, M.M., Jiles, R., & Le, W. (2023). An empirical study of deep learning models for vulnerability detection. In 2023 IEEE/ACM 45th International Conference on Software Engineering (ICSE), pp. 2237–2248. IEEE.
24. Curran, K., & Snodgrass, A. (2015). A novel cue-based picture-word-shape-character password creation scheme. International Journal of Digital Crime and Forensics, 7(3), pp. 37–59. https://doi.org/10.4018/ijdcf.2015070103