Deep Mining 2024 – P Andrieux & D Cumming-Potvin (eds)

doi:10.36487/ACG_repo/2465_63

Responsive short-term seismic forecasting: a web-based tool for mining efficiency and safety

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Abstract

Predicting the rock mass response to future mining is crucial for ensuring the safety and efficiency of operations in seismically active mines. Long-term forecasts often rely on historical seismic data and various inputs that may be available such as faults, geology, mining sequences, stress measurements and numerical modelling. Short-term predictions – spanning a few days to a week – demand a more dynamic and responsive approach. This paper introduces an online web application based on a hierarchical Bayesian prediction model tailored for continuously updated short-term seismic activity forecasts. Further, the activity can easily serve as inputs to post-processing analysis such as hazard assessments while preserving prediction uncertainties.

The approach integrates recent seismic activity, production plans, depth, size of production, and a seismic exposure term within different volumes of the mine and lets them share information through a hierarchical model structure. Notably, for short-term predictions, many covariates considered in long-term forecasts are constant and summarised by an overall seismic exposure term in each volume.

Implemented as an online web application, this model provides direct seismic insights to personnel across various devices, from control room displays to smartphones. Its dynamic interface visualises historical and predicted seismic activity with prediction intervals, empowering decision-makers for safe and efficient mine operations. This study highlights the effectiveness of combining online web applications and robust Bayesian methods, enhancing safety protocols and operational efficiency in seismically active mines.

Keywords: *short-term forecast, mine seismic activity, mining seismicity, production plans, web application, hierarchical Bayesian model*

1 Introduction

It is a challenge to forecast rock mass response to mining activities, especially in seismically active environments, to ensure operational safety and efficiency. Traditional long-term forecasts rely on historical seismic data and various inputs, while short-term predictions – crucial for day-to-day operations – require a more dynamic approach. The dynamic behaviours associated with past mining-induced seismicity were investigated in Polish mines by Węglarczyk & Lasocki (2009) through the evaluation of the auto-correlation function. However, in this paper, the focus lies on employing a model that incorporates the dynamic characteristic within its structure to enhance prediction accuracy. A straightforward approach to capture this dynamic behaviour is by implementing an autoregressive model where the seismic activity from the previous week is included as a predictor.

The contribution in this paper lies in the development of a computationally fast implementation of the hierarchical Bayesian prediction model presented earlier in Martinsson & Törnman (2020) and a web application user interface. The model, which is finely tuned for continuously updated short-term seismic activity forecasts, integrates a multitude of factors such as recent seismic activity (one day or one week for

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daily or weekly forecasts, respectively), production plans, depth, size of production, and seismic exposure within different volumes of the mine.

Unlike the focus in Martinsson & Törnman (2020), the emphasis here lies on the predictive capabilities of the model rather than drawing conclusions from model parameters or inferring similarities between orebodies. Additionally, attention is dedicated to the dynamic functionality enabling on-demand generation of new forecasts based on varying user preferences. Validation of the proposed model is also presented, as described in Martinsson & Törnman (2020), based on testing in two underground mines; one with volumes associated to specific orebodies and another with volumes associated to blocks within a larger orebody.

Geotechnical engineers often focus on various mine volumes experiencing different expressions of mining-induced seismicity. These variations may stem from factors like geology, spatial location (e.g. hanging wall, footwall, or sidewall), hazard zones, stress conditions, rock quality, mining depth, and volumes responding to production differently. The volume-based approach has the benefit of being sensitive to local conditions and distinct responses to mining activities, allowing granularity that a single mine-wide volume can obscure.

On the other hand, treating each volume individually ignores similarities between volumes and prevents the use of such similarities in the prediction, if they are present. This higher-level relationship implies the suitability of hierarchical modelling proposed in Martinsson & Törnman (2020). With this approach, the model parameters for each volume are viewed as a single observation drawn from a broader distribution representing the collective behaviour of all volumes in the mine. This allows leveraging of similarities across volumes, enhancing prediction accuracy and efficiency, particularly in scenarios with sparse data (for example see Kruschke 2014; Gelman & Hill 2007; Gelman et al. 2004 for an overview of hierarchical and multilevel modelling).

Moreover, the hierarchical model incorporates dynamic behaviours of seismic activity, such as autoregression, enabling better predictions by accounting for past activity. By including commonly available predictors like weekly production, recent seismicity, mining depth, and production size, this model facilitates short-term seismicity predictions with realistic uncertainties, empowering decision-makers to customise production rates while mitigating risks related to induced seismicity.

Importantly, this study emphasises practical applicability by focusing on data commonly available in most mines that have a seismic system installed (i.e. measured seismic activity and production plan), making our proposed model relevant and feasible for similar settings. While deeper insights into underlying causes and correlations are valuable, the objective remains to provide a practical approach with actionable forecasts for enhanced safety protocols and operational efficiency in seismically active mines.

2 Methodology

The following sections provide a short overview of the model proposed in Martinsson & Törnman (2020), the estimation and prediction aspects of seismic activity, and the implementation of the model as an online dynamic web application.

2.1 Modelling mining-induced seismic activity

Figure 1 provides an overview of the proposed three-level hierarchical Bayesian model outlined in Martinsson & Törnman (2020), following the structure described by Kruschke (2014). This figure presents the complete hierarchy, summarising the model using simple graphs and figures without extensive notations of distributions and dependencies between parameters. For detailed guidance on how to implement the model, refer to resources like Kruschke (2014) for explanations. The choice of model structure and distributions follow standard practices in Bayesian hierarchical modelling (Kruschke 2014; Gelman & Hill 2007; Gelman et al. 2004) including standard notations to match the structure of this model more easily with standard models found in these references.

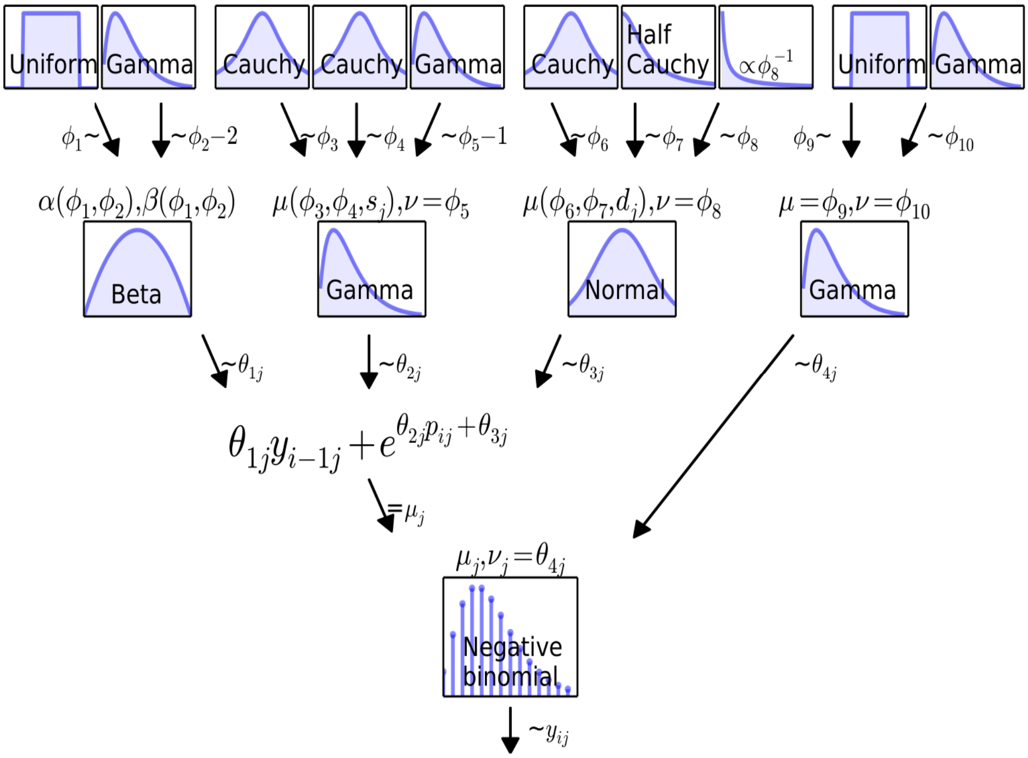

Figure 1 Overview of the three-level hierarchical Bayesian model. This figure has been adapted from previous work by Martinsson & Törnman (2020) where it was originally published. The first level (bottom part) shows the individual model for each volume. The second level (middle part) shows the prior distributions for the parameters at the first layer and describes the mine-wide distribution, i.e. the distribution of the group of volumes. The third level (top part) shows the hyperprior distributions for the parameters in the prior distributions at the second level

The following is a summary of the layers in the hierarchical model. For a more detailed explanation including an extensive model validation, refer to Martinsson & Törnman (2020).

2.1.1 First level

At the first level of the hierarchy, individual models are established for each volume in the mine, characterised by model parameters denoted by θ. These models describe the observed seismic activity, represented by y_{ij}, which denotes the number of detected events per time interval within the ith time interval and the jth volume. Given the model parameters θ_j and covariates, y_{ij} is assumed independent and negative binomially distributed

$$y_{ij} \sim NB(\mu_j, \nu_j) \tag{1}$$

where

$$\mu j = \theta_{1j}\, y_{i-1,j} + \exp(\theta_{2j}\, p_{ij} + \theta_{3j}) \tag{2}$$

$$\nu_j = \theta_{4j} \tag{3}$$

This distribution is specified in terms of the mean value μ_j and the dispersion parameter ν_j, making it suitable for regression analysis (Hilbe 2011). The model parameters have specific interpretations: θ_{1j} describes the seismic decay, θ_{2j} represents the multiplicative effects of the production, θ_{3j} captures the seismic exposure term, and $\nu_j = \theta_{4j}$ denotes the dispersion parameter. These models are applied over observed time intervals (i.e. i = 1, 2, . . . , n_j) across different volumes (i.e. j = 1, 2, . . . , J). Additionally, within the jth volume, the covariates include the seismic activity measured from the prior time interval $y_{i-1,j}$ and the estimated cumulative rock mass (tonnes) retrieved by production blasts p_{ij} during the current time interval.

2.1.2 Second level

The second level of the hierarchy encapsulates mine-wide characteristics, setting prior distributions for level one parameters with hyperparameters denoted by ϕ. Unlike non-hierarchical models, this model estimates second level parameters and the group-level predictors production depth d_j and production size s_j, revealing similarities within volume groups. This shared mine-wide information enhances estimation accuracy at the individual level and is crucial for robust estimation in data-poor volumes.

2.1.3 Third level

At the third level, prior distributions for hyperparameters are defined, finalising the hierarchical structure.

2.2 Estimating and predicting mining-induced seismic activity

The inference process relies on Markov Chain Monte Carlo (MCMC) methods (Gelman et al. 2004; Kruschke 2014; Chen et al. 2000), offering realistic estimates of posterior predictive intervals. Slice sampling (Neal 2003) is employed and inference is derived from 10,000 samples drawn from the posterior distribution with converged chains. In Martinsson & Törnman (2020), 100,000 samples were utilised for analysis, but here this number is reduced to one-tenth to shorten computational time.

2.3 Model implementation, deployment and visualisation

The Bayesian computations described in Martinsson & Törnman (2020) were originally implemented in Python but are implemented here in Julia (Bezanson et al. 2017) for faster computations.

The seismic events used in the application are from Luossavaara-Kiirunavaara AB's (LKAB) underground iron ore mines in Kiruna and Malmberget, Sweden, and are automatically processed by RockSigma's compute engine BEMIS (for example, see Martinsson 2013; Törnman & Martinsson 2020). Using default settings, blasts and mining noise are automatically removed by the BEMIS classifier. The mine volumes are defined by LKAB using mXrap software (Harris & Wesseloo 2015) and exported and provided in JSON format. Currently, these volumes are bundled within the application, but future versions may enhance flexibility by allowing users to upload their own defined volumes. Production blasts and events inside each volume are considered in the modelling and prediction.

The seismic activity forecasting is implemented as a dynamic online web application for continuous insights accessible to engineers and support personnel on multiple devices, ranging from control room displays to smartphones. The objective is to provide practical and easy access to continuous forecasts without any software installation. The application is built using the open source libraries Dash and Plotly (Hossain 2019; Sievert 2020) and deployed as a docker container on LKAB's on-premises Kubernetes cluster known as LOMI.

3 Results

Figure 2 shows the user interface of the web application, illustrating recent historical seismic activity and seven-day forecasts for three distinct volumes of interest within LKAB's underground iron ore mine in Kiruna.

Each volume is represented by two columns in one row. The left column shows for the past week:

- Observed (actual) seismic activity as cyan dots (events/week).
- Forecast activity (events/week), median as a red line, and 50 and 95% prediction intervals as pink and blue areas, respectively.
- Production (tonnes) as a green staircased line.

This combination of data enables intuitive visual validation of the model's performance against past data.

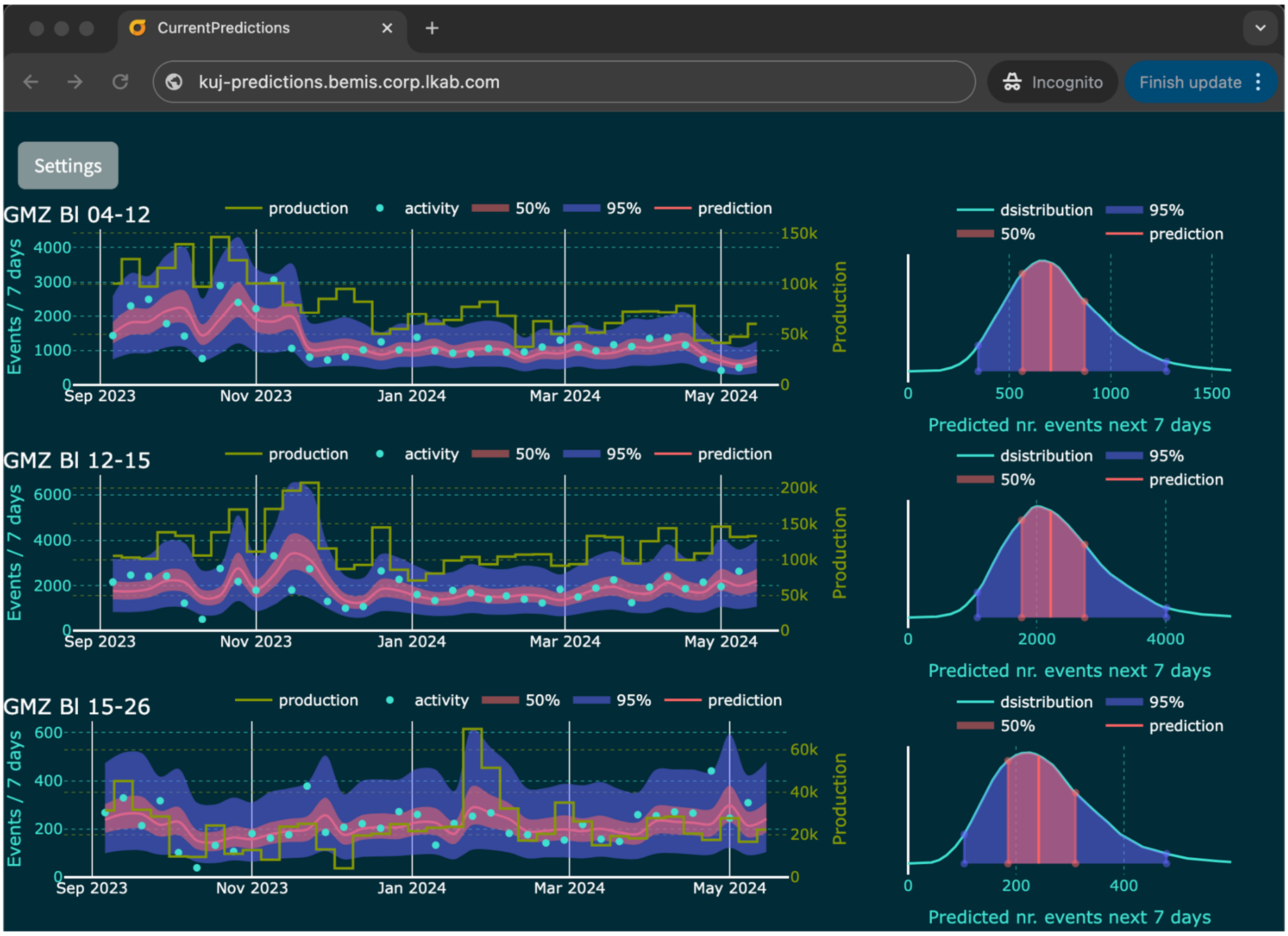

Figure 2 **User interface overview of the web application deployed at LKAB visualising seismic activity, production, and activity forecasts in three volumes in the Kiruna mine (three out of seven volumes shown for readability). Each row represents one mine volume. The left column shows observed weekly activity (number of events, cyan dots) together with the median prediction (number of events, red line) and 50 and 95% prediction intervals as pink and blue areas, respectively. The green staircased line represents production (tonnes) in the volume with values corresponding to the right y-axis in green. The right column displays the forecast distribution for the coming week (also shown in the rightmost section of the left figure, where the cyan dot for observed seismicity is missing).**

Additional details such as event counts, predictions, prediction intervals, are designed to be interactively accessed by hovering over the posterior predictive distribution and the historical observation figure.

The right column displays the forecast for the coming week using the full predictive distribution along with prediction intervals. Looking closely in the left column, the forecast is also visible at the rightmost end of the graph where the cyan dot for observed seismicity is missing.

The proposed layout incorporates continuous quality assurance, including back-analysis, in one view, to instil confidence in the forecast of future seismic activity.

The application is interactive and a user can trigger customised forecasts based on different user settings. Changes will start a new forecast to be computed on the server and received by the user. The turnaround time between triggering and receiving a new customised forecast is around one minute but may be reduced with parallelisations combined with more computational resources. Currently, the users can choose two different time periods to do forecasts: one-day or seven-day prediction of the activity.

The one-day forecasts are shown in Figure 3 and here we have limited the number of datapoints used in the computations to a maximum of 90 points per volume to reduce computational time. Additionally, the maximum location error of the events retrieved from RockSigma's compute engine BEMIS (www.rocksigma.com) can be adjusted, as well as the magnitude range. Increasing the maximum location error means that more uncertain events can be used in the estimation and prediction step, with the possibility of increasing the amount of input data if data is sparse, depending on instrumentation or activity. Adjusting the magnitude range will include only the events within a certain magnitude range as input to the forecasts. This may be useful in exploring data violating the Gutenberg Richter relationship (Gutenberg & Richter 1944).

Figure 3 Daily forecasts. Visualising seismic activity, production, and activity forecasts in the first three (out of seven) volumes in the Kiruna mine. See Figure 2 for a detailed explanation of the elements of the graphs

Figure 4 provides an overview of daily forecasts at LKAB's mine in Malmberget. In the Malmberget mine, there are a total of 12 volumes of interest, some with little to no observed activity or production. In fact, there are only three volumes with an average daily event count above 10. Naturally, with few events in a volume, a relationship with the production is difficult to infer. Here, the robustness and strength of hierarchical modelling is shown, providing valid predictions in scenarios with sparse data (Martinsson & Törnman 2020). Although valid, users may choose to hide volumes with sparse data for visualisation purposes.

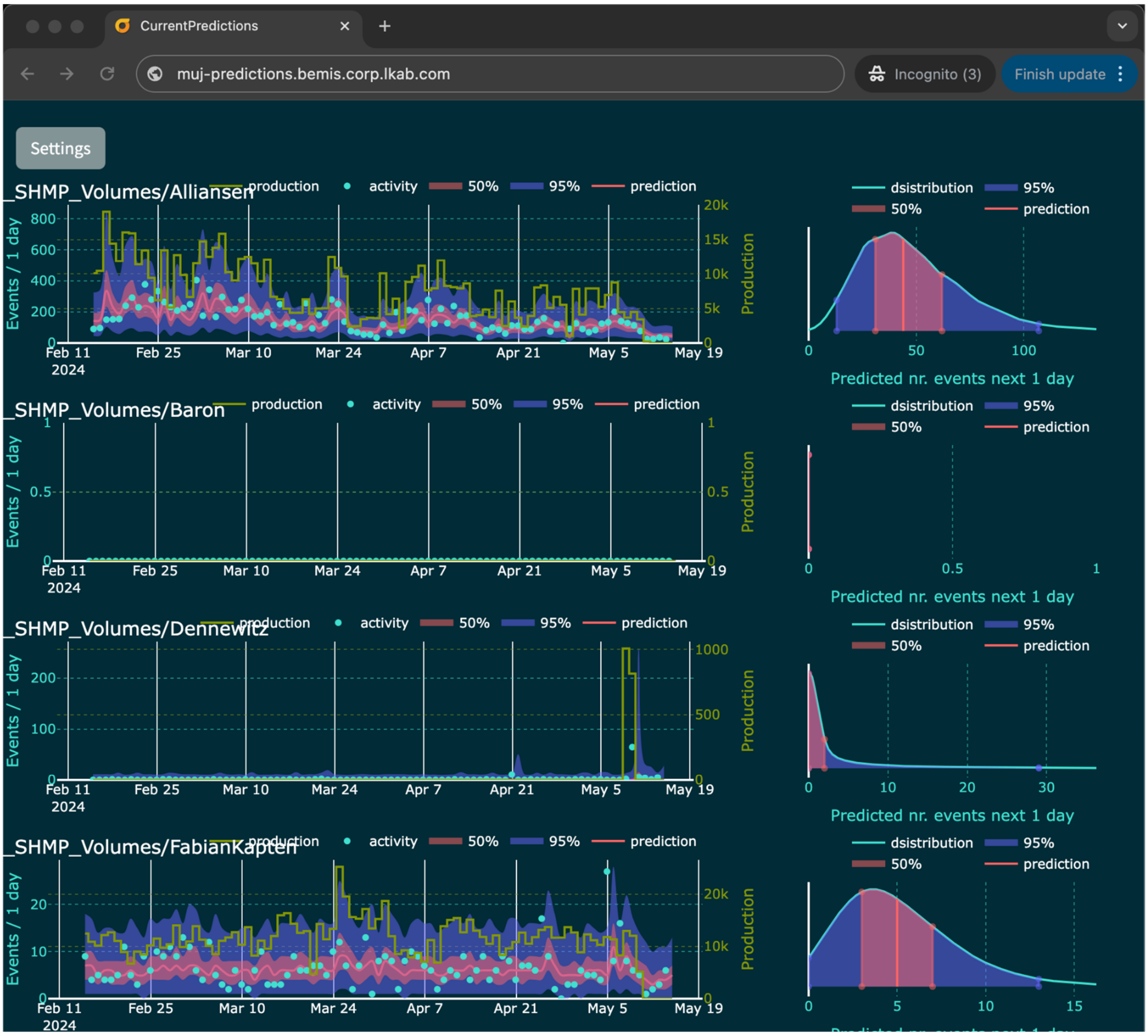

Figure 4 **Daily forecasts. Visualising seismic activity, production, and activity forecasts in the first four (out of 12) different volumes of interest in the Malmberget mine. Interestingly, there is no data for the 'Baron' volume and very little data for 'Dennewitz'**

4 Conclusion

The development of a responsive seismic forecasting application represents an important step forward in ensuring safety and efficiency in seismically active mining operations. By implementing a hierarchical Bayesian prediction model and integrating it into an interactive online web application, decision-makers gain direct insights into short-term seismic activity forecasts as a function of recent production plans. The application's dynamic interface is accessible across various devices, making it easy for users to access critical information wherever they are and without software installation.

Through the use of commonly available predictors combined with dynamic modelling techniques, the model provides accurate short-term seismic activity predictions, enabling customised production plans to mitigate induced seismicity. The model's hierarchical structure enhances estimation accuracy by utilising similarities across mine volumes, ensuring robust predictions in volumes with limited data.

The implementation of the model using a high-performance programming language, combined with open source web technologies and utilisation of container orchestration platforms, shows its practical applicability and scalability. The application's layout incorporates features for interactive exploration and continuous quality assurance to enhance its reliability for decision-making.

As the application continues to evolve, it may deliver forecasts on additional parameters as well as other enhancements, like user-defined volumes and adjustable parameters, to further tailor the tool to specific mining contexts. The extensive use of MCMC means that the forecasts of activity can easily serve as inputs to post-processing analysis such as hazard assessments while preserving prediction uncertainties.

Acknowledgement

The authors acknowledge the collaboration with LKAB and express gratitude to their rock mechanics team for valuable discussions during this work. Special thanks to Savka Dineva for commenting on the manuscript and Thomas Wettainen for collecting and providing us with feedback in the development process.

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