Exploring volcanic monitoring and eruption data with Uninet

Annemarie Christophersen, Anca Hanea,
Yannik Behr and Craig Miller

ABNMS 2022, Sydney, 17 November 2022

Outline

- Background and motivation
- Some reflections over the years
- Building an eruption forecast model for Mount Ruapehu
  - Conceptual model
  - Data
  - Results
- Exploring data with Uninet
- Conclusions and outlook

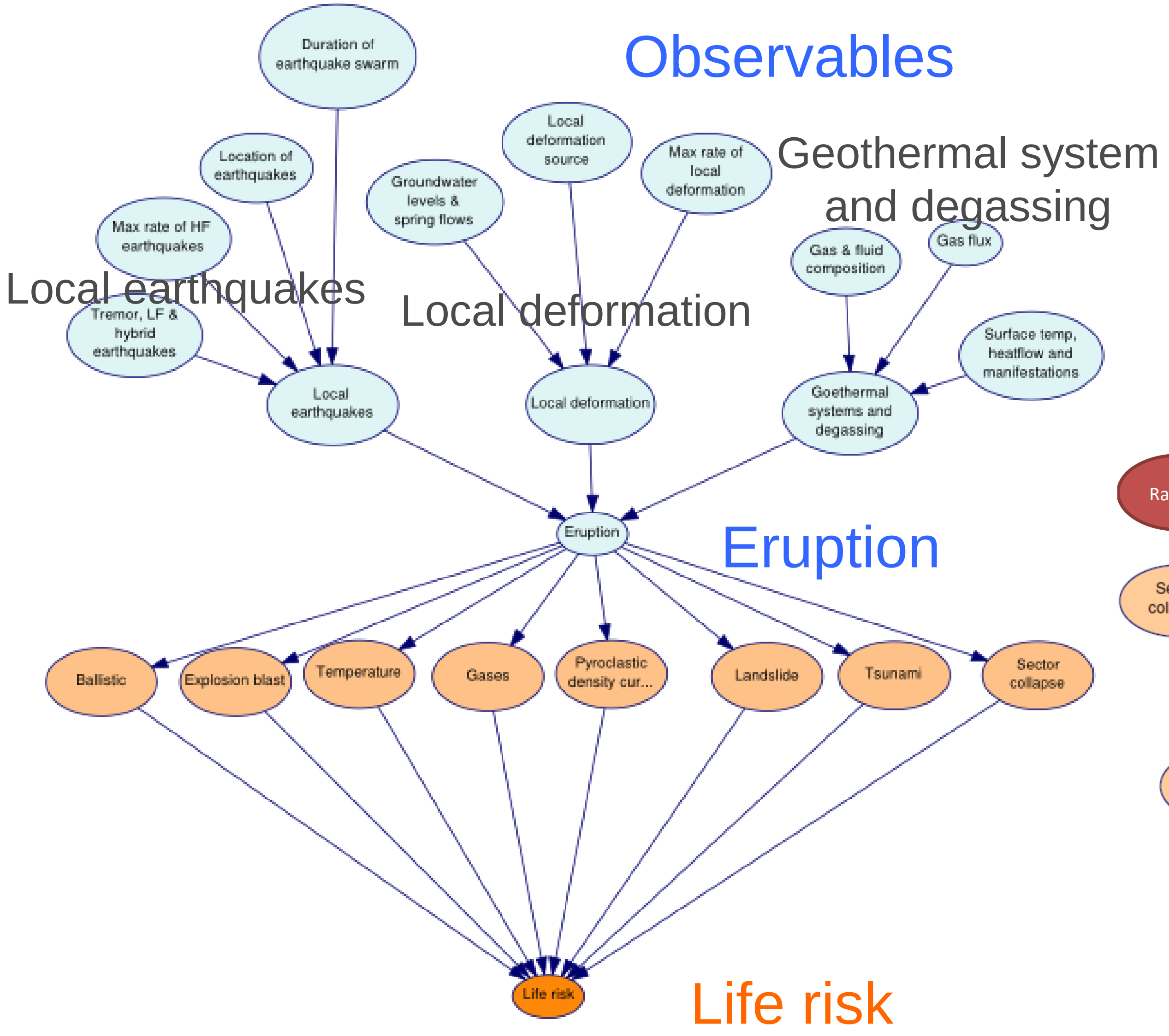
Background and motivation

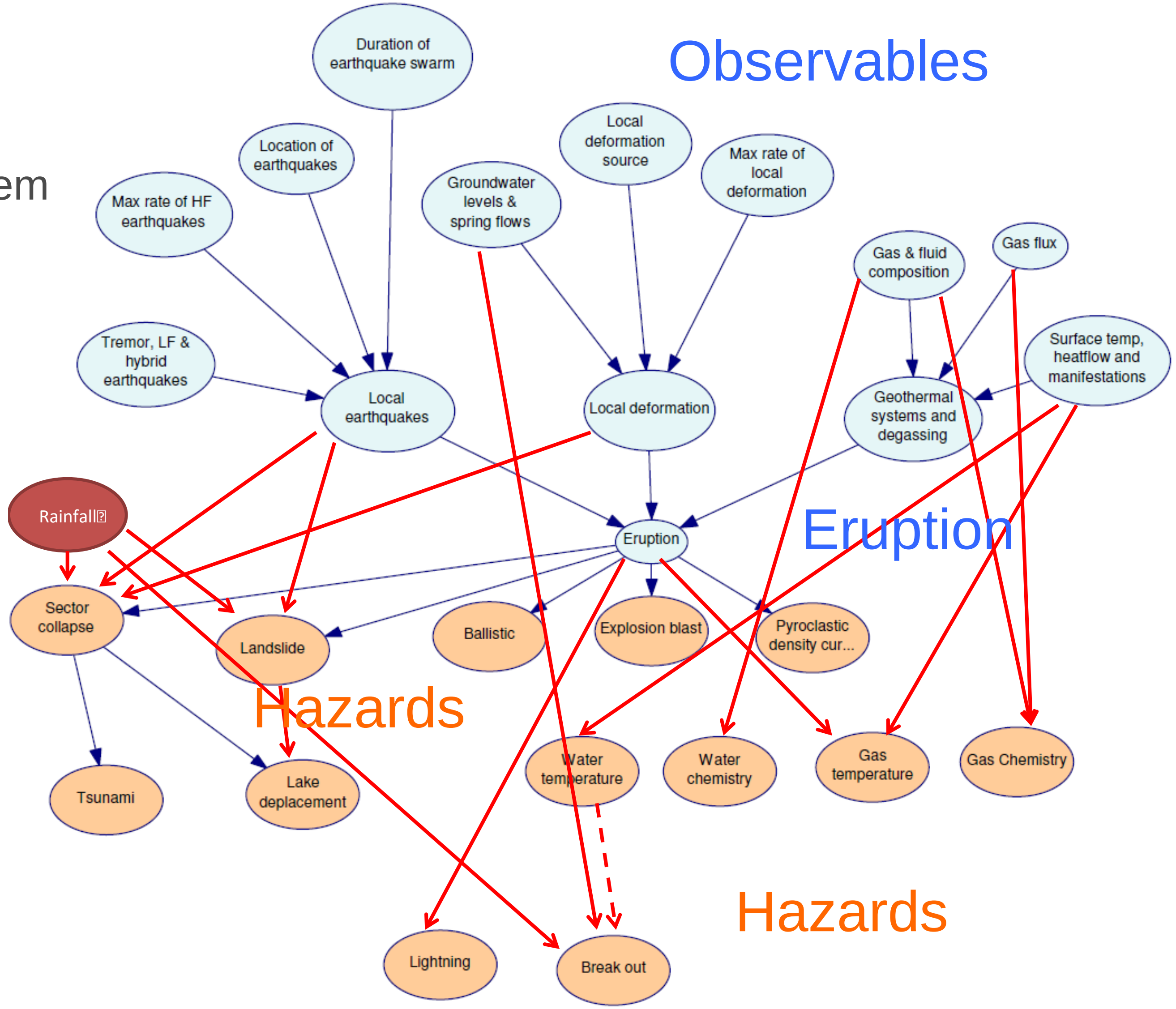
- GeoNet/GNS volcanologists analyse volcano monitoring data and provide geological advice to government agencies
- They regularly estimate eruption probabilities for volcanoes in unrest for time windows of 28 or 91 days to calculate hourly risk of fatality
- Hourly risk of fatality
  - $>10^{-3}$ no access
  - 10^{-3} - 10^{-4} high level managerial sign off
  - 10^{-4} -10^{-5} Volcano Science Advisor sign off
  - $< 10^{-5}$ normal field procedures
- Challenge to estimate small probabilities and to integrate different strands of data
- Trial Bayesian networks to create a model context like in earthquake forecasting

Photo: Brad Scott

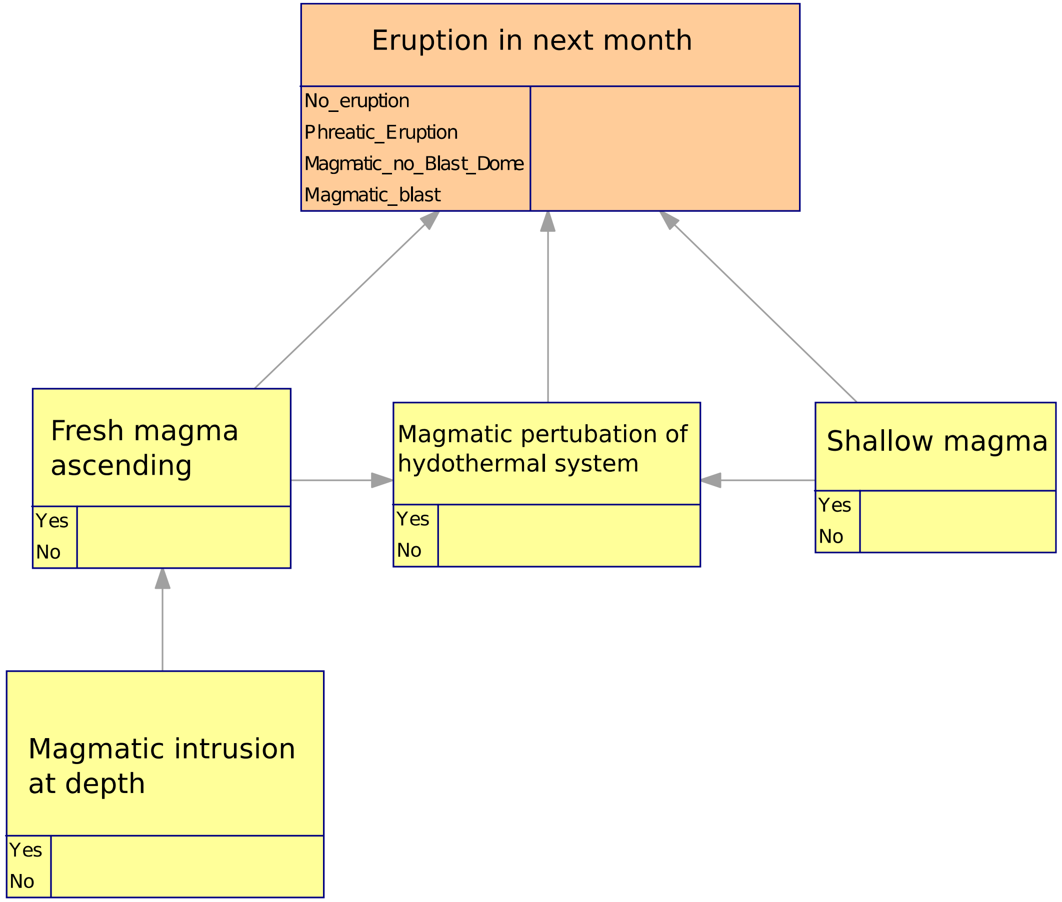
Hourly risk of fatality work: Deligne et al. (2018) J Applied Volc

ABNMS 2014: Rotorua, New Zealand





ABNMS 2014: Rotorua, New Zealand



Hincks *et al. Journal of Applied Volcanology* 2014, 3:3
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RESEARCH Open Access

Retrospective analysis of uncertain eruption precursors at La Soufrière volcano, Guadeloupe, 1975–77: volcanic hazard assessment using a Bayesian Belief Network approach

Thea K Hincks[1*], Jean-Christophe Komorowski[2], Stephen R Sparks[1] and Willy P Aspinall[1,3]

Abstract

Background: Scientists monitoring active volcanoes are increasingly required to provide decision support to civil authorities during periods of unrest. As the extent and resolution of monitoring improves, the process of jointly interpreting multiple strands of indirect evidence becomes increasingly complex. Similarities with uncertainties in medical diagnosis suggest a formal evidence-based approach, whereby monitoring data are analysed synoptically to provide probabilistic hazard forecasts. A statistical tool to formalize such inferences is the Bayesian Belief Network (BBN). By explicitly representing conditional dependencies between the volcanological model and observations, BBNs use probability theory to treat uncertainties in a rational and auditable manner, as warranted by the strength of the scientific evidence. A retrospective analysis is given for the 1976 Guadeloupe crisis, using a BBN to provide inferential assessment of the state of the evolving magmatic system and probability of incipient eruption. Conditional dependencies are characterized quantitatively by structured expert elicitation.

Results: Analysis of the available monitoring data suggests that at the height of the crisis the probability of magmatic intrusion was high, in accordance with scientific thinking at the time. The corresponding probability of magmatic eruption was elevated in July and August 1976 and signs of precursory activity were justifiably cause for concern. However, collective uncertainty about the future course of the crisis was also substantial. Of all the possible scenarios, the most likely outcome evinced by interpretation of observations on 31 August 1976 was 'no eruption' (mean probability 0.5); the chance of a magmatic eruption/blast had an estimated mean probability of ~0.4. There was therefore no evidential basis for asserting one scenario to be significantly more likely than another.

Conclusions: Our analysis adds objective probabilistic expression to the volcanological narrative at the time of the 1976 crisis, and demonstrates that a formal evidential case could have supported the authorities' concerns about public safety and decision to evacuate. Revisiting the episode highlights many challenges for modern, contemporary decision making under conditions of considerable uncertainty, and suggests the BBN is a suitable framework for marshalling multiple, uncertain observations, model results and interpretations. The formulation presented here can be developed as a tool for ongoing use in the volcano observatory.

Keywords: Volcanic hazards; Multi-parameter monitoring; Bayesian inference; Uncertainty; Decision making; Expert judgement

ABNMS 2015: Melbourne, Australia

White Island: Model summary

- Four unobservable nodes that represent the driving processes on the volcano
- Three eruptions or results nodes
- 22 observable nodes
- Each node has ‘yes’ and ‘no’ states
- 115 conditions to assess
- Vague description of states like ‘increase’, ‘elevated’, ‘high’
- Elicitation will ask experts for their definition
- Elicitation will ask for best estimate and 80% uncertainty, thus 10th, 50th and 90th percentile
- Elicitation also features a ‘rant box’.

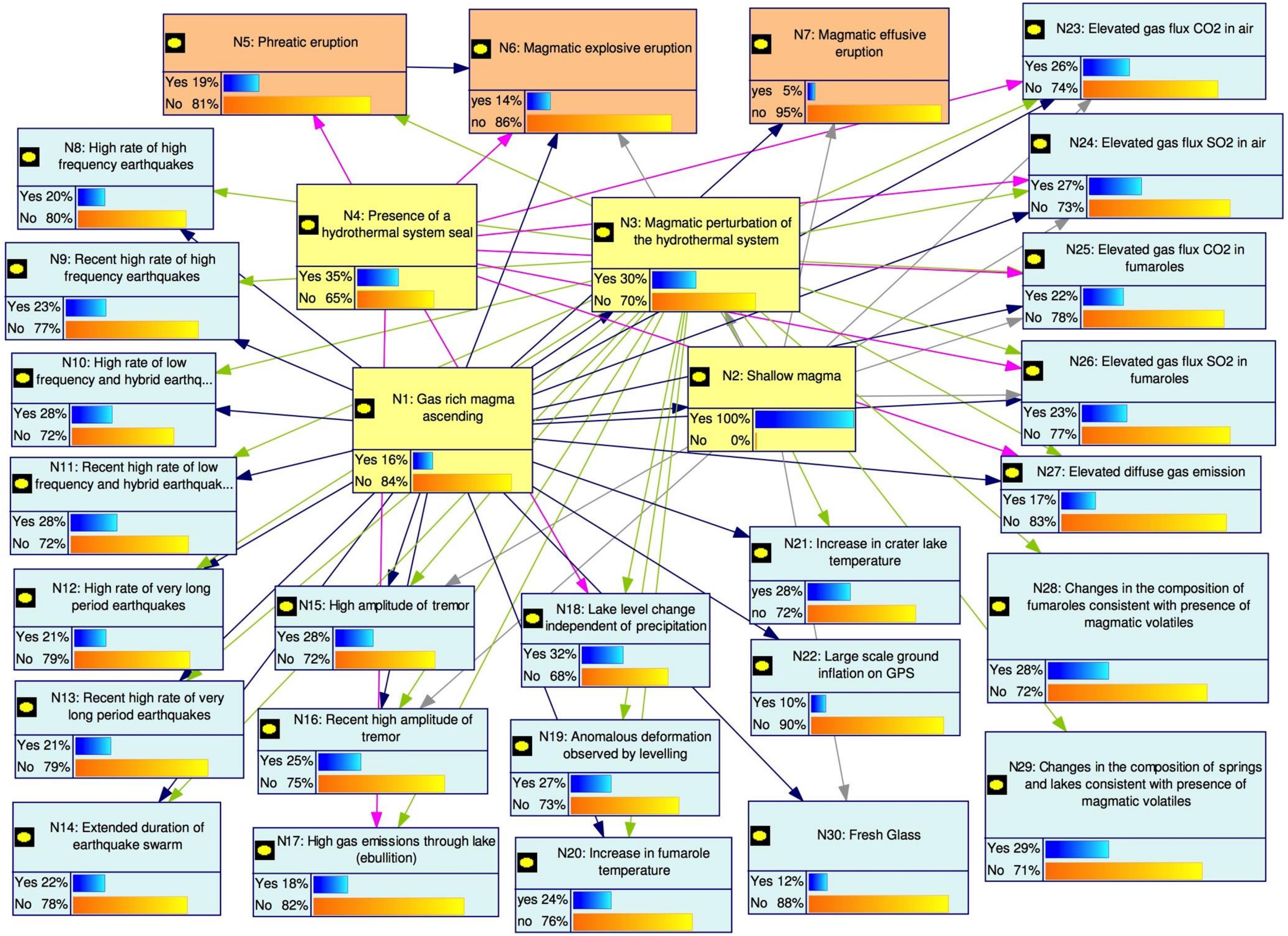
ABNMS 2017: Melbourne, Australia

Glimpses of results

More in: http://dx.doi.org/10.21420/G20G9B

Key lessons so far

- Many different conceptual models how a volcano works
- BNs are great tool to facilitate discussion among multi-disciplinary volcanologists
- Challenge to define nodes, in particular to set thresholds



ABNMS 2019: Wellington, New Zealand

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Bayesian Network Modeling and Expert Elicitation for Probabilistic Eruption Forecasting: Pilot Study for Whakaari/White Island, New Zealand

Annemarie Christophersen[1], Natalia I. Deligne[1], Anca M. Hanea[2], Lauriane Chardot[3], Nicolas Fournier[4] and Willy P. Aspinall[5,6]*

[1] GNS Science, Avalon, Lower Hutt, New Zealand, [2] Centre of Excellence for Biosecurity Risk Analysis, The University of Melbourne, Melbourne, VIC, Australia, [3] Earth Observatory of Singapore, Nanyang Technological Institute, Singapore, Singapore, [4] Wairakei Research Centre, GNS Science, Wairakei, New Zealand, [5] School of Earth Sciences and Cabot Institute, University of Bristol, Bristol, United Kingdom, [6] Aspinall & Associates, Tisbury, United Kingdom

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***Correspondence:**
Annemarie Christophersen
a.christophersen@gns.cri.nz

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Bayesian Networks (BNs) are probabilistic graphical models that provide a robust and flexible framework for understanding complex systems. Limited case studies have demonstrated the potential of BNs in modeling multiple data streams for eruption forecasting and volcanic hazard assessment. Nevertheless, BNs are not widely employed in volcano observatories. Motivated by their need to determine eruption-related fieldwork risks, we have worked closely with the New Zealand volcano monitoring team to appraise BNs for eruption forecasting with the purpose, at this stage, of assessing the utility of the concept rather than develop a full operational framework. We adapted a previously published BN for a pilot study to forecast volcanic eruption on Whakaari/White Island. Developing the model structure provided a useful framework for the members of the volcano monitoring team to share their knowledge and interpretation of the volcanic system. We aimed to capture the conceptual understanding of the volcanic processes and represent all observables that are regularly monitored. The pilot model has a total of 30 variables, four of them describing the volcanic processes that can lead to three different types of eruptions: phreatic, magmatic explosive and magmatic effusive. The remaining 23 variables are grouped into observations related to seismicity, fluid geochemistry and surface manifestations. To estimate the model parameters, we held a workshop with 11 experts, including two from outside the monitoring team. To reduce the number of conditional probabilities that the experts needed to estimate, each variable is described by only two states. However, experts were concerned about this limitation, in particular for continuous data. Therefore, they were reluctant to define thresholds to distinguish between states. We conclude that volcano monitoring requires BN modeling techniques that can accommodate continuous variables. More work is required to link unobservable (latent) processes with observables and with eruptive patterns, and to model dynamic processes. A provisional application of the pilot model revealed several

Bayesian networks as decision-support tools in the next volcanic crisis

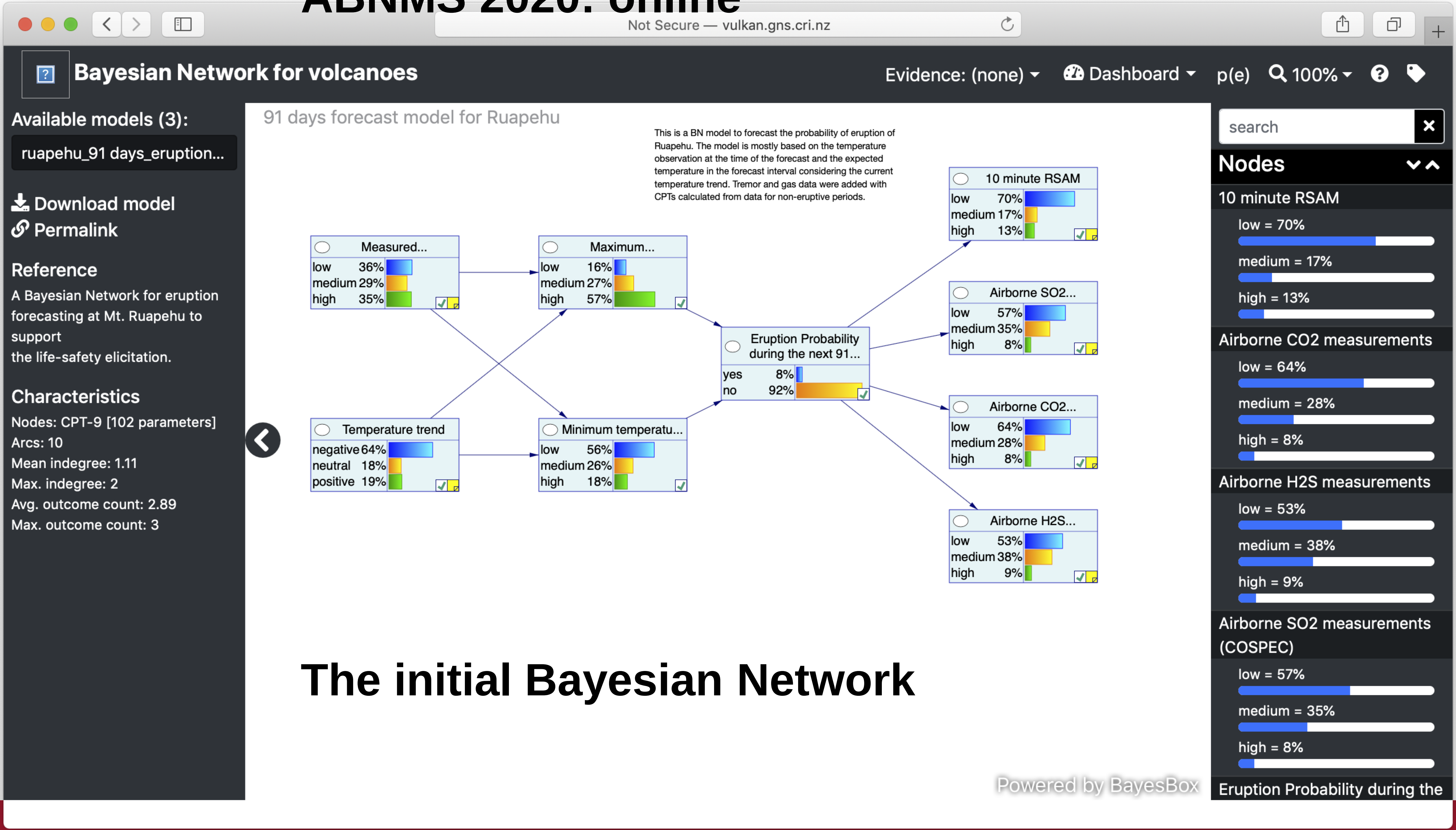
A pilot study for eruption forecasting on Whakaari/White Island

Presenter: Annemarie Christophersen, Hazard and Risk Scientist
Coauthors: Natalia Deligne, Anca Hanea, Lauriane Chardot, Nico Fournier & Willy Aspinall

Risk and Decision-making conference, 13-14 November 2019

GNS SCIENCE TE PŪ AO

ABNMS 2020: online



The initial Bayesian Network

Building an eruption forecast model for Mount Ruapehu

Model input

- Conceptual model
- Available data = monitoring data
- Experts = volcano monitoring group

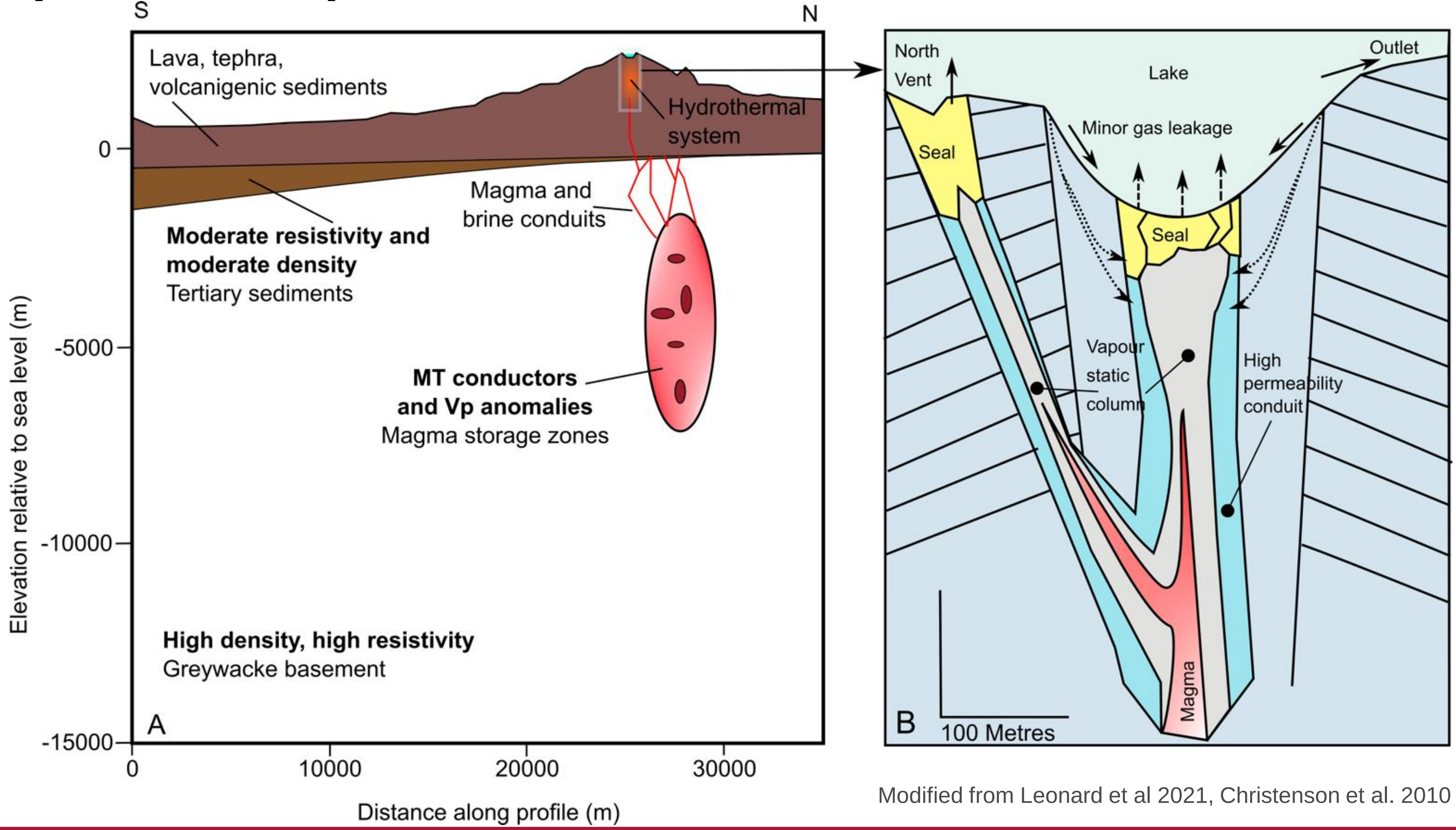
Tools:

- Data analysis: Jupyter Notebooks
- BN implementation: Python programming language; SMILE reasoning engine for graphical probabilistic models
- Deployment on GNS Science's CI/CD platform

Photo: Lloyd Homer

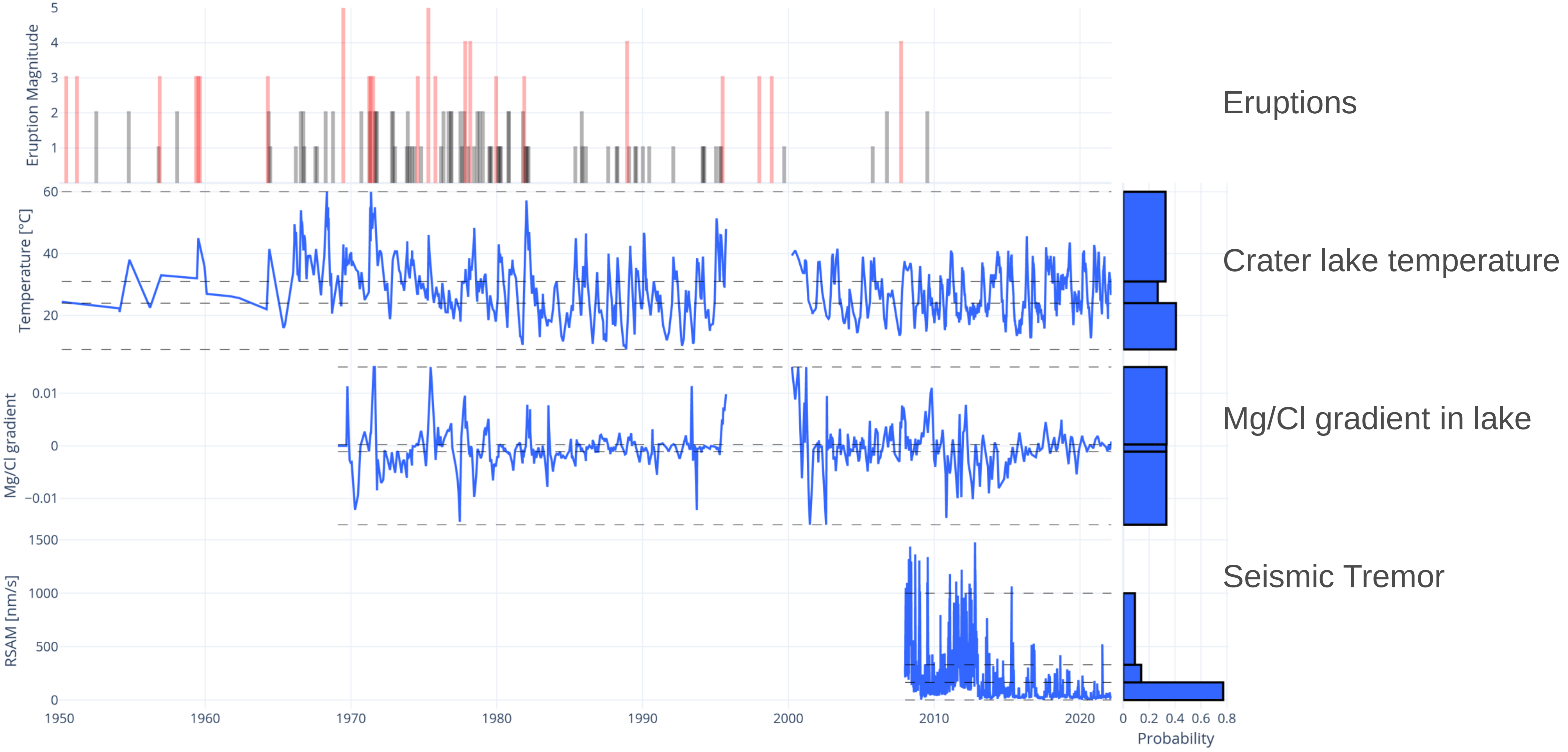
Christophersen, Behr, Miller, Frontiers in Earth Science, 2022

Ruapehu conceptual model



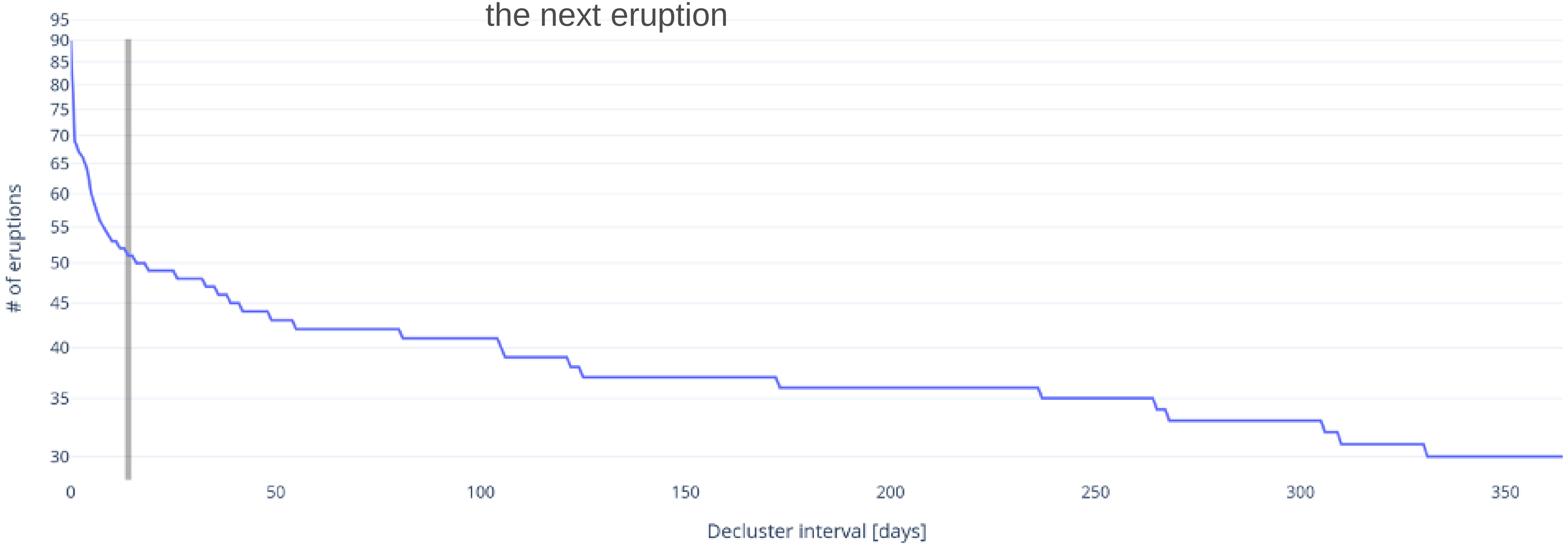
Modified from Leonard et al 2021, Christenson et al. 2010

Ruapehu: Time series of key parameters



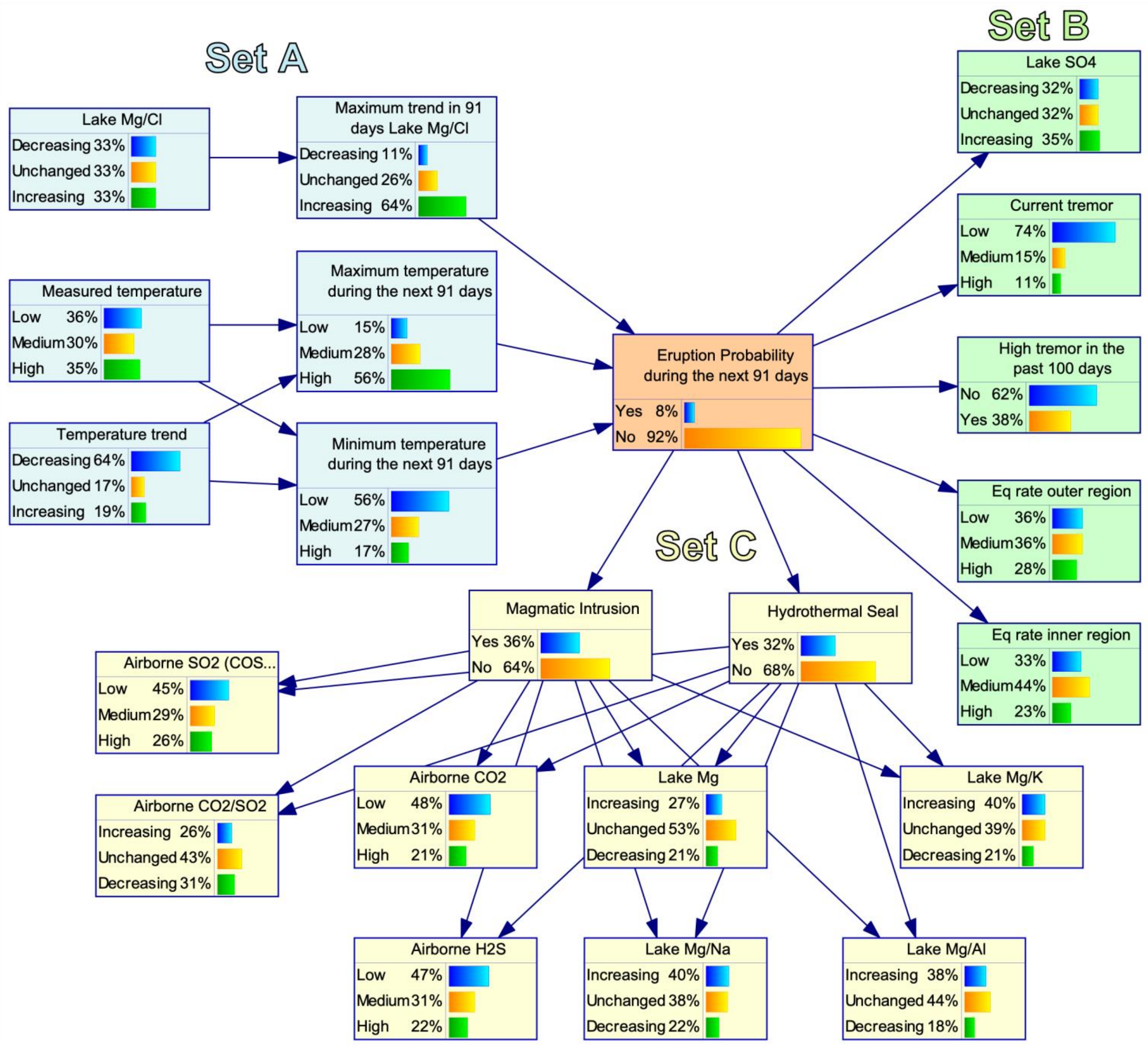
Declustering the eruption catalogue

Rationale: Forecasting the onset of an eruptive period, not the next eruption

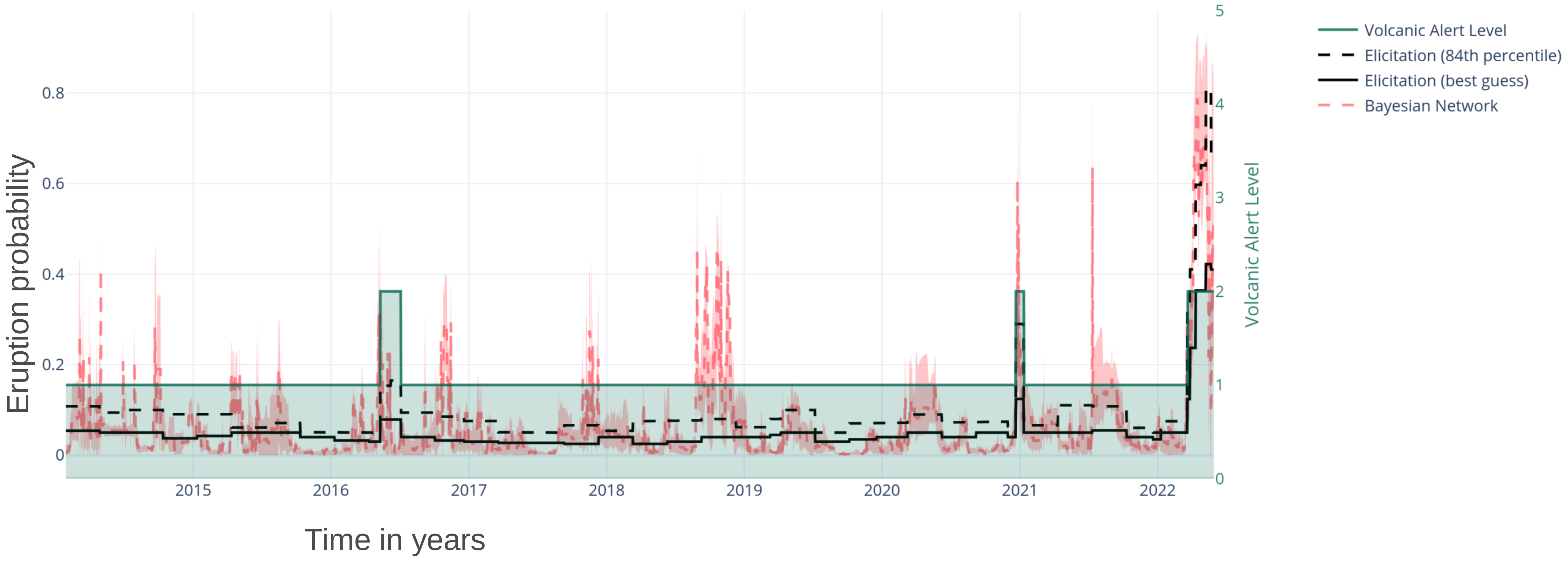


Developing and parameterising the model

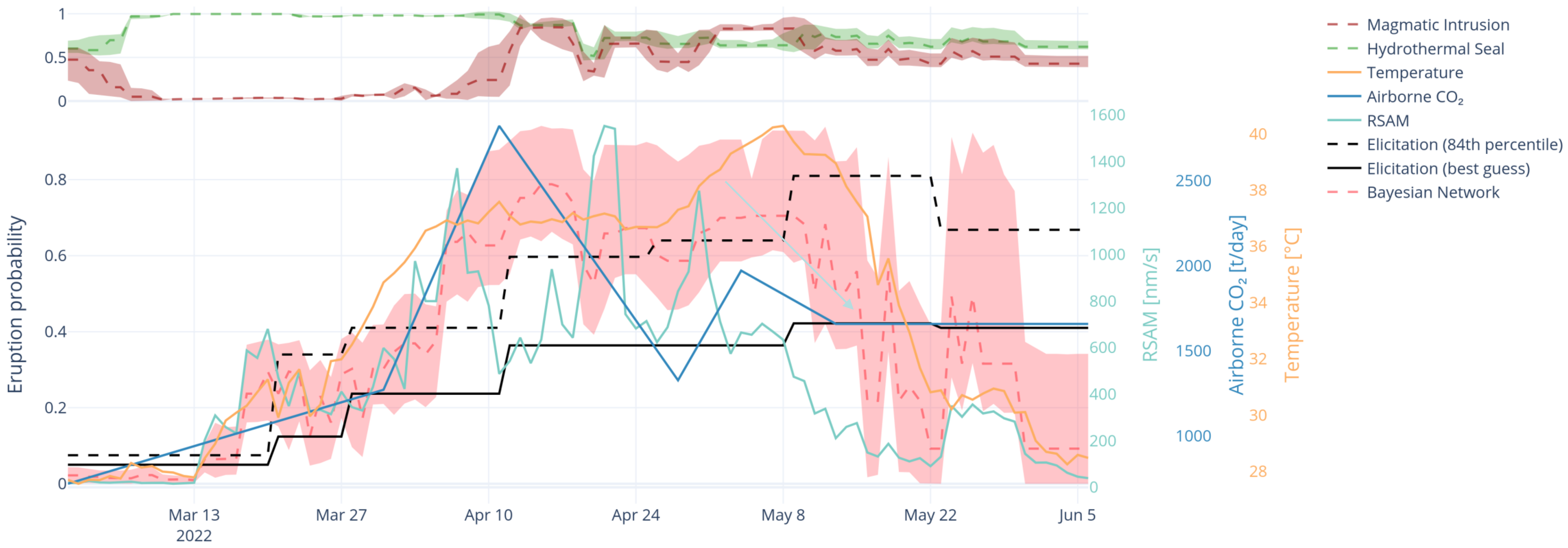
- Three sets of parameters, A (blue), B (green), and C (yellow)
  - A – data learned
  - B – partially data learned
  - C – fully expert elicited



Estimating model uncertainty and forecast comparison

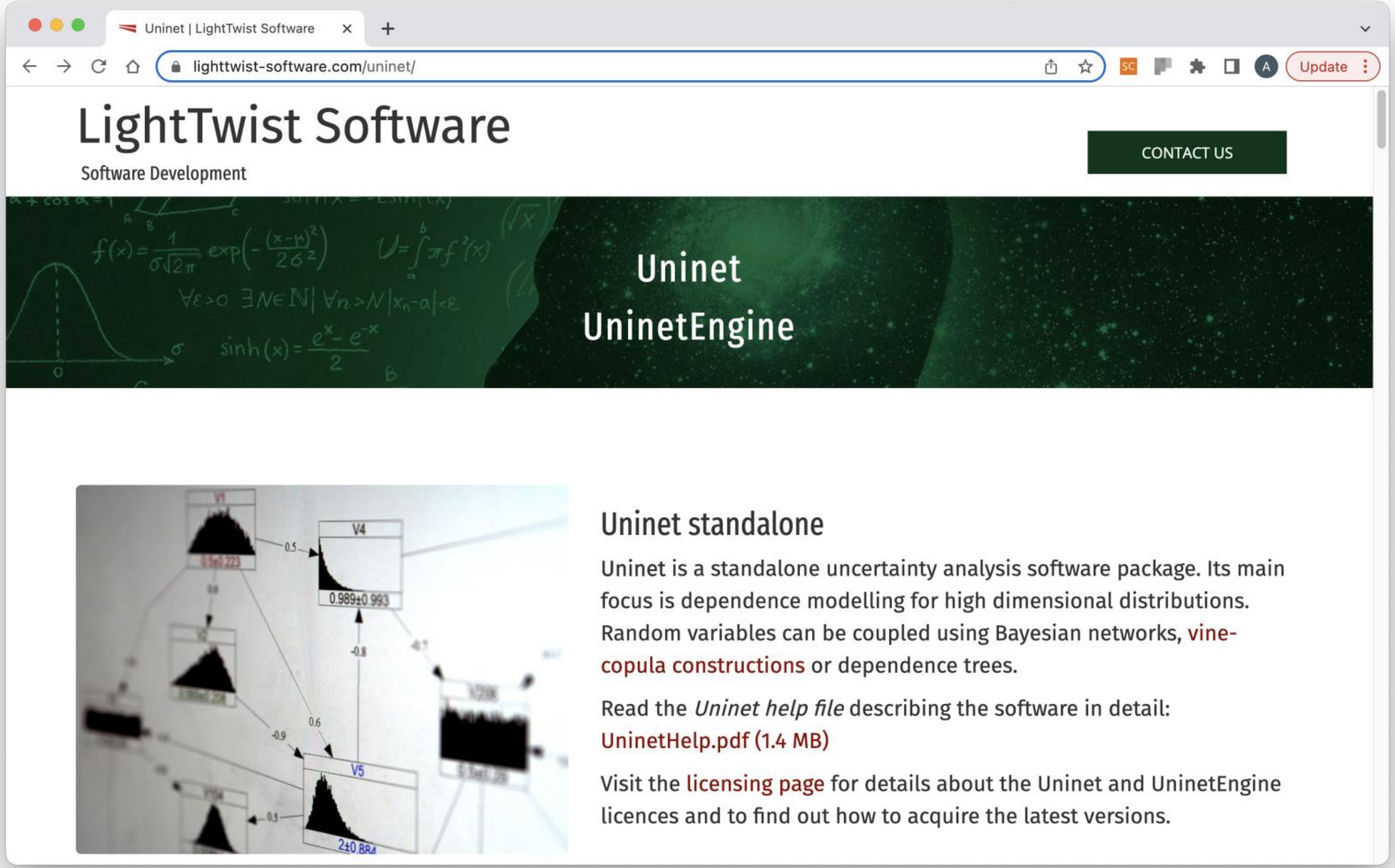


Case Study: March/April 2022

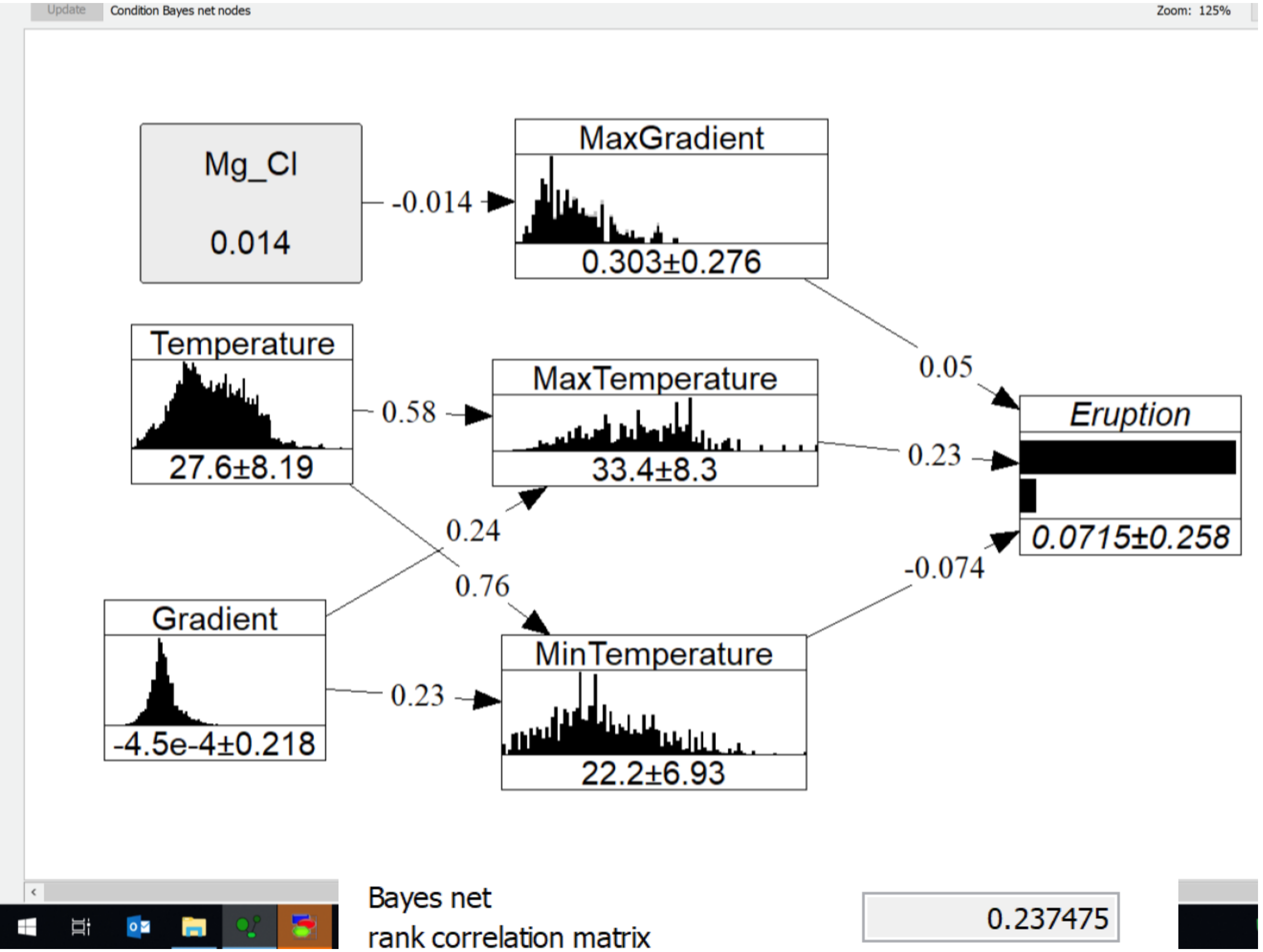


Uninet

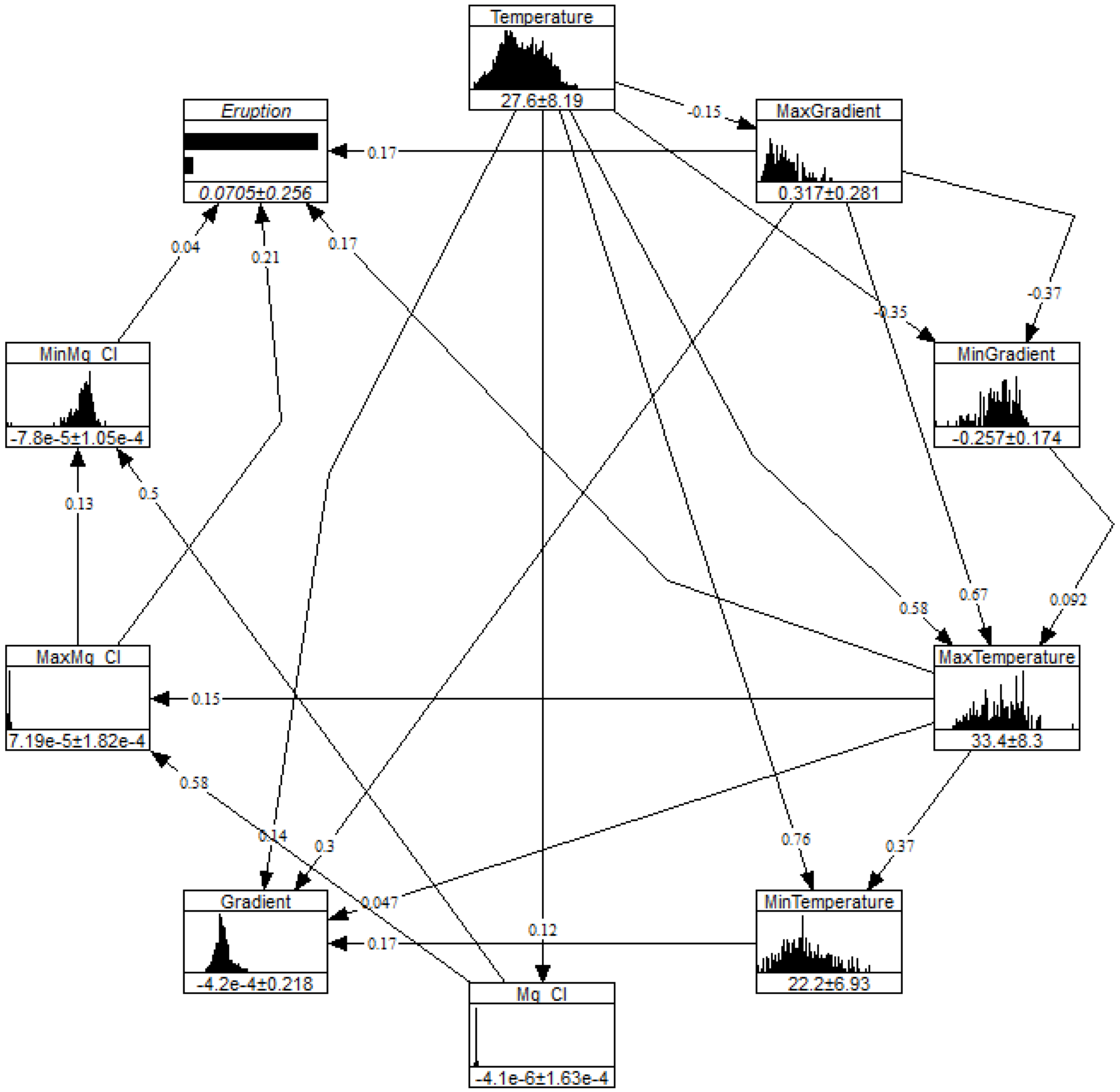
- Software for continuous BNs, some discrete nodes possible
- Parameterization consists of defining margins for all nodes and parameterizing the dependence by (conditional) rank correlations
- Learning structure and parameterization is based on the empirical rank correlation matrix



Uninet



Bayes net rank correlation matrix	0.237475
Empirical normal rank correlation matrix	0.105977
Empirical rank correlation matrix	0.0908196



Correlation Matrices

Bayes net | Empirical normal | Empirical | Determinants

Bayes net rank correlation matrix

	emperatur	axGradien	MinGradient	xTemperatu	nTemperatu	Mg_Cl	Gradient	MaxMg_Cl	MinMg_Cl	Eruption
Temperature	1	-0.147	-0.348	0.577	0.76	0.115	0.141	0.131	0.0688	0.109
MaxGradient	-0.147	1	-0.283	0.441	0.0451	-0.0177	0.268	0.0378	-0.00213	0.169
MinGradient	-0.348	-0.283	1	-0.351	-0.313	-0.0418	-0.152	-0.0631	-0.0272	-0.0976
MaxTemperature	0.577	0.441	-0.351	1	0.639	0.0685	0.273	0.146	0.0509	0.23
MinTemperature	0.76	0.0451	-0.313	0.639	1	0.0892	0.258	0.122	0.0563	0.134
Mg_Cl	0.115	-0.0177	-0.0418	0.0685	0.0892	1	0.0169	0.58	0.501	0.145
Gradient	0.141	0.268	-0.152	0.273	0.258	0.0169	1	0.04	0.0132	0.0784
MaxMg_Cl	0.131	0.0378	-0.0631	0.146	0.122	0.58	0.04	1	0.388	0.235
MinMg_Cl	0.0688	-0.00213	-0.0272	0.0509	0.0563	0.501	0.0132	0.388	1	0.126
Eruption	0.109	0.169	-0.0976	0.23	0.134	0.145	0.0784	0.235	0.126	1

Less <<

Determinant 0.038221

Highlight parent-child correlations

Highlight the "k" highest non parent-child correlations 1

Export

Update

Correlation Matrices

Bayes net | Empirical normal | Empirical | Determinants

Empirical normal rank correlation matrix

	emperatur	axGradien	MinGradient	xTemperatu	nTemperatu	Mg_Cl	Gradient	MaxMg_Cl	MinMg_Cl	Eruption
Temperature	1	-0.147	-0.348	0.577	0.76	0.115	0.141	0.0974	0.0488	0.0114
MaxGradient	-0.147	1	-0.283	0.441	0.0401	-0.0135	0.268	0.0688	0.0927	0.169
MinGradient	-0.348	-0.283	1	-0.351	-0.0937	-0.0551	0.0434	-0.0381	-0.0553	0.0411
MaxTemperature	0.577	0.441	-0.351	1	0.639	0.0908	0.273	0.146	0.0994	0.23
MinTemperature	0.76	0.0401	-0.0937	0.639	1	0.0656	0.256	0.0983	0.0233	0.0962
Mg_Cl	0.115	-0.0135	-0.0551	0.0908	0.0656	1	-0.0315	0.582	0.501	0.0953
Gradient	0.141	0.268	0.0434	0.273	0.256	-0.0315	1	0.0285	0.0477	0.0169
MaxMg_Cl	0.0974	0.0688	-0.0381	0.146	0.0983	0.582	0.0285	1	0.389	0.238
MinMg_Cl	0.0488	0.0927	-0.0553	0.0994	0.0233	0.501	0.0477	0.389	1	0.143
Eruption	0.0114	0.169	0.0411	0.23	0.0962	0.0953	0.0169	0.238	0.143	1

Less <<

Determinant 0.0288211

Highlight parent-child correlations

Highlight the "k" highest non parent-child correlations 1

Export

Update

Correlation Matrices

Bayes net | Empirical normal | Empirical | Determinants

Empirical rank correlation matrix

	emperatur	axGradien	MinGradient	xTemperatu	nTemperatu	Mg_Cl	Gradient	MaxMg_Cl	MinMg_Cl	Eruption
Temperature	1	-0.177	-0.351	0.592	0.759	0.0755	0.143	0.0695	0.00997	0.0169
MaxGradient	-0.177	1	-0.331	0.449	0.0296	-0.0112	0.259	0.0473	0.0912	0.163
MinGradient	-0.351	-0.331	1	-0.375	-0.095	-0.0961	0.0221	-0.0348	-0.105	0.0341
MaxTemperature	0.592	0.449	-0.375	1	0.653	0.062	0.293	0.111	0.0727	0.206
MinTemperature	0.759	0.0296	-0.095	0.653	1	0.0259	0.277	0.0953	-0.0423	0.118
Mg_Cl	0.0755	-0.0112	-0.0961	0.062	0.0259	1	-0.0323	0.582	0.512	0.0722
Gradient	0.143	0.259	0.0221	0.293	0.277	-0.0323	1	0.0356	0.037	0.00767
MaxMg_Cl	0.0695	0.0473	-0.0348	0.111	0.0953	0.582	0.0356	1	0.36	0.22
MinMg_Cl	0.00997	0.0912	-0.105	0.0727	-0.0423	0.512	0.037	0.36	1	0.113
Eruption	0.0169	0.163	0.0341	0.206	0.118	0.0722	0.00767	0.22	0.113	1

Less <<

Determinant 0.0221147

Highlight parent-child correlations

Highlight the "k" highest non parent-child correlations 1

Export

Update

Bayes net rank correlation matrix	0.038221
Empirical normal rank correlation matrix	0.0288211
Empirical rank correlation matrix	0.0221147

Conclusions and outlook

- With persistence, enthusiasm and support from external colleagues, a lot can be achieved with time.
- Bayesian network have started to be useful and used in volcanic monitoring.
- There is still a lot to learn!

Going forward we plan to:

- Apply the method to other volcanoes
- Extend the questions to address other volcanic hazards and their impacts
- Model time dependence better

Photo: Lloyd Homer

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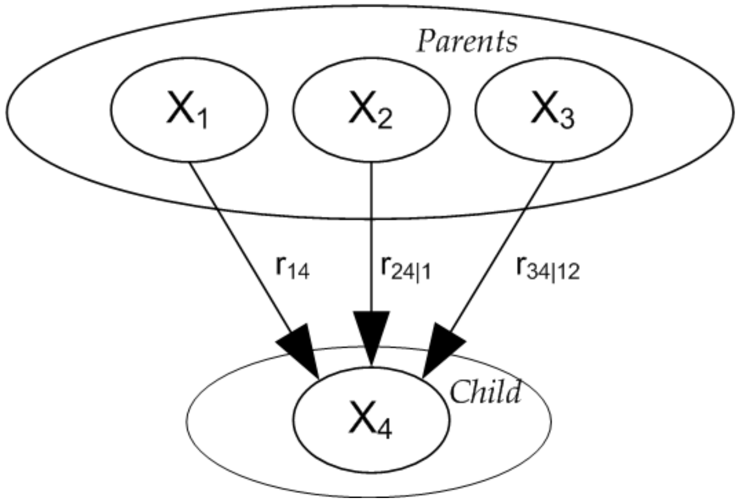
- Bruce Christenson and Agnes Mazot for sharing their insights into the geochemical dynamics of Ruapehu.
- Rob Buxton provided valuable advice during initial discussions on applying BNs to volcanic monitoring.
- GeoNet and its sponsors EQC, GNS Science, LINZ, NEMA and MBIE for providing the data used in this study.

Photo: Lloyd Homer

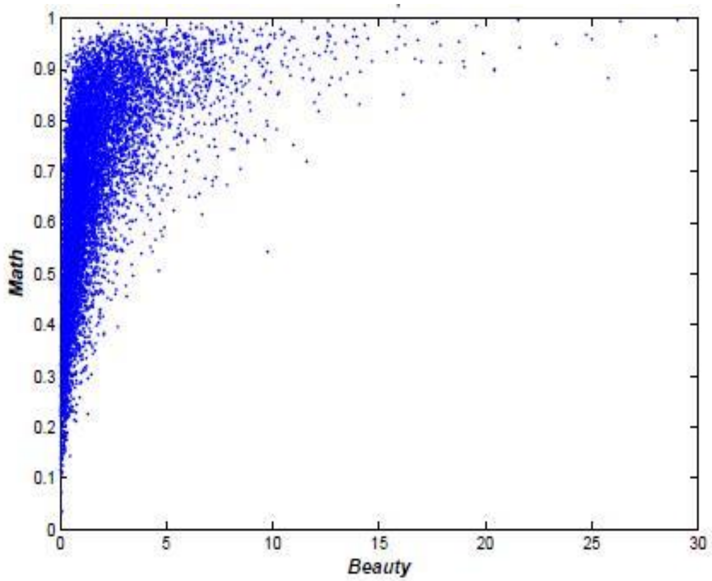
Non Parametric Bayesian Networks (NPBNs)

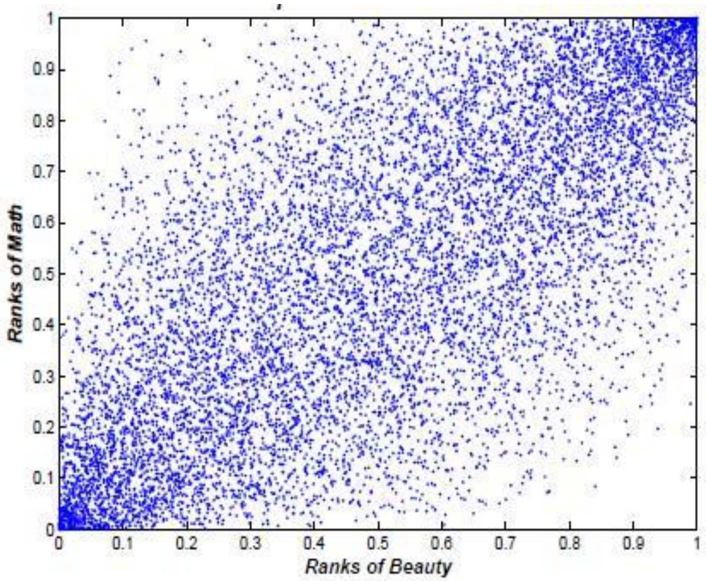
- **Any continuous variables**
  - ✓ marginal distributions
  - ✓ a measure of bivariate dependence
  - ✓ an assumption about the “shape” of the bivariate dependence



Non Parametric **Bayesian** Networks (NPBNs)

- **A measure of bivariate dependence**





$$\rho(X,Y)=\frac{E(XY)-E(X)E(Y)}{\sigma_X\sigma_Y}$$

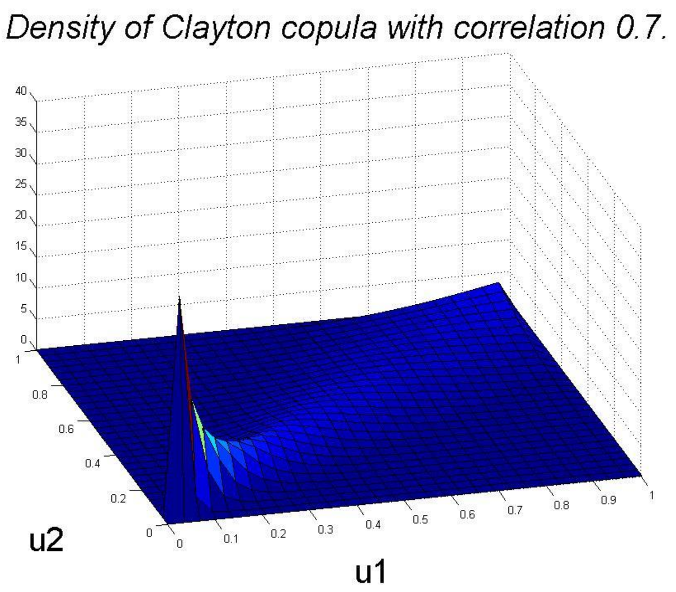
$$r(X,Y)=\rho(F_X(X),F_Y(Y))$$

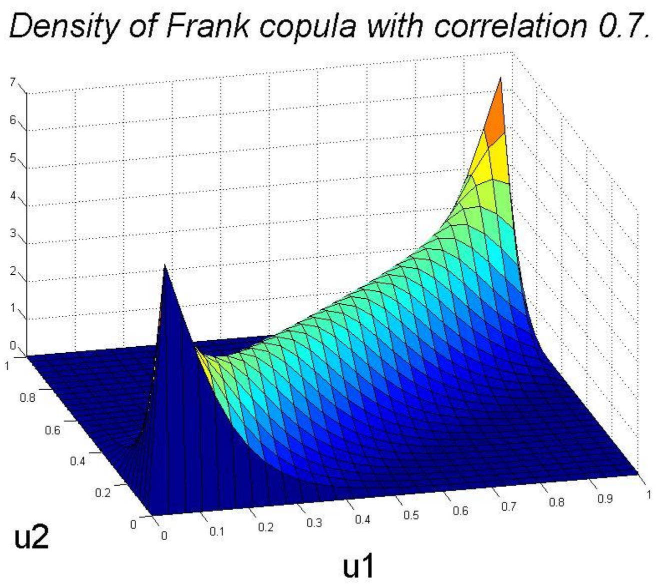
Why the Rank Correlation?

- ***always exists***
- ***does not depend on the marginal distributions (non-parametric measure of correlation)***
- ***measures monotone dependence***
- ***it parametrizes the chosen "shape of dependence" (copula)***

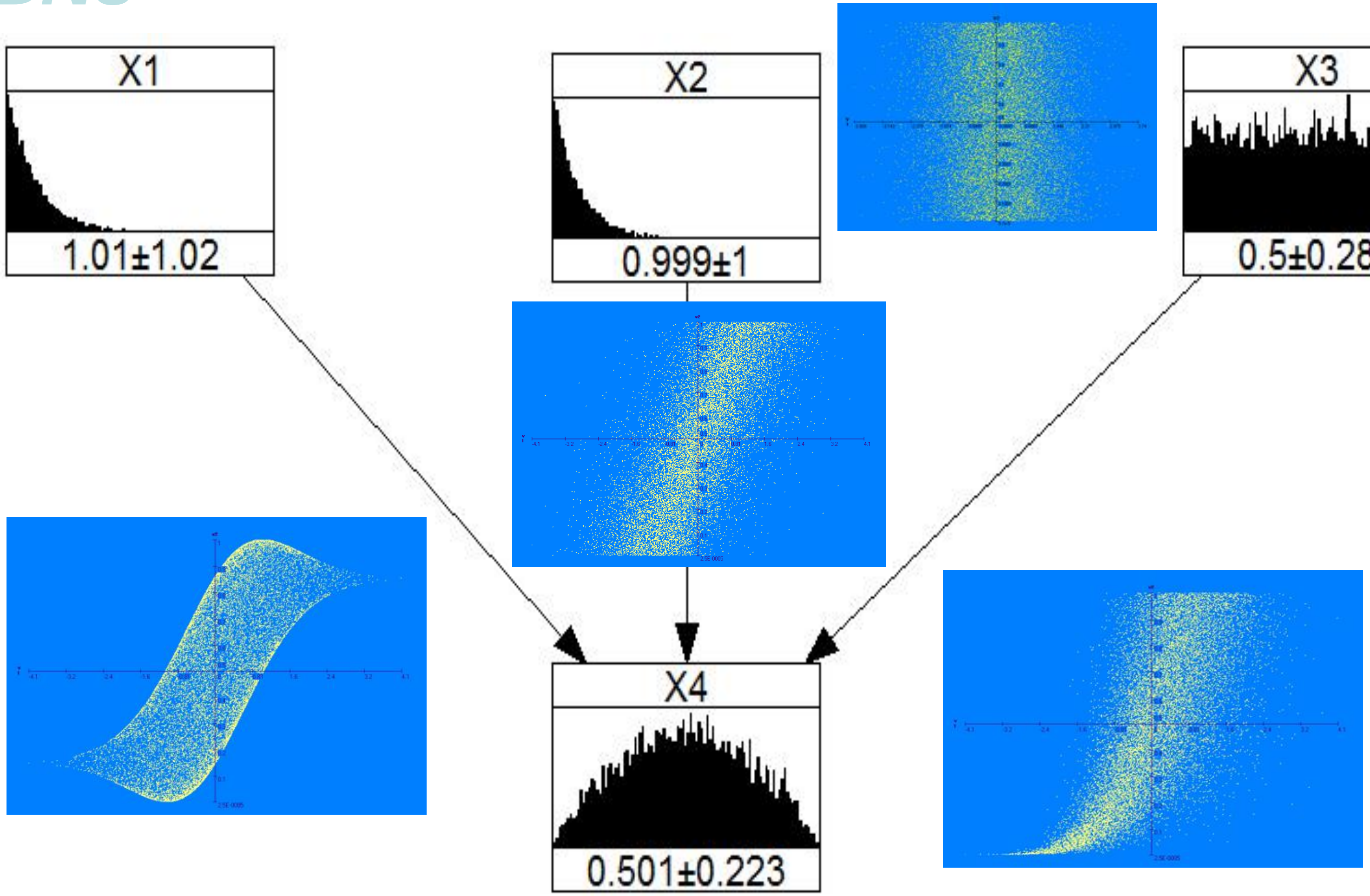
NPBNs

- **An assumption about the bivariate dependence - *copula***

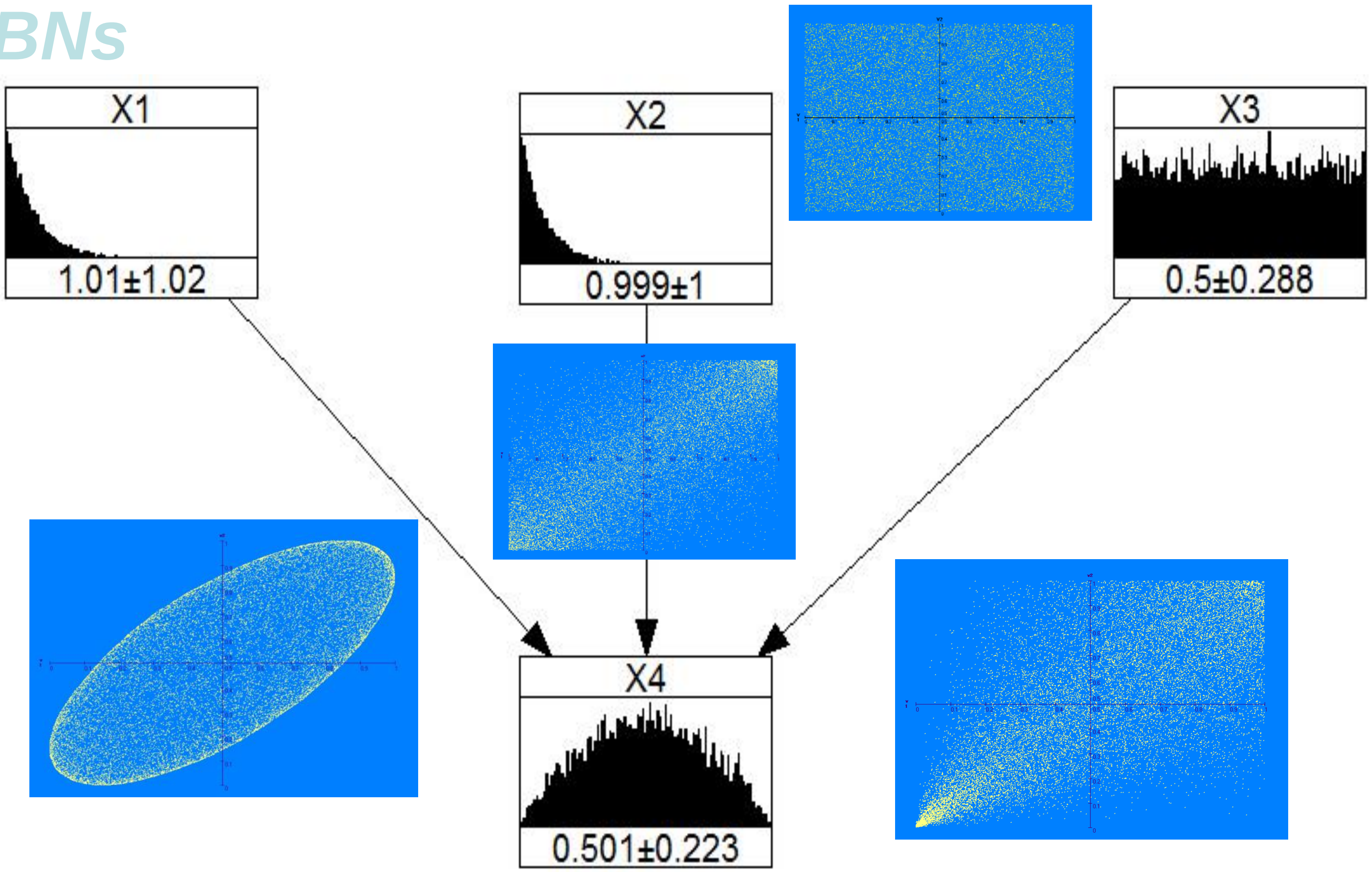




NPBNs



NPBNs



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