

A shape optimization approach towards improving the understanding of magmatic plumbing system

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Key Points:

- We present a novel approach to allow for assessment of volcanic magma domains shape based on level-set shape optimization.
- It relies on numerical finite element models iteratively modified to minimize the discrepancy to observed surface displacements
- We found strong dependence of best solution to initialization when benchmarked with synthetic data but application on data from Svartsengi 2022 inflation outputted relevant results.

Abstract

In volcano geodesy, pressure sources in volcano roots responsible for surface movements are inverted using ground deformation data after defining a forward parametric model for the source. Such models are most of the time relying on predefined shape for the source, which can limit their accuracy. On the contrary, we propose here a shape optimization method to invert for pressure sources without any prior shape assumption. With that flexibility, the optimal shape of a pressurized magma body is determined by minimizing the discrepancy between observed and modelled displacement. We explore the capabilities of this approach with synthetic data first for validation and then apply it to observed ground deformation at the Svartsengi volcanic system in Iceland, demonstrating its potential to improve volcanic hazard assessment after maturation with further work.

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1 Introduction

In volcano geodesy, inverse problems are central to estimating the position of pressurized magma bodies at depth in volcano roots, using observed crustal deformation as a proxy. The displacement is measured by e.g. Global Navigation Satellite System (GNSS) point positioning, leveling campaigns, or interferometry analysis of synthetic aperture radar (InSAR) in a volcanic region (Dzurisin, 2007). The subsurface processes causing the movement are inferred from these observations. Magmatic sources are modeled as pressurized cavities that deform the surrounding host rocks and cause the surface to move. Various inversion methods based on parametric analytical or numerical models aim at finding the optimal values for the vector of d free parameters $\underline{m} \in \mathbb{R}^d$ of a model. An error function $J(\underline{m})$ is representative of the misfit between the observed displacements and the prediction of the model. \underline{m}_{opt} can then be found using various inversion techniques minimizing J : global optimization based on analytic (Cervelli et al., 2001) or numerical models (Hickey & Gottsmann, 2014; Charco & Galán del Sastre, 2014), Bayesian inference (Bagnardi & Hooper, 2018; Trasatti, 2022), or genetic algorithms (Velez et al., 2011) on analytic models. The choice of the method can be influenced by what is feasible regarding the number of evaluations of $J(\underline{m})$: numerical models handle a complex description of the system, but are computationally expensive compared to analytic models, which on the other hand rely on strong simplifying assumptions (Taylor et al., 2021).

However, each of these finite-dimensional optimization methods is limited by the intrinsic assumption of a definite parametric shape for the source. In fact, analytic expressions can be derived for only a few regular shapes such as point source (Mogi, 1958), finite sphere source (McTigue, 1987), or ellipsoidal source (Yang et al., 1988), and any numerically generated shape must be parameterized to be inverted. A workaround would be an approach relying on shapes parameterized with more parameters, such as B-splines surfaces, to allow more exploration in the possible shapes. This implies optimization within a high-dimension domain, bringing unpleasant phenomena known as the curse of dimensionality. The goal of this paper is not to give a definitive answer to these limitations, but rather to lay the first stone for a new approach that overcomes these difficulties.

1.1 Shape optimization

Shape optimization generally aims to minimize a cost function depending on the domain. This practice is very popular in various disciplines, such as structural mechan-

63 ics, where one typically wishes to improve the stiffness of a solid structure (Bendsoe &
 64 Sigmund, 2004), fluid mechanics, where it is applied to the design of pipes, heat exchangers or flying obstacles (Fepon et al., 2020), or again electromagnetism (Lucchini et al.,
 65 2022). Beyond academic investigations, it has aroused a tremendous enthusiasm in in-
 66 dustry; nowadays, most Finite Element simulation and design softwares include a shape
 67 optimization module (Frei, 2015), (Slavov & Konsulova-Bakalova, 2019), (Le Quilliec,
 68 2014). However, the use of these techniques in volcano geodesy is new to the best of our
 69 knowledge.

70
 71 Multiple shape and topology optimization frameworks are available, see e.g. the
 72 review in (Sigmund & Maute, 2013). One popular strategy describes the design as a den-
 73 sity function ρ on a large, fixed computational domain: ρ takes values 0 and 1 in the void
 74 and material regions, respectively, and intermediate values in between account for a fic-
 75 titious mixture of both (Sigmund, 2001; Bendsoe & Sigmund, 2004). One major draw-
 76 back of this approach is that it does not feature a clear representation of the boundary
 77 of the optimized design; in particular, approximations are needed to calculate physical
 78 quantities related to the domain at play. To alleviate this issue, we rely on a recent ver-
 79 sion of the Level Set method for shape optimization, which benefits from an explicit rep-
 80 resentation of the boundary at each step of the optimization.

81 2 Method

82 This section describes the considered shape optimization problem and its practi-
 83 cal implementation. For a more complete mathematical background, we refer to e.g. (Allaire
 84 et al., 2021).

85 2.1 Presentation of the physical model

The region under scrutiny is represented by a fixed bounded domain $D \subset \mathbb{R}^3$, which writes as the disjoint reunion:

$$D = \Omega \cup \Omega^c, \text{ where } \Omega^c := D \setminus \overline{\Omega}.$$

86 In this setting, illustrated on Fig. 1 (a),

- 87 • The cavity $\Omega \Subset D$ stands for the magma chamber, whose shape is to be recon-
 88 structed. Its boundary $\Gamma = \partial\Omega$ is subjected to the force $\mathbf{f} = -\Delta P \mathbf{n}$, aligned
 89 with the unit normal vector $\mathbf{n} : \Gamma \rightarrow \mathbb{R}^3$ to Γ pointing outward Ω , and whose
 90 magnitude equals the (given) pressure difference ΔP between the cavity and the
 91 surrounding crust, see Section 5 for a discussion about this point.
- 92 • The complement Ω^c of Ω represents the surrounding Earth crust. It is filled by
 93 a homogeneous, isotropic elastic material. The displacement of the bottom side
 94 Γ_b of ∂D is set to $\mathbf{0}$ and the other boundary regions of D are free of stress.

The displacement $\mathbf{u}_\Omega : \Omega^c \rightarrow \mathbb{R}^3$ of the crust in these circumstances is the solution to the system of linearized elasticity:

$$\left\{ \begin{array}{ll} -\text{div}(Ae(\mathbf{u}_\Omega)) = \mathbf{0} & \text{in } \Omega^c, \\ \mathbf{u}_\Omega = \mathbf{0} & \text{on } \Gamma_b, \\ Ae(\mathbf{u}_\Omega)\mathbf{n} = \mathbf{f} & \text{on } \Gamma, \\ Ae(\mathbf{u}_\Omega)\mathbf{n} = \mathbf{0} & \text{on } \partial D \setminus \overline{\Gamma_b}, \end{array} \right. \quad (1)$$

95 where $e(\mathbf{u}) := \frac{1}{2}(\nabla \mathbf{u} + \nabla \mathbf{u}^T)$ is the strain tensor induced by a displacement \mathbf{u} and A
 96 is the Hooke's law of crust material.

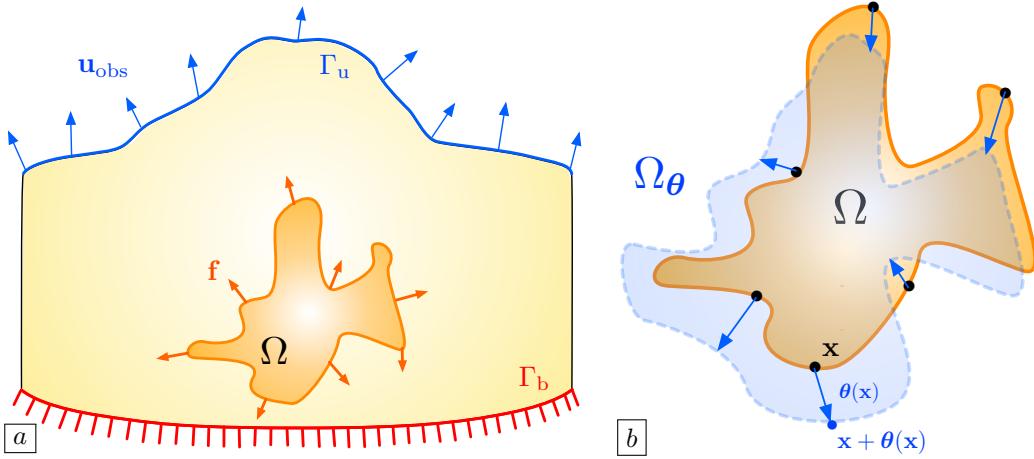


Figure 1. (a) Sketch of the physical model; (b) Variation Ω_θ of Ω .

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2.2 Shape optimization for the reconstruction of the magma chamber

In the applications of this article, the shape Ω of the magma chamber is unknown. From the datum of observed values $\mathbf{u}_{\text{obs}} : \Gamma_u \rightarrow \mathbb{R}^3$ of the displacement of the crust on the upper surface Γ_u of D , we intend to identify Ω as the solution to the following shape optimization problem:

$$\min_{\Omega \subset D} J_{\text{LS}}(\Omega), \text{ where } J_{\text{LS}}(\Omega) := \int_{\Gamma_u} |\mathbf{u}_\Omega - \mathbf{u}_{\text{obs}}|^2 \, ds, \quad (2)$$

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featuring the least-square discrepancy between the prediction \mathbf{u}_Ω of the physical model (1), and the observed displacement \mathbf{u}_{obs} on Γ_u .

99

2.3 Shape derivatives

The solution of (2) calls for a notion of derivative for a function $J(\Omega)$ of the domain Ω . In this work, we rely on the boundary variation method of Hadamard, see (Allaire, 2006; Allaire et al., 2021; Henrot & Pierre, 2018; Murat & Simon, 1976). In short, variations of a reference domain Ω are considered under the form

$$\Omega_\theta := (\text{Id} + \boldsymbol{\theta})(\Omega), \text{ where } \boldsymbol{\theta} : \mathbb{R}^3 \rightarrow \mathbb{R}^3 \text{ is a “small” vector field,}$$

see Fig. 1 (b). The shape derivative $J'(\Omega)(\boldsymbol{\theta})$ of a function $J(\Omega)$ at Ω is the derivative of the underlying mapping $\boldsymbol{\theta} \mapsto J(\Omega_\theta)$, which produces the following expansion:

$$J(\Omega_\theta) = J(\Omega) + J'(\Omega)(\boldsymbol{\theta}) + o(\boldsymbol{\theta}), \text{ where } \frac{o(\boldsymbol{\theta})}{\|\boldsymbol{\theta}\|} \xrightarrow{\boldsymbol{\theta} \rightarrow 0} 0. \quad (3)$$

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104

In practice, $J'(\Omega)(\boldsymbol{\theta})$ is used to identify a descent direction $\boldsymbol{\theta}$, i.e. a vector field such that $J'(\Omega)(\boldsymbol{\theta}) < 0$. Intuitively, the perturbed shape $\Omega_{\tau\boldsymbol{\theta}}$ by such a descent direction for a “small enough” descent step $\tau > 0$ performs “better” than Ω in terms of the criterion $J(\Omega)$, i.e. $J(\Omega_{\tau\boldsymbol{\theta}}) < J(\Omega)$, see (3).

The calculation of the shape derivative of the functional $J_{\text{LS}}(\Omega)$ in (2) is a tedious, but classical issue. It can be realized thanks to the adjoint method, see e.g. (Cea, 1986; Plessix, 2006) and (Allaire et al., 2004) in this particular mathematical context:

$$J'_{\text{LS}}(\Omega)(\boldsymbol{\theta}) = \int_{\Gamma} v_\Omega (\boldsymbol{\theta} \cdot \mathbf{n}) \, ds, \text{ where } v_\Omega := Ae(\mathbf{u}_\Omega) : e(\mathbf{p}_\Omega) + \Delta P \operatorname{div}(\mathbf{p}_\Omega), \quad (4)$$

and the adjoint state \mathbf{p}_Ω is the solution to the following problem:

$$\begin{cases} -\operatorname{div}(Ae(\mathbf{p}_\Omega)) = \mathbf{0} & \text{in } \Omega^c, \\ \mathbf{p}_\Omega = \mathbf{0} & \text{on } \Gamma_b, \\ Ae(\mathbf{p}_\Omega)\mathbf{n} = \mathbf{0} & \text{on } \partial D \setminus (\overline{\Gamma_u} \cup \overline{\Gamma_b}), \\ Ae(\mathbf{p}_\Omega)\mathbf{n} = -2(\mathbf{u}_\Omega - \mathbf{u}_{\text{obs}}) & \text{on } \Gamma_u. \end{cases} \quad (5)$$

The expression (4) paves the way to a natural descent direction for $J_{\text{LS}}(\Omega)$:

$$\boldsymbol{\theta} = -v_\Omega \mathbf{n}. \quad (6)$$

105 2.4 Level-set representation

The magma chamber $\Omega \subset D$ is represented via the Level Set method, see e.g. (Osher & Fedkiw, 2006; Sethian, 1999), and the article (Allaire et al., 2004) about its introduction in shape and topology optimization. Briefly, Ω is described implicitly, as the negative region of a scalar, “level set” function $\phi : D \rightarrow \mathbb{R}$, see Fig. 2 (a).

$$\forall \mathbf{x} \in D, \quad \begin{cases} \phi(\mathbf{x}) < 0 & \text{if } \mathbf{x} \in \Omega, \\ \phi(\mathbf{x}) = 0 & \text{if } \mathbf{x} \in \Gamma, \\ \phi(\mathbf{x}) > 0 & \text{if } \mathbf{x} \in \Omega^c. \end{cases} \quad (7)$$

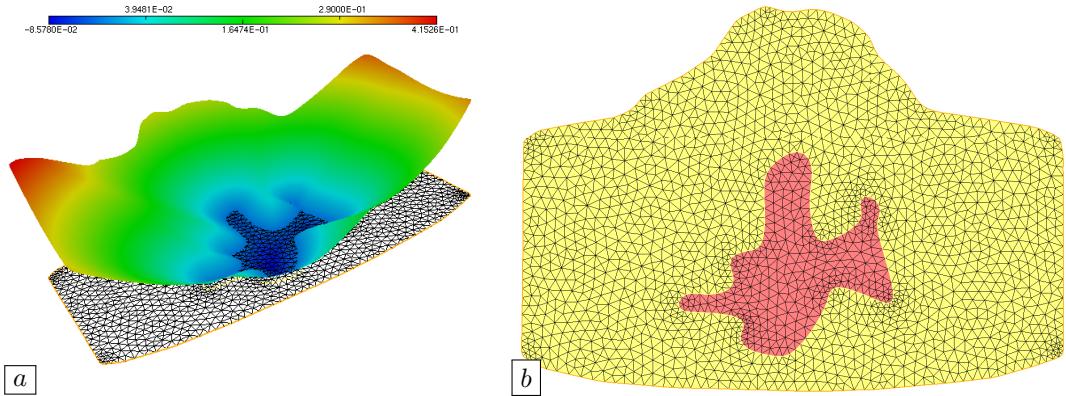


Figure 2. (a) Graph of a level set function $\phi : D \rightarrow \mathbb{R}$ for the cavity Ω ; (b) Meshed representation of Ω (in red), as a submesh of the total mesh of D .

The evolution of a domain $\Omega(t)$ through a velocity field $\mathbf{V}(t, \mathbf{x})$, over a time period $(0, T)$ is conveniently captured in terms of an associated level set function $\phi(t, \cdot)$ (i.e. (7) holds for all $t \in [0, T]$); the latter indeed solves the following advection equation:

$$\forall t \in (0, T), \mathbf{x} \in D, \quad \frac{\partial \phi}{\partial t}(t, \mathbf{x}) + \mathbf{V}(t, \mathbf{x}) \cdot \nabla \phi(t, \mathbf{x}) = 0. \quad (8)$$

In this framework, dramatic changes of $\Omega(t)$ can be accounted for, including topological changes, i.e. merging of holes, or creation of holes.

In our application where $\Omega(t)$ is the sought solution of (2), the velocity field is the (negative) descent direction $\boldsymbol{\theta}$ in (6) and the time T stands for the descent step.

110 2.5 Numerical implementation

Our practical implementation leverages a recent variant of the level set method for shape optimization, introduced in (Allaire et al., 2014) – an open source implementation of which is proposed in (Dapogny & Feppon, 2023). The latter features an additional

114 step at each optimization iteration $n = 0, \dots$, during which remeshing algorithms are
115 used to create a meshed description of Ω^n , as a submesh of the computational domain
116 D , see Fig. 2

117 Our numerical workflow is sketched in Alg. 1, and the code is freely available in
 (Perrot, 2024).

Algorithm 1 Shape optimization algorithm for the reconstruction of a magma chamber.

Initialization: Initial shape $\Omega^0 \subset D$, mesh \mathcal{T}^0 of D a submesh $\mathcal{T}_{\text{cav}}^0$ of which accounts for Ω^0 .
for $n = 0, \dots$, until convergence **do**
 1. Calculate a level set function $\phi^n : D \rightarrow \mathbb{R}$ for Ω^n on \mathcal{T}^n .
 2. Calculate the state \mathbf{u}_{Ω^n} and adjoint state \mathbf{p}_{Ω^n} on $\mathcal{T}_{\text{cav}}^n$.
 3. Calculate a descent direction $\boldsymbol{\theta}^n$ for J_{LS} , from Ω^n on \mathcal{T}^n .
 4. Update the level set function by solving the advection equation (8) on \mathcal{T}^n .
 5. Create a new mesh \mathcal{T}^{n+1} of D in which Ω^{n+1} exists as a submesh.
end for
return Optimized shape $\Omega^n \subset D$ of the cavity.

118

119 The initial geometry is created thanks to the open-source software **Gmsh** (Geuzaine
120 et al., 2009). At each iteration n , the computational domain D is discretized by a mesh
121 \mathcal{T}^n which encloses a discretization of the actual shape Ω^n of the magma chamber as a
122 submesh $\mathcal{T}_{\text{cav}}^n$. The state and adjoint systems (1) and (5) for \mathbf{u}_{Ω^n} and \mathbf{p}_{Ω^n} are solved on
123 this mesh by the open-source Finite Element library **FreeFem** (Hecht, 2012). A descent
124 direction $\boldsymbol{\theta}^n$ is then obtained by (6), and a level set function ϕ^n for the next iterate Ω^{n+1}
125 is obtained by solving (8) thanks to the open-source library **Advect** (Bui et al., 2012).

126

3 Validation with synthetic data

127 To test the method, the idea is to do a kind of cross-validation. On the one hand,
128 we form synthetic observation data from a known source. On the other hand, we initialized
129 the algorithm with a first guess for the source shape and location. We expect the
130 algorithm to iteratively modify the shape of the source and converge to the correct shape
131 and location. In fact, the 3D location of the source (e.g., its center of gravity for a ran-
132 dom shape) is not directly optimized as a vector of discrete parameters, but is modified
133 by the simple fact that the boundary is free to move in any direction, and thus can take
134 on a kind of "average rigid body motion" as it gradually moves the center in a given di-
135 rection.

136

In practice, the synthetic observed surface displacement field is derived from the
 McTigue (1987) solution, an analytical approximation of the displacement caused by a
 uniformly pressurized spherical cavity (the magma domain) embedded in an isotropic,
 homogeneous, and planar elastic medium (the host crust) with elastic constants $\nu = E =$
 10GPa and $\mu = 0.25$.

141

Usually, the quantities to be determined with parametric inversion based on a Mc-
 Tigue model are the location and the radius. The pressure change can also be left as a
 free parameter, but is interchangeable with the radius, so one must be fixed to determine
 the other, see Greiner (2021) for more details. For the synthetic source, we fixed these
 free parameters to $z = -5\text{km}$, $\Delta P = 10\text{MPa}$, $R = 1.5\text{km}$, which are typical values
 for inverted magmatic domains.

147 `magmaOpt` is then allowed to run freely, without any termination condition, to see
148 whether or not it succeeds in converging from the ellipsoid to the McTigue sphere we
149 used to generate the synthetic displacement.

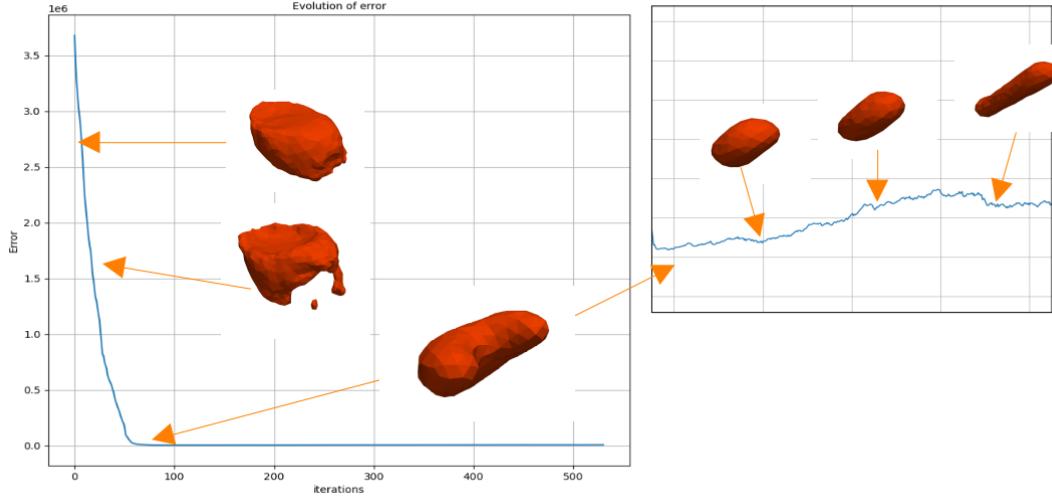


Figure 3. Evolution of error and successive shapes taken by the magma source during an optimization loop. The initial guess is a flat ellipsoid of semi-axes $r_x = 2\text{km}$, $r_y = 3\text{km}$, $r_z = 1\text{km}$ centered on the true spherical source. The minimum is reached at iteration 82.

150 As shown in the figure 3, the algorithm seems to converge to a minimum. After that,
151 the slope of the cost function is positive because a small increase in J is allowed. It is
152 obvious that no other minima are found, as the shape evolves towards a stick-shaped fea-
153 ture, far from the expected solution. We can also discuss the minima found. The sur-
154 face reached is obviously not a sphere, but it is closer than any shape found before. We
155 expect the shape to be closer to a sphere with a finer mesh defined. Many improvements
156 could be realized: for example, once it is obvious that the algorithm will not converge
157 to a better solution, we could restart the algorithm on the best solution found, set new
158 evolution parameters, and allow a finer mesh. By repeating this process automatically,
159 it may be possible to arrive at a more likely shape for the magma reservoir.

160 4 Real test case : Svartsengi 2022 inflation

161 We now apply the method to infer the shape of a magma domain in a recent pe-
162 riod of volcanic unrest and eruption in SW Iceland by evaluating the shape of a magma
163 body responsible for the ground inflation observed from 21 April to 14 June 2022 at Svart-
164 engi on the Reykjanes peninsula. This is one of 5 inflation episodes that preceded catas-
165 trofic dike breaches and eruptions at the Sundhnúkur crater row, which caused the de-
166 struction of the city of Grindavík (Sigmundsson et al., 2024).

The observational data used are the line-of-sight (LOS) displacement maps of the area from Cosmo SkyMed available in (Parks et al., 2024), the data used by Sigmundsson et al. (2024). After uniform downsampling and mesh reprojection (the data points must be aligned on the mesh nodes), the ascending A32 and descending D132 tracks were both

used in the RMS error function we adapted to the LOS geometry.

$$J(\Omega) = \sum_{i \in tck} \alpha_i \int_{\Gamma_u} (L_i(u(x)) - l_o^i(x))^2 dS \quad (9)$$

Where $tck = \{A125, D132\}$. For each track i , α_i is the weight of the track ($\forall i, \alpha_i = 1$ here), $L_i : \mathbb{R}^3 \mapsto \mathbb{R}$ is the function that projects the 3D surface displacement given by the model into the LOS geometry, and l_o^i is the observed LOS displacement.

We then used the framework developed above, only projecting the InSAR data onto the mesh of D and modifying the expression of the error function in `magmaOpt`.

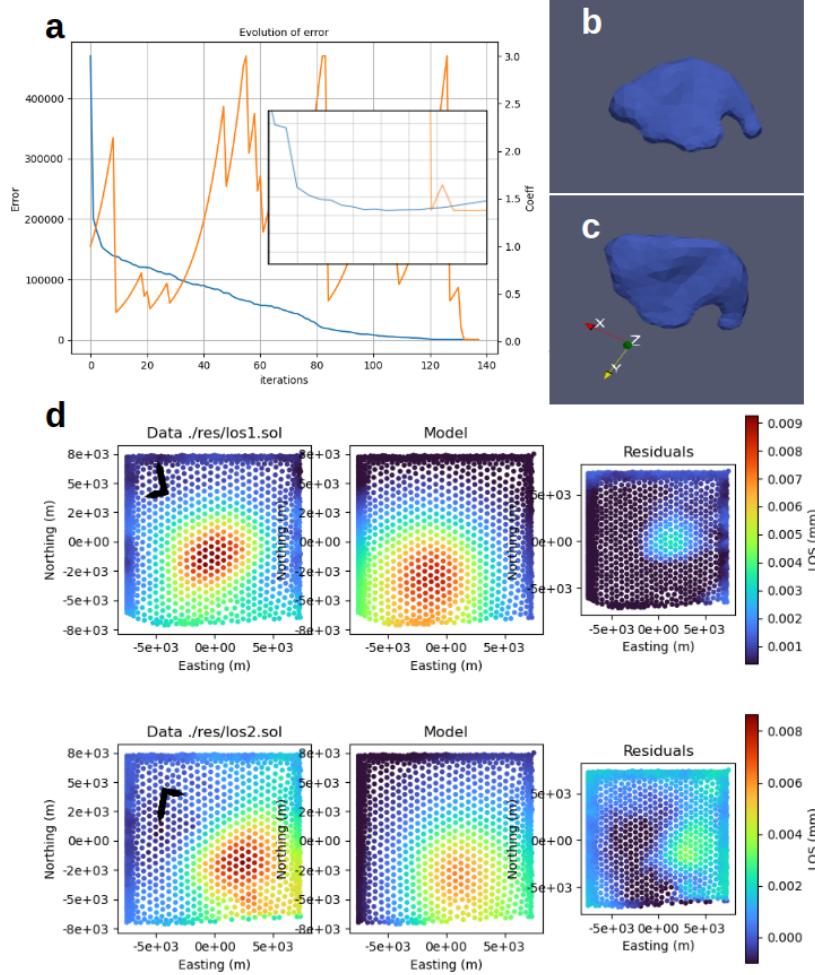


Figure 4. a) Convergence plot with embedded zoom. The blue line is the error and the orange line is the evolution of τ . Minima are reached at iteration 128. b,c) Side and top view of the source Γ_s minimizing J . d) Data, model and residuals of the LOS displacements at iteration 128 for the two InSAR tracks A32 (top) and D132 (bottom). Black arrows are heading and looking directions, coordinates are ISN16 (Valsson, 2019) shifted to a local origin (2529373E, 179745N).

The results shown in figure 4 are encouraging: after providing an initial guess located at the center of inflation at depth for a sphere of radius RR, the algorithm is able

174 to iteratively change the shape and depth of the magma domain to finally result in a sill-
 175 like flattened spheroid whose centroid is located at DD depth. This is consistent with
 176 the presumed depth found in the supporting information of (?, ?), which performs an
 177 analytical model-based inversion. Although the pressure must be fixed, as explained in
 178 1.1, the result can be used to compare the final shape of the magmatic intrusion and give
 179 a richer insight into it. Here we see interesting features, such as an increasing thickness
 180 on the north side, that can't be traced by any other method. The algorithm produces
 181 features that we consider to be artifacts, probably due to mesh refinement problems, such
 182 as small holes or horn-shaped features.

183 5 Discussion

184 This work paves the way for a new class of methods that tackle an unknown ge-
 185 ometry of the magmatic domains, thus giving the possibility to explore irregular shapes
 186 that are more likely to exist compared to any other usually assumed regular shapes. How-
 187 ever, even if the first results presented are promising, many questions remain to be an-
 188 swered. First of all, the internal pressure of the chamber must be specified, which is a
 189 strong hypothesis. In this context, the precise shape of the source should be determined
 190 as a second step. The traditional analytical model-based inversion would be run first,
 191 giving a pressure and a first educated guess for the position and shape of Ω_0 . Then a
 192 more realistic shape could be sought with a shape optimization taking the output of the
 193 inversion as an initial guess.

194 Adding constraints may also be an interesting way to explore. For example, the vol-
 195 ume of the source could be constrained to be within bounds or even to match a certain
 196 value. The implemented shape optimization is certainly able to handle constraints as de-
 197 scribed by Allaire et al. (2021). The physical meaning of the best shape might benefit
 198 from a more constrained problem, and the less influencing deeper part of the source might
 199 be less random.

200 To better understand the influence of data partitioning and variablitiy, additional
 201 tests could be run with synthetic data. We can think of tests such as masking part of
 202 the surface displacement field, introducing noise and parasitic signals, reducing the num-
 203 ber of data points, as is often the case in reality with areas of volcanic systems lacking
 204 data coverage (glacier, river, lava, forest) and subjected to perturbations (atmospheric
 205 distortion, weather).

206 It is also important to mention that the behavior of the algorithm is influenced by
 207 numerous parameters of varying importance, starting from the discretization length (el-
 208 ement size) or the domain extent, to the limits of the step size τ , the regularization length,
 209 or the number of iterations allowed by the line search. A systematic study of each of these
 210 parameters would be beneficial in assessing the quality of the shape inferred.

211 Exploring a way to quantify the uncertainty of the answer is also crucial. For ex-
 212 ample, a sensitivity analysis approach could be considered, as well as the inclusion of a
 213 probabilistic quantity.

214 6 Conclusion

215 The present study has successfully demonstrated the application of inverse prob-
 216 lems and computational methods to infer the shape of a magma domain beneath a vol-
 217 cano using ground inflation data from satellite observations. The shape optimization tech-
 218 nique used in this research showed a new way to identify the most likely shape of the magma
 219 chamber. It was intended as an opening to new methods rather than a complete solu-
 220 tion.

221 We have shown that modifying a shape optimization algorithm to handle geophys-
 222 ical problems is feasible and of interest. Tests on synthetic data showed to some extent
 223 the relevance of the approach, although the best sources found exposed the limitations
 224 faced by these first attempts of shape optimization for volcano geodesy. The test on real
 225 data showed a concrete case of how the method could be used after being more mature.

226 The perspectives are numerous. The numerical nature of the models allows to easily
 227 add complexities to the modeling, such as complex mechanical behavior of the crust
 228 (plasticity, viscoelasticity, poroelasticity), additional loads (tectonic stress, tidal loads,
 229 glacier weights), or inhomogeneities. We hope that the open source code `magmaOpt` de-
 230 veloped by us will be modified and extended by future work.

231 By addressing these limitations and extending this approach, researchers can fur-
 232 ther improve the accuracy and reliability of magma domain shape inference. Ultimately,
 233 the development of more sophisticated models will enable geophysicists to better mon-
 234 itor volcanic activity, predict eruptions, and provide critical support for hazard mitiga-
 235 tion strategies.

236 Open Research Section

237 This section MUST contain a statement that describes where the data supporting
 238 the conclusions can be obtained. Data cannot be listed as "Available from authors" or
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244 The Authorship: Inclusion in Global Research policy aims to promote greater eq-
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 253 include a disclosure statement pertaining to the ethical and scientific considerations of
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 261 Gutiérrez et al. (<https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2023JG007554>),
 262 Tully et al. (<https://agupubs.onlinelibrary.wiley.com/doi/epdf/10.1029/2022JG007128>)
 263 Please note that these statements are titled as "Global Research Collaboration Statements"
 264 from a previous pilot requirement in JGR Biogeosciences. The pilot has ended and state-
 265 ments should now be titled "Inclusion in Global Research Statement".

266 Acknowledgments

267 Enter acknowledgments here. This section is to acknowledge funding, thank colleagues,
 268 enter any secondary affiliations, and so on.

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