First MODE Workshop on Differentiable Programming

Machine Learning Application to Volcano Eruption Forecasting using Muography

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on behalf of the

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6th September 2021

Outline

I. Motivation

II. Muography of Sakurajima Volcano

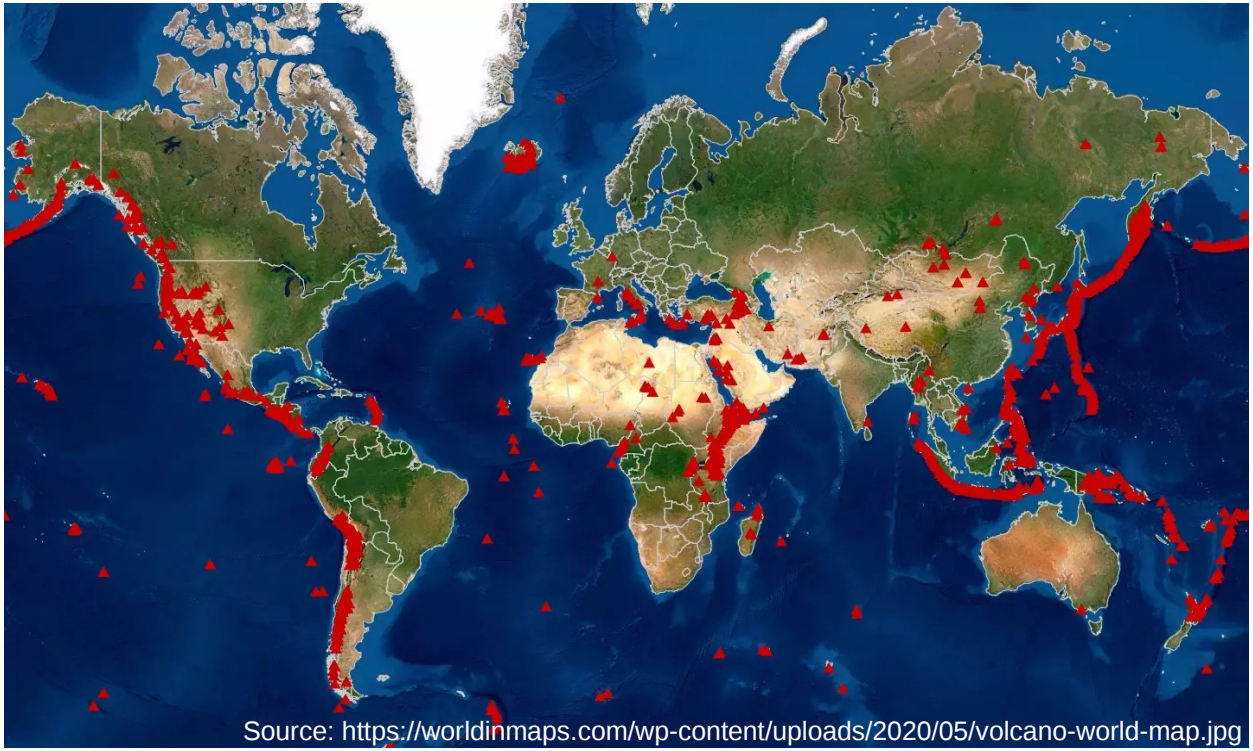
III. Data Reconstruction and Analysis

IV. Eruption Forecasting by Machine Learning of Muographic Data

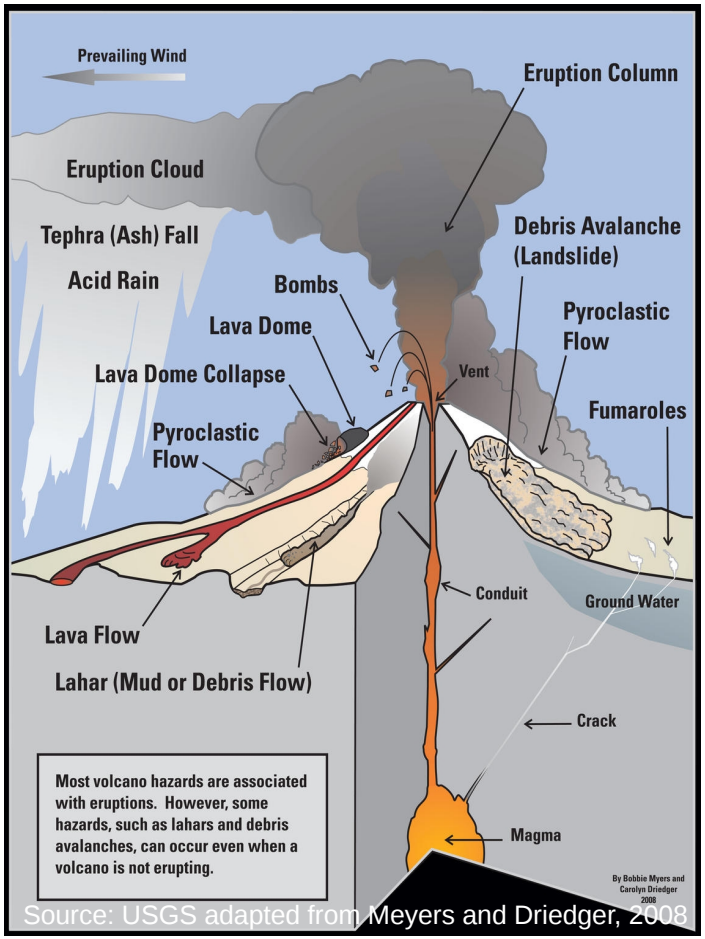
V. Summary and Discussion

I. Motivation: Volcanic Hazards

- More than 500 volcanoes confirmed historical eruptions (69 volcanoes erupted in 2021)
- Approx. 10 % of Earth's population live around volcanoes
- Volcanic hazards can cause serious socioeconomic loss:
  - syn-eruptive hazards: bombs, tephra fall, pyroclastic flows, etc
  - post-eruptive hazards: lahars, debris avalanche, etc



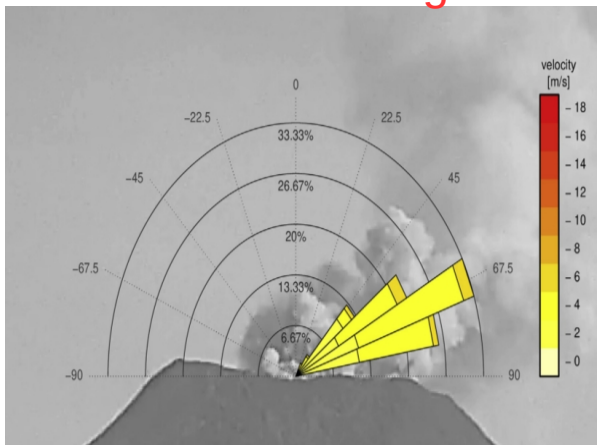
Source: https://worldinmaps.com/wp-content/uploads/2020/05/volcano-world-map.jpg



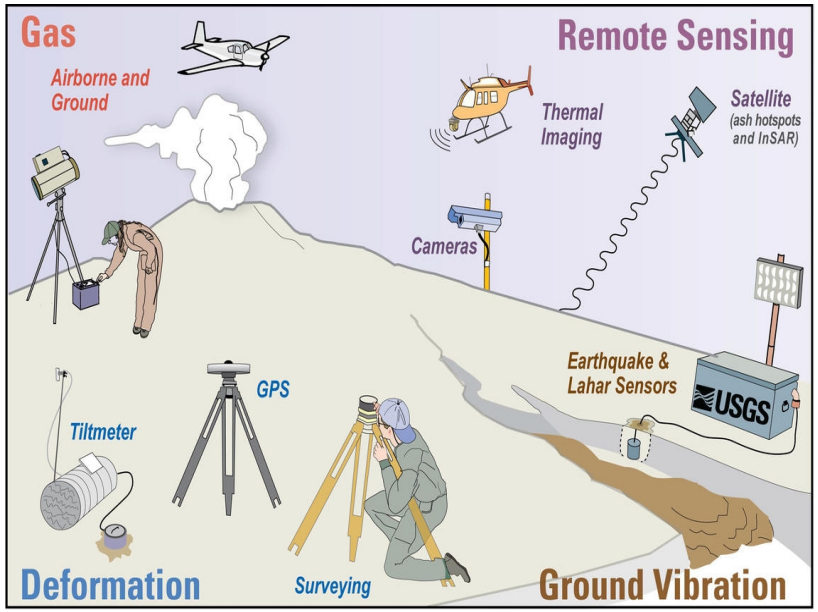
Source: USGS adapted from Meyers and Driedger, 2008

I. Motivation: Volcano Monitoring

Video recording

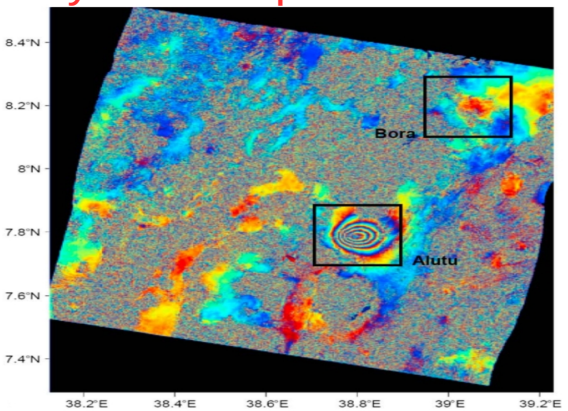


Source: https://doi.org/10.1016/j.gsf.2020.01.016



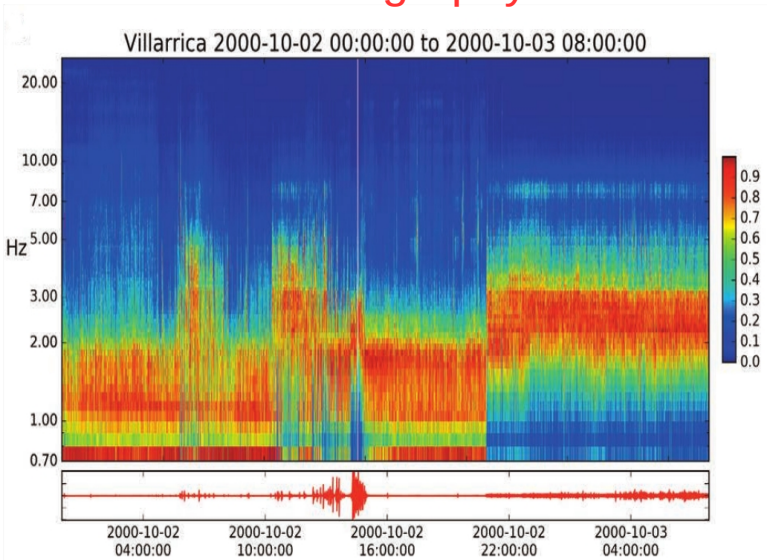
Source: USGS from Faust, Lisa

Synthetic Aperture Radar



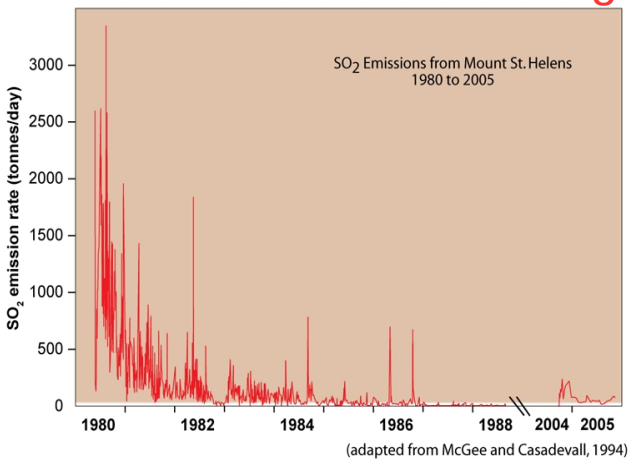
Source: https://doi.org/10.1029/2018JB015911

Seismography



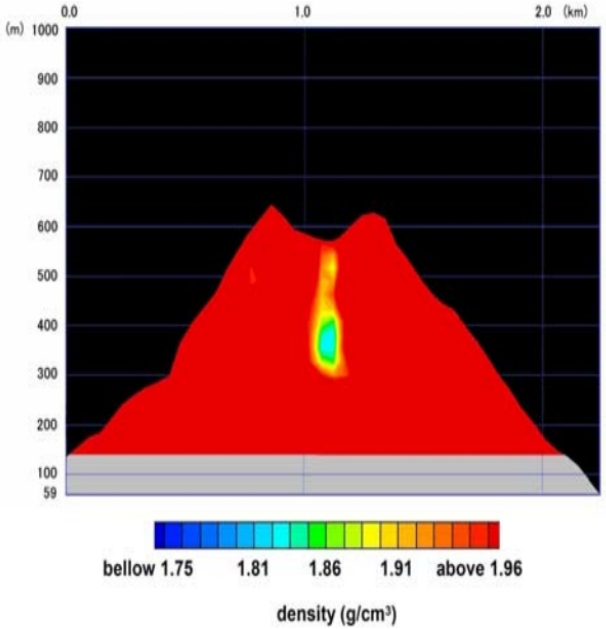
Source: https://doi.org/10.4401/ag-7655

Gas Emission Monitoring



Source: USGS

Cosmic-ray Muography

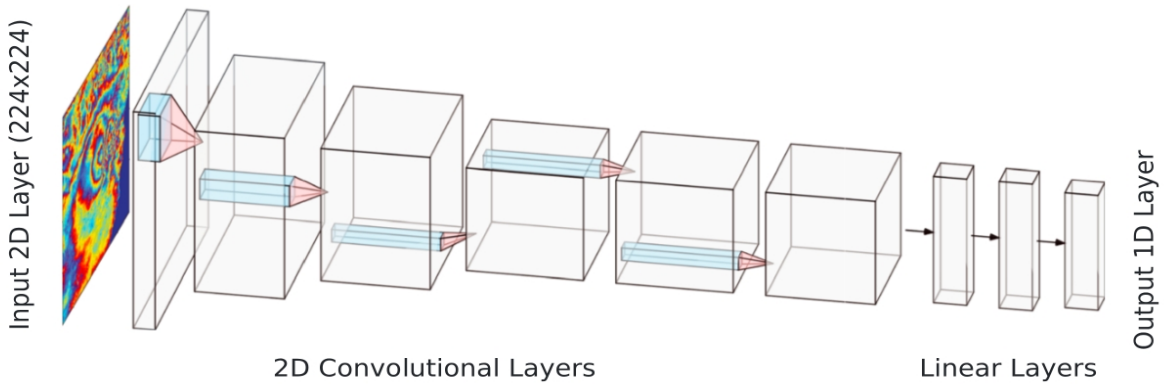


Source: https://doi.org/10.1029/2008GL036451

L. Oláh 1st MODE WS 2021

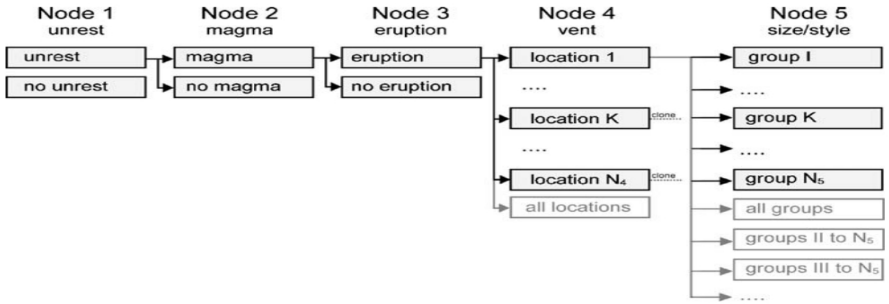
I. Motivation:
Machine Learning (ML) of Volcanic Signals

- Convolutional Neural Networks for classification of volcanic deformation



Source: https://doi.org/10.1029/2018JB015911

- Bayesian Event Trees for long-term eruption forecasting



Source: https://doi.org/10.1007/s00445-009-0311-9

- **Goal:** real-time eruption forecasting by ML of remote sensing data

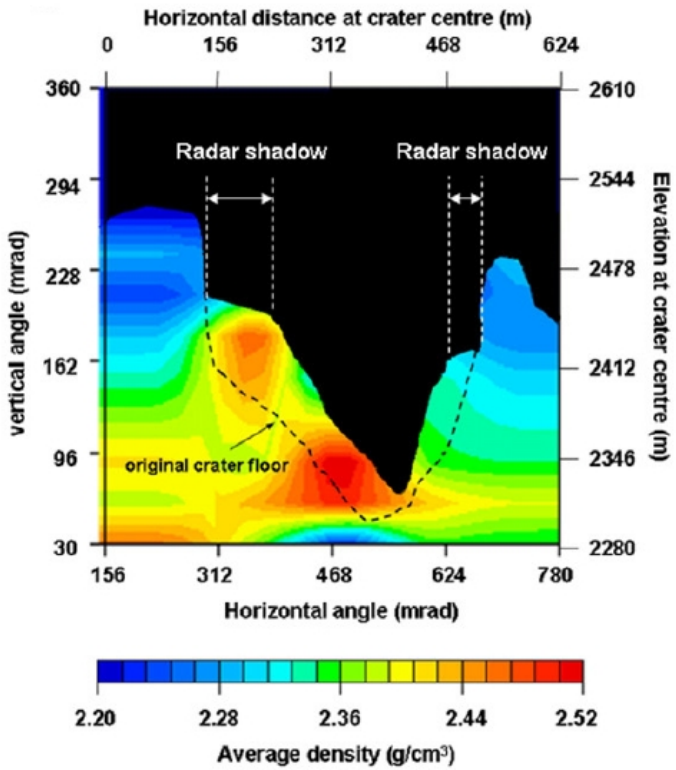
II. Muography of Sakurajima Volcano

Cosmic-ray Muography

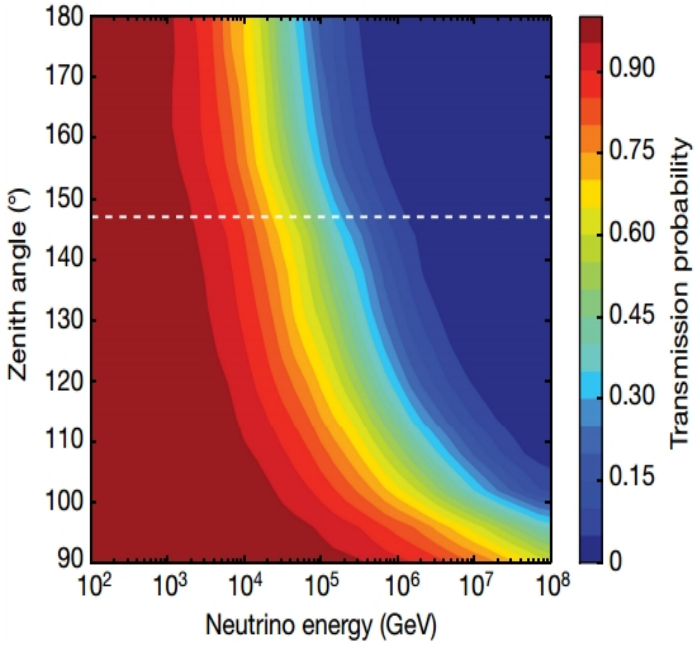
- **Muography: a non-invasive remote sensing technique that is based on the measurement of the flux of cosmic-ray muons that penetrated through the investigated structure**
- Versatile applicability: volcanology, nuclear security, civil engineering, archeology, etc.
- High imaging resolution: (even a few meter segmented) images of volcanoes can be captured
- High penetration power: accessibility to the shallow parts of volcanoes located beneath crater floors

X-ray radiography: – few m
W.C. Röntgen:
On a new kind of rays, 1895

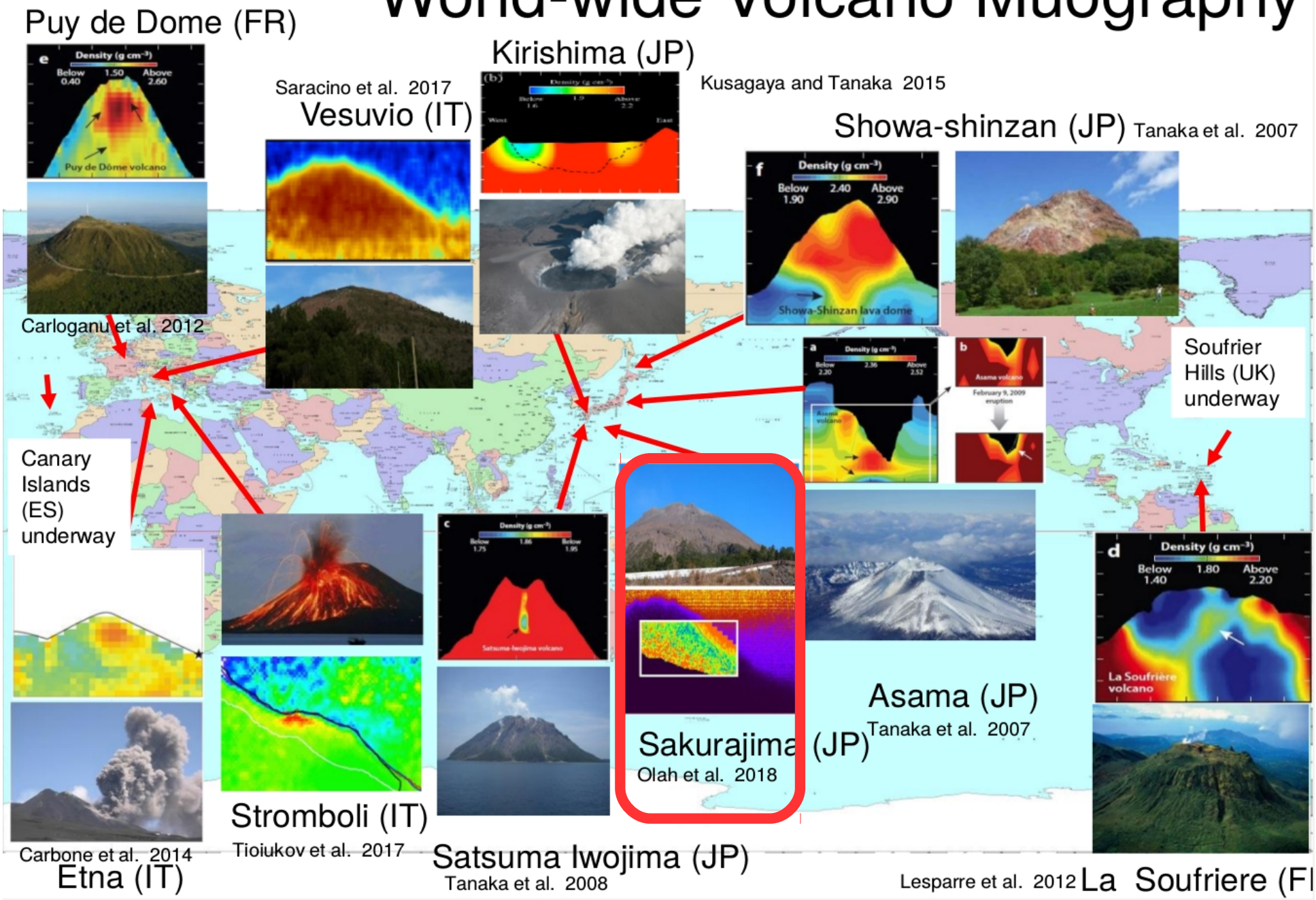
Muography: few m – few km
H. Tanaka et al.: EPL 263 (2007) 104



Neutrino radiography: ~ few 1000 km
ICECUBE: doi:10.1038/nature24459



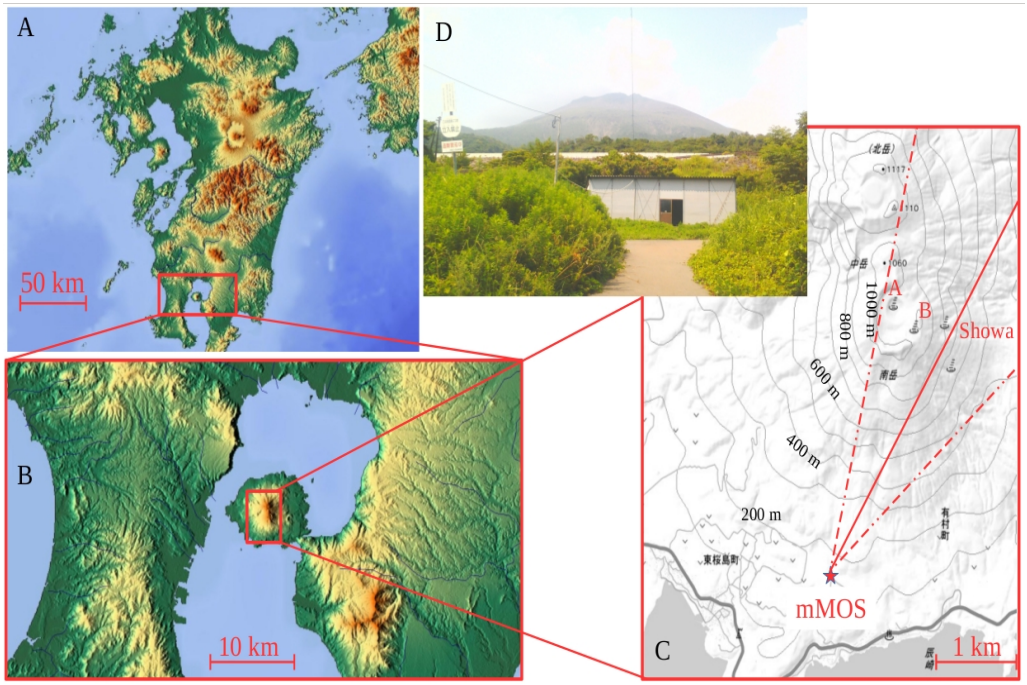
World-wide Volcano Muography



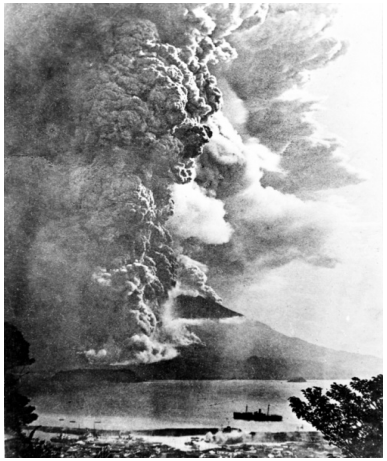
Source: H. K. M. Tanaka

The Sakurajima Volcano, Kyushu, Japan

- Sakurajima volcano is an active stratovolcano on the "Ring of fire" within the Aira caldera in Kagoshima Bay
- Latest plinian eruption occurred in 1914 → Next plinian eruption is expected in 25 years https://doi.org/10.1038/srep32691
- Two craters of the southern peak (the connected Vents A and B, as well as Showa crater) erupted consecutively in the recent years → A few hundreds of (explosive) short-term eruptions per year
- Short-term eruptions eject aerosols and gas with a bulk volume of below 10^7 m^3 to a height of 1000–5000 meter above the crater rims, throwing fragments of volcanic plug and lava bombs usually within approx. 3000 m radius
- **Protection of tourists motivates the forecasting of short-term eruptions of the Sakurajima volcano**



Source: https://doi.org/10.1038/s41598-018-21423-9

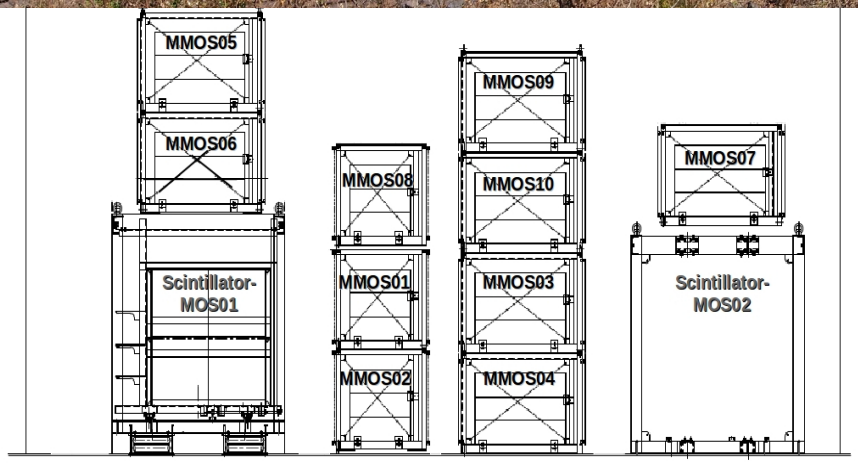


Source: Wikipedia

Source: Kimon Berlin, CC BY-SA 2.0

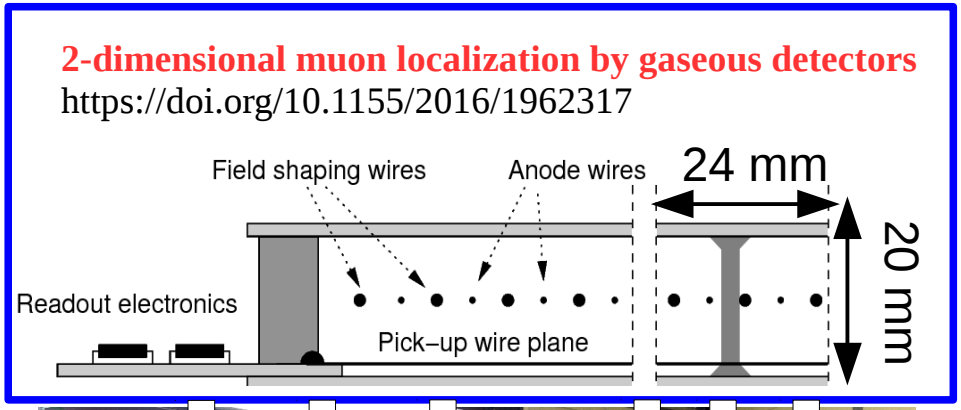
The Sakurajima Muography Observatory (SMO)

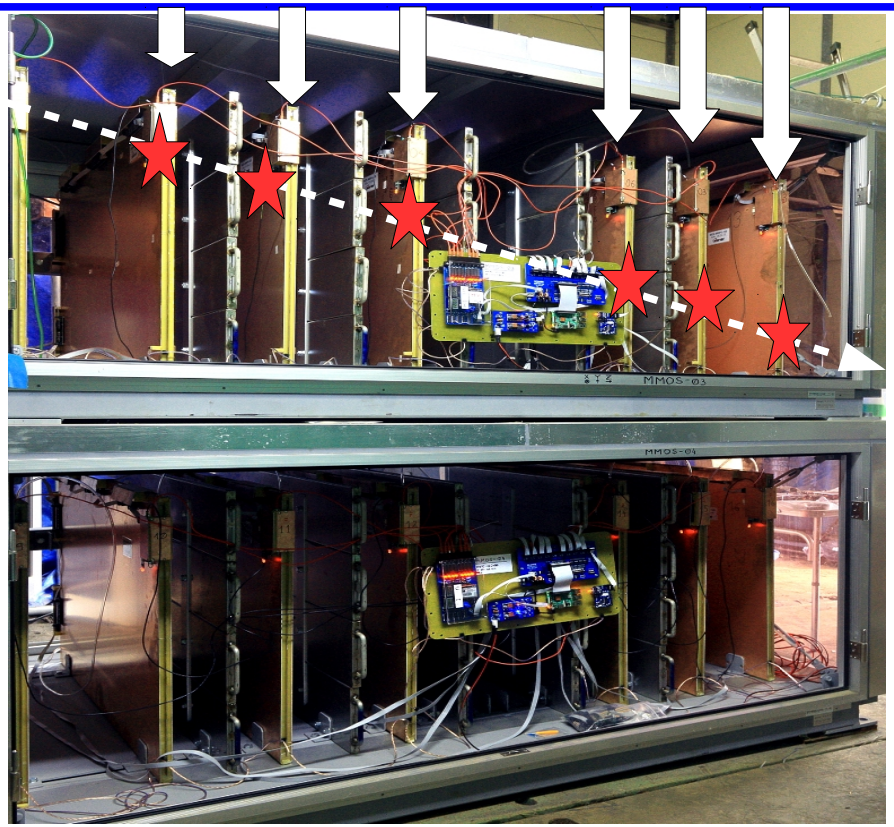
Multi-Wire Proportional Chamber (MWPC)-based Muography Observation System (MMOS)



2017: 0.5 m² **2018: 5 m²** **2019: 10 m²** **T**

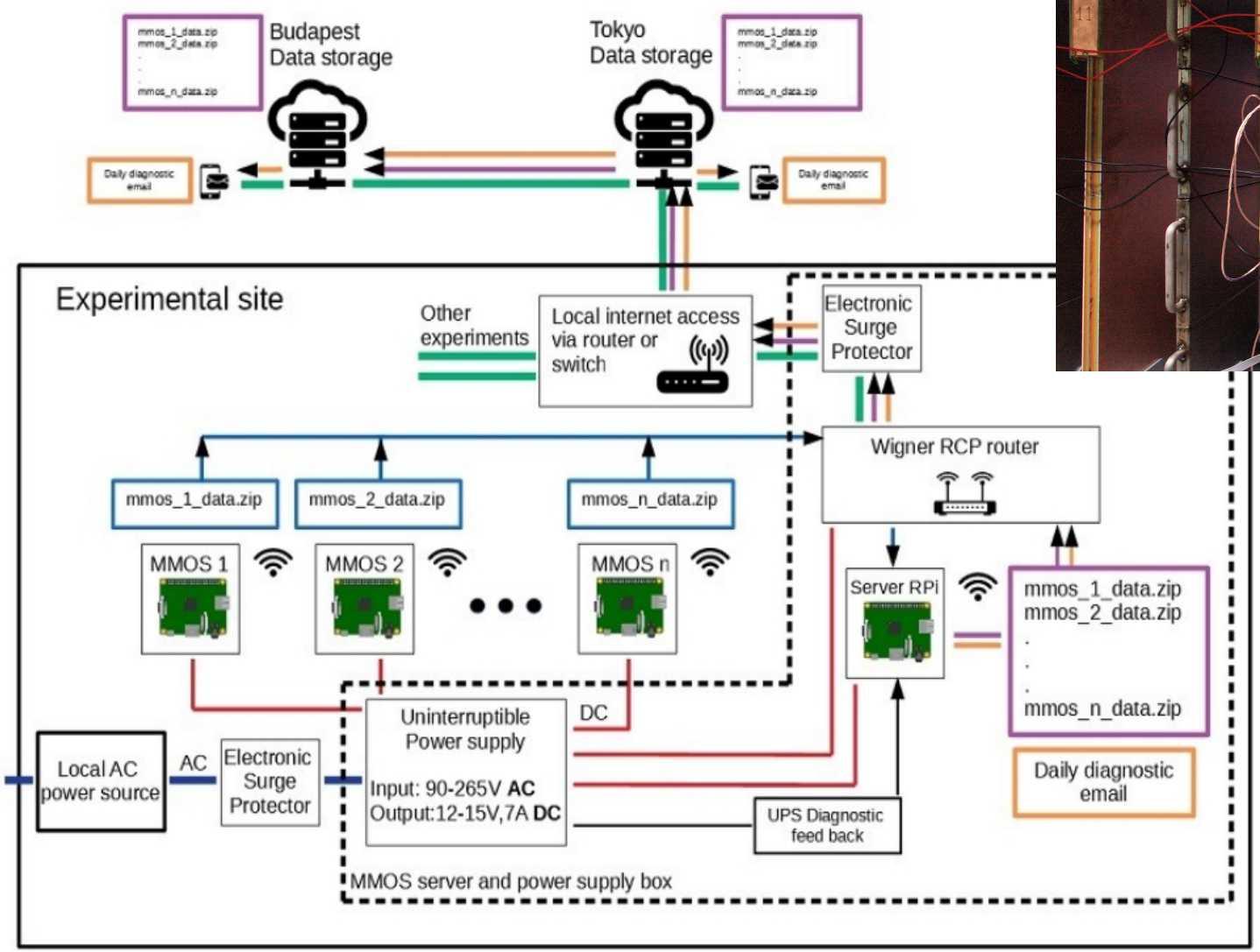
2-dimensional muon localization by gaseous detectors
https://doi.org/10.1155/2016/1962317

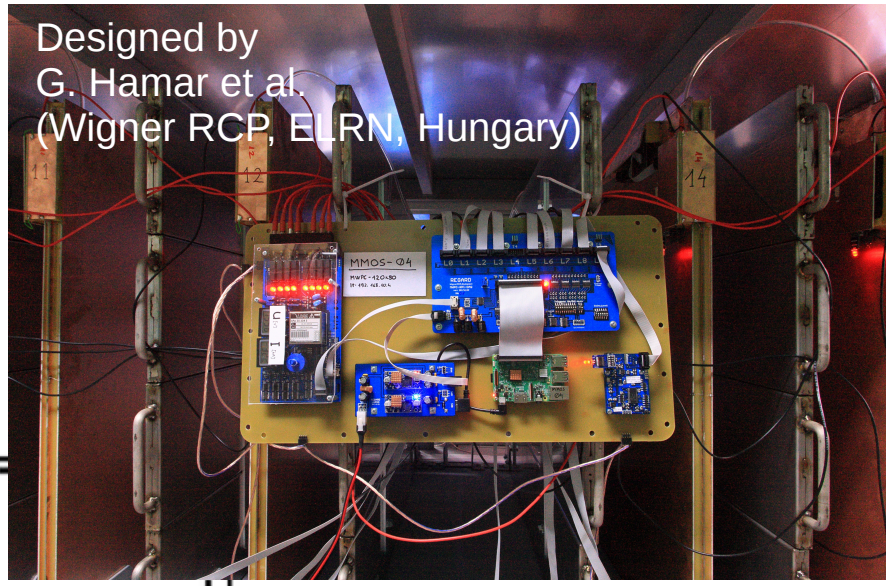




Patent: Muographic Observation Instrument (WO 2017/187308 A1)
Publications:
https://doi.org/10.1038/s41598-018-21423-9
https://doi.org/10.1029/2019GL084784
https://doi.org/10.1016/j.nima.2019.05.077

System Plan: Data Acquisiton





- Custom-designed electronics
- Power consumption:
  ~ 6 W per MMOS
- **Micro-computer controlled**
  → real-time DAQ & analysis
- Data transferred and stored on remote computers

Source: Szabolcs József Balogh (Wigner RCP, ELRN, Hungary)
See more in Varga et al.
https://doi.org/10.1016/j.nima.2019.05.077

III. Data Reconstruction and Analysis

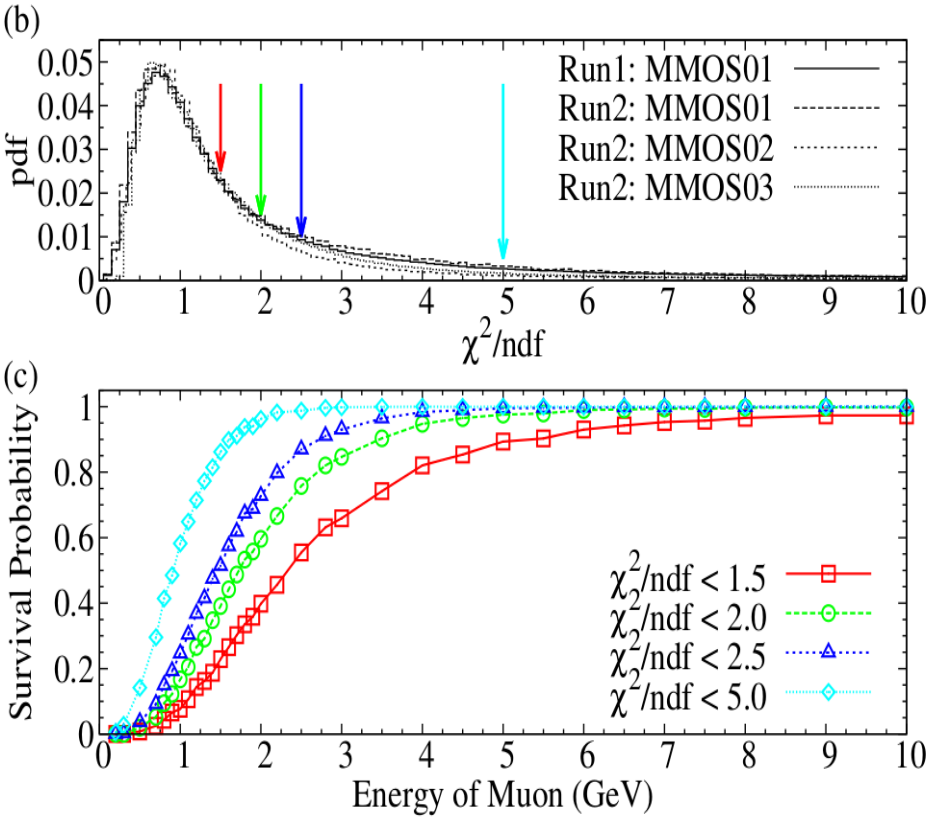
III. Data Reconstruction and Analysis

- Event-by-event offline track reconstruction (slopes in 1+1 dim and χ^2/n.d.f.) was applied independently for each MMOS module
- Pre-analysis was applied for alignment of detector layers and exclusion of noisy or malfunctioned electronics channels
- Track selection was based on χ^2/n.d.f.

See more at https://doi.org/10.1038/s41598-018-21423-9

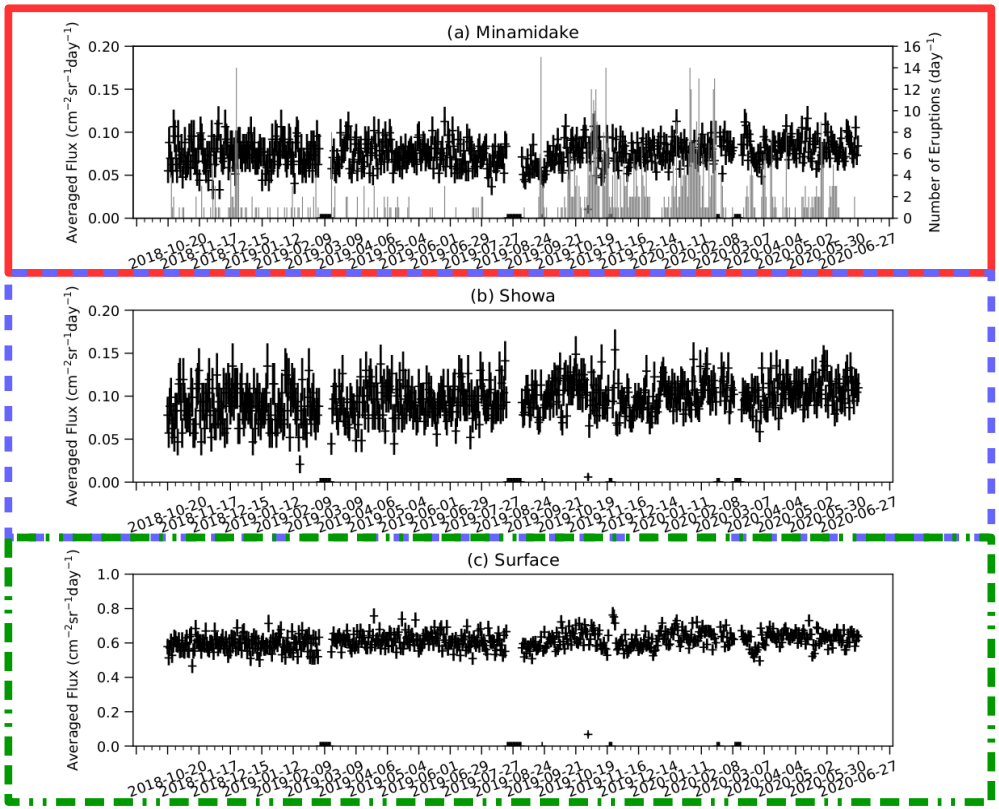
- GEANT4-based detector simulations were applied to set energy cuts of muons to approx. 1 GeV that corresponded to χ^2/n.d.f. < 1.5
- Directions of different MMOS modules were oriented to the reference direction that was 30.25° from North and horizontal
- Muon fluxes were weighted with the inverse of their relative errors, and thereafter averaged

See more at https://doi.org/10.1029/2019GL084784

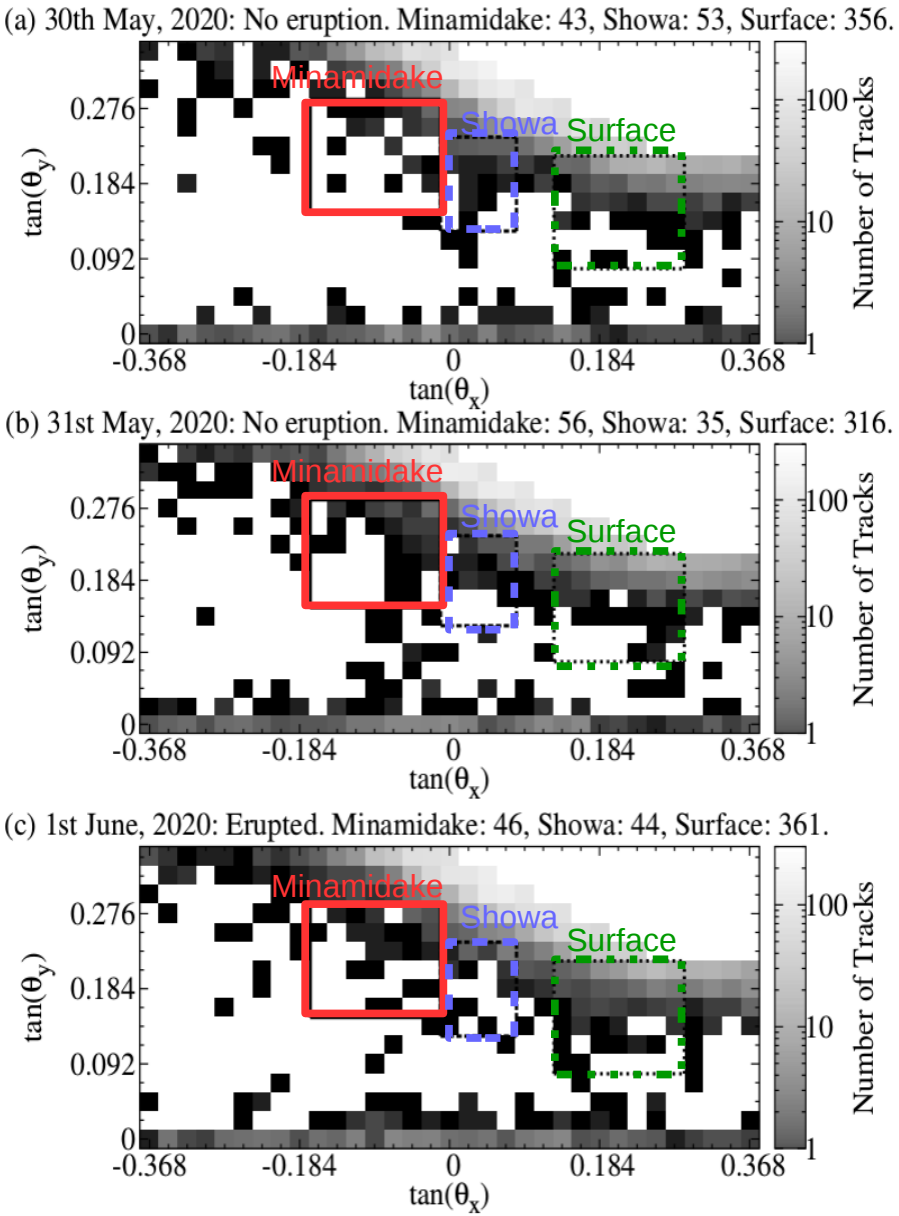


Preparation to Supervised Machine Learning

- Daily muograms were determined for period from October 2018 to June 2020
- **Average flux values and sub-images** were extracted from three selected regions:
  - Active Minamidake crater,
  - Dormant Showa crater,
  - Surface region.
- **Eruption labels** were also derived to all days
  Eruption → 1, No eruption → 0

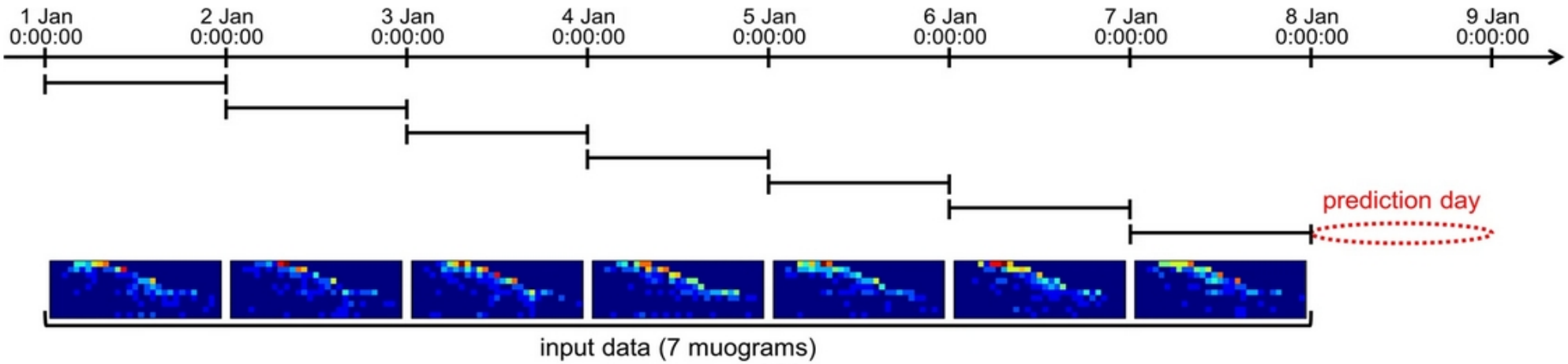


Muographic image resolution:
23 mrad x 23 mrad → 60 m x 60 m



IV. Eruption Forecasting by Machine Learning of Muographic Data

This study applied the concept that was developed by Nomura et al. for forecasing of the eruptions of Showa crater and achieved a ROC AUC of 0.726 (https://doi.org/10.1038/s41598-020-62342-y) using the data collected with two scintillator-based tracking systems (https://www.nature.com/articles/s41598-020-71902-1) between 2014 and 2016.



The data collected by the MWPC-based tracking system for forecasting the eruptions of Minamidake crater were organized as follows.

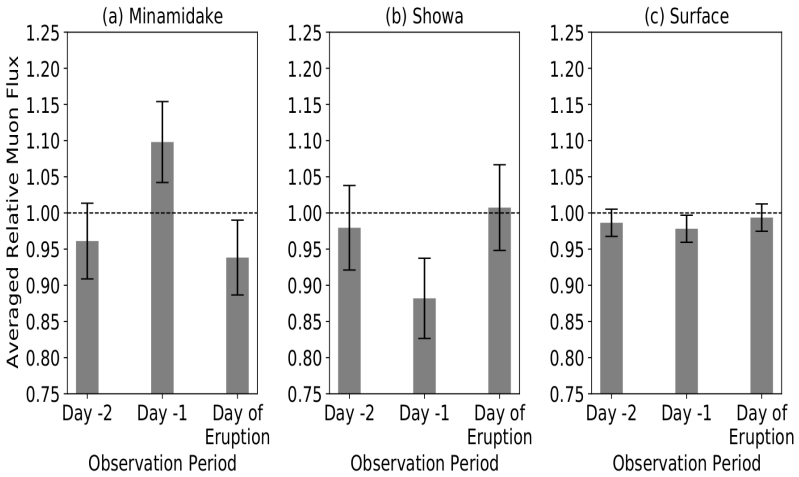
Training data: 394 days with 146 eruption days (only Minamidake erupted)
Validation data: 110 days with 48 eruption days (only Minamidake erupted)
Test data: 109 days with 56 eruption days (only Minamidake erupted)

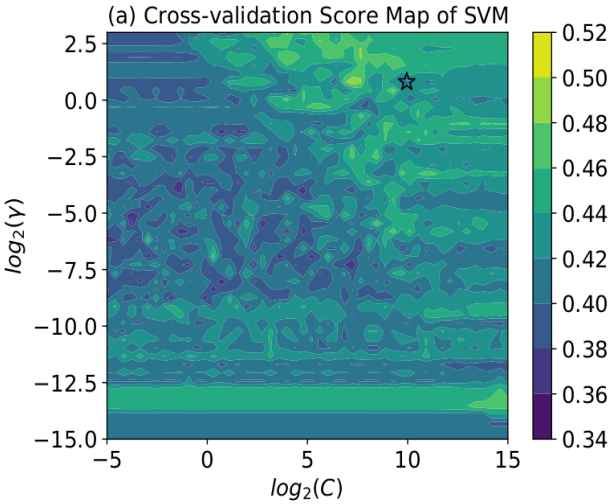
Applied Software: scikit-learn version 0.22.1, Keras version 2.4.3 and Tensorflow version 2.3.0

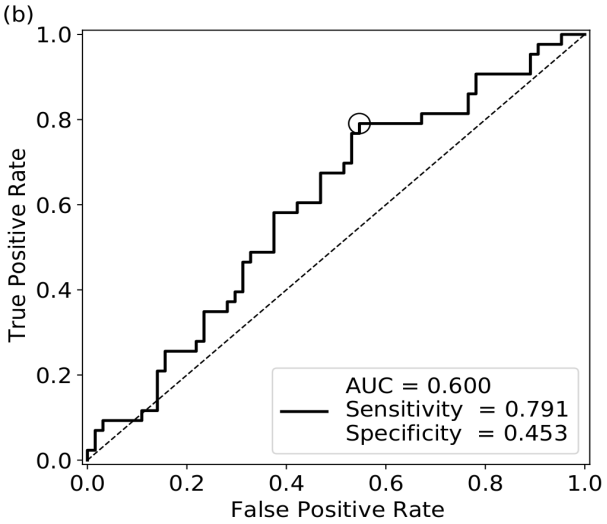
Receiver Operating Characteristic (ROC) analysis was applied to determine eruption forecasting performances

Learning of Average Flux Values with Support Vector Machine

- Relative flux values were averaged for 16 turns: an increase above 2.5 sigma was observed 1 day before eruption hints the explosion of volcanic plug beneath Minamidake before eruption
- Support Vector machine with radial basis kernel (C and γ parameters) was trained with the average flux values and eruption labels from training data set
- Parameters were selected based on their cross-validation score: C=925.827 and γ=1.74564
- Results of Reciever Operating Characteristic (ROC) analysis using test data set: Moderate accurracy of 0.6 → SVM (and other ML models, e.g. ANN) can not capture the patterns created by uprision magma or plug explosion before the occurrence of volcano eruption

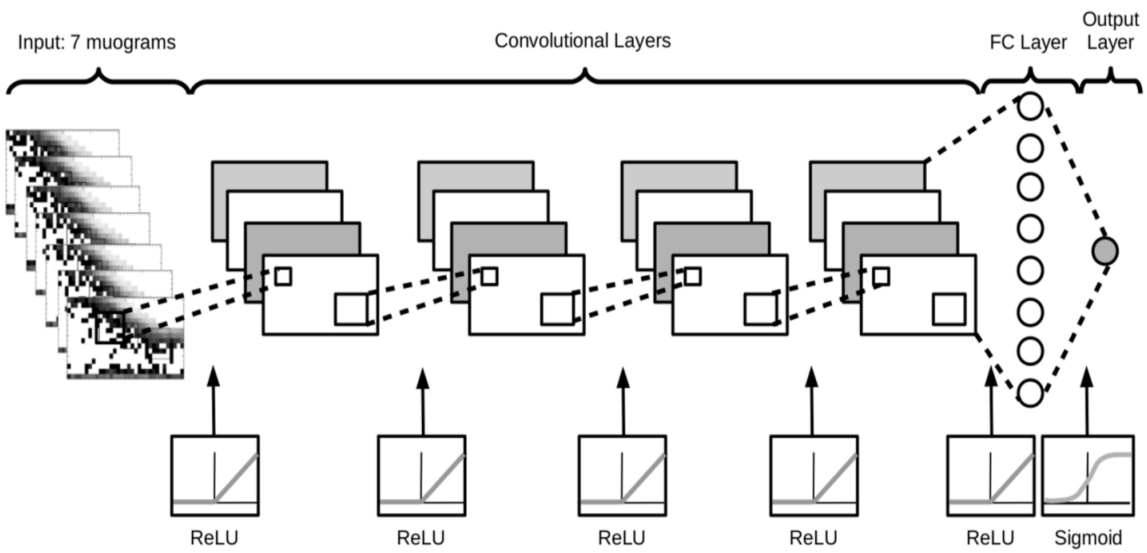






Learning of Muographic Images with Convolutional Neural Network

- Application of a series of convolutional layers allows to reveal the hidden features of images on layer-by-layer basis, and fully-connected neurons can process the extracted features to predict the eruptions.
  A fix filter size of 3x3 was used in this analysis.
- CNN was trained using Adam method.
- The hyperparameters of the CNN model were tuned with Bayesian optimization and selected by ROC analysis. The Number of epochs was found to be 100 and number of early patience was found to be 10.



Region	Minamidake	Showa	Surface
Convolutional Layers	2	2	3
Filters on 1st Conv. Layer	16	64	8
Filters on 2nd Conv. Layer	64	32	8
Filters on 3rd Conv. Layer	-	-	4
Neurons on FC Layer	32	128	32
Dropout	0.215	0.313	0.332
Batch Size	16	8	32
Learning Rate	0.000448	0.002749	0.00002
Decay Rate	0.926	0.969	0.981

Learning of Muographic Images with Convolutional Neural Network

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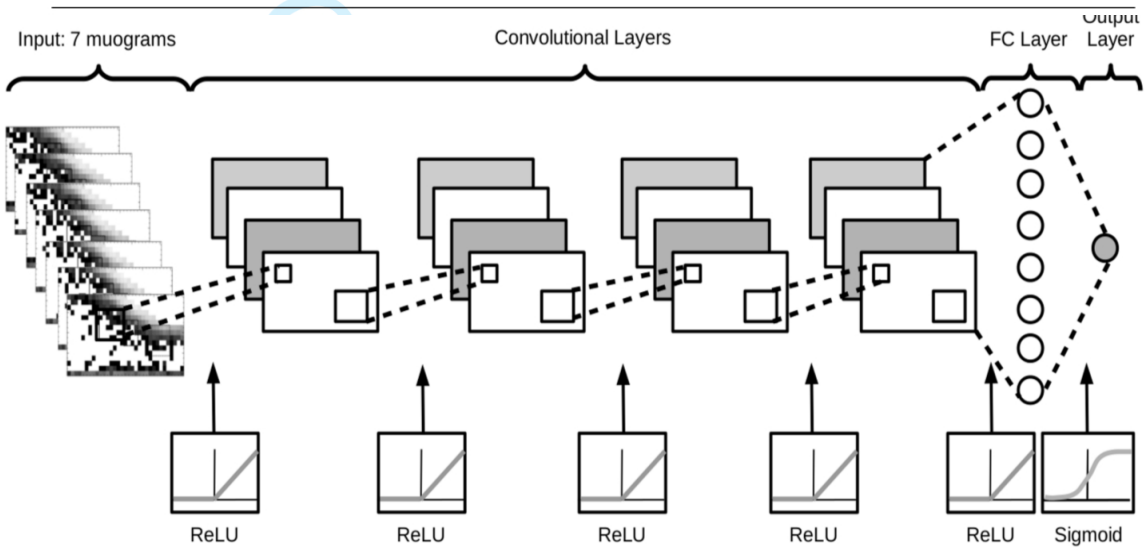
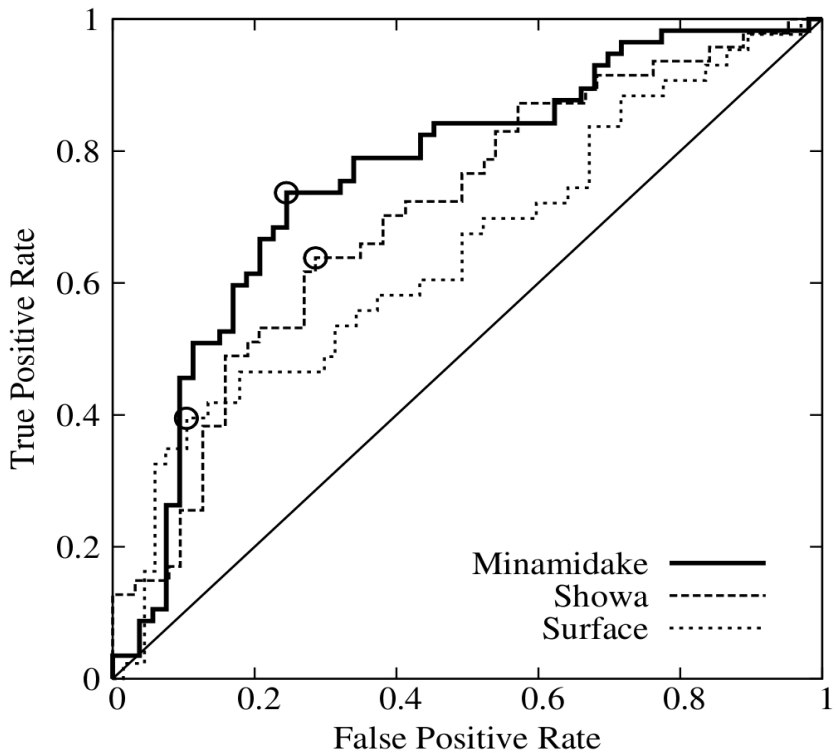
  A fix filter size of 3x3 was used in this analysis.
- CNN was trained using Adam method.
- The hyperparameters of the CNN model were tuned with Bayesian optimization and selected by ROC analysis. The optimal number of epochs was found to be 100 and number of early patience was found to be 10.
- Results of ROC analysis showed that CNN achieved a fair AUC of 0.761 in Minamidake from the eruptions occurred

	Minamidake	Showa	Surface
Area Under the Curve	0.761	0.704	0.644
Sensitivity	0.737	0.638	0.395
Specificity	0.755	0.714	0.896





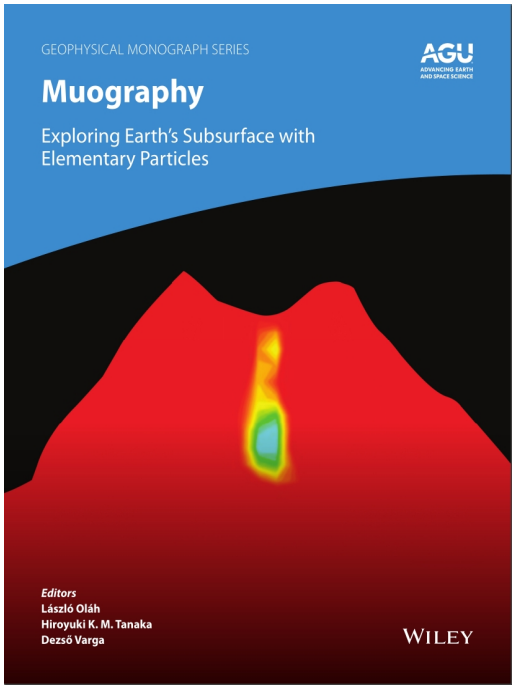
V. Summary and Discussion

- **GOAL:** Volcano eruption forecasting with machine learning of volcanic signals
- Muography allows continuous remote monitoring of volcanoes and can complement standard techniques
- Convolutional Neural Networks could capture hidden features of muographic images and achieved a fair AUC score of 0.761
- **Comparison to the results of Nomura et al. (forecasting of Showa's eruptions with ROC AUC of 0.726) and this work (forecasting of Mindamidake's eruptions with ROC AUC of 0.761):** Despite the application of upgraded muography obsrevation system with enlarged (5 sqm → 8 sqm) sensitive surface area and higher angular resolution (33 mrad→ 23 mrad), the forecasting performance was not drastically improved probably due to the following reasons:
  - smaller number of eruptions occurred in Minamidake (832) than in Showa (1432) that resulted in smaller amount of training data,
  - smaller amount of mass was transportated beneath the Minamidake than Showa that resulted in smaller variations in muographic images,
  - the geometrical difference between the two craters is also assumed to be an influencing factor.

TODO:

- Recurrent Neural Network with Long-Short Term Memory is expected to improve forecasting
- Integration of muographic data with other remote sensing data
- CNN works as a black box function
  → Interpretable machine learning

The presented study will published in a chapter (https://doi.org/10.1002/9781119722748.ch4) in the book ISBN 9781119723028 by L. Oláh and H. K. M. Tanaka



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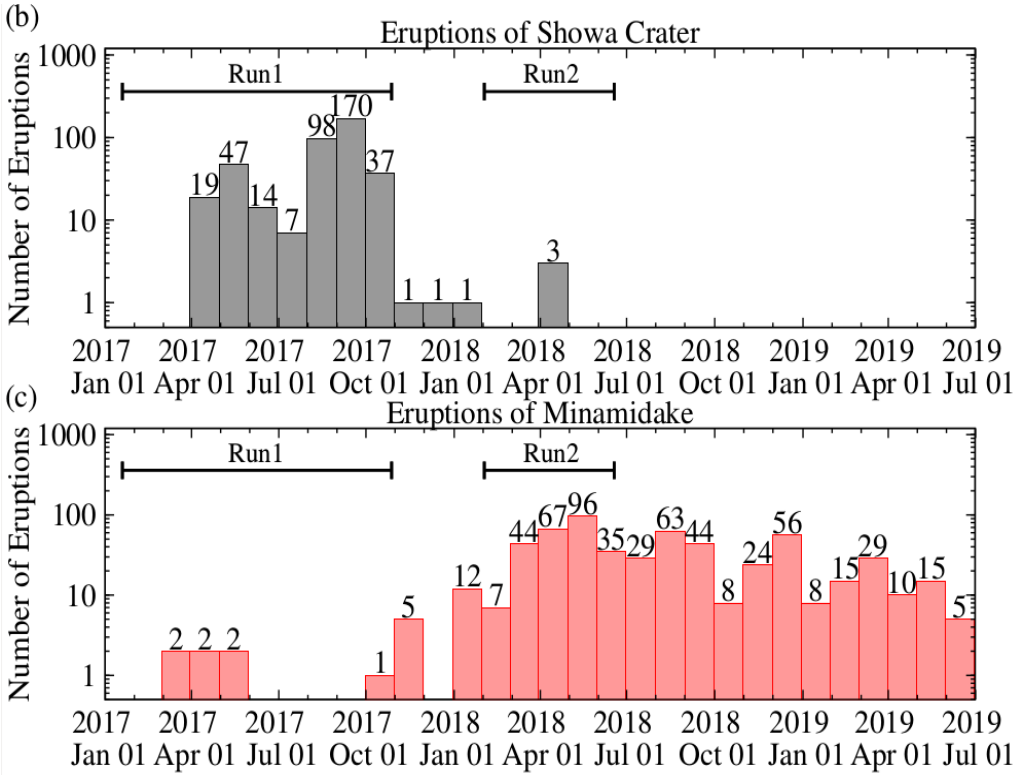
Thank you for your attention!

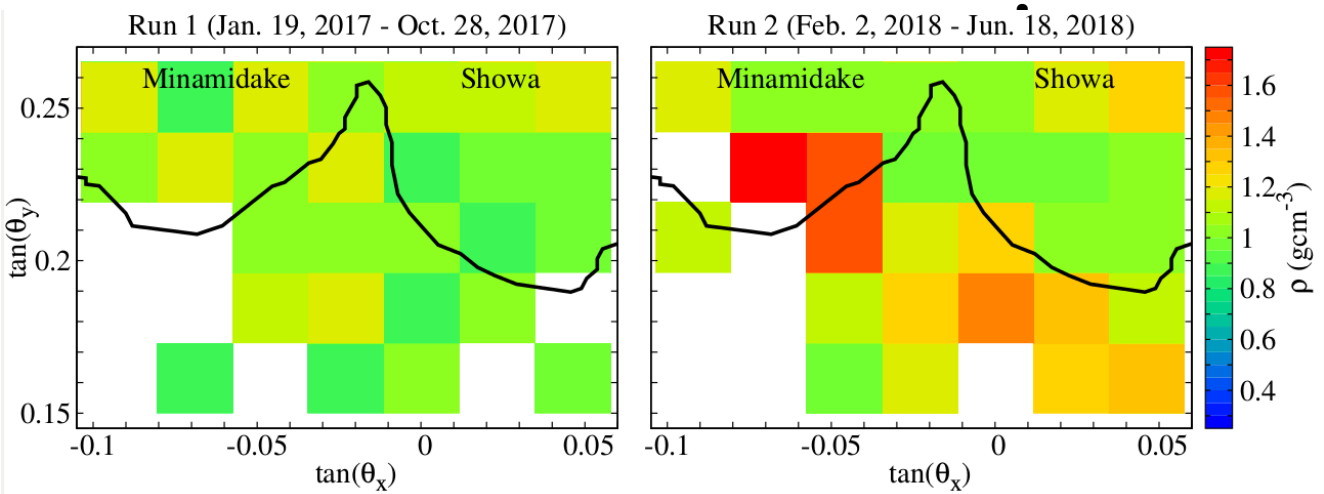
Backup Slides

Magmatic Plug Formation Imaged With Muography



- **What is the cause of the shift of eruption sequence from Showa to Minamidake?**
- Two data sets were analysed:
  Run 1: January - November 2017;
  Run 2: February - June 2018.
- Systematics effects on muon flux: < 5 %

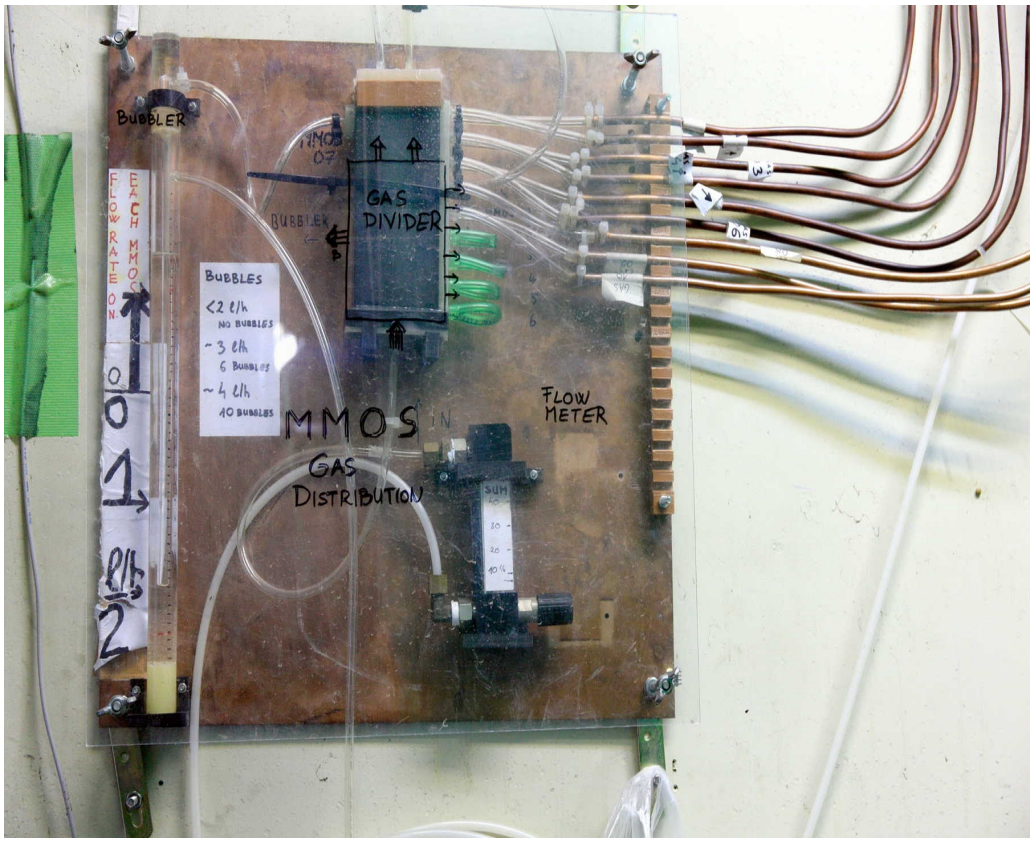
L. Oláh et al.: GRL, Vol. 46 Issue 17-18 10417-10424
https://doi.org/10.1029/2019GL084784



- Significant density increase from 2σ-4σ was observed bin-by-bin across Minamidake and beneath Showa crater (~7 Mt)

Gas System of MMOS

- Detector operation is provided by continuous flow of non-flammable, non-toxic Ar-CO_2 gas mixture with a flow of 2 Liters/hour
- 3-5 months continuous operation by a cluster of gas bottles (a volume of 40 Liters at a pressure of 140 bars each)



Nucl. Instrum. and Meth. A
https://doi.org/10.1016/j.nima.2019.05.077

III. Automated Muographic Visualization Framework