Complex dynamical transitions in granular flow

Augmented intelligence models for real-time decision-making from factory floor to open fields

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Plan of this talk

- Industry-academia collaboration in particulate science and technologies (PST)
  - Data-driven modelling of processes in **mixed granular regimes** at large scale (field, regional, continental) under a changing climate

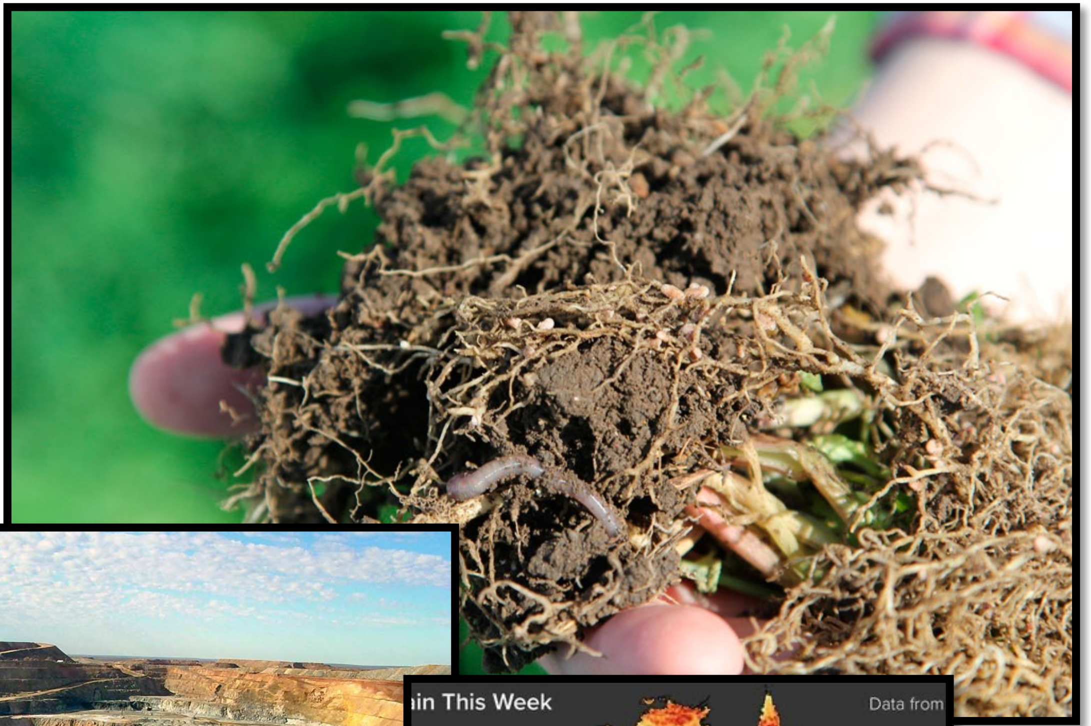
- Safe-blasting
  - Example case study on slope stability analytics for precision rock fragmentation

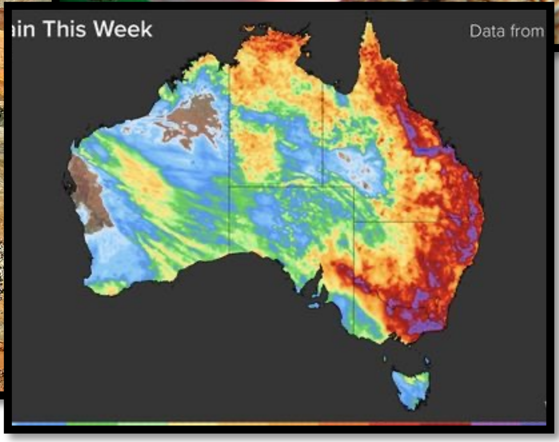
Objective of this talk

- Share experiences in harnessing basic science for precision 'green' PST
  - integrate basic research in granular media mechanics & physics with big data analytics
  - extract actionable insights from live, continuous monitoring data in real-time

Research with industry & govt.

- Helping to build data-driven tools for resilience building & sustainability
- Related topics
  - Landslides, slope stability under fragmentation & dewatering
  - Extreme precipitation
  - Soil carbon
- Exploits data from sensing & imaging technologies

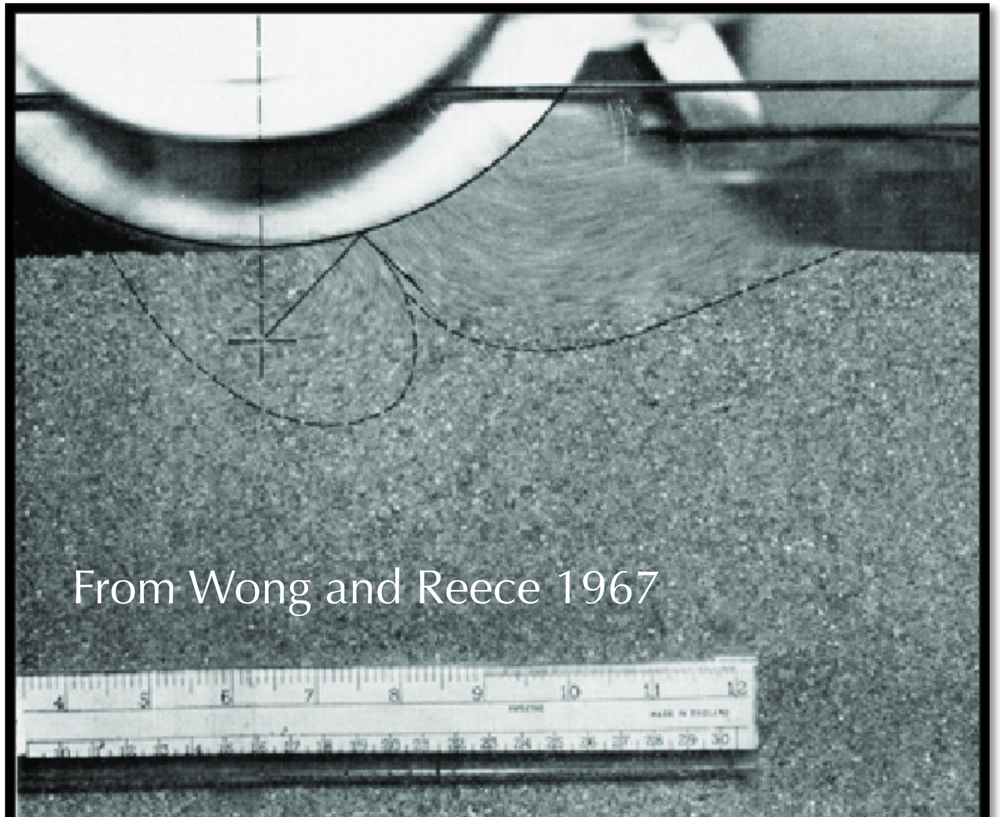




https://en.wikipedia.org/wiki/Mining_in_Australia
image credit: Hitachi ABB Power Grids

Not quite Fine Particle Science & Technology

- Link to IFPRI? Some similar processes, but fines (<4mm) undesired
- Processes rooted in trade-offs between strength & failure (intact solid & flow)

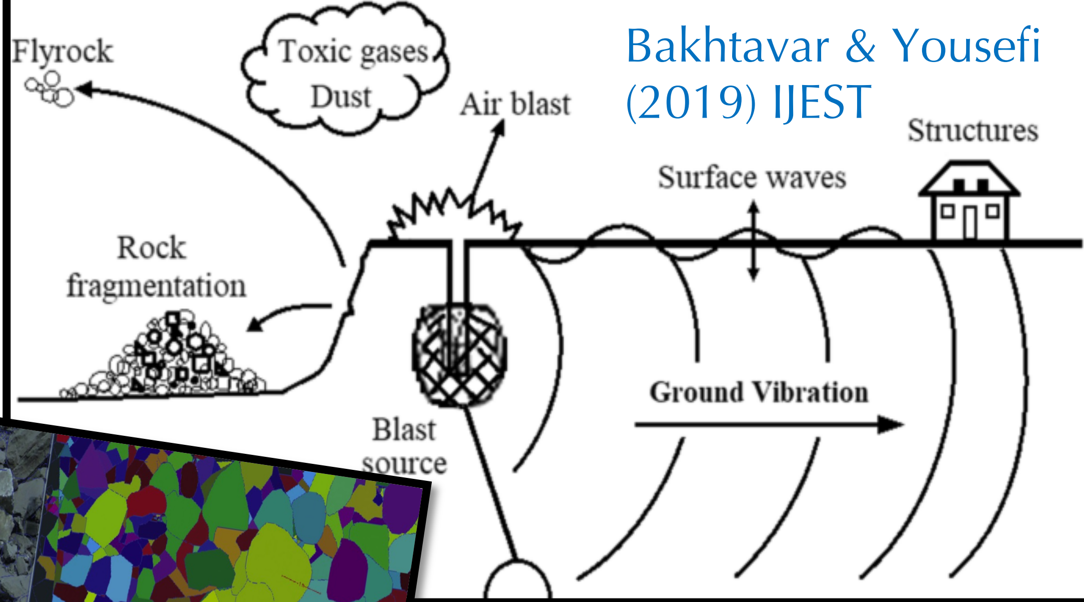


From Wong and Reece 1967

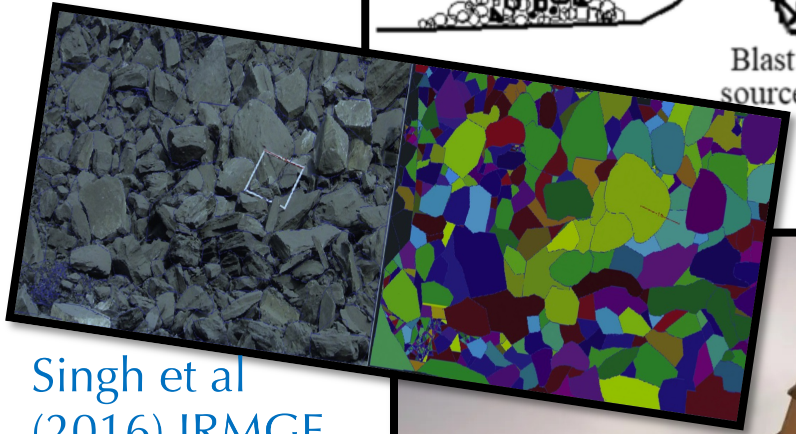

Safe-blasting

Mineral extraction

- Optimized rock fragmentation under regulation & safety
- 3 critical quality attributes
  - PSD (product quality)
  - S (safety)
  - PPV (regulatory)
- Blast parameters
  - Design (controlled)
  - Rock properties (uncontrolled)
- Connecting PSD, S and PPV to fracture properties of slope remains a challenge
- Today, **big data, anywhere, anytime**
- Data-driven tools
  - black box machine learning (PSD-PPV)
  - thresholds, Fukuzono inverse-velocity (S)



Bakhtavar & Yousefi (2019) IJEST



Singh et al (2016) JRMGE

An autonomous haulage truck collects more than 600 million times more data per day than Apollo 11's computer in RAM (Image credit C Sprogoe)

Research Aim, Goal, Objective

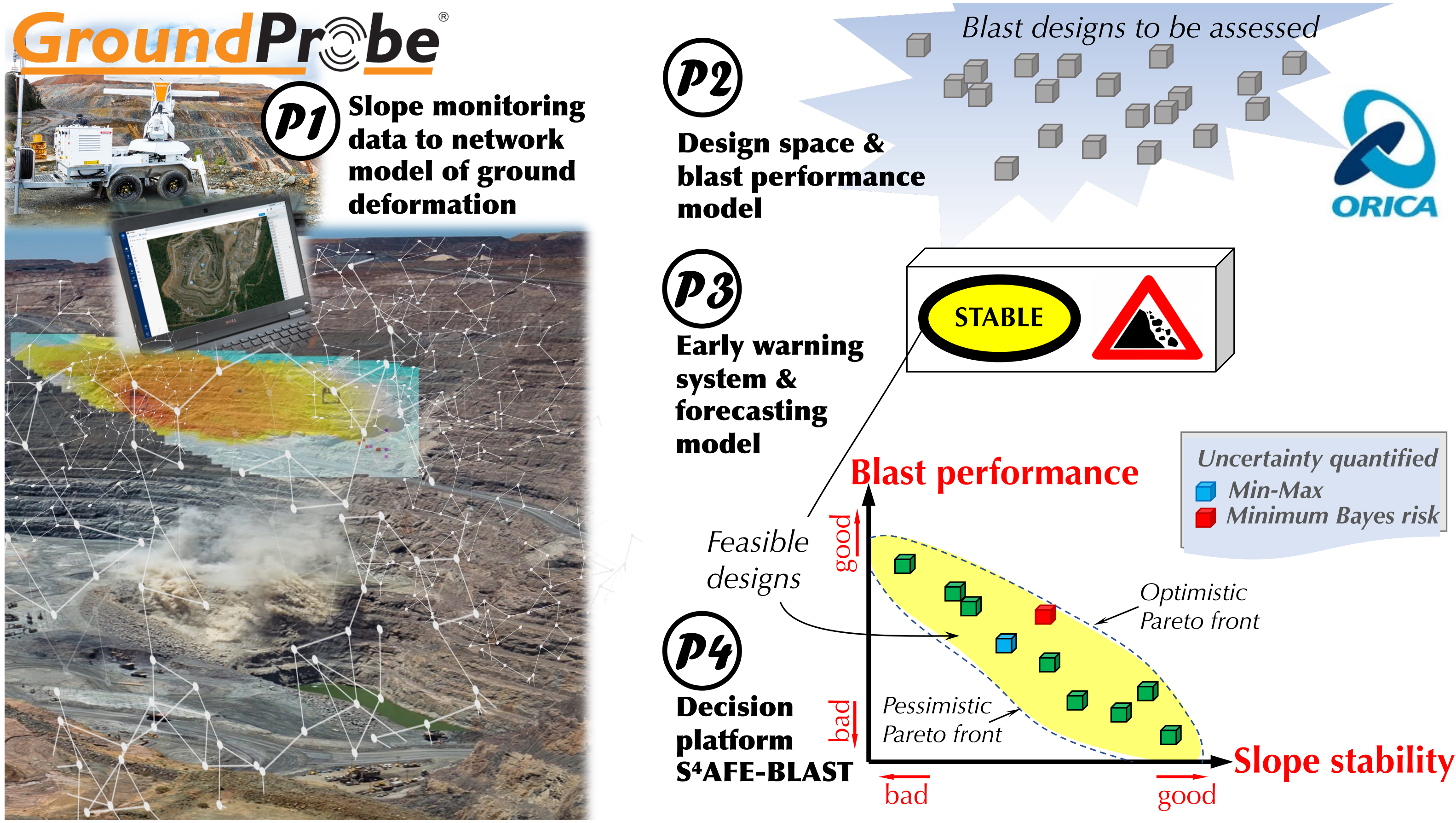
- Integrated monitoring-analytics-decision-making
- Target rock size distribution from blast design matched to geology & past-present-future slope response and properties
- **Future focused slope stability & what-if-scenario analytics**

9 am, 31 May 2021, Rio Tinto Kennecott mine, Bingham Canyon Utah, USA (Still from a Youtube video)

Basic idea behind S⁴AFE-Blast

- Integrate dynamics of blast performance & slope performance
- Dynamic optimization of two competing objectives

- Rest of this talk
  → *focus on* S⁴AFE which ***learns & forecasts slope performance*** *from data*



Tordesillas, Qian, Campbell, Bellett (2020) Integrated slope stability analytics for optimised blast performance.

S⁴AFE = Stochastic Spatiotemporal Slope Stability Analytics for Failure Estimation

Input data

Process profiling in digital age *in real time*

'With every click, we're like Hansel and Gretel leaving our breadcrumbs through the digital woods'
Eleanor Blackwood

From https://right.ly/our-views-and-opinions/what-data-profiling-and-how-does-it-affect-you/

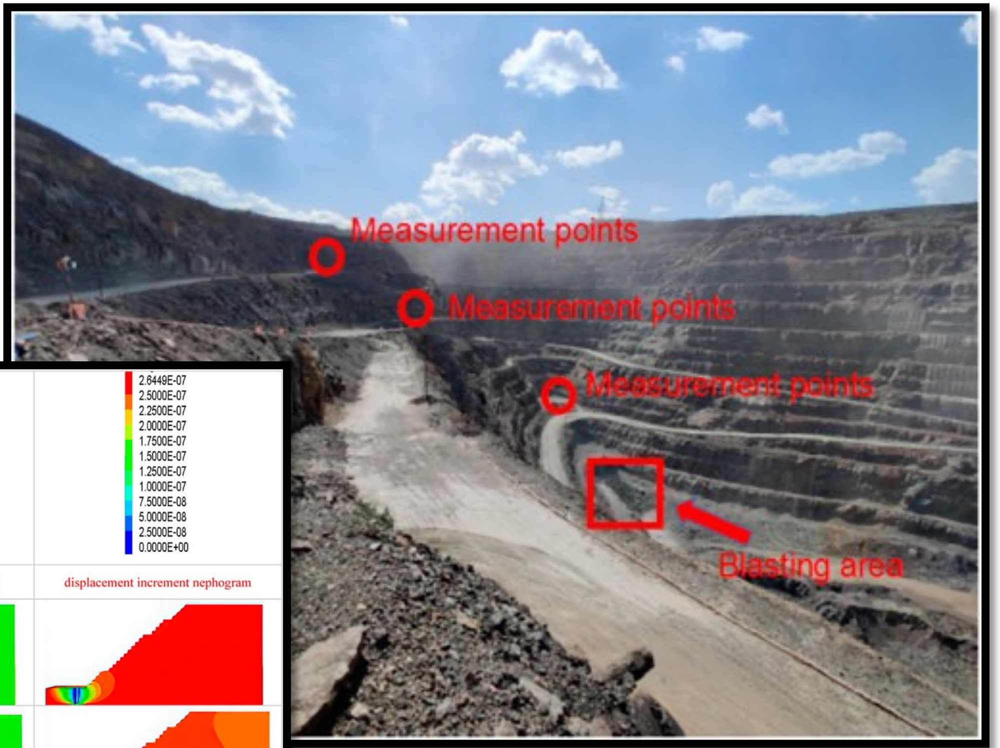
Slope deformation profiling – from monitoring data

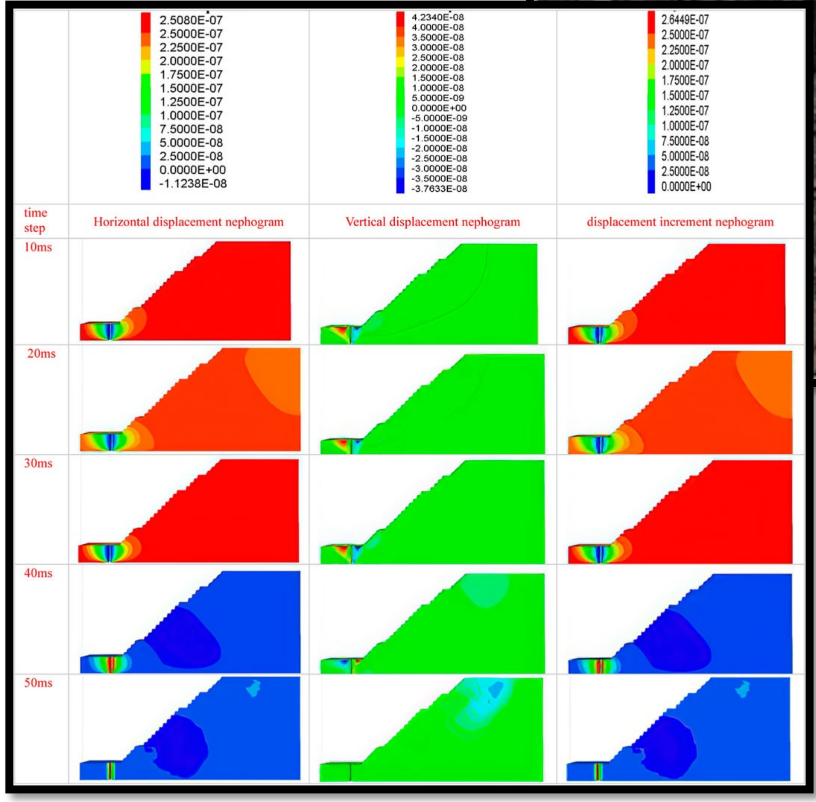
- Approach 1: Traditional
  - **model** (set of governing eqns.) of **real process** **+** input parameters ('static' measurements) deliver an output (predictions on CQA)
- Approach 2: Data-driven
  - output variable (CQA=slope motion) is continuously monitored at high spatial and temporal resolution (near real-time or real-time)
  - critical process parameters (e.g., rock properties) and exogenous variables (e.g., blasting, weather) also continuously monitored across space and time
  - **strategy: let the real process shape the model through the data**
  - use statistical learning and deep learning to **adaptively learn the model from streaming, historical data on CQA & CPP**, then use the model to forecast values 'anywhere, anytime' in some space-time horizon with quantified uncertainty

Approach 1

Measured On-At-line blast properties →FLAC3D

- Traditional approach
- INPUT: 'Online+Atline' data on blasting used as input to a numerical continuum model
- OUTPUT: Safety factor, slope displacement but not relatable to actual slope motion





Su & Ma (2022) Front. Earth Sci

Approach 2

Measured In-On-At-line blast properties →S^4AFE

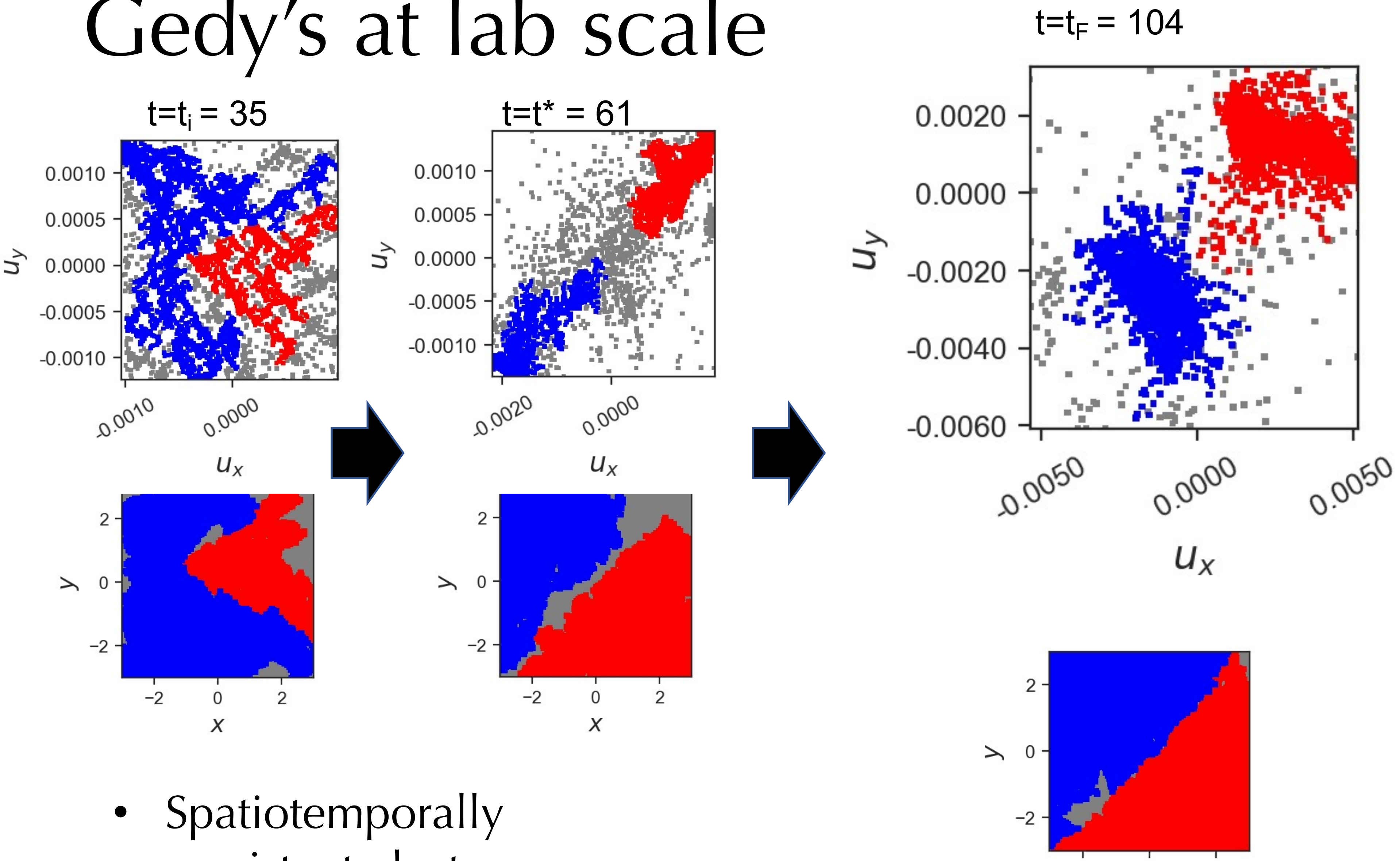
- Data-driven approach
- INPUT: 'Inline+Online+Atline' blast data + 'Inline' historical slope motion data
- OUTPUT: Future slope motion at high confidence

  + actionable insights (where, when, what if)

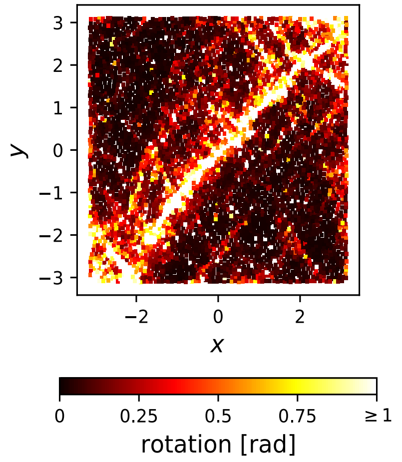
- Data profiling tools exploit synergies between HI and AI.
  - Various functions: Fusion, Dynamic 'declutterer', Forecasting, Multi-objective Bayesian optimization
- Builds on the **generic dynamics (the gedy's)** found from micromechanics
- Find the **most informative** data features for **quick & early** failure prediction
  - Where: Clustering & local intrinsic dimension of ground motion data
  - When: Adaptive spatiotemporal Fukuzono
  - What if scenarios: Dynamics & extreme event analysis


Gedy's in complex dynamical transitions in granular media
Informative the dynamics of clustering patterns in motions is
In space and time, you will see
Regardless of scale, it applies
Ground motions today,
Or, grain motions tomorrow, there is no lie!
Authors thank the companies who have shared SSR data on real catastrophic failure for this work, and for providing permission for publication on the condition of anonymity.

Gedy's at lab scale



Start of steady "critical state" regime



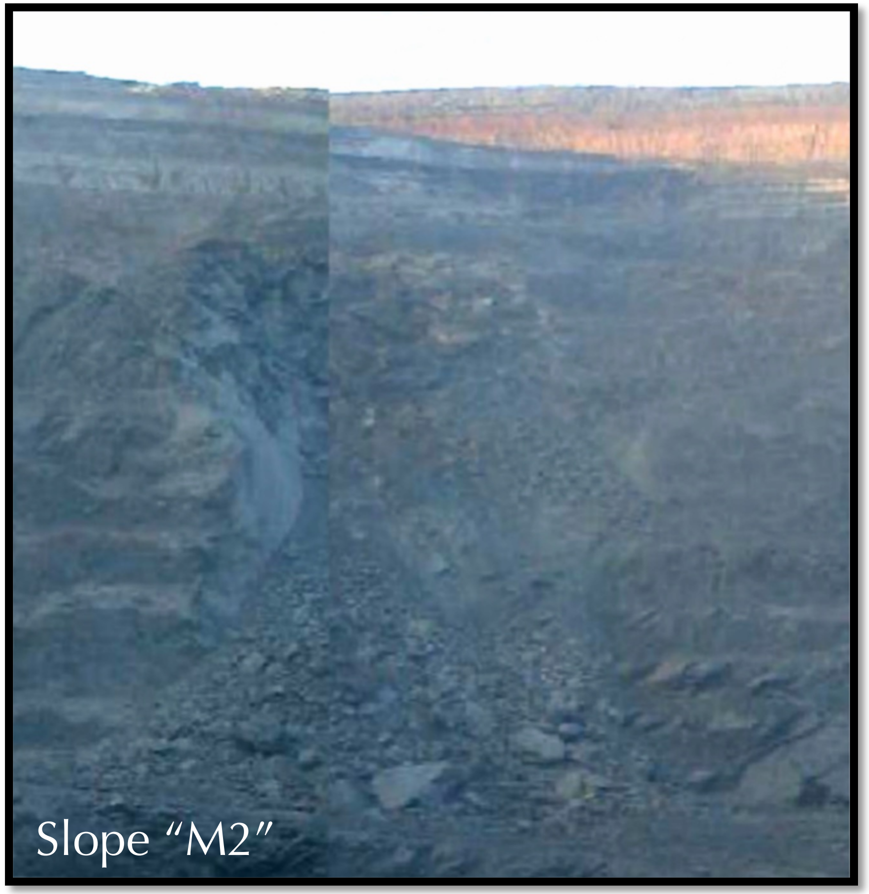
Ultimate shear band pattern

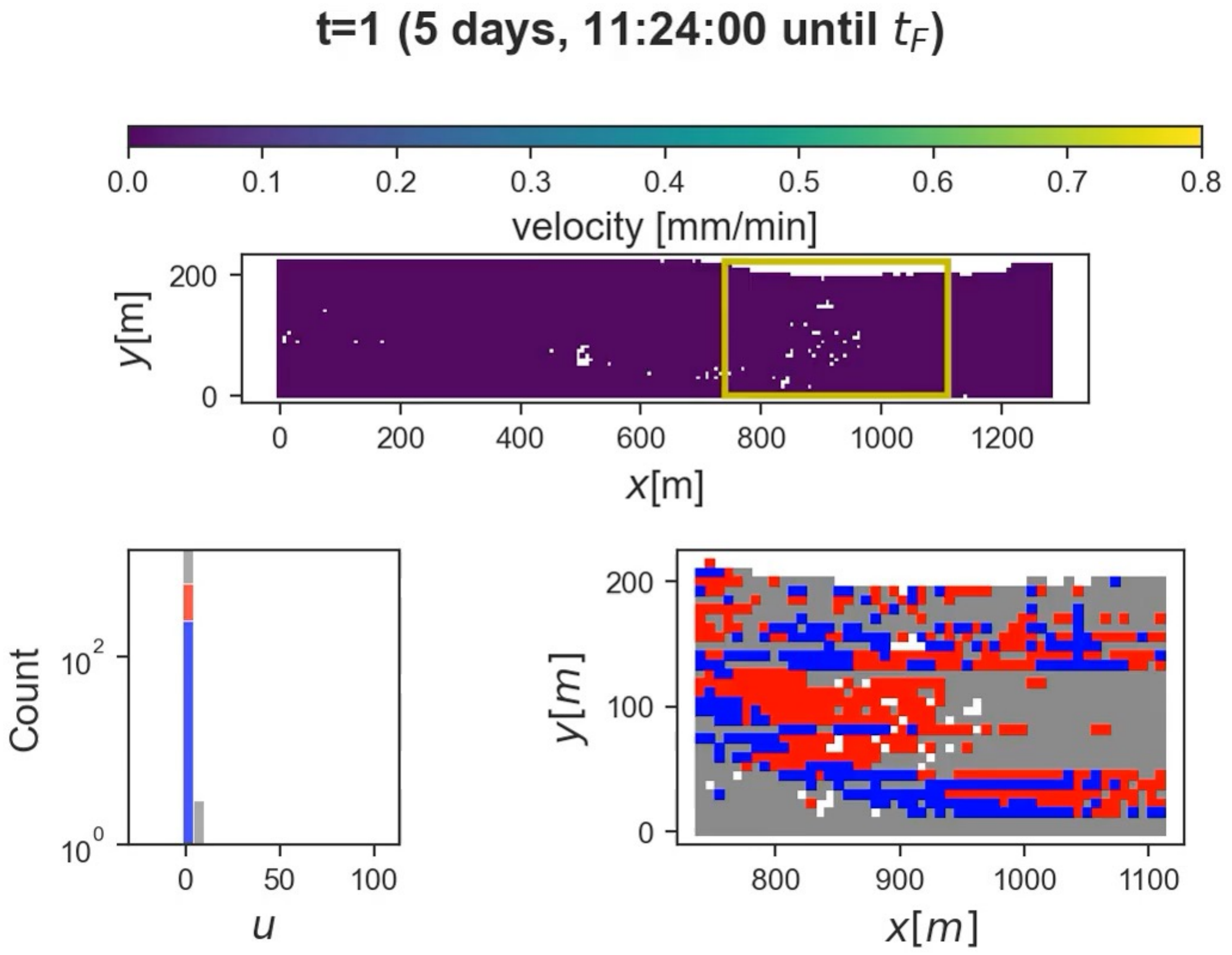
- Spatiotemporally persistent clusters

Rockslide somewhere in Australasia in presence of ‘at-line’ blasting

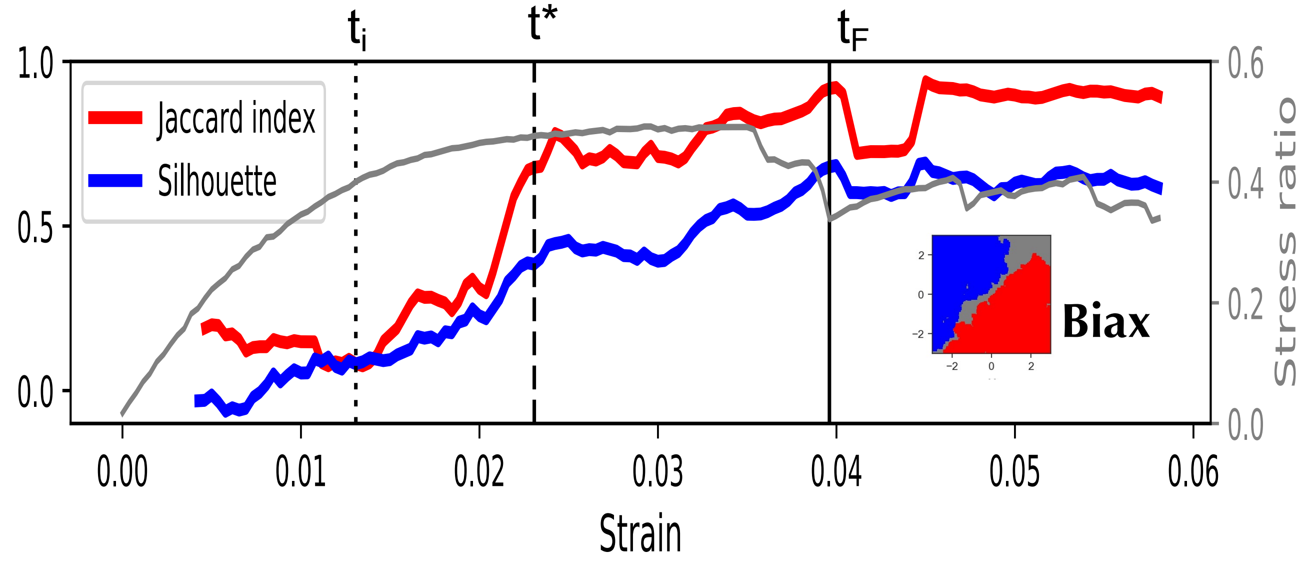
Gedy's at field scale

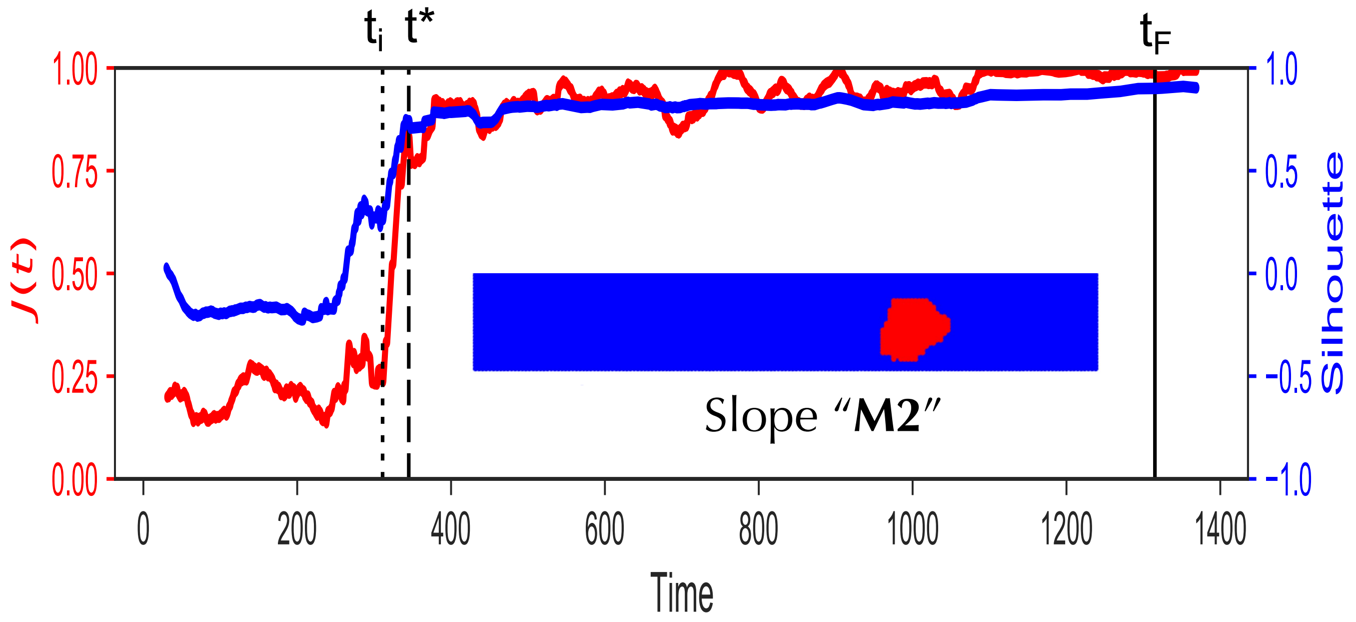
- Spatiotemporally persistent clusters





Quantifying clustering persistence





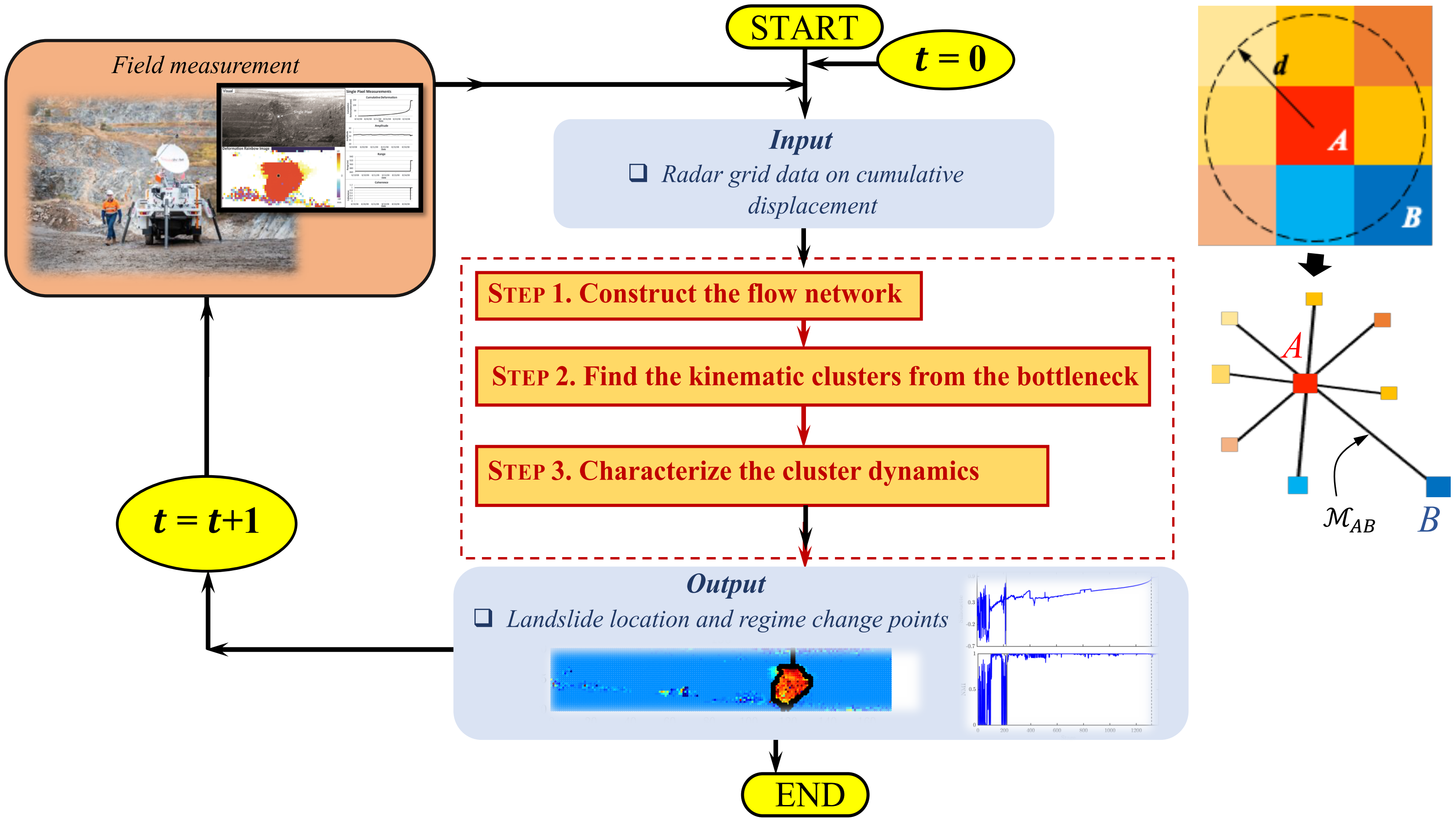
Regime shifts	Biax	M2
t_i	35	311
t^*	61	345
t_F	104	1315
$t_F - t^*$	43	970 ~4 days

Silhouette $-1 \leq S \leq 1$ measures quality of clustering (S>0.2 clustering detected)

Jaccard index $0 \leq J \leq 1$ measures persistence of clustering

SSSAFE

- Spatiotemporal Slope Stability Analytics for Failure Estimation
- Deterministic
- Where & when, with time to act

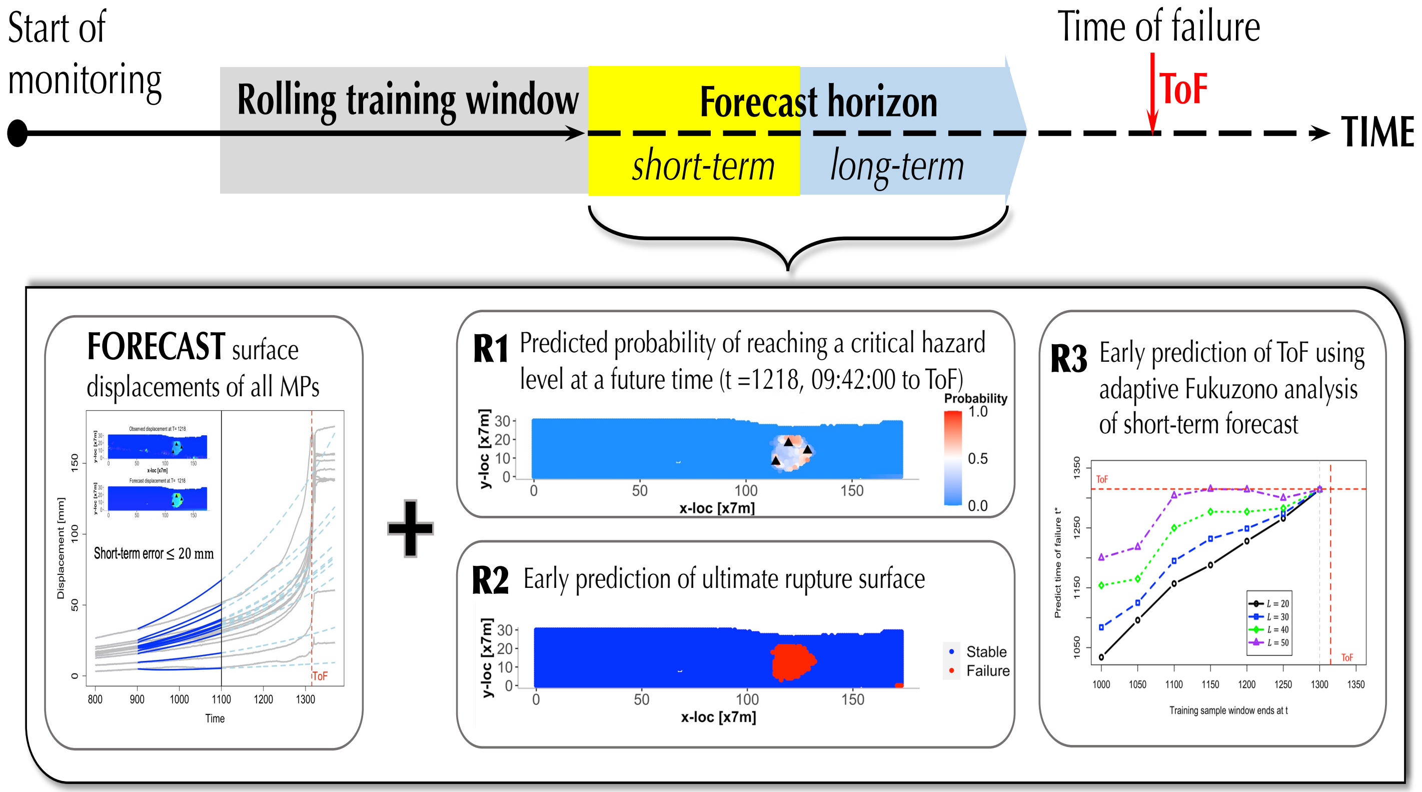


Tordesillas, Kahagalage, Campbell, Bellett, Intrieri, Batterham (2021) Spatiotemporal slope stability analytics for failure estimation (SSSAFE): linking radar data to the fundamental dynamics of granular failure. Sci Rep

S^4AFE

- Stochastic SSSAFE
- Forecasting tool accounts for endogenous & exogenous trigger (e.g., rainfall) factors
- Buys time for integrated process optimization & risk mitigation
- Basis for S^4AFE-Blast

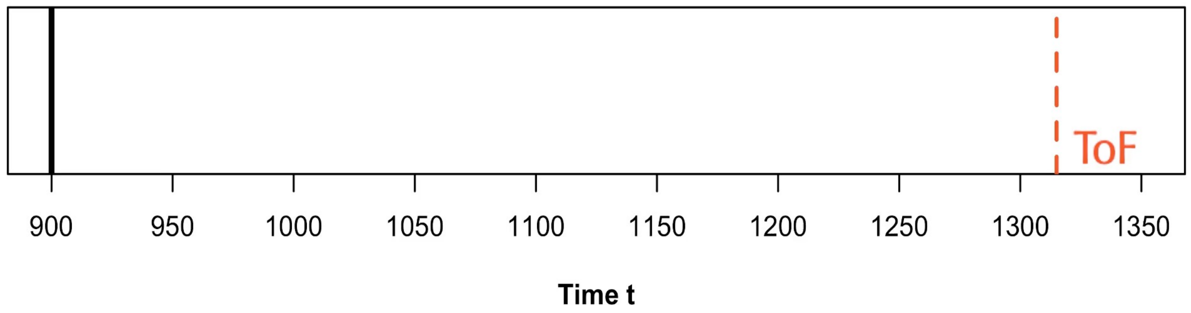
$$\Delta \boldsymbol{z}_t = \overbrace{\boldsymbol{\alpha y}_{t-1} + \sum_{i=1}^{p-1} \boldsymbol{\Phi}_i \Delta \boldsymbol{z}_{t-i}}^{\text{(A.1) Nonstationary space-time filter}} + \overbrace{\boldsymbol{c}(t)}^{\text{(A.2) Nonlinear trend}} + \overbrace{\boldsymbol{\varepsilon}_t}^{\text{(A.3) Stochastic noise}}$$

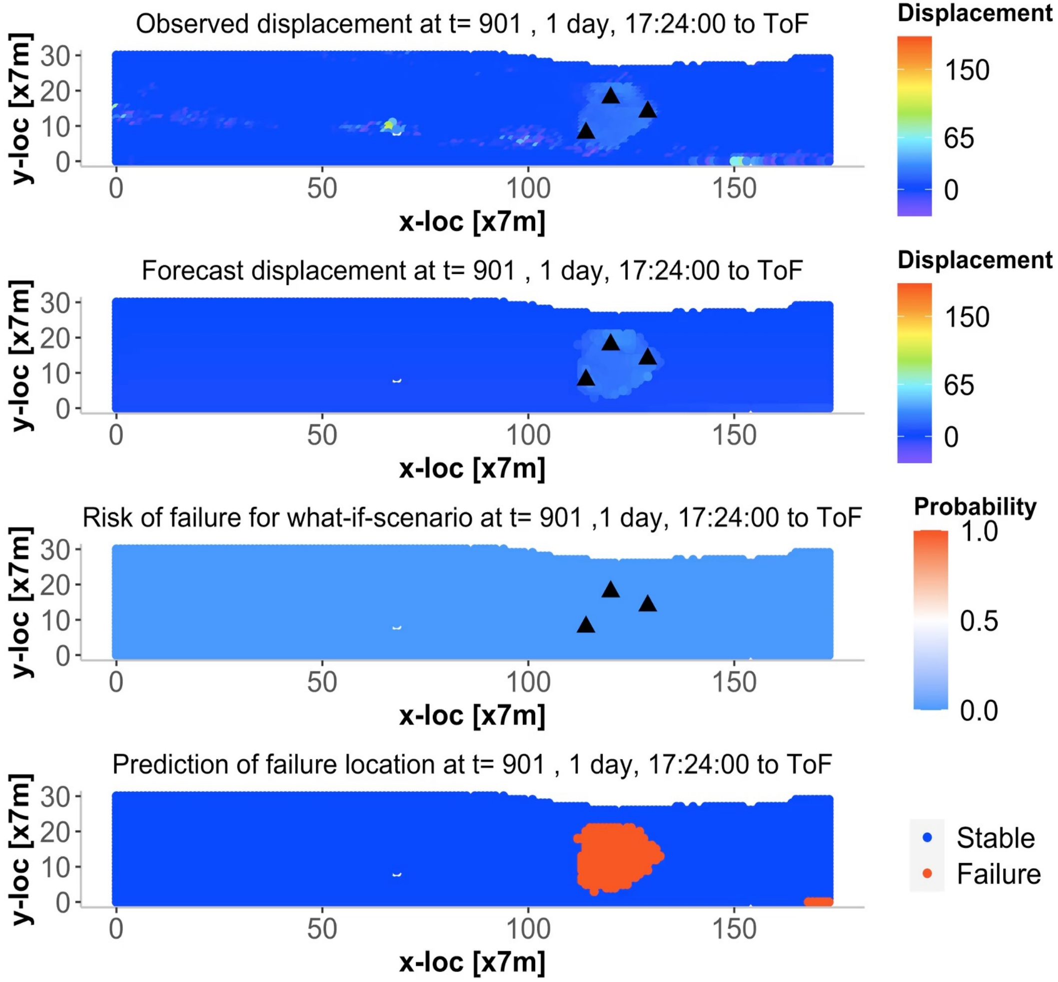


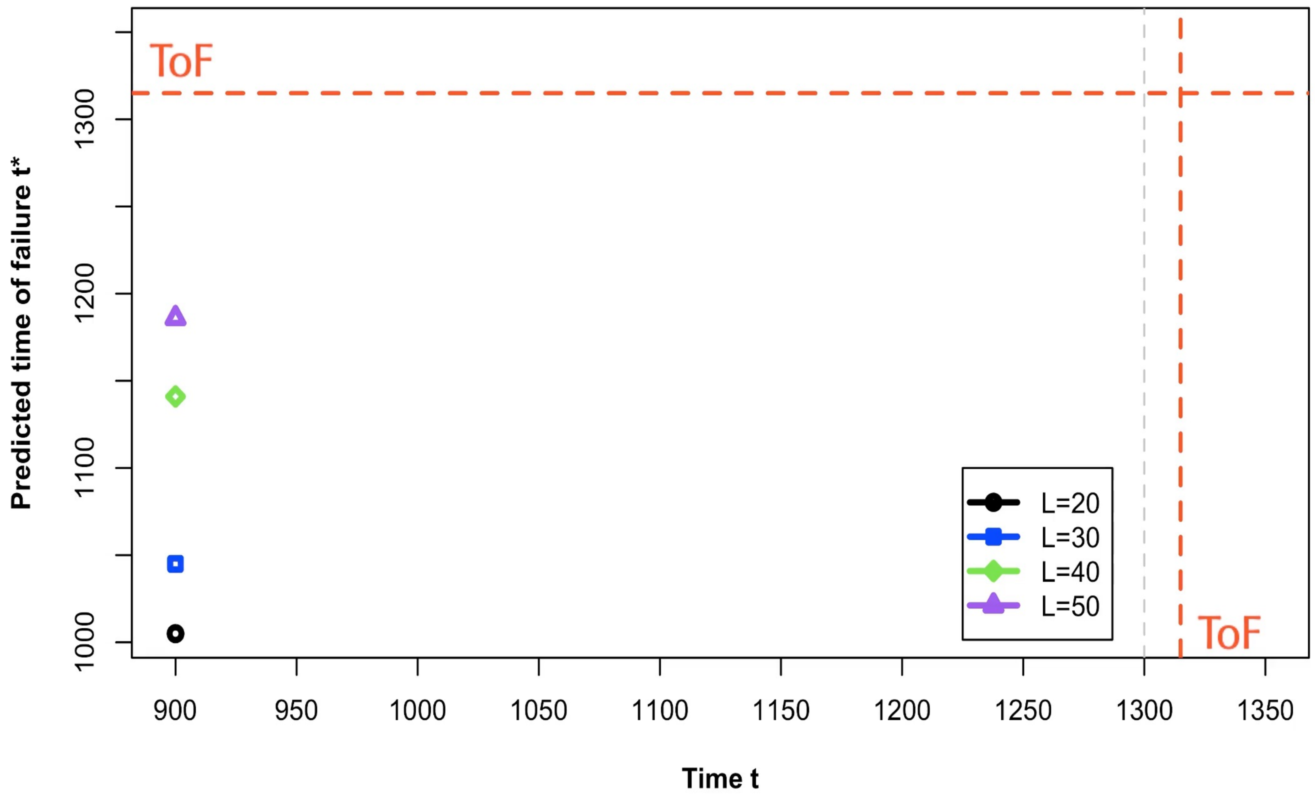
Tordesillas, Qian, Zheng, Saunders, Bellett (2023) Augmented intelligence forecasting and what-if-scenario analytics with quantified uncertainty for big real-time slope monitoring data

Hines, Qian, Tordesillas (2022) Mapping Australia's precipitation: harnessing the synergies of multi-satellite remote sensing and gauge network data. GIScience & Remote Sensing

Current time t (right). Forecast, R1, R2 (bottom left) is for a fixed training window [1,900]. Fukuzono analysis (bottom right) is for a rolling training window.







Concluding remarks

- Awash with data from sensor & imaging technologies, digital twins, IIoT etc: both a blessing & a curse
- Harness research in big data analytics <u>and</u> granular mechanics & physics to ***extract – impactful insights quickly – not digital clutter***

Thank you !

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ABSTRACT
Oh, the curses of in-betweens! Regimes in between granular solid and granular flow pose multifactorial challenges: multiphysics, multiscale, multiphase, multidimensional etc. It is very difficult if not impossible to model these regimes using traditional continuum and/or discrete approaches. Traditional models deliver output predictions of future system behaviour from 'static' inputs: measurements of the system from selected fixed states in space and historical time. Whether these prescribed inputs capture enough information for the model to predict "emergent phenomena" that invariably arise in complex granular systems is essentially anyone's guess. This problem is even more acute in open field conditions which are subject to climate change. Here we share experiences from recent efforts with industry partners to tackle this problem in a way that exploits the unprecedented advances in remote monitoring and sensing technologies from Industrial Internet of Things (IIoT) coupled with big data analytics and AI. These efforts shift the focus to a continuous monitoring of the system -- whether this is under the controlled conditions of a factory floor to the uncontrolled conditions of an open field -- to deliver data at high precision and high space-time resolution for input to a data-driven augmented intelligence model. The model is then configured to continuously and efficiently learn from the streaming, big spatiotemporal data the essential governing relations and their associated parameters, with quantified uncertainty, for real-time decision support.