Falsification of magmatic intrusion models using outcrops, drillholes, and geophysics

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Summary

Magmatic intrusions can host a variety of minerals and often serve as key targets in mineral exploration endeavors. During exploration, the manual construction of an "optimal" intrusion model based on the available data is a standard practice, which then forms the foundation for subsequent interpretations and decision-making processes. However, this optimal-model-to-interpretation paradigm that relies heavily on expertise presents a significant challenge in assessing the uncertainty of the inferred model. To address the problem, we have developed an innovative and automatic framework with a core component: falsification. The first step involves the stochastic construction of prior magmatic intrusion models using outcrop and drillhole data. We can also derive a prior distribution of the physical property (e.g., density contrast) for the intrusive body from rock sample measurements or textbooks. The second step attempts to falsify the prior geometric representations and the prior physical property, obtained from the first step, using geophysical data. The unfalsified prior models can serve as realistic and valid priori for diverse Bayesian inversion methods, resulting in more reliable quantification of the posterior uncertainty. Our study highlights the necessity and significance of falsification in the prior model construction.

Introduction

The significance of intrusive magmatic deposits cannot be overstated in mineral exploration and mining activities due to their potential to host diverse economically valuable minerals. A standard practice of the exploration is to manually construct an "optimal" intrusion model based on the drillhole data and expert knowledge through a commercial software. The resulting model typically serves as a pivotal reference in guiding subsequent interpretations and decision-making processes. This standard paradigm has been widely accepted and applied for exploration activities, but it still has much space for improvement. First, manual construction heavily depends on experts' subjective judgments. Second, the "optimal" model leads to a deterministic representation of the intrusive body, which may not adequately capture the inherent variability and uncertainty in the subsurface.

To overcome these challenges, we introduce a novel framework that enables construction of prior models as well as falsification of prior models. The prior modeling process aims to represent both the geometry and physical properties of an intrusive body. The falsification attempts to falsify the prior models, resulting in realistic and valid prior models, i.e., unfalsified models. Our framework is predicated on two essential steps:

The first step, stochastic construction of prior models, begins by creating a set of prior intrusion models based on outcrop and drillhole data. These models show spatial extensions of the intrusion that are constrained by the data but have not achieved a perfect match, acknowledging the inherent uncertainty and complexity of the shape of the intrusion. We also focus on the physical properties of the intrusive body, such as density contrast. The physical property directly influences the interpretation of geophysical data. We can derive a prior distribution of the physical property from the rock sample measurements or literature and textbooks.

The second step, falsification of prior models, involves rigorously testing the intrusion's geometry and prior physical property using geophysical data. Both the geometry and physical property acquired from the first step are not as reliable representations of an intrusion but as hypotheses, which thus require a scientific evaluation and/or falsification. The falsified geometrical models and prior physical property would not be involved in our posterior uncertainty analysis. Falsification, generally combined with Bayes' theorem, has been applied to the subsurface uncertainty quantification with a variety of applications (Satija and Caers, 2015; Hermans et al., 2018; Athens and Caers, 2019; Yin et al., 2020; Pradhan and Mukerji, 2020; Athens and Caers, 2021).

Our framework generates a comprehensive set of prior intrusion models that encapsulate both geometric and physical characteristics. Our framework can falsify the prior and results in a set of realistic and unfalsified prior models, which can serve as inputs for diverse Bayesian inversion methods (Zhao et al., 2022; Wei et al., 2023). Our framework is pivotal in reliably quantifying posterior uncertainty, a process that is instrumental in guiding future drilling deployments, and enhancing the effectiveness of mineral exploration activities.

An overview of the data sets

Figure 1a shows the data sets used in stochastic construction. The outcrops and drillholes follow a binary format, namely, intrusion and non-intrusion. The outcrop and drillhole data have been aligned with the topography to closely mimic the real-world scenario. We set a homogeneous density contrast value of the intrusion body as 0.8 g/cm^3. Figure 1b shows the simulated gravity data. We added an independent

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Gaussian noise with a mean of zero and a standard deviation of 0.003 mGal.

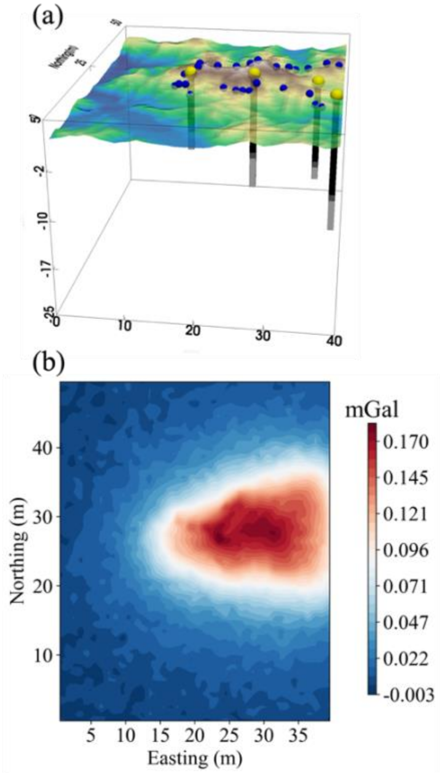

Figure 1: (a) Outcrop and drillholes data. The blue and yellow balls mark the locations of outcrops and drillholes, respectively. The background color represents the topography. (b) Gravity data.

Prior model construction using outcrop and drillhole data

Case 1: Outcrop data

We constructed intrusion models using the stochastic Markov chain Monte Carlo level set method (Wang et al., 2023) and outcrop data only. We implemented one sampling chain with 5000 steps. We decimated the last 50% models with a factor of three to increase the independence. The resulting mean model (Figure 2a) shows a high level consistency with the outcrops. We also observe that the intrusion extends to a depth of, around, five meters. Figure 2b displays the standard deviations where the higher standard deviation values follow the boundary of the intrusive body, indicating a significant disagreement among the sampled models regarding the delineation of the intrusion's boundary.

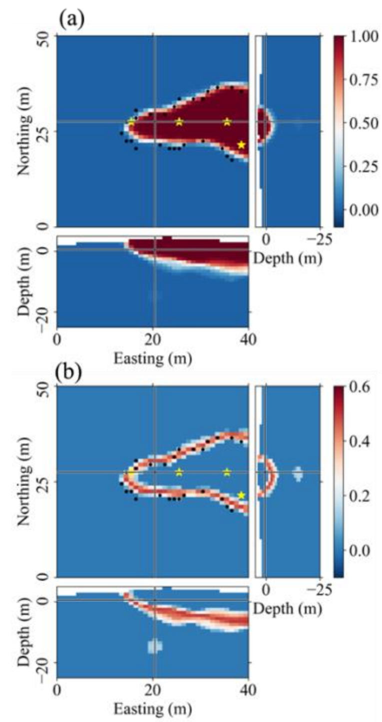

Figure 2: The mean model (a) and standard deviations (b) using outcrop data only. The black dots mark the location of outcrops.

Case 2: Drillhole data

In the second case, we employed the drillhole data only to construct the intrusion model. The sampling strategy is consistent with the Case 1. Figure 3a is the mean model, the depth slice of which is not consistent with the distribution of outcrops marked by the black dots. The mean model also indicates an extension to a greater depth compared to the previous Case 1. This suggests that the drillholes (marked by the yellow stars) have provided a better constraint on depth, allowing for a more reliable representation of the intrusion's vertical extension. In the lower panel of Figure 3b, which represents a cross-section at the north, the standard deviations are lower directly at the drillhole locations, and higher in the interspersed regions between the drillholes.

Case 3: Outcrop and drillhole data

In the last case, we integrated outcrop and drillhole data to construct reliable intrusion models. The outcrops constrain the intrusive body near the surface and the drillholes provide critical constraints on the depth extent, thereby enabling the recovery of geologically plausible intrusion models. The resulting mean and standard deviations are shown in Figure 4.

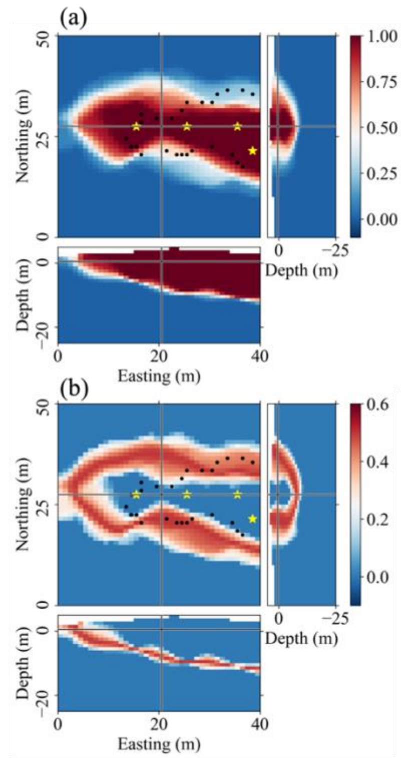

Figure 3: The mean model (a) and standard deviations (b) using drillhole data only. The yellow stars represent the location of drillholes. Black dots indicate the outcrops.

Prior model falsification using geophysical data

Falsifying the prior physical property

In the realistic synthetic study, where the true density contrast is known, i.e., 0.8 g/cm^3, we intentionally set the range of prior density contrast between 0.1 g/cm^3 to 0.5 g/cm^3. For each constructed intrusion model, a constant value from this prior was randomly sampled and assigned. We implemented the forward modeling to obtain the predicted data, as represented by the gray lines in Figure 5a. We observed that predictions are consistently lower than the observation. This discrepancy indicates a falsified prior assumption. We then expanded the prior ranging from 0.5 g/cm^3 to 1 g/cm^3. The predicted gravity data, derived from the new prior, are displayed as gray lines in Figure 5b. This updated prior assumption is deemed reasonable, evidenced by the fact that the predictions effectively encapsulate the observation.

Falsifying the prior geometric models

Based upon the unfalsified prior physical property, we have the opportunity to falsify or refine the prior geometric models. A variety of algorithms can be employed to derive the posterior models, such as Ensemble Smoothing and Monte Carlo sampling. We, alternatively, perform a simpler approach involving the use of a predefined tolerance value. This flexibility in methodology allows for optimizing models based on the reliable prior assumptions. The predictions derived from the posterior data are represented as blue lines in Figure 5b. There is a narrowed range in the predictions, indicating a higher degree of alignment with the observed data, reproduced by the unfalsified prior intrusive bodies that were constructed through outcrop and drillhole data. Figure 5c shows the prior and posterior distributions of density contrast values. The mean of the posterior distribution is close to the true density contrast value.

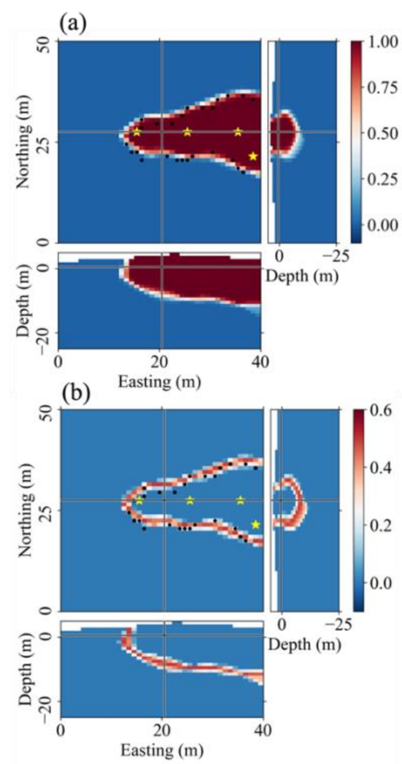

Figure 4: The mean model (a) and standard deviations (b) using outcrop and drillhole data.

Figure 6 presents the mean and standard deviations calculated from the unfalsified models. A reduction in uncertainty is observable, as indicated by the black arrow in Figure 6. This reduction highlights the effectiveness of the falsification process in enhancing the reliability of the model construction. We acknowledge that the uncertainty reduction is not markedly evident. The primary reason is attributed to our implementation with only a single Markov Chain Monte Carlo sampling.

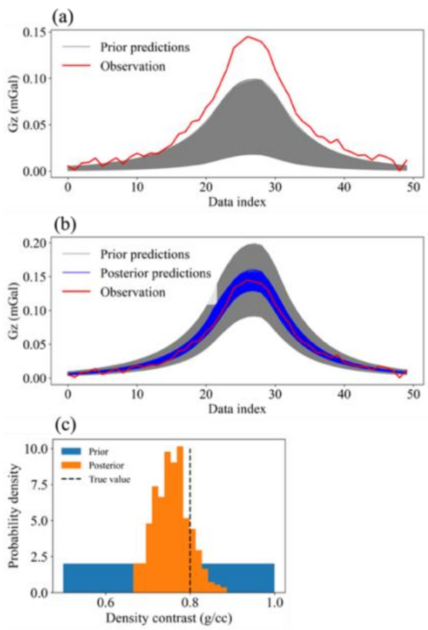

Figure 5: (a) The observation (red line) and gravity predictions (gray lines) which falsifies the prior density contrast ranging from 0.1 g/cm^3 to 0.5 g/cm^3. (b) The gravity data predictions based on the unfalsified prior density contrast ranging from 0.5 g/cm^3 to 1 g/cm^3. The gray and blue lines represent predictions from the prior and posterior models, respectively. (c) The true density contrast value as well as the prior and posterior distributions of density contrast values.

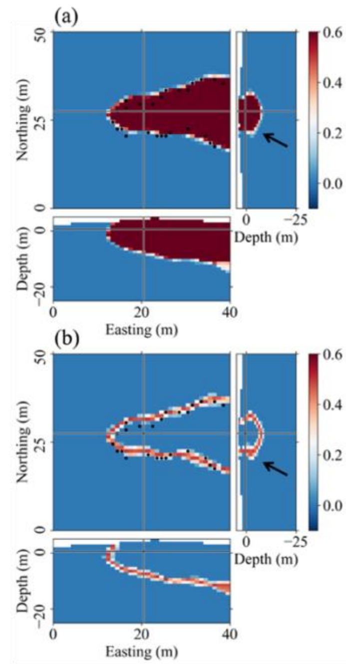

Figure 6: The posterior mean model (a) and standard deviation (b) using outcrop and drillhole data.

Conclusions

We develop an innovative framework to automatically construct intrusion models through stochastic construction and falsification approaches. We generate multiple intrusion models, revealing the uncertainty in delineating the geometry of an intrusive body, using outcrop and drillhole data. The geometric intrusive models and the prior physical property can be falsified by geophysical data. After the falsification, the refined models offer a more objective and data-driven basis for interpreting intrusive bodies. Our framework plays a crucial role in informed decision-making for mineral explorations.

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