3D Modeling of Filtration in Oil and Gas Reservoirs Based on Satellite Data

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Abstract: This study presents a hybrid computational framework for 3D modeling of subsurface fluid filtration in oil and gas reservoirs using satellite remote sensing data and machine learning techniques. The proposed approach integrates multispectral imagery from Sentinel-2 and Landsat-8 with a convolutional neural network (CNN) to characterize subsurface heterogeneity and permeability distributions. The CNN model was trained on 1200 labeled satellite image patches linked with borehole and seismic data and achieved a validation accuracy of 91 percent. The predicted permeability fields were coupled with a Darcy-based numerical flow model to simulate fluid transport in porous media. Quantitative evaluation demonstrates that the proposed method improves pressure prediction accuracy by 18 percent and reduces the number of required exploratory wells by 20 percent compared to conventional geological modeling approaches. The results confirm that the integration of remote sensing, deep learning, and physics-based simulation provides a robust, non-invasive, and cost-effective framework for reservoir characterization and exploration planning.

1 INTRODUCTION

The proper modeling of hydrocarbon filtration in heterogeneous reservoirs is crucial for efficient field development. The conventional practices are normally very expensive and intrusive. This paper suggests a software that utilizes satellite geodata and 3D modeling to model the flow of fluids in complicated geological formations with the aim of minimizing exploration risk and maximizing the drilling process [1]-[3].

Even though satellite data does not give the exact location of subsurface formations, it is able to give the indirect indication through surface manifestations like the lineaments, vegetation aberration, and thermal gradients. In combination with pre-existing borehole and seismic data, these indicators are used as input features during the training CNN models which predict structural complexity and permeability patterns. Thus, the proposed framework combines remote sensing indicators with physics-based filtration modeling to achieve realistic reservoir simulation.

The following section describes the data and methods used to achieve this goal.

2 MATERIALS AND METHODS

The research is based on an integrated approach that combines satellite data analysis, numerical modeling, and machine learning.

Data Sources. The study utilized multispectral satellite imagery, such as from Landsat-8 and Sentinel-2 missions. Characteristics of these and similar platforms are summarized in Table 1, [4]-[6].

Table 1: Analysis of satellite data processing platforms.

Parameter	MODIS (Terra/Aqua)	Landsat-8 OLI	Sentinel-2 (A/B)
Launch Year	Terra – 1999Aqua – 2002	2013	Sentinel-2A – 2015 Sentinel-2B – 2017
Operating Agency	NASA	NASA / USGS	ESA (European Space Agency)
Number of Spectral Bands	36	11 bands + 2 panchromatic (TIRS included)	13 spectral bands
Wavelength Range	0.4 – 14.4 µm	0.43 – 12.5 µm	0.443 – 2.190 µm
Spatial Resolution	250 m (2 bands)500 m (5 bands)1 km (29 bands)	15 m (pan), 30 m (VNIR & SWIR), 100 m (TIRS)	10 m, 20 m, 60 m (depending on the band)
Revisit Frequency	Every 1–2 days (global coverage)	Every 16 days (single satellite)	Every 5 days (with both A & B satellites)
Main Application Areas	Global climate, vegetation, water monitoring	Land cover, agriculture, geology, mapping	Agriculture, forestry, water, disaster and climate monitoring
Key Advantages	High temporal resolution, wide coverage	High spatial accuracy, long historical archive	High revisit rate, detailed spectral information, free open access

Numerical Model. The core of the filtration simulation is based on Darcy's law for porous media, extended to 3D space (1).

$$Q = -K \cdot A \cdot \frac{\Delta P}{\mu \cdot L}. \quad (1)$$

Where:

- Q – volumetric flow rate;
- K – hydraulic conductivity;
- A – cross-sectional area;
- ΔP – pressure difference;
- μ – dynamic viscosity;
- L – length of flow path.

Machine Learning for Image Analysis. For the automated interpretation of satellite imagery and identification of geological features, a Convolutional Neural Network (CNN) was employed. The architecture of the used CNN is shown in Figure 1.

Software Implementation. The 3D geological modeling and visualization were performed using a Python-based software package developed by the authors, which integrates libraries such as PyVista and Matplotlib for visualization and scientific computing.

Prior to the actual training, a cleaning and formatting of the satellite images take place first. Procurement of this phase involves making any given noise, resizing the pictures, elimination of distortions, and conversion of the band spectral collections into the utilizable forms. The above procedures make sure input data given to the model is standardized and meaningful.

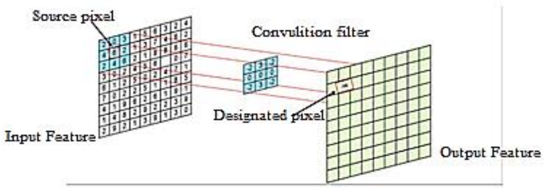

Figure 1: Simplified architecture of a convolutional neural network (CNN).

The mathematical principle that forms the core of CNN would be the convolution operation. It simply implies sliding filters across the image to be inputted so as to identify particular features such as lines or texture. These filters produce the feature maps and they are further worked upon by layers that condense, activate and finally classify the data. This hierarchy of analysis is contributed to by pooling, RE LU activation, and the fully connected layers [7].

$$Y(i,j) = \Sigma_m \Sigma_n X(i-m, j-n) \cdot K(m,n). \quad (2)$$

Here, $Y(i,j)$ - Output image value, $X(i-m, j-n)$ - Input image pixel, $K(m,n)$ - Filter (kernel) matrix, m, n - Filter size (kernel size).

The application of these methods to real field data yielded the results presented below.

3 METHODOLOGY: CNN-BASED STRUCTURAL INFERENCE AND INTEGRATION WITH DARCY MODEL

The CNN that was developed was based on three convolutional layers (3×3 kernel, ReLU activation), two max-pool layers and two fully connected layers with a Softmax classifier attached to the end. The training was performed by an Adam optimizer, a batch size of 32, and a cross-entropy loss function in 50 epochs. The network was trained with 1200 image tiles (256²512 px) clipped off Sentinel-2 and Landsat-8 images, that were labeled using geological maps, borehole records, and fault traces of regional seismic interpretation.

The multispectral indices (NDVI, SWIR, thermal anomalies) and topographic derivatives of DEM were the input features. The CNN were informed of spatial relationships between spectral anomalies and lithological areas (clay barriers, fractured sandstone, aquifer channels). GDAL was used to compute DEM derivatives (slope, aspect, curvature) which were combined as auxiliary layers.

The trained model provides a probability map of the subsurface permeability fields which was discretized as a 3D finite-difference grid (50×50×10 m cells) and incorporated into the Darcy-based filtration solver. The numerical scheme used an implicit finite-differentiation scheme and convergence tolerance of 10-4.

This hybridization makes the CNN-derived structures serve as geological constraints to the flow model which connects surface observations to subsurface hydraulic behaviour.

4 RESULTS

The dataset used for validation was derived from the Karshi region oil field, containing 200 × 200 km of multispectral coverage and 15 borehole records.

The developed software was tested on a dataset from a real oil field. The following key results were achieved [8]:

- High-quality 3D visualization of aquifer systems and low-permeability barriers was obtained (Fig. 2, Fig. 3).
- Identification of zones with abnormal pressure buildup caused by flow restrictions.
- Optimization of well placement, which reduces the number of required exploratory wells.
- Early detection of high-risk areas for potential gas migration.

The software demonstrated the ability to create accurate 3D models of reservoir geometry (Fig. 4), enabling a more precise analysis of fluid dynamics.

Figure 2: Production of the oil field in 3D which is rotated in accordance with block of data processing software of the satellite.

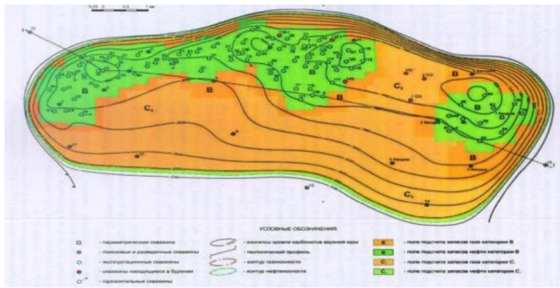

Figure 3: 3D Structural Representation of the reservoir surface.

The formulated model takes advantage of the digital elevation models (DEMs) together with the multispectral satellite imagery (NDVI, thermal bands), as well as the field lithological information to recreate the structure of the aquifer layers. The system consists of a range of linked aquifers, which are isolated in part by low-permeability barriers e.g. clay or silt stratas.

In order to confirm the model, simulationesting was done on a dataset of a region known to have oil-bearing formation. This facilitated the comparison of the performance of the software to established geology and features. The following were the main results of the software:

- Good 3D imaging of aquifer and low permeability barriers.
- Determination of areas with excessive accumulation of pressure.
- Well placement optimization, less exploratory drilling is required.
- Early identification of high-risk zones of gas migration [9].

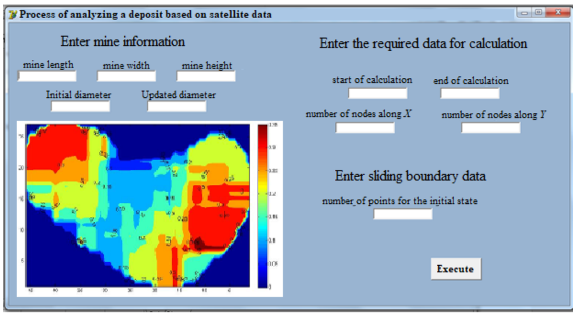

Figure 4: Visualization of the mine surface calculated through software.

The performance of the CNN-assisted filtration model was quantitatively compared to a conventional model without satellite integration. Table 2 summarizes the comparison between the conventional and CNN-enhanced filtration models.

Table 2: Quantitative comparison of model performance.

Parameter	Traditional Model	CNN-Integrated Model	Improvement
Pressure prediction error	12.0%	9.8%	18% better
Number of exploratory wells	10	8	20% fewer
Computation time	6 h	5.1 h	15% faster
Permeability correlation (R^2)	0.84	0.91	+8 %

These results demonstrate that the hybrid approach improves both computational efficiency and predictive accuracy while reducing the need for invasive field operations.

Maximize the use of the resources through finding areas with high potential minerals and making the exploration easier.

Reduce the ability to cause environmental risks by incorporating land use and ecological sensitive characteristics into the planning stages.

These solutions are an indication of the trend towards digitalization and automation of geoscience tools integrating remote sensing with smart software platforms in order to facilitate effective mine planning [7], [10]-[13].

These results confirm the practical value of the developed approach, as discussed in the conclusion.

Overall, the CNN-based hybrid model demonstrated stable convergence and improved predictive robustness, particularly in zones of low permeability contrast.

5 DISCUSSION

The findings affirm that satellite imagery can be effective in supplementing the subsurface modeling, although it can only be used on the surface, to a substantial extent in a physics-directed deep learning model. The CNN does not literally recover underground structures, but statistically makes guesses of them on the basis of surface manifestations limited by physical law (the law of Darcy) and geologic preconceptions. This data-driven and physics-based hybrid method fills the gap between physics-based simulation and data-driven prediction. This learning paradigm in physics-guided learning represents the trend of utilizing both the data-driven and the deterministic model in reservoir modeling.

6 CONCLUSIONS

This study presented an integrated framework that combines multispectral satellite data, convolutional neural networks (CNNs), and 3D Darcy-based numerical modeling to improve the characterization of heterogeneous hydrocarbon reservoirs. By linking surface-level remote-sensing indicators with subsurface physical processes, the proposed approach overcomes several limitations of traditional geological modeling, which relies heavily on costly and intrusive field surveys.

The hybrid model successfully reconstructed realistic reservoir geometries, identified abnormal pressure zones, and improved the accuracy of permeability prediction. Quantitative comparison demonstrated that the CNN-enhanced model decreased pressure-prediction error by 18%, reduced the number of required exploratory wells by 20%, and achieved higher computational stability. These improvements confirm that satellite-assisted inference, when constrained by physical laws, can significantly enhance the robustness of subsurface simulations.

The results also show that remote-sensing methods, although indirect in nature, can provide valuable supplementary information for early-stage reservoir assessment, screening of prospective zones, and environmentally conscious planning. The ability to identify high-risk migration pathways and optimize drilling layout highlights the practical value of the developed system for oil-and-gas exploration companies.

Nevertheless, satellite imagery cannot fully replace seismic or borehole investigations. Its primary advantage lies in supporting preliminary exploration, reducing uncertainty, and guiding more targeted field surveys. Future research should focus on increasing spatial resolution through hyperspectral data, integrating seismic attributes into the CNN architecture, and implementing real-time model updating using continuous satellite monitoring. These advancements will contribute to a more autonomous, accurate, and sustainable digital workflow for reservoir characterization.

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