



Investigation of Kula Volcanic Field (Türkiye) Through the Inversion of Aeromagnetic Anomalies Using Success-History-Based Adaptive Differential Evolution with Exponential Population Reduction Strategy

YUNUS LEVENT EKINCI,^{1,2} ÇAĞLAYAN BALKAYA,³ HANBING AI,⁴ ARKA ROY,⁵ and ŞENOL ÖZYALIN⁶

Abstract—The Kula Field is the youngest volcanic center in western Türkiye, and consists of various well-preserved volcanic products. Although many geological studies have been conducted in the region, geophysical anomalies have not been studied in detail. Therefore, we analyzed the aeromagnetic anomalies of these volcanic products by performing inversion studies with a recently proposed global optimizer. This study is the first attempt to use success-history-based adaptive differential evolution algorithm (SHADE) for inverting magnetic anomalies. To reduce the computational cost, we introduced the E-SHADE scheme by incorporating an exponential population reduction strategy into the optimizer. A synthetic anomaly study revealed the mathematical nature of the handled inverse problem. Some pre- and post-inversion analyses showed the efficiency of the proposed algorithm. Additionally, we observed that the E-SHADE algorithm produced better results than a commonly used derivative-based local optimizer. Nine profile data sets including magnetic anomalies of some volcanic cones in the Kula region were inverted. It was determined that the basaltic intrusions that allow the mantle material to uplift rapidly are not very deep in the subsurface. Therefore, it is possible that the three-phased volcanism may become active again and generate new alkaline basaltic lava flows in a new phase through these shallow dykes.

Keywords: Kula Volcanic Field, intrusions, aeromagnetic anomalies, dyke approximation, inversion, global optimization.

1. Introduction

Because of the detectable magnetic contrasts between the rocks, ground, shipborne and airborne magnetic surveys are frequently performed to investigate the geological structure of subsurface (Alvandi et al., 2023; Ekinci & Yiğitbaş, 2012; Ekinci et al., 2020; Ekwok et al., 2023; Eppelbaum et al., 2023). These contrasts originate from the different amounts of Fe-Oxides in the contents of magnetized rocks. Thus, magnetic surveys can be easily performed in both small- and large-scale geological investigations. Igneous rocks, formed as a result of the solidification of magma, have higher magnetic properties than others, and they mostly produce clear and high-amplitude magnetic anomalies (Kearey et al., 2002). Therefore, magnetic method is widely used, especially in geological investigations of volcanic regions (Büyüksaraç et al., 2005; Cassidi et al., 2007; Xu et al., 2011; Kosaroglu et al., 2016; Sawires & Aboud, 2019; Saribudak, 2023). Among many data processing methodologies, edge detection and inversion techniques are the commonly used processing tools in magnetic anomaly interpretation (Ai et al., 2022; Eldosouky et al., 2022; Pham & Oliveira, 2023; Prasad et al., 2022). Some directional derivative-based algorithms including special trigonometric functions are used in source edge detection studies, while more complex mathematical procedures are required in the inversion studies to estimate some model parameters of the source bodies. The inverse magnetic problem is solved using either linear or nonlinear system of equations. If the magnetization distribution in a geometrically defined geophysical model is approximated, the problem is linear. On the

¹ Department of Art History, Bitlis Eren University, Bitlis, Türkiye. E-mail: ylekcinci@yahoo.com

² Faculty of Engineering and Architecture, Muş Alparslan University, Muş, Türkiye.

³ Department of Geophysical Engineering, Süleyman Demirel University, Isparta, Türkiye.

⁴ School of Geophysics and Geomatic, China University of Geosciences, Wuhan, China.

⁵ Solid Earth Research Group, National Centre for Earth Science Studies, Trivandrum, India.

⁶ Department of Geophysical Engineering, Dokuz Eylül University, İzmir, Türkiye.

other hand, nonlinearity is pronounced for the inverse problem if some parameters of the source body such as depth, thickness, location, width, dip angle, etc. are estimated with using some physical constraints. In both cases, the inversion process is prone to error and ambiguity because of the mathematical background of the problem, presence of noise content in the observed data and deficient observations (Menke, 2012; Tarantola, 2005; Zhdanov, 2002). In inverse magnetic problems, the cost function (Cf) to be minimized is characterized by some complexities. Thus, it is crucial to examine the reliability of the model outputs obtained from the inversion studies. In this respect, derivative-free global optimizers using nature-inspired metaheuristic approaches are more advantageous than their derivative-based local counterparts. The model solutions obtained from a number of independent runs can be analyzed statistically and therefore mathematical credibility of the model estimations can be examined comprehensively. Additionally, unlike to local optimizers, the success of these population-based optimization algorithms does not directly depend on the choice of the initial model. Another advantage of the global solvers is that they scan broader sectors in model space for the parameters to be estimated. An effective global optimizer tries to find the global optimum by exploring the pre-defined model search space extensively without getting stuck in local minima (Ai et al., 2023; Ekinçi et al., 2021a). Because the optimization in each run starts from a different location in the model space, global solvers explore the model space in much more detail than local solvers using derivative information. In recent years, powerful computer systems have minimized the computational cost disadvantages of global optimizers. Therefore, solving an inverse magnetic problem with a global optimizer has become increasingly popular.

Here, we studied the Kula Volcanic region located in the West Anatolian Extensional Province (WAEP) in Türkiye using aeromagnetic anomalies. The volcanic products in the region are closely connected with the well-known active tectonics of the country (Richardson-Bunbury, 1996). The study area is one of the regions where basaltic volcanoes fed by material rising directly from the mantle. This kind of geological occurrence can be rarely seen in the world.

The volcanic field is about 600 km² and is one of the global geoparks certificated by UNESCO. The basaltic intrusions in this region produce very distinctive and clear magnetic anomalies. Because of the computational superiorities of the global optimizers mentioned above, these magnetic anomalies were inverted through a recently proposed algorithm (Ekinçi et al., 2023) which is built on the basis of success-history-based adaptive differential evolution (SHADE) procedure (Tanabe & Fukunaga, 2013). The proposed E-SHADE algorithm uses an exponential population size reduction strategy which reduces the computational cost remarkably. The efficiency of this optimizer was previously demonstrated on the inversion of gravity anomalies (Ekinçi et al., 2023). Here, using some synthetic noise-free and noisy data sets and magnetic anomalies of some well-known volcanic intrusions which are well-constrained by geological knowledge, we showed that successful and reliable parameter estimations can be achieved via E-SHADE algorithm. Nine profile data sets extracted from the reduced-to-the-pole magnetic anomalies (RTPA) of the Kula region were inverted. In the selection of the profiles, the locations of the cones in the region, highest-amplitude responses of the magnetic anomalies and anomaly shapes that could represent the dyke models were taken into consideration. For each profile data set, 30 independent runs were executed in the optimizations. By means of these multiple runs, the reliability of the obtained model parameter solutions of volcanic intrusions was analyzed using some statistical methods. Finally, the spatial distributions of causative basaltic intrusions were revealed and they were compared with the solutions reported previously.

2. Methodology

2.1. Forward Modelling

The total field magnetic anomaly (TMA) of an infinitely elongated tabular dyke structure (Fig. 1) at an observation point (x_i) is defined as follows (Venkata Raju, 2003)

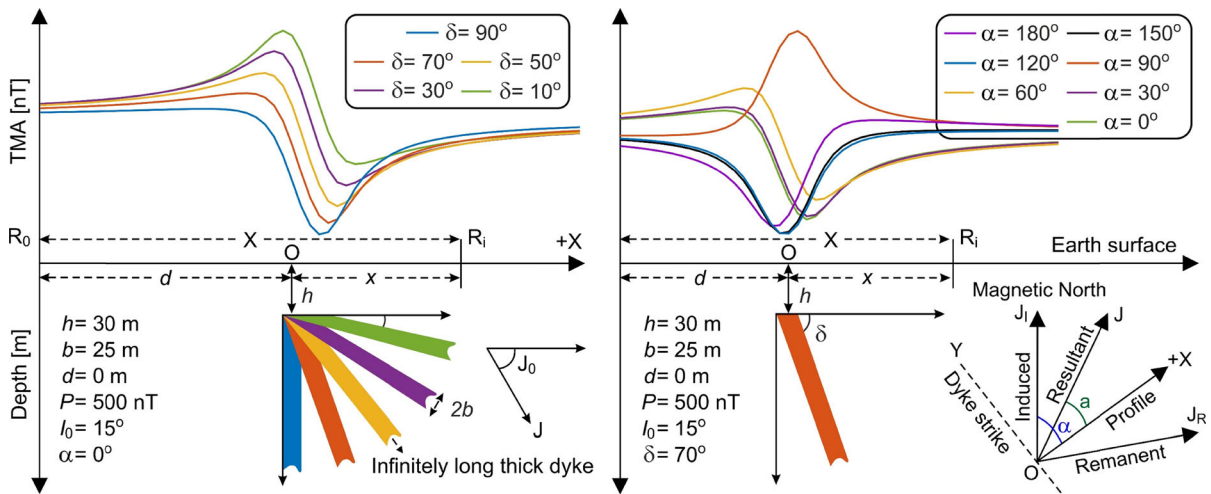


Figure 1

The cross-sectional views of dyke structure with different δ and α angles and their corresponding magnetic anomalies

$$\Delta T(x_i) = P \left\{ \cos Q \left[\tan^{-1} \frac{(x_i - d + b)}{h} - \tan^{-1} \frac{(x_i - d - b)}{h} \right] + \frac{\sin Q}{2} \ln \left[\frac{(x_i - d + b)^2 + h^2}{(x_i - d - b)^2 + h^2} \right] \right\} \quad i = 1, 2, 3, \dots, N \quad (1)$$

where the terms P and Q denote the amplitude coefficient and index parameter, respectively. Their definitions are given by (Venkata Raju, 2003)

$$P = 2KT\beta(1 - \cos^2 I_0 \sin^2 \alpha)^{1/2} (1 - \cos^2 I_0 \sin^2 a)^{1/2} \quad (2)$$

$$Q = I^1 + J^1 - \delta - 90 \quad (3)$$

where

$$\beta = \sin \delta \quad (4)$$

$$I^1 = \tan^{-1}(\tan I_0 / \cos \alpha) \quad (5)$$

$$J^1 = \tan^{-1}(\tan J_0 / \cos a) \quad (6)$$

In the definitions given above, K is the susceptibility contrast, T denotes the intensity of Earth's magnetic field, I_0 and J_0 are the inclinations of the ambient field and resultant magnetization, respectively, and α is the profile azimuth of the source dyke from magnetic north. The other terms are defined in Fig. 1. It should be noted that for induced magnetization the following definitions are used $J_0 = I_0$, $a = \alpha$, $J^1 = I^1$.

2.2. The E-SHADE Algorithm

The evolution-based and gradient-free stochastic SHADE optimization procedure is constructed on an integration of mutation and crossover steps for searching the global minimum in the pre-defined model space (Tanabe & Fukunaga, 2013). This nature-inspired and population-based efficient algorithm uses a special historical-memory that keeps previously successful values of algorithm-based control parameters, namely crossover rate and scaling factor, and produces new ones by sampling the model space in the vicinity of these successful values obtained before. Thus, the user does not need to perform some comprehensive and time-consuming parameter tuning procedures. In the following years, a new efficient variant named L-SHADE optimizer was introduced based on adjusting the above-mentioned control parameters and reducing the population size/number (NP) gradually to further decrease the computational time (Tanabe & Fukunaga, 2014). The L-SHADE-based optimization tools have proven their superiority in many IEEE-CEC competitions over the last decade. The competitions were carried out using some challenging engineering and science problems and also on several criterion functions (Piotrowski et al., 2023). On the other hand, a recent study proposed a new strategy that is more successful than L-SHADE algorithm in optimizing

geophysical data sets (Ekinici et al., 2023). E-SHADE algorithm, which proposes an exponential reduction in the NP against to iteration number, was used to invert gravity anomalies and produced very successful results in determining the basement topographies in sedimentary basins (Ekinici et al., 2023). Here, therefore, the E-SHADE optimizer was applied to invert aeromagnetic data sets obtained from the Kula Volcanic region. The application examples of these differential evolution-based schemes in potential field anomaly inversion are reported in some studies (Balkaya & Kaftan, 2021; Ekinici et al., 2021a, 2021b, 2023; Roy et al., 2021a). Like other evolutionary optimization algorithms, an initial population is produced randomly as $x_i = (x_1, x_2, \dots, x_D)$, $i = 1, \dots, NP$ where D denotes the number of unknown parameters. The process of choosing trial vectors is repeated during the optimization. The step-by-step flow of the algorithm can be summarized as given below (Tanabe & Fukunaga, 2014).

A historical-memory regulates the algorithm-based control parameters. The algorithm stores the memory with H entries. This memory contains the control parameters M_{CR} and M_F ($CR \in [0, 1]$ and $F \in [0, 1]$). The mutation operator is designed by F . First, every $M_{CR,k}, M_{F,k}$ ($k = 1, \dots, H$) are set 0.5. In each generation/iteration G , CR_i and F_i are reproduced by using an index r_i from $[1, H]$. The SHADE algorithm follows the sequences of JADE for undesired values that disrupt the limits of CR_i and F_i . Thus, the values of control parameters for the individuals are set as follows.

$$CR_i = \begin{cases} 0 & \text{if } M_{CR,r_i} = \perp \\ randn_i(M_{CR,r_i}, 0.1) & \text{otherwise} \end{cases} \quad (7)$$

$$F_i = randc_i(M_{F,r_i}, 0.1) \quad (8)$$

Then, the trial vectors are regenerated. A mutant vector $v_{i,G}$ is determined using the current population members via a mutation strategy of JADE. In this stage, the greediness is modifiable through the parameter p .

$$v_{i,G} = x_{i,G} + F_i \cdot (x_{pbest,G} - x_{i,G}) + F_i \cdot (x_{r_1,G} - x_{r_2,G}) \quad (9)$$

In the above equation $x_{pbest,G}$ is arbitrarily selected from the top $N \times p$ ($p \in [0, 1]$) individuals of

generation. The terms r_1 and r_2 are randomly chosen from $[1, N]$. The term p balances the exploration and exploitation processes and effects the greediness of the strategy. A bound constraint regularization is also performed for the mutated vector elements that exceed the search space (i.e., x_j^{min}, x_j^{max}) bounds. In this stage, the trial vector $u_{i,G}$ is obtained by crossing $v_{i,G}$ with its parent vector $x_{i,G}$ as given below.

$$u_{j,i,G} = \begin{cases} v_{j,i,G} & \text{if } rand[0, 1] \leq CR_i \text{ or } j = j_{rand} \\ x_{j,i,G} & \text{otherwise} \end{cases} \quad (10)$$

where j_{rand} is an index of the decision variables selected from $[1, D]$.

Then, using the previously obtained trial vectors ($u_{i,G}, 0 \leq i \leq N$), the survivors that will exist in following iteration are selected. In this step, comparison between each individual $x_{i,G}$ with its corresponding trial vector $u_{i,G}$ are made and the better individual is stored. The definition of the comparison is given as follows.

$$x_{i,G+1} = \begin{cases} u_{i,G} & \text{if } f(u_{i,G}) \leq f(x_{i,G}) \\ x_{i,G} & \text{otherwise} \end{cases} \quad (11)$$

The SHADE algorithm uses an external archive to keep the diversity. A comparison between parent and trial vectors are made and the worse parent vectors are retained. The archive $x_{r_2,G}$ is selected from the union of the population P and the archive A ($P \cup A$). When the defined archive size $|A|$ is exceeded by the size of the archive, arbitrarily selected members are removed to provide space for newly added individuals. The updating of the historical-memory is then performed by the algorithm. CR_i and F_i supply a trial vector that is better than the parent individual. The memory contents are updated at the end of each generation (Tanabe & Fukunaga, 2014). Here, we used an exponential NP reduction strategy to further increase the performance of the algorithm and also to reduce the computational time remarkably. The NP in NP_{G+1} can be obtained after each generation as given below.

$$NP_{G+1} = round \left[NP^{max} \cdot e^{-\lambda(max_NFE - (max_NFE - NFE))} \right] \quad (12)$$

where λ is the decay rate that reduces NP^{max} to the smallest NP^{min} value. This constant number is obtained prior to optimization process by a simple search between $[0, 1e-3]$ with an interval of $1e-9$. The value, that makes $NP^{max} = NP^{min}$ is assigned as λ . The pseudo-code of the E-SHADE algorithm is given in Fig. 2.

3. Synthetic Data Applications with the E-SHADE Algorithm

3.1. Pre-Inversion Studies with the Modal and Sensitivity Analyses

Modal analyses based on producing Cf surface landscapes indicate the structures of inverse problems in terms of resolvability properties of the model parameters to be estimated. Besides, the dependencies between the parameters can be revealed (Ekinci et al., 2017). The shapes of the contours around the global minima give clues about possible dependencies. Hence, the possible uncertainty levels in the model solutions can be revealed. These significant procedures should be carried out before the inversion studies to obtain prior information about the reliability of the parameter solutions to be estimated. In these analyses, Cf values of a parameter pair for each value in a user defined model space are calculated by fixing the other model parameters to their true values. By this way, 2D Cf surface topography maps are generated where the horizontal and vertical axes represent two different parameters. Based on this assumption, we produced the TMA of a synthetic dyke with the model parameter values given in Table 1. We set $I_0 = 15^0$ as shown in Fig. 1. Using Eq. (1), the synthetic data were obtained along a 600 m profile with spacing of 10 m. We used the relative error to calculate Cf, which is given by

$$Cf(m) = \frac{\|\Delta T_{obs} - \Delta T(m)\|_2}{\|\Delta T_{obs}\|_2} \times 100 \quad (13)$$

where ΔT_{obs} is the observed anomaly (true anomaly in our synthetic cases) and $\Delta T(m)$ represents the TMA of the estimated dyke model. The error topography maps produced for all parameter pairs are illustrated in Fig. 3. The centers of these error maps

marked by white circles show the global minima. The axes values in each map are the model space bounds for corresponding model parameters.

It can be observed from the maps that the contour lines have three different characteristics. In some maps ($P - d$, $d - b$, $\delta - b$, $d - h$, $\delta - h$, $P - \delta$, $b - \alpha$, $h - \alpha$, $P - \alpha$) almost round contour lines surrounding the global minima are observed. This property shows that both parameters in each map are not correlated with each other. This is a desired situation in inverse problems because these parameters can be solved independently. In other four maps ($P - h$, $\delta - d$, $h - b$, $d - \alpha$) elliptical contour lines surround the global minima. The curved contours clearly indicate that both parameters in each map are correlated with each other. Although the solutions of the parameters are dependent on each other, it is possible to make an estimate about the solution ranges. The Cf topography map $P - b$ is characterized by unclosed contour lines. In this case a complete solution cannot be found for these parameters. Provided that the sum of this parameter values is a constant, all values that satisfy this sum form a solution set. If the value of one parameter is increased, the other should be decreased. Thus, there is a negative correlation between these parameters. On the other hand, the equivalence Cf topography map of $\delta - \alpha$ showed the most difficult case. A banana-shaped image characterizes the relationship between these two parameters. In this inverse problem, it is not possible to solve α accurately and the solutions will probably involve high-degree of uncertainties. The map also shows that the solution range of the parameter δ is narrower than α and there is a possibility that this parameter can be solved. The modal analyzes performed here showed that most of the parameters in this inverse magnetic problem are independent of each other, except for a few pairs. Apart from modal analyses, we also applied sensitivity analysis for each model parameter based on a derivative-free calculation procedure (Ai et al., 2024). The same synthetic data set was considered. We used 50% perturbations of the true model parameter values listed in Table 1. Figure 4 shows the findings obtained from sensitivity analyses. We calibrated the color bar to the model parameter variabilities. It is clearly observed that the parameter

```

1:  function E-SHADE ( input parameters )
2:   $G \leftarrow 1$ ,  $NP_G = NP^{max}$ ,  $\lambda$ , Archive  $A \leftarrow \emptyset$  % Initialization
3:  Initialize population randomly,  $P_G = (x_{1,G}, \dots, x_{N,G})$ 
4:  Set all values in  $M_F$  and  $M_{CR}$  to 0.5
5:   $k \leftarrow 1$  % Index counter
6:  while  $G < Gmax$  % Main loop
7:       $S_F \leftarrow \emptyset$ ,  $S_{CR} \leftarrow \emptyset$ 
8:      for  $i = 1$  to  $NP$  do
9:           $r_i = \text{select randomly from } [1, H]$ 
10:         if  $M_{CR,ri} = \perp$  then  $CR_{i,G} \leftarrow \emptyset$  else  $CR_{i,G} = randn_i(M_{CR,ri}, 0.1)$  end % Normal distribution generation
11:          $F_{i,G} = randc_i(M_{F,ri}, 0.1)$  % Cauchy distribution generation
12:          $v_{i,G} \leftarrow \text{current-to-pbest/1}$  % Mutant vector generation by the mutation operation
13:         Apply bound constraints to  $v_{i,G}$  elements outside the parameter search space ranges
14:          $u_{i,G} \leftarrow \text{Binomial Crossover}$  % Trial vector generation by the crossover operation
15:     end
16:     for  $i = 1$  to  $NP$  do
17:         if  $f(u_{i,G}) \leq f(x_{i,G})$  then  $x_{i,G+1} \leftarrow u_{i,G}$  else  $x_{i,G+1} = x_{i,G}$  end % Selection
18:         if  $f(u_{i,G}) < f(x_{i,G})$  then  $x_{i,G+1} \rightarrow A$   $F_{i,G} \rightarrow S_F$   $CR_{i,G} \rightarrow S_{CR}$  end % Selection
19:     end
20:     if necessary shrink  $A$ 
21:     if  $S_F \neq \emptyset$  and  $S_{CR} \neq \emptyset$  then % Memory update
22:         if  $M_{CR,k,G} = \perp$  or  $\max(S_{CR}) = 0$  then
23:              $M_{CR,k,G+1} \leftarrow \perp$ 
24:         else
25:              $M_{CR,k,G+1} \leftarrow \text{mean}_{wl}(S_{CR})$  % Weighted Lehmer mean
26:         end
27:          $M_{F,k,G+1} \leftarrow \text{mean}_{wl}(S_F)$  % Weighted Lehmer mean
28:          $k \leftarrow k + 1$ 
29:         if  $k > H$  then  $k \leftarrow 1$  end
30:     else
31:          $M_{F,k,G+1} \leftarrow M_{F,k,G}$ ,  $M_{CR,k,G+1} \leftarrow M_{CR,k,G}$ 
32:     end
33:     Calculate  $NP_{G+1}$  % Exponential population size reduction strategy
34:     if  $NP_G < NP_{G+1}$  then
35:         Sort individuals in  $P$  based on their fitness values and delete lowest  $NP_G - NP_{G+1}$  members
36:         Resize Archive size  $|A|$  based on the new  $|P|$ 
37:     end
38:      $G \leftarrow G + 1$  % Next generation
39: end % End of the main loop

```

Figure 2

Pseudo-code showing the SHADE algorithm (modified from Tanabe & Fukunaga, 2013, 2014) with the use of exponential population size reduction

d is the highest sensitive one. Therefore, this parameter can be solved more precisely. However, the other parameters have different sensitivity levels. The parameter α is the lowest sensitive one. Changes in the value of this parameter do not produce remarkable variations in the data like the parameter

d . These different sensitivity levels of the model parameters may affect the inversion stabilities. Thus, based on the findings obtained from modal and sensitivity analyses, it is clear that there may be high uncertainty levels in the solutions of some parameters. This result necessitates some post-inversion

Table 1

True model parameters, search limits and inversion results of synthetic data cases

Parameters	True values	Search spaces		Estimations	
		Min	Max	Noise-free case	Noisy case
h [m]	30	1	100	30	30.16
b [m]	25	1	100	25	22.99
d [m]	0	- 100	100	0	- 0.03
δ [°]	70	0	180	68.30	67.99
P [nT]	500	10	2000	500	544.41
α [°]	50	0	180	47.89	45.61
Mean run time [s]				0.83	0.81
Min Cf [%]				1.55e-04	1.12e + 01
Max Cf [%]				1.60e-04	1.12e + 01
std Cf [%]				9.05e-07	4.23e - 12

studies to understand the reliability of the inversion outputs. Moreover, inversion procedures should be performed by using multiple independent runs to carry out some statistical experiments.

3.2. Inversion of Synthetic Data with the E-SHADE Algorithm

The performance of the E-SHADE optimization tool on model parameter estimation in the present magnetic problem was tested with the TMA used in modal and sensitivity analyses. Search space bounds together with the true values of each model parameter are given in Table 1. In the inversion processes, 30 independent runs were executed to see the stability of the optimizer and to make some statistical analyses. Initially, the NP was determined as 150, but it was exponentially decreased with the iterations and reached 4 in the last iteration to reduce the computational cost remarkably. We set maximum iteration number as 7200. Although this may seem like a large number, it should be noted that the computational time of each independent run was quite less than 1 s. Inversion results obtained with some statistical findings are listed in Table 1.

In this noise-free data experiment, model parameter values were estimated satisfactorily. In each independent run, the inversion reached the global optimum without getting stuck in any local minimum. Additionally, it is clearly seen that standard deviation (std) of Cf values of independent runs are quite low. This finding shows the stability and robustness of the

optimizer used. Convergence behaviors for each parameter and the fit between the true and calculated data in the most successful run are illustrated in Fig. 5. The two data sets overlap exactly. The sudden drop in the Cf curve at the beginning of the inversion process is noteworthy. This fast convergence rate shows that the global optimum is determined before the optimization reaches the maximum iteration number. This situation can be seen more clearly in the convergence behaviors of the parameters. The model parameters reached their true values before the 5000th iteration. However, it should be noted that the solutions of parameters α and δ contain high-degree uncertainties. The degree of uncertainty in the solutions of the latter parameter is relatively lower because the solution set is in a narrower range. Such a result was already expected by the knowledge obtained from the modal and sensitivity analyses. Nevertheless, these uncertainties of these two parameters do not affect the solutions of the other parameters solutions. In the next step, a noise content was added to the synthetic data to examine the response of the E-SHADE algorithm to the noise content. The inversion procedures were performed using the same run number, iteration number, NP and same search space bounds. The data set was contaminated using zero-mean pseudo-random values with a std of 24.5 nT, which correspond to a noise content of 11.7%. The resultant estimations for model parameters are shown in Table 1. The E-SHADE algorithm determined a dyke model with 11.2% Cf. This error value is very close to added noise content.

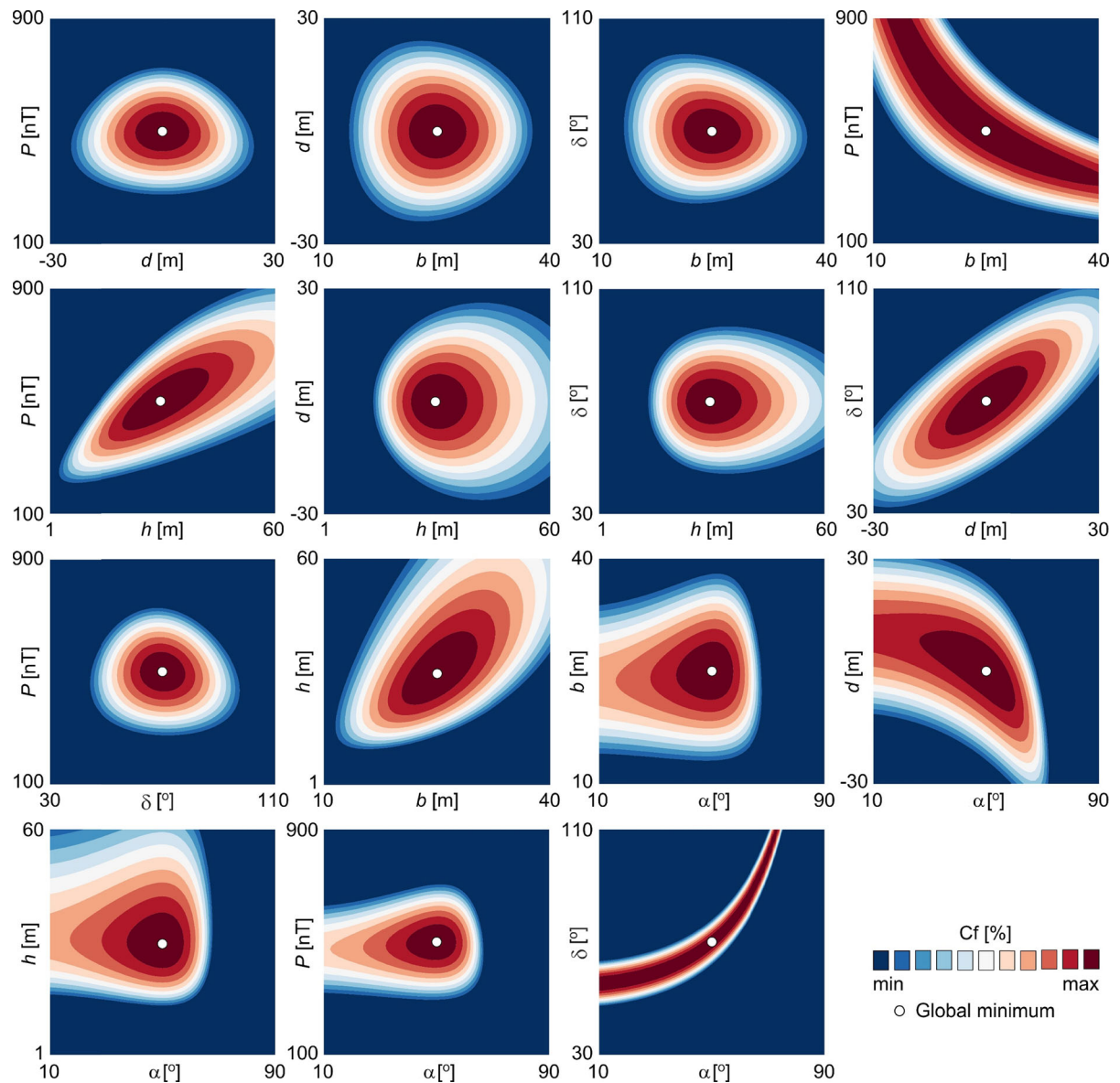


Figure 3
Cf topography maps for all model parameter pairs

In addition, std of the difference between observed and calculated data sets is 23.6 nT, which is quite close to std of added noise content. Therefore, we can mention that there is no overfitting of the data in this noisy case. It is also observed that std of the Cf values obtained from 30 independent runs is almost zero (Table 1). This finding clearly shows that although the algorithm started the optimization from different locations in the model space in each run, it avoided

local minima and converged the optimum solution by means of its well-balanced exploratory and exploitative nature. The inversion outputs obtained are illustrated in Fig. 6. The similar uncertainties, which does not affect the spatial parameters, namely depth, width and location of the dyke, were observed in the solutions of parameters δ and α . Successful results were obtained for other parameters mentioned before. The sudden decrease in Cf values and efficient

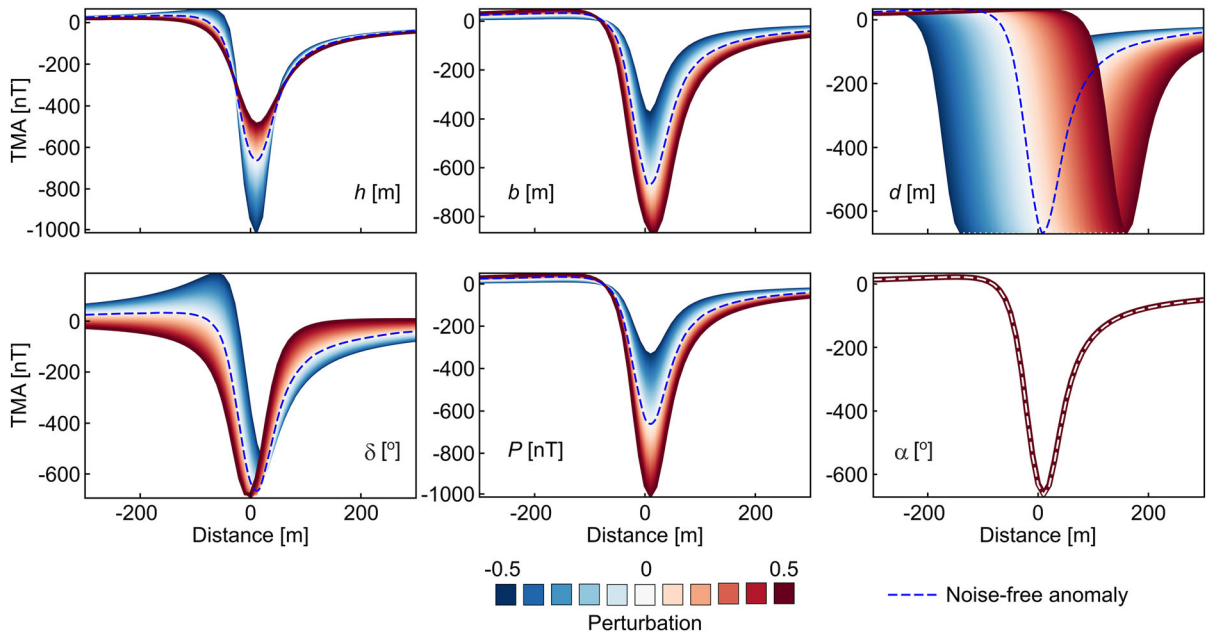


Figure 4
Model parameter sensitivities in the presented inverse magnetic problem

convergence rates to the optimum values are noteworthy even in the noisy synthetic data case. Therefore, it can be mentioned that the E-SHADE optimizer proved its efficiency in the presented inverse magnetic problem.

3.3. Post-Inversion Studies with the Principal Component Analysis

The principal component analysis is similar to modal analysis but it is performed after the inversion procedure. This analysis is based on producing the error landscape map by reducing the multidimensional model parameters into two basic components. This reduction process does not cause loss of information and retains the general properties of model parameters estimated (Alpaydın, 2020; Jackson, 1991; Jolliffe, 2006). In brief, this orthogonal transformation projects the multidimensional parameter set into a new coordinate system produced using the directions of largest variance (Munoz-Romero et al., 2016). The covariance matrix is defined by

$$C = (M - m)^T \cdot (M - m) \quad (14)$$

where M is the matrix that stores the estimated model parameters in each iteration and m denotes the mean of these parameters. Principle components are obtained by calculating the eigenvalues and eigenvectors of C . The new coordinate system is produced using the first two components. The Cf values of each iteration and corresponding coordinates are used together to produce the 2D principal component space. The use of this analysis in geophysical data inversion can be found in the literature (Ekinici et al., 2023; Pallero et al., 2015, 2017; Roy et al., 2021b, 2022; Sungkono et al., 2023). Figure 7 shows the interpolated Cf topographies for two synthetic data cases. The locations of true and best models in 2D space are marked with colored triangles. The model solutions that are higher than a certain cutoff value ($> 25\%$) were not taken into consideration. In the constructed error topography map for noise-free case, the best model obtained from the inversion procedure overlays true model in the lowest error region. In the 2D plane, a depictive minima region is

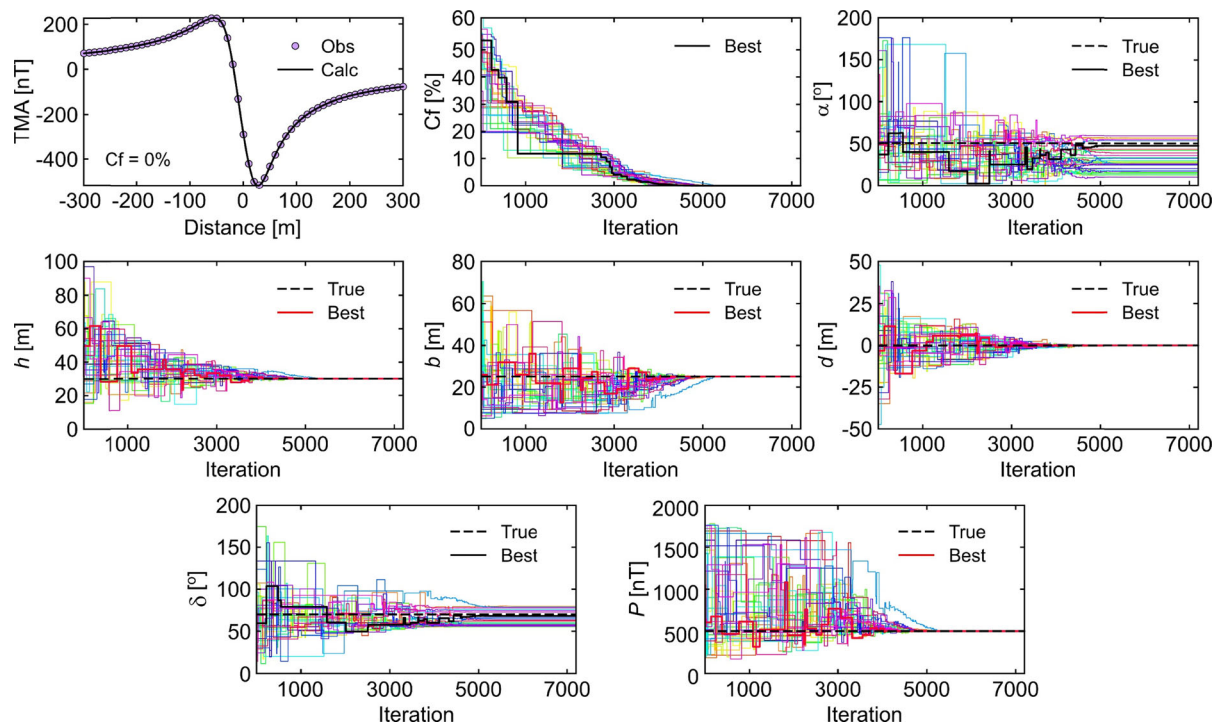


Figure 5

Noise-free case. The fit between the true and calculated data sets. The behavior of Cf against iterations. Convergence behaviors of each parameter in 30 independent runs against iterations

also observed. Although the optimization discovered the depictive minima and searched for solutions around them, it succeeded to move away from that region and reach the global optimum. This finding clearly shows that the E-SHADE algorithm balances its exploratory and exploitative properties well. In the second synthetic case, the best model did not overlap with the true model because of the noise content. However, the location of best model is not far from true model, and it can be mentioned that there is no overfitting of the data. It is also observed that the CF value of the best model is less than the true model, and this is an expected result in the inversion of noisy data cases as clearly explained in Fernández-Martínez et al., (2014a, 2014b).

3.4. Inversion of Synthetic Data with the Conjugate Gradient-Based Least-Squares Algorithm

A least-squares-based minimization approach in conjunction with the Conjugate Gradient algorithm

(CGLS) was used to compare the performance of the E-SHADE algorithm. The CGLS algorithm is a powerful iterative technique to solve nonlinear systems, especially those involving symmetric and positive definite matrices. Unlike direct approaches, such as Gaussian elimination, which aim to find the solution in a finite number of steps, the CGLS algorithm iteratively refines approximations to converge toward the accurate solution. This method's reliance on matrix–vector multiplications makes it more efficient in both time and space. Thus, the CGLS algorithm acts as an iterative solver rather than calculating the matrix inverse directly. Here, we used the same noise-free and noisy anomalies for the inversion through the local optimizer. The Jacobian matrix was computed using the forward finite-difference approach. Maximum iteration number was set to 25. Initial model parameters and estimated ones are listed in Table 2. Additionally, the inversion results are illustrated in Fig. 8. Initial model parameters close to the correct values were selected for the

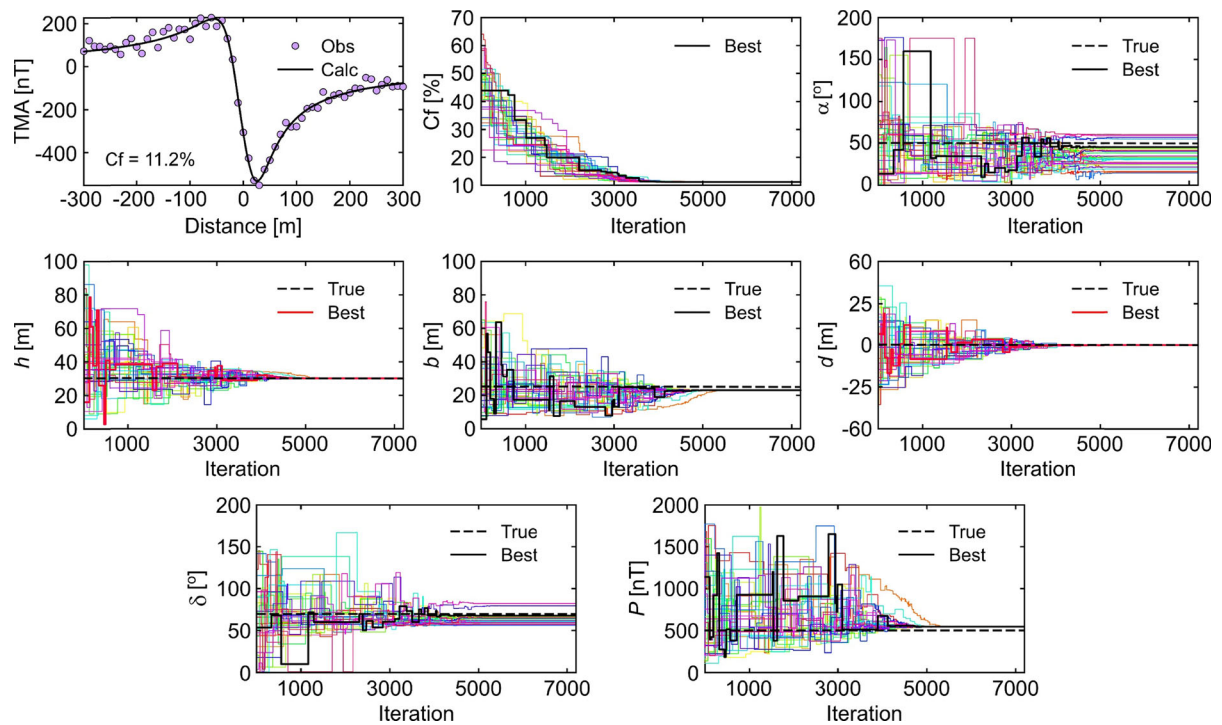


Figure 6

Noisy case. The fit between the true and calculated data sets. The behavior of Cf against iterations. Convergence behaviors of each parameter in 30 independent runs against iterations

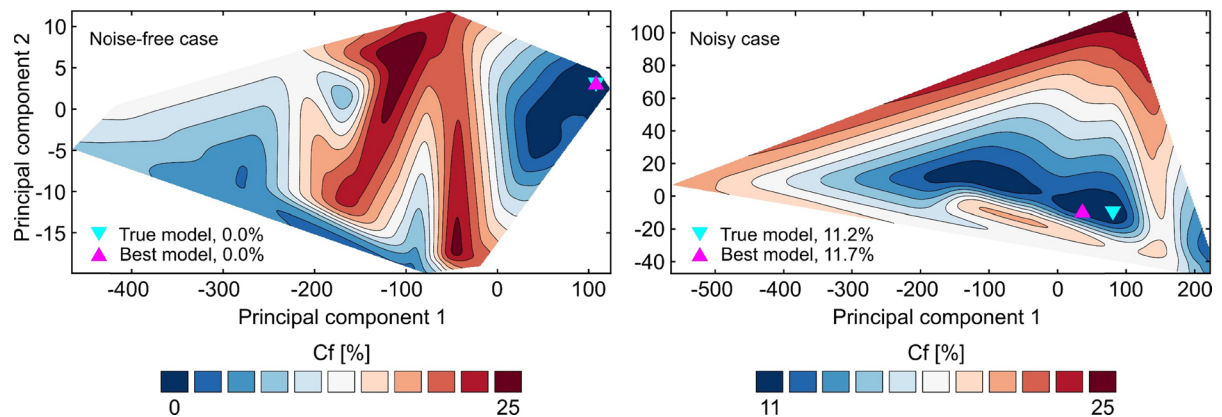


Figure 7

Cf landscapes produced in 2D principal component space for synthetic data cases. Contours are smoothed for better demonstrations

gradient-based inversion procedure. In both synthetic cases, except for the dips and profile azimuths of the sources, the other parameters were determined successfully. Additionally, the CGLS algorithm terminated the inversions with slightly less

computation time. The inversion procedures were completed with the same Cf values as obtained via E-SHADE algorithm. However, it is clear that the E-SHADE optimizer, which searches in a very large model space, determined these angle values better. It

Table 2

True model parameters and CGLS solutions obtained from synthetic data cases

Parameters	True values	Initial values	Estimations	
			Noise-free case	Noisy case
h [m]	30	42	30	30.35
b [m]	25	35	25	22.65
d [m]	0	15	0	-0.04
δ [°]	70	98	56.68	56.91
P [nT]	500	357	500	553.43
α [°]	50	36	20.57	13.80
Run time [s]			0.29	0.29
Cf [%]			$1.55e - 04$	$1.12e + 01$

should be noted that the CGLS local optimizer failed when the initial model parameters were obtained by adding 50% perturbations to the true ones. These examples clearly showed that the E-SHADE algorithm, which does not require a well-constructed initial model, is much more advantageous than its local counterpart.

4. Validation of E-SHADE Inversion with Known Intrusions that are Well-Constrained

by Geological Data

In order to further test the validity of the E-SHADE algorithm before the inversions of Kula anomalies, we used two magnetic data set associated with volcanic intrusions that are well-constrained by geological data. The first anomaly is originated from an olivine diabase dyke located in Pishabo Lake, Ontario (McGrath & Hood, 1970). This outcropped intrusion is a member of Sudbury dyke swarm and produces high-amplitude magnetic response. The aeromagnetic data set was acquired with a terrain clearance of about 305 m (McGrath & Hood, 1970). The TMA maps of the region were published by Geological Survey of Canada (1965). McGrath and Hood (1970) processed this magnetic anomaly using a curve-matching method and linear fit criterion. They reported depths of about 301.5 m and 306.5 m, respectively. Additionally, based on the information obtained from the outcrop mass in the field, they reported that the width of the dyke body was approximately 100 m. Abdelrahman et al. (2012) determined the residual component of this magnetic anomaly and used an inversion procedure which produced a depth of 320 m to the top of the outcropped dyke. Here, we used the residual anomaly for the inversion via the proposed algorithm. The search space bounds for the model parameters of diabase dyke are given in Table 3. As clearly seen, search

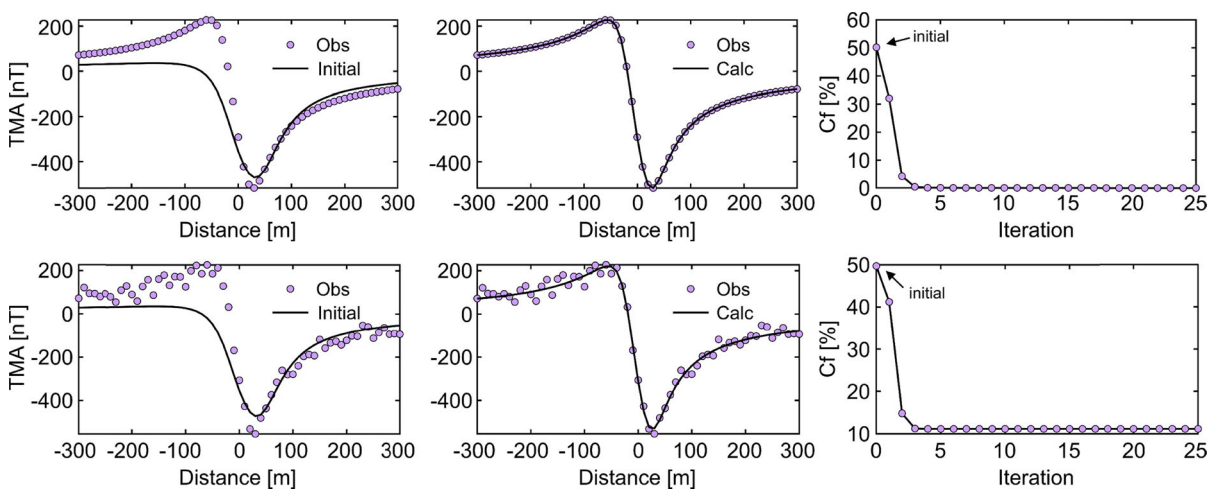


Figure 8
CGLS inversion results of noise-free (upper panel) and noisy (lower panel) data cases

Table 3

Search space bounds, estimated model parameter values and some statistical results for Ontario and North Carolina magnetic anomaly cases

Parameters	Ontario case		North Carolina case			
	Search spaces		Search spaces		Estimations	
	Min	Max	Min	Max		
h [m]	50	1000	307.42	1	50	6.59
b [m]	50	1000	177.84	1	50	36.31
d [m]	500	1500	999.29	10	60	40.67
δ [°]	0	180	122.14	0	180	99.91
P [nT]	50	2000	395.63	50	2000	293.79
α [°]	0	180	78.30	0	180	40.94
Mean run time [s]			0.82			0.83
Min Cf [%]			5.63			6.95
Max Cf [%]			5.63			6.95
std Cf [%]			2.4e – 15			9.1e – 14

ranges for depth and width values were designed on the basis of priori information mentioned above. In addition, wide search ranges were used for other parameters. We performed 30 independent runs with a NP of 150, and a maximum iteration number of 7200, as used in the synthetic cases. Inclination of the Earth’s magnetic field was set to 76.3 degrees. The inversion outputs are demonstrated in Fig. 9. A satisfactory fit between the two data sets was obtained. A depth of 307.4 m was obtained for the outcropped intrusion. As in the synthetic cases, some uncertainties were observed in the solutions of parameters δ and α . However, statistically reliable solutions were obtained for the other parameters. Although the optimization started in different points in solution space, these parameters reached the convergence plain in every single run. The obtained depth via the E-SHADE optimizer is quite close to the flight height. Thus, we obtained geologically reliable depth solution.

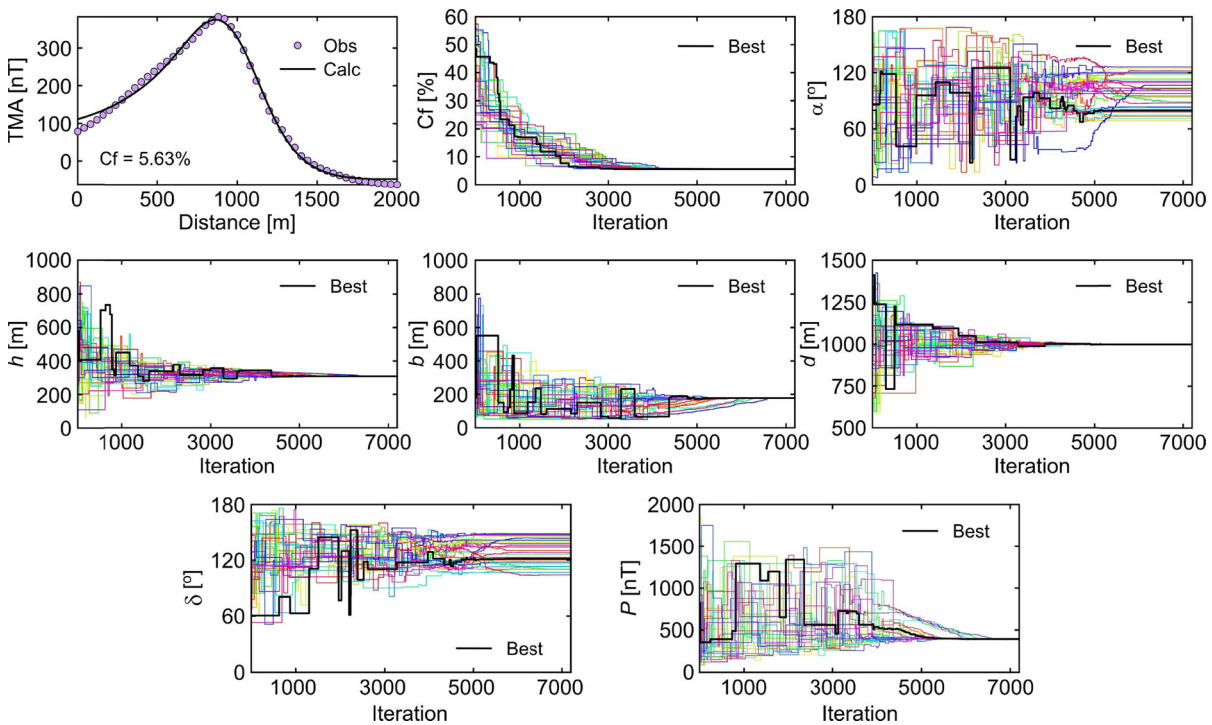


Figure 9

Ontario case. The fit between the observed and calculated data sets. The behavior of Cf against iterations. Convergence behaviors of each parameter in 30 independent runs against iterations

In the second example, we used the anomaly of a diabase dyke located in the Durham Triassic basin, North Carolina (Won, 1981). Many Triassic diabase dykes in the region are known to accumulate significant amounts of fracture-induced groundwater. Some diabase dykes in that area produce high-amplitude magnetic anomalies while others exhibit non-magnetic responses. The varying magnetic properties are probably originated from different chemical compositions of the dykes or changes in the mineralogical composition of the host rock lithologies surrounding the diabase masses (Burt et al., 1978). The majority of these dykes are of limited width, less than 30 m. According to the information obtained from the wells drilled with hammer drills, it was reported that the tops of the dykes were at depths of several meters (Won, 1981). A depth of 7.97 m to the top of the dyke mass and a width of 39.4 m were obtained using Gauss's method (Won, 1981). Kara et al. (2022) analyzed this anomaly and they reported 8.4 m and 39.24 m for the depth and width of the diabase dyke,

respectively. Table 3 lists the search space bounds for the model parameters of diabase dyke. We used the geological priori information in selecting the search spaces for parameters of depth and width. Wide search ranges were used for other model parameters. We inverted the magnetic anomaly using the same algorithm-based control parameters. The inclination angle for the Earth's magnetic field was set to 67 degrees. Figure 10 illustrates the inversion results. A Cf of 6.95% was obtained between the observed and calculated magnetic data set. The depth to the top of the diabase dyke was obtained as 6.6 m. This value is very close to the solutions of previous works and also to the geological information. The estimated width value is also geologically reasonable. The statistical reliability of the solutions is the same as in the previous example. The equivalence error topographies of two cases are shown in Fig. 11. The model solutions higher than a certain cutoff value ($> 25\%$) were not taken into consideration in producing the Cf maps. In the Ontario magnetic anomaly

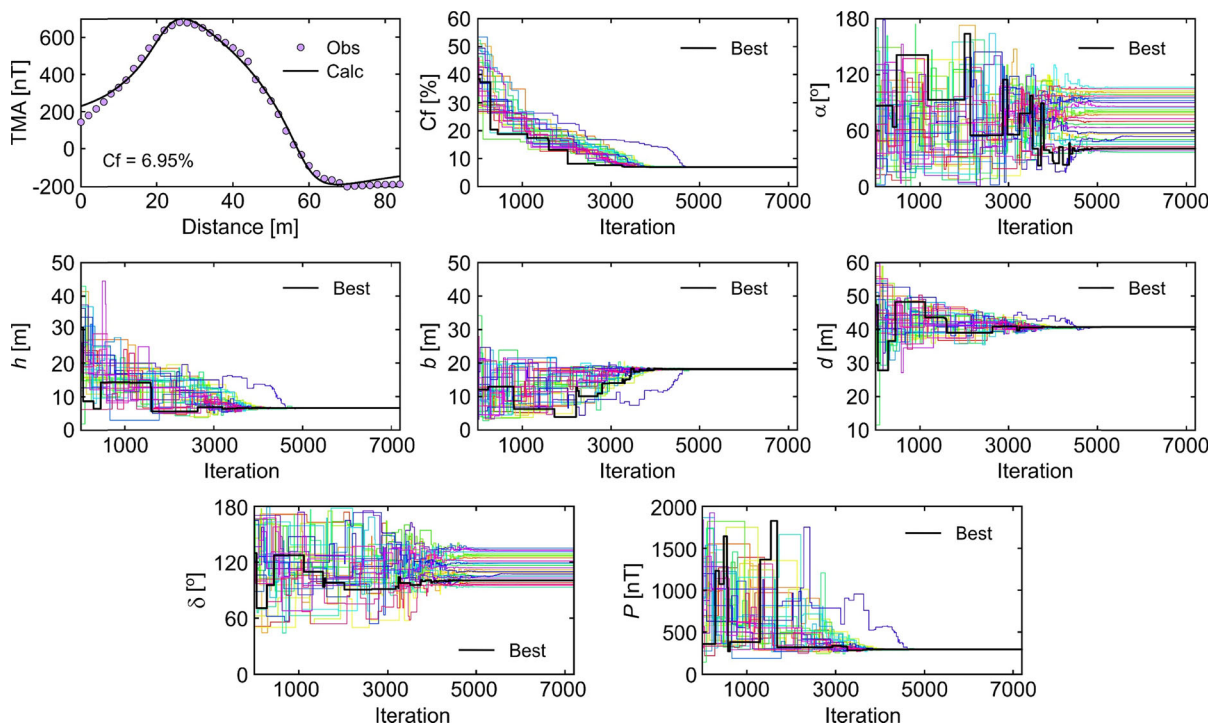


Figure 10

North Carolina case. The fit between the observed and calculated data sets. The behavior of Cf against iterations. Convergence behaviors of each parameter in 30 independent runs against iterations

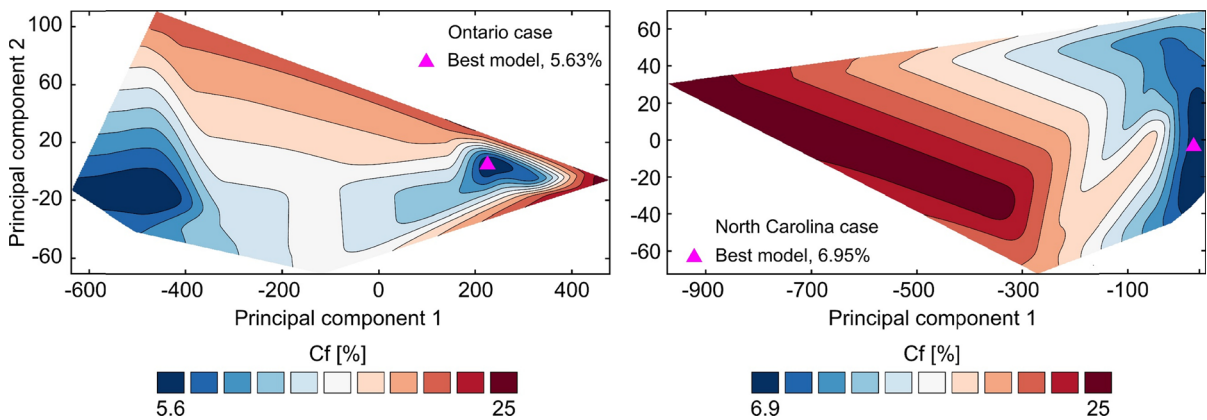


Figure 11

Cf landscapes produced in 2D principal component space for two field data cases. Contours are smoothed for better demonstrations

case, a deceptive minima region is clearly observed. Although the existence of this difficulty, the E-SHADE algorithm reached the minima valley with its well-balanced global exploratory and local exploitative capabilities. In the North Carolina magnetic anomaly case, a wide model solution space was scanned and the global minimum was discovered by the algorithm. We can mention that these two known anomaly cases validated the quality and reliability of the E-SHADE algorithm both statistically and geologically.

5. Kula Volcanic Field and Aeromagnetic Anomaly Inversion with the E-SHADE Algorithm

5.1. Geology of the Study Area

Türkiye is located in a geological complex region which is a part of the Alpine-Himalayan orogenic belt. This significant belt extends from the Mediterranean Sea to the Himalayas, and it is characterized by significant tectonic activities such as the collision of some continental plates. During the Late Cretaceous-Eocene, the Neo-Tethys Ocean closed (Şengör & Yilmaz, 1981), and in the Early-Middle Miocene time period, the Anatolian and Arabian Plates collided. This collision caused the development of the Bitlis-Zagros Thrust Zone (BZTZ) (Ring & Layer, 2023; Şengör & Yilmaz, 1981). Because of this collision, Anatolian Plate moves westward with

counterclockwise rotation along the dextral North Anatolian Fault Zone (NAFZ) and the sinistral East Anatolian Fault Zone (EAFZ) (Fig. 12). After this collision, an intense crustal extension began in WAEP starting from the Oligo-Miocene (Seyitoğlu & Scott, 1991, 1992; Sozbilir, 2002; Bozkurt & Mittweide, 2005). Additionally, the subduction of the African Plate beneath the Anatolian Plate along the Aegean and Cyprean Arcs remarkably contributes to this extension (Fig. 12). Western Anatolia is one of the regions in a world scale where continental extension is most active. Following this extension, metamorphic basement rocks forming the Menderes Massif emerged (Bozkurt & Park, 1994; Şengör et al., 1984). With the evolution of the Menderes Massif which is a metamorphic core complex (Şengör et al., 1984), approximately E-W oriented Pliocene-Quaternary aged grabens and NE-SW oriented Miocene aged basins were developed in the region (Ciftci & Bozkurt, 2009; Şen et al., 2014; Westaway et al., 2004). The Kula Volcanic Field is located in one of these basins, namely on crystalline rocks of the Menderes Massif (Bozkurt, 2001; Koralay et al., 2004). The region is tectonically very active and characterized by regular NE-trending normal faults separating the crystalline rocks, Neogene sediments and volcanic rocks (Tokçaer et al., 2005). In the region that covers NE-SW oriented basins, volcanism is mostly associated with crustal thinning (Şen et al., 2014). The study area hosts one of the youngest volcanics of the country and is clearly distinguished

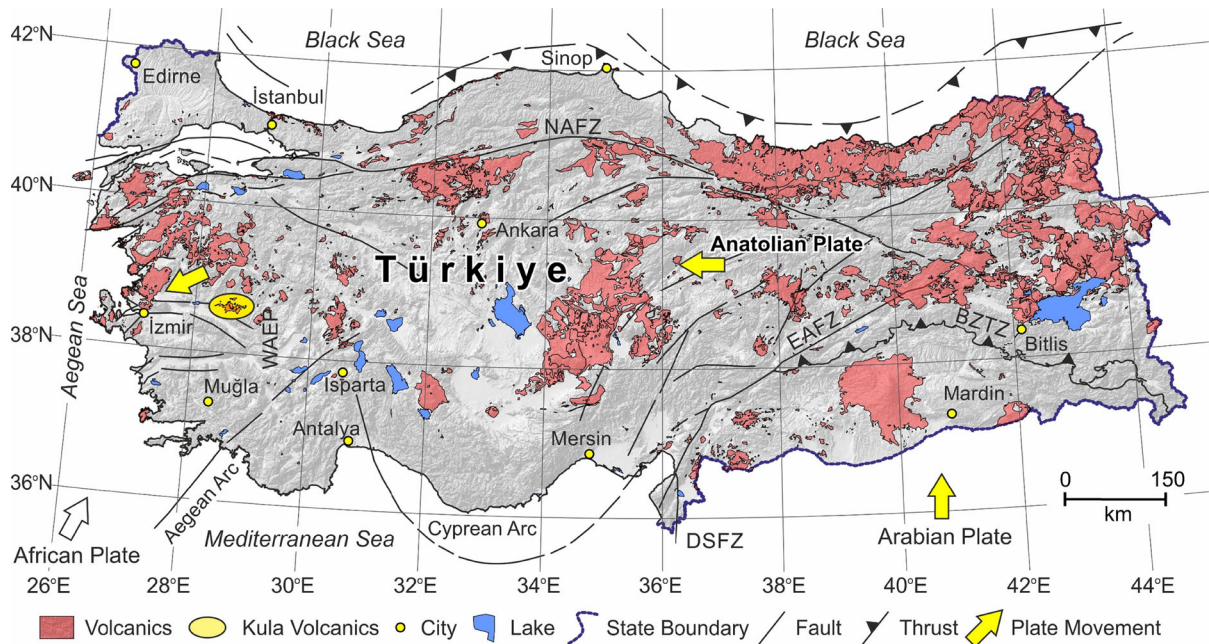


Figure 12

The map showing the volcanic rock distribution in Türkiye (modified from Ertekin et al. (2021)). The location of Kula volcanics is highlighted by yellow ellipse

from other volcanoes of the whole country by being of basaltic origin. Quaternary alkaline basaltic rocks are dominant in the region. The distribution of volcanics of the country together with the study area are shown in Fig. 12. The Kula Volcanics are located in an area consisting of many large and small volcanoes spread in a wide region in the west of the country. Basaltic rocks of the region are unique example of rapid uplifting of asthenosphere material in western Anatolia (Tokçaer et al., 2005). In addition, the region consists of many well-preserved lava tubes, fairy chimneys, canyons, cinder cones, maars and other volcanic products. The volume of the eruption products was reported to be small. The volcanic products spread in an area exceeding 200 km² (Bunbury et al., 2001). The geology map of the region is shown in Fig. 13. All volcanic occurrences in the Kula region are located on a plateau with an altitude of 600–700 m (Koçman, 2004). The topographic map of the region is shown in the upper panel of Fig. 14. It is generally accepted that volcanism has developed in three phases. The primary phase of volcanic activity occurred between 1.1 my and 0.01

my ago, as reported by Aydar (1998). The volcanics of the first phase are located on the hills as plateau basalts on the older units. The lava flows covering the Neogene fillings occurred in this phase. This phase was followed by an uplift and river valleys and cleavage, and then the second and third phases occurred at short intervals. Lava emerged from most of the cones belonging to the second phase. These are shaped as pyroclastic cones. More than 80 cinder cones that occurred between the first two phases were reported (Tokçaer et al., 2005). The cones of the third phase are steep and the lava flows are fresh (Koçman, 2004). In the last period of volcanic activities, lava flows were produced by the youngest craters to form the second plateau basalts, and the presence of plateau lavas in large volumes indicates the rapid uplift of the mantle material which was validated by some geochemical analyses (Tokçaer et al., 2005). There is no obvious petrographic difference between the lavas of three phases.

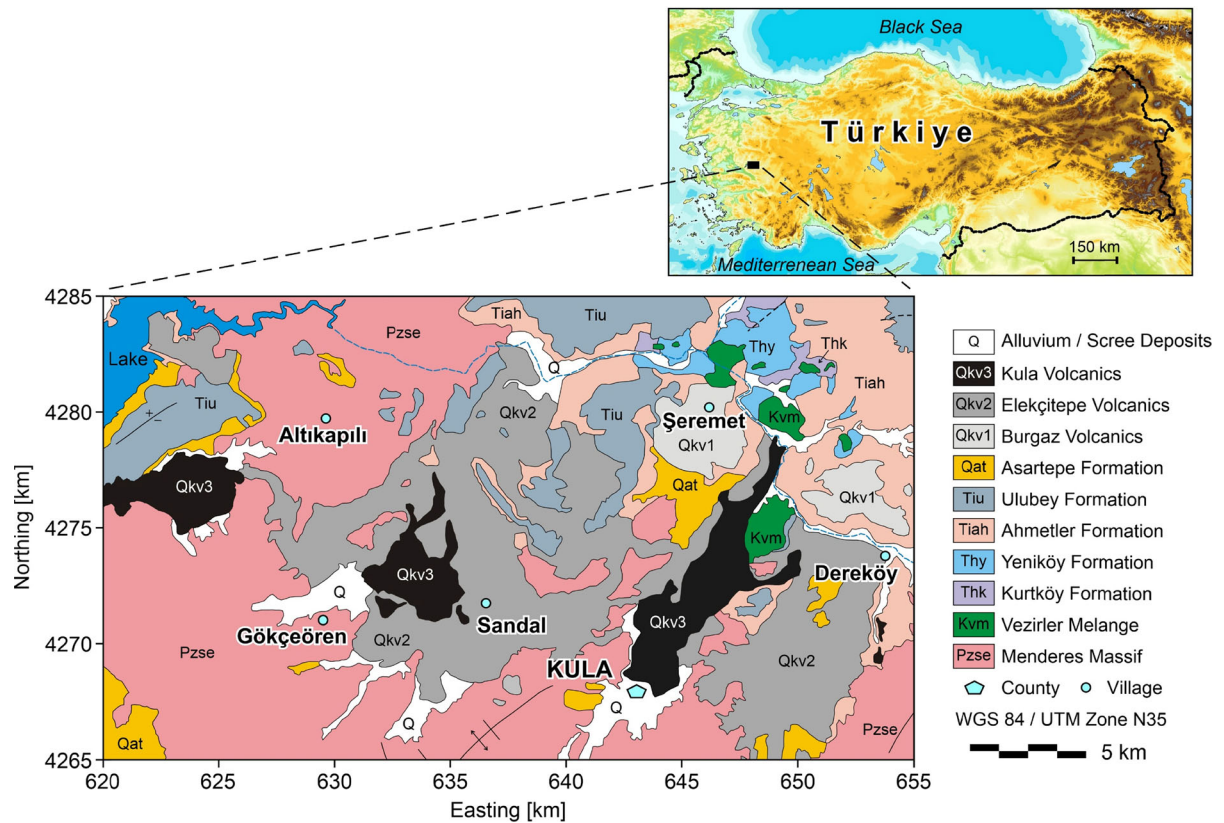


Figure 13
The location and geology maps of study area (modified from Özyalın (2023))

5.2. Aeromagnetic Data of the Study Area

The aeromagnetic anomalies of the Kula Volcanic region were obtained by a national institution of Türkiye, the General Directorate of Mineral Research and Exploration (MTA). It was aimed to map the spatial distributions of volcanic rocks and also determining magnetic-highs in the region. The required methodological steps including IGRF correction were performed by the same institute. In the data acquisition step, N-S flight lines were used. In this aeromagnetic survey, MTA used a nominal terrain clearance of 150 m which was controlled by a radar altimetry system. The observed data were then gridded using 100 m intervals in both directions. First, a horizontal trend was removed from TMA map and a reduction-to-the-pole process was applied. For the inclination and declination of the ambient field, 55° and 2° were used, respectively. RTPA map of the

study region is shown in the lower panel of Fig. 14. The distinct magnetic anomalies exhibiting high-amplitudes can be easily followed. It should be noted that the one of the highest-amplitude magnetic anomalies in western Anatolia are the responses of the volcanic rocks located in the Kula region. The cones produce clear magnetic-highs. Thus, it is clear that high-amplitude anomalies represent the basaltic intrusions of the region well. Considering the volcanic products in the area, nine profiles consisting high magnetic anomalies (Fig. 14, lower panel) were extracted from the RTPA map and inversion procedures were carried out by using the novel E-SHADE optimization algorithm.

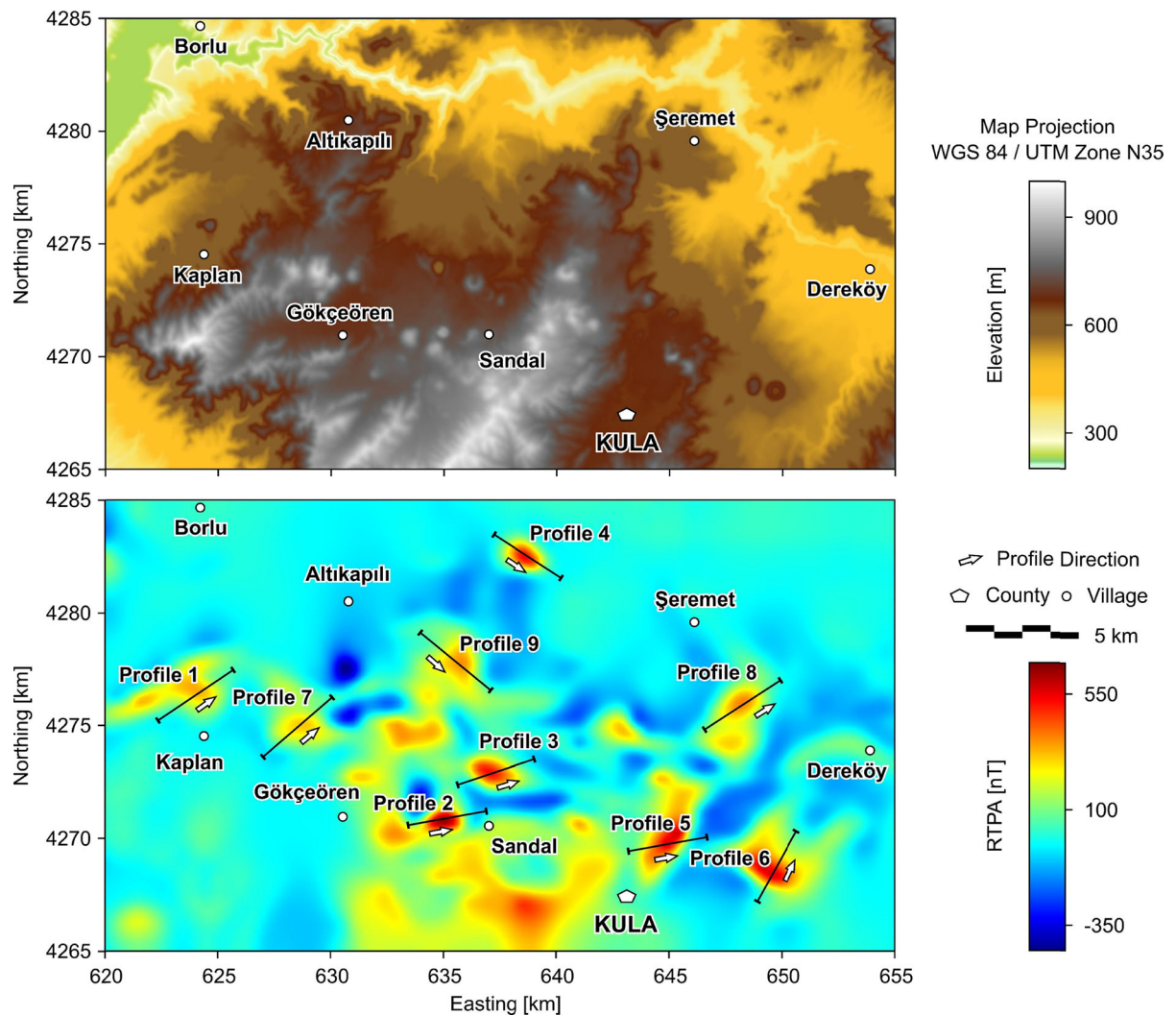


Figure 14

The topographic and RTPA maps of study area. The nine profiles extracted are also shown in the RTPA map

5.3. Inversion of Airborne Magnetic Data of Kula Volcanics

As mentioned before, some of the volcanic products that have the highest-amplitude magnetic anomalies in western Anatolia are located in the Kula Volcanic Field. The lavas formed by partial melting of peridotite on the mantle are spread over a wide area in the region. The causative magnetized bodies, most likely basaltic intrusions, produce significant magnetic contrasts compared to their surroundings. The high-amplitude magnetic anomalies can be clearly observed (Fig. 14, lower panel). There are

some volcanic cones in the study region. The small sizes of the Kula cinder cones are probably the result of magma rising to the surface at a very low flow. In the region, however, plateau basalts and associated lava flows of first two phases do not produce remarkable magnetic-highs. The very prominent magnetic-highs are associated with the volcanic cones in the Kula region. To determine some model parameters of these magnetized source bodies, nine anomaly profiles were selected for the inversion. The profiles cutting the high-amplitude anomalies were extracted from the RTPA map. These profiles were

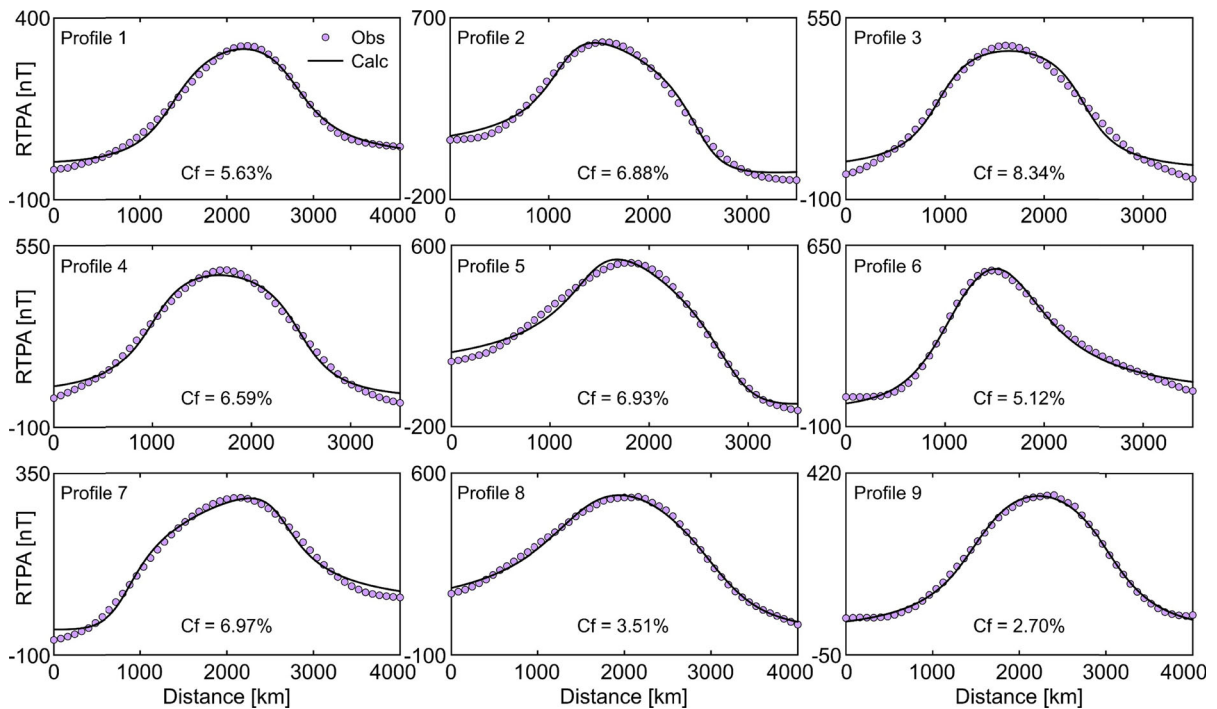


Figure 15

The fits between the observed and calculated data sets of each profile. Cf values for each profile are also shown in each plot

resampled with a data spacing of 50 m. The Profile 1 shows the magnetic anomaly of Kaplan volcanic cone (Fig. 14). Two eruption centers were reported on this field (Özyalın, 2023). Although this anomaly produces significantly low-amplitude anomaly than the others, it represents the geology well. This magnetic response extends westwards, following the direction of volcanic lava flow. The fact that the anomaly is lower in amplitude than the other ones may be related to the depth of the source structure. The Profile 2 is the magnetic anomaly of Sandal, the most important volcanic cone in the region of latest phase volcanic activities. This anomaly represents the volcano well and does not spread over other areas (Fig. 12). Although the Profile 3 presents a clear anomaly there is no volcanic cone in that area. This case may indicate the presence of a volcanic intrusion which has no trace on the ground surface. The Profile 4 shows a strong magnetic-high, but in that area, there is no cone. This anomaly is most probably the response of a buried volcanic intrusion that could not reach the Earth's surface. The Profile 5 shows the

response of Kula volcanic cone which is the product of latest phase volcanic activities. Lava flows spread over the entire surface of Kula County and along the sedimentary rocks in a SE-NW direction. Like the other ones, Profile 6 exhibits a remarkable anomaly amplitude (Fig. 14) which is due to the products of second phase volcanic activities. Although there are no volcanic cones in the areas of Profile 7, 8 and 9, we inverted these anomalies since they produce high-amplitudes in the region and present a smooth geometry. Considering the shapes of the presented nine anomalies, it is clear that they are suitable for modeling the volcanic intrusions located at the subsurface. In the inversion of Kula Volcanic Field anomalies, we applied the same procedures used in synthetic and two field data cases. Some trial-and-error studies were carried out to determine the boundaries of the model parameter search spaces. From these studies, we observed that choosing wider search space limits has no effect on the model solutions. The same solutions were reached when the searches were made in different ranges. This finding

Table 4
Search space bounds, estimated model parameter values and some statistical results for Kula Volcanic Field magnetic anomalies

Parameters	Search spaces	Estimations								
		P1	P2	P3	P4	P5	P6	P7	P8	P9
	Min/Max									
h [m]	10/1000	399.93	279.14	294.28	318.30	358.69	494.94	299.69	641.04	493.70
b [m]	10/1500	705.37	698.85	732.03	740.63	712.40	370.63	909.71	818.44	757.47
d [m]	200/3200	2059.28	1854.02	1668.71	1755.71	2142.97	1366.81	1712.47	2266.87	2270.55
δ [°]	0/180	80.53	118.09	91.19	94.65	128.62	68.30	61.60	113.37	93.49
P [nT]	10/4000	149.01	242.96	181.33	190.80	253.85	442.72	113.86	216.78	181.60
α [°]	0/180	33.34	17.49	33.16	25.05	169.91	85.44	75.02	151.30	132.43
Mean run time [s]		0.80	0.81	0.83	0.80	0.81	0.83	0.80	0.82	0.81
Min Cf [%]		5.63	6.88	8.34	6.59	6.93	5.12	6.97	3.51	2.70
Max Cf [%]		5.63	6.88	8.34	6.59	6.93	5.13	6.97	3.52	2.72
std Cf [%]		2.1e − 15	4.6e − 15	1.3e − 14	6.5e − 15	8.1e − 15	1.2e − 03	5.3e − 15	3.1e − 03	8.1e − 03

Flight height is not included in the depth solutions

Flight height is not included in the depth solutions

shows that the E-SHADE algorithm is quite stable and reach directly the global minima. We obtained model solutions with Cf values ranging from 2.70% to 8.34%. These values are quite satisfactory in the inversion of real data sets. Observed and calculated magnetic data sets of each profile are illustrated in Fig. 15. The detailed inversion results including model search spaces used, model parameter estimations and some statistical data are listed in Table 4.

It is noticeable that the std values of the solutions obtained from 30 independent inversions of each anomaly are almost 0 (Table 4). This finding shows the stability of the algorithm used. In addition, although the algorithm started the optimization with a different initial population, it achieved to reach the same optimum solution in every single run. The convergence curves of each parameter obtained from 30 independent runs are demonstrated in Figs. 16, 17, 18, 19, 20, 21. In each plot, except for the parameter α , it is generally seen that the optimization procedure showed some sudden changes in the model parameter values as the iterations continue and then reached the optimal values at about the 5000th iteration. Variations were not observed in the model parameter values after these stabilizations. Therefore, it is clear that the optimizations were completed in less time than the mean run times given in Table 4. Very stable and consistent solutions were obtained for the parameters *b*, *h*, and *d* (Figs. 16, 17, 18, respectively). Every independent run yielded the same solutions for these parameters. Thus it is clear that there are no uncertainties in the solutions of these parameters.

The statistically reliable solutions for the parameters *h*, *b* and *d* confirm the knowledge obtained from the modal and sensitivity analyses. There are no uncertainties in the solutions of these model parameters. In addition, these three model parameters are significant for determining the spatial distributions of the source bodies causing the magnetic anomalies. Surprisingly, dislike to the experiments performed with synthetic and field data cases presented before, the solutions of parameter δ were determined without uncertainties in the Kula Volcanic field anomalies (Fig. 19). The convergence curves of 30 independent runs in each plot show that the same solutions were reached. The dips of the volcanic intrusions in the

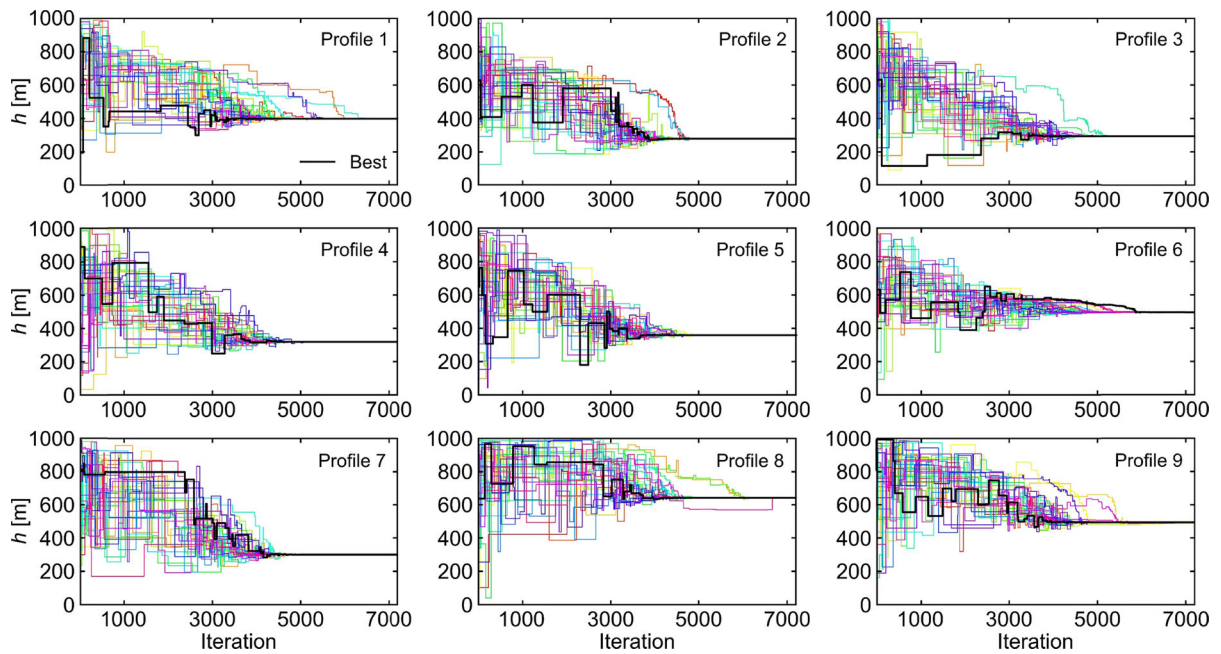


Figure 16

The convergence curves of the model parameter h against iterations. The best solutions are also depicted with black thick solid line in each plot

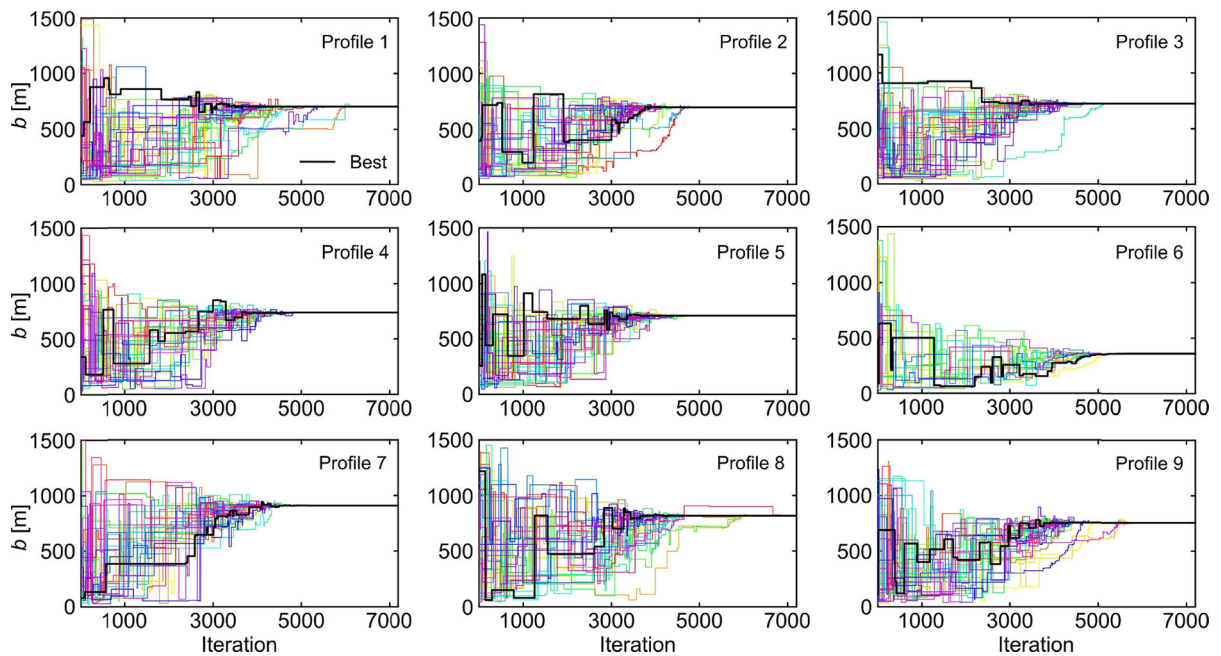


Figure 17

The convergence curves of the model parameter b against iterations. The best solutions are also depicted with black thick solid line in each plot

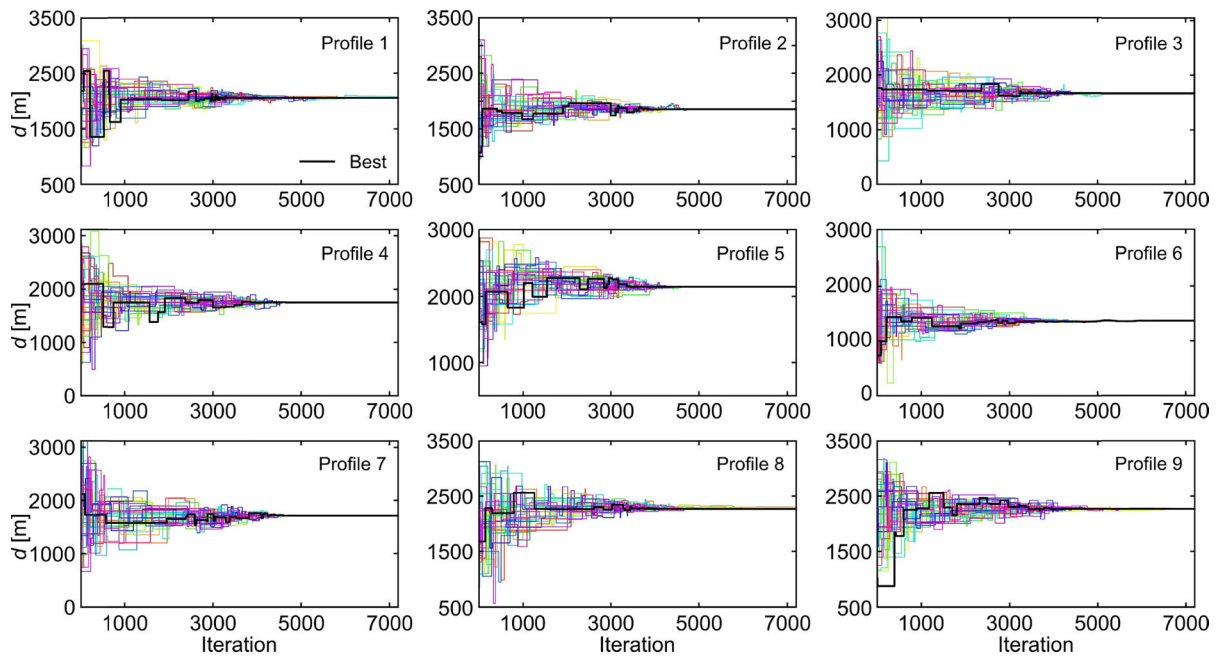


Figure 18

The convergence curves of the model parameter d against iterations. The best solutions are also depicted with black thick solid line in each plot

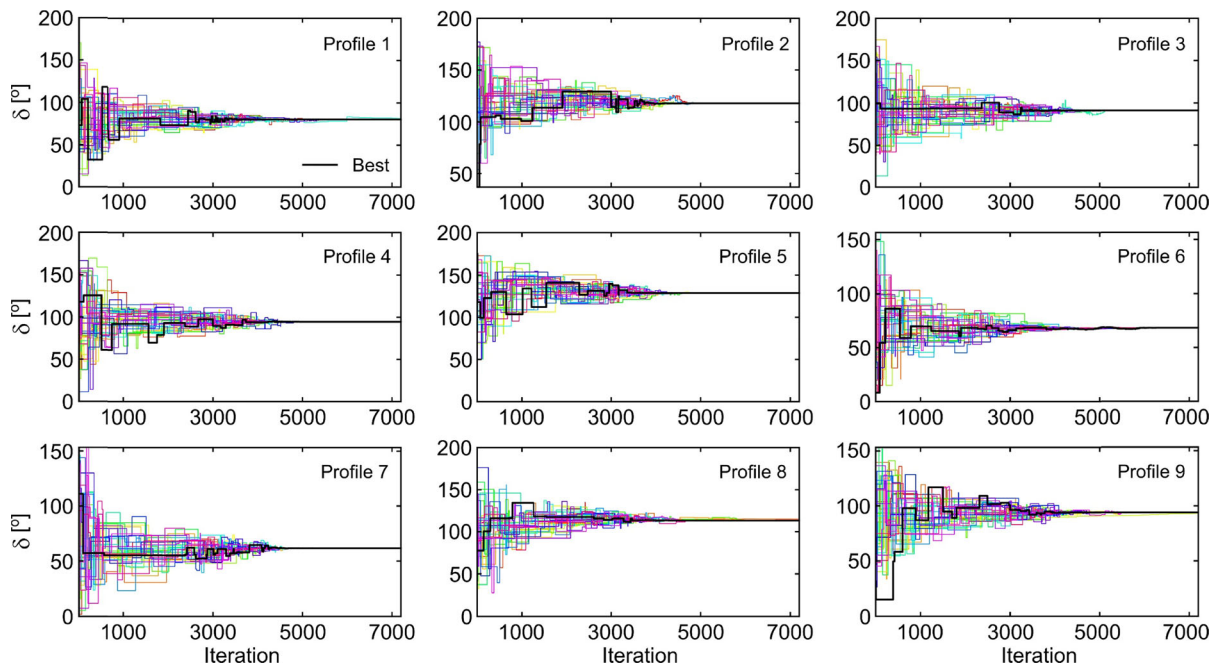


Figure 19

The convergence curves of the model parameter δ against iterations. The best solutions are also depicted with black thick solid line in each plot

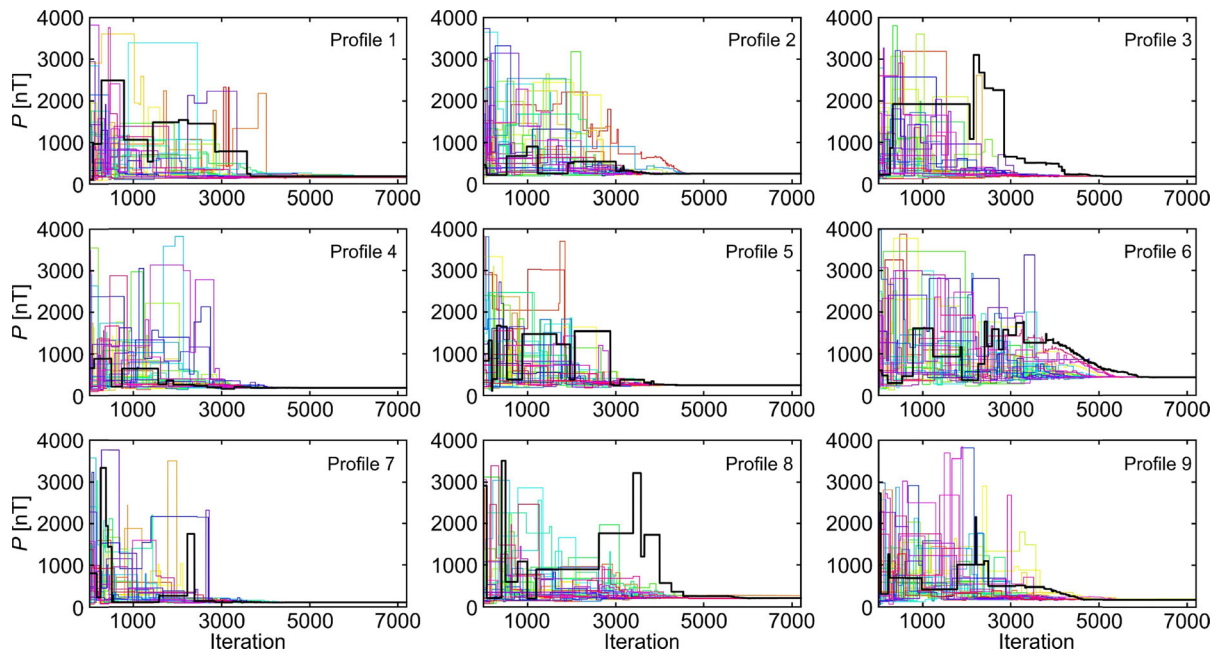


Figure 20

The convergence curves of the model parameter P against iterations. The best solutions are also depicted with black thick solid line in each plot

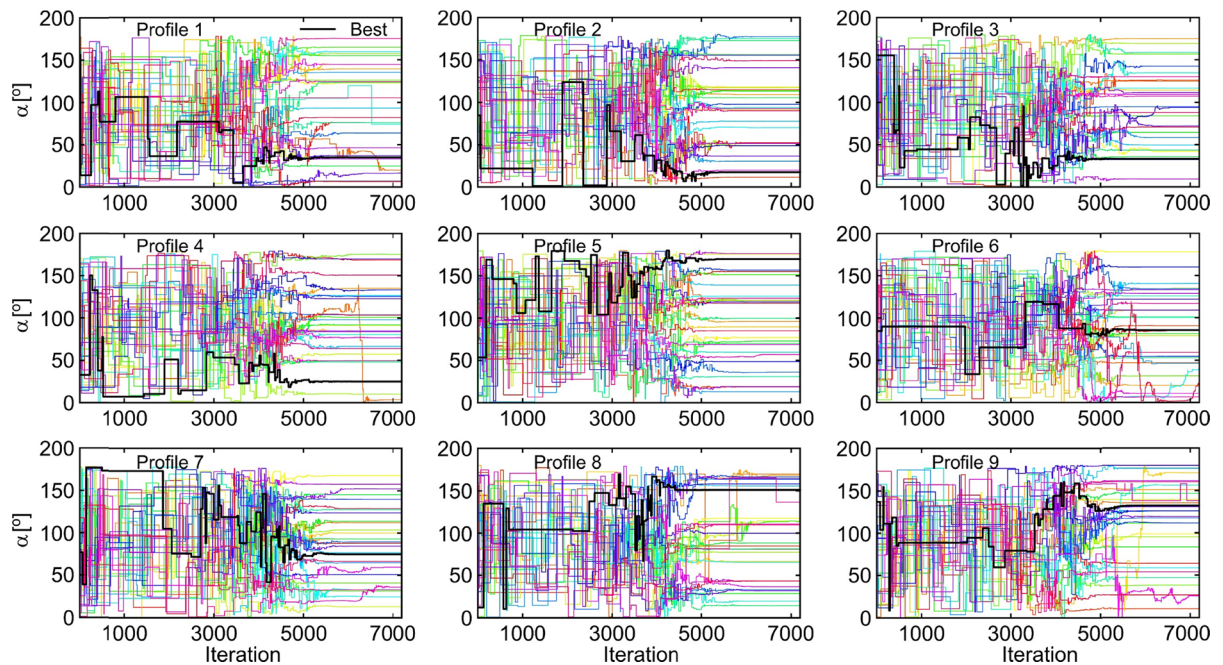
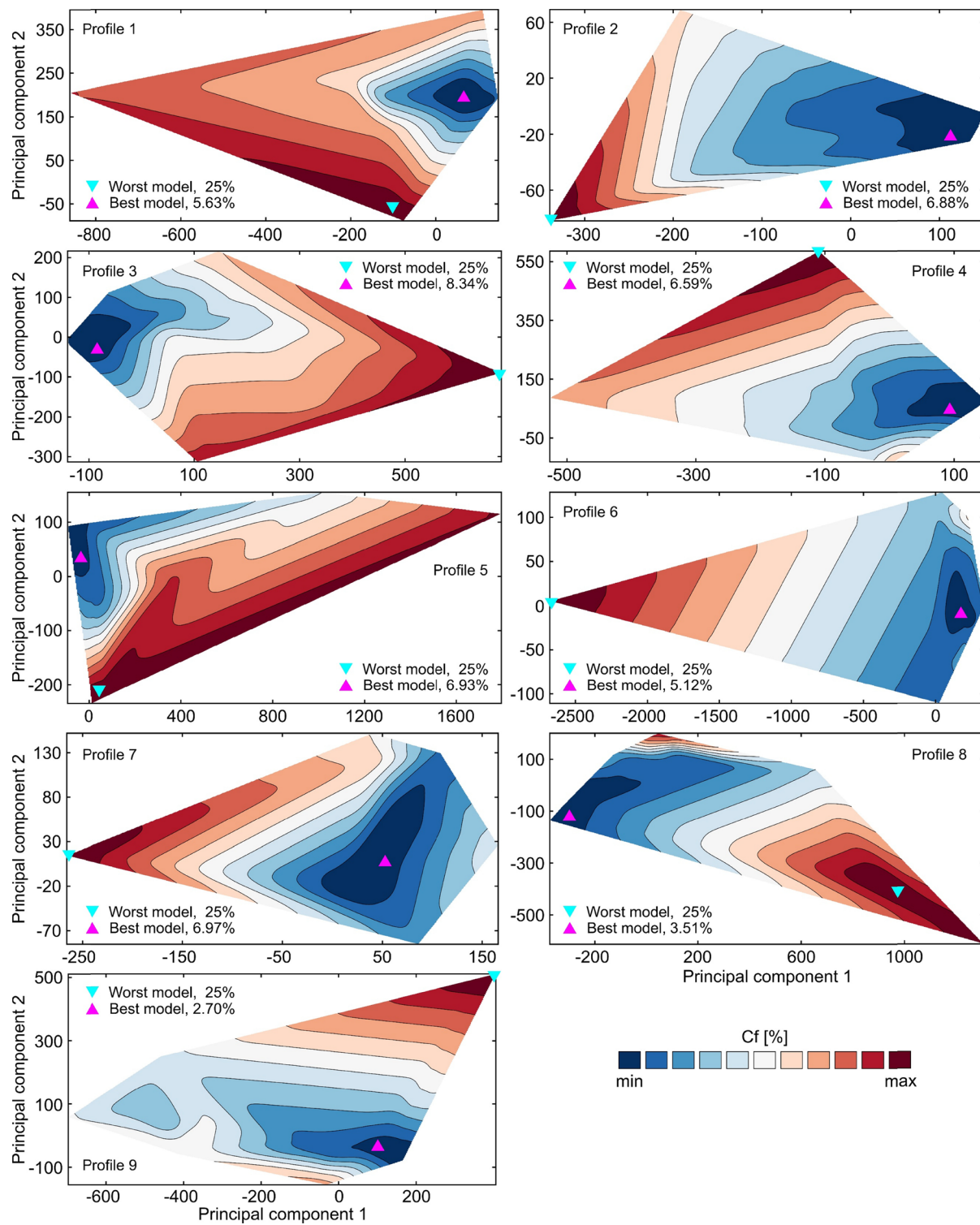


Figure 21

The convergence curves of the model parameter α against iterations. The best solutions are also depicted with black thick solid line in each plot



◀Figure 22

Cf landscapes produced in 2D principal component space for Kula Volcanic Field profile anomalies. Contours are smoothed for better demonstrations

Kula region range between 61.6° and 128.6° which are geologically reasonable (Table 4). Figure 20 shows the convergence curves of the parameter P for each profile. Satisfactory solutions were obtained from statistical point of view. On the other hand, we obtained unreliable α solutions for each profile. The uncertainties can be clearly followed from Fig. 21. The solutions obtained for this parameter change in wide ranges for each profile. Nevertheless, the inversion results showed that the uncertainties in the solutions of parameter α do not affect the reliability of other model parameters solutions. It should be noted that the flight altitude was not taken into consideration in the estimated depth solutions of the intrusive dykes given in Table 4. We obtained shallower depths for the magnetized dykes in the Kula Volcanic Field compared to previously reported results (Özyalın, 2023). In addition, in the previous study it was stated that some model parameters solutions were outside the 95% confidence interval according to probability density function analyses. Another point to be considered in previous study (Özyalın, 2023) is that there are high std values in the parameter solutions obtained from independent runs. Additionally, the parameter α was ignored in every single run. Therefore, we can mention that the present study produced statistically more reliable results.

In the last step, Cf topography maps were also produced by reducing the multidimensional model parameters into two basic components (Fig. 22). The model solutions that are higher than 25% error value were not taken into consideration in the computations. In these error landscape maps, the valleys containing lowest Cf values are closed by contours and are easily observed. Additionally, although the global maximum regions are spread over a wide area in all equivalence Cf maps, the E-SHADE algorithm performed a successful search in the model space and reached the lowest error valley containing the global

minimum. The absence of complex topographical changes in the error function maps clearly showed the superiority of the proposed algorithm in scanning the model solution space and ignoring unnecessary sectors through the use of historical-memory.

6. Conclusions

We investigated the aeromagnetic anomalies of the Kula region which hosts well-preserved volcanic products. Although many geological studies have been carried out in this volcanic area, geophysical anomalies have not been analyzed sufficiently. Thus, we focused on estimating some model parameters of the volcanic intrusions by performing inversion studies. The derivative-free and population-based E-SHADE optimizer was used for the inversion procedures. We demonstrated the effectiveness of this global optimization algorithm through noise-free and noisy synthetic magnetic anomalies. Additionally, inversion studies with the anomalies of known volcanic intrusions that are well-constrained by geological data showed the validity of the algorithm. It also produced more accurate results in comparison to a local optimizer. Modal and sensitivity analyses with noise-free magnetic anomaly revealed the resolvability characteristics of the model parameters. Synthetic applications indicated that the algorithm works in a robust structure and provides a good trade-off between global exploration and local exploitation which are essential stages of optimization procedure. Principle component analysis using error topography maps also showed the efficiency of the algorithm.

Inversion studies performed with nine profiles extracted from RTPA of Kula region produced geologically reasonable and statistically reliable results. We determined shallower depths for the basaltic intrusions compared to the results of a previous study. In the region, magmatic feeding from the mantle is carried out by these shallow volcanic dykes. The lavas formed by partial melting of peridotite on the mantle are spread over a wide area. Due to the ongoing activity of the rift system in the Kula region, it is possible that the three-phased volcanism may become active again and produce new alkaline basaltic lava flows in a new phase by means of near-

surface dykes that are determined here. Another important finding of our study is that the proposed E-SHADE global optimization scheme is efficient in terms of convergence behavior and avoiding local minima present in the equivalence error space. In addition, inversion with E-SHADE algorithm does not require extensive and time-consuming parameter tuning studies, and a well-structured initial guess in the model space. Although, this algorithm requires slightly more computational time than derivative-based local optimizers, it is a powerful inversion tool for the interpretation of magnetic anomalies. It can also be used effectively in other geophysical inverse problems. Lastly, this study also revealed that the parameter α which denotes the profile azimuth of the causative dyke body from magnetic north cannot be estimated reliably in the presented inverse magnetic problem. However, the statistical uncertainties in this model parameter solutions do not affect the credibility of other model parameter estimations.

Acknowledgements

We thank anonymous reviewers for their useful comments and suggestions.

Author Contributions All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by all authors. The first draft of the manuscript was written by Y.L.E and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Funding

There was no funding obtained for this study.

Data Availability

The synthetic and real profile data sets that support the results of this study are available from the corresponding author upon reasonable request.

Declarations

Conflict of Interest The authors declare no competing interests.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor (e.g. a society or other partner) holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.

REFERENCES

- Abdelrahman, E. M., Abo-Ezz, E. R., & Essa, K. S. (2012). Parametric inversion of residual magnetic anomalies due to simple geometric bodies. *Exploration Geophysics*, 43, 178–189.
- Ai, H., Ekinici, Y. L., Balkaya, Ç., Alvandi, A., Ekinici, R., Roy, A., Su, K., & Pham, L. T. (2024). Modified barnacles mating algorithm for the inversion of self-potential anomalies due to ore deposits. *Natural Resources Research*. <https://doi.org/10.1007/s11053-024-10331-7>
- Ai, H., Ekinici, Y. L., Balkaya, Ç., & Essa, K. S. (2023). Inversion of geomagnetic anomalies caused by ore masses using hunger games search algorithm. *Earth and Space Science*, 10, e2023EA003002. <https://doi.org/10.1029/2023EA003002>
- Ai, H., Essa, K. S., Ekinici, Y. L., Balkaya, Ç., Li, H., & Géraud, Y. (2022). Magnetic anomaly inversion through the novel barnacles mating optimization algorithm. *Scientific Reports*, 12, 22578. <https://doi.org/10.1038/s41598-022-26265-0>
- Alpaydin, E. (2020). *Introduction to machine learning*. The MIT Press.
- Alvandi, A., Su, K., Ai, H., Ardestani, V. E., & Lyu, C. (2023). Enhancement of potential field source boundaries using the hyperbolic domain (Gudermannian function). *Minerals*, 13, 1312. <https://doi.org/10.3390/min13101312>
- Aydar, E. (1998). Early miocene to quaternary evolution of volcanism and the basin formation in western Anatolia: A review. *Journal of Volcanology and Geothermal Research*, 85, 69–82. [https://doi.org/10.1016/S0377-0273\(98\)00050-X](https://doi.org/10.1016/S0377-0273(98)00050-X)
- Balkaya, Ç., & Kaftan, I. (2021). Inverse modelling via differential search algorithm for interpreting magnetic anomalies caused by 2D dyke-shaped bodies. *Journal of Earth System Science*, 130, 135. <https://doi.org/10.1007/s12040-021-01614-1>
- Bozkurt, E. (2001). Late Alpine evolution of the central Menderes Massif, western Anatolia, Turkey. *International Journal of Earth Sciences*, 89, 728–744. <https://doi.org/10.1007/s005310000141>

- Bozkurt, E., & Mittweide, S. K. (2005). Introduction: Evolution of continental extensional tectonics of western Turkey. *Geodinamica Acta*, 18, 153–165. <https://doi.org/10.3166/ga.18.153-165>
- Bozkurt, E., & Park, L. R. G. (1994). Southern Menderes Massif: An incipient metamorphic core complex in western Anatolia. *Journal of Geological Society of London*, 151, 213–216. <https://doi.org/10.1144/gsjgs.151.2.0213>
- Bunbury, J. M., Hall, L., Anderson, G. J., & Stannard, A. (2001). The determination of fault movement history from the interaction of local drainage with volcanic episodes. *Geological Magazine*, 138, 185–192. <https://doi.org/10.1017/S0016756801005271>
- Burt, E.R., Carpenter, P.A., McDaniel, R.D., & Wilson, W.F. (1978). Diabase dikes of the eastern piedmont of North Carolina, Information Circular 23. North Carolina department of natural resources and community development division of land resources geological survey section.
- Büyüksaraç, A., Jordanova, D., Ateş, A., & Karloukovski, V. (2005). Interpretation of the gravity and magnetic anomalies of the Cappadocia Region, Central Turkey. *Pure and Applied Geophysics*, 162, 2197–2213. <https://doi.org/10.1007/s00024-005-2712-9>
- Cassidy, J., Sian, J. F., & Locke, C. A. (2007). Gravity and magnetic investigation of maar volcanoes, Auckland volcanic field, New Zealand. *Journal of Volcanology and Geothermal Research*, 159, 153–163. <https://doi.org/10.1016/j.jvolgeores.2006.06.007>
- Ciftci, B., & Bozkurt, E. (2009). Evolution of the Miocene sedimentary fill of the Gediz Graben, SW Turkey. *Sedimentary Geology*, 216, 49–79. <https://doi.org/10.1016/j.sedgeo.2009.01.004>
- Ekinci, Y. L., Balkaya, Ç., & Göktürkler, G. (2021a). Backtracking search optimization: A novel global optimization algorithm for the inversion of gravity anomalies. *Pure and Applied Geophysics*, 178, 4507–4527. <https://doi.org/10.1007/s00024-021-02855-3>
- Ekinci, Y. L., Balkaya, Ç., Göktürkler, G., & Ai, H. (2023). 3-D gravity inversion for the basement relief reconstruction through modified success-history-based adaptive differential evolution. *Geophysical Journal International*, 235, 377–400. <https://doi.org/10.1093/gji/ggad222>
- Ekinci, Y. L., Balkaya, Ç., Göktürkler, G., & Özyalın, Ş. (2021b). Gravity data inversion for the basement relief delineation through global optimization: A case study from the Aegean Graben system, western Anatolia, Turkey. *Geophysical Journal International*, 224, 923–944. <https://doi.org/10.1093/gji/ggaa492>
- Ekinci, Y. L., Büyüksaraç, A., Bektaş, Ö., & Ertekin, C. (2020). Geophysical investigation of Mount Nemrut Stratovolcano (Bitlis, eastern Turkey) through aeromagnetic anomaly analyses. *Pure and Applied Geophysics*, 177, 3243–3264. <https://doi.org/10.1007/s00024-020-02432-0>
- Ekinci, Y. L., Özyalın, Ş., Sındırgı, P., Balkaya, Ç., & Göktürkler, G. (2017). Amplitude inversion of the 2D analytic signal of magnetic anomalies through the differential evolution algorithm. *Journal of Geophysics and Engineering*, 14, 1492–1508. <https://doi.org/10.1088/1742-2140/aa7ffc>
- Ekinci, Y. L., & Yiğitbaş, E. (2012). A geophysical approach to the igneous rocks in the Biga Peninsula (NW Turkey) based on airborne magnetic anomalies: Geological implications. *Geodinamica Acta*, 25, 267–285. <https://doi.org/10.1080/09853111.2013.858945>
- Ekwok, S. E., Eldosouky, A. M., Essa, K. S., George, A. M., Abdelrahman, K., Fnais, M. S., András, P., Akaerue, E. I., & Akpan, A. E. (2023). Particle swarm optimization (PSO) of high-quality magnetic data of the Obudu basement complex. *Nigeria. Minerals*, 13, 1209. <https://doi.org/10.3390/min13091209>
- Eldosouky, A. M., Ekwok, S. E., Akpan, A. E., Achadu, O.-I.M., Pham, L. T., Abdelrahman, K., Gómez-Ortiz, D., & Alarifi, S. S. (2022). Delineation of structural lineaments of Southeast Nigeria using high resolution aeromagnetic data. *Open Geosciences*, 14, 331–340. <https://doi.org/10.1515/geo-2022-0360>
- Eppelbaum, L. V., Katz, Y. I., & Ben-Avraham, Z. (2023). Geodynamic aspects of magnetic data analysis and tectonic–paleomagnetic mapping in the Easternmost Mediterranean: A review. *Applied Sciences*, 13, 10541. <https://doi.org/10.3390/app131810541>
- Ertekin, C., Ekinci, Y. L., Büyüksaraç, A., & Ekinci, R. (2021). Geoheritage in a mythical and volcanic terrain: An inventory and assessment study for geopark and geotourism, Nemrut Volcano (Bitlis, Eastern Turkey). *Geoheritage*, 13, 73. <https://doi.org/10.1007/s12371-021-00593-5>
- Fernández-Martínez, J. L., Pallero, J. L. G., Fernández-Muñoz, Z., & Pedruelo-González, L. M. (2014a). The effect of noise and Tikhonov’s regularization in inverse problems. Part I: The linear case. *Journal of Applied Geophysics*, 108, 176–185. <https://doi.org/10.1016/j.jappgeo.2014.05.006>
- Fernández-Martínez, J. L., Pallero, J. L. G., Fernández-Muñoz, Z., & Pedruelo-González, L. M. (2014b). The effect of noise and Tikhonov’s regularization in inverse problems. Part II: The nonlinear case. *Journal of Applied Geophysics*, 108, 186–193. <https://doi.org/10.1016/j.jappgeo.2014.05.005>
- Geological Survey of Canada (1965). Aeromagnetic map 1491 G, Timagami, Ontario: NTS 31 M/4, 1 inch to 1 mile.
- Jackson, J. E. (1991). *A user’s guide to principal components*. Wiley.
- Jolliffe, I. T. (2006). *Principal component analysis*. Springer-Verlag.
- Kara, İ., Tarhan Bal, O., & Tekelli, A. B. (2022). A graph method for interpretation of magnetic anomalies over 2D dikes and vertical faults. *Bulletin of the Mineral Research and Exploration*, 168, 1–10. <https://doi.org/10.19111/bulletinofmre.928467>
- Kearey, P., Brooks, M., & Hill, I. (2002). *An introduction to geophysical exploration*. New Jersey, USA: Blackwell Science Ltd.
- Koçman, A. (2004). Natural wonders of the “Burnt Land (Katakekaumene)”: volcanic features of Kula area. *Aegean Geographical Journal*, 13, 5–15.
- Koralay, O. E., Dora, O. Ö., Chen, F., Satır, M., & Candan, O. (2004). Geochemistry and geochronology of orthogneisses in the Derbent (Alaşehir) area, eastern part of the Ödemiş-Kiraz sub-massif, Menderes Massif: Pan-African magmatic activity. *Turkish Journal of Earth Sciences*, 13, 37–61.
- Kosaroglu, S., Buyuksarac, A., & Aydemir, A. (2016). Modeling of shallow structures in the Cappadocia region using gravity and aeromagnetic anomalies. *Journal of Asian Earth Sciences*, 124, 214–226. <https://doi.org/10.1016/j.jseas.2016.05.005>
- McGrath, P. H., & Hood, P. J. (1970). The dipping dike case: A computer curve-matching method of magnetic interpretation. *Geophysics*, 35, 831–848. <https://doi.org/10.1190/1.1440132>
- Menke, W. (2012). *Geophysical data analysis-discrete inverse theory*. Academic Press.

- Munoz-Romero, S., Gomez-Verdejo, V., & Arenas-Garcia, J. (2016). Regularized multivariate analysis frame work for interpretable high-dimensional variable selection. *IEEE Computational Intelligence Magazine*, 11, 24–35. <https://doi.org/10.1109/MCI.2016.2601701>
- Özyalın, Ş. (2023). Interpretation of volcanic magnetic anomalies using differential search algorithm: Case study from the Kula volcanic park, western Türkiye. *Acta Geophysica*, 71, 1203–1224. <https://doi.org/10.1007/s11600-022-00975-5>
- Pallero, J. L. G., Fernandez-Martinez, J. L., Bonvalot, S., & Fudym, O. (2015). Gravity inversion and uncertainty assessment of basement relief via particle swarm optimization. *Journal of Applied Geophysics*, 116, 180–191. <https://doi.org/10.1016/j.jappgeo.2015.03.008>
- Pallero, J. L. G., Fernandez-Martinez, J. L., Bonvalot, S., & Fudym, O. (2017). 3D gravity inversion and uncertainty assessment of basement relief via particle swarm optimization. *Journal of Applied Geophysics*, 139, 338–350. <https://doi.org/10.1016/j.jappgeo.2017.02.004>
- Pham, L. T., & Oliveira, S. P. (2023). Edge enhancement of magnetic sources using the tilt angle and derivatives of directional analytic signals. *Pure and Applied Geophysics*, 180, 4175–4189. <https://doi.org/10.1007/s00024-023-03375-y>
- Piotrowski, A. P., Napiorkowski, J. J., & Piotrowska, A. E. (2023). Particle swarm optimization or differential evolution—a comparison. *Engineering Applications of Artificial Intelligence*, 121, 106008. <https://doi.org/10.1016/j.engappai.2023.106008>
- Prasad, K. N. D., Pham, L. T., Singh, A. P., Eldosouky, A. M., Abdelrahman, K., Fnais, M. S., & Gómez-Ortiz, D. (2022). A novel enhanced total gradient (ETG) for interpretation of magnetic data. *Minerals*, 12, 1468. <https://doi.org/10.3390/min12111468>
- Richardson-Bunbury, J. M. (1996). The Kula Volcanic Field, western Turkey: The development of a Holocene alkali basalt province and the adjacent normal-faulting graben. *Geological Magazine*, 133, 275–283. <https://doi.org/10.1017/S0016756800009018>
- Ring, U., & Layer, P. W. (2023). High-pressure metamorphism in the Aegean, eastern Mediterranean: Underplating and exhumation from the late cretaceous until the miocene and recent above the retreating hellenic subduction zone. *Tectonics*, 22, 1022. <https://doi.org/10.1029/2001TC001350>
- Roy, A., Dubey, C. P., & Prasad, M. (2021a). Gravity inversion for heterogeneous sedimentary basin with b-spline polynomial approximation using differential evolution algorithm. *Geophysics*, 86, F35–F47. <https://doi.org/10.1190/geo2019-0779.1>
- Roy, A., Dubey, C. P., & Prasad, M. (2021b). Gravity inversion of basement relief using particle swarm optimization by automated parameter selection of Fourier coefficients. *Computer & Geosciences*, 156, 104875. <https://doi.org/10.1016/j.cageo.2021.104875>
- Roy, A., Kumar, T. S., & Sharma, R. K. (2022). Structure estimation of 2D listric faults using quadratic Bezier curve for depth varying density distributions. *Earth and Space Science*. <https://doi.org/10.1029/2021EA002061>
- Saribudak, M. (2023). Inner structure of monogenetic Pilot Knob submarine volcano (Austin, Texas) revealed by electrical resistivity tomography and magnetic surveys. *Geophysics*, 88, B207–B220. <https://doi.org/10.1190/geo2022-0658.1>
- Sawires, R., & Aboud, E. (2019). Subsurface structural imaging of Ceboruco Volcano area, Nayarit, Mexico using high-resolution aeromagnetic data. *Journal of Volcanology and Geothermal Research*, 371, 162–176. <https://doi.org/10.1016/j.jvolgeores.2019.01.012>
- Şen, E., Aydar, E., Bayhan, H., & Gourgaud, A. (2014). Volcanological characteristics of alkaline basalt and pyroclastic deposits, Kula volcanoes, western Anatolia. *Yerbilimleri*, 35, 141–168. <https://doi.org/10.17824/huyuamd.20663>
- Şengör, A. M. C., Satur, M., & Akkök, R. (1984). Timing of tectonic events in the Menderes Massif, western Turkey. Implications for tectonic evolution and evidence for Pan-African basement in Turkey. *Tectonics*, 3, 693–707. <https://doi.org/10.1029/TC003i007p00693>
- Şengör, A. M. C., & Yılmaz, Y. (1981). Tethyan evolution of Turkey: A plate tectonic approach. *Tectonophysics*, 75, 181–241. [https://doi.org/10.1016/0040-1951\(81\)90275-4](https://doi.org/10.1016/0040-1951(81)90275-4)
- Seyitoğlu, G., & Scott, B. C. (1991). Late Cenozoic crustal extension and basin formation in west Turkey. *Geological Magazine*, 128, 155–166. <https://doi.org/10.1017/S0016756800018343>
- Seyitoğlu, G., & Scott, B. C. (1992). Late Cenozoic volcanic evolution of the NE Aegean region. *Journal of Volcanology and Geothermal Research*, 54, 157–176. [https://doi.org/10.1016/0377-0273\(92\)90121-S](https://doi.org/10.1016/0377-0273(92)90121-S)
- Sozibilir, H. (2002). Geometry and origin of folding in the Neogene sediments of the Gediz Graben, western Anatolia, Turkey. *Geodinamica Acta*, 15, 277–288. [https://doi.org/10.1016/S0985-3111\(02\)01093-8](https://doi.org/10.1016/S0985-3111(02)01093-8)
- Sungkono, R., & A.M., Warnana, D.D., & Alwi, H.. (2023). Grandis, H. Self-adaptive bare-bones teaching–learning-based optimization for inversion of multiple self-potential anomaly sources. *Pure and Applied Geophysics*, 180, 2191–2222. <https://doi.org/10.1007/s00024-023-03247-5>
- Tanabe, R., & Fukunaga, A. (2013). Evaluating the performance of SHADE on CEC 2013 benchmark problems. In 2013 IEEE congress on evolutionary computation, 1952–1959. <https://doi.org/10.1109/CEC.2013.6557798>
- Tanabe, R., & Fukunaga, A.S. (2014). Improving the search performance of SHADE using linear population size reduction. In 2014 IEEE congress on evolutionary computation, 1658–1665. <https://doi.org/10.1109/CEC.2014.6900380>
- Tarantola, A. (2005). Inverse problem theory and methods for model parameter estimation. other titles in applied mathematics: Society for industrial and applied mathematics, Philadelphia, USA.
- Tokçaer, M., Agostini, S., & Savaşçın, M. Y. (2005). Geotectonic setting and origin of the youngest Kula volcanics (Western Anatolia), with a new emplacement model. *Turkish Journal of Earth Sciences*, 14, 143–166.
- Venkata Raju, DCh. (2003). LIMAT: A computer program for least-squares inversion of magnetic anomalies over long tabular bodies. *Computer & Geosciences*, 29, 91–98. [https://doi.org/10.1016/S0098-3004\(02\)00108-5](https://doi.org/10.1016/S0098-3004(02)00108-5)
- Westaway, R., Pringle, M., Yurtmen, S., Demir, T., Bridgland, D., Rowbotham, G., & Maddy, D. (2004). Pliocene and quaternary

- regional uplift in western Turkey: The Gediz river terrace staircase and the volcanism at Kula. *Tectonophysics*, 391, 121–169. <https://doi.org/10.1016/j.tecto.2004.07.013>
- Won, I. J. (1981). Application of Gauss's method to magnetic anomalies of dipping dikes. *Geophysics*, 46, 211–215. <https://doi.org/10.1190/1.1441192>
- Xu, Y., Hao, T., Zhao, B., Lihong, Z., Zhang, L., Li, Z., & Huang, S. (2011). Investigation of igneous rocks in Huanghua depression, North China, from magnetic derivative methods. *Journal of Geophysics and Engineering*, 8, 74–82. <https://doi.org/10.1088/1742-2132/8/1/009>
- Zhdanov, M. S. (2002). *Geophysical inverse theory and regularization problems*. Elsevier.

(Received June 30, 2024, revised August 23, 2024, accepted August 31, 2024, Published online September 18, 2024)