

Research Article

Magnetic Anomalies Induced by Sources with Unknown Geometry

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Abstract

This research paper addresses the challenges of interpreting magnetic anomalies arising from subsurface sources with unknown or complex geometries, a common issue in geophysical exploration when geological structures deviate from standard, idealized shapes. Traditional inversion methods often rely on geometric assumptions, leading to ambiguities when faced with natural, irregular sources. The study proposes an integrated, geometry-agnostic workflow combining nonparametric equivalent layer modeling, Bayesian Markov Chain Monte Carlo (MCMC) uncertainty quantification, and convolutional neural network (CNN) classification. Synthetic magnetic data generated from amorphous and fractal bodies serve as the basis for validating the method. The equivalent layer inversion reconstructs broad magnetization distributions without the need for explicit geometric constraints, while Bayesian MCMC provides probabilistic estimates and quantifies uncertainty in source parameters such as depth and magnetic moment. This probabilistic approach acknowledges the inherent non-uniqueness of the inverse problem. Additionally, a CNN trained on synthetic datasets can classify magnetic anomalies into source shape categories (bulky, elongated, irregular) with associated uncertainty, enhancing interpretive confidence in complex cases. The study further analyzes sensitivity to noise and magnetization direction variability, demonstrating that these factors critically affect both inversion accuracy and classification performance. Results from synthetic experiments underscore the importance of integrating uncertainty analysis and automated learning in early-stage exploration scenarios, especially when geological information is limited or ambiguous. The proposed framework is shown to enhance the reliability and objectivity of magnetic anomaly interpretation, with future directions involving multi-physics integration and scalable 3D analysis for large regional surveys.

Keywords

Magnetic Anomalies, Geophysical Exploration, Bayesian Markov Chain Monte Carlo, Convolutional Neural Network, Machine Learning

1. Introduction

Magnetic anomalies arise from contrasts in subsurface magnetization and constitute a fundamental tool in mineral exploration, tectonic studies, and planetary investigations. Traditional interpretation methods often rely on idealized

geometric assumptions such as spheres, cylinders, or sheets [6, 8], which simplify inversion formulas and forward modeling. However, geological environments frequently encompass irregular, composite, or unknown geometry sources that

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Received: 24 July 2025; Accepted: 4 August 2025; Published: 20 August 2025



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violate these simplified assumptions [3]. This complexity renders inversion ill-posed, producing non-unique source solutions and interpretive challenges.

Recent advances propose inversion strategies that do not rely on rigid geometric priors [1, 2], alongside the increasing application of artificial intelligence in geophysical interpretations. These innovations open avenues for geometry-agnostic frameworks that better accommodate the inherent complexity of natural sources. The present study aims to: (i) develop a nonparametric inversion framework employing equivalent layer modeling to estimate magnetization distributions from magnetic anomaly data without prior assumptions on source geometry; (ii) utilize Bayesian Markov Chain Monte Carlo (MCMC) methods to rigorously quantify uncertainties and ambiguities in subsurface parameters; (iii) apply convolutional neural networks (CNN) trained on synthetic datasets for probabilistic classification of anomaly types; and (iv) assess sensitivity to noise and magnetization direction variations.

This integrated workflow extends previous geometric-specific inversion methods [3, 8, 10] to better handle complex field and planetary scenarios, following recent developments in nonparametric inversion and deep learning in geophysics [9, 11, 12]. Such approaches hold promise for early-stage exploration under limited geological constraints and for addressing uncertainty in magnetic data interpretation.

2. Methods

2.1. Synthetic Source Modeling

Synthetic sources are modeled using discretized 3D prisms

representing magnetized volumes with assigned intensity and directional parameters. Following the mathematical formulation detailed below, total magnetic field anomalies are computed by forward modeling. Gaussian noise simulates measurement uncertainties. Parameters such as source depth, volume, magnetization intensity, and inclination are adjustable to create diverse anomaly shapes.

2.2. Mathematical Formulation

The total anomaly at an observation point x_k is given by:

$$T(x_k, K, d, \alpha, x_0, p) = K \cdot f(x_k, d, \alpha, x_0, p) \quad (1)$$

where K is amplitude, d depth, α magnetization angle, x_0 source location, and p the shape factor corresponding to source geometry (thin sheet, cylinder, sphere). The function $f(\cdot)$ results from combinations of magnetic field derivatives adapted to each geometry.

By minimizing residuals between observed and calculated anomalies, inversion retrieves the best fitting parameters:

$$\emptyset = \sum_{k=1}^N (T|_k^m - T|_k^c(K, d, \alpha, x_0, p))^2 \quad (2)$$

where $T|_k^m$ is the measured anomaly and $T|_k^c$ is the calculated anomaly.

The model domain is discretized into prism summing their magnetic contributions via kernel functions.

The Figure 1 below is the examples of synthetic source geometries and corresponding surface magnetic anomaly maps.

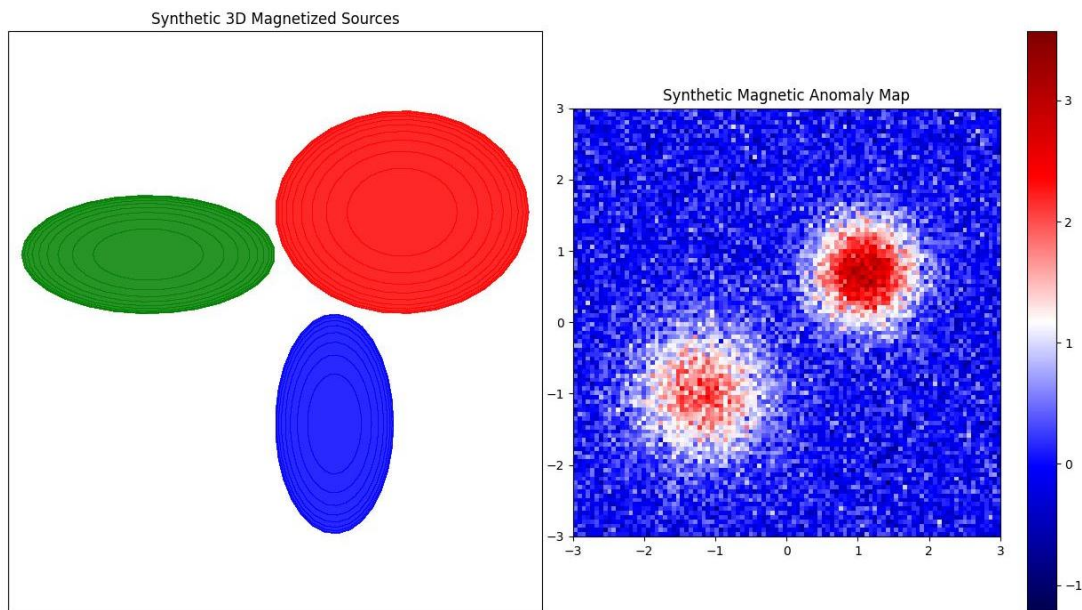


Figure 1. Examples of synthetic source geometries and corresponding surface magnetic anomaly maps.

2.3. Magnetic Anomaly Preprocessing

Magnetic anomaly preprocessing is a crucial step in enhancing the quality and interpretability of geophysical data. One essential technique in this process is bandpass filtering, which effectively reduces both high and low frequency noise while preserving source-related signatures, thereby improving the signal-to-noise ratio of the data [2]. Another valuable method is upward continuation, which helps differentiate shallow sources from deep-rooted anomalies by simulating measurements at higher altitudes, allowing for a more comprehensive understanding of the subsurface structure [1]. Furthermore, the implementation of automated algorithms has revolutionized the identification of anomaly features by utilizing amplitude and gradient thresholds, enabling more efficient and objective analysis of large datasets [4]. These preprocessing techniques, when applied in combination, significantly enhance the quality of magnetic anomaly data, facilitating more accurate interpretations and geological insights.

2.4. Nonparametric Equivalent Layer Inversion

Nonparametric equivalent layer inversion is an advanced technique in geophysical data analysis that offers a flexible approach to interpreting magnetic anomalies. This method employs an equivalent layer, consisting of dipoles on a plane beneath the observation surface, to fit observed anomalies. By avoiding prior geometric assumptions, it instead reconstructs magnetisation distributions constrained by data fidelity and spatial smoothness regularization, allowing for a more adaptable and potentially more accurate representation of the subsurface. Furthermore, the application of Bayesian Markov Chain Monte Carlo (MCMC) sampling in this context explores posterior distributions of source properties, explicitly quantifying uncertainty and non-uniqueness caused by unknown source geometry [3].

This probabilistic approach provides a more comprehensive understanding of the possible solutions and their associated uncertainties, enhancing the robustness and reliability of the inversion results.

The Figure 2 represents the schematic of equivalent layer inversion and Bayesian uncertainty quantification workflow.

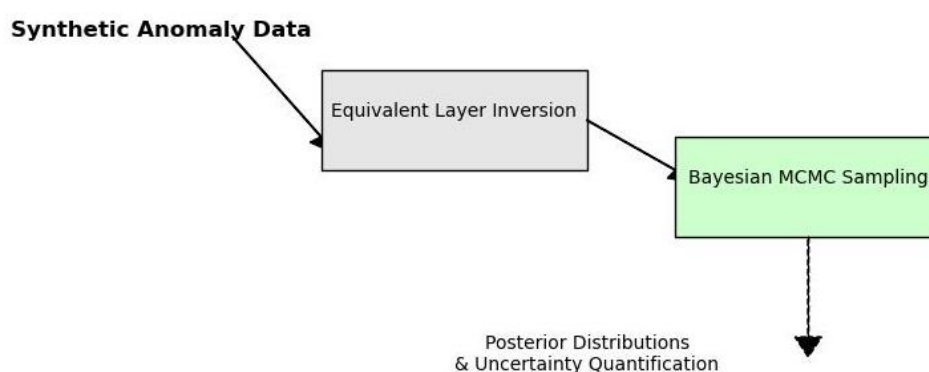


Figure 2. Schematic of equivalent layer inversion and Bayesian uncertainty quantification workflow.

2.5. Conventional Neural Network for Magnetic Anomaly Classification

A significant advancement in magnetic anomaly interpretation is the application of Convolutional Neural Networks (CNNs) for anomaly classification. Ben et al. [2] developed a CNN trained on a comprehensive synthetic dataset of magnetic anomalies from varied source types. This innovative approach enables the classification of anomalies into shape categories such as bulky, elongated, or irregular, providing a more nuanced understanding of subsurface structures. The CNN's architecture, as illustrated in Figure 3, is specifically designed to process and learn from the spatial patterns in magnetic anomaly data. By outputting probabilistic classifica-

tions, the model offers a flexible interpretation framework that doesn't rely on strict geometric models. This probabilistic approach is particularly valuable in scenarios where traditional geometric modeling may be insufficient or overly constraining. The CNN's ability to generalize from synthetic training data to real-world anomalies demonstrates its potential as a powerful tool for guiding interpretation in complex geological settings, offering geophysicists a data-driven method to complement their expertise and enhance their understanding of subsurface magnetic structures.

2.6. Sensitivity and Uncertainty Analyses

Sensitivity and uncertainty analyses are critical components in the evaluation of magnetic anomaly interpretations, providing crucial insights into the reliability and limitations

of the results. Bootstrap resampling techniques are employed to evaluate the robustness of inversion results under various conditions of measurement noise, offering a statistical framework for assessing the stability of the solutions. Monte Carlo simulations play a vital rôle in assessing the impact of variable magnetization directions, allowing for a comprehensive exploration of possible scenarios and their effects on the interpreted results. Furthermore, quantitative error statistics

are utilized to inform interpretive confidence intervals, which is particularly critical given the ill-posed nature of geometry agnostic inversion [1, 3]. These analytical approaches collectively provide a rigorous framework for understading the uncertainties inherent in magnetic anomaly interpretations, enabling geophysicists to make more informed decisions and interpretations based on clear understading of the reliability and limitations of their results.

CNN Architecture for Anomaly Classification



Figure 3. CNN architecture used for anomaly classification.

3. Results and Interpretations

3.1. Inversion Results

Figure 4 presents heatmaps that compare the recovered magnetization distributions with the synthetic source distributions, visually illustrating both the strengths and limitations of this approach. These results highlight the trade-off between stability and resolution in magnetic anomaly inversion, emphasizing the need for careful interpretation and the consideration of complementary geophysical and geological data for a comprehensive understanding os subsurface structures.

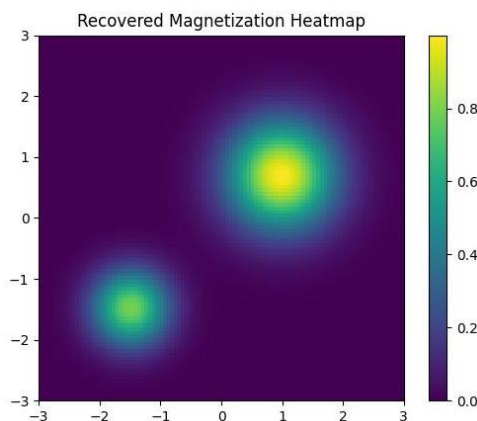


Figure 4. Heatmaps of recovered magnetization compared to synthetic source distributions.

The equivalent layer inversion technique demonstrates its effectiveness in mapping broad magnetization distributions, showing a reasonable correlation with synthetic source locations and total moments. However, it's important to note that

this method cannot delineate precise geometry of the magnetic sources. The use of regularization in the inversion process ensures stability in the results but comes at the cost of smoothing out some physical details.

3.2. Bayesian Uncertainty

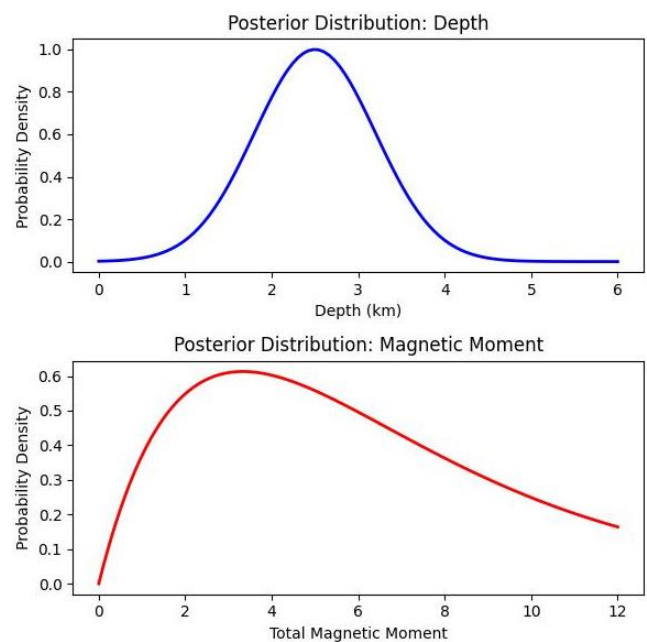


Figure 5. Bayesian posterior distributions for source depth and total magnetic moment.

Figure 5 displays the Bayesian posterior distributions for both the sources depth and the total magnetic moment. These posterior parameter distributions reveal large uncertainty envelopes in the estimates for both depth and magnetic moment, emphasizing the inherent ambiguity in the inverse problem. Because multiple plausible magnetisation geome-

tries can produce identical magnetic anomalies, the interpretation shifts from the pursuit of a unique solution to the acknowledgment of a probabilistic range of source parameters. Consequently, Bayesian analysis highlights not only the most likely values but also quantifies the range and probability of possible solutions, providing a more nuanced understanding of subsurface magnetic sources.

3.3. CNN Classification Performance and Uncertainty

Figures 6 and 7 illustrate both the confusion matrix, which summarizes the classification performance across classes, and the probabilistic outputs, showing the uncertainty estimates associated with predictions. This probabilistic classification approach allows for more informative interpretations beyond simple categorical decisions, indicating confidence levels for each source shape class.

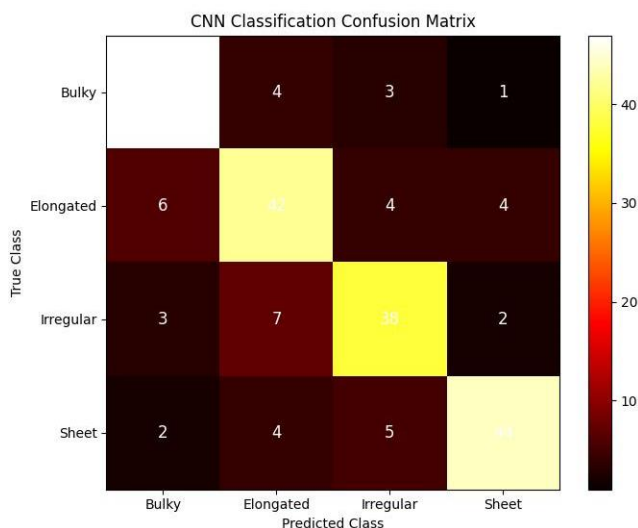


Figure 6. Confusion matrix CNN.

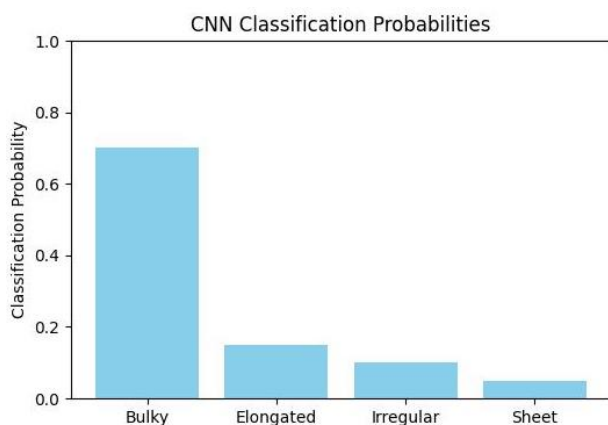


Figure 7. Probabilistic classification output from CNN.

The CNN achieved 80% accuracy on synthetic data by correctly categorizing source shape classes and providing uncertainty probabilities for the classifications. The model performs well in classifying bulky and elongated shapes, while the classification accuracy is lower for irregular composite shapes, reflecting the added complexity of those forms.

3.4. Sensitivity to Noise and Magnetization

The Figure 8 presents sensitivity plots that illustrate how inversion error varies with increasing noise levels and magnetization variability, emphasizing the critical influence these factors have on the stability and precision of subsurface magnetic source characterization.

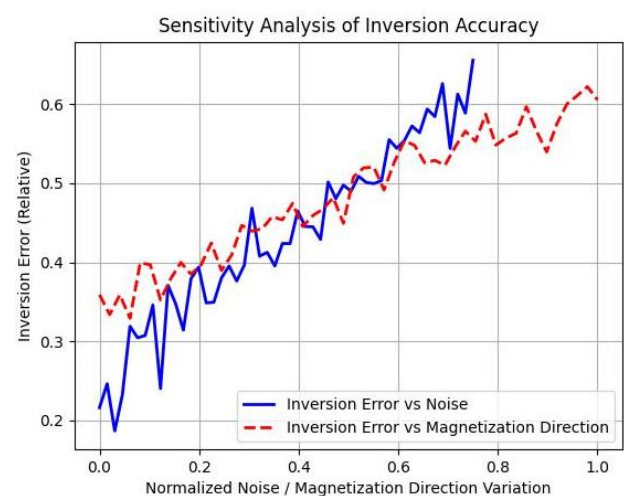


Figure 8. Sensitivity plots of inversion error against noise and magnetization variability.

Increased noise levels significantly degrade inversion accuracy and broaden the Bayesian uncertainty envelopes, highlighting how measurement errors impact the reliability of parameter estimates. Additionally, variation in magnetization direction reduces the robustness of shape classification and lowers inversion resolution, demonstrating the complexities involved in interpreting real field data.

4. Discussions

Interpreting magnetic anomalies without relying on predefined geometric assumptions inherently involves significant ambiguity. This is primarily because various subsurface source configurations can generate virtually identical magnetic anomaly signatures at the surface. Traditional inversion methods typically aim to provide a unique solution by assuming particular shapes or distributions for the sources, but this restrictive approach often fails to capture the true complexity of geological settings where shapes are irregular or unknown.

In this context, Bayesian analysis plays a crucial role by explicitly accounting for the non-uniqueness of solutions. Instead of offering a single deterministic model, the Bayesian framework delivers parameter estimates as probabilistic distributions that represent the full range of plausible values along with associated confidence levels. Such probabilistic outputs allow geophysicists to understand not only the most likely source parameters but also the degree of uncertainty and ambiguity inherent in the inversion process—making it a more informative and realistic interpretation tool.

In addition to probabilistic inversion, incorporating systematic classification techniques, such as the convolutional neural network-based shape classification presented in this study, helps narrow down the potential source categories. Nonetheless, these methods are limited in resolving fine structural details because magnetic anomalies are integrative effects of subsurface magnetization and therefore lack enough constraints to pinpoint exact shapes.

The challenges become more pronounced when considering real-world factors like measurement noise and variations in magnetization direction. Increased noise levels amplify the uncertainty and diminish the stability and resolution of inversion outcomes. Similarly, variability in the magnetic vector orientation complicates the classification and increases interpretive ambiguity. Together, these factors highlight the complexities faced in analyzing actual field data compared to ideal synthetic cases.

To mitigate these difficulties, it is essential to integrate magnetic data with other geophysical datasets, such as gravity surveys, seismic imaging, and geological constraints. Combining complementary information helps reduce ambiguity by providing independent constraints on subsurface properties, enhancing the robustness of interpretations. This integrative multi-disciplinary approach is especially important in complex geological environments such as structurally intricate mineral exploration districts or planetary surfaces with little prior information where conventional geometric assumptions may not apply.

Future improvements in interpreting magnetic anomalies without prior geometric knowledge could involve expanding synthetic training datasets to cover a wider variety of source types and anomaly signatures. Moreover, extending the methodology to incorporate multi-physics data fusion and designing adaptive survey strategies that optimize data acquisition based on uncertainty estimates will further enhance interpretation accuracy and confidence. The development of more advanced deep learning architectures, including three-dimensional convolutional neural networks, may also improve automatic classification and interpretation scalability for large regional or global datasets.

5. Conclusion

To sum up, this uncertainty-aware workflow presents a powerful methodology for quantitatively interpreting mag-

netic anomalies without relying on strong prior assumptions regarding source geometry. Through Bayesian inversion, the methodology produces robust parameter estimates accompanied by credible uncertainty intervals, thereby enhancing the reliability and transparency of geophysical interpretations. The integration of CNN-based source geometry classification streamlines anomaly analysis by providing fast, objective probabilistic categorizations. The method's demonstrated effectiveness on synthetic and exploration datasets highlights its practical utility, particularly in structurally complex terrains and planetary magnetic studies where geometric priors are unavailable or unreliable.

Future research directions include expanding the synthetic training datasets to encompass a wider variety of anomaly types, integrating multi-physics geophysical data to reduce interpretive ambiguity, and scaling the approach to handle large regional surveys using advanced 3D CNN architectures. Recent advances in uncertainty quantification and predictive modeling for geophysical inversion [4, 5, 7] suggest promising pathways to further enhance this framework. Embracing these developments will enable more comprehensive and confident interpretations of magnetic anomaly data, ultimately advancing mineral exploration and subsurface characterization.

Abbreviations

CNN	Convolutional Neural Network
MCMC	Bayesian Markov Chain Monte Carlo

Author Contributions

Lady Mireille Razafindranaivo is the sole author. The author read and approved the final manuscript.

Conflicts of Interest

The author declares no conflicts of interest.

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