# MLAI for Infrastructure: Climate Hazards

Alison Peard

*Intelligent Earth CDT, 13th December 2024*

## Lecture structure (30 mins)

Introduction (3 mins)

Hazard Modelling Fundamentals (6 mins)

Compound Hazards (3 mins)

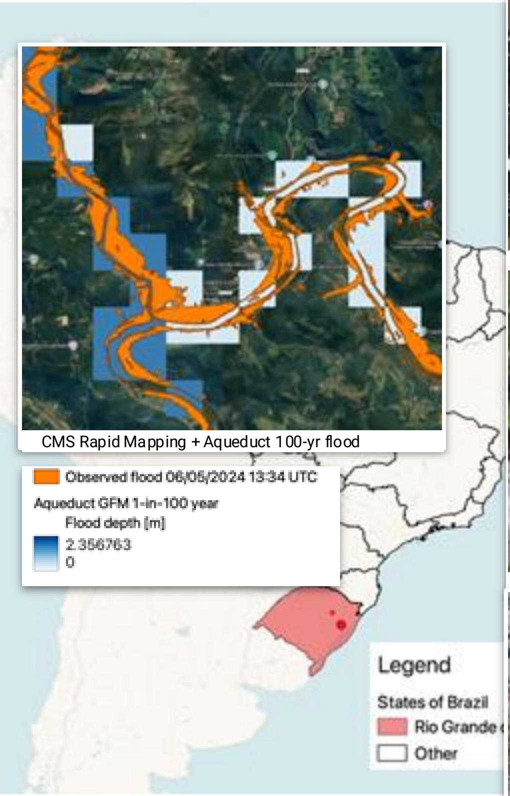
Hazard Mapping and Catastrophe Modelling (7 mins)

Deep Learning Applications (7 mins)

Conclusion and Future Directions (4 mins)

# Introduction

# **Introduction** 2024 Rio Grande do Sul floods




CMS Rapid Mapping + Aqueduct 100-yr flood

BBC Brasil

BBC Brasil

Porte Alegre flooded, Wikipedia

**Extreme rainfall** in April-May Caused **landslides** and **flooding**

**181** dead
**809+** injured
**580,000** displaced

**$3.7 billion** damages
**500,000** people without power or clean water

Flood defence **deterioration** and poor **land-use policies** contributed to damage extent

https://rapidmapping.emergency.copernicus.eu/EMSR720/reporting

# Hazard Modelling Fundamentals

# Hazard Modelling Fundamentals Core objectives vs climate modelling

| | Climate Modelling | Hazard modelling |
|---|---|---|
| **Focus** | Physical processes and Earth System dynamics | Extreme events and their impacts |
| **Key Users** | Scientists and policymakers | Insurers, engineers, governments |
| **Timeframe** | Decades to centuries | Event-based or probabilities |
| **Priority** | Scientific accuracy and completeness | Practical utility and loss estimation |

# **Hazard Modelling Fundamentals** Key stakeholders

**Insurers**
Statistics of potential losses

**Government**
Probability, severity, and locations of potential damages and losses

**Emergency Services**
Expected event severities and worst case scenarios

**NGOs**
Hotspots for adaptation

# Hazard Modelling Fundamentals Key terms and concepts

Return period

Risk profile/curve

Event footprint

Hazard map

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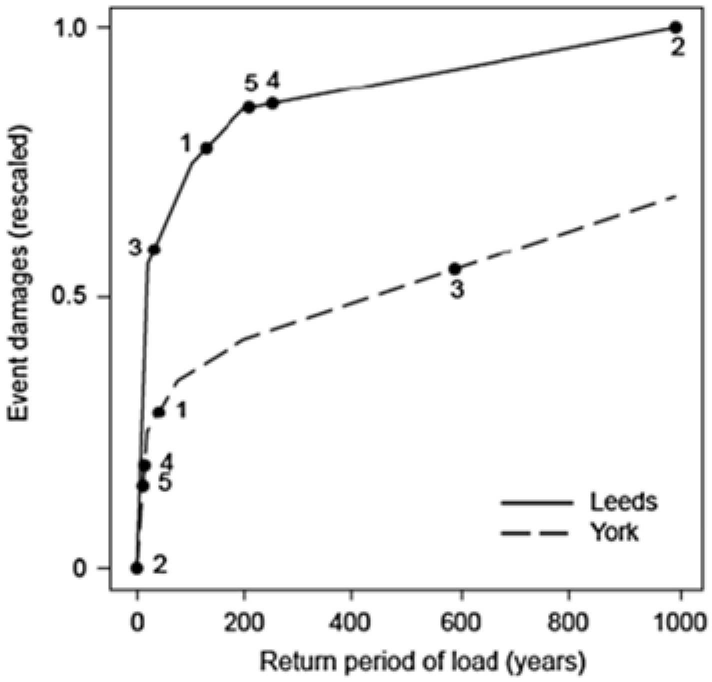
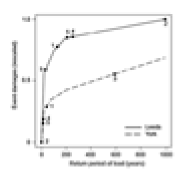



Lamb, R., Keef, C., Tawn, J., Laeger, S., Meadowcroft, I., Surendran, S., ... & Batstone, C. (2010). A new method to assess the risk of local and widespread flooding on rivers and coasts. *Journal of Flood Risk Management*, *3*(4), 323-336.

# Hazard Modelling Fundamentals Key terms and concepts

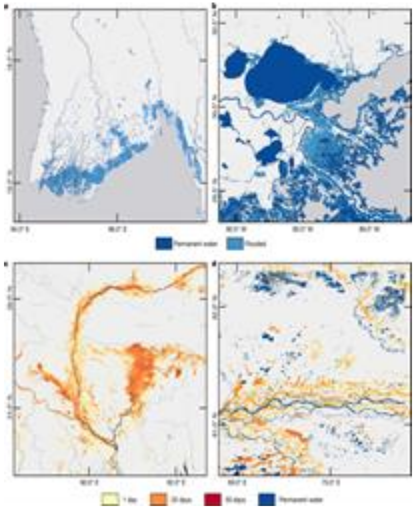
Return period

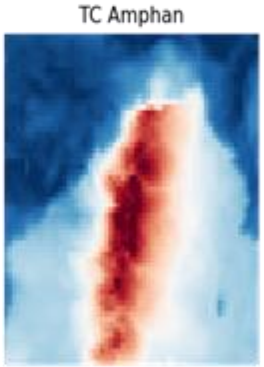


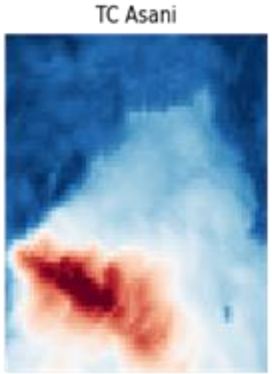
Risk profile

Event footprint

Hazard map

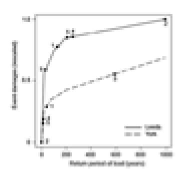




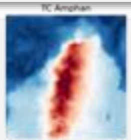
# **Hazard Modelling Fundamentals** Key terms and concepts

Return period

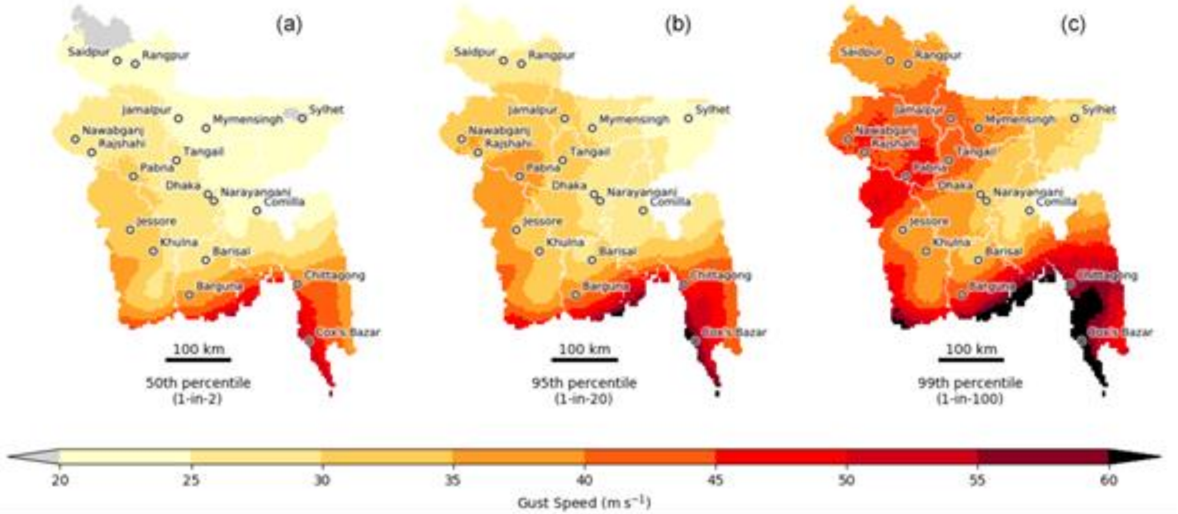


Risk profile

Event footprint



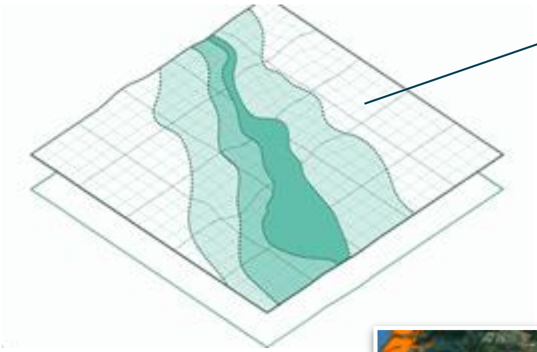

Hazard map

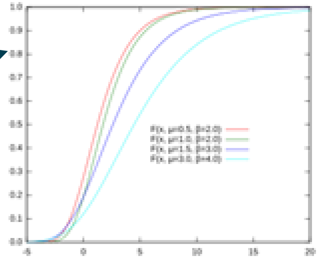



Steptoe, H., & Economou, T. (2021). Extreme wind return periods from tropical cyclones in Bangladesh: insights from a high-resolution convection-permitting numerical model. *Natural Hazards and Earth System Sciences*, *21*(4), 1313-1322.

# Hazard Mapping and Catastrophe Modelling

# Mapping and Catastrophe Modelling Hazard maps





CMS Rapid Mapping + Aqueduct 100-yr flood

Observed flood 06/05/2024 13:34 UTC

Aqueduct GFM 1-in-100 year

Flood depth [m]

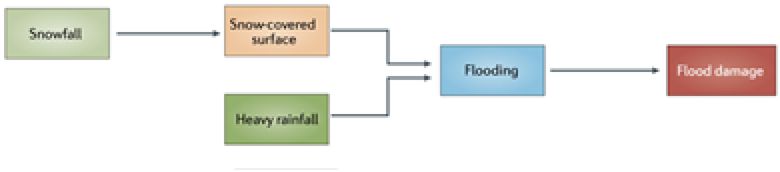
2.356763

0

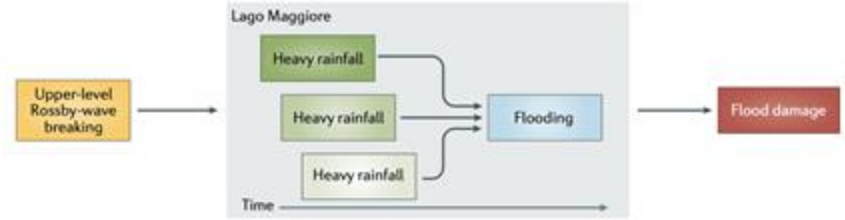
| Features | |
|---|---|
| Probabilistic: one map per return period | |
| Lightweight and efficient | |
| Easy to interpret | |
| No compound effects | Univariate |
| | Spatial independence |
| | Atemporal |

# **Compound Hazards** When hazards intersect

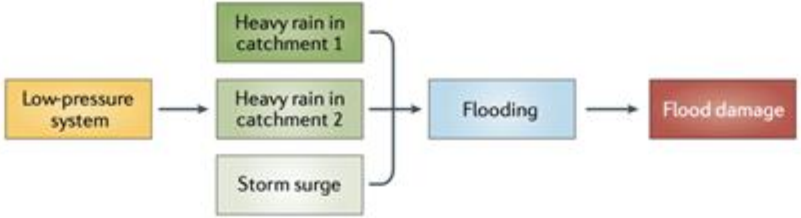
## Preconditioned



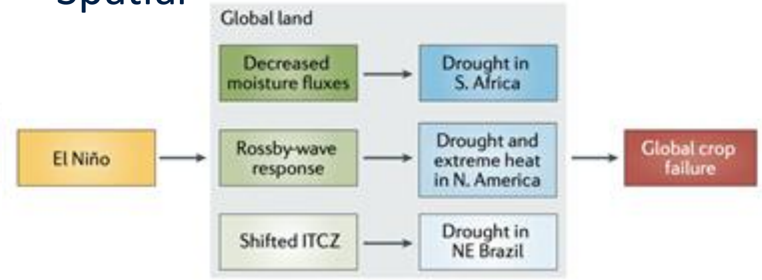

## Temporal




## Multivariate




## Spatial




Zscheischler *et al.* (2020) *A typology of compound weather and climate events*

# **Compound Hazards** When hazards intersect


**Extreme rainfall** in April-May
Caused **landslides** and
**flooding**

**181** dead
**809⁺** injured
**580,000** displaced

**$3.7 billion** damages
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Flood defence **deterioration**
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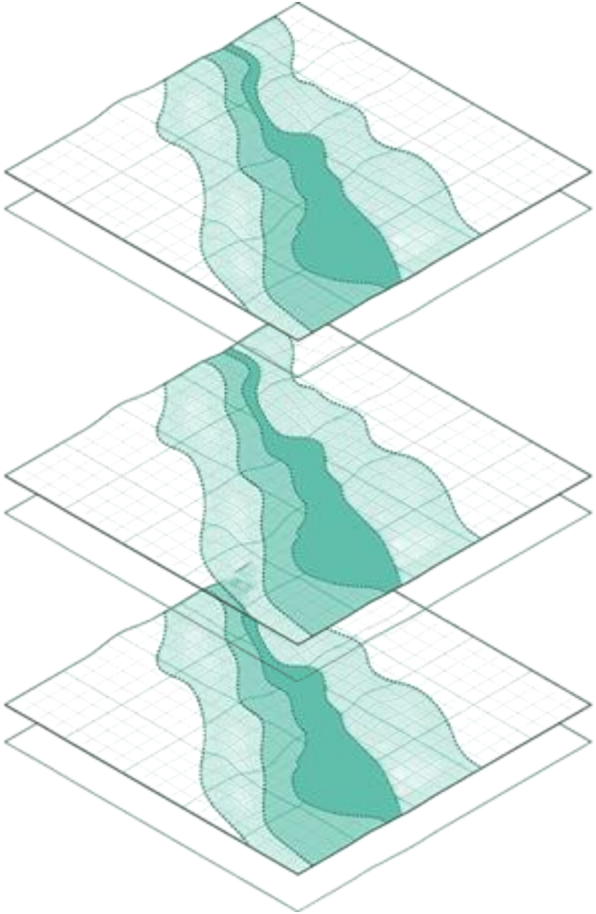
# Mapping and Catastrophe Modelling Catastrophe model



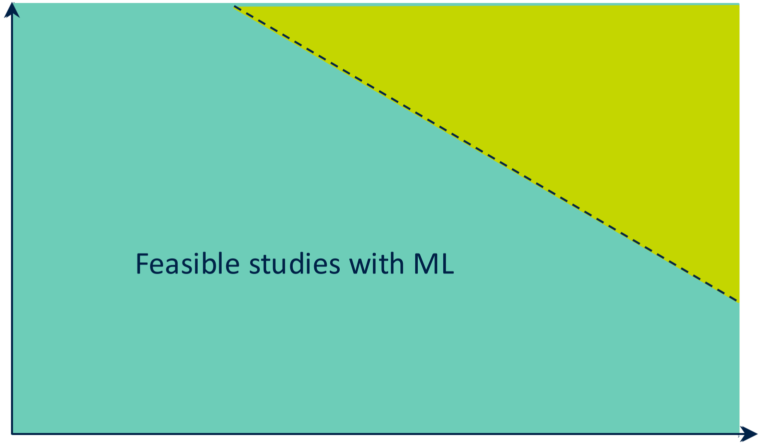
| Features |
| --- |
| Portfolio of 1000s of events |
| Modelling is expensive |
| Numerical, stochastic, or hybrid simulations |
| Calculate statistics over losses from entire portfolio |
| Multivariate or region events |

# Mapping and Catastrophe Modelling Summary

| | Hazard maps | Catastrophe models |
|---|---|---|
| **Format** | One event map per return period | Thousands of possible event footprints |
| **Memory and compute** | Medium | High |
| **Ease of use** | High | Low |
| **Compound events** | No | Potentially |
| **Calculate statistics** | At every point | Over final losses |

# Deep Learning Applications

# Introduction Relevance to ML researchers




**Model sophistication**

- Less approximations made
- Relationships accounted for

**Model scale**

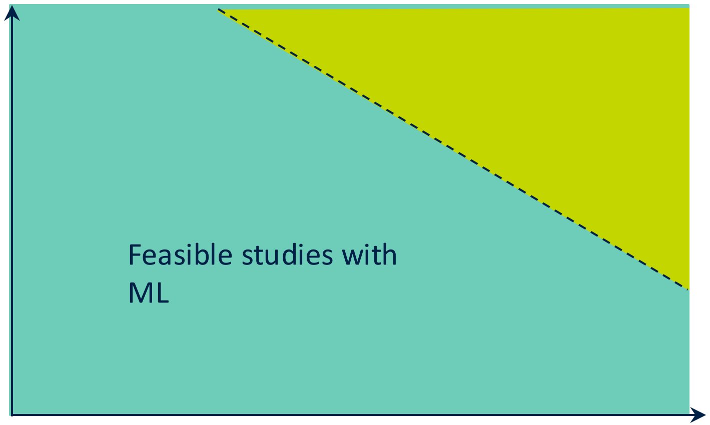
- Spatial range
- Temporal range
- Number of variables

# **Deep Learning Applications** Key research directions

- Before modelling
  - Parameterizing
  - Equation discovery
- Modelling
  - Surrogates
  - Sub models
  - PINNs/hybrid models
- After modelling
  - Bias correction
  - Downscaling
- Bypass modelling
  - Event sampling

**Model sophistication**

- Fewer approximations
- Interdependencies




**Model scale**

- Spatial scale
- Temporal scale
- Number of variables

# **Deep Learning Applications** Differentiable parameter learning (dPL)

- LSTM Surrogate hydrological model
  - gradient tracking
- Optimise for parameters which minimise model error

- Better physical coherence
- Improves data scaling
- Outperforms in classic methods
- Soil moisture and streamflow

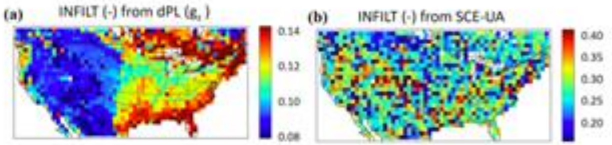
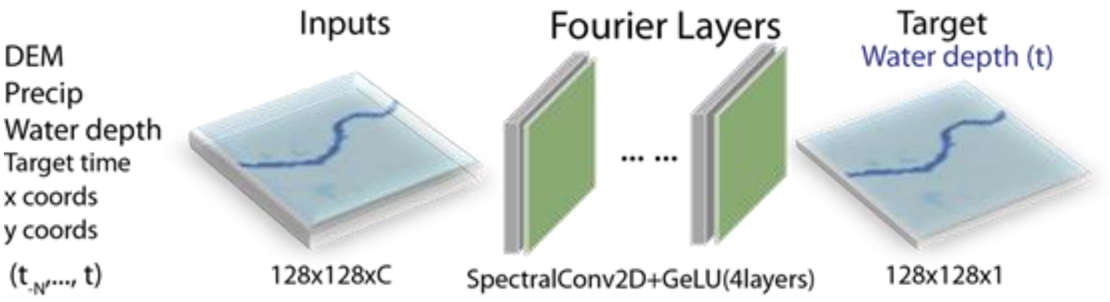



**Fig. 5 Comparison of parameters generated by dPL and SCE-UA.** The continuous, spatially representative patterns of **a** dPL-inferred parameters are noteworthy, especially in comparison to the discontinuous, random appearance of **b** SCE-UA-inferred parameters from site-by-site calibration. Both were trained with a $1/8^2$ sampling density.


Tsai, W. P., Feng, D., Pan, M., Beck, H., Lawson, K., Yang, Y., ... & Shen, C. (2021). From calibration to parameter learning: Harnessing the scaling effects of big data in geoscientific modeling. *Nature communications*, *12*(1), 5988.

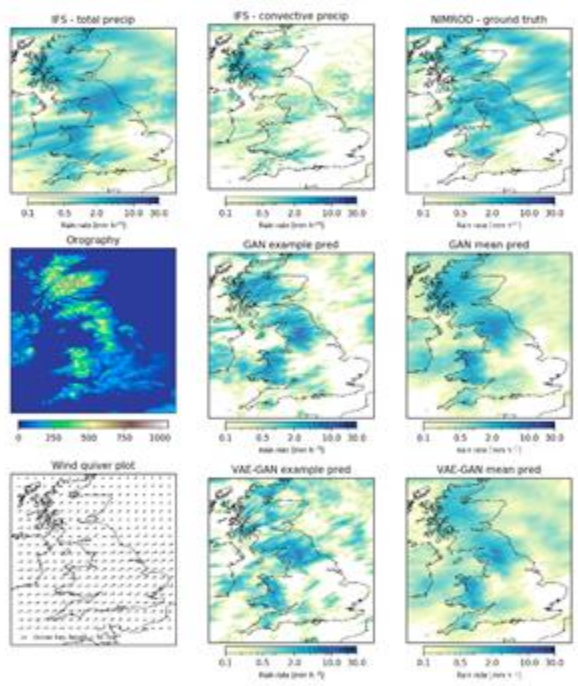
# Deep Learning Applications FNO flood model




- Efficient
- Zero-shot resolution - learns in Fourier space
- Doesn't need to be retrained for parameter changes

Sun, A. Y., Li, Z., Lee, W., Huang, Q., Scanlon, B. R., & Dawson, C. (2023). Rapid flood inundation forecast using Fourier neural operator. In Proceedings of the IEEE/CVF International Conference on Computer Vision (pp. 3733-3739)

# **Deep Learning Applications** Post-processing precipitation forecasts

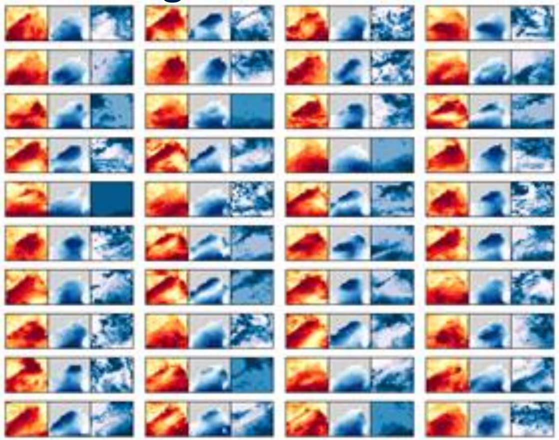



- Conditional GAN
- Condition on forecast and related variable (orography)
- Downscale to higher resolution

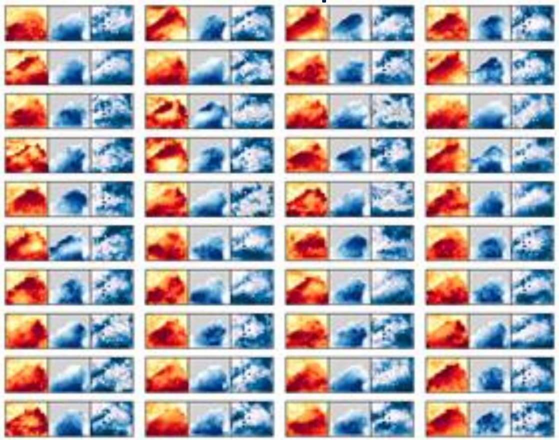

Harris, L., McRae, A. T., Chantry, M., Dueben, P. D., & Palmer, T. N. (2022). A generative deep learning approach to stochastic downscaling of precipitation forecasts. *Journal of Advances in Modeling Earth Systems*, *14*(10), e2022MS003120.

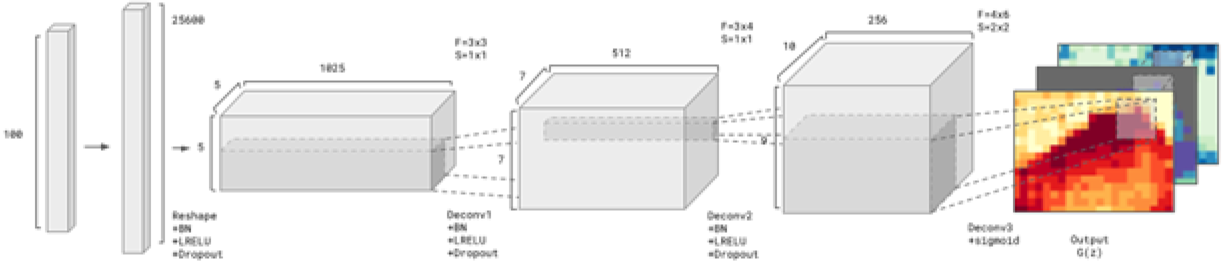
# **Deep Learning Applications** Event sampling

Training data



Generated samples






Peard, A., & Hall, J. (2023). Combining deep generative models with extreme value theory for synthetic hazard simulation: a multivariate and spatially coherent approach. *arXiv preprint arXiv:2311.18521*.

# Conclusion and Future Directions

# Conclusion and Future Directions Recap

1. Hazard modelling generates actionable insights
2. Two main types of hazard modelling
   a. Probabilistic hazard maps
   b. Cat (event-based) modelling
3. ML can increase scale and complexity of hazard modelling
   a. Compound events
   b. Larger scales
   c. Higher resolution
4. Many interesting areas for improvement

# Thanks for listening!