Research paper

MAX UnMix: A web application for unmixing magnetic coercivity distributions

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It is common in the fields of rock and environmental magnetism to unmix magnetic mineral components using statistical methods that decompose various types of magnetization curves (e.g., acquisition, demagnetization, or backfield). A number of programs have been developed over the past decade that are frequently used by the rock magnetic community, however many of these programs are either outdated or have obstacles inhibiting their usability. MAX UnMix is a web application (available online at http://www.irm.umn.edu/maxunmix), built using the shiny package for R studio, that can be used for unmixing coercivity distributions derived from magnetization curves. Here, we describe in detail the statistical model underpinning the MAX UnMix web application and discuss the program's functionality. MAX UnMix is an improvement over previous unmixing programs in that it is designed to be user-friendly, runs as an independent website, and is platform independent.

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1. Introduction

Magnetic minerals are ubiquitous in a variety of natural systems. Progress in the fields of environmental and rock magnetism has increasingly led to an ability to quantify the abundance, grain size, and chemical composition of various magnetic minerals, which has been critical in enhancing our understanding of an array of natural and anthropogenic processes (see recent reviews by Maher, 2011; Liu et al., 2012; Hatfield, 2014; Maxbauer et al., 2016). In particular, there are a variety of methods available that allow for the statistical unmixing of measured magnetization curves (Robertson and France, 1994; Stockhausen, 1998; Kruiver et al., 2001; Heslop et al., 2002; Egli, 2003; Heslop and Dillon, 2007; Heslop, 2015 provide an excellent review). These methods are widely applied in the literature and have helped to advance our understanding of the processes which govern magnetic mineral formation, transformation, and deposition.

Robertson and France (1994) made the seminal observation that the shape of isothermal remanent magnetization (IRM) acquisition curves for an assemblage of grains of a single magnetic mineral could be approximated by a cumulative log-Gaussian function given three parameters: the mean coercivity of an individual component is given by Robertson and France (1994):

\[ IRM(B) = \frac{M}{DP(2\pi e)^{1/2}} \int_{-\infty}^{\infty} \exp \left[ -\frac{(\log(B) - \log(B_0))^2}{2DP^2} \right] d\log(B) \]  

(1)

In the case that a specimen is composed of multiple magnetic mineral components, the individual IRM acquisition functions (given by Eq. (1)) for each component can be added linearly to approximate the measured data (Robertson and France, 1994; Kruiver et al., 2001). Kruiver et al. (2001) popularized the use of a gradient acquisition plot (GAP) to assist in curve fitting. Subsequent studies refer to the GAP as the coercivity distribution (or spectra; e.g., Heslop et al., 2002, 2004; Egli, 2003), which is the absolute value of the first derivative of the magnetic acquisition dataset (Egli, 2003). Coercivity distributions can be modeled in a similar way to IRM acquisition curves by approximation of a probability density function using the same three parameters (Kruiver et al., 2001; Heslop et al., 2002):

\[ f(B) = \sum_{i=1}^{n} M_k B; B_0; DP \]  

(2)

where \( n \) is the number of magnetic mineral components within a specimen and \( k \) corresponds to a log-normal probability density function. From Eq. (2), it is possible to calculate a function that represents the continuous realization of the discrete measured data. Various statistical procedures are used to determine the
goodness of fit for a particular model compared to the measured data using either statistical tests (F-test and t-test; Kruiver et al., 2001) or automated iterative approaches (Expectation Algorithm; Heslop et al., 2002). These models are accessible for readers to use through downloads of an excel workbook (IRM-CLG; Kruiver et al., 2001) and a Fortran90 executable program (IRM UnMix, available for PCs; Heslop et al., 2002). Fitting is achieved through either manual entry (Kruiver et al., 2001) or through automated optimization (Heslop et al., 2002).

The functions described by Eqs. (1) and (2) operate under the assumption that coercivities of a given magnetic mineral grain population can be closely approximated by a log-normal distribution (Robertson and France, 1994; Kruiver et al., 2001; Heslop et al., 2002; Egli, 2003). However, it is well known that many natural samples contain magnetic mineral components whose coercivities are not log-normal (Egli, 2003, 2004b; Heslop et al., 2004). To account for non-normality, Egli (2003) introduced the skew generalized Gaussian (SGG) function:

\[
SGG(x, \mu, \sigma, q, p) = \frac{1}{2^{1+1/p}_p} \left( e^{\mu x + q} + e^{-\mu x + q} \right) \frac{1}{\left( 1 + |e^{\mu x + q}|^p \right)^{1/2}}
\]

where \(x\) is equivalent to \(B\) in Eqs. (1) and (2), \(\mu\) is the equivalent of \(B_p\) or \(D_P\), \(q\) is related to skewness, and \(p\) is related to kurtosis (Egli, 2003). The variable \(x_r\) arises from a substitution of \(x\) with \(x_r\); where \(x_r = g(x, q)\) (see Egli, 2003, for details). A Gaussian distribution is equivalent to the SGG when \(q = 1\) and \(p = 2\) (decreasing \(q\) from 1 to 0 creates left skewed distributions, changing the sign creates right skewed distributions; decreasing \(p\) enhances peakedness and increasing \(p\) enhances squaredness, Egli, 2003). The SGG function has major advantages over simple Gaussian distributions because it can better account for non-normal behavior that is common in natural samples. Deviations from normality can necessitate the need for additional normal or log-normal components within a model to achieve a satisfactory fit, whereas a single skew-component may prove sufficient (see Egli, 2003; Heslop, 2015). The MAG-MIX method of Egli (2003) is available as a set of Mathematica notebooks (CODICA, for deriving coercivity distributions and GECA, for analyzing coercivity distributions) that include graphical user interfaces to assist in data processing. MAG-MIX has been used to analyze the coercivity spectra from a wide range of natural samples and details of those results can be found in Egli (2004a,b,c).

The methods provided by Kruiver et al. (2001), Heslop et al. (2002), and Egli (2003) have proven to be an excellent basis for more detailed interpretation of the magnetic mineralogy of sediments and other geologic samples. However, despite the certain advances presented by Egli (2003), which continues to be utilized by researchers (e.g., Lascu and Plank, 2013; Li et al., 2013; Ludwig et al., 2013; Liu et al., 2014), many studies continue to utilize older methods from Kruiver et al. (2001) (recent examples include Font et al., 2012; Yamazaki and Ikehara, 2012; Ao et al., 2013; Hu et al., 2013; Abrajevitch et al., 2015) and Heslop et al. (2002) (e.g., Roberts et al., 2012; Channell and Hodell, 2013; Weil et al., 2014; Dorfman et al., 2015). This may be in response to difficulties in applying the SGG method, or in response to the software being available only for Mathematica users (which requires expensive licensure). Here, we present a new program, MAX UnMix, that was designed in the statistical computing language R (which is open source and available for MAC, PC, and Linux; R-Core-Team, 2015) and built using shiny for R studio (Chang et al., 2015). The application functions as a web application (available online at http://www.irm.umn.edu/maxunmix) where users interact with the model via a graphical user interface. Supporting information, including instructional videos and a user manual, are available on the MAX UnMix webpage. Below, we describe the statistical model underpinning MAX UnMix and provide a number of examples to highlight aspects of the model’s performance.

2. Model description

The observed coercivity distribution, \(C\), of a measured set of magnetization data (\(M\); may be acquisition, demagnetization, or backfield curves) is defined as the absolute value of the first derivative of the raw data:

\[
C = \left| \frac{dM}{d\log(B)} \right|
\]

where \(M\) and \(B\) are the respective magnetization and field values for a given dataset. Note we define \(C\) in Eq. (4) using the \(\log(B)\) scaling, however various field scalings can be used by simple substitution (e.g., Egli, 2003). MAX UnMix utilizes the predict() function to calculate \(C\) on either a \(\log_{10}\) or linear scale, depending on user selection. In line with previous methods, we recommend fitting magnetization curves with a minimum of 25 data points, although generally it is advantageous to have more if possible (Kruiver et al., 2001).

It is often necessary to remove measurement noise within datasets by either application of a spline function (Heslop et al., 2002) or more sophisticated filtering (e.g., the CODICA program described by Egli, 2003). In MAX UnMix, a simple spline function, smooth.spline(), allows the user to determine the appropriate level of smoothing. The smoothing factor, \(sf\), can be varied between 0 and 1, where \(sf = 0\) is equivalent to no smoothing and \(sf = 1\) is the maximum degree of smoothing for a given dataset. Spline fitting prevents large influences of measurement noise; however, over smoothing of data can result in spurious features (typically at low and high-fields; see Heslop et al., 2002; Heslop, 2015) and careful observation of this balance should be monitored by users. To avoid complications resulting from smoothing, users have the option to perform smoothing on either raw magnetization data (“Magnetization smoother”, \(C\) derived from smoothed magnetization data) or raw coercivity data (“Coercivity smoother”, \(C\) is smoothed directly from raw coercivity data). These choices work variably well at low and high fields and users can determine which method is optimal for a given dataset. As a general rule, the effects of measurement noise are best reduced by maximizing the degree of smoothing imposed on a data set, while taking special care to avoid ‘over-smoothing’, which can create artifacts.

When a suitable \(C\) has been determined from the measured data, the aim is to determine a model function that approximates \(C\) for a given set of field values, \(B\). Within the MAX UnMix framework this is achieved using a skew-normal distribution from the fGarch package in R (Wuertz and Chalabi, 2015). The dnorm() function within the package creates skew-normal probability density functions that we use within our model in the following form:

\[
f_{\text{unmix}}(B) = \sum_{i=1}^{n} p_i w_i(B; B_{\text{unmix}}; DP; S_i)
\]

where \(p_i\) is a proportion factor that describes the height of the distribution for each component (\(p\) can range from 0 to 1, normalized such that a value of 1 is equivalent to the maximum of \(C\), \(w_i\) is the skew-normal probability density function, \(S_i\) is a parameter describing skewness (for \(S_i\) less than 1 distributions skew left, and vice versa), and \(f_{\text{unmix}}\) represents the modeled approximation of \(C\). In the special case that \(S_i = 1\), \(w_i\) is equivalent to the
normal probability function, $k$), utilized by previous studies (Eq. (2); Kruiver et al., 2001; Heslop et al., 2002). Skew-left distributions ($S < 1$) are the result of thermal effects and interactions between magnetic particles in a grain population (Heslop et al., 2004) and have been shown to be common in natural populations (Egli, 2004a,b). Skew-right distributions ($S > 1$) are less well understood on a physical basis and may indicate mixed mineralogy within a single skew-right component (Heslop et al., 2004). Accordingly, care should be taken when interpreting results for components with $S$ values much greater than 1. Note that our skew-normal function does not incorporate kurtosis (which is included in the SGG function of Egli, 2003), however nearly all natural samples are successfully fit when $p = 2$ meaning that kurtosis is not a feature common to natural magnetic mineral components (see Egli, 2004a).

The user determines an initial set of values for $b_0$, $DP$, $p$, and $S_j$ to set the initial model parameters, $P_m$. Determining initial inputs is a subjective process achieved through an interactive user interface where values are selected with slider bar inputs. We emphasize that initial component fits should be constructed with care and consideration for known parameters of magnetic mineral components. Initial starting components can be saved within a user-session so that a number of datasets may be analyzed from a consistent and objective starting point. Optimization of $P_m$ is achieved using the $\text{optim()}$ function, which iteratively determines the ideal values of $P_m$ to minimize the residual sum squared (RSS) between $C$ and $C_m$. Results for an optimized set of parameters $P_{opt}$ are returned along with the minimized RSS value. In order to determine the number of magnetic mineral components to be used in the model, there is functionality built in to the web application to perform an F-test for models with variable numbers of components. We suggest that additional information and data regarding the likely components in a sample be used to aid in determining the proper number of components to use in model fitting, as statistical significance is not an absolute measure of the quality of a model. Many common components in natural samples have been described by Egli (2004a,b,c) and a table summarizing many of those components is provided on the ‘Fitting’ page of MAX UnMix for reference.

In addition to determining the optimal number of magnetic mineral components within a specimen, it is often of interest to calculate the relative contribution of each component to the total measured magnetization. Here, both the observed and extrapolated contribution (OC and EC, respectively) of each model component are determined as the integrated area under individual component distributions relative to the area under $C_m$ for the observed set of field values $B$ (OC) or an extended set of field values such that all components are saturated (EC). In the case of full saturation, OC will equal EC exactly. Previous methods (e.g., Kruiver et al., 2001; Heslop et al., 2002) extrapolate magnetic contributions of unsaturated components and so EC will be the most comparable parameter to other methods. It is important to note that our calculation of OC and EC is independent of the user-defined $p$, the parameter controlling distribution amplitude, meaning that values of $p$ need not be equal to 1 during model fitting.

A resampling routine is used to assign uncertainty for the optimized model parameters and resultant $C_m$ (method similar to that of Egli, 2003). For a user-defined number of resampling events, $j$, the model calculates a newly optimized $C_m$ and set of parameters $P_{opt}$ based on a Monte-Carlo style resampling of all input parameters ($P_m$ and $C$). For $P_m$, random sampling assumes a normally distributed error of 2%. Each iteration recalculates $C$ from a random subset of $M$ based on a proportion set by the user (0.95 as default can range from 0.8 to 1.0). Mean values and standard deviations for the resultant set of $P_{opt}$ and $C_{m,opt}$ are returned and available for download. An approximate 95% confidence interval (2.5 and 97.5 percentiles) is used to display uncertainty in component and model distributions in the final output plot. The final set of results provides users with a robust sense of uncertainty and model quality.

### 3. Example datasets and model comparison

In order to evaluate the performance of the MAX UnMix model we analyzed data from three natural samples using the MAX UnMix model described here, the CODICA and GECA programs provided by Egli (2003), IRM UnMix (Heslop et al., 2002), and the IRM-CLG method of Kruiver et al. (2001). For each sample, we compare the $B_0$ and $DP$ values for each model component (see Figs. 1–3). These model parameters are common amongst all four methods and are often used as diagnostic indicators in assigning magnetic mineralogy to model components (e.g., Egli, 2004a,b; Lindquist et al., 2011; Bourne et al., 2015, other parameters from each model are reported in Table 1). The analyzed samples ranged from lake sediments (G010 and Birch-05; Egli, 2003; Lascu and Plank, 2013, respectively) to an Eocene paleosol B-horizon (PCB-01-TRB-050). Magnetization data for each specimen varied from ARM demagnetization (G010; Egli, 2003), IRM demagnetization...
A characteristic of a given analysis of G010 (anoxic lake sediment) presented by Egli (2003). However, the IRM UnMix software was unable to produce a satisfactory fit to the G010 dataset using its automated fitting routine (Heslop et al., 2002). A major advantage of having an automated fitting routine is that objectivity can be maintained and results can be easily replicated by different users. Despite these advantages, there are certain cases, including G010, where it becomes beneficial to have a higher degree of user control (which is possible in IRM UnMix, but not in a user friendly way). In contrast, the IRM-CLG model is entirely subjective to user control and includes no optimization or error analysis. Results for the IRM-CLG method show good correlation for G010 (and in other examples described below), but these results are in part due to the difficulty in remaining objective while model fitting. MAX UnMix, in a similar way to the MAG-MIX software from Egli (2003), allows for subjectivity in determination of an initial model fit, but retains objectivity by performing automated optimization and error analysis in order to produce a final model.

Decomposition of the Birch-05 IRM demagnetization data from Lascu and Plank (2013) using MAX UnMix reveal two primary magnetic components (Fig. 2A). The low coercivity component (component 1) is characterized by a \( B_h \) of 1.19 (± 0.02) log\(_{10}\) units (15.5 mT) and a \( DP \) of 0.38 (± 0.01; see Fig. 2A). Component 2 has a \( B_h \) of 1.58 (± 0.01) log\(_{10}\) units (38 mT) and a \( DP \) of 0.27 (± 0.01; see Fig. 2A). Lascu and Plank (2013) reported results of coercivity unmixing using the CODICA and GECAn programs of Egli (2003) for a sequence of lake sediments (including Birch-05) and identified detrital soft (\( B_h \) 10–30 mT, \( DP \) 0.3–0.5) and biogenic soft (\( B_h \) 30–50 mT, \( DP \) 0.15–0.32) components that are entirely consistent with components 1 and 2, respectively.

**Fig. 2.** (A) Model fit example for sample Birch-05 (lake sediment) from Lascu and Plank (2013). Coercivity distribution (data shown in grey circles, spline fit partially visible as black line) derived from IRM demagnetization measurements. Shaded area represents error envelopes of 95% confidence intervals. In the cases where no shading is present, confidence intervals are thinner than line. (B) Comparison of \( B_h \) and \( DP \) parameters for individual model components across methods. Percentage difference calculated relative to results for MAX UnMix. Shaded region represents plus or minus 10%. GECA program from Egli (2003), IRM UnMix from Heslop et al. (2002), and IRM CLG from Kruiver et al. (2001).

**Fig. 3.** (A) Model fit example for sample PCB-01-TRB-050 (paleosol B horizon). Coercivity distribution (data shown in grey circles, spline fit partially visible as black line) derived from backfield remanence data up to 1 T. Shaded area represents error envelopes of 95% confidence intervals. In the cases where no shading is present, confidence intervals are thinner than line. (B) Comparison of \( B_h \) and \( DP \) parameters for individual model components across methods. Percentage difference calculated relative to results for MAX UnMix. Shaded region represents plus or minus 10%. GECA program from Egli (2003), IRM UnMix from Heslop et al. (2002), and IRM CLG from Kruiver et al. (2001).

(Birch-05; Lascu and Plank, 2013), and backfield remanence data (PCB-01-TRB-050).

Evaluation of the G010 ARM demagnetization sample data set from Egli (2003) reveals a broad consistency of results across methods (see Fig. 1). MAX UnMix modeling results in a three component model with a primary low coercivity component (component 1) with a \( B_h \) of 1.37 (± 0.02) log\(_{10}\) units (23.4 mT) and a \( DP \) of 0.32 (± 0.01). The intermediate component 2 is characterized by a \( B_h \) of 1.88 (± 0.01) log\(_{10}\) units (75.9 mT) and a \( DP \) of 0.14 (± 0.01). A final high coercivity component 3 has a \( B_h \) of 2.24 (± 0.05) log\(_{10}\) units (75.9 mT) and a \( DP \) of 0.24 (± 0.04). The original analysis of G010 (anoxic lake sediment) presented by Egli (2003) reported three primary components that are closely replicated here. The low coercivity component (component 1) was identified as detrital magnetite and could also be identified from fluvial sediments elsewhere in the lake catchment (see Egli, 2003, for details). Components 2 and 3 are nearly identical to the biogenic magnetite and oxidized magnetite (or hematite) components reported by Egli (2003).

The resultant \( B_h \) and \( DP \) values for both GECA and IRM-CLG are within ± 10% of the values resulting from MAX UnMix and suggest that comparable results are obtainable across methods despite certain differences in the statistical models (see also Spassov et al., 2003). However, the IRM UnMix software was unable to produce a satisfactory fit to the G010 dataset using its automated fitting routine (Heslop et al., 2002).
Table 1
Results of model fitting for three specimen using variable unmixing methods: MAX UnMix (described here), GECA (Egli, 2003), IRM-UnMix (Heslop et al., 2002), and IRM-CLG (Kruiver et al., 2001). Note that all parameters (Bh, DP, S, OC, and EC) are labeled according to the nomenclature in MAX UnMix with the exception of q, which refers to kurtosis in the SGG function of Egli (2003). Specimen G010 (ARM demagnetization) and Birch-05 (IRM demagnetization) are lake sediments from Egli (2003) and Lascu and Plank (2013), respectively. Specimen TRA-050 (backfield remanence data up to 1 T) is an Eocene paleosol B-horizon.

<table>
<thead>
<tr>
<th>Specimen</th>
<th>Method</th>
<th>Component 1</th>
<th>Component 2</th>
<th>Component 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bh</td>
<td>Dp</td>
<td>S</td>
<td>q</td>
</tr>
<tr>
<td>G010</td>
<td>Max UnMix</td>
<td>1.37</td>
<td>0.32</td>
<td>0.87</td>
</tr>
<tr>
<td></td>
<td>GECa</td>
<td>1.34</td>
<td>0.34</td>
<td>0.60</td>
</tr>
<tr>
<td></td>
<td>IRM-UnMix</td>
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<td>–</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>IRM-CLG</td>
<td>1.41</td>
<td>0.35</td>
<td>–</td>
</tr>
<tr>
<td>Birch-05</td>
<td>Max UnMix</td>
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<td>0.44</td>
<td>0.44</td>
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<tr>
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<td>0.34</td>
<td>–</td>
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<td></td>
<td>IRM-CLG</td>
<td>1.13</td>
<td>0.34</td>
<td>–</td>
</tr>
<tr>
<td>TRB-050</td>
<td>Max UnMix</td>
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<td>0.34</td>
<td>1.09</td>
</tr>
<tr>
<td></td>
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<td>0.36</td>
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<tr>
<td></td>
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<td>0.32</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>IRM-CLG</td>
<td>2.65</td>
<td>0.32</td>
<td>–</td>
</tr>
</tbody>
</table>

Reanalysis of the Birch-05 data using CODICA and GECA (Egli, 2003) as well as IRM-UnMix (Heslop et al., 2002) and IRM-CLG (Kruiver et al., 2001) produces results that are mostly consistent for Bh and DP (see Fig. 2B). In general, data across methods is within ± 10% of the results obtained from Max UnMix. There is more variability in the results for DP compared with the consistency observed in Bh (Fig. 2). The variability in DP is primarily related to a relatively high degree of skewness in both model components (S1 = 0.72 and S2 = 0.71) which is accounted for in slightly different ways in Max UnMix compared with the SGG function (Eq. (3)) of Egli (2003), or in the case of the other methods is not incorporated.

Remanence is held by two primary components in PCB-01-TRB-050. The high-coercivity component (component 1) is characterized by Bh of 2.66 (± 0.02) log10 units (~457 mT) and a DP of 0.34 (± 0.01; see Fig. 3). The low coercivity component (component 2) has a Bh of 1.51 (± 0.01) log10 units (~32 mT) and a DP of 0.51 (± 0.01). These components are interpreted to represent partially oxidized pedogenic magnetite (component 2) and fine grained hematite (component 1).

Similar to the results for Birch-05, increased skewness also increases variability in results obtained from various methods for component 2 in specimen PCB-01-TRA-050 (Fig. 3B) where skewness is also considerable (S1 = 0.68). In contrast, the model parameters for component 1 in PCB-01-TRB-050 are only slightly skewed (S1 = 1.09) and the Bh and DP for component 1 are highly consistent across methods. This variability is important to recognize, particularly when comparing results from studies where unmixing analyses were conducted using different methods and highlights the need for consistent methodology to be utilized moving forward if possible.

Results from TRB-050 highlight that care should be taken when interpreting results for dispersion and skewness. Model fits for TRB-050 show that component 1 is slightly skew-right and component 2 has DP values that are in excess of 0.5 in all models (see Table 1). In general, values of DP far exceeding 0.5 should be interpreted with caution, as it can infer that a magnetic mineral component is both "hard" and "soft". For skewness, as previously mentioned, skew-right distributions (S > 1) are poorly understood and should be avoided in fitting if possible. Component 1 is interpreted to be primarily pigmentary hematite, although it is possible that more minor contributions from goethite may be responsible for the skew-right behavior. Component 2 is interpreted as partially oxidized pedogenic magnetite that likely represents a mixture of magnetite and partially (or fully) oxidized magnetite/maghemite, which increases the range of coercivities (and thus DP) within a single component. In the case that DP > 0.5 and S > 1, it may be an indicator for mixed mineralogy within a single component (Heslop et al., 2004) and physical interpretations such as those reported here should accompany results of this type.

Comparison of EC calculated by Max UnMix to the contribution calculated by other methods is mostly consistent for components in both TRB-050 and G010 (generally within ± 8%). The variability in EC for Birch-05 is more considerable (± 14%) and is particularly poor when comparing results from MAX UnMix and GECa to those of IRM-UnMix and IRM-CLG (see Table 1). The potential for variability in estimated contribution to remanence for model components highlights the need for transparency and consistency in methodology for quantifying component remanence using coercivity unmixing methods.

4. Conclusions
MAX UnMix is a new method for the statistical unmixing of magnetization data. The program functions as a web application (available online at http://www.irn.umn.edu/maxunmix) and was written in R studio using the package shiny (both open source and available for Mac, PC, and Linux). Model results are comparable to existing methods that are frequently used within the environmental and rock magnetic community. In contrast to older methods, MAX UnMix provides users a friendly interface that is available online (with the code accessible via open source, platform independent software). Moving forward, future work should aim to utilize coercivity unmixing methods that are consistent and account for skewness of component distributions as increased skewness has a considerable impact on affecting other model parameters. Given the accessibility and user-friendly nature of MAX UnMix it should serve as a useful resource for future work.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.cageo.2016.07.009.

References


