

**MELVIS: An open-source web application for computing and modelling
the viscosity of volcanic melts**

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Abstract

The viscosity of volcanic melts governs magma transport, eruption dynamics, and a broad range of magmatic processes, so predicting it as a function of temperature, composition, and dissolved water content is central to physical volcanology. Yet no freely accessible tool integrates global machine-learning predictions, physically motivated viscosity equations, and composition-specific models calibrated to avoid nanocrystallization and water-loss artefacts — experimental biases that can lead conventional viscometry to overestimate melt viscosity. Nor can existing tools show how different assumptions about the dependence of melt fragility on dissolved water propagate into viscosity predictions at eruptive temperatures — a debated question with direct consequences for conduit-flow modelling and eruption-style assessment.

Here we present MELVIS (MELt VIScosity), an open-source web application built with Python and Streamlit. MELVIS comprises three integrated modules: (1) a viscosity calculator based on the artificial neural network of Langhammer et al. (2022), developed using a database of 3,482 measurements spanning basanite to rhyolite including hydrous compositions, with batch processing and TAS-based compositional classification; (2) a hydrous modelling module that parameterises the glass transition temperature $T_g(\text{H}_2\text{O})$ and melt fragility $m(\text{H}_2\text{O})$ under three alternative fragility–water relationships, making explicit how model assumptions propagate into viscosity predictions at eruptive temperatures; and (3) a library of seven composition-specific, artefact-free MYEGA models for key volcanic systems. All modules yield closed-form MYEGA parameterisations suitable for direct implementation in numerical eruption models.

35 **Keywords:** viscosity; volcanic melt; artificial neural network; glass transition
36 temperature; melt fragility; nanocrystallization; Streamlit; open-source software

1. Introduction

The shear viscosity (η) of volcanic melts exerts a dominant control on the fluid dynamics of magmas and, consequently, on the style, intensity, and hazard potential of volcanic eruptions (Dingwell, 1996; Gonnermann and Manga, 2007; Papale, 1999). Viscosity governs magma ascent rates, the rheological response to deformation, degassing and outgassing regimes, and the transition between effusive and explosive behavior (Cassidy et al., 2018; Sparks, 2003). Given that the viscosity of natural magmas spans more than fifteen orders of magnitude — from approximately 10^{-2} to 10^{12} Pa·s — primarily in response to variations in temperature, melt composition, dissolved volatile content (especially H₂O), and the presence of suspended crystals and bubbles, its accurate prediction is critical for numerical models of volcanic eruptions, pyroclastic density current scenarios, and ash-cloud transport simulations (Gonnermann and Manga, 2012; Marzocchi et al., 2012). Because viscosity is a primary input to the conservation equations solved in conduit, plume, and pyroclastic-flow codes (de' Michieli Vitturi and Aravena, 2021; Gonnermann and Manga, 2012; La Spina et al., 2016), even modest uncertainties in its value propagate into large differences in simulated mass eruption rate (La Spina et al., 2021, 2017; Mastin, 2002; Melnik, 2000; Papale, 1999; Textor et al., 2005), fragmentation depth (Dominijanni et al., 2026), and dispersal footprint, making accurate viscosity prediction essential for forecasting the range of plausible scenarios at active volcanic systems.

Over the past five decades, much effort has gone into developing predictive models for melt viscosity. Early Arrhenian models (Bottinga and Weill, 1972; Shaw, 1972) were effective at high (near-liquidus) temperatures but failed when extrapolated to the low-temperature regime near the glass transition temperature, where silicate melts exhibit pronounced non-Arrhenian behavior (Richet and Bottinga, 1995). Subsequent models adopted three-parameter non-Arrhenian formulations. The Vogel-Fulcher-Tammann (VFT) equation (Fulcher, 1925;

Tammann and Hesse, 1926; Vogel, 1921) is an empirical expression in which viscosity diverges at a finite temperature T_0 , with parameters $\log \eta_\infty$, a pseudo-activation constant B , and T_0 ; Giordano et al. (2008) recast VFT in terms of the viscosity at infinite temperature ($\log \eta_\infty$), the glass transition temperature (T_g), and the steepness index or fragility (m) (Angell, 1995). The MYEGA (Mauro-Yue-Ellison-Gupta-Allan) equation (Mauro et al., 2009) is instead derived from the Adam-Gibbs configurational-entropy framework and is natively expressed in the same ($\log \eta_\infty$, T_g , m) parameters, providing a physically grounded link between viscosity and intrinsic melt transport properties.

Global chemical models have been developed to predict viscosity across a wide compositional range. The model of Giordano et al., (2008) (hereafter GRD) uses a VFT formulation with 18 adjustable parameters calibrated on more than 1,770 measurements, and the model of Hui and Zhang (2007) (hereafter HZ) employs a four-parameter empirical equation with 37 coefficients fitted to 1,451 data points. More recently, Langhammer et al. (2022) trained an artificial neural network (ANN) on a database of 3,482 viscosity measurements for volcanic melts spanning virtually the entire compositional space of terrestrial magmas. The ANN uses melt composition (including H_2O), temperature, a structural polymerization parameter, and the alkali ratio as inputs, and achieves significantly higher predictive accuracy ($\text{RMSE} = 0.45 \log_{10}$ on unseen test data) than the GRD ($\text{RMSE} = 1.23 \log_{10}$) and HZ ($\text{RMSE} = 0.89 \log_{10}$) models on the same test set. To provide physically sound interpolation at eruptive temperatures — where no training data exist due to the experimental gap between 10^5 and $10^8 \text{ Pa}\cdot\text{s}$ — Langhammer et al. (2022) introduced a “synthetic data” approach: the ANN generates viscosity values in the high- and low-viscosity ranges, and these are fitted with the MYEGA equation to produce continuous, physically motivated viscosity curves. More recently, Le Losq et al. (2025) trained a greybox ANN refined by a Gaussian process on a larger database of 28,898 measurements covering phospho-alumino-silicate melts

from SiO₂ to multicomponent magmatic compositions and pressures up to 30 GPa, achieving a comparable accuracy (RMSE $\approx 0.4 \log_{10}$) while extending predictions to high-pressure regimes relevant to deep magmatic and planetary settings.

A further, increasingly recognised limitation concerns the input data on which these models are calibrated. Numerous studies have shown that the low-temperature viscosity of volcanic melts measured by conventional viscometry (micropenetration, parallel plate) around the glass transition temperature (T_g) is frequently affected by amorphous unmixing and by the nanocrystallization of transition-metal-bearing phases — most commonly Fe-Ti oxides — as well as by water loss and iron oxidation during the measurement itself (Abeykoon et al., 2026; Bondar et al., 2025; Di Genova et al., 2020, 2017; Fanesi et al., 2025; Kleest et al., 2020; Okumura et al., 2022; Scarani et al., 2022; Valdivia et al., 2025, 2023). These processes systematically increase the measured viscosity relative to that of the homogeneous, crystal-free melt, with deviations that can reach up to two orders of magnitude in the worst cases (Di Genova et al., 2020; Scarani et al., 2022). Because viscosity measurements in the T_g region constrain the steepness of the viscosity–temperature curve, biased data propagate directly into a biased estimate of the melt fragility (m) — the parameter that, in MYEGA and related non-Arrhenian formulations, controls the extrapolation from the high-viscosity regime to the much lower viscosities relevant at eruptive temperatures. A current frontier in viscosity modelling is therefore the derivation of the correct fragility for natural melts and the explicit treatment of its uncertainty (Cassetta et al., 2021; Di Genova et al., 2023; Stopponi et al., 2026; Valdivia et al., 2025). To date, none of the global models discussed above allows the user to quickly compute the viscosity of a given composition as a function of temperature and water content while exploring the effect of plausible variations in melt fragility — a capability that is essential both for propagating measurement uncertainty into eruption simulations (Abeykoon et al., 2026; Dominijanni et al., 2026) and for assessing how nanocrystallization- and/or water loss-related

biases in the underlying database may affect predicted viscosities at eruptive conditions (Fanesi et al., 2025; Valdivia et al., 2025, 2023).

Alongside these scientific questions, there is also a practical need to make viscosity predictions readily accessible to the volcanological community. Several global models are distributed only as equations, spreadsheets, or standalone scripts, and a few have been made available as browser-based applications (Langhammer et al., 2022; Le Losq et al., 2025). Building on these resources, there remains room for a tool that brings together a global multi-component predictor for volcanic melts, composition-specific MYEGA parameterisations, and the ability to modulate melt fragility. Such a tool would let users examine, for a given composition, how plausible variations in fragility propagate into the predicted viscosity–temperature–water relationship and into the uncertainty on extrapolated eruptive viscosities. Equally important, it should return, for any user-defined composition, a closed-form parameterisation of viscosity versus temperature and dissolved water content that can be plugged directly into conduit and magma-ascent models, where the viscosity– T – H_2O relationship is a primary input controlling ascent velocity, fragmentation, and expected eruptive style.

Here we present MELVIS (MELt VIScosity), an open-source web application that fills this gap. MELVIS integrates three complementary computational modules into a single, browser-based interface: (1) a global ANN viscosity calculator for multi-component anhydrous and hydrous melts (Langhammer et al., 2022), (2) a module for parameterizing temperature-, water- and fragility-dependent viscosity using the MYEGA equation coupled with the literature T_g model (Langhammer et al., 2021; Schneider et al., 1997), and (3) a library of pre-calibrated viscosity models for specific volcanic compositions in which the bias introduced by sub-liquidus nanocrystallisation and/or water loss on the original viscosity measurements has been quantified and removed, providing parameterizations representative of the homogeneous,

crystal-free melt. The application is built with Python 3.11 and Streamlit, is hosted online, and its complete source code is available on [GitHub](#) under an open-source license.

2. Design and implementation

2.1. Software architecture and technology stack

MELVIS is implemented entirely in Python 3.11 and deployed as a web application using the Streamlit framework. The core computational dependencies include TensorFlow Lite (tflite-runtime, for lightweight ANN inference), NumPy for numerical operations, the pyrolite library (Williams et al., 2020) for geochemical data handling and oxide-to-mole-fraction conversions, and openpyxl for Excel file input/output. The application is structured as a multi-page Streamlit app with a home landing page and three functional modules, each accessible via the sidebar navigation.

The ANN model is stored as a TensorFlow Lite (.tflite) file and loaded once per session using Streamlit's `@st.cache_resource` decorator, ensuring efficient memory use and fast inference across multiple user queries. All viscosity equations and helper functions (mole-fraction conversion, MYEGA evaluation, composition normalization preserving H₂O) are implemented as inline Python functions within the application code, avoiding external compiled dependencies.

2.2. Module 1: ANN-based viscosity calculator

The first module implements the trained ANN of Langhammer et al. (2022), which predicts the viscosity of volcanic melts as a function of chemical composition and temperature. Users input oxide compositions (SiO₂, TiO₂, Al₂O₃, FeO, MnO, MgO, CaO, Na₂O, K₂O, P₂O₅, Cr₂O₃, Fe₂O₃, H₂O) in weight percent, either manually for a single sample or via batch upload of a CSV file enabling multi-sample calculations.

Before ANN inference, the application performs the following preprocessing steps automatically. First, iron redistribution is applied using a factor of 1.11 to account for the higher molar weight of Fe_2O_3 (Langhammer et al., 2022): if only total iron as FeO_T is reported ($\text{Fe}_2\text{O}_3 = 0$), it is split as $\text{FeO} = \text{FeO}_T/2$ and $\text{Fe}_2\text{O}_3 = \text{FeO}_T \times 1.11/2$; if only total iron as Fe_2O_{3T} is reported ($\text{FeO} = 0$), it is split as $\text{FeO} = \text{Fe}_2\text{O}_{3T}/(2 \times 1.11)$ and $\text{Fe}_2\text{O}_3 = \text{Fe}_2\text{O}_{3T}/2$. This step ensures that both ferrous and ferric iron are always represented in the input vector, consistent with the ANN training protocol. Second, the composition is normalised to 100 wt.% with H_2O preserved outside the anhydrous normalisation. Third, mole fractions are computed from the normalised weight percentages. Two derived structural parameters are then calculated from the mole fractions: the structural modifier SM, defined as the sum of the mole fractions of FeO , MnO , MgO , CaO , Na_2O and K_2O ; and the alkali ratio, defined as $\text{K}_2\text{O}/(\text{Na}_2\text{O} + \text{K}_2\text{O})$. Note that Cr_2O_3 is included in the composition input but its mole fraction is not passed to the ANN, consistent with the original model architecture of Langhammer et al. (2022). The resulting 15-element input vector (temperature, 12 oxide mole fractions, SM, and the alkali ratio) is then z-score standardised using the mean and variance of the ANN training dataset. The ANN model is loaded in TensorFlow Lite format and cached in memory at application startup to avoid repeated loading across user interactions.

For each composition, the module generates synthetic viscosity data by inverting the ANN via bisection. The bisection search is performed in the normalised temperature space used during ANN training, with the search bracket corresponding to the physical range of 300–3000 K. The target $\log_{10}\eta$ values used to generate synthetic data points depend on the SiO_2 content of the composition: for mafic melts ($\text{SiO}_2 \leq 60$ wt%), the low-viscosity targets are $\log_{10}\eta = 0.0, 0.5, 1.0, 1.5, 2.0$, while for more silicic compositions ($\text{SiO}_2 > 60$ wt%), they are $\log_{10}\eta = 2.0, 2.5, 3.0, 3.5, 4.0, 4.5$. In both cases, the high-viscosity targets are $\log_{10}\eta = 9.5, 10.0, 10.5, 11.0, 11.5$. These synthetic temperature–viscosity pairs are then fitted with the two-parameter

MYEGA equation (Mauro et al., 2009) with fixed pre-exponential term $A = \log_{10}\eta_{\infty} = -2.9$ (Langhammer et al., 2022):

$$\log_{10}\eta(T) = A + (12 - A) \frac{T_g}{T} \cdot \exp \left[\left(\frac{m}{12 - A} - 1 \right) \left(\frac{T_g}{T} - 1 \right) \right], \quad (1)$$

where T_g is the glass transition temperature (defined at $\log_{10}\eta = 12$), m is the melt fragility index (Angell, 1995), and T is the temperature in Kelvin. Fitting Eq. (1) to the synthetic data yields T_g and m for each composition, which are then used to reconstruct smooth viscosity–temperature curves over a user-defined temperature range.

The module produces two main outputs. The first is an interactive viscosity–temperature plot displaying MYEGA curves for all samples (Fig. 1), together with a Total Alkali–Silica (TAS) diagram (Le Bas et al., 1986) (Fig. 2) that classifies each sample by volcanic rock type and rock subclass (sodic vs. potassic series), following the scheme of Middlemost (1994) using the pyrolite library (Williams et al., 2020).

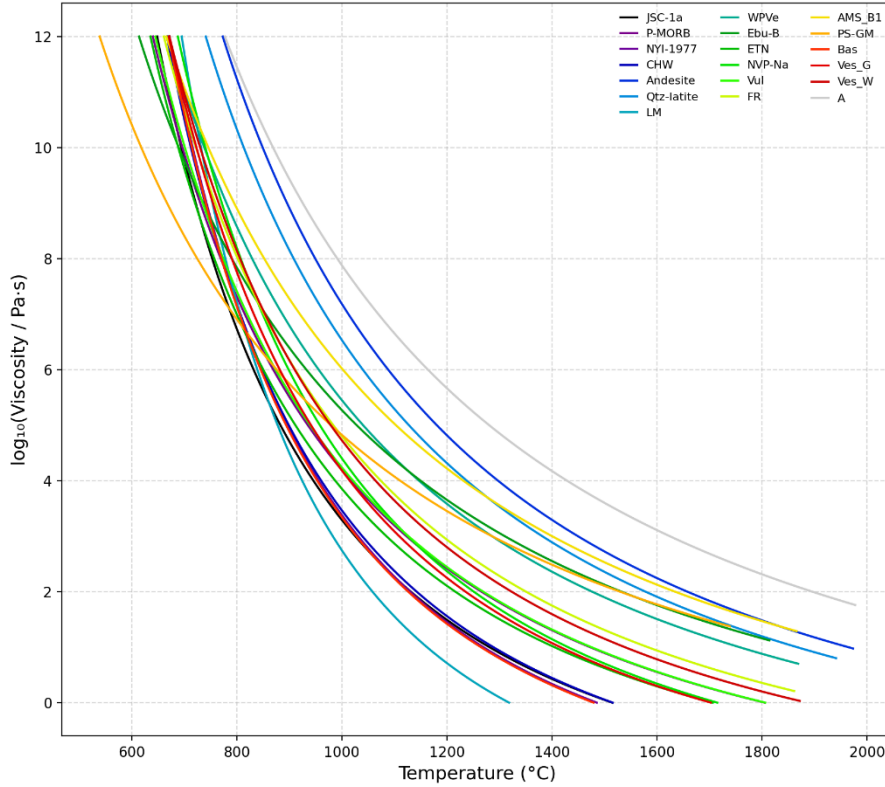
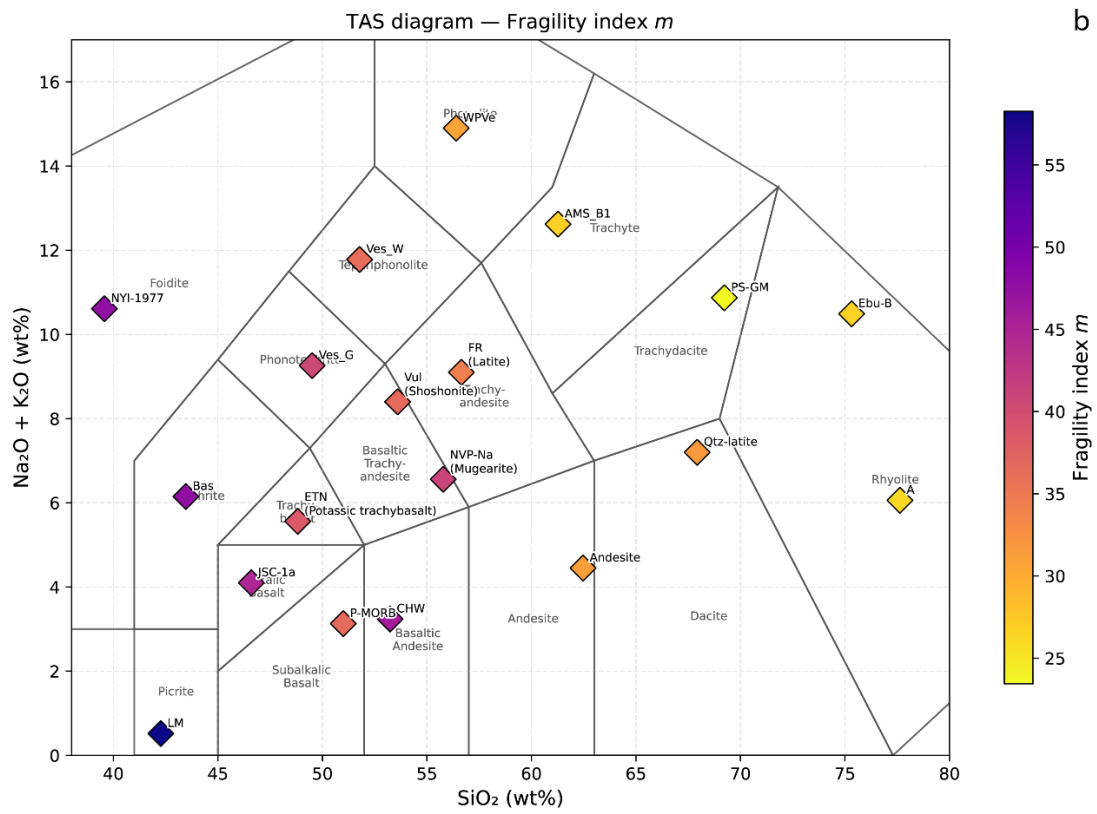
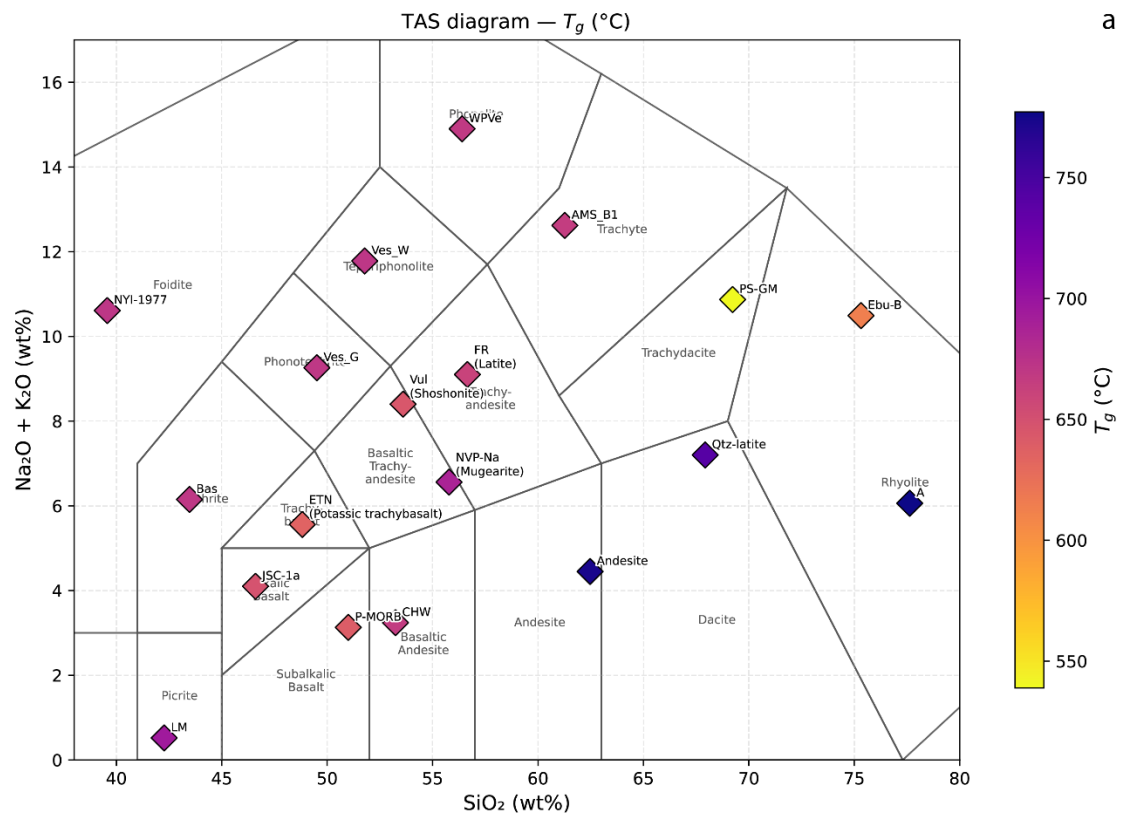


Figure 1. Anhydrous melt viscosity as a function of temperature for the 19 volcanic and experimental compositions included in the MELVIS default example dataset. Curves are MYEGA fits (Eq. 1) with $A = -2.9$ (Langhammer et al., 2022, 2021) computed from glass transition temperatures T_g and fragility indices m derived from the ANN synthetic data approach (Langhammer et al., 2022). Sample abbreviations follow the original publications (see Table S1). The figure is generated automatically by Module 1 (Viscosity Calculator) upon batch upload of a CSV file.

Each sample is plotted as a symbol colour-coded according to a user-selected petrological property: the glass transition temperature T_g (°C) (Fig. 2a), the fragility index m (Fig. 2b), or the melt viscosity $\log_{10}\eta$ at a user-specified temperature (1200 °C in Fig. 2c). This combination allows the user to visualise, at a glance, systematic compositional trends in melt physical properties across a suite of volcanic samples. The second is a downloadable Excel file containing two sheets: (i) the normalised input compositions with the iron redistribution flag for each sample, and (ii) the viscosity curves including T_g , m , and temperature–viscosity pairs, with the MYEGA equation embedded as an Excel formula in a dedicated column to allow independent recalculation by the user.



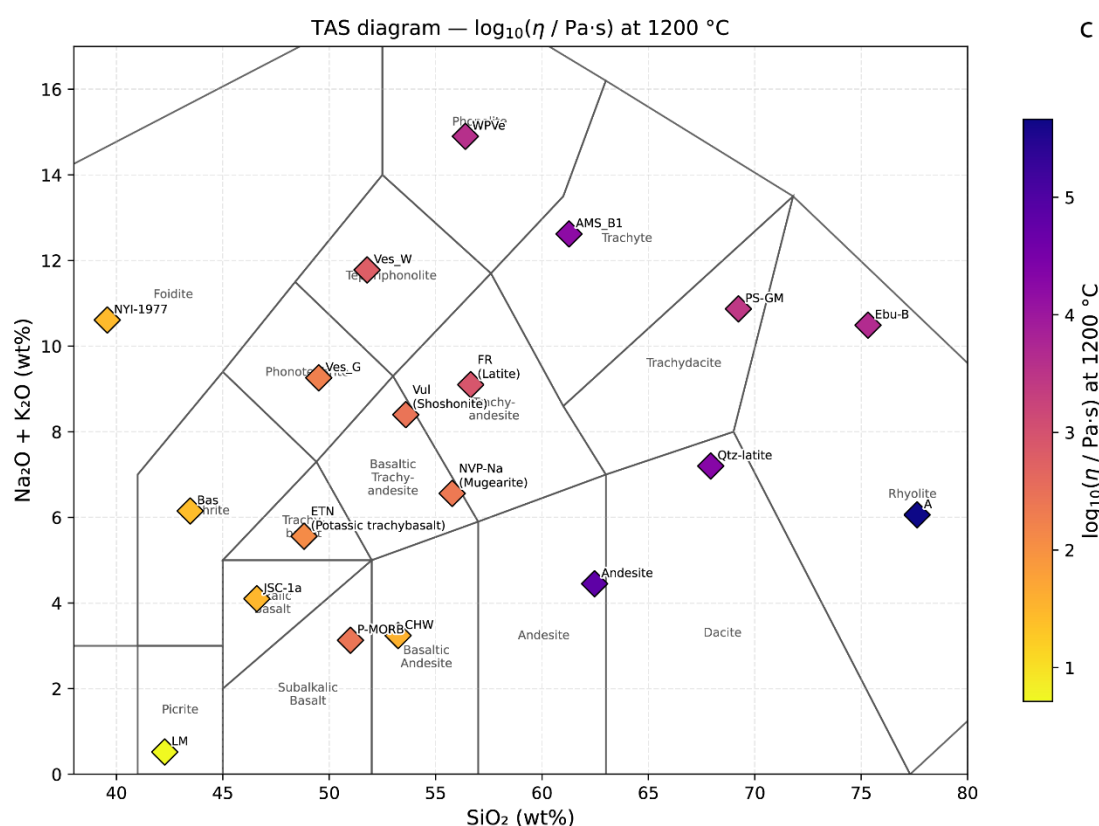


Figure 2. Total Alkali–Silica (TAS) diagram (Le Bas et al., 1986) for the 19 compositions of the default MELVIS dataset (Table S1), generated automatically by Module 1 (Viscosity Calculator). Rock fields and sub-classifications (sodic vs. potassic series) follow Middlemost (1994) as implemented in the pyrolite library (Williams et al., 2020). Each symbol is colour-coded according to a user-selected rheological property: (a) glass transition temperature T_g (°C), (b) fragility index m , and (c) melt viscosity $\log_{10}\eta$ (η in Pa·s) at a fixed temperature of 1200 °C. All values are derived from MYEGA fits to ANN-generated synthetic viscosity data (Langhammer et al., 2022). The colour scale is shown to the right of each panel.

2.3. Module 2: Anhydrous and hydrous viscosity modelling

The second module enables users to parameterise the dependence of melt viscosity on both temperature and dissolved water content, combining the MYEGA equation (Eq. 1) with the $T_g(\text{H}_2\text{O})$ model of Schneider et al. (1997) as implemented by Langhammer et al. (2021). The user provides an anhydrous composition (entered manually or selected from the batch results of Module 1) and a list of H_2O contents in wt.% at which to evaluate viscosity. The anhydrous composition undergoes the same iron redistribution and normalisation preprocessing described in Section 2.2.

For each specified H₂O content, the ANN is queried by adding water to the anhydrous composition and recomputing the normalised input vector, with H₂O preserved outside the anhydrous normalisation. The ANN inversion procedure (Section 2.2) is then applied to each hydrous composition to obtain the corresponding glass transition temperature T_g and fragility index m , yielding a set of ANN-derived (T_g, m) pairs as a function of water content.

The glass transition temperature is parameterised as a function of water content in mol% using a power concentration expansion of the Gordon and Taylor (1952) equation (Eqs. 9–10 of Langhammer et al., 2021):

$$T_g(x_{H_2O}) = w_1 \cdot T_{g,H_2O} + w_2 \cdot T_{g,d} + c \cdot w_1 \cdot w_2 (T_{g,d} - T_{g,H_2O}) + d \cdot w_1 \cdot w_2^2 (T_{g,d} - T_{g,H_2O}), \quad (2)$$

with

$$w_1 = \frac{x_{H_2O}}{b(100-x_{H_2O})+x_{H_2O}} \quad \text{and} \quad w_2 = \frac{b(100-x_{H_2O})}{b(100-x_{H_2O})+x_{H_2O}}, \quad (3)$$

where x_{H_2O} is the mol% of dissolved water, $T_{g,d}$ is the anhydrous glass transition temperature obtained from the ANN, $T_{g,H_2O} = 136$ K is the glass transition temperature of pure water (Kohl et al., 2005), w_1 and w_2 are weighting functions dependent on x_{H_2O} and a fitting parameter b , and c and d are additional fitting parameters. Nonlinear least-squares optimisation is used to fit b , c and d to the ANN-derived T_g values.

Three models are implemented for the fragility index as a function of water content. The first assumes m constant and equal to the anhydrous value m_d . The second uses the analytical relationship between T_g and m derived from the MYEGA equation (Eq. 12 of Langhammer et al., 2021):

$$m(xH_2O) = m_d + (12 - A) \cdot \ln\left(\frac{T_g(xH_2O)}{T_{g,d}}\right), (4)$$

The third model fits an exponential saturation function to the ANN-derived m values at each water content, anchored at m_d at zero water content:

$$m(xH_2O) = m_{inf} + (m_d - m_{inf}) \cdot \exp(-k \cdot xH_2O), (5)$$

where m_{inf} is the limiting fragility approached at high water contents and k is a decay rate constant. ANN-derived m values that violate a monotonically decreasing trend are excluded before fitting, and bounds enforcing $m_{inf} < m_d$ and $k > 0$ are applied. The model is fitted by a grid search over initial parameter values to minimise the root-mean-square residual. Importantly, the choice to impose a decreasing $m(H_2O)$ relationship is not grounded in a universal physical expectation: fragility is theoretically expected to remain approximately constant or even increase with dissolved water content (see Section 4.3 for a detailed discussion). Rather, the monotonically decreasing behaviour is observed empirically in viscosity datasets and models of volcanic melts from the literature (Giordano et al., 2008) and has been tentatively attributed to nanocrystallization and/or water loss during high-temperature viscosity measurements (Cassetta et al., 2021; Dominijanni et al., 2026; Stopponi et al., 2026; Valdivia et al., 2025, 2023). Indeed, the composition-specific models provided in Module 3 (Sections 2.4 and 4.3), whose fragility was calibrated from datasets depurated of measurement artefacts, predominantly show fragility that remains constant or increases with dissolved water content. The three fragility models implemented here — constant m , Eq. 4, and Eq. 5 — are therefore not mutually exclusive physical descriptions but complementary tools that allow the

user to explore how different assumptions about $m(\text{H}_2\text{O})$ propagate into the reconstructed viscosity–temperature– H_2O relationships.

The module produces two groups of outputs. The first group is displayed immediately after the ANN calculations and consists of five panels: T_g vs. H_2O , m vs. H_2O (showing all three fragility models alongside the ANN-derived points, with excluded non-monotone points marked), and one viscosity–temperature curve panel per fragility model (Fig. 3).

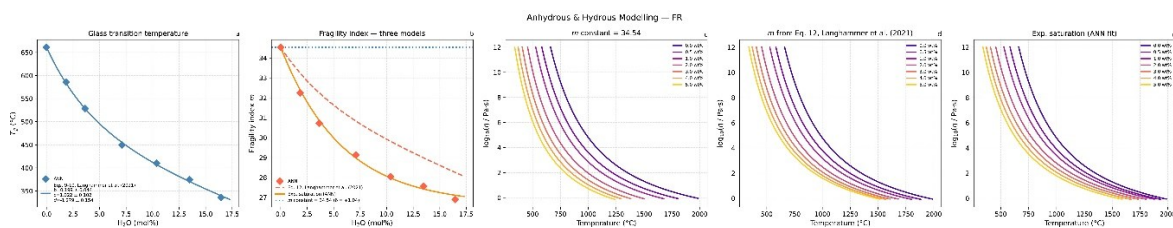


Figure 3. Hydrous viscosity modelling outputs from Module 2 (Anhydrous and Hydrous Modelling) for the Fondo Riccio latite composition from Campi Flegrei (FR; Di Genova et al., 2014)(Di Genova et al., 2014). From left to right: (a) glass transition temperature T_g (°C) as a function of H_2O content (mol%), showing ANN-derived values (symbols) and the literature fit (Langhammer et al., 2021; Schneider et al., 1997) (Eq. 2; solid line) with fitted parameters b , c , and d ; (b) fragility index m as a function of H_2O content, showing the three fragility models implemented in MELVIS — constant m (dotted line), Eq. 4 after Langhammer et al. (2021) (dashed line), and exponential saturation fit (Eq. 5) to ANN-derived m values (solid line), with ANN-derived m values; and (c-e) three panels of melt viscosity $\log_{10}\eta$ (η in $\text{Pa}\cdot\text{s}$) as a function of temperature for H_2O contents ranging from 0 to 5 wt.%, computed using the constant m , Eq. 4, and Eq. 5 fragility models, respectively. All MYEGA curves use $A = -2.9$ (Langhammer et al., 2022).

The second group is an optional section "Viscosity vs H_2O at a fixed temperature", where the user specifies a temperature, an H_2O range, and several evaluation points. The module then computes $\log_{10}\eta$ at the fixed temperature as a function of H_2O content for each of the three fragility models, smoothed using a monotone cubic spline (PCHIP interpolation), and displays three individual panels and a combined overlay figure (Fig. 4).

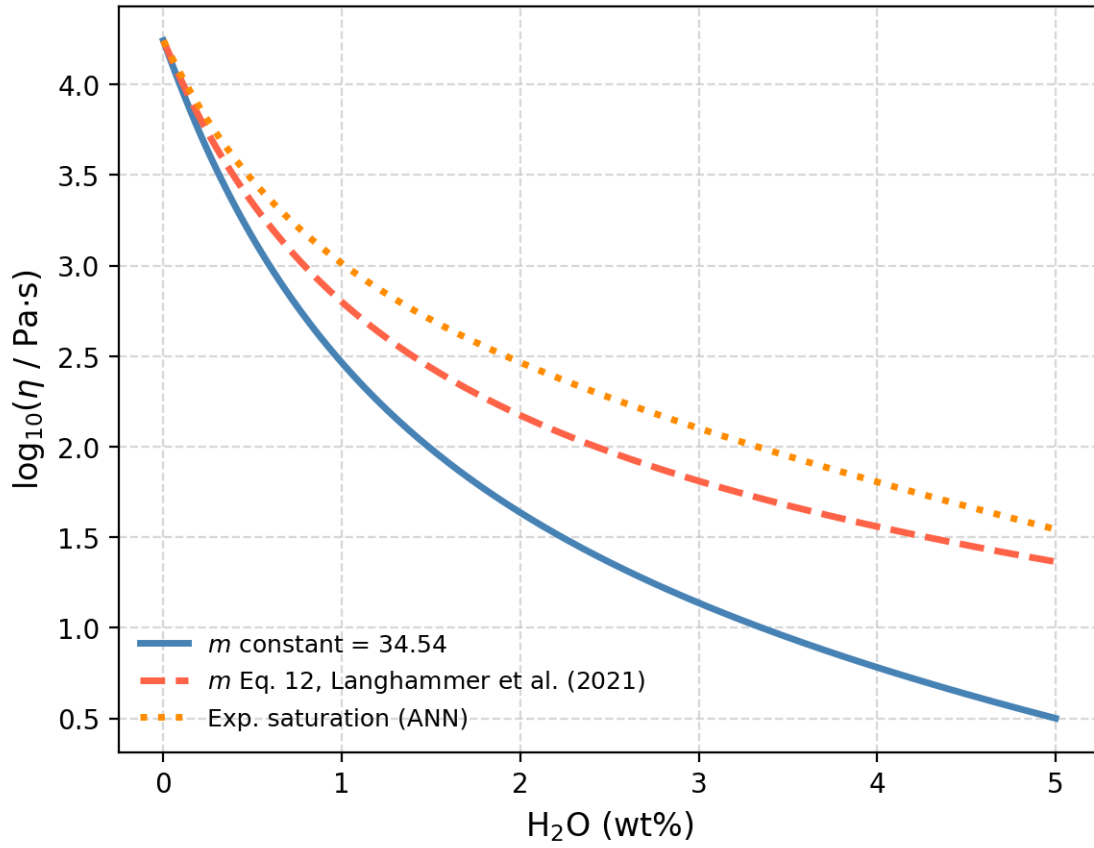


Figure 4. Melt viscosity $\log_{10}\eta$ (η in $\text{Pa}\cdot\text{s}$) as a function of dissolved H_2O content at a fixed temperature of 1050 °C for the Fondo Riccio trachytic composition (FR; Di Genova et al., 2014), computed by the optional "Viscosity vs H_2O at a fixed temperature" section of Module 2 (Anhydrous and Hydrous Modelling). Results are shown for the three fragility models implemented in MELVIS: (i) constant m , (ii) m following Eq. 4 (Langhammer et al., 2021), and (iii) exponential saturation fit (Eq. 5) to ANN-derived m values. Curves are monotone cubic spline interpolations (PCHIP) through viscosity values computed at discrete H_2O contents via MYEGA fits (Eq. 1; $A = -2.9$; Langhammer et al., 2022). The spread among the three panels illustrates the sensitivity of viscosity predictions at eruptive temperatures to the assumed fragility–water relationship.

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All results are exported to a downloadable Excel file containing six sheets: (i) a

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Parameters sheet reporting all fitted model parameters (b , c , d , m_{inf} , k , RMSE values) with

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descriptions; (ii) a T_g and m vs H_2O sheet tabulating the ANN-derived and fitted T_g and m

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values at each water content for all three fragility models; (iii) a chemistry check sheet showing

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the input composition, the composition after iron redistribution, and the composition

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normalised to 100 wt.% used for ANN inference, together with mol% values; and (iv–vi) three

viscosity curve sheets (one per fragility model) containing temperature–viscosity pairs with the MYEGA equation embedded as an Excel formula for independent user verification.

2.4. Module 3: Specific composition models

The third module provides pre-calibrated viscosity models for seven specific volcanic and experimental compositions, each parameterised using data from viscometry, differential scanning calorimetry (DSC), and/or spectroscopic measurements. All models are implemented as MYEGA curves with composition-specific parameters; however, unlike Modules 1 and 2, no ANN inference is performed here — all MYEGA parameters are hardcoded from their respective published calibrations.

The compositions and their parameterisations differ in the nature of the independent variable, the fragility model, and the wt.%–to–mol% conversion used:

(1) Stromboli basalt (Valdivia et al., 2023): A hydrous basaltic model (0–5 wt.% H₂O) using the $T_g(\text{H}_2\text{O})$ parameterisation (Eq. 2) and constant fragility $m = 40.7$. The wt.%–to–mol% conversion uses the effective molar weight of the dry melt ($MW_{dry} = 64.28$ g/mol), calculated from the Stromboli composition reported in Valdivia et al. (2023). This model was calibrated to correct for viscosity measurement artefacts arising from nanocrystallization and/or water loss during conventional high-temperature viscometry.

(2) Peridotite (Di Genova et al., 2023): A hydrous model calibrated using micropenetration and DSC-derived viscosities combined with high-temperature viscometry and Brillouin spectroscopy. $T_g(\text{H}_2\text{O})$ follows Eq. 2, and fragility decreases linearly with H₂O content in mol% due to the extremely depolymerised melt structure. No TAS classification is displayed for this composition, as peridotite plots outside the standard TAS diagram range. The wt.%–to–mol% conversion uses $MW_{dry} = 51.01$ g/mol.

(3) Andesite (Valdivia et al., 2025): An anhydrous model in which the independent variable is not H₂O content but rather the weight fraction of transition metals (FeO_T + TiO₂ + MnO) relative to the fully transition-metal-bearing end-member composition AND100 ($x = 0$ –100%). Both T_g and m vary as linear to quadratic functions of this parameter, addressing the effects of nanoscale chemical heterogeneities on andesitic melt viscosity.

(4) Colli Albani tephri-phonolite (Fanesi et al., 2025): A hydrous model (0–5 wt.% H₂O) for the Pozzolane Nere magma. $T_g(\text{H}_2\text{O})$ follows Eq. 2, with an empirical quadratic wt%–to–mol% conversion. Fragility increases linearly with dissolved water content, revealing a 4300-fold viscosity increase upon dehydration at eruptive temperature.

(5) Metaluminous/peralkaline haplogranite HPG8 (Stopponi et al., 2026): An anhydrous model in which the independent variable is excess Na₂O content in mol% ($x = 0$ –20 mol%). This model departs from the standard MYEGA formulation: A varies with x as $A = -1.55 - 6.35 \cdot 0.55^x$, T_g varies as $T_g = 1034 \cdot (1 + x)^{-0.1}$ K, and m varies linearly as $m = 22.95 + 0.70 \cdot x$, with all coefficients calibrated from experimental data.

(6) Vesuvius 472 CE phonotephrite (Dominijanni et al., 2026): A hydrous model with $T_g(\text{H}_2\text{O})$ following Eq. 2, an empirical quadratic wt%–to–mol% conversion, and fragility increasing linearly with dissolved water content.

(7) AMS-B1 trachyte (Abeykoon et al., 2026): A hydrous model for this Campi Flegrei composition implementing two MYEGA variants: one with fixed $A \approx -5.01$ and one with A varying with H₂O content as $A \approx -2.22 - 2.85 \cdot 0.40^x$, where x is H₂O in mol%. In both variants, $T_g(\text{H}_2\text{O})$ follows Eq. 2 and fragility increases linearly with dissolved water. The wt%–to–mol% conversion uses a linear empirical calibration.

For all compositions, the module displays the reference composition on an interactive TAS diagram (except Peridotite), together with the MYEGA parameter table. Upon calculation, three figures are produced: (i) viscosity as a function of temperature at the specified

water contents (or compositional parameter values), showing both the linear $m(\text{H}_2\text{O})$ model and the constant m model as solid and dotted lines respectively; (ii) T_g and m as a function of the independent variable, displayed on a shared axis with a secondary fragility axis, showing both the linear and constant m parameterisations; and (iii) $\log_{10}\eta$ at a user-specified fixed temperature as a function of the independent variable, again comparing both fragility treatments (Fig. 5). Individual figures and an Excel file containing all viscosity curves with embedded MYEGA formulas are available for download.

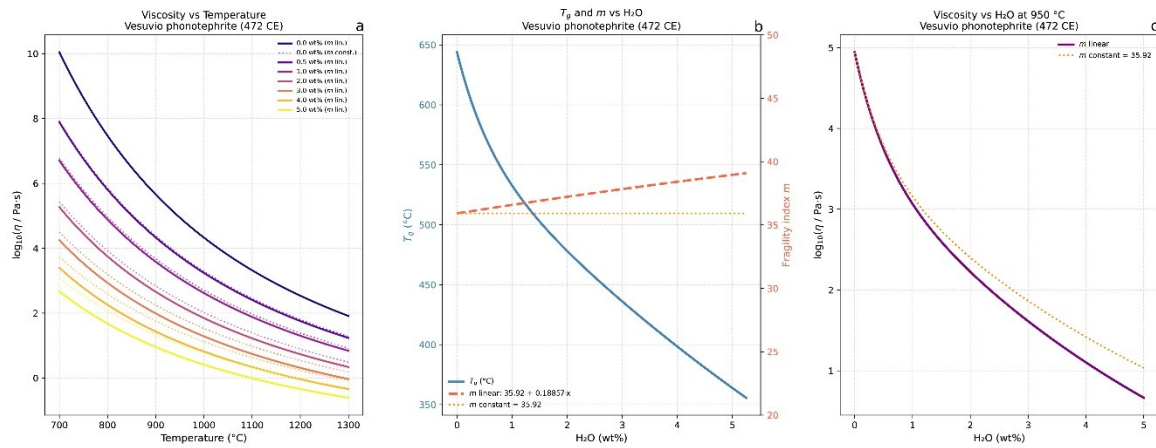


Figure 5. (a) Viscosity modelling outputs from Module 3 (Specific Composition Models) for the Vesuvius 472 CE phonotephrite (Dominijanni et al., 2026). (a) Melt viscosity $\log_{10}\eta$ (η in Pa·s) as a function of temperature for H₂O contents of 0–5 wt.%, computed using a linearly varying fragility $m(\text{H}_2\text{O})$ (solid lines) and constant m (dotted lines). (b) Glass transition temperature T_g (°C, blue, left axis) and fragility index m (orange/red, right axis) as a function of H₂O content, showing the linear m parameterisation (dashed red line: $m = 35.92 + 0.18857 \cdot x$, where x is H₂O in mol%) and the constant m model (dotted orange line: $m = 35.92$). (c) Melt viscosity $\log_{10}\eta$ (η in Pa·s) at the estimated eruptive temperature of 950 °C as a function of dissolved H₂O content, comparing the linear m model (solid purple line) and constant m model (dotted orange line). All MYEGA curves use $A = -2.9$ (Langhammer et al., 2022).

3. Computational workflow and algorithms

3.1. ANN inference pipeline

The ANN architecture and training follow Langhammer et al. (2022). The network consists of two hidden layers with 256 and 208 neurons, respectively, using the leaky ReLU

activation function ($\alpha = 0.3$). The output layer returns a single value ($\log_{10}\eta$, with η in Pa·s). The model was trained using the Adam optimiser with AMSGrad on a database containing 3,194 training/validation points and 288 test points. In MELVIS, the original TensorFlow SavedModel is deployed in TensorFlow Lite format, which is architecturally equivalent but optimised for lightweight inference and loaded once at application startup via a cached resource.

The ANN input vector consists of 15 features: temperature, the mole fractions of 12 oxides (SiO_2 , TiO_2 , Al_2O_3 , FeO , MnO , MgO , CaO , Na_2O , K_2O , P_2O_5 , Fe_2O_3 , H_2O ; note that Cr_2O_3 is included in the user input but excluded from the ANN input vector, consistent with the original model architecture), the structural modifier SM, and the alkali ratio $\text{K}_2\text{O}/(\text{Na}_2\text{O} + \text{K}_2\text{O})$. All 15 features are standardised prior to inference. Temperature is first normalised by dividing by the maximum temperature in the training dataset (2023 K, corresponding to the Ne375 composition), and then z-score standardised along with all other input features, using the mean and variance of the training dataset.

ANN inference is used inversely to generate synthetic viscosity–temperature data points: for a given composition, the bisection method is applied in the standardised temperature space to find the temperature corresponding to each target $\log_{10}\eta$ value. The physical temperature search bracket of 300–3000 K is mapped to its standardised equivalents and bisection iterates until the residual between the predicted and target viscosity is less than $10^{-3} \log_{10}$ (compared to 10^{-5} used in the original implementation of Langhammer et al., 2022). The recovered temperatures are then back-transformed to Kelvin. The resulting synthetic $(T, \log_{10}\eta)$ pairs are subsequently fitted with the MYEGA equation to extract T_g and m (Section 3.2).

3.2. MYEGA fitting procedure

The two-parameter MYEGA equation (Eq. 1) with $A = -2.9$ fixed is fitted to the ANN-derived synthetic $(T, \log_{10}\eta)$ data pairs using `scipy.optimize.curve_fit` with initial guesses $T_g = 900$ K and $m = 30$, and bounds constraining both parameters to positive values. Since bounds are specified, the underlying algorithm is the Trust Region Reflective method rather than Levenberg–Marquardt. The fit yields T_g and m for the anhydrous composition (or for each hydrous composition in Module 2), which are then used to reconstruct smooth viscosity–temperature curves via Eq. 1.

For the $T_g(\text{H}_2\text{O})$ parameterisation in Module 2 (Eq. 2), a different strategy is employed because the three-parameter objective surface (b, c, d) contains multiple local minima that make gradient-based methods unreliable. A grid search over 150 combinations of initial values ($b_0 \in \{0.05, 0.1, 0.2, 0.3, 0.5, 1.0\}$, $c_0 \in \{0.5, 1.0, 1.5, 2.0, 3.0\}$, $d_0 \in \{-3.0, -2.0, -1.5, -1.0, -0.5\}$) is performed, and each starting point is refined by Nelder–Mead minimisation of the RMSE between the ANN-derived T_g values and the model predictions, with the physical constraint $b > 0$ enforced. The best solution across all starting points is retained, and early termination is applied if $\text{RMSE} < 0.5$ K is achieved. The anhydrous $T_{g,d}$ is held fixed at the ANN-derived value and is not a free parameter in this fit.

For the exponential saturation fragility model $m(x_{\text{H}_2\text{O}})$ (Eq. 5), fitting is also performed via a grid search over 30 combinations of initial values ($m_{\text{inf},0} \in \{0.5m_d, 0.6m_d, 0.7m_d, 0.8m_d, 20, 25\}$, $k_0 \in \{0.1, 0.2, 0.3, 0.5, 1.0\}$), each refined by `scipy.optimize.curve_fit` (Trust Region Reflective) with bounds $0 < m_{\text{inf}} < m_d - 0.1$ and $10^{-4} < k < 10$. The best solution by RMSE is retained. If no solution converges within the specified bounds, the model falls back to a linear anchored approximation with $m_{\text{inf}} = 0.7m_d$ and $k = 0.2$.

4. Verification and example applications

4.1. ANN module verification

The ANN implemented in MELVIS reproduces the performance reported in Langhammer et al. (2022), from which the model weights are taken without modification. The raw ANN achieves $\text{RMSE} = 0.09$ and $0.12 \log_{10}$ on the training and validation sets (3,194 points), respectively, and $\text{RMSE} = 0.45 \log_{10}$ on an independent test set (288 points), compared to $\text{RMSE} = 0.89$ (HZ) and 1.23 (GRD) on the same test set. The synthetic MYEGA model, which constrains the η – T relationship to a physically motivated functional form, achieves $\text{RMSE} = 0.20 \log_{10}$ on the training/validation set and $\text{RMSE} = 0.52 \log_{10}$ on the test set (Langhammer et al., 2022).

To facilitate user-level verification, MELVIS provides two built-in tools. First, a default example dataset of 19 well-characterised volcanic compositions (Table S1) spanning the range from basanite to rhyolite is pre-loaded in Module 1, allowing users to immediately reproduce published viscosity curves without supplying their own data (Clocchiatti et al., 1994; Di Fiore et al., 2022; Di Genova et al., 2017, 2014, 2013; Giordano and Dingwell, 2003; Hofmeister et al., 2016; Iacono Marziano et al., 2007; Morrison et al., 2020, 2019; Richet et al., 1996; Romano et al., 2003; Sehlke and Whittington, 2016, 2015; Stabile et al., 2016; Vetere et al., 2007). Second, the downloadable Excel output includes the MYEGA equation embedded as a live spreadsheet formula, enabling users to independently recalculate $\log_{10}\eta$ at any temperature directly from the exported T_g and m values and confirm consistency with the application output.

Users are advised to verify that their input compositions fall within the chemical training domain of the Langhammer et al. (2022) model before interpreting results. Compositions that are strongly anomalous relative to the training database — such as highly reduced melts, carbonate-rich compositions, or compositions with unusually high Cr_2O_3 — may yield unreliable ANN predictions, and the application does not currently implement an explicit domain boundary check.

4.2. Specific composition example: metaluminous/peralkaline haplogranite HPG8

The metaluminous-to-peralkaline haplogranite HPG8 (Stopponi et al., 2026) is selected here as the illustrative example for Module 3 because it showcases a compositional regime and a MYEGA formulation that are fundamentally different from all other entries in the module. Unlike the hydrous volcanic compositions discussed in sections 2.4 and 4.3, HPG8 is an anhydrous system in which the independent variable is excess Na_2O content in mol% ($x = 0$ –20 mol%), representing the progressive peralkalinity of the melt. Moreover, the pre-exponential MYEGA term A is not fixed but varies with composition as $A(x) = -1.55 - 6.35 \cdot 0.55^x$.

To reproduce this example, the user selects "Anhydrous metaluminous and peralkaline haplogranitic melts — Stopponi et al. (2026)" from the Module 3 dropdown and sets $T_{\min} = 700$ °C, $T_{\max} = 1500$ °C, excess Na_2O values of 0, 5, 10, 15, 20 mol%, and a fixed temperature of 800 °C for the viscosity vs composition panel. Three figures are produced upon calculation (Fig. 6).

The viscosity–temperature panel (Fig. 6a) shows that increasing excess Na_2O from 0 to 20 mol% dramatically reduces melt viscosity across the entire temperature range, from 10^{12} Pa·s near T_g at metaluminous conditions to values approaching low-viscosity melts at high peralkalinity. This reflects the combined effect of decreasing T_g — from 760.8 °C at $x = 0$ to 489.5 °C at $x = 20$ mol% — and increasing fragility from $m = 22.95$ at $x = 0$ to $m = 36.95$ at $x = 20$ mol% (Fig. 6b). The simultaneous decrease in T_g and increase in m with peralkalinity reflects the depolymerising role of excess Na_2O on the haplogranitic network (Stopponi et al., 2026). At the fixed temperature of 800 °C (Fig. c), viscosity decreases by approximately 7 log units from metaluminous ($x = 0$) to the most peralkaline composition ($x = 20$ mol%), demonstrating the sensitivity of melt mobility to alkali excess at magmatic temperatures relevant to peralkaline silicic volcanism.

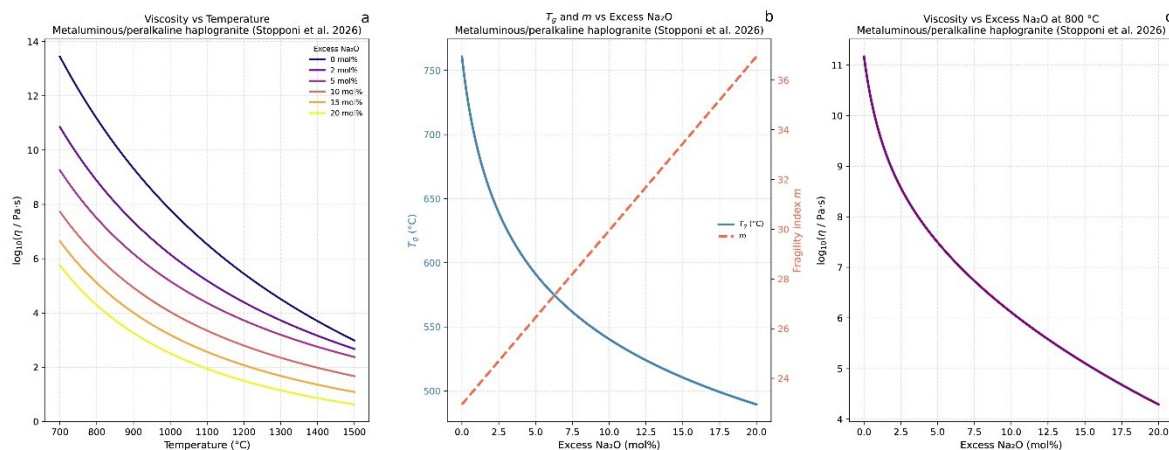


Figure 6. Viscosity modelling outputs from Module 3 (Specific Composition Models) for the metaluminous-to-peralkaline haplogranite HPG8 (Stopponi et al., 2026), as a function of excess Na₂O content ($x = 0$ –20 mol%). (a) Melt viscosity $\log_{10}\eta$ (η in Pa·s) as a function of temperature (700–1500 °C) for excess Na₂O contents of 0, 5, 10, 15, and 20 mol%. The pre-exponential MYEGA term A varies with composition as $A(x) = -1.55 - 6.35 \cdot 0.55^x$. (b) Glass transition temperature T_g (°C, left axis) following $T_g(x) = 1034 \cdot (1 + x)^{-0.1}$ K, and fragility index m (right axis) following $m(x) = 22.95 + 0.70 \cdot x$, both as functions of excess Na₂O content. T_g decreases while m increases with peralkalinity, reflecting the depolymerising effect of excess Na₂O on the haplogranitic melt structure. (c) Melt viscosity $\log_{10}\eta$ (η in Pa·s) at 800 °C as a function of excess Na₂O content, illustrating the strong compositional control on melt mobility at magmatic temperatures relevant to peralkaline silicic volcanism. All curves are computed from the calibration of Stopponi et al. (2026).

4.3. Fragility–water parameterisation and its effect on eruptive viscosity: Stromboli

basalt

Stromboli basalt is chosen for this comparison for a specific and important reason: its viscosity was first characterised by Misiti et al. (2009) using conventional viscometry, and those data were subsequently incorporated into the training databases of the Langhammer et al. (2022) ANN. The viscosity data of Misiti et al. (2009) are therefore directly embedded in the global ANN model that underlies MELVIS Module 2. Valdivia et al. (2023) later reinvestigated the same composition using a combination of DSC-derived viscosities, Brillouin spectroscopy, and analysis of nanocrystallization and/or water-loss effects, producing a revised, artefact-free parameterisation that forms the basis of the Module 3 entry. The availability of two independent calibrations for the same composition — one potentially

contaminated by nanocrystallization and/or water-loss artefacts and embedded in global models, one corrected for these effects — makes Stromboli basalt uniquely suited to quantify how artefact-affected training data propagate into viscosity predictions at eruptive conditions, and to test the practical consequences of different fragility–water assumptions.

The Stromboli composition is entered in Module 2 ("Anhydrous and Hydrous Modelling", Fig. 7a,b) to generate ANN-based viscosity–water curves under three fragility parameterisations, and the same composition is then accessed via Module 3 ("Specific Composition Models", Fig. 7c) to retrieve the artefact-free calibration of Valdivia et al. (2023). All results are compared at the eruptive temperature of 1150 °C across a water content range of 0–5 wt.%.

Module 2 produces three viscosity–H₂O curves at 1150 °C (Fig. 7a), each corresponding to a different fragility model. Under model (i), fragility is held constant at $m = 41.1$, the anhydrous value returned by the ANN for this composition. Under model (ii), fragility decreases with water content following Eq. 4 (Langhammer et al., 2021), approaching $m \approx 35$ at 5 wt.% H₂O. Under model (iii), fragility approaches approximately 36 at 5 wt.% H₂O following the exponential saturation fit (Eq. 5) applied to ANN-derived m values at each discrete water content, with fitted parameters. At 5 wt.% H₂O and 1150 °C, the three models predict viscosity values of $10^{-0.22}$, $10^{0.34}$, and $10^{0.32}$ Pa·s respectively, corresponding to viscosity ratios relative to the anhydrous value ($10^{2.46}$ Pa·s) of 479-fold, 132-fold, and 138-fold. The spread among the three curves directly quantifies the uncertainty introduced by the choice of fragility parameterisation alone, independently of any compositional uncertainty.

Figure 7b shows the underlying fragility–water relationships for the three models. Two models (ii and iii) exhibit a monotonically decreasing m with increasing H₂O content, as imposed by the ANN model inference combined with the constraints described in Section 3.2. The same monotonic decrease of m with dissolved water is built into widely used global

parameterisations: the GRD model of Giordano et al. (2008), for instance, predicts a systematic reduction in both T_g and m with increasing volatile content. As discussed in recent literature (Valdivia et al., 2023; 2025; Stopponi et al., 2026 and references therein), this apparent decrease is likely an artefact of nanocrystallization and/or water loss during conventional viscometry around T_g , which systematically inflate viscosity measurements and thus produce an artificially steep fragile-to-strong transition. Configurational heat capacity data, Brillouin spectroscopy, and melt dynamics studies predominantly indicate that melt fragility either remains approximately constant or increases with dissolved water content (Cassetta et al., 2021; Fanesi et al., 2025; Stopponi et al., 2026; Valdivia et al., 2023). The spread among the three Module 2 fragility curves, therefore, reflects both the potential influence of experimental artefacts on the calibration data (models ii and iii) and the choice of a physically based fragility parameterisation that holds (at least) m constant (model i). This constitutes an irreducible epistemic uncertainty that cannot be resolved without independent spectroscopic or calorimetric constraints on $m(\text{H}_2\text{O})$.

Figure 7c shows the viscosity curve from Module 3, which uses the artefact-free calibration of Valdivia et al. (2023): a constant fragility of $m = 40.7$ — spectroscopically, viscometrically, and DSC validated — combined with the $T_g(\text{H}_2\text{O})$ parameterisation of Eq. 2. At 5 wt.% H_2O and 1150 °C, this model predicts $10^{-0.14}$ Pa·s, compared to $\approx 10^{0.33}$ Pa·s from the two ANN-based curves in Module 2, where fragility decreases upon water dissolution. Notably, the anhydrous ANN fragility ($m = 41.1$) and the Valdivia et al. (2023) spectroscopic value ($m = 40.7$) differ by 0.4 units, which is within the stated uncertainty of the ANN (Langhammer et al., 2022), confirming the consistency of the two approaches at anhydrous conditions.

Fig. 7 demonstrates the complementary value of the two modules: Module 2 provides a rapid, chemistry-agnostic assessment of how viscosity responds to water dissolution under

different fragility assumptions, while Module 3 delivers a physically grounded, artefact-free prediction for systems where nanocrystallization during viscometry is a documented concern. The ability to overlay and compare these outputs within a single application is one of the principal design objectives of MELVIS.

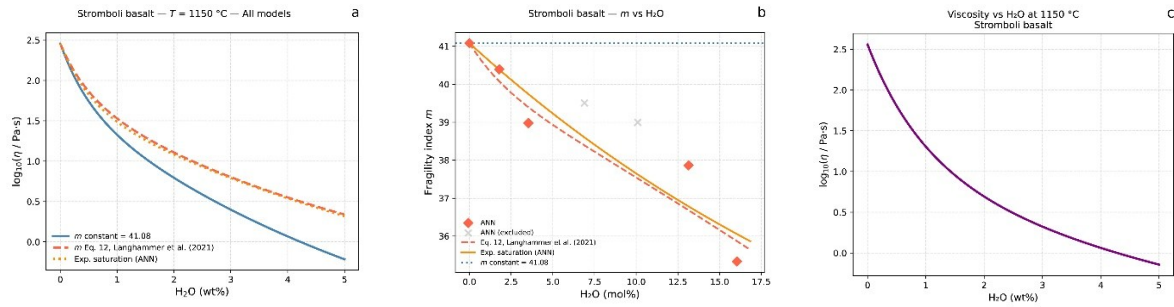


Fig. 7. Comparison of hydrous viscosity predictions at the eruptive temperature of 1150 °C for the Stromboli basalt (Valdivia et al., 2023). (a) Melt viscosity $\log_{10}\eta$ (η in Pa·s) as a function of dissolved H₂O content (0–5 wt.%) computed by Module 2 (Anhydrous and Hydrous Modelling) under three fragility parameterisations: constant $m = 41.1$ (model i), m decreasing with H₂O following Eq. 4 (model ii; Langhammer et al., 2021), and m following an exponential saturation fit to ANN-derived values (model iii; Eq. 5). The spread among the three curves quantifies the epistemic uncertainty introduced by the choice of fragility–water assumption alone. (b) Fragility index m as a function of H₂O content for the three Module 2 models. Models ii and iii show a monotonically decreasing trend with increasing H₂O content, reflecting the behaviour of viscosity models calibrated on conventional viscometry data potentially affected by nanocrystallization and/or water-loss artefacts. (c) Melt viscosity $\log_{10}\eta$ (Pa·s) at 1150 °C as a function of H₂O content from Module 3 (Specific Composition Models), using the artefact-free calibration of Valdivia et al. (2023): constant fragility $m = 40.7$ combined with the Langhammer et al. (2021) $T_g(\text{H}_2\text{O})$ parameterisation (Eq. 2). The anhydrous viscosities from Module 2 ($m = 41.1$) and Module 3 ($m = 40.7$) are mutually consistent within ANN uncertainty (Langhammer et al., 2022), while predictions diverge with increasing H₂O content due to the different fragility–water assumptions. All MYEGA curves use $A = -2.9$ (Langhammer et al., 2022).

5. Discussion

5.1. Advantages of an integrated platform

MELVIS addresses a practical need in the volcanological community by combining three complementary modelling approaches within a single, browser-accessible interface. Existing web-based tools estimate the viscosity of individual compositions at specified temperatures, but none offers hydrous modelling with user-adjustable fragility, artefact-

corrected composition-specific calibrations, or batch processing of multi-sample datasets in one environment. MELVIS combines these capabilities in one platform, reducing data transfer between tools.

The ANN module (Module 1) enables rapid viscosity estimation across a broad chemical space, from foidite/basanite to rhyolite, including hydrous compositions. Its batch processing mode accepts multi-sample CSV files and returns viscosity curves, T_g and m values, and a TAS diagram for all samples simultaneously. The TAS diagram is coloured by a user-selected rheological property — T_g , fragility index m , or $\log_{10}\eta$ at a fixed temperature — allowing compositional and physical property information to be visualised jointly across a suite of samples, a capability not available in existing viscosity tools. All results are exported to structured Excel files in which the MYEGA equation is embedded as a live spreadsheet formula, enabling users to independently recalculate viscosities at any temperature directly within their own workflows without any programming.

The hydrous modelling module (Module 2) allows researchers to parameterise $T_g(\text{H}_2\text{O})$ and $m(\text{H}_2\text{O})$ from ANN-derived data and to compare three physically distinct fragility–water models side by side, propagating each into viscosity–temperature– H_2O surfaces. This explicit treatment of fragility modulation is particularly relevant for assessing how experimental artefacts in viscometry data affect model predictions, as discussed in Section 4.3.

The specific composition library (Module 3) provides access to the most recent experimentally validated, nanocrystallization-free viscosity models for key volcanic systems. The module is designed for extensibility: adding a new composition requires only defining a Python dictionary of MYEGA parameters and their water-content dependencies. New models from ongoing experimental campaigns can therefore be incorporated rapidly as they are published.

The web-based deployment via Streamlit removes all barriers associated with software installation, dependency management, and platform compatibility — users access MELVIS from any browser without installing Python or any library. For advanced users and for long-term reproducibility, the full source code is openly available on GitHub and archived on Zenodo with a permanent DOI (<https://doi.org/10.5281/zenodo.19945908>). The requirements.txt lists all dependencies needed to reproduce the application locally (with numpy constrained to versions below 2 for interpreter compatibility).

5.2. Limitations and future directions

Several limitations of the current implementation should be acknowledged to guide the appropriate use of MELVIS.

Training domain boundaries. The ANN of Langhammer et al. (2022) is inherently interpolative, and predictions for compositions outside the training database may be unreliable. The approximate training domain spans $\text{SiO}_2 = 37\text{--}80$ wt.% and $\text{H}_2\text{O} = 0\text{--}6$ wt.% for most compositions. MELVIS currently does not implement an automated domain-boundary check: the application will return a numerical result for any input composition without warning the user if that composition is chemically anomalous relative to the training set.

Iron redox assumption. When only total iron is provided (as either FeO or Fe_2O_3 alone), MELVIS redistributes it. Since FeO and Fe_2O_3 exert different structural roles in silicate melts (Chevrel et al., 2013; Kolzenburg et al., 2018; Mysen et al., 1980), the magnitude of the resulting viscosity error is composition-dependent and is not currently quantified by the application. Users working with compositions of known redox state are advised to specify both FeO and Fe_2O_3 explicitly.

Cr_2O_3 handling. Although Cr_2O_3 is accepted as an input oxide, its mole fraction is silently excluded from the ANN input vector, consistent with the original model architecture

of Langhammer et al. (2022). For ultramafic or mantle-derived compositions with significant Cr_2O_3 contents — such as komatiites or picrites — this exclusion introduces an unquantified compositional error in the normalised input vector. The training domain of the ANN does not cover these compositions well, regardless, but this limitation should be borne in mind.

Fragility–water parameterisation in Module 2. Of the three fragility models available in Module 2, two (models ii and iii) are constrained to be monotonically decreasing with water content, reflecting the empirical behaviour observed in conventional viscometry datasets that may be affected by nanocrystallization and/or water loss artefacts (Section 4.3), while the third (model i) holds fragility constant at the anhydrous value. Consequently, none of the Module 2 models can currently capture an increase in fragility with dissolved water — behaviour that is physically expected and experimentally supported by spectroscopic measurements for several compositions (Cassetta et al., 2021; Valdivia et al., 2023; Fanesi et al., 2025; Stopponi et al., 2026). For such systems, the composition-specific models of Module 3 provide the appropriate framework. A future direction is to allow Module 2 users to freely specify the sign and functional form of $m(\text{H}_2\text{O})$, including increasing or non-monotone parameterisations.

Numerical robustness of $T_g(\text{H}_2\text{O})$ fitting. The Nelder–Mead grid search used to fit the (Langhammer et al., 2021; Schneider et al., 1997) parameters (b , c , d) may not converge to a physically meaningful solution, particularly when the input water content array is sparse, irregular, or covers a narrow range. In such cases, the application falls back to a linear approximation, which may not adequately represent the curvature of $T_g(\text{H}_2\text{O})$. Users should inspect the RMSE of the T_g fit reported in the Excel output and treat results with $\text{RMSE} > 5 \text{ K}$ with caution.

Volatile species beyond H_2O . The ANN and all Module 3 models consider H_2O as the only dissolved volatile. The effects of dissolved CO_2 , Cl, F, and S on melt viscosity are not

accounted for. Integration of multi-volatile viscosity models is a natural future extension of MELVIS.

Pressure effects. All viscosity calculations in MELVIS assume ambient pressure. Pressure effects on silicate melt viscosity, which become significant at depths greater than a few kilometres for low-viscosity mafic melts (Liebske et al., 2005), are not currently implemented. This limits the applicability of MELVIS to near-surface and syn-eruptive conditions. Pressure-dependent viscosity models now exist (Duan, 2014; Le Losq et al., 2025) and can be used if necessary.

Multiphase rheology. MELVIS models the viscosity of bubble-free, crystal-free silicate melts. Natural magmas ascending through volcanic conduits commonly carry suspended crystals and/or bubbles, both of which modify the bulk rheology substantially. Established multiphase models (Costa et al., 2009; Kolzenburg et al., 2022; Vona et al., 2011) could be integrated in future releases as optional correction layers applied to the melt viscosity output, providing a more complete description of magma rheology under natural eruptive conditions.

6. Conclusions

MELVIS is an open-source, browser-based platform for computing the viscosity of volcanic and experimental silicate melts, developed to bridge the gap between recent advances in experimental volcanology — particularly the identification of nanocrystallization and water-loss artefacts in conventional viscometry — and their practical application in research and teaching workflows.

The platform integrates three complementary modelling approaches. The ANN module (Module 1) implements the trained network of Langhammer et al. (2022) and provides rapid viscosity estimation across a broad chemical space from basanite to rhyolite, with batch processing of multi-sample datasets, TAS-based classification coloured by rheological

properties, and reproducible Excel outputs with embedded MYEGA formulas. The hydrous modelling module (Module 2) allows users to parameterise $T_g(\text{H}_2\text{O})$ and to compare three fragility–water models side by side, making explicit how different assumptions about $m(\text{H}_2\text{O})$ propagate into viscosity predictions at eruptive temperatures — a capability not available in existing web-based viscosity tools. The specific composition library (Module 3) provides pre-calibrated, artefact-free MYEGA models for seven volcanic and experimental compositions spanning Stromboli basalt, Peridotite, Andesite, Colli Albani tephriphonolite, Vesuvius CE phonotephrite, Campi Flegrei trachyte AMS-B1, and metaluminous–peralkaline haplogranite HPG8.

The example applications presented in this paper demonstrate the practical consequences of model choice. For the Stromboli basalt, comparison between Module 2 and Module 3 shows that the choice of fragility parameterisation alone introduces substantial spread in the predicted viscosity–water relationship at eruptive temperature, underscoring that melt fragility modulation with dissolved water remains one of the primary sources of uncertainty in hydrous viscosity modelling.

MELVIS is freely accessible at <https://annviscositycalculator.streamlit.app/>, with full source code archived on GitHub and Zenodo (<https://github.com/DiGenovaDanilo/ViscosityCalculator> and <https://doi.org/10.5281/zenodo.19945908>) to ensure long-term reproducibility. Future developments will focus on automated training-domain boundary checking, integration of multi-volatile effects (CO_2 , Cl, F), and multiphase rheology corrections for crystal- and bubble-bearing magmas. The modular architecture of the platform is designed to accommodate new composition-specific models as they emerge from ongoing experimental campaigns, and contributions from the community are welcomed through the GitHub repository.

Code availability

MELVIS is open-source software available at:

Online deployment: <https://annviscositycalculator.streamlit.app/>

Zenodo archive: <https://doi.org/10.5281/zenodo.19945908>

GitHub repository: <https://github.com/DiGenovaDanilo/ViscosityCalculator>

The application is implemented in Python 3.11 and depends on the following libraries: streamlit, tflite-runtime, numpy (<2), pandas, matplotlib, scipy, openpyxl, pyrolite, plotly, and streamlit-plotly-events. The trained ANN is distributed as a TensorFlow Lite file (model.tflite) and loaded through the tflite-runtime interpreter. The repository includes all source code, the model.tflite file, and a requirements.txt listing the dependencies for local deployment.

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