Āhea riri ai ngā maunga puia? *When will our volcanoes become angry?*

Jon Procter & Christina Magill

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RESILIENCE TO NATURE'S CHALLENGES

Kia manawaroa – Ngā Ākina o Te Ao Tūroa

MASSEY UNIVERSITY TE KUNENGA KI PŪREHUROA UNIVERSITY OF NEW ZEALAND

THE UNIVERSITY OF AUCKLAND NEW ZEALAND Te Whare Wānanga o Tāmaki Makaurau

UC UNIVERSITY OF CANTERBURY Te Whare Wānanga o Waitaha

VICTORIA UNIVERSITY OF WELLINGTON

GNS SCIENCE TE PŪ AO

UNIVERSITY of OTAGO Te Whare Wānanga o Otāgo NEW ZEALAND

Āhea riri ai ngā maunga puia? *When will our volcanoes become angry?*

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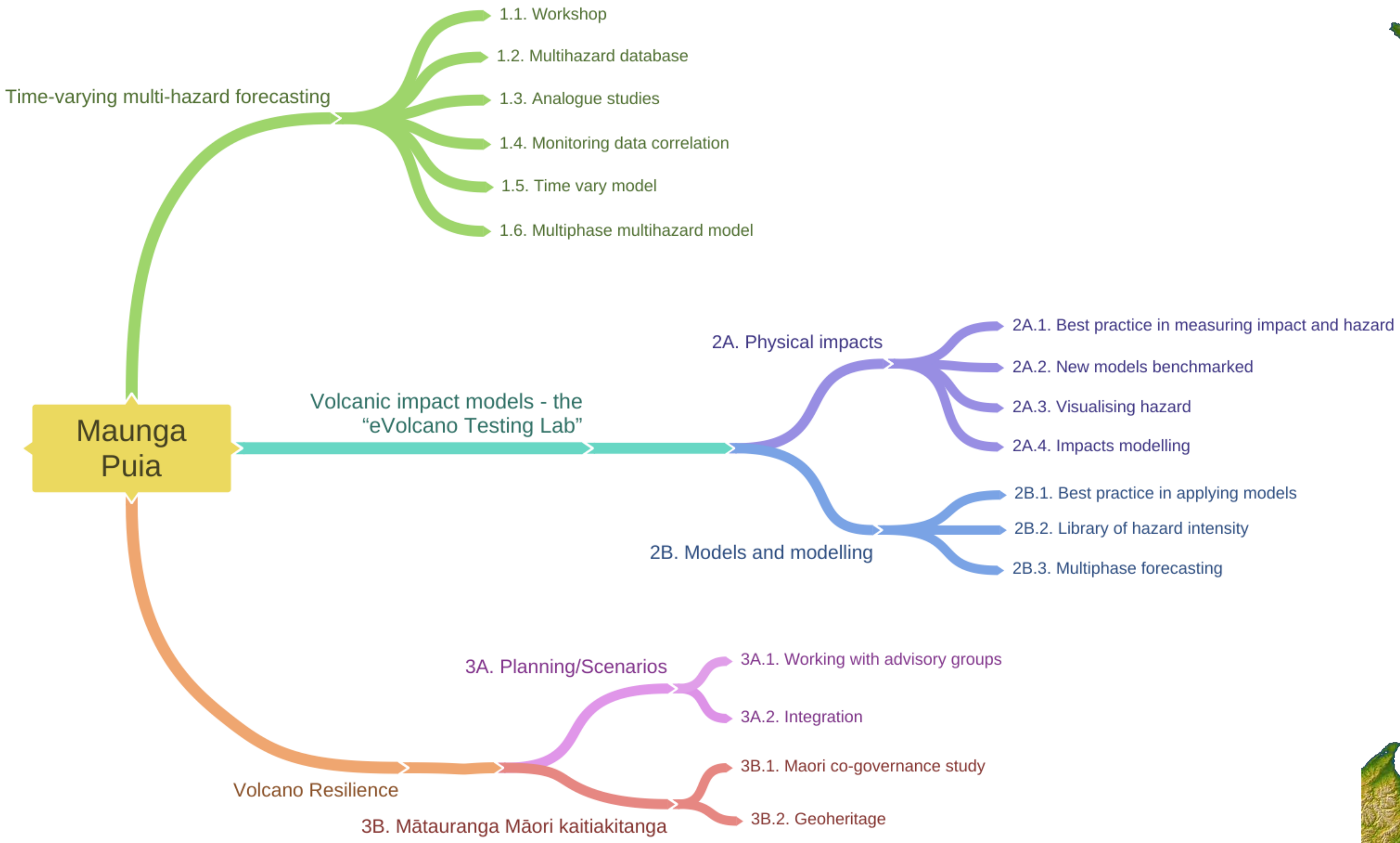

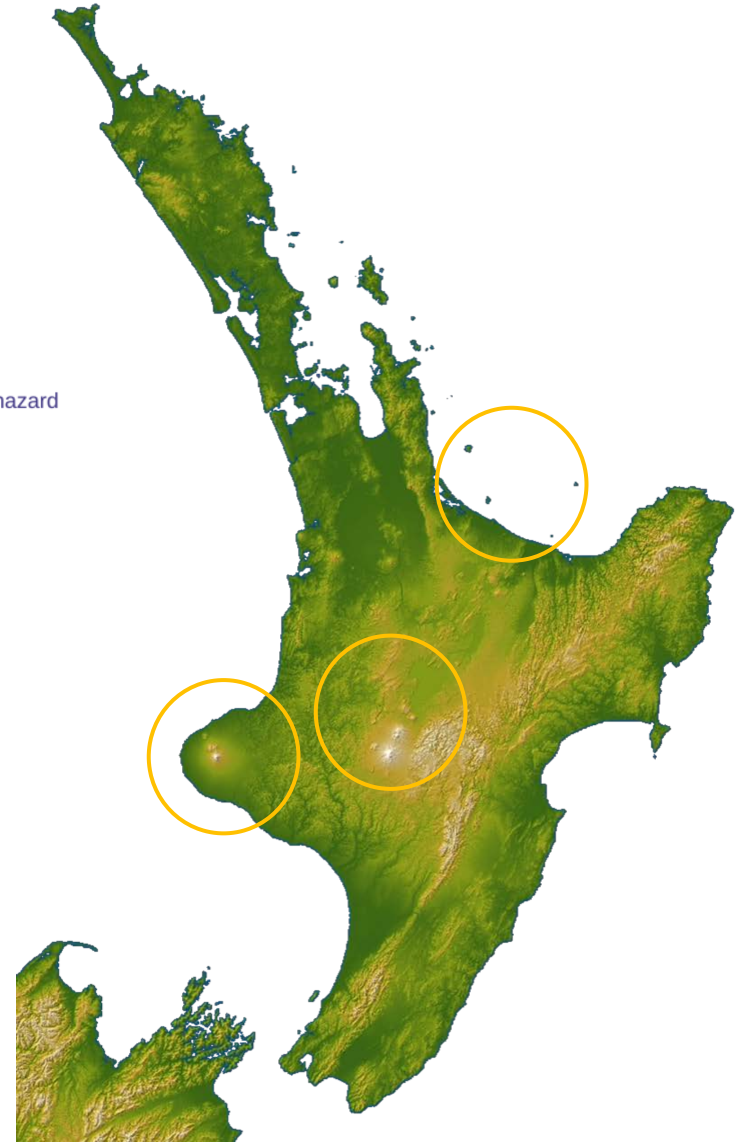

How do volcanologists forecast eruptions?

Melody Whitehead	Volcanic Risk Solutions, Massey
Jonathan Procter	Volcanic Risk Solutions, Massey
Mark Bebbington	Volcanic Risk Solutions, Massey
Matthew Irwin	Volcanic Risk Solutions, Massey
Paul Viskovic	GNS
Geoff Kilgour	GNS

How do volcanologists forecast eruptions?

Whitehead MG & Bebbington MS (2021)

Method selection in short-term eruption forecasting

Journal of Volcanology and Geothermal Research, *419*, p.107386.

Whitehead MG, Bebbington MS, Procter JN, Irwin ME & GPD Viskovic (2022)

An initial assessment of short-term eruption forecasting options in New Zealand

New Zealand Journal of Geology and Geophysics, DOI:10.1080/00288306.2022.2080236.

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Glossary

Prediction	*a definitive statement on future behaviour*
Forecast	*an uncertain statement on future behaviour*
Short-term	*hours to months*
Probabilistic	*probability of an event incorporating uncertainties*
Quantitative	*measurable, numeric*

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RESILIENCE TO NATURE'S CHALLENGES

Kia manawaroa – Ngā Ākina o Te Ao Tūroa

~~How do~~ Can volcanologists ~~forecast~~ predict eruptions?

"This volcano will erupt next Thursday"

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RESILIENCE TO NATURE'S CHALLENGES

Kia manawaroa – Ngā Ākina o Te Ao Tūroa

Can ~~How do~~ volcanologists forecast eruptions?

"There might be an ENORMOUS eruption before I am 4 and a half!"

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RESILIENCE TO NATURE'S CHALLENGES

Kia manawaroa – Ngā Ākina o Te Ao Tūroa

Can ~~How do~~ volcanologists accurately forecast eruptions?

"*Forecasting is a central goal of volcanology.*" (p1)

"*…in certain respects volcanoes are inherently unpredictable. As in other dynamical systems, very slight changes in initial conditions or slight changes in controlling parameters might have completely different long-term outcomes.*" (p12)

Sparks RSJ (2003) Forecasting volcanic eruptions. *Earth and Planetary Science Letters*, *210*(1-2), 1-15.

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Kia manawaroa – Ngā Ākina o Te Ao Tūroa

~~How do~~ Can volcanologists accurately forecast eruptions?

"Despite much progress over the last century, however, volcanoes still erupt with no detected precursors, lives and livelihoods are lost to eruptive activity, and forecasting the onsets of eruptions remains fraught with uncertainty." (p1)

"It may never be possible to forecast every eruption on a time scale and with a degree of confidence that is useful to society, but we believe that great progress is on the horizon." (p24)

Poland MP & Anderson KR (2020) Partly cloudy with a chance of lava flows: Forecasting volcanic eruptions in the twenty-first century. *Journal of Geophysical Research: Solid Earth*, *125*(1).

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Kia manawaroa –
Ngā Ākina o
Te Ao Tūroa

Can ~~How do~~ volcanologists accurately forecast eruptions?

"This inherent complexity [of volcanoes] and the large uncertainty in the knowledge of these processes lead to the practical impossibility of predicting deterministically, or even with a small uncertainty, the onset time, location, and size of the impending eruption." (p1777)

"Uncertainties cannot be completely eliminated….but they can be reduced significantly through the development of more reliable and skilled forecasting models." (p1800)

Marzocchi W & Bebbington MS (2012) Probabilistic eruption forecasting at short and long time scales. *Bulletin of volcanology*, *74*(8), 1777-1805.

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Can ~~How do~~ volcanologists accurately forecast eruptions?

Maybe?

Sometimes?

Not yet?

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How do volcanologists forecast eruptions?

Question:

When and how will this volcano erupt?

INTERPRETAT

(what d

OLATION

hat does this mean about the future)

Assumptions

Knowledge & Data:

General

Scientific principles
Global volcano database
Published literature
Monitoring database

Volcano-specific

Eruption history
Published literature
Monitoring data

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RESILIENCE TO NATURE'S CHALLENGES

Kia manawaroa – Ngā Ākina o Te Ao Tūroa

How do volcanologists forecast eruptions?

Question:

When and how will this volcano erupt?

← **FORECASTING METHODS** ←

Knowledge & Data:

General

Scientific principles
Global volcano database
Published literature
Monitoring database

Volcano-specific

Eruption history
Published literature
Monitoring data

Assumption 1 – Previous behaviour informs future behaviour
Assumption 2 – Data that can be observed are related to the question we are trying to answer

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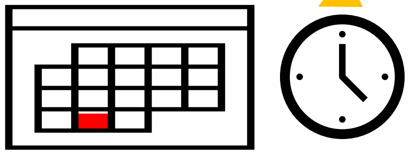
Kia manawaroa – Ngā Ākina o Te Ao Tūroa

Eruption Parameters

When and how will this volcano erupt?



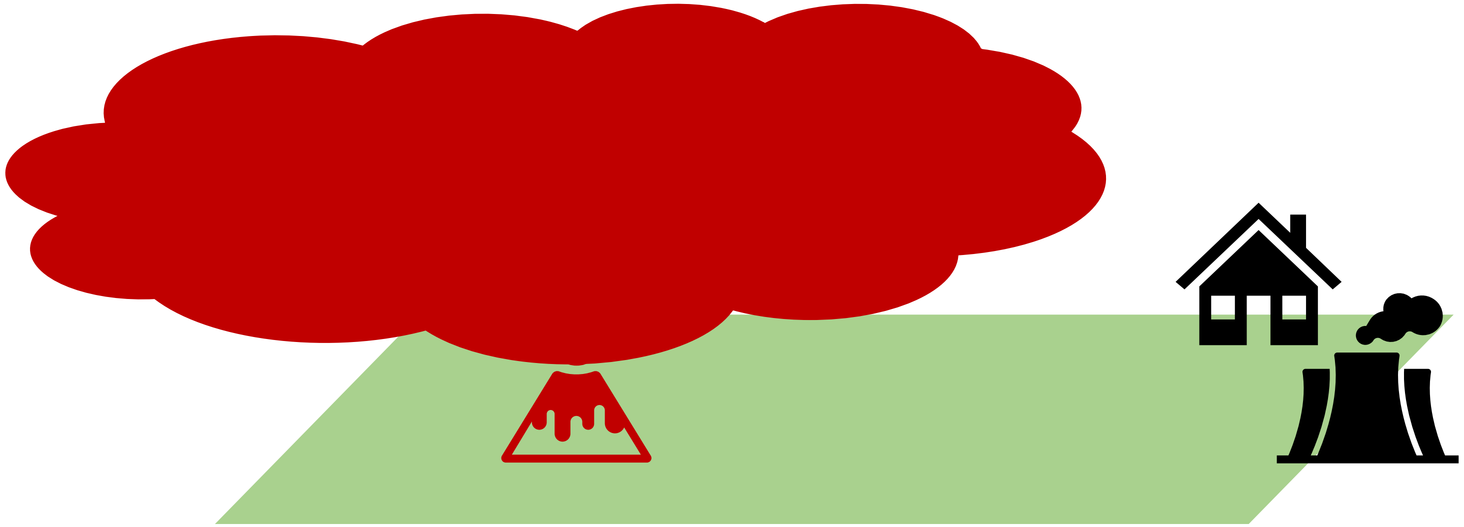
Eruption Parameters:

Eruption start time

Eruptive vent location(s)

Eruption Parameters

When and how will this volcano erupt?



Eruption Parameters:

Eruption start time

Eruptive vent location(s)

Eruption size

Eruption Parameters

When and how will this volcano erupt?

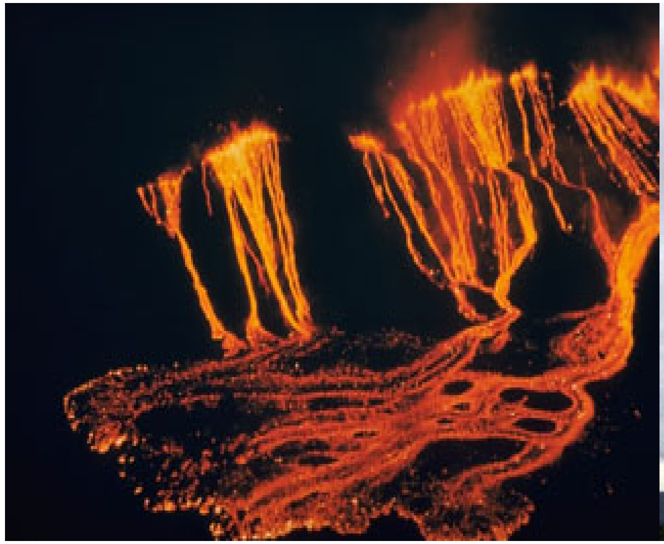
Eruption Parameters:

Eruption start time

Eruptive vent location(s)

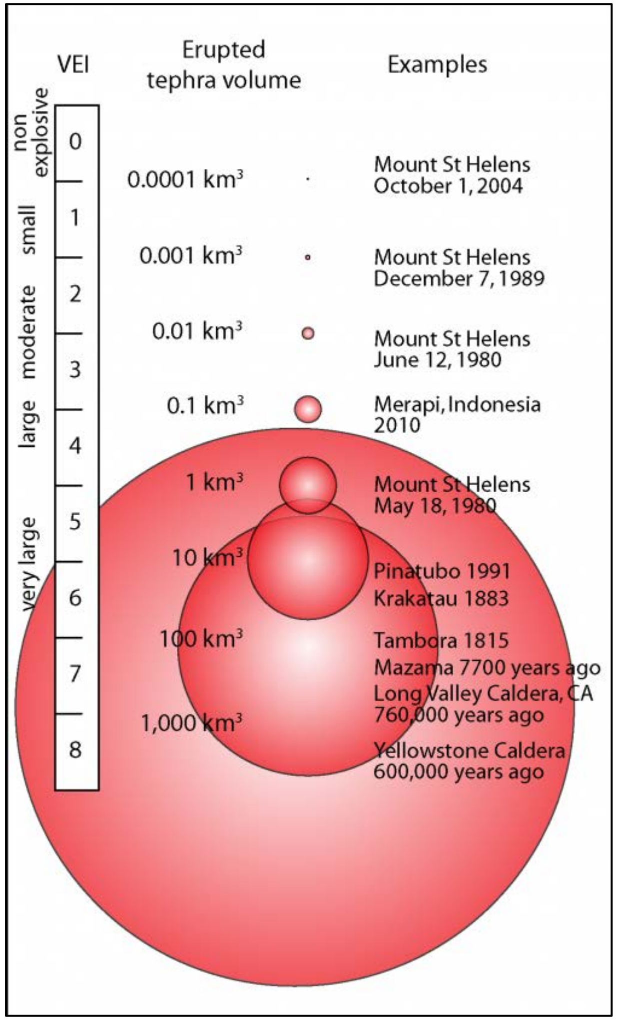
Eruption size

Initial eruption style



EFFUSIVE
Lava fountains, Kilauea 1959

EXPLOSIVE
Ash plume, Sinabung 2013



Newhall & Self (1982)

Images: https://volcano.si.edu/ (GVP)
Newhall CG & Self S (1982) The volcanic explosivity index (VEI) an estimate of explosive magnitude for historical volcanism. *Journal of Geophysical Research: Oceans*, *87*(C2), 1231-1238.

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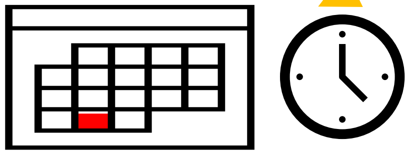
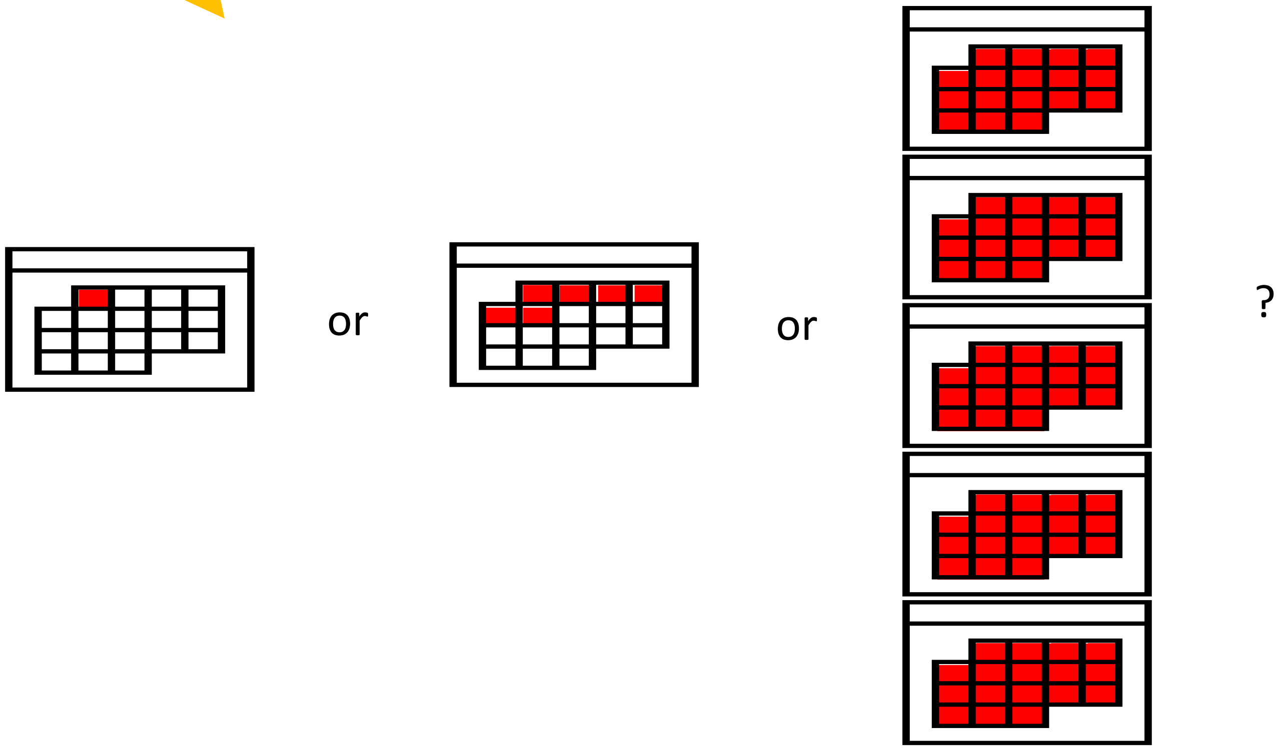
Kia manawaroa – Ngā Ākina o Te Ao Tūroa

Eruption Parameters

When and how will this volcano erupt?





Eruption Parameters:

Eruption start time

Eruptive vent location(s)

Eruption size

Initial eruption style

Eruption phase duration

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RESILIENCE TO NATURE'S CHALLENGES

Kia manawaroa – Ngā Ākina o Te Ao Tūroa

Eruption Parameters

When and how will this volcano erupt?

Eruption Parameters:

Eruption start time

Eruptive vent location(s)

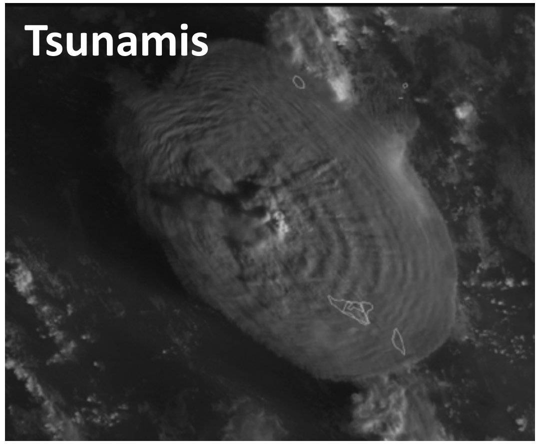
Eruption size

Initial eruption style

Eruption phase duration

Phase specific hazards

Mayon, 1984 [P. Pena/PIVS]



Hunga Tonga-Hunga Ha'api, 2022 [NOAA GOES West]

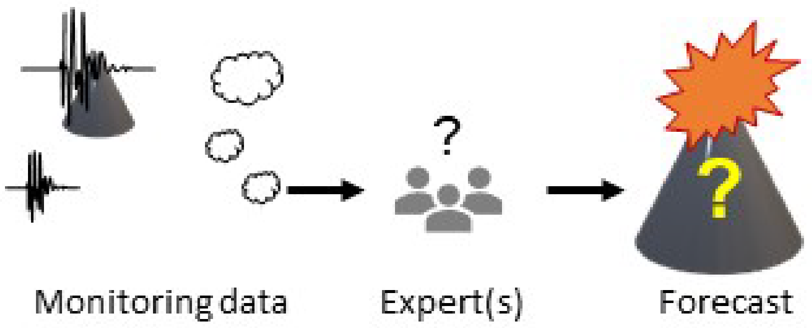
Pinatubo, 1991 [C. Newhall/USGS]

Pinatubo, 1991 [V. Gempis/USAF]

(1) Expert Interpretation

Eruption Parameters:

Eruption start time
Eruptive vent location(s)
Eruption size
Initial eruption style
Eruption phase duration
Phase specific hazards



Requirements:

Expert personnel
Forecasting algorithm
☆ General monitoring equipment

☆ Previous monitoring data
☆ Previous eruption data
Previous expert elicitation

LIMITATIONS

Experts are subjective

High stress and time-constraints during volcanic unrest

Assumption 1 – Previous behaviour informs future behaviour
Assumption 2 – Data that can be observed are related to the question we are trying to answer
Assumption 3 - The expert (or group of experts) can produce an accurate eruption forecast
Assumption 4 - The method/expert performs as expected

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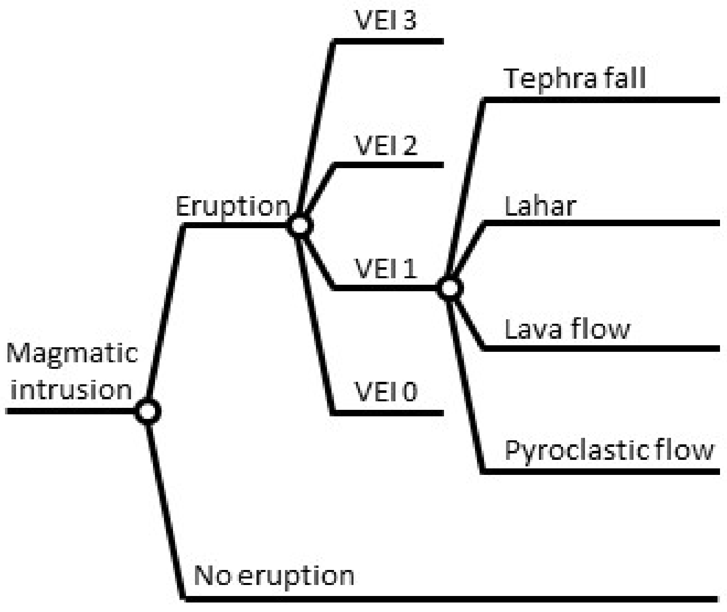
RESILIENCE TO NATURE'S CHALLENGES

Kia manawaroa – Ngā Ākina o Te Ao Tūroa

(2) Event tree

Eruption Parameters:

Eruption start time
Eruptive vent location(s)
Eruption size
Initial eruption style
Eruption phase duration
Phase specific hazards



Requirements:

Expert personnel
Forecasting algorithm
☆ General monitoring equipment

Previous monitoring data
☆ Previous eruption data
Previous expert elicitation

LIMITATIONS

No eruption start time

Experts are subjective

Assumption 1 – Previous behaviour informs future behaviour
Assumption 2 – Data that can be observed are related to the question we are trying to answer
Assumption 3 - The conceptual model is correct and includes all potential out-comes
Assumption 4 - The underlying process producing the data exhibits time homogeneity on longer scales
Assumption 5 - The method / expert performs as expected
Assumption 6 - Assignment of base rate and/or conditional probabilities are correct
Assumption 7 - Assignment of threshold values or conditions or classifications are correct

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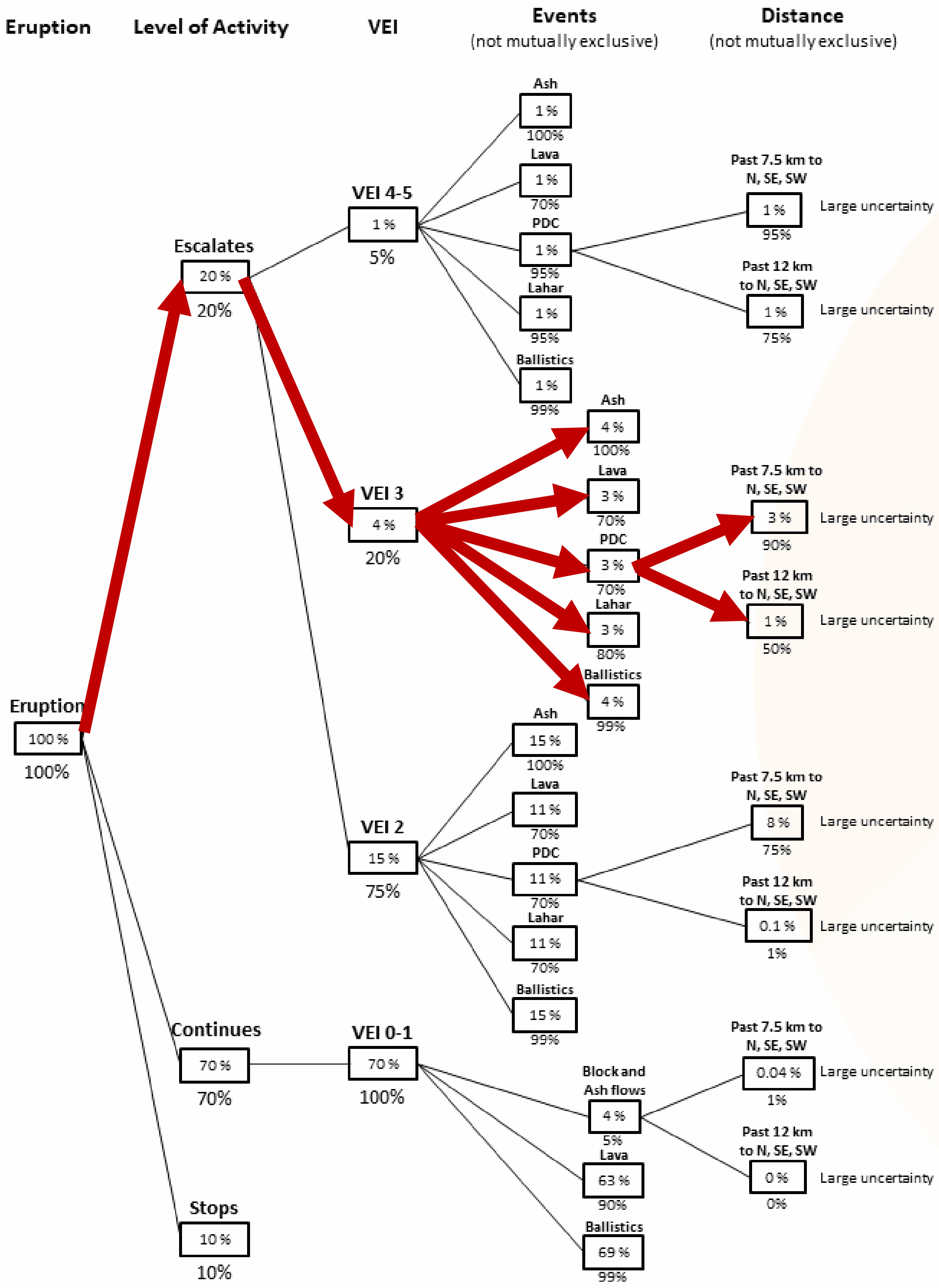
Kia manawaroa – Ngā Ākina o Te Ao Tūroa



(2) Event Tree

An event tree used during the Agung eruption for the look-forward period of two weeks from: 23 Jan – 6 Feb 2018.

Syahbana DK et al. (2019) The 2017–19 activity at Mount Agung in Bali (Indonesia): Intense unrest, monitoring, crisis response, evacuation, and eruption. *Scientific reports*, *9*(1), 1-17.

Images: https://volcano.si.edu/ (GVP)

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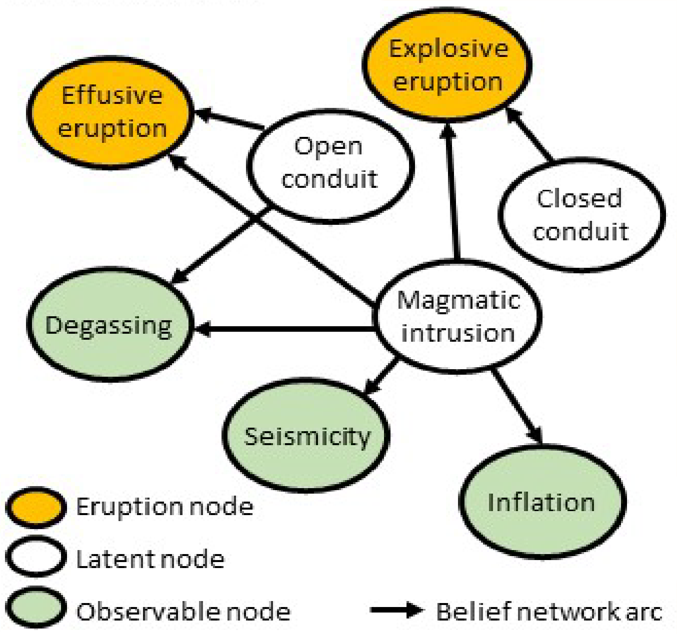
RESILIENCE TO NATURE'S CHALLENGES

Kia manawaroa – Ngā Ākina o Te Ao Tūroa

(3) Belief Network

Eruption Parameters:

Eruption start time
Eruptive vent location(s)
Eruption size
Initial eruption style
Eruption phase duration
Phase specific hazards



Requirements:

Expert personnel
Forecasting algorithm
General monitoring equipment

☆ Previous monitoring data
☆ Previous eruption data
Previous expert elicitation

LIMITATIONS

No eruption start time

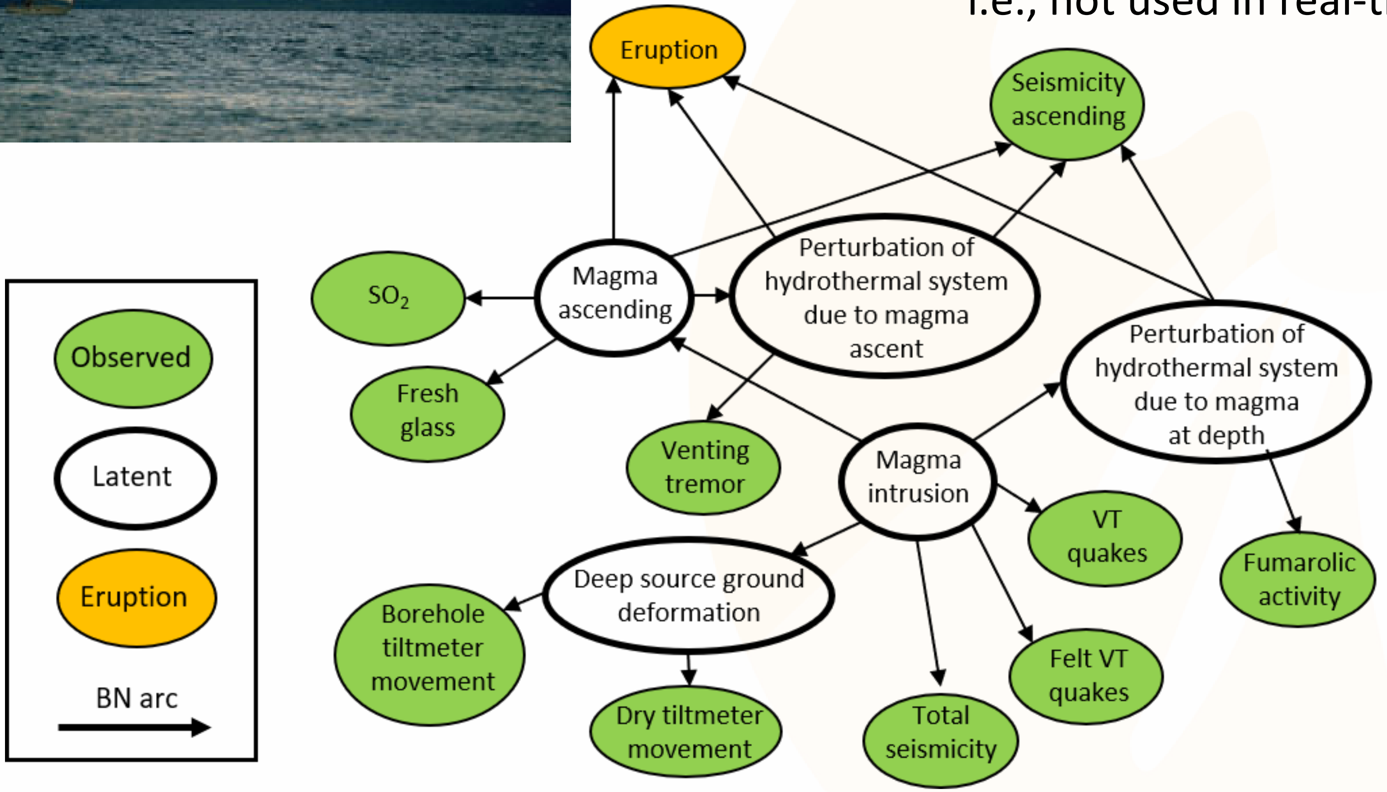
Training requires previous eruption and monitoring data

Experts are subjective

Assumption 1 – Previous behaviour informs future behaviour
Assumption 2 – Data that can be observed are related to the question we are trying to answer
Assumption 3 - The conceptual model is correct and includes all potential out-comes
Assumption 4 - The underlying process producing the data exhibits time homogeneity on longer scales
Assumption 5 - The method / expert performs as expected
Assumption 6 - Assignment of base rate and/or conditional probabilities are correct
Assumption 7 - Assignment of threshold values or conditions or classifications are correct

(3) Belief Network

Bayesian belief network for La Soufrière.
Created with hindsight for the 1975-1977 eruption, i.e., not used in real-time.



Hincks TK et al. (2014) Retrospective analysis of uncertain eruption precursors at La Soufrière volcano, Guadeloupe, 1975–77: volcanic hazard assessment using a Bayesian Belief Network approach. *J. of Applied Volcanology*, *3*(1).

Images: https://volcano.si.edu/ (GVP)

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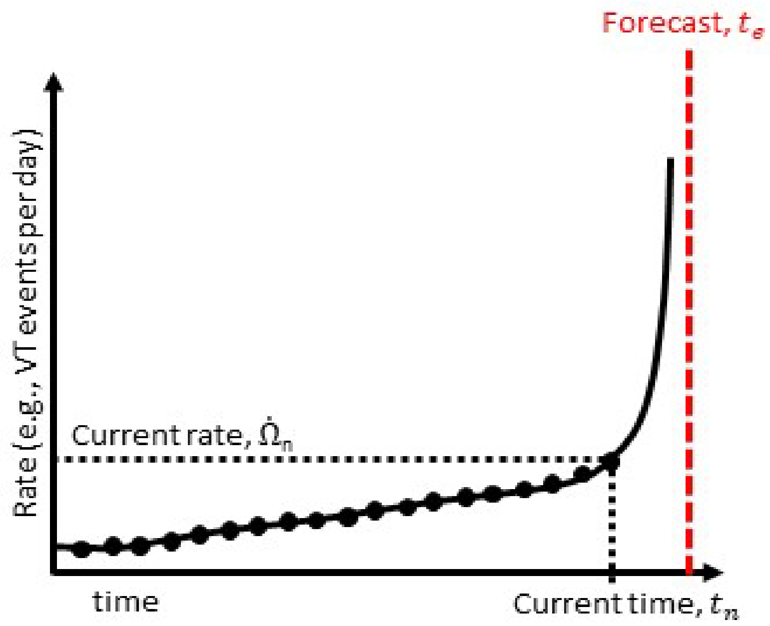
RESILIENCE TO NATURE'S CHALLENGES

Kia manawaroa – Ngā Ākina o Te Ao Tūroa

(4) Failure Forecasting

Eruption Parameters:

Eruption start time
Eruptive vent location(s)
Eruption size
Initial eruption style
Eruption phase duration
Phase specific hazards



Requirements:

Expert personnel
Forecasting algorithm
General monitoring equipment

Previous monitoring data
Previous eruption data
Previous expert elicitation

LIMITATIONS

ONLY eruption start time

Must observe accelerating signal

Left-truncating data is subjective

Assumption 1 – Previous behaviour informs future behaviour
Assumption 2 – Data that can be observed are related to the question we are trying to answer
Assumption 3 - The eruption is preceded by any accelerating phenomenon
Assumption 4 - Data provides sufficient information to forecast required eruption parameters
Assumption 5 - The method/expert performs as expected
Assumption 6 - Assignment of threshold values, parameters, conditions, or classifications are correct (alpha)
Assumption 7 - Data truncation point is correct (after which time all data are used to fit the failure forecasting equation)
Assumption 8 - Curve-fitting equation is correct

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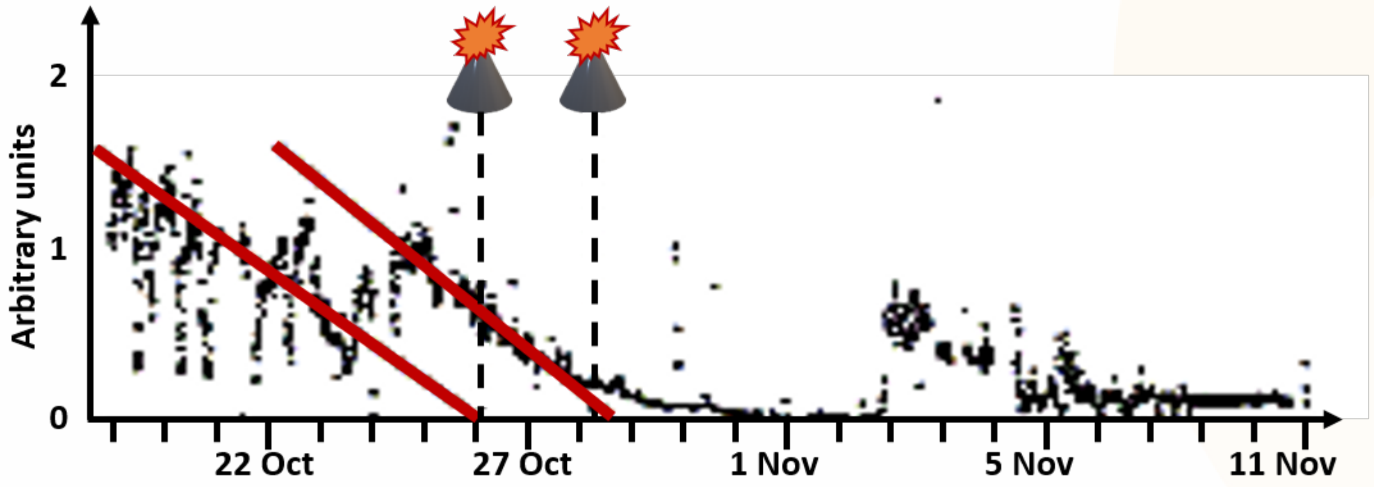
RESILIENCE TO NATURE'S CHALLENGES

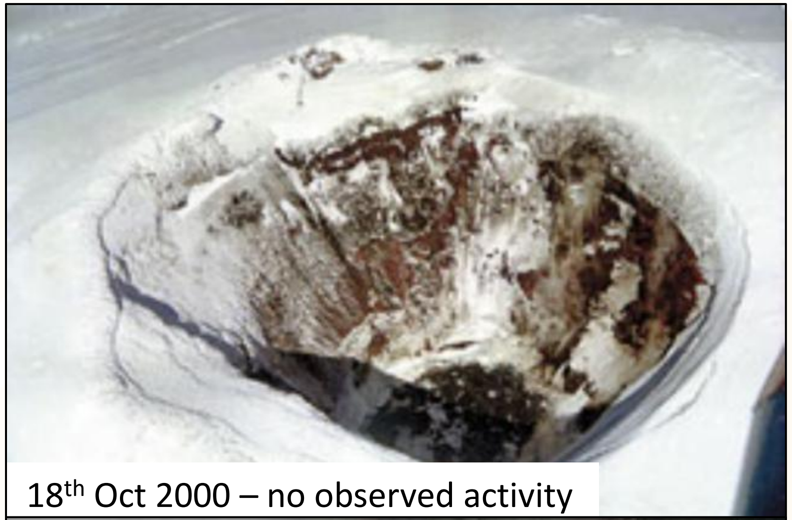
Kia manawaroa – Ngā Ākina o Te Ao Tūroa

(4) Failure Forecasting

Hindcasting of two explosions at Villarrica, Chile in 2000, produced **<u>after</u>** the fact. Explosions detected on GOES images. Used the inverse of the amplitude of the seismic signal: 1/normalized(RSAM)



Ortiz R et al. (2003) Villarrica volcano (Chile): characteristics of the volcanic tremor and forecasting of small explosions by means of a material failure method. *Journal of Volcanology and Geothermal Research*, *128*(1-3), 247-259.



18th Oct 2000 – no observed activity

24th Oct 2000 – significant heating

Images: https://volcano.si.edu/ (GVP)

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RESILIENCE TO NATURE'S CHALLENGES

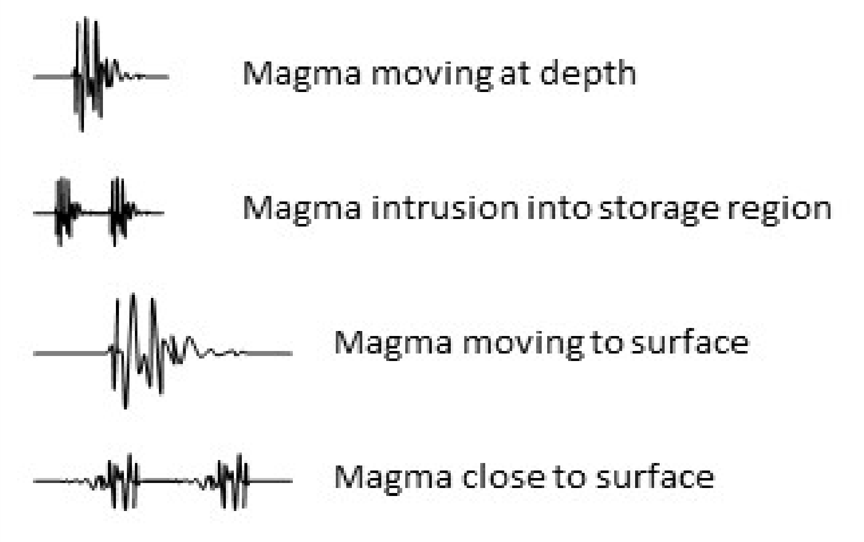
Kia manawaroa – Ngā Ākina o Te Ao Tūroa

(5) Process/Source models

Eruption Parameters:

Eruption start time
Eruptive vent location(s)
Eruption size
Initial eruption style
Eruption phase duration
Phase specific hazards

(seismic example)



Requirements:

Expert personnel
Forecasting algorithm
General monitoring equipment

☆ Previous monitoring data
☆ Previous eruption data
Previous expert elicitation

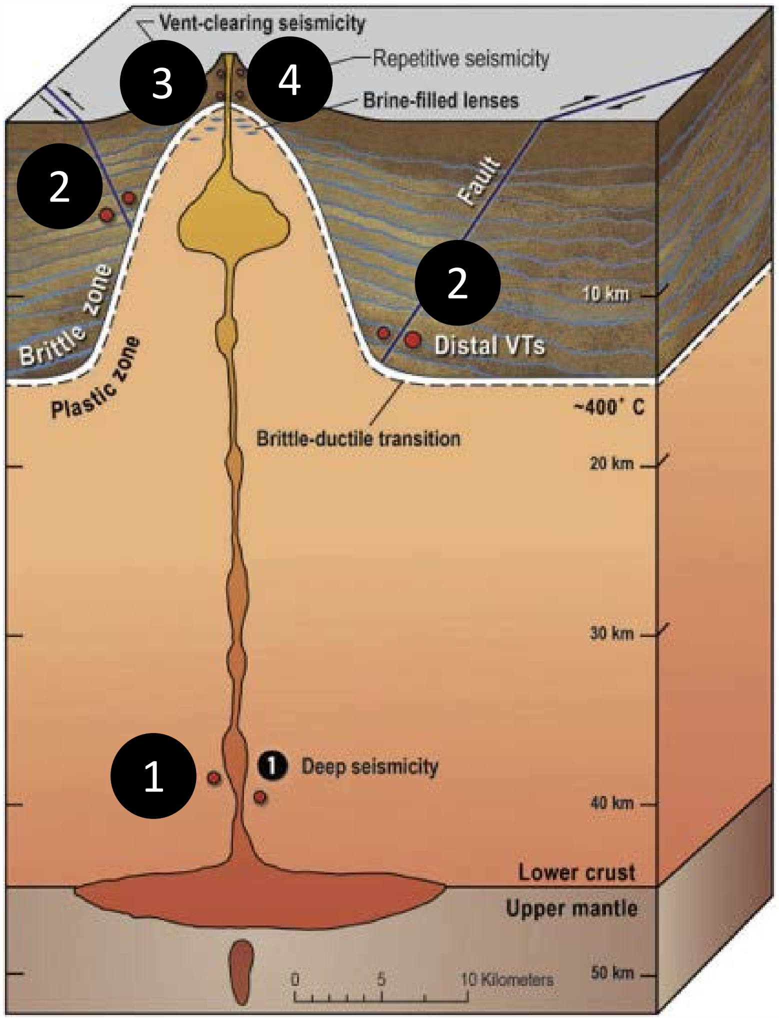
LIMITATIONS

Still mainly conceptual stage

Assumption 1 – Previous behaviour informs future behaviour
Assumption 2 – Data that can be observed are related to the question we are trying to answer
Assumption 3 - The conceptual model is correct and includes all potential outcomes
Assumption 4 - Data provides sufficient information to forecast required eruption parameters
Assumption 5 - The method/expert performs as expected
Assumption 6 - Assignment of threshold values, parameters, conditions, or classifications are correct

(5) Process/Source models

CONCEPTUAL but has been used to inform other forecasting models (e.g., Event Trees, Sinabung, 2013)



4 Final ascent of magma to surface

3 Magma moving upwards from upper magma storage to surface

2 Magma intruding into an upper magma storage region

1 Magma rising from a lower crustal storage region

McCausland WA et al. (2019) Using a process-based model of pre-eruptive seismic patterns to forecast evolving eruptive styles at Sinabung Volcano, Indonesia. *Journal of Volcanology and Geothermal Research*, *382*, 253-266.

Images: https://volcano.si.edu/ (GVP)

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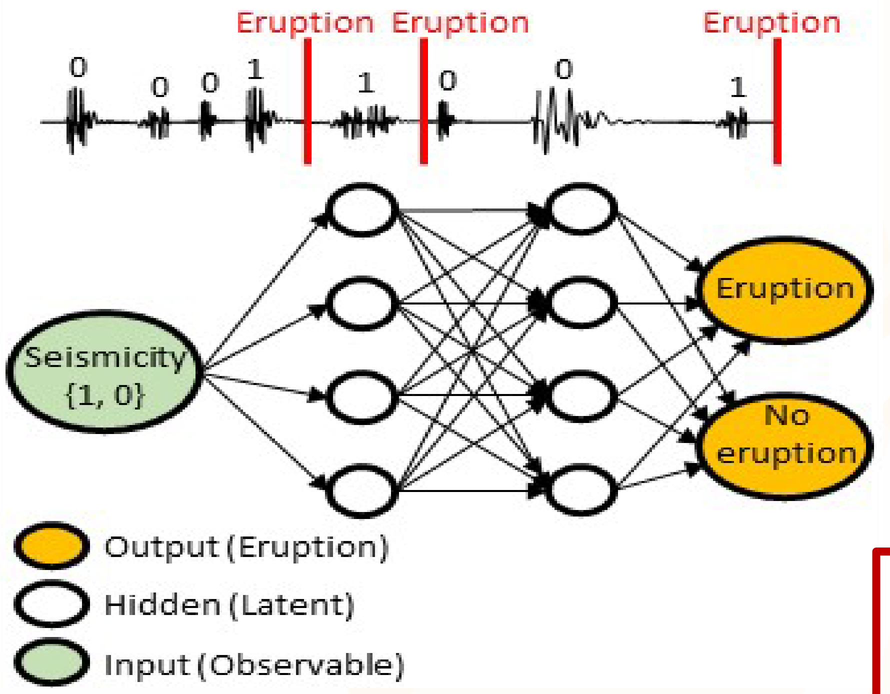
RESILIENCE TO NATURE'S CHALLENGES

Kia manawaroa – Ngā Ākina o Te Ao Tūroa

(6) Machine Learning

Eruption Parameters:

Eruption start time
Eruptive vent location(s)
Eruption size
Initial eruption style
Eruption phase duration
Phase specific hazards



Requirements:

Expert personnel
Forecasting algorithm
General monitoring equipment

Previous monitoring data
Previous eruption data
Previous expert elicitation

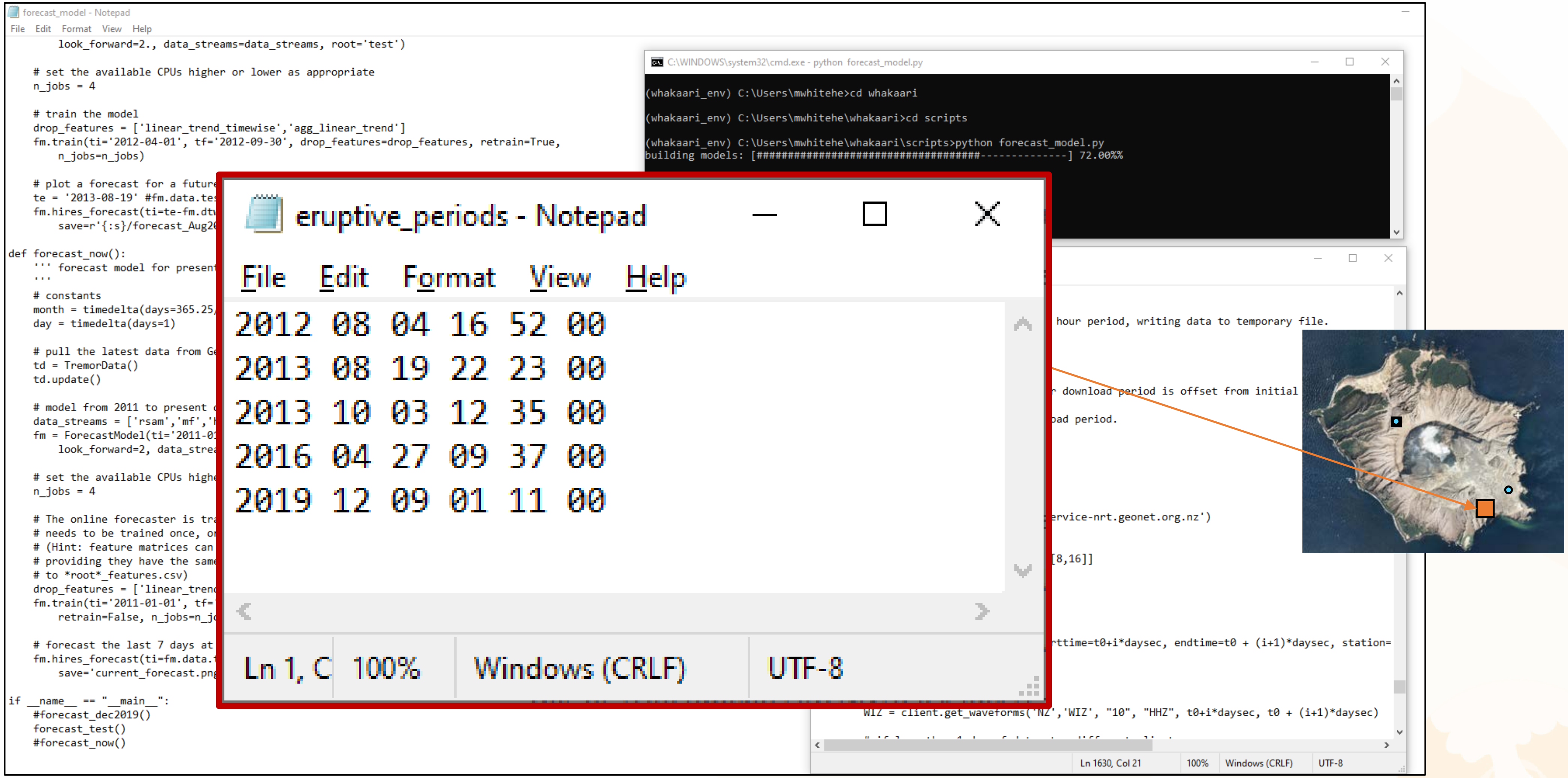
LIMITATIONS
Need enough training data
(recommendation is > 50 per class*)

Assumption 1 – Previous behaviour informs future behaviour
Assumption 2 – Data that can be observed are related to the question we are trying to answer
Assumption 3 - The underlying process producing the data exhibits time homogeneity on longer scales
Assumption 4 - Data provides sufficient information to forecast required eruption parameters
Assumption 5 - Sufficient data are available to train and test the model
Assumption 6 - There is sufficient variation within the data to cover most outcomes
Assumption 7 - The method/expert performs as expected
Assumption 8 - Assignment of threshold values, parameters, conditions, or classifications are correct

**"in order to train supervised models…..20 labeled events per class is a good starting point, but a minimum of 50 labeled events per class is recommended."*
(Carneil & Guzmán, 2020, Machine Learning in Volcanology)

Malfante et al. (2018) – 800 events per class, and ran the whole thing 50 times to get statistically stable results

(6) Machine Learning



All code from: https://github.com/ddempsey/whakaari

Dempsey DE, Cronin SJ, Mei S, Kempa-Liehr AW (2020) Automatic precursor recognition and real-time forecasting of sudden explosive volcanic eruptions at Whakaari, New Zealand. Nature communications. 11(1):1-8.

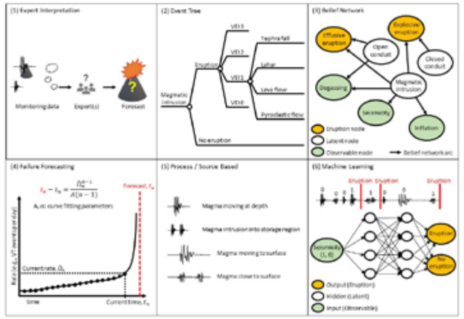
How do volcanologists forecast eruptions?

RESILIENCE TO NATURE'S CHALLENGES

Kia manawaroa – Ngā Ākina o Te Ao Tūroa

Eruption Parameters:

Eruption start time
Eruptive vent location(s)
Eruption size
Initial eruption style
Eruption phase duration
Phase specific hazards



What forecasting methods are feasible?

Requirements:

Expert personnel
Forecasting algorithm
General monitoring equipment

Previous monitoring data
Previous eruption data
Previous expert elicitation

What do we need to know for this volcano?

What requirements are met at this volcano?

Aotearoa New Zealand's volcanoes

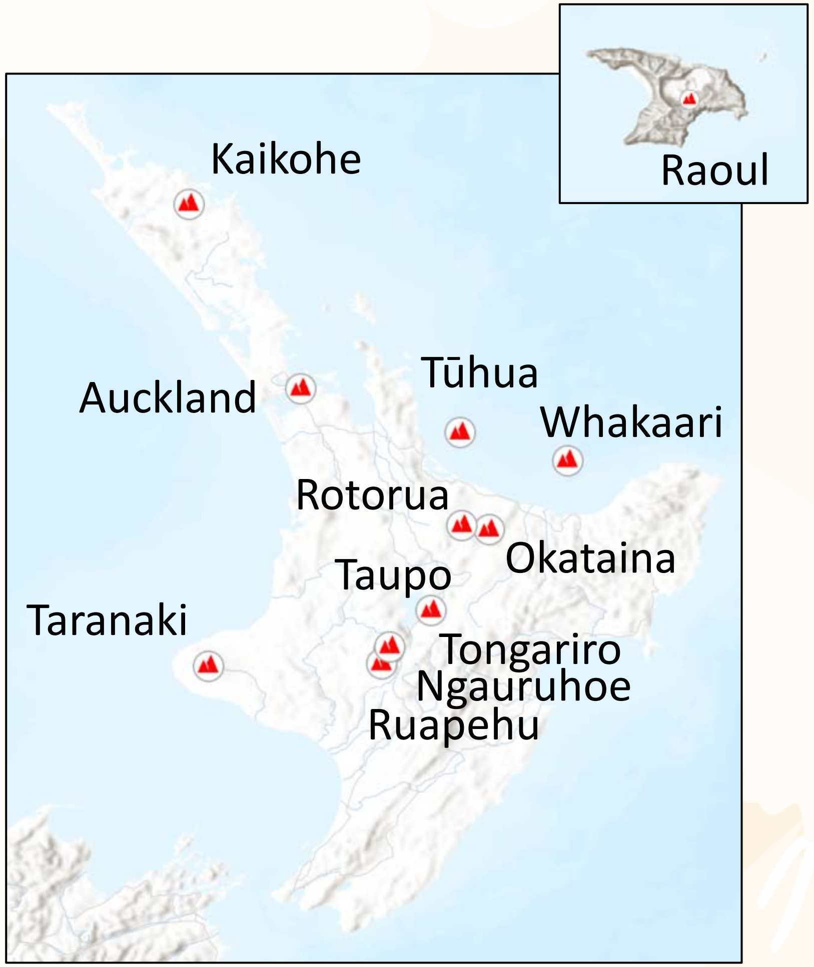
RESILIENCE TO NATURE'S CHALLENGES

Kia manawaroa – Ngā Ākina o Te Ao Tūroa

What forecasting methods are feasible?

What do we need to know for this volcano?

What requirements are met at this volcano?



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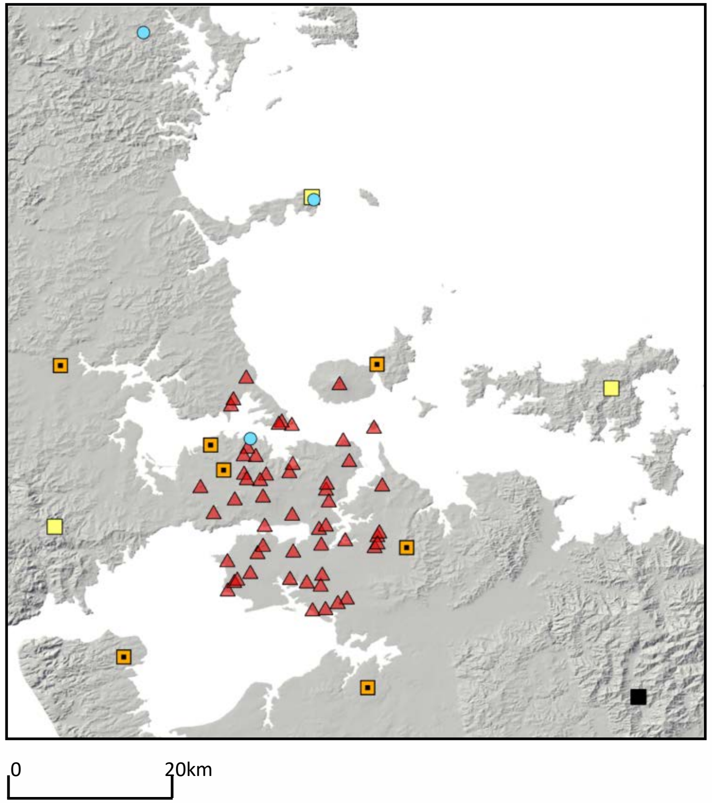
Kia manawaroa – Ngā Ākina o Te Ao Tūroa

Auckland Volcanic Field



3 GNSS station
1 Broadband seis.
7 Short Period Borehole seis.
3 Short Period seis.
AVF vents

Area used: "Auckland Region"

Expert elicitation already completed for Bayesian Event Tree (Lindsay et al. 2010 -> Wild et al. 2022)

Failure forecasting method difficult at a distributed volcanic system

Insufficient data to train a belief network or machine learning algorithms

	Expert Interpretation	Event Trees	Belief Networks	Belief Networks with training	Failure Forecasting	Process/Source based	Machine Learning
Eruption onset time							
Eruption size							
Eruption style/type							
Eruption duration							
Eruption specific hazards							
Location specific parameters							

Negligible effort/time
Some effort/time
Medium effort/time
Significant effort/time
Not currently feasible

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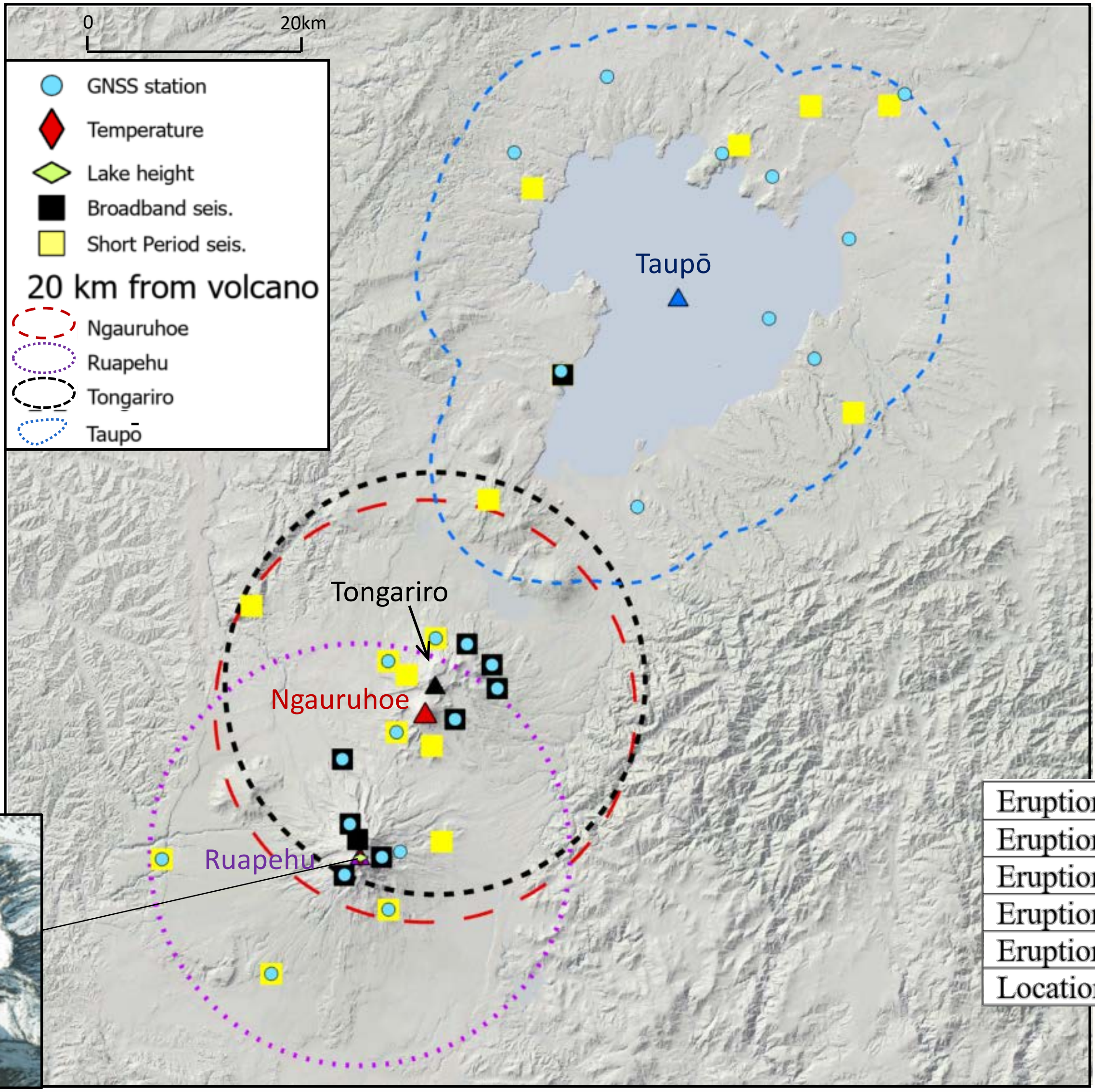
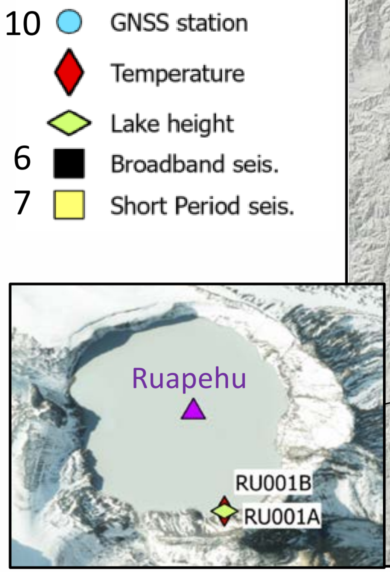
RESILIENCE TO NATURE'S CHALLENGES

Kia manawaroa – Ngā Ākina o Te Ao Tūroa

Ruapehu





Area used: < 20 km from crater lake

Sufficient seismic stations (> 6 broadband) suggests relative ease of application of FFM.

Several eruption-monitoring pairs available for belief network training. Data to train machine learning algorithms are available but must first be vectorised from paper seismograms.

	Expert Interpretation	Event Trees	Belief Networks	Belief Networks with training	Failure Forecasting	Process/Source based	Machine Learning
Eruption onset time	Negligible	Significant	Significant	Significant	Negligible	Some	Significant
Eruption size	Negligible	Some	Some	Some	Medium	Some	Significant
Eruption style/type	Negligible	Some	Some	Some	Significant	Medium	Significant
Eruption duration	Negligible	Significant	Significant	Significant	Significant	Medium	Significant
Eruption specific hazards	Negligible	Some	Some	Some	Significant	Medium	Significant
Location specific parameters	Negligible	Some	Some	Some	Medium	Some	Significant

Negligible effort/time | Medium effort/time | Significant effort/time
Some effort/time | Not currently feasible

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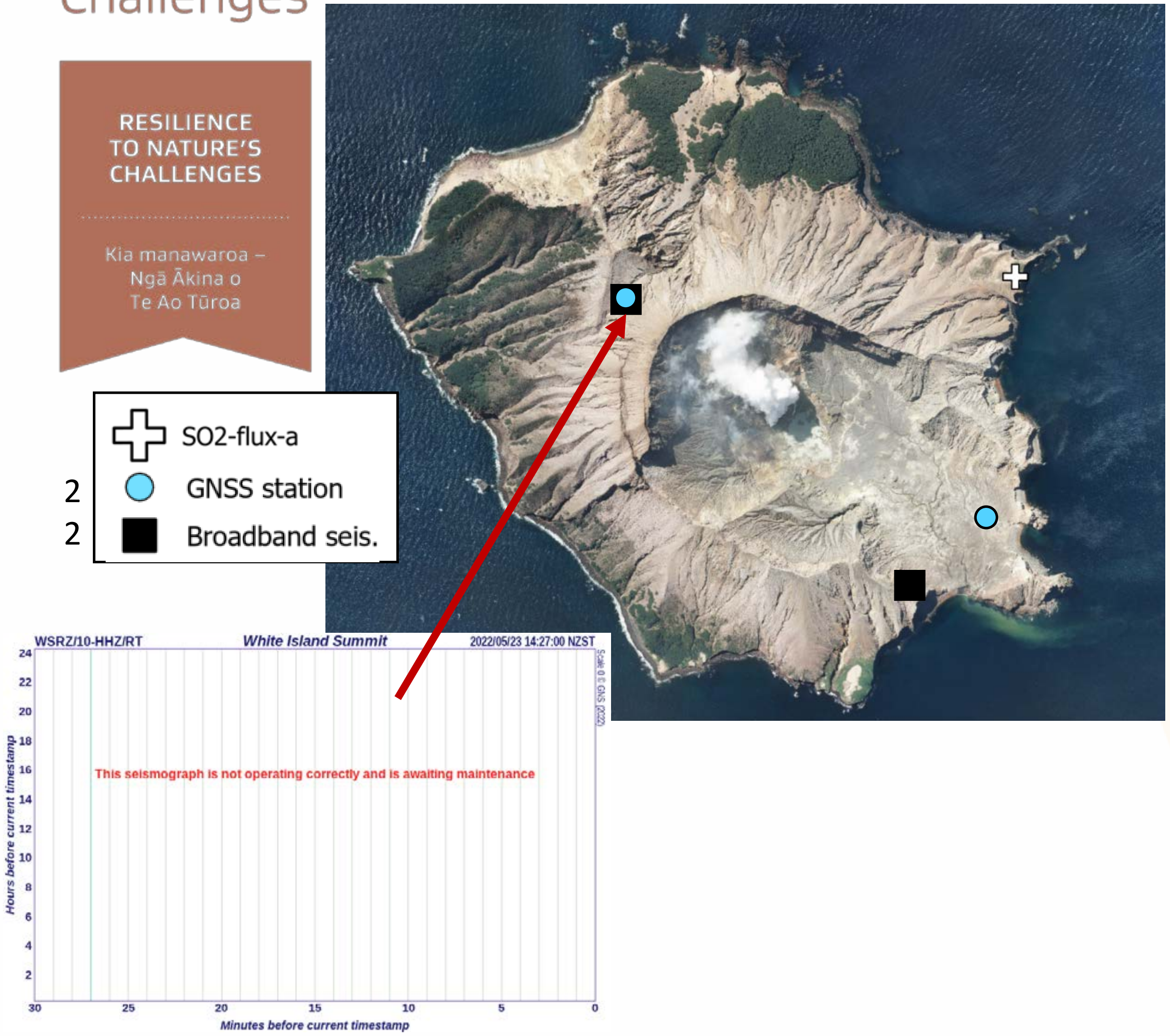
Kia manawaroa – Ngā Ākina o Te Ao Tūroa

Whakaari



Seismogram, May 2022: https://www.geonet.org.nz/volcano/monitoring/whiteisland

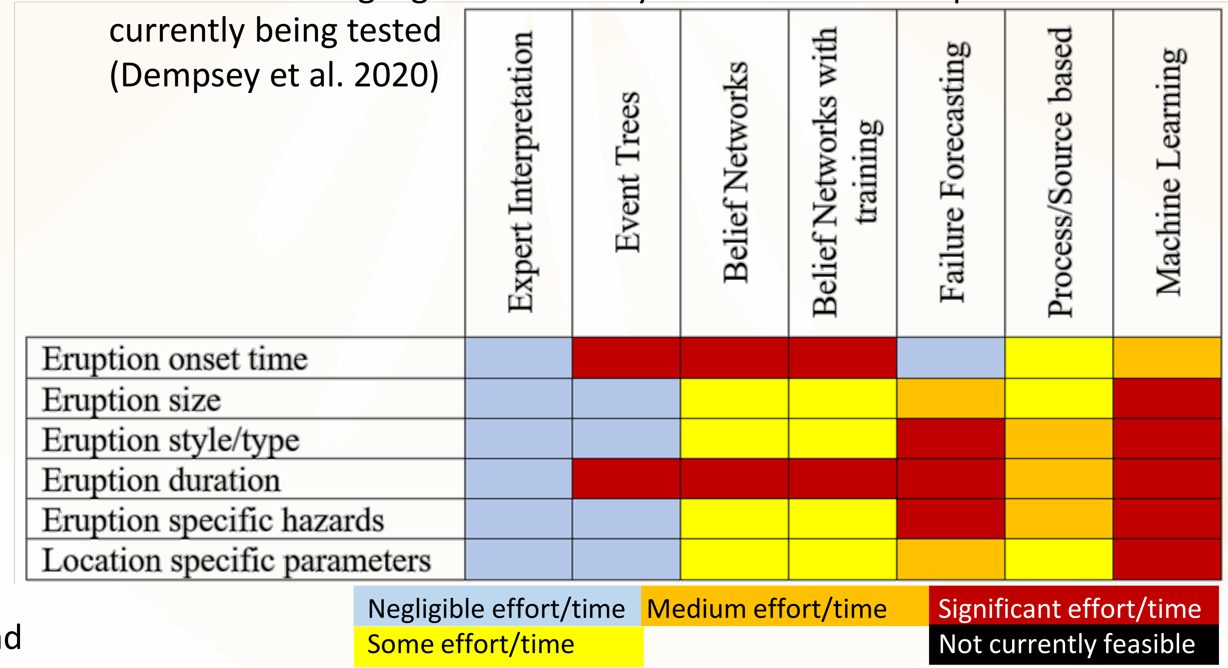
Area used: On island

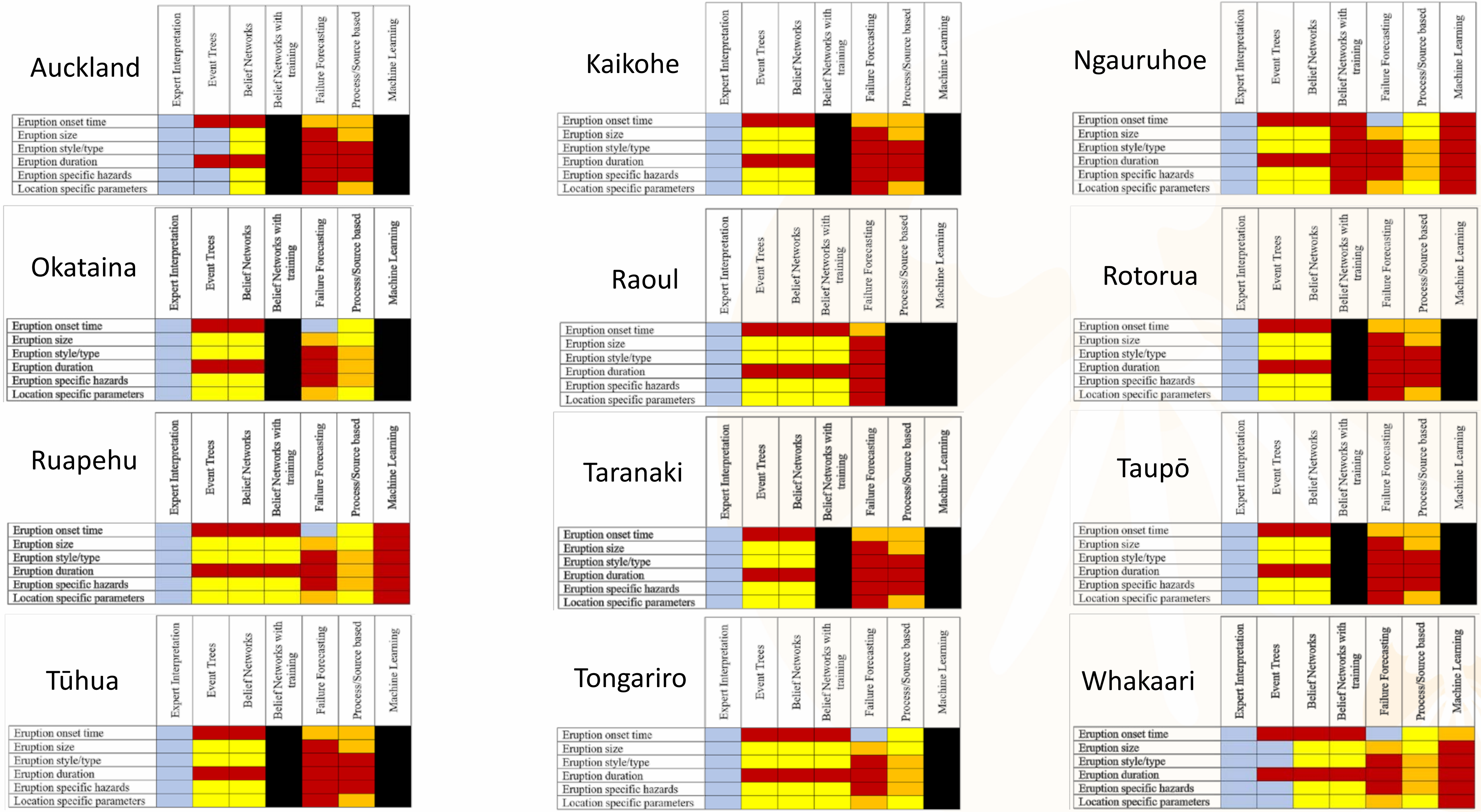
Data to train machine learning algorithms are available but must first be vectorised from paper seismograms

Several eruption-monitoring pairs available for belief network training

Expert elicitation exists for belief networks (Christophersen et al. 2018) and potentially allowing easier application of event trees

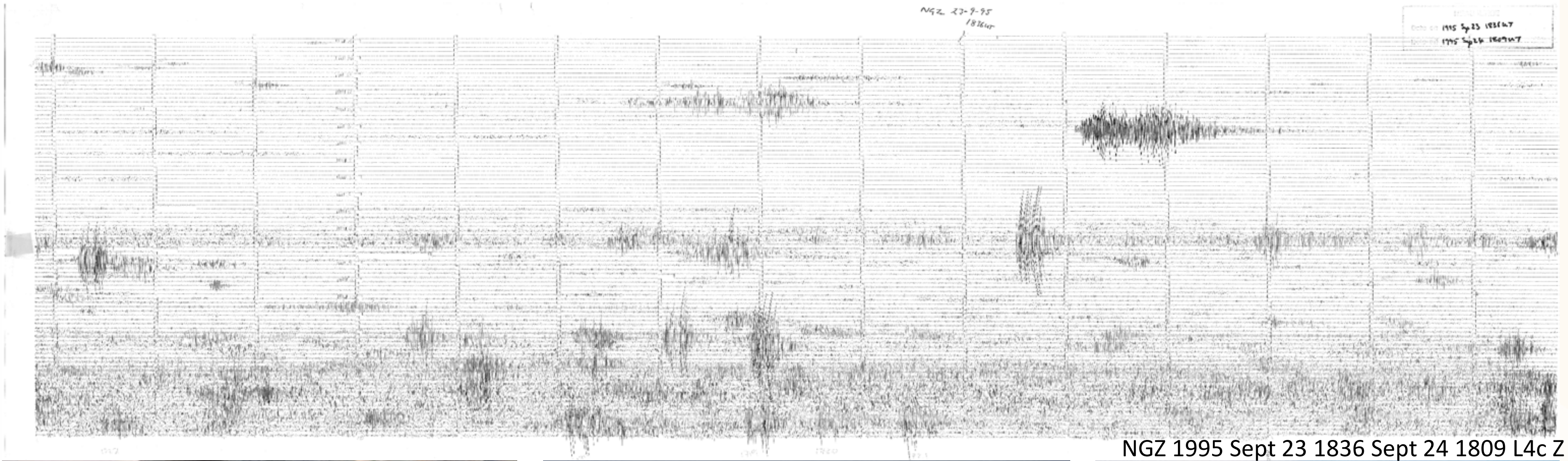
Machine-learning algorithm already constructed for eruption onset & currently being tested (Dempsey et al. 2020)




Auckland
Kaikohe
Ngauruhoe
Okataina
Raoul
Rotorua
Ruapehu
Taranaki
Taupō
Tūhua
Tongariro
Whakaari
Expert Interpretation
Event Trees
Belief Networks
Belief Networks with training
Failure Forecasting
Process/Source based
Machine Learning
Eruption onset time
Eruption size
Eruption style/type
Eruption duration
Eruption specific hazards
Location specific parameters

Example: Ruapehu, 23 Sept 1995

Paul Viskovic (GNS)



NGZ 1995 Sept 23 1836 Sept 24 1809 L4c Z

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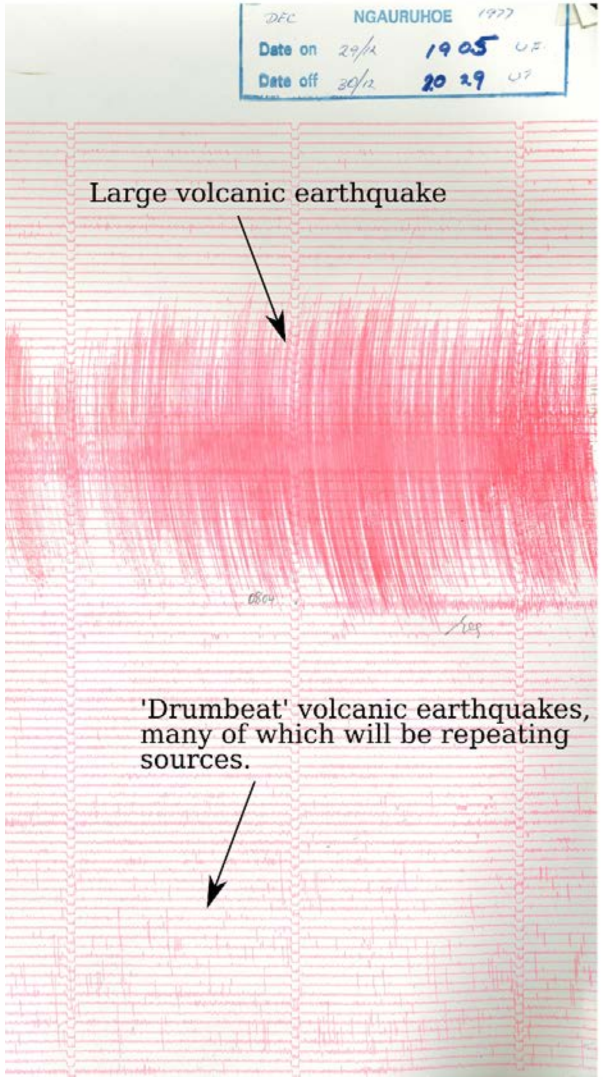
Kia manawaroa – Ngā Ākina o Te Ao Tūroa

Example: Ngauruhoe, 1970s

Paul Viskovic (GNS)



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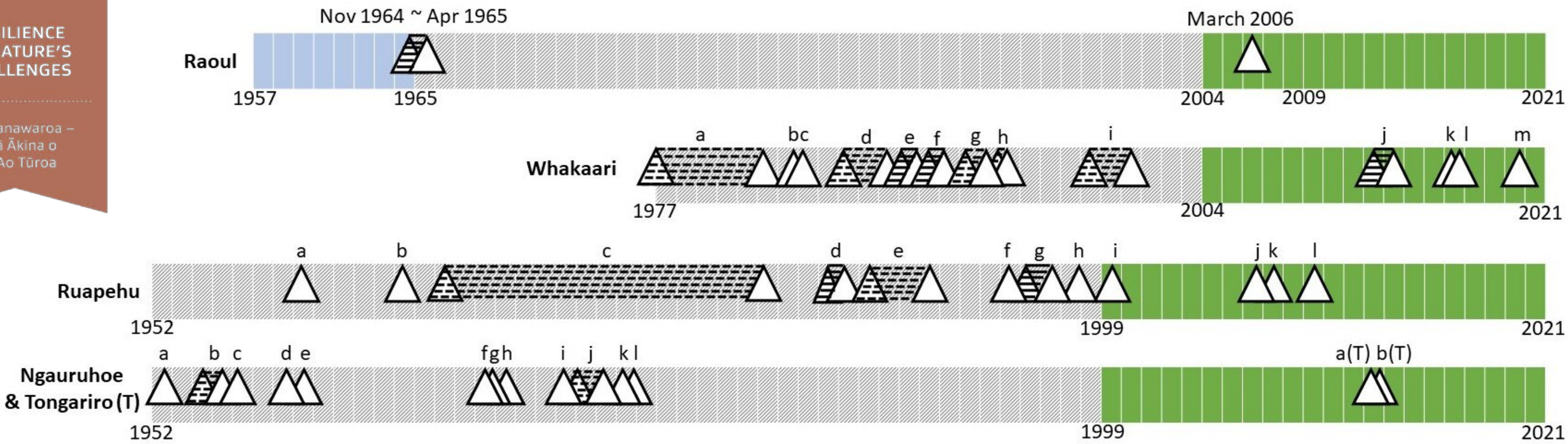
Kia manawaroa – Ngā Ākina o Te Ao Tūroa

Seismic data yet to be exploited



Film

Paper

Digital

Ruapehu

- a. May – Aug 1959
- b. Apr - June 1964
- c. Mar 1966 – Mar 1982
- d. May 1985 – Feb 1986
- e. Aug 1987 – June 1990
- f. Feb – Mar 1994
- g. Jan 95 – Sep 1996
- h. Oct 97 – Jan 1998
- i. Sep – Oct 1999
- j. Oct 2006
- k. Sep 2007
- l. July 2009

Whakaari

- a. Dec 1976 – Jan 1982
- b. Dec 1983
- c. Feb 1984
- d. Feb 1986 - Apr 1988
- e. Jan - Nov 1989
- f. May 1990 - Mar 1991
- g. Feb 1992 - Apr 1993
- h. Oct 1993 – Mar 1994
- i. Mar 1998 – Jul 2000
- j. Aug 2012 – Oct 2013
- k. Apr 2016
- l. Sep 2016
- m. Dec 2019

Ngauruhoe & Tongariro

- a. Nov 1952
- b. May 1954 – Mar 1955
- c. Jan 1956
- d. Nov 1958
- e. Jun 1959
- f. Jul 1968
- g. Dec 1968
- h. Jul 1969
- i. Apr 1972
- j. Jan 1973 - Mar 1974
- k. Feb 1975
- l. May 1975
- a(T). Aug 2012 (Tongariro)
- b(T). Nov 2012 (Tongariro)

Eruption records

Ra: Christenson et al. (2013)
Ru: Scott (2013)
Ng: Latter et al. (1985), Hobden et al. (2002)
To: Scott and Potter (2014)
Wh: Kilgour et al. (2021)

How do volcanologists forecast eruptions?

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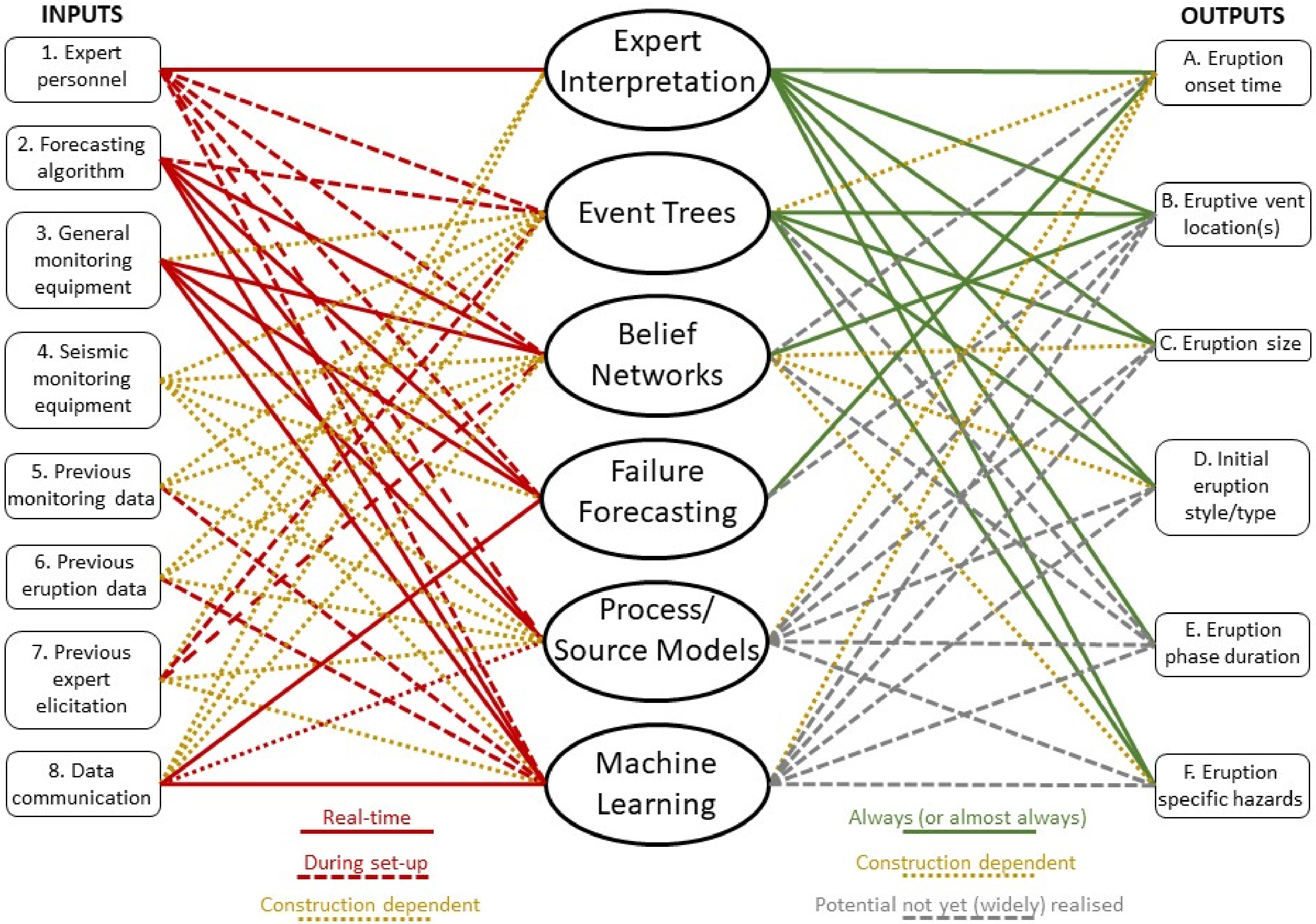
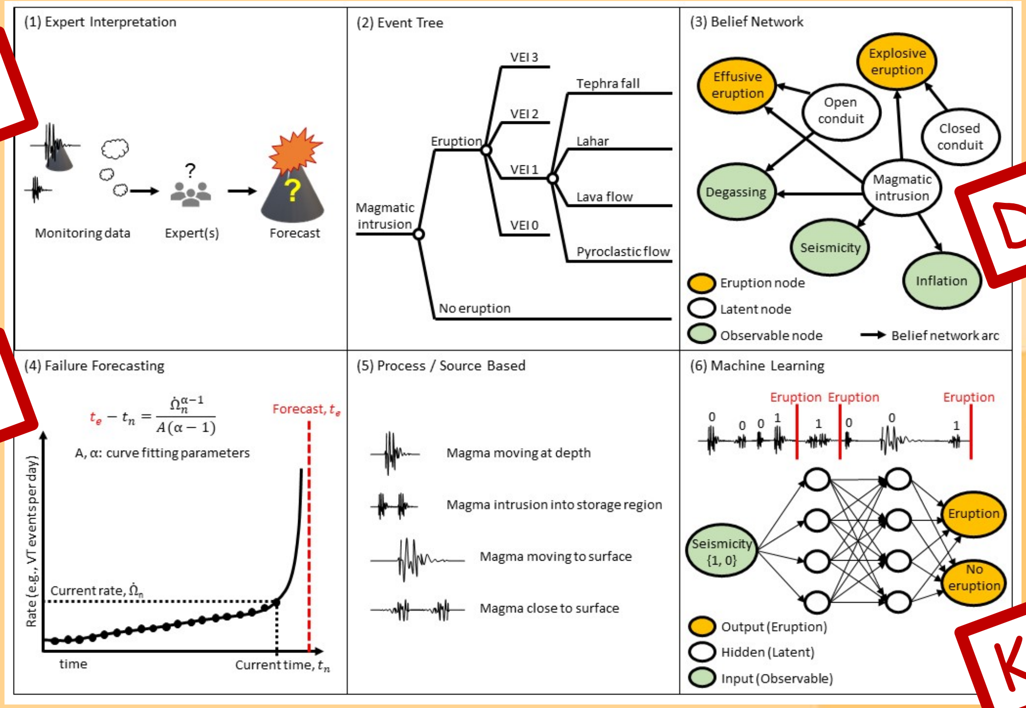


How do volcanologists forecast eruptions?

Assumptions

Data requirements



Forecast parameters

Knowledge requirements

Responsibly develop as many methods as possible for each volcano to better characterize epistemic uncertainty and to cover all required eruption parameters

Disclaimer: *The results here are based on practical implementation requirements with no implied assumption that those methods that are easiest to apply will provide the most accurate estimates. This work has addressed the matter of method feasibility; however, questions remain about which methods are most accurate and which are more likely to be trusted.*

For discussion

- Forecasting parameters

  What forecasting parameters may be most valuable and in what situations
  Is eruption start time more useful than the explosivity of eruption?

- Warning time

  Is a forecast of an eruption in the next day more useful than a forecast of an eruption sometime in the next two weeks?

- Uncertainty

  Do we expect volcanic eruptions to be forecast to the same degree as weather?
  How comfortable are we with what degree of uncertainty around volcanic eruptions?

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References

Carniel R, Guzmán SR. 2020. Machine Learning in Volcanology: A Review. Volcanoes-Updates in Volcanology.

Christenson BW et al. 2007. Hazards from hydrothermally sealed volcanic conduits. Eos, Transactions American Geophysical Union, 88(5):53-5.

Christophersen A et al. 2018. Bayesian network modeling and expert elicitation for probabilistic eruption forecasting: Pilot study for Whakaari/White Island, New Zealand. Frontiers in Earth Science, 6, 211.

Dempsey DE et al. 2020. Automatic precursor recognition and real-time forecasting of sudden explosive volcanic eruptions at Whakaari, New Zealand. Nature communications. 11(1):1-8.

Hincks TK et al. 2014. Retrospective analysis of uncertain eruption precursors at La Soufrière volcano, Guadeloupe, 1975–77: volcanic hazard assessment using a Bayesian Belief Network approach. *J. App. Volc., 3*(1).

Hobden BJ et al. 2002. Growth of a young, frequently active composite cone: Ngauruhoe volcano, New Zealand. Bulletin of Volcanology, 64(6), 392-409.

Kilgour G et al. 2021. Whakaari/White Island: a review of New Zealand's most active volcano. 2021. New Zealand Journal of Geology and Geophysics, 64(2-3):273-95.

Latter JH. 1985. Frequency of eruptions at New Zealand volcanoes. *Bulletin of the New Zealand Society for Earthquake Engineering*, *18*(1), pp.55-110.

Lindsay J et al. 2010. Towards real-time eruption forecasting in the Auckland Volcanic Field: application of BET_EF during the New Zealand National Disaster Exercise 'Ruaumoko'. Bull. of Volc., 72(2), 185-204.

Malfante M et al. 2018. Machine learning for volcano-seismic signals: Challenges and perspectives. IEEE Signal Processing Magazine, 35(2), 20-30.

Marzocchi W, Bebbington MS. 2012. Probabilistic eruption forecasting at short and long time scales. *Bulletin of volcanology*, *74*(8), 1777-1805.

McCausland WA et al. 2019. Using a process-based model of pre-eruptive seismic patterns to forecast evolving eruptive styles at Sinabung Volcano, Indonesia. J. of Volcanology and Geothermal Research, 382, 253-266.

Ortiz R et al. 2003. Villarrica volcano (Chile): characteristics of the volcanic tremor and forecasting of small explosions by means of a material failure method. J. of Volc. and Geo. Res., 128(1-3), 247-259.

Poland MP, Anderson KR. 2020. Partly cloudy with a chance of lava flows: Forecasting volcanic eruptions in the twenty-first century. Journal of Geophysical Research: Solid Earth, 125(1).

Scott B. 2013. A revised catalogue of Ruapehu volcano eruptive activity: 1830-2012. GNS Science Report 2013/45. 133 p.

Scott BJ Potter SH. 2014. Aspects of historical eruptive activity and volcanic unrest at Mt. Tongariro, New Zealand: 1846–2013. Journal of volcanology and geothermal research, 286, pp.263-276.

Sparks RSJ. 2003. Forecasting volcanic eruptions. Earth and Planetary Science Letters, 210(1-2), 1-15.

Syahbana DK et al. 2019. The 2017–19 activity at Mount Agung in Bali (Indonesia): Intense unrest, monitoring, crisis response, evacuation, and eruption. Scientific reports, 9(1), 1-17.

Wild A, Bebbington M, Lindsay J. Short-term eruption forecasting for crisis decision-support in the Auckland Volcanic Field, New Zealand. Frontiers in Earth Science.:874.

Whitehead MG, Bebbington MS. 2021. Method selection in short-term eruption forecasting. Journal of Volcanology and Geothermal Research, 419, p.107386.

Whitehead MG, Bebbington MS, Procter JN, Irwin ME & GPD Viskovic. 2022. An initial assessment of short-term eruption forecasting options in New Zealand. New Zealand Journal of Geology and Geophysics.

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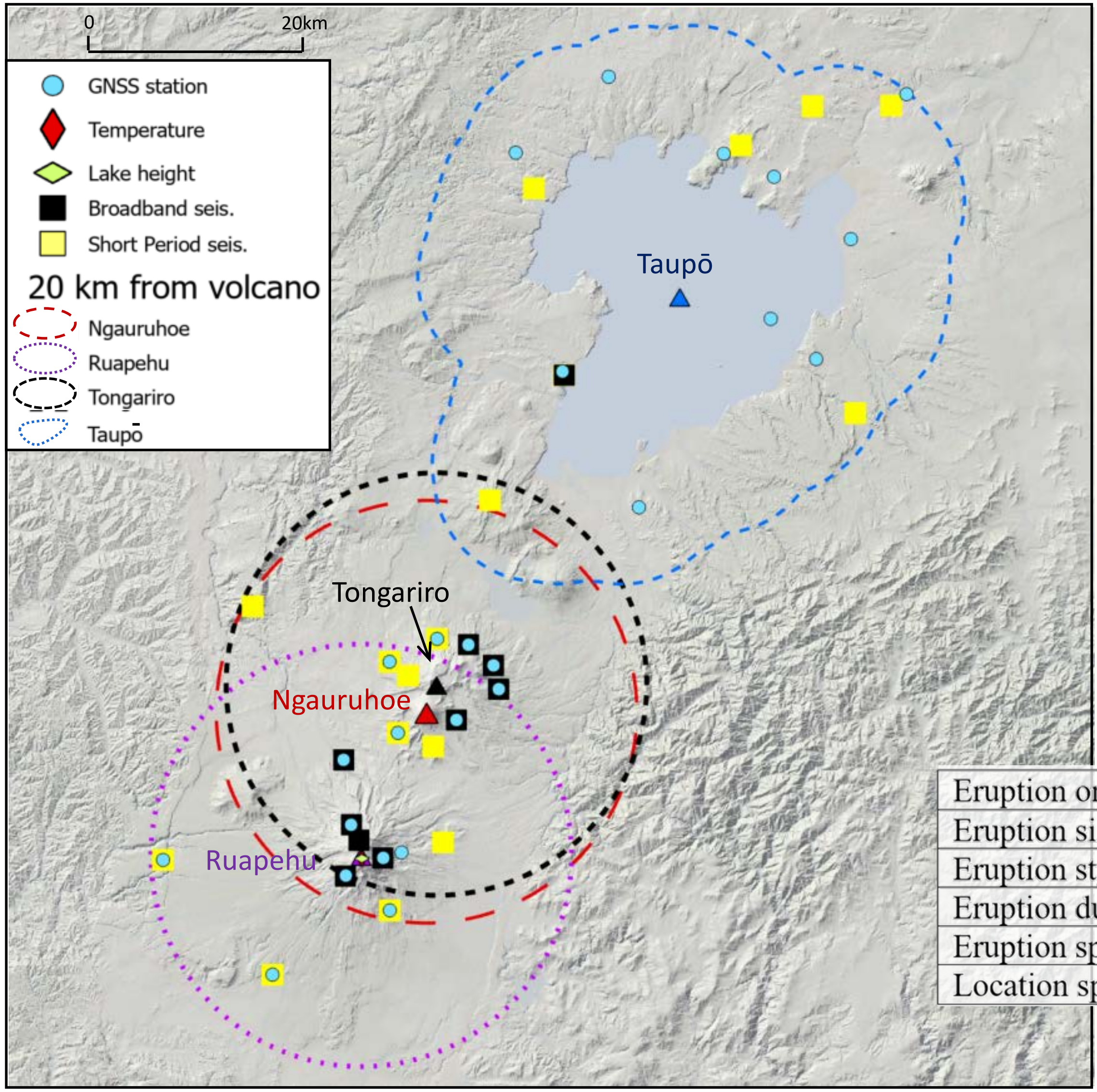
Kia manawaroa – Ngā Ākina o Te Ao Tūroa

Ngauruhoe



13 GNSS station
9 Broadband seis.
8 Short Period seis.

Area used: < 20 km from most recent eruptive centre

Sufficient seismic stations (> 6 broadband) suggests relative ease of application of FFM.

Data to train machine learning algorithms are available but must first be vectorised from paper seismograms.

	Expert Interpretation	Event Trees	Belief Networks	Belief Networks with training	Failure Forecasting	Process/Source based	Machine Learning
Eruption onset time	Blue	Red	Red	Red	Blue	Yellow	Red
Eruption size	Blue	Yellow	Yellow	Red	Orange	Yellow	Red
Eruption style/type	Blue	Yellow	Yellow	Red	Red	Orange	Red
Eruption duration	Blue	Red	Red	Red	Red	Orange	Red
Eruption specific hazards	Blue	Yellow	Yellow	Red	Red	Orange	Red
Location specific parameters	Blue	Yellow	Yellow	Red	Orange	Yellow	Red

Negligible effort/time
Some effort/time
Medium effort/time
Significant effort/time
Not currently feasible

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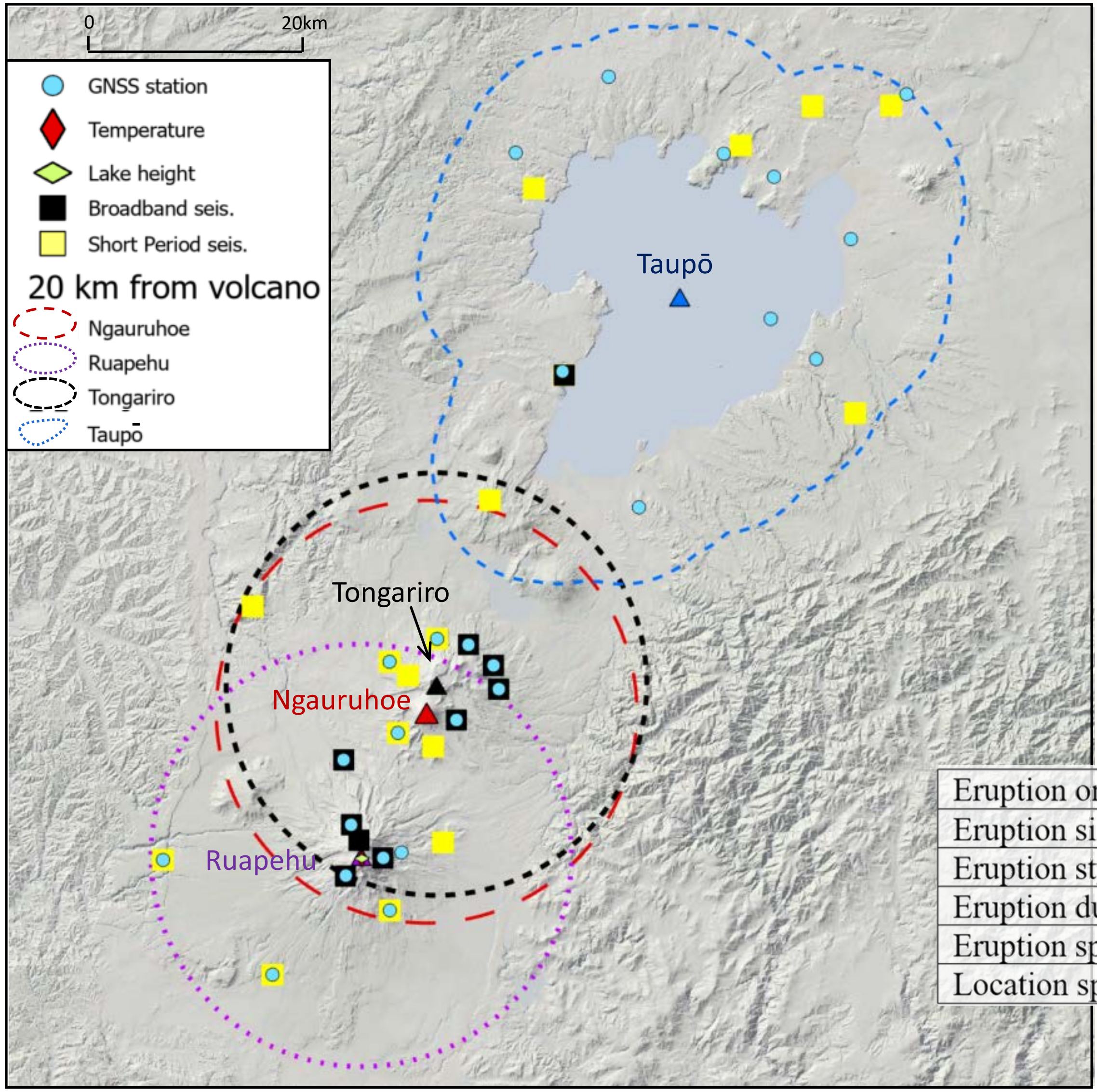
Kia manawaroa – Ngā Ākina o Te Ao Tūroa

Tongariro



11 GNSS station
8 Broadband seis.
7 Short Period seis.

Area used: < 20 km from mid-point (Te Maari:Ngauruhoe)

Sufficient seismic stations (> 6 broadband) suggests relative ease of application of FFM.

Insufficient data to train machine learning algorithms but potentially two eruption-monitoring pairs to inform a belief network.

	Expert Interpretation	Event Trees	Belief Networks	Belief Networks with training	Failure Forecasting	Process/Source based	Machine Learning
Eruption onset time	Negligible	Significant	Significant	Significant	Negligible	Some	Not currently feasible
Eruption size	Negligible	Some	Some	Some	Medium	Some	Not currently feasible
Eruption style/type	Negligible	Some	Some	Some	Significant	Medium	Not currently feasible
Eruption duration	Negligible	Significant	Significant	Significant	Significant	Medium	Not currently feasible
Eruption specific hazards	Negligible	Some	Some	Some	Significant	Medium	Not currently feasible
Location specific parameters	Negligible	Some	Some	Some	Medium	Some	Not currently feasible

Negligible effort/time
Some effort/time
Medium effort/time
Significant effort/time
Not currently feasible

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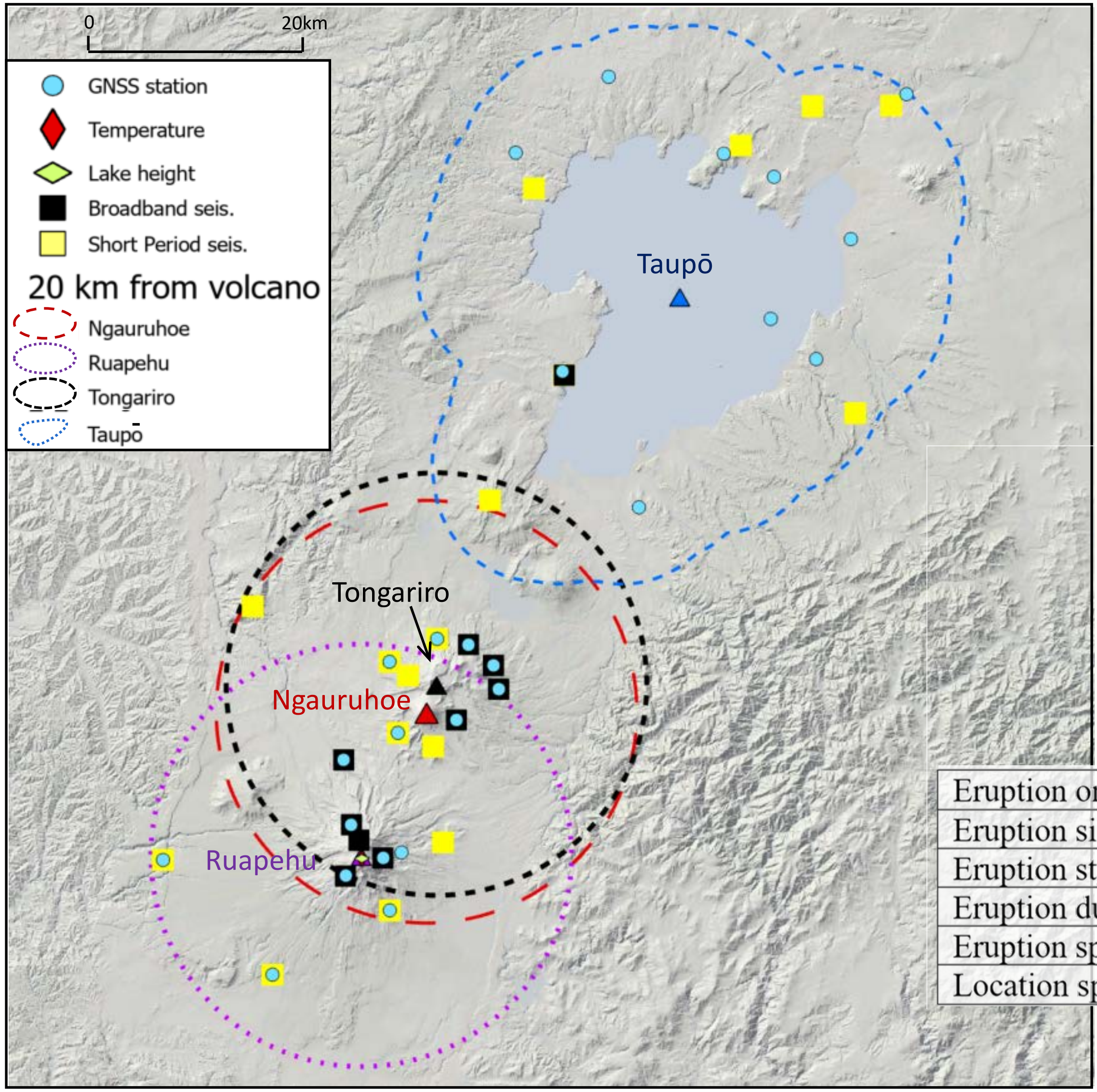
Kia manawaroa – Ngā Ākina o Te Ao Tūroa

Taupō



10 GNSS station
1 Broadband seis.
7 Short Period seis.

Area used: < 10 km from lake edge

Failure forecasting method difficult to apply where there are limited sensor-suitable locations (such as Lake Taupō)

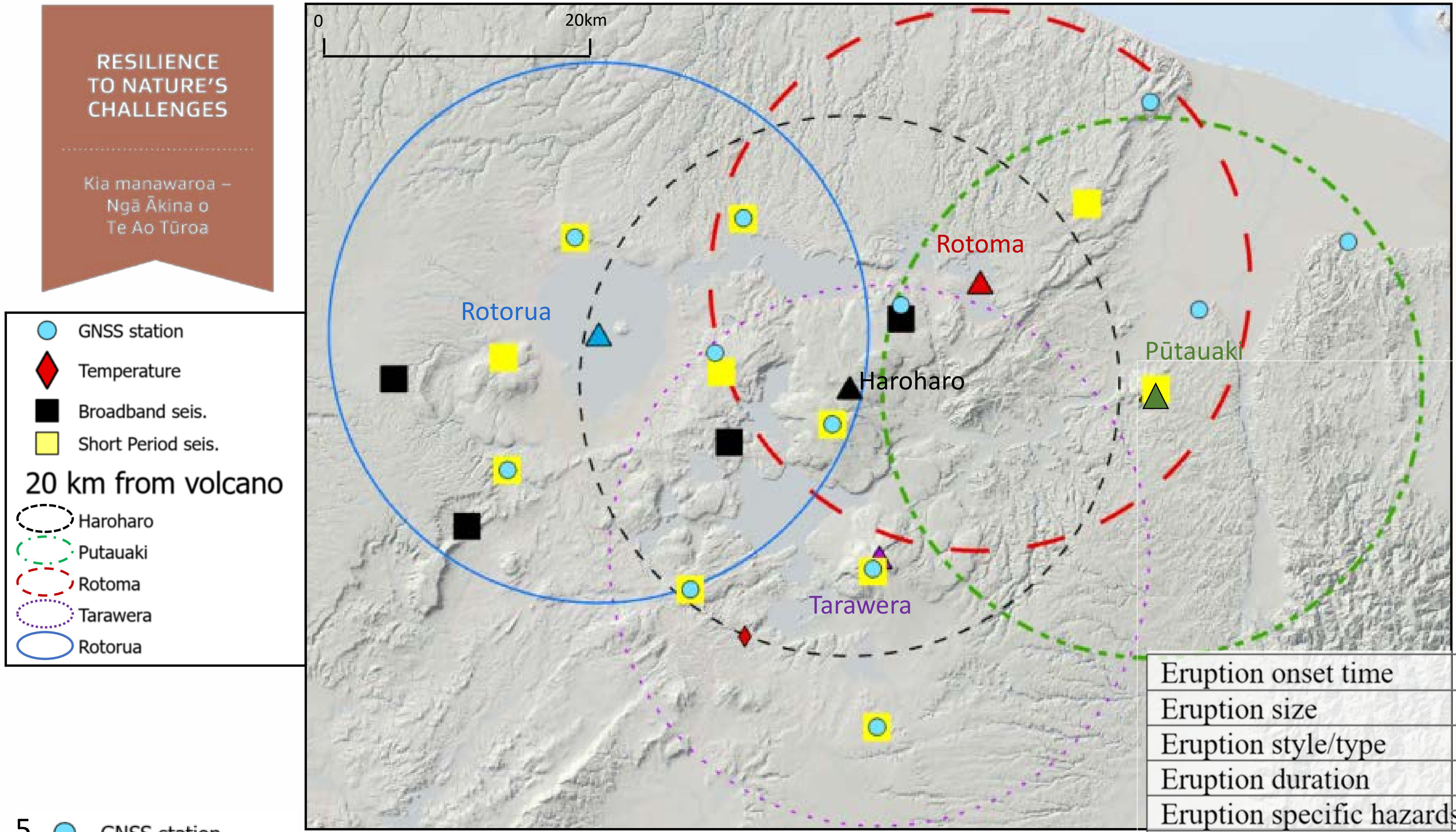
Insufficient data to train a belief network or machine learning algorithms

Note – an event tree is under construction for Taupō

	Expert Interpretation	Event Trees	Belief Networks	Belief Networks with training	Failure Forecasting	Process/Source based	Machine Learning
Eruption onset time	Blue	Red	Red	Black	Orange	Orange	Black
Eruption size	Blue	Yellow	Yellow	Black	Red	Orange	Black
Eruption style/type	Blue	Yellow	Yellow	Black	Red	Red	Black
Eruption duration	Blue	Red	Red	Black	Red	Red	Black
Eruption specific hazards	Blue	Yellow	Yellow	Black	Red	Red	Black
Location specific parameters	Blue	Yellow	Yellow	Black	Red	Orange	Black

Negligible effort/time (blue)
Some effort/time (yellow)
Medium effort/time (orange)
Significant effort/time (red)
Not currently feasible (black)

Rotorua



5 GNSS station
3 Broadband seis.
6 Short Period seis.

Area used: < 20 km from lake centre

Failure forecasting method difficult to apply where there are limited sensor-suitable locations (such as Lake Rotorua)

Insufficient data to train a belief network or machine learning algorithms

	Expert Interpretation	Event Trees	Belief Networks	Belief Networks with training	Failure Forecasting	Process/Source based	Machine Learning
Eruption onset time							
Eruption size							
Eruption style/type							
Eruption duration							
Eruption specific hazards							
Location specific parameters							

Negligible effort/time
Some effort/time
Medium effort/time
Significant effort/time
Not currently feasible

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Kia manawaroa – Ngā Ākina o Te Ao Tūroa

Okataina Volcanic Centre

Haroharo

6 GNSS station
2 Broadband seis.
5 Short Period seis.

Tarawera

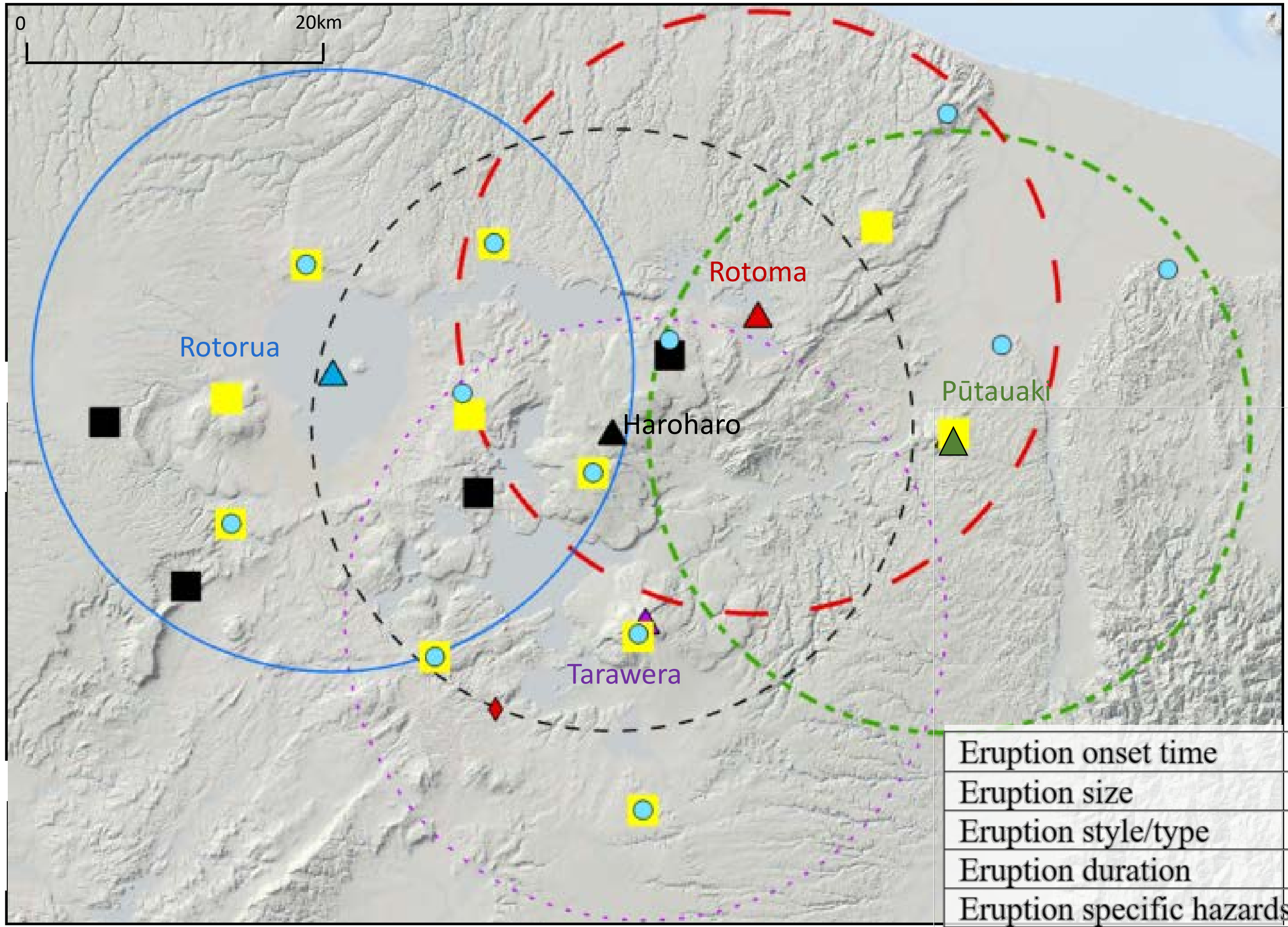
6 GNSS station
Temperature
2 Broadband seis.
5 Short Period seis.

Rotoma

5 GNSS station
1 Broadband seis.
4 Short Period seis.

Pūtauaki

3 GNSS station
1 Broadband seis.
2 Short Period seis.



Area used: < 20 km from eruptive centres

GNSS station located < 0.5 km to Tarawera suggesting relative ease of application of the FFM at this eruptive centre.

Insufficient data to train a belief network or machine learning algorithms

	Expert Interpretation	Event Trees	Belief Networks	Belief Networks with training	Failure Forecasting	Process/Source based	Machine Learning
Eruption onset time	Negligible	Significant	Significant	Not feasible	Negligible	Some	Not feasible
Eruption size	Negligible	Some	Some	Not feasible	Medium	Some	Not feasible
Eruption style/type	Negligible	Some	Some	Not feasible	Significant	Medium	Not feasible
Eruption duration	Negligible	Significant	Significant	Not feasible	Significant	Medium	Not feasible
Eruption specific hazards	Negligible	Some	Some	Not feasible	Significant	Medium	Not feasible
Location specific parameters	Negligible	Some	Some	Not feasible	Medium	Some	Not feasible

Negligible effort/time
Some effort/time
Medium effort/time
Significant effort/time
Not currently feasible

Mel Whitehead, Jon Procter, Mark Bebbington

Volcano

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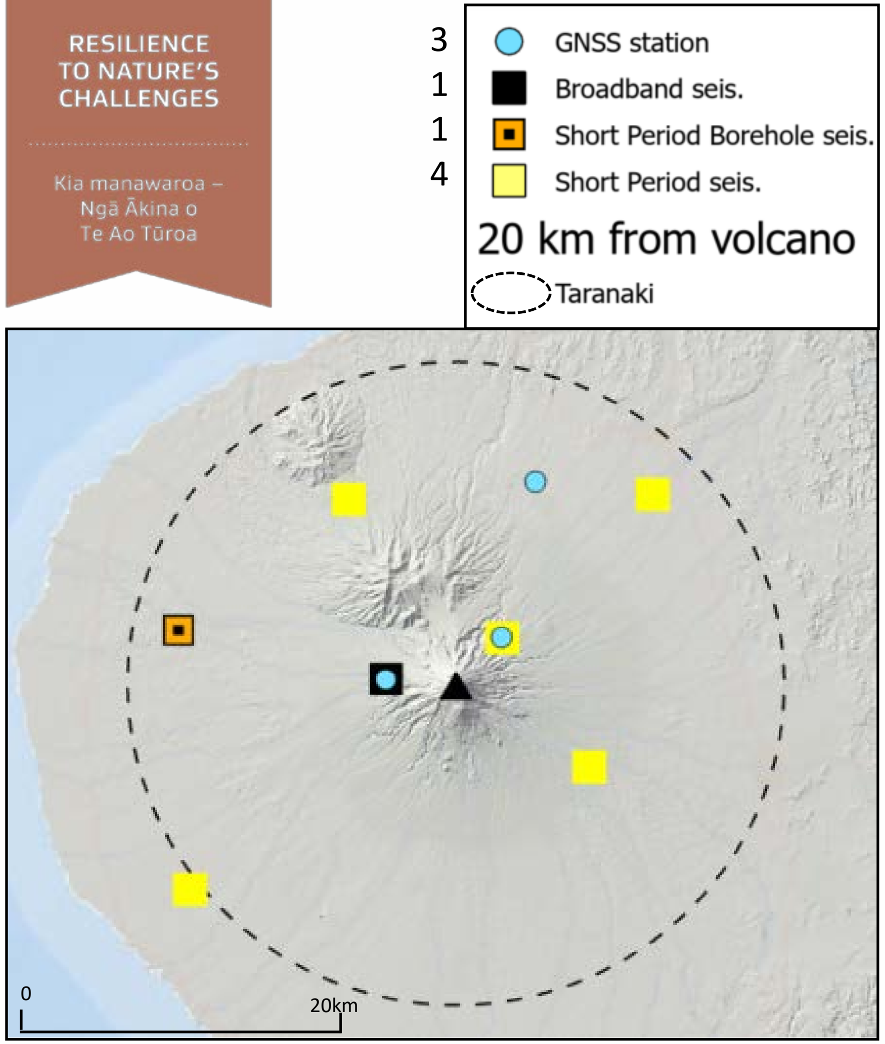
Kia manawaroa – Ngā Ākina o Te Ao Tūroa

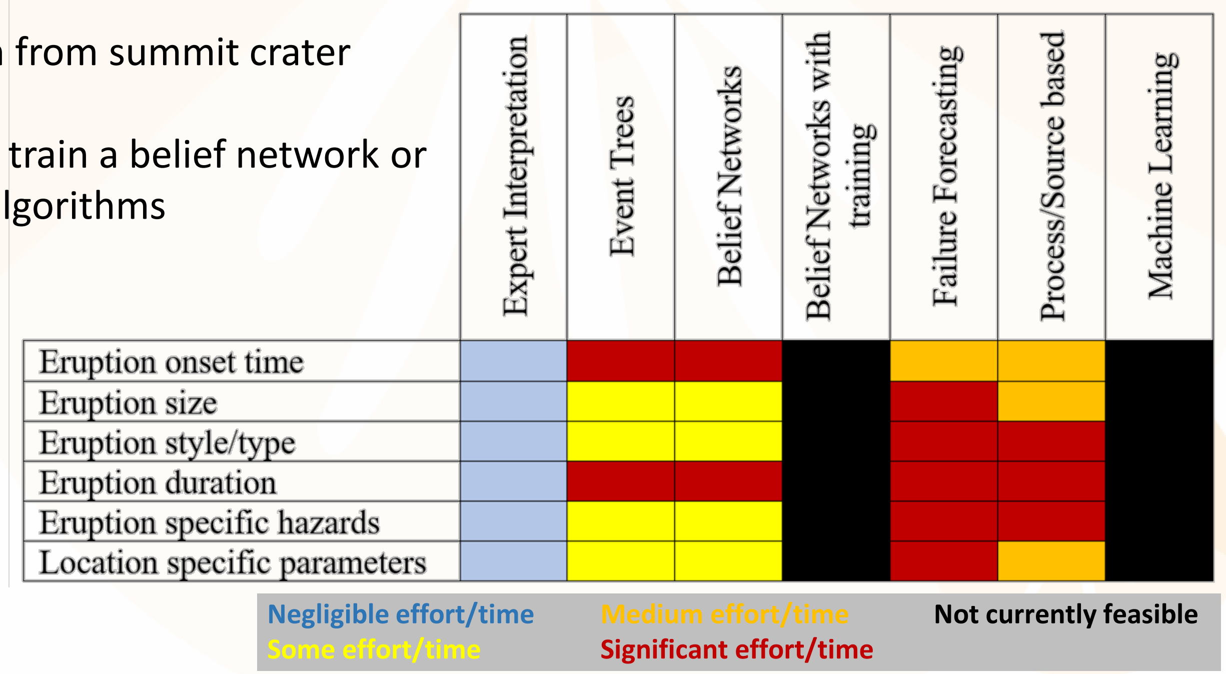
Taranaki



[Image: https://www.gns.cri.nz/]

Area used: < 20 km from summit crater

Insufficient data to train a belief network or machine learning algorithms



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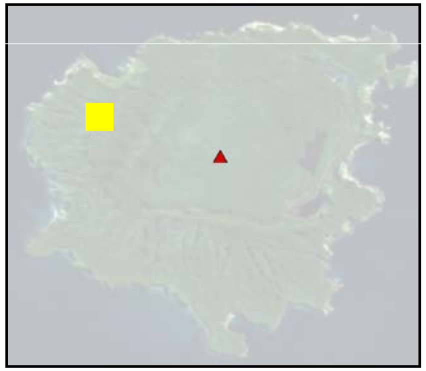
Kia manawaroa – Ngā Ākina o Te Ao Tūroa

Tūhua

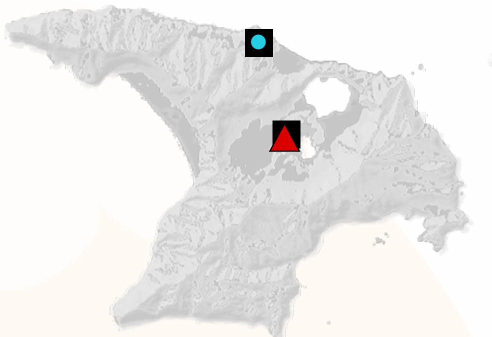
Area used: On island

Insufficient data to train a belief network or machine learning algorithms



	Expert Interpretation	Event Trees	Belief Networks	Belief Networks with training	Failure Forecasting	Process/Source based	Machine Learning
Eruption onset time							
Eruption size							
Eruption style/type							
Eruption duration							
Eruption specific hazards							
Location specific parameters							

Raoul



Area used: On island

Insufficient monitoring equipment (< 3 seismometers) for process/source models

Insufficient data to train machine learning algorithms but potentially two eruption-monitoring pairs to inform a belief network

	Expert Interpretation	Event Trees	Belief Networks	Belief Networks with training	Failure Forecasting	Process/Source based	Machine Learning
Eruption onset time							
Eruption size							
Eruption style/type							
Eruption duration							
Eruption specific hazards							
Location specific parameters							

Negligible effort/time
Some effort/time
Medium effort/time
Significant effort/time
Not currently feasible

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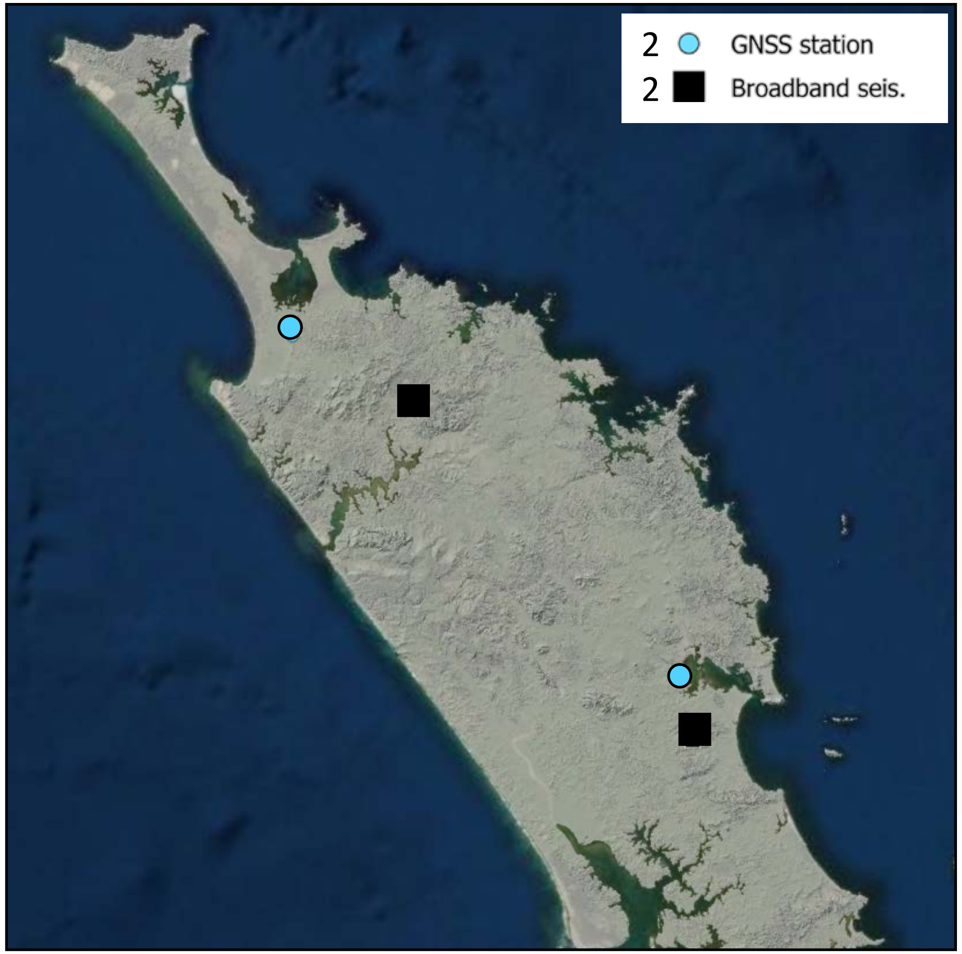
Kia manawaroa – Ngā Ākina o Te Ao Tūroa

Kaikohe-Bay of Islands



Area used: "Northland Region"

Failure forecasting method difficult at a distributed volcanic system

Insufficient data to train a belief network or machine learning algorithms

	Expert Interpretation	Event Trees	Belief Networks	Belief Networks with training	Failure Forecasting	Process/Source based	Machine Learning
Eruption onset time							
Eruption size							
Eruption style/type							
Eruption duration							
Eruption specific hazards							
Location specific parameters							

Negligible effort/time
Some effort/time
Medium effort/time
Significant effort/time
Not currently feasible

Mel Whitehead, Jon Procter, Mark Bebbington