

#ICML2023

# Machine Learning with **Social Purpose**

Shakir Mohamed

# OUR PLAN



## ML & EARTH SYSTEMS

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Generative models and research in the Earth Systems create all the pathways to impact we want.



## SOCIOTECHNICAL AI

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Research in technology and society be done together: so deepen a sociotechnical AI research portfolio.



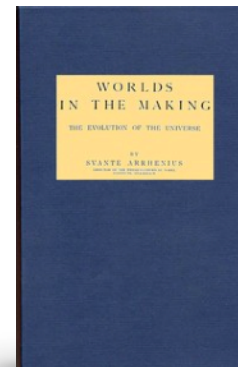
## GLOBAL AI

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A more global field and industry can shift machine learning to be more general.

01

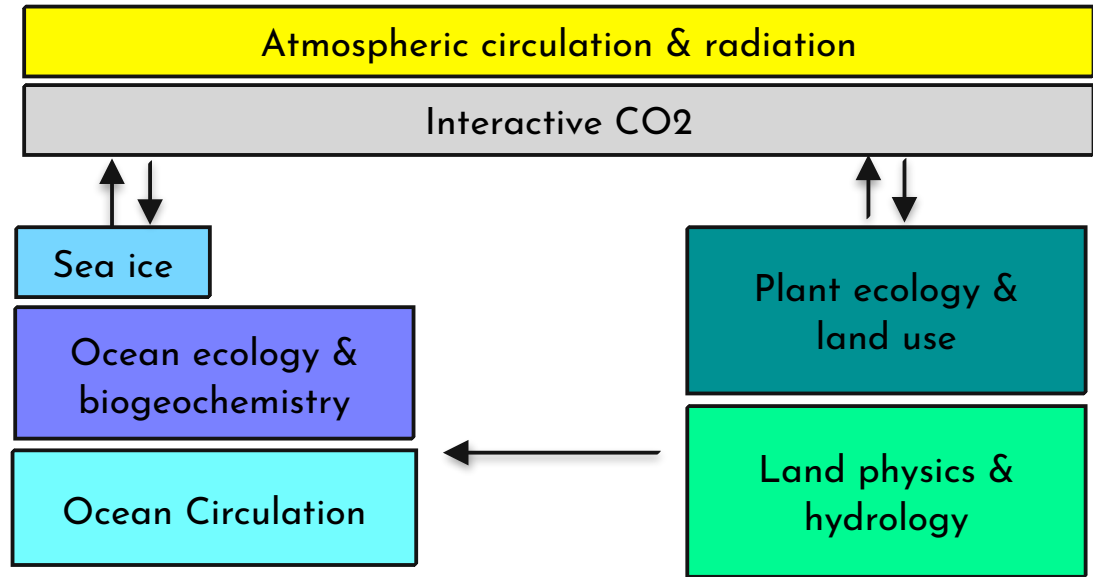
WORLDS IN  
THE MAKING



# Earth System Models

The Earth System is a representation of all the processes on our planet.

Typically we can represent the earth system using the physical equations that represent the state of the world.



# Forecasting Timescales



NOWCASTING

---

High-resolution (100m-1km) predictions of variables up to 2 hours ahead.



MEDIUM-RANGE

---

Global forecasts (10-80km) of atmospheric state up to 10 days head.



SUBSEASONAL TO SEASONAL

---

1-3 months



DECADAL

---

10 years



CLIMATE

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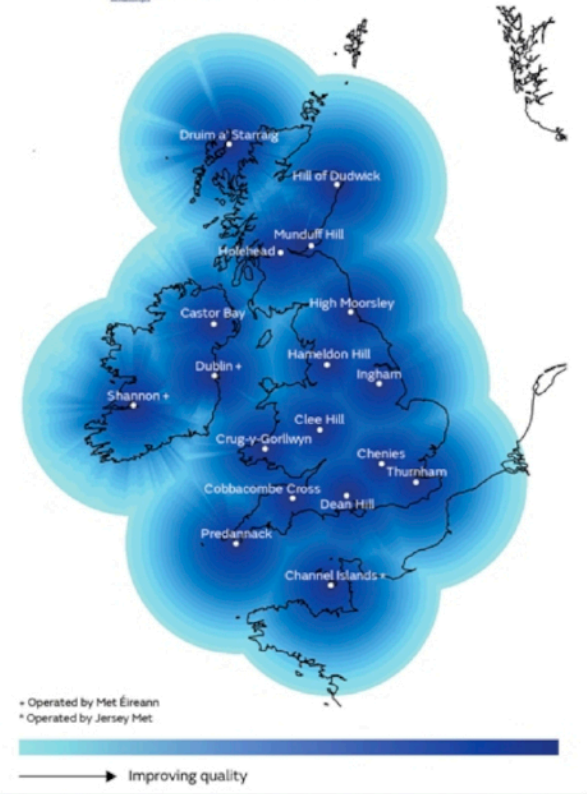
100 years



# Nowcasting



Supported by Infrastructure Directorate Cyfoeth Naturiol Cymru Natural Resources Wales



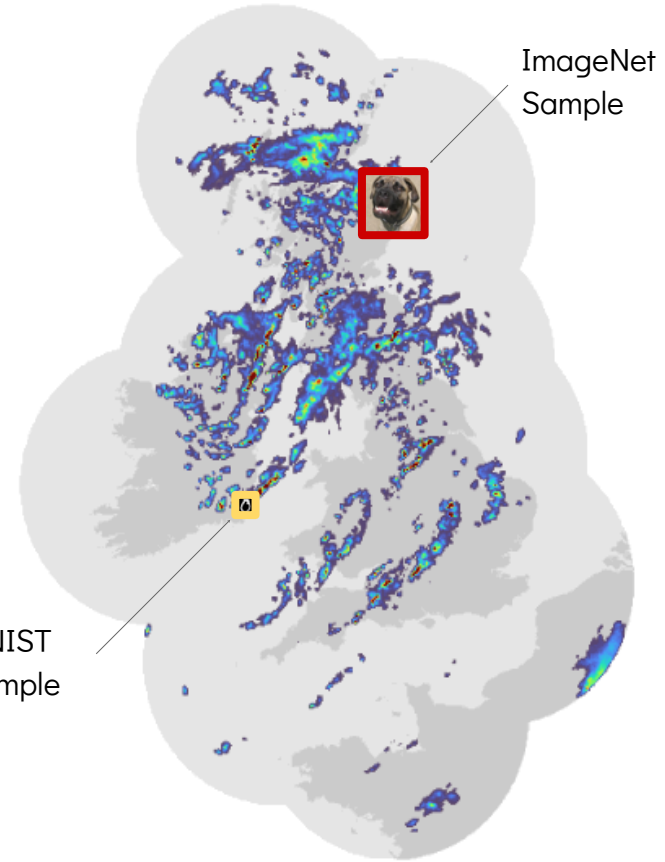
The radar network covers over 99% of the UK

## UK Radar Data

- Met Office RadarNet4 Data
- Every 5 minutes, 288/day
- 1536 x 1280 pixels at 1km x 1km grids
- Data from 2016-2020

**Focus on heavy rain** that is of specific interest to operational meteorologists: more rare, but where protection of life and property is high priority.

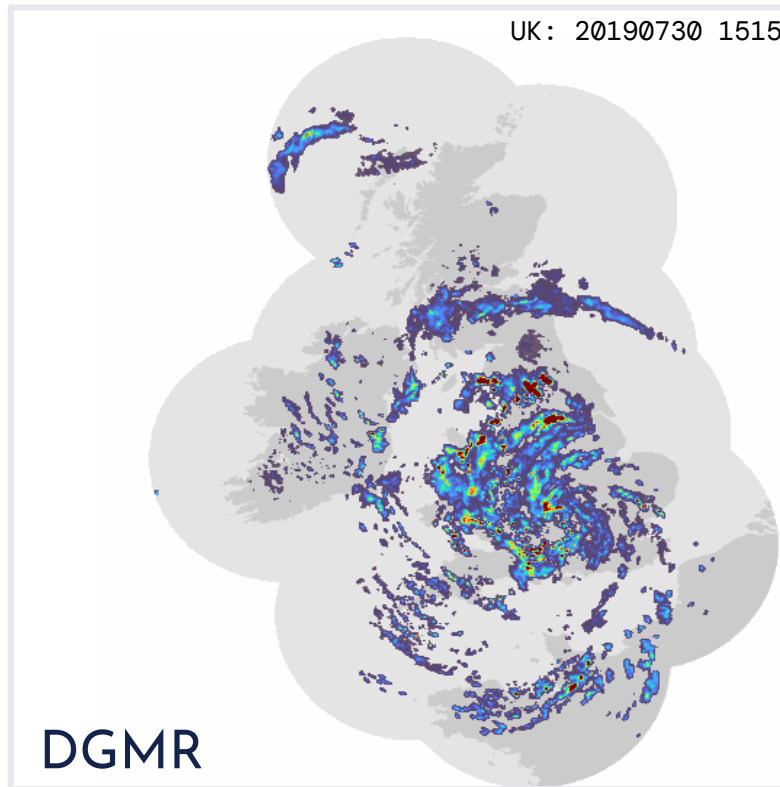
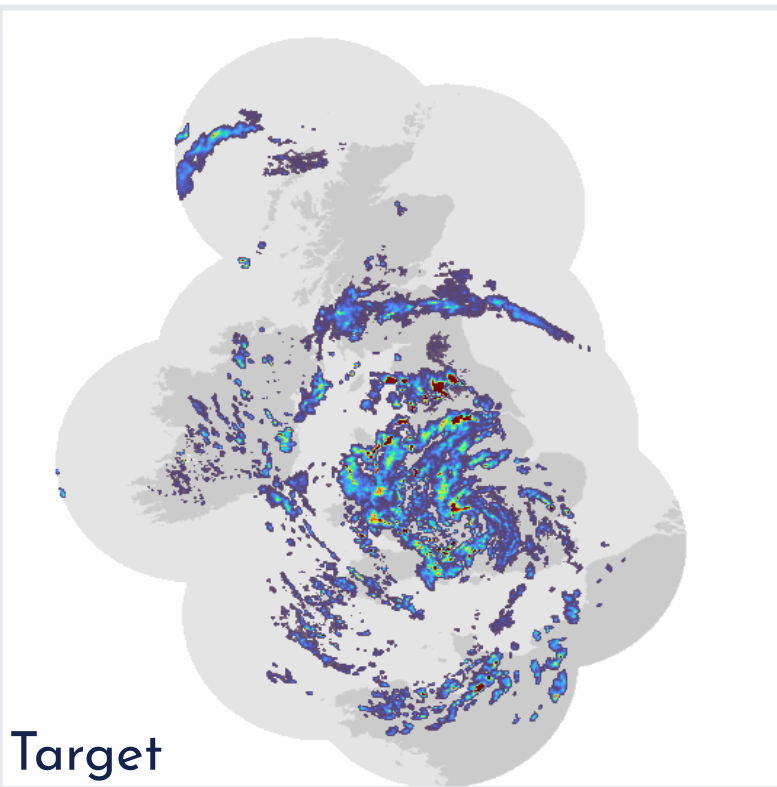
MNIST  
Sample

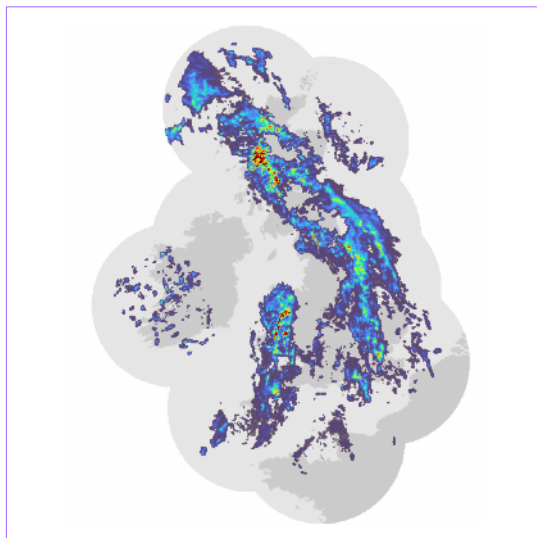


ImageNet  
Sample

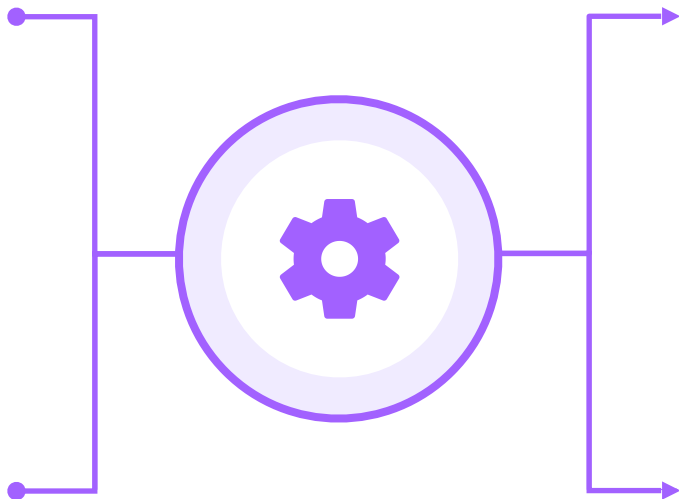


# Deep Generative Models of Rain

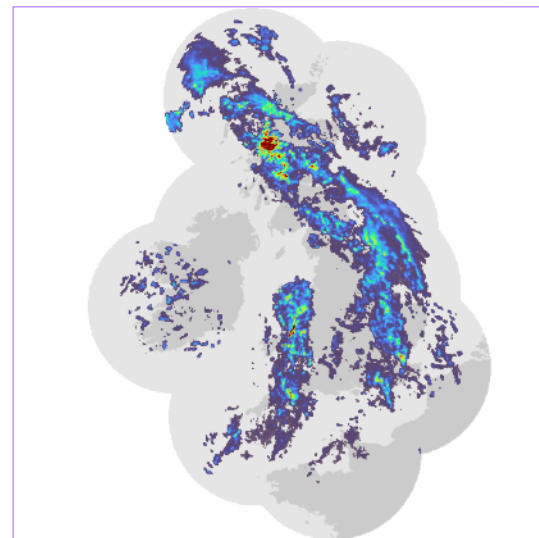




Context  
Past 20mins



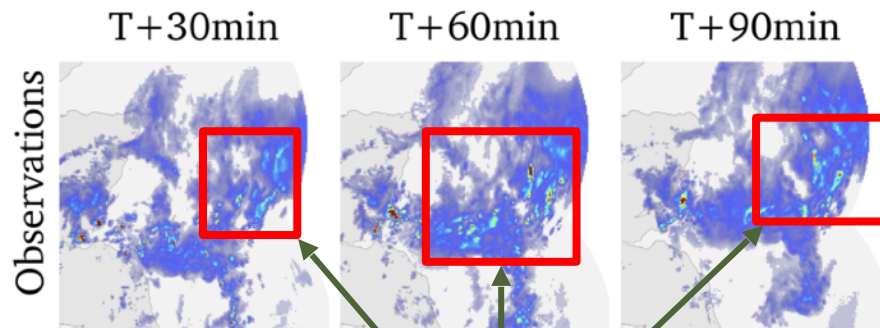
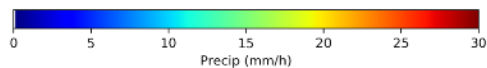
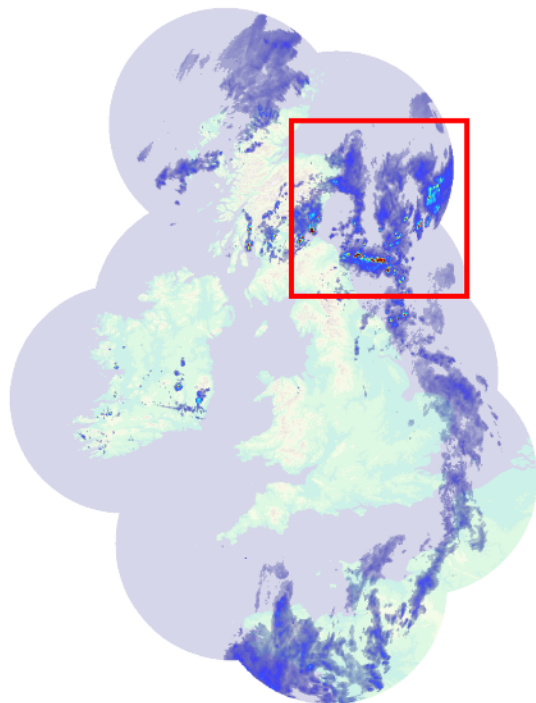
Deep Generative  
Model of Rain



Nowcast  
Next 90mins

Paper: Skillful precipitation nowcasting using deep generative models of radar.

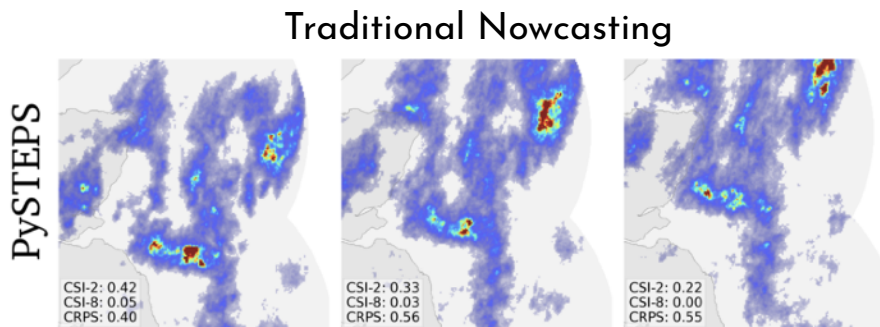
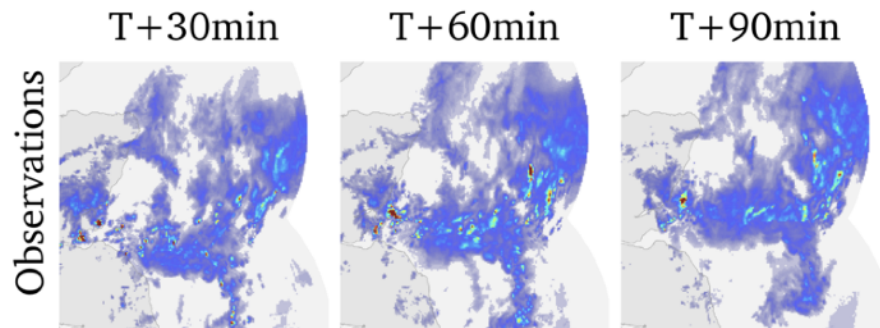
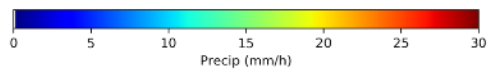
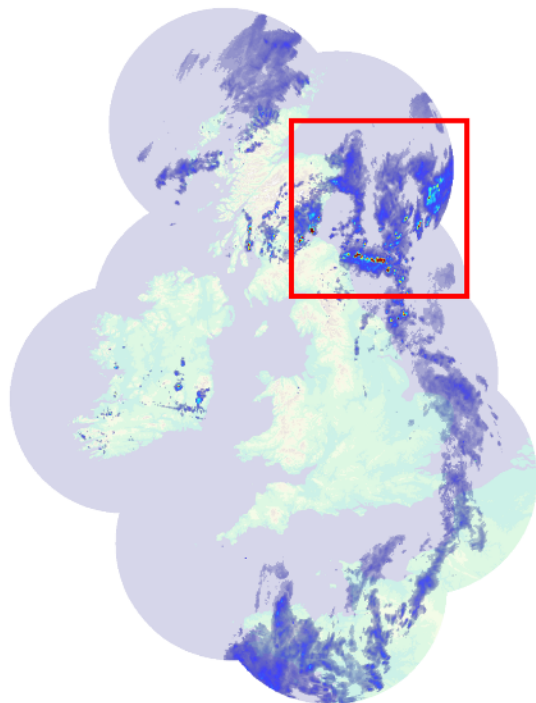
24/06/2019 at 16:15



Important (and difficult) to predict convective cells

Difficult case chosen by the Chief Forecaster who is independent of the project team.

24/06/2019 at 16:15





Minute  
Earth

frontal rain



convective rain



### Why Weather Forecasts Suck



MinuteEarth ✓  
2.79M subscribers

Join

Subscribe

👍 12K



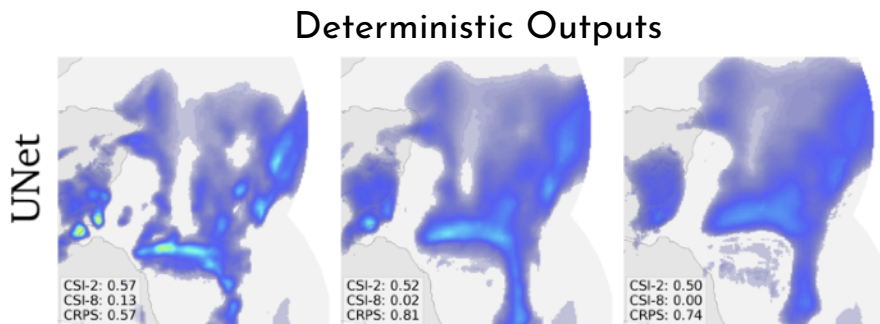
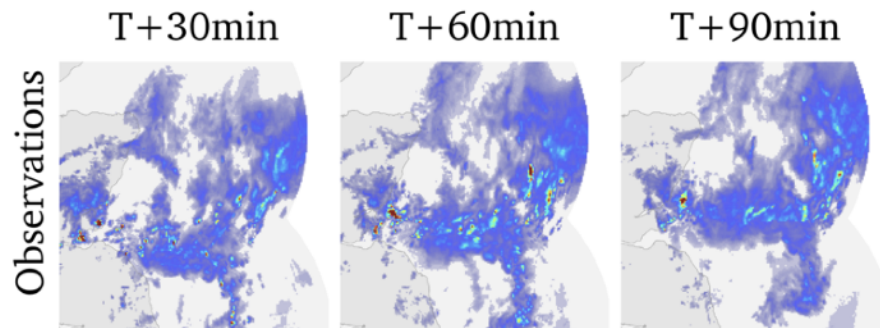
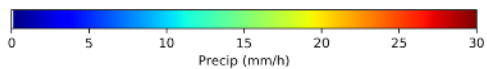
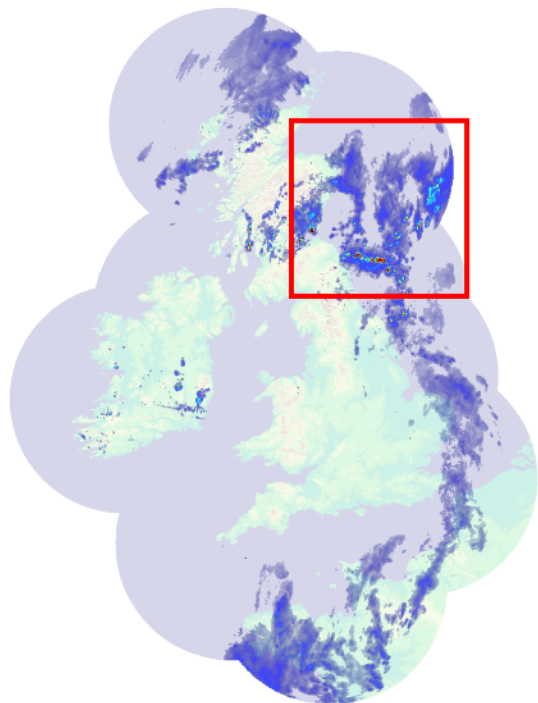
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⬇️ Download

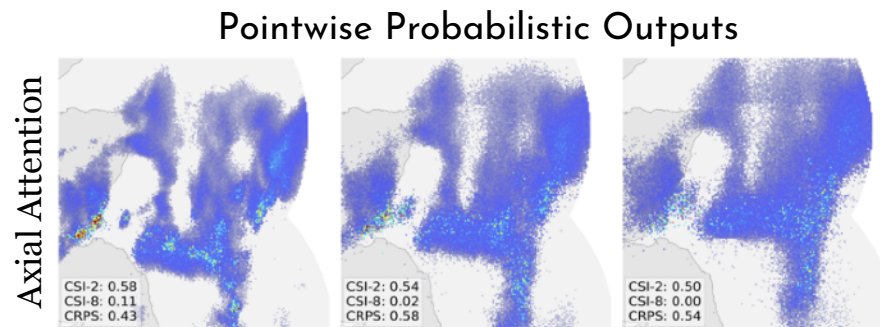
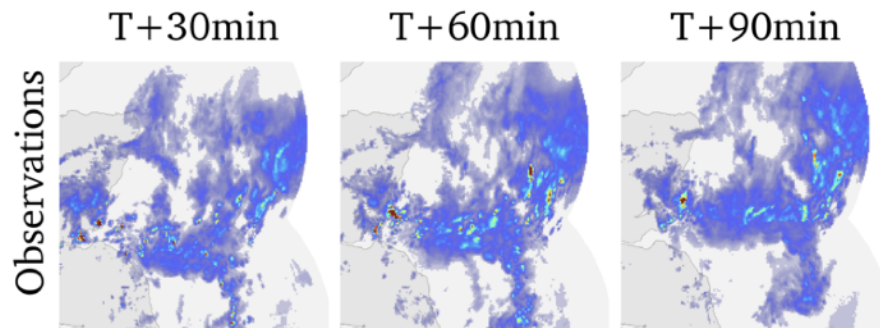
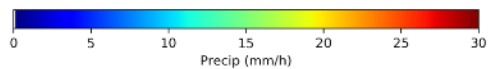
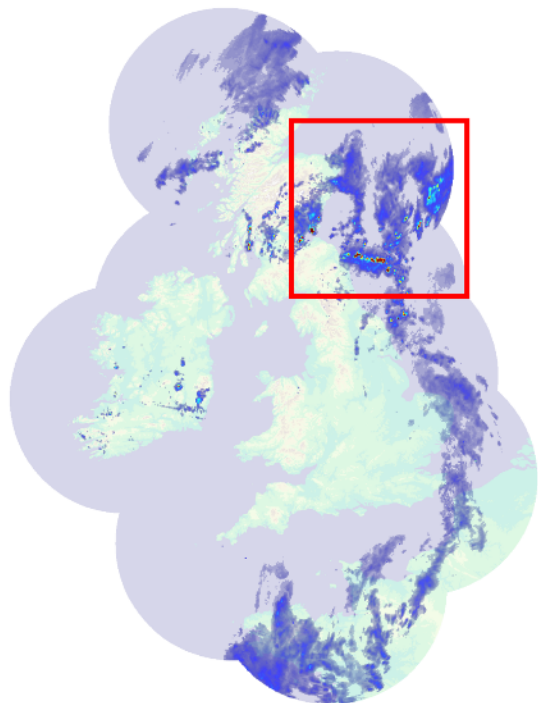


<https://youtu.be/snCo0Z0dt-k>

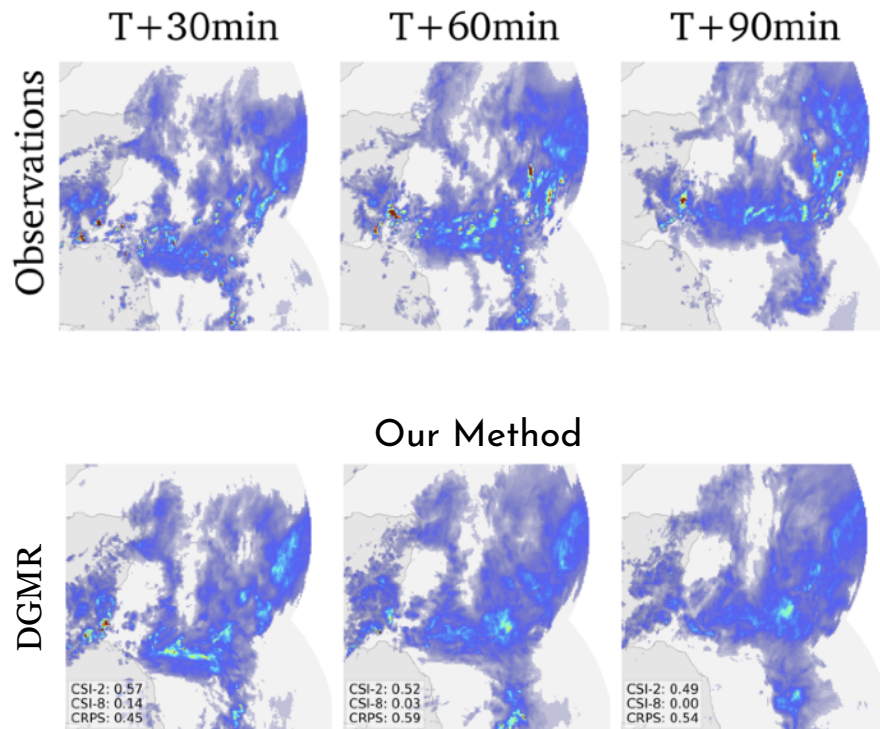
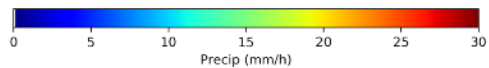
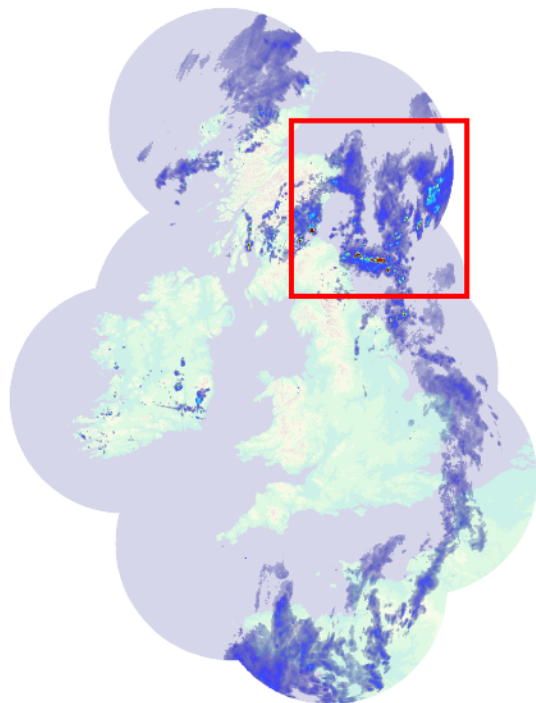
24/06/2019 at 16:15



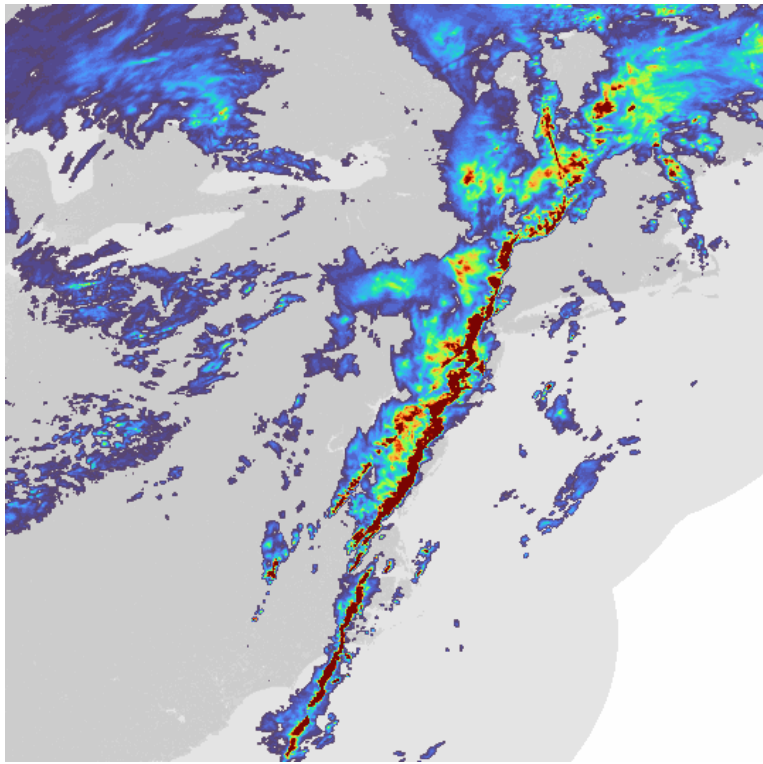
24/06/2019 at 16:15



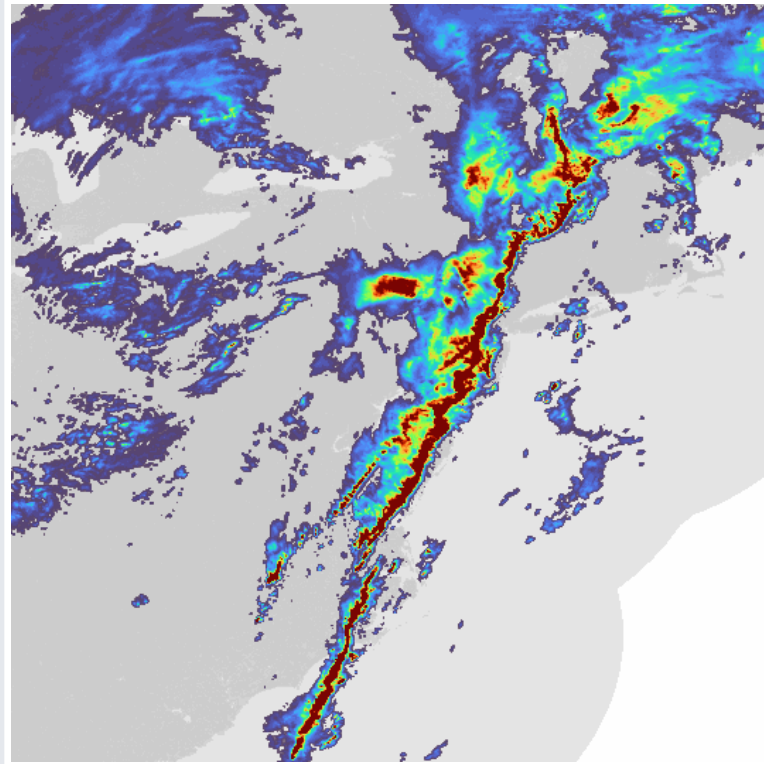
24/06/2019 at 16:15







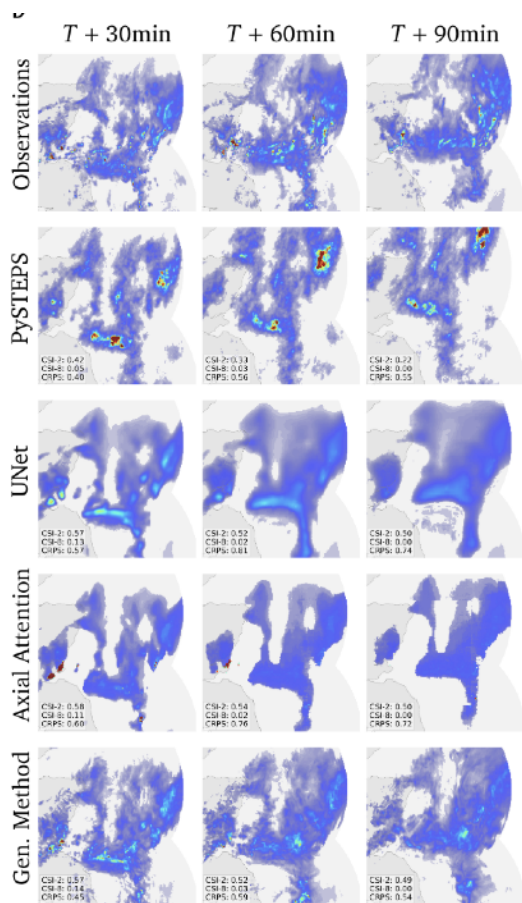
Target



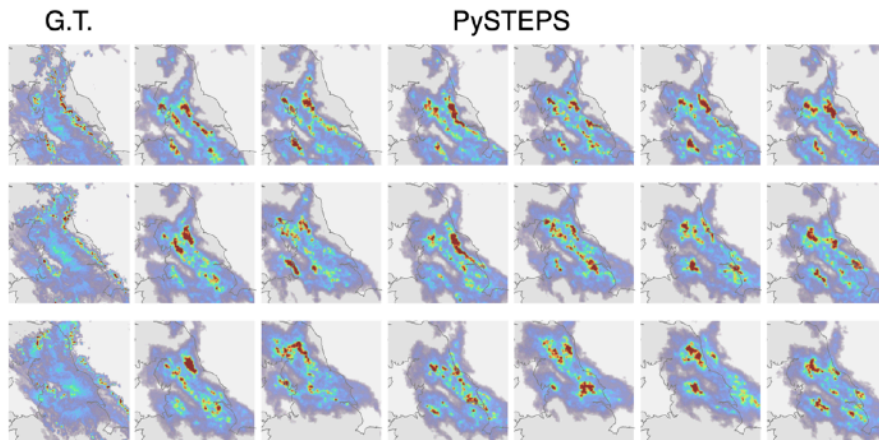
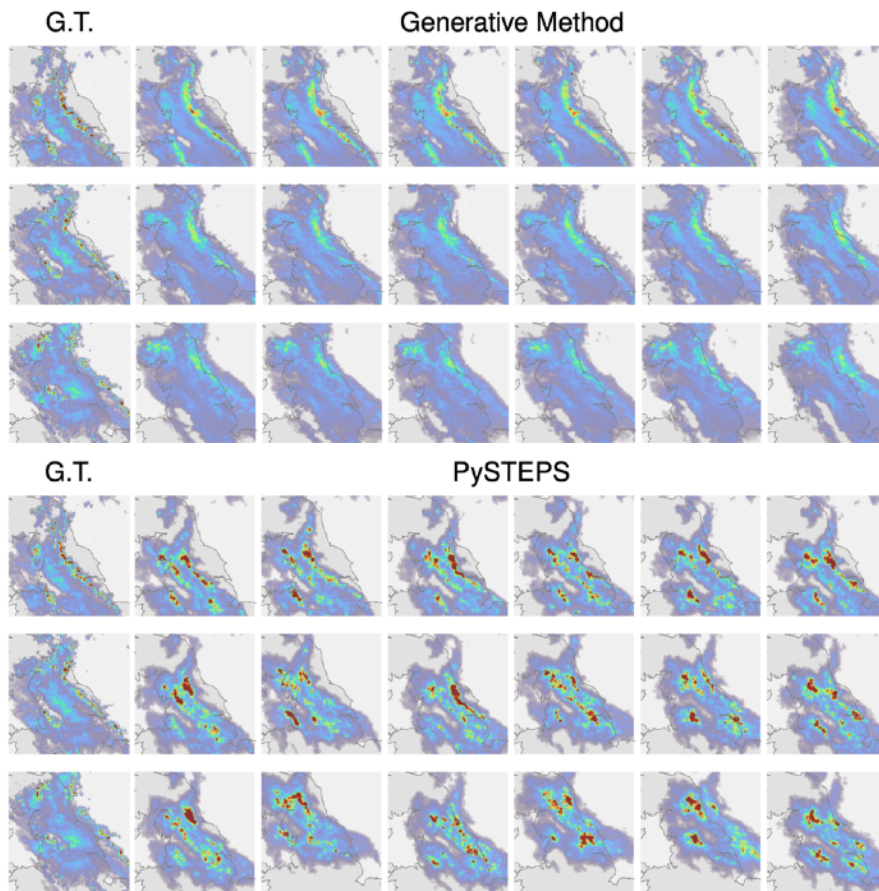
DGMR

US-East: 20190415 0930

## Intercomparison

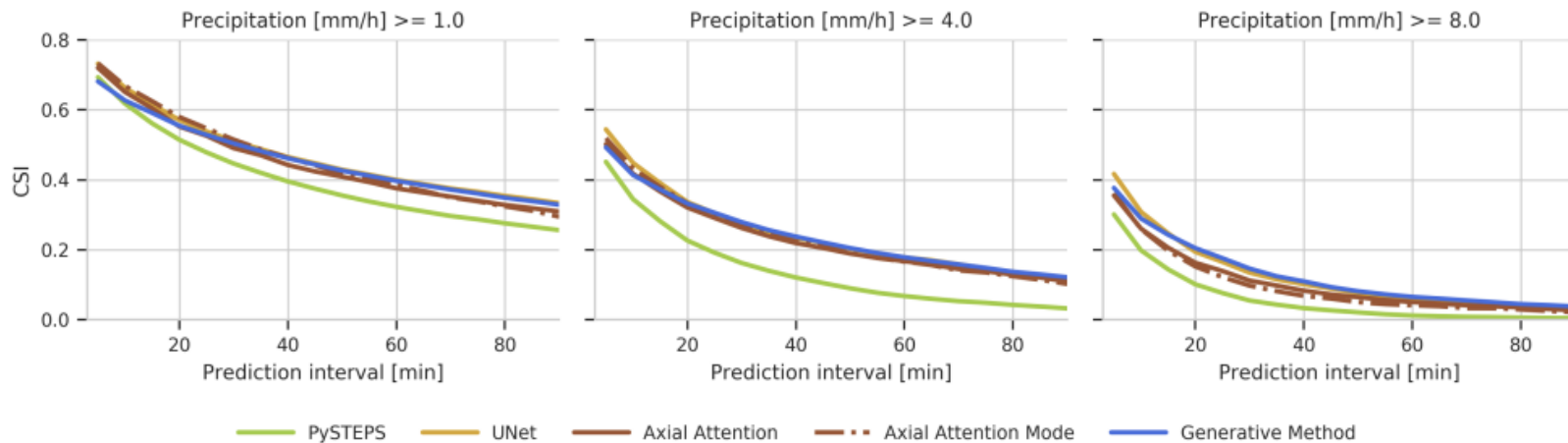


## Postage stamp plots to assess sample spread and uncertainty



# Critical Success Index (CSI)

CSI allows us to measure location accuracy of the forecast at various rain rates, and is a single summary of binary classification performance that rewards both precision and recall.

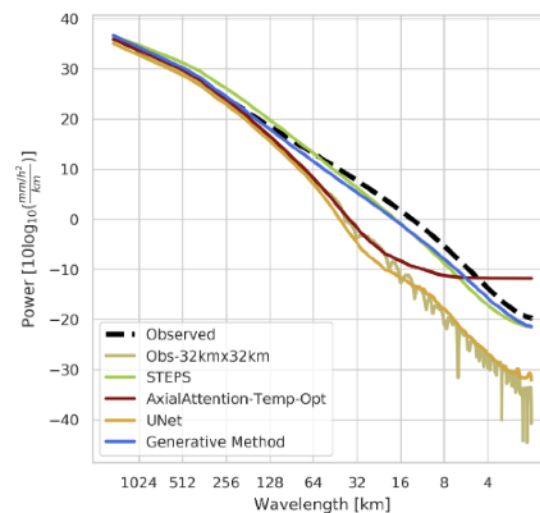
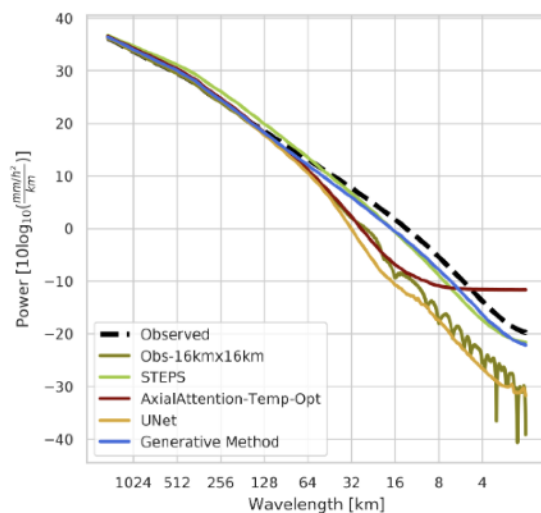
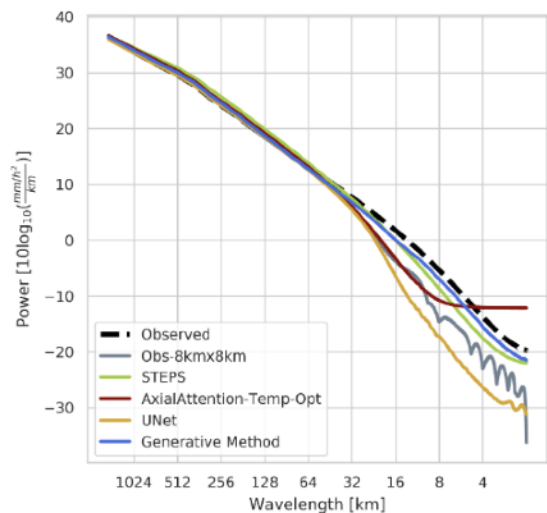


$$CSI = \frac{TP}{TP+FP+FN} = \frac{f_1}{2-f_1}$$

CSI doesn't account for all the ways a model can make predictions or can 'cheat' in making predictions (e.g., by blurring).

# Power Spectral Density (PSD)

PSD measures how power is distributed across a range of spatial frequencies in each model's forecasts and to compare the spectrum with observed data.

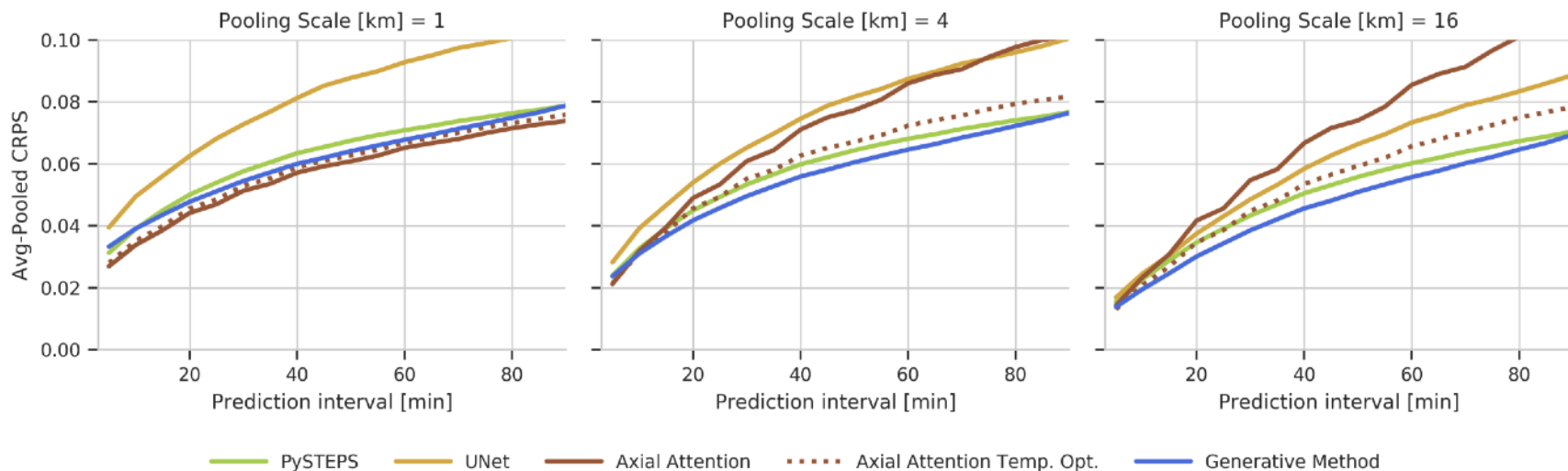


After 30mins, other models make predictions at a resolution on 8x8km, whereas the generative approach maintains predictions at the resolution of the data.

# Continuous Ranked Probability Score (CRPS)

CRPS is a proper scoring rule for univariate distributions, which we use to score the per-grid-cell marginals of a model's predictive distribution against observations.

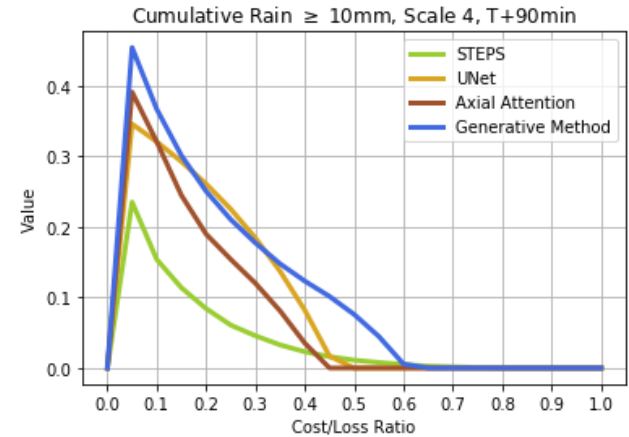
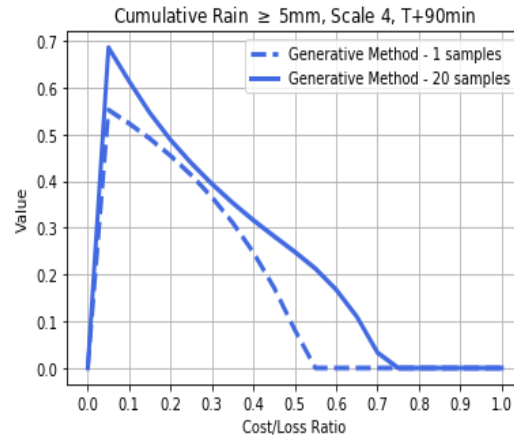
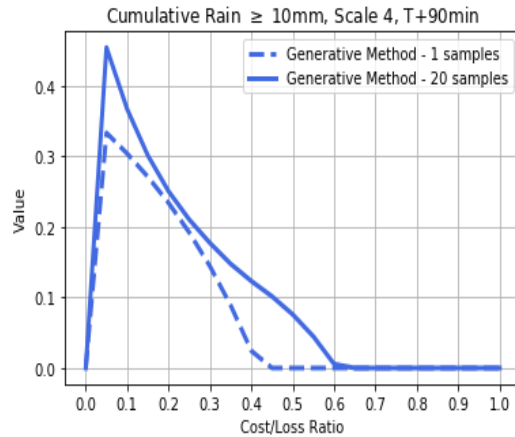
$$\mathbb{E}[F - Obs] - \frac{1}{2}\mathbb{E}[F - F']$$



Also show pooled versions, which are scores on neighbourhood aggregations that show whether a prediction is consistent across spatial scales.

# Relative Economic Value

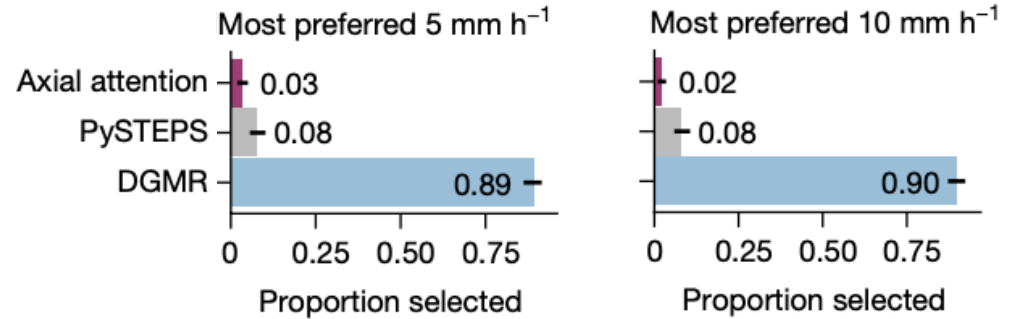
Shows the relative economic value in the decision to take, or not to take, a precautionary action in response to different rainfall thresholds.



This evaluation uses a cost-loss decision model. If we take precautions we incur a fixed cost  $C$ ; if we don't and a weather event occurs, we incur a loss  $L$ . We can compute the value which is the ratio of expenses for the forecast versus a perfect forecast. Value is only a function of  $C/L$ .

# Expert Judgements

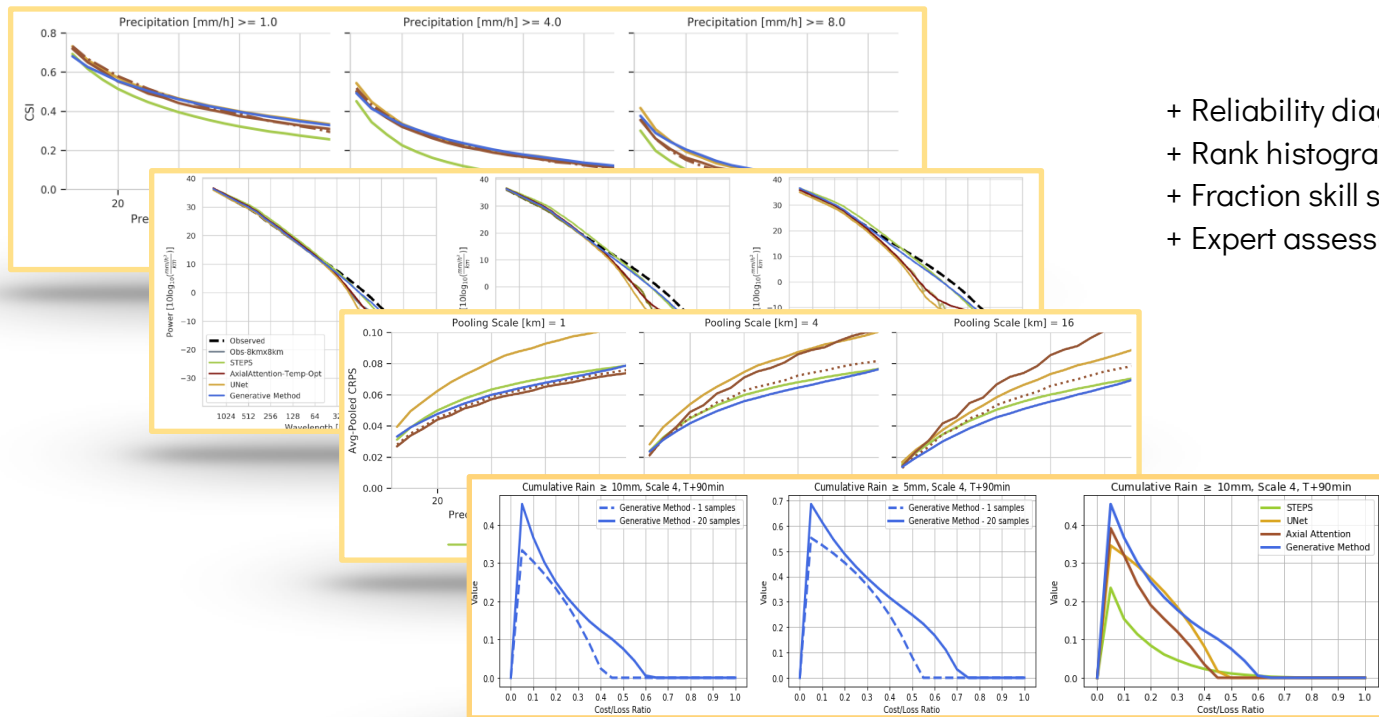
Worked with expert meteorologists who work in the 24/7 operational forecasting centre. Developed a two stage assessment to understand quality and value.



## Participant Comments

- ❖ “I like things to look slightly realistic even if they’re not in the right place so that I can put some of my own physics knowledge into it.”
- ❖ “I would prefer the model to underdo intensities but get a much better spatial variation”
- ❖ “This looks much higher detail compared to what we’re used to at the moment. I’ve been really impressed with the shapes compared with reality. I think they’re probably better than what we’re currently using. The shapes in particular, some of them do look really high resolution”

# Forecast Quality, Consistency & Value



- + Reliability diagram
- + Rank histogram
- + Fraction skill score
- + Expert assessments

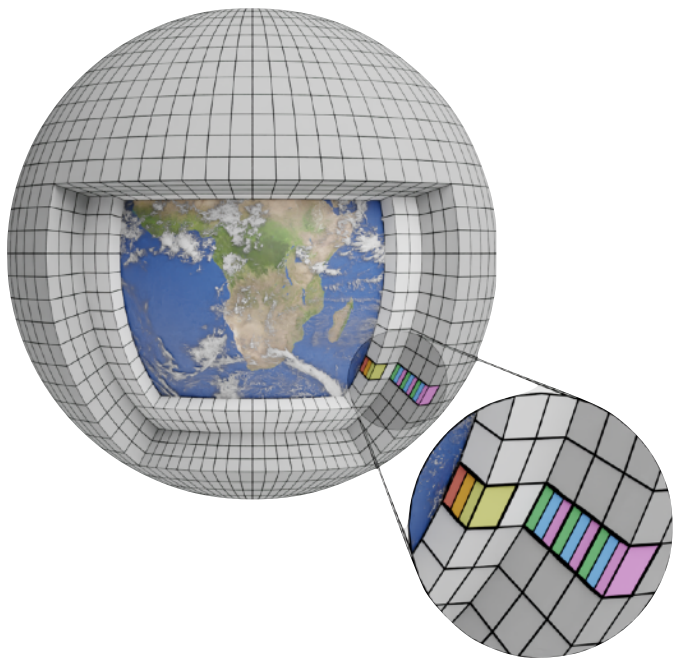




# Global Forecasting

# Medium-Range Weather Forecasting

Task: Predict atmospheric state at 6 hour intervals for the next 10 days, at high resolution.



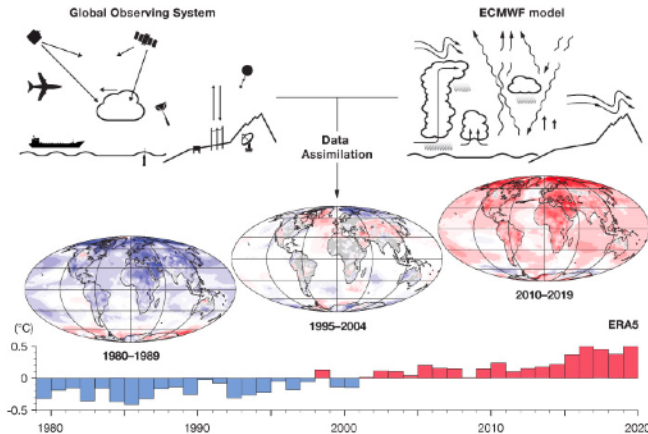
A location (or “pixel”) in this grid is a column that contains:

- 5 **surface** variables (incl. 2m temperature, 10m winds, precipitation, sea-level pressure)
- 6 **atmospheric** variables each at 37 **vertical** pressure levels (incl. geopotential, temperature, wind, humidity)
- 227 variables per grid point and a total of 235,000 targets at any point.

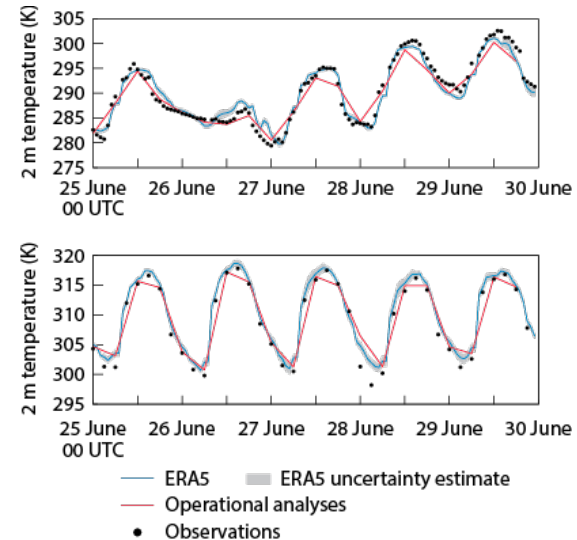
# ECMWF Forecast Data

ECMWF produce several data sets. Two we use:

- HRES: A **deterministic forecast called HRES**, and an ensemble forecast called ENS.
- ERA 5: A **reanalysis dataset called ERA5** from 1979-present at 0.25deg resolution.

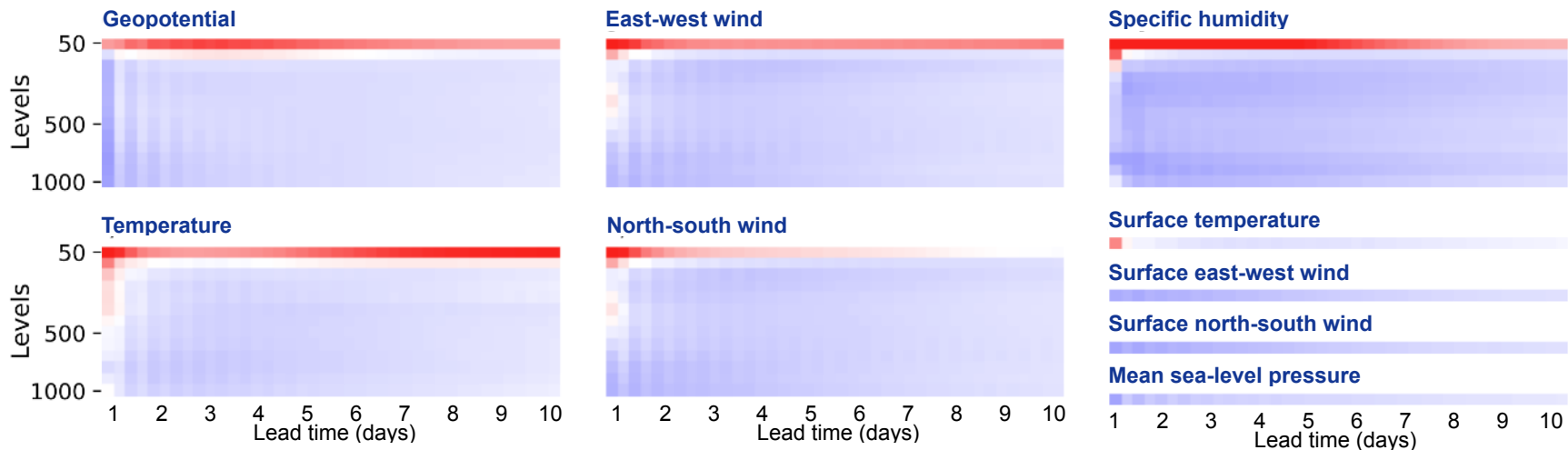


Atmospheric **reanalysis** combines past weather observations from a range of sources with model information to provide a **complete and consistent record** of meteorological conditions.



# Performance Scorecard

Scorecards summarise differences in performance between models across multiple attributes.

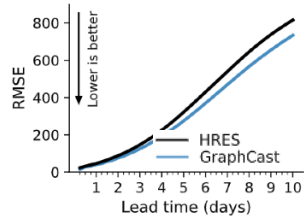


GraphCast is better on 90% of 2760 targets.

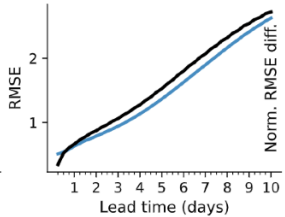
Paper: GraphCast: Learning skillful medium-range global weather forecasting

# Machine Learning Weather Predictions

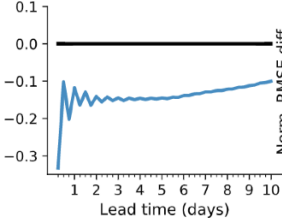
RMSE: Geopotential at 500



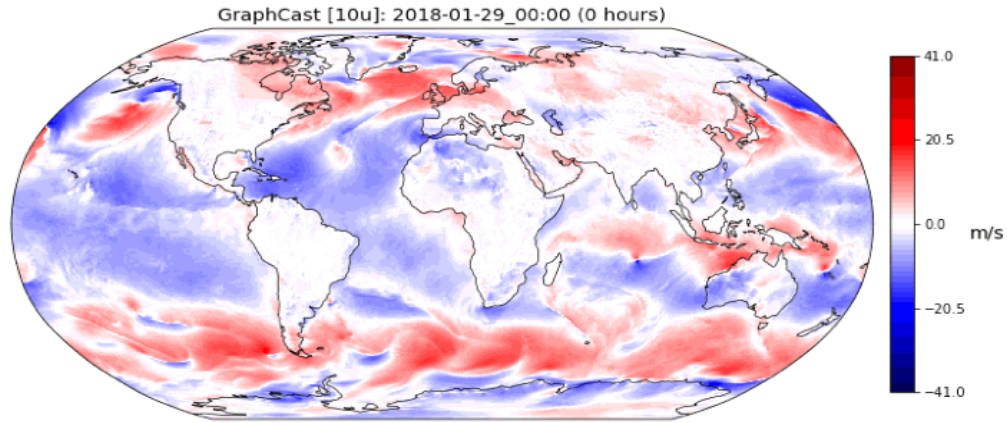
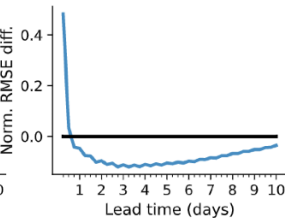
RMSE:



RMSE (relative):



RMSE (relative): 2m

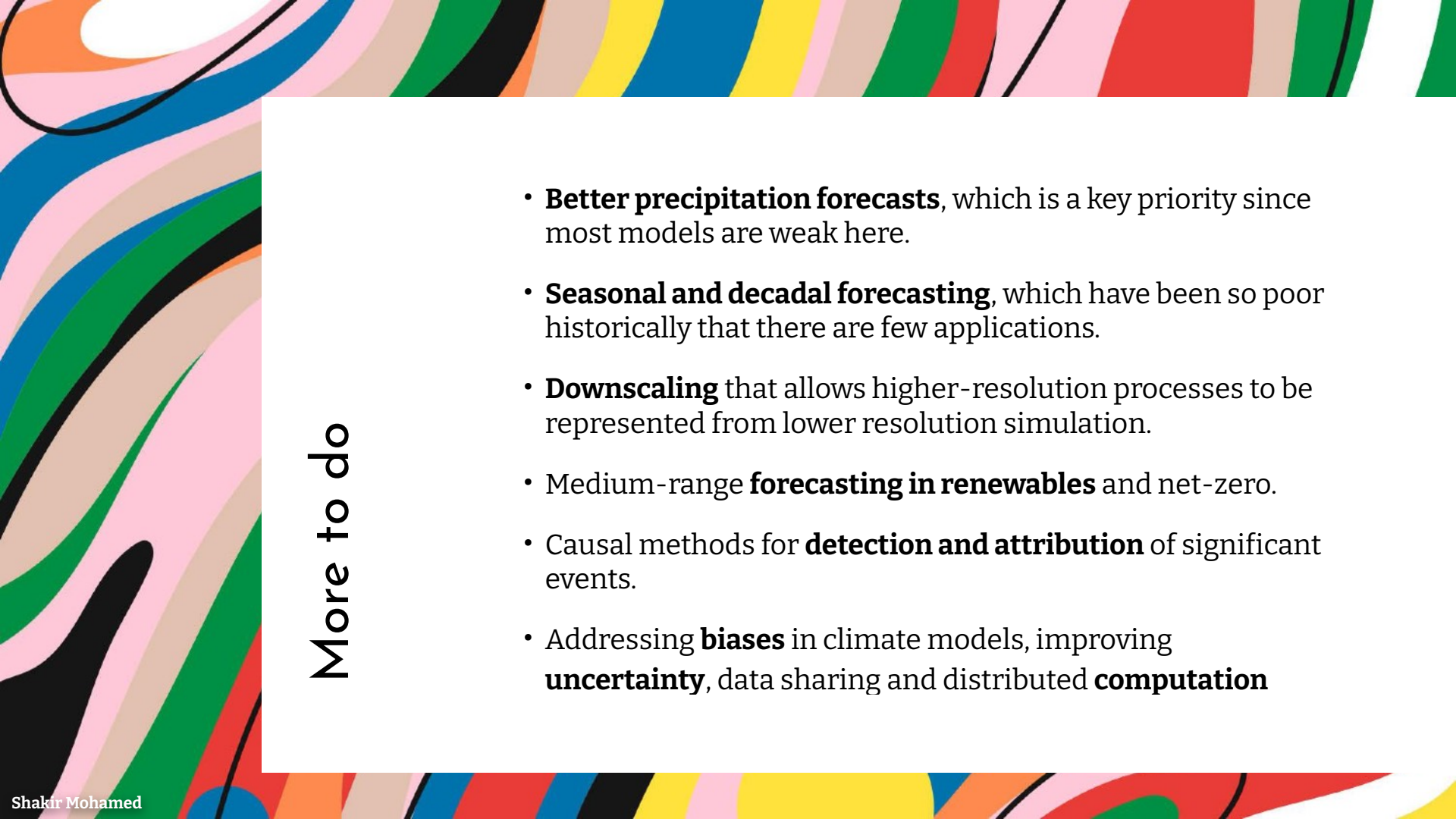


GraphCast against ERA5 [10u]: 2018-01-29\_00:00 (0 hours)



ML predictions we can outperform operational forecasts.

Paper: GraphCast: Learning skillful medium-range global weather forecasting

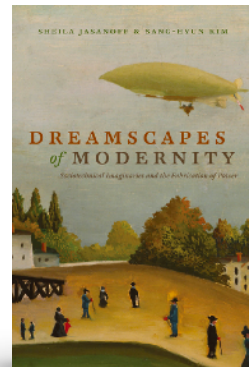


## More to do

- **Better precipitation forecasts**, which is a key priority since most models are weak here.
- **Seasonal and decadal forecasting**, which have been so poor historically that there are few applications.
- **Downscaling** that allows higher-resolution processes to be represented from lower resolution simulation.
- Medium-range **forecasting in renewables** and net-zero.
- Causal methods for **detection and attribution** of significant events.
- Addressing **biases** in climate models, improving **uncertainty**, data sharing and distributed **computation**

02

DREAMSCAPES  
OF MODERNITY



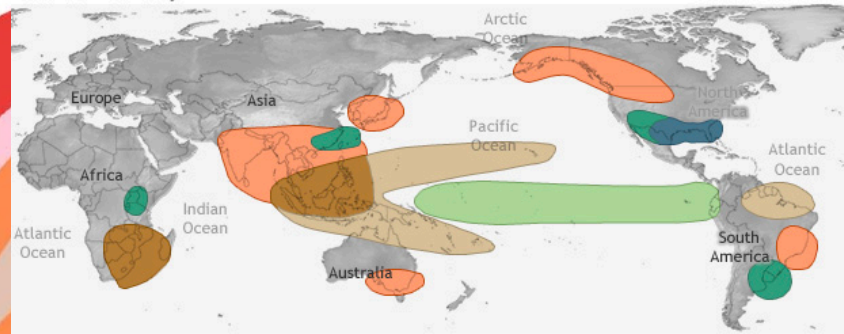


# Equity in Forecasting

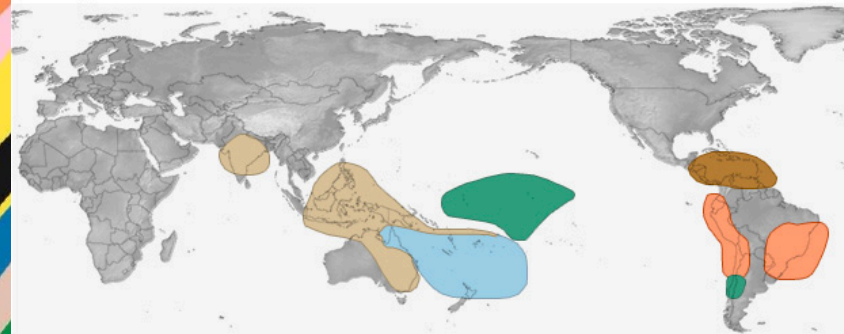


## EL NIÑO CLIMATE IMPACTS

December-February



June-August



From: NOAA  
Climate.gov



## Integrating Climate Forecasts and Societal Decision Making: Challenges to an Emergent Boundary Organization

Shardul Agrawala, Kenneth Broad and David H. Guston

Science, Technology, & Human Values

Vol. 26, No. 4, Special Issue: Boundary Organizations in Environmental Policy and Science (Autumn, 2001), pp. 464-477 (24 pages)

## The Use of Seasonal Climate Forecasting in Policymaking: Lessons from Northeast Brazil

[Maria Carmen Lemos](#), [Timothy J. Finan](#), [Roger W. Fox](#), [Donald R. Nelson](#) & [Joanna Tucker](#)

[Climatic Change](#) 55, 479-507 (2002) | [Cite this article](#)

Published: September 2002

## Effective and Equitable Dissemination of Seasonal-to-Interannual Climate Forecasts: Policy Implications from the Peruvian Fishery during El Niño 1997-98

[Kenneth Broad](#), [Alexander S. P. Pfaff](#) & [Michael H. Glantz](#)

[Climatic Change](#) 54, 415-438 (2002) | [Cite this article](#)

# Sociotechnical Systems



Our technical work is deeply intertwined with our social world, and rarely separable.

Asks us to adjust the conceptual apertures we use in our work



---

Ask our technical and engineering work to account for a wider and more expansive set of considerations



---

Bringing focus and manageability to the seeming vastness of social considerations

# A Sociotechnical Stack

Community & Cooperation

Governance & Accountability

Deployment &  
Commercialisation

Research & Innovation

# A Sociotechnical Stack

Research & Innovation

Deployment & Commercialisation

Governance & Accountability

Community & Cooperation

Ethics Principles

Data debiasing

Fairness

Documentation Practices

Environmental Impacts

Humanities and sociology

Privacy and consent

Research Institutes

Data Sharing

Research Ethics committees

Audits

Red teams

Bug bounty

Interoperability

Oversight

Codes of conduct

Watermarking & provenance

Licences

Workers rights

Cultural inclusion

Regulation

Standards

Citizens Jury

Citizen science

Compliance

Certification

Co-design

SDGs

Rights to science

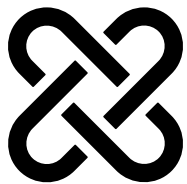
Protected disclosures

Diversity & equity

Community & capacity building



# Participatory AI



## PARTICIPATION

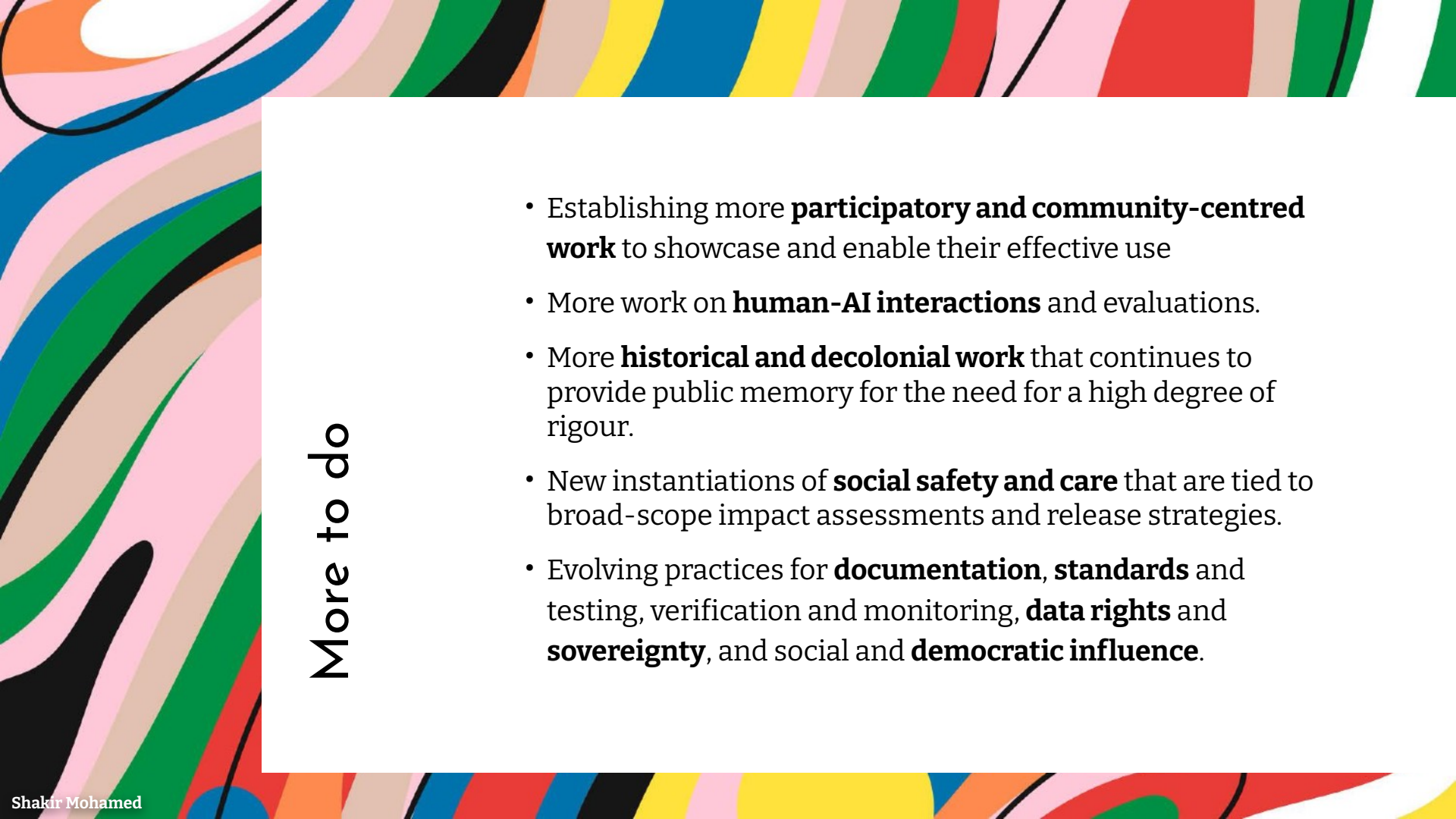
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The ways that broader communities of people, especially of those most vulnerable, are involved in technology design

Participation means including people in the design of our methods, and being open to changing what we work and how we work, based on their input.

1. EVERYONE HAS THE RIGHT TO PARTICIPATE FREELY IN THE CULTURAL LIFE OF THE COMMUNITY, TO ENJOY THE ARTS AND TO SHARE IN SCIENTIFIC ADVANCEMENT AND ITS BENEFITS.

2. EVERYONE HAS THE RIGHT TO THE PROTECTION OF THE MORAL AND MATERIAL INTERESTS RESULTING FROM ANY SCIENTIFIC, LITERARY OR ARTISTIC PRODUCTION OF WHICH HE IS THE AUTHOR



## More to do

- Establishing more **participatory and community-centred work** to showcase and enable their effective use
- More work on **human-AI interactions** and evaluations.
- More **historical and decolonial work** that continues to provide public memory for the need for a high degree of rigour.
- New instantiations of **social safety and care** that are tied to broad-scope impact assessments and release strategies.
- Evolving practices for **documentation, standards** and testing, verification and monitoring, **data rights** and **sovereignty**, and social and **democratic influence**.



03

THE HUMAN  
CONDITION





# Empirical Likelihood

# Testing Problem

Check whether the mean of an unknown distribution  $P$  is equal to a known constant  $c$

n data points

$$x_1, \dots, x_n \in \mathbb{R}^d$$

Mean condition

$$c \in \mathbb{R}^d$$

Empirical distribution

$$\hat{P}_n(x) = \sum_i n^{-1} \delta_{[x=x_i]}$$

Weighted distribution

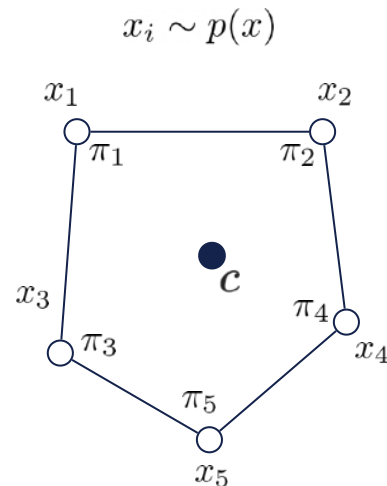
$$P_\pi(x) = \sum_{i=1}^n \pi_i \mathbb{I}_{[x_i=x]}$$

Likelihood

$$\prod_i \pi_i \quad \sum_i \pi_i = 1, \pi_i \geq 0$$

Objective

$$\{\pi \mid \sum_i \pi_i = 1, \pi_i \geq 0\} \min D[\hat{P}_n \parallel P_\pi] \quad \text{s.t.} \quad \sum \pi_i x_i = c$$



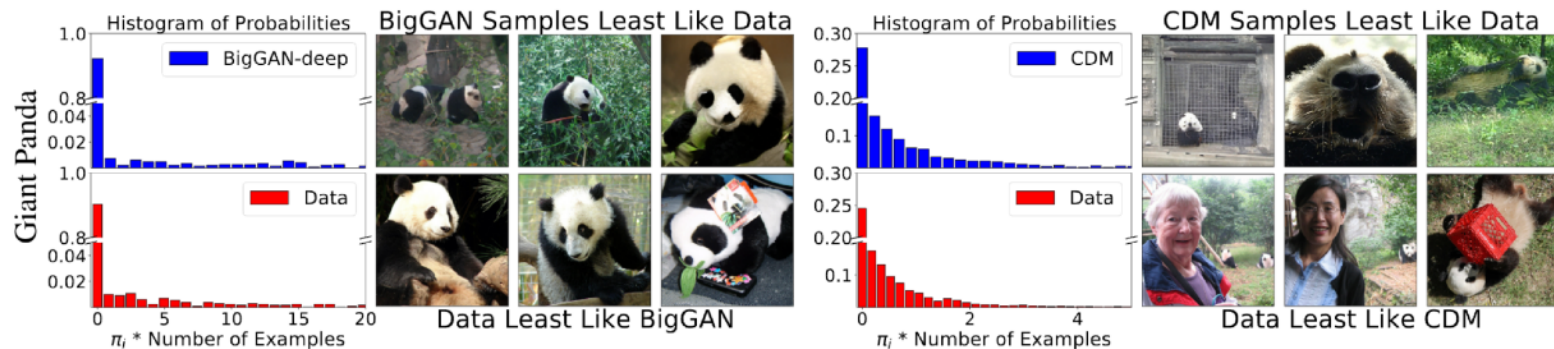
# Generalised Empirical Likelihood (GEL)

General moment condition

$$\mathbb{E}_{X \sim P_\pi} [m(X; c)] = \mathbf{0}$$

Generalised Empirical Likelihood (GEL)

$$\min_{\{\pi \mid \sum_i \pi_i = 1, \pi_i \geq 0\}} D[\hat{P}_n \parallel P_\pi] \quad \text{s.t.} \quad \mathbb{E}_{X \sim P_\pi} [m(X; c)] = \mathbf{0}$$



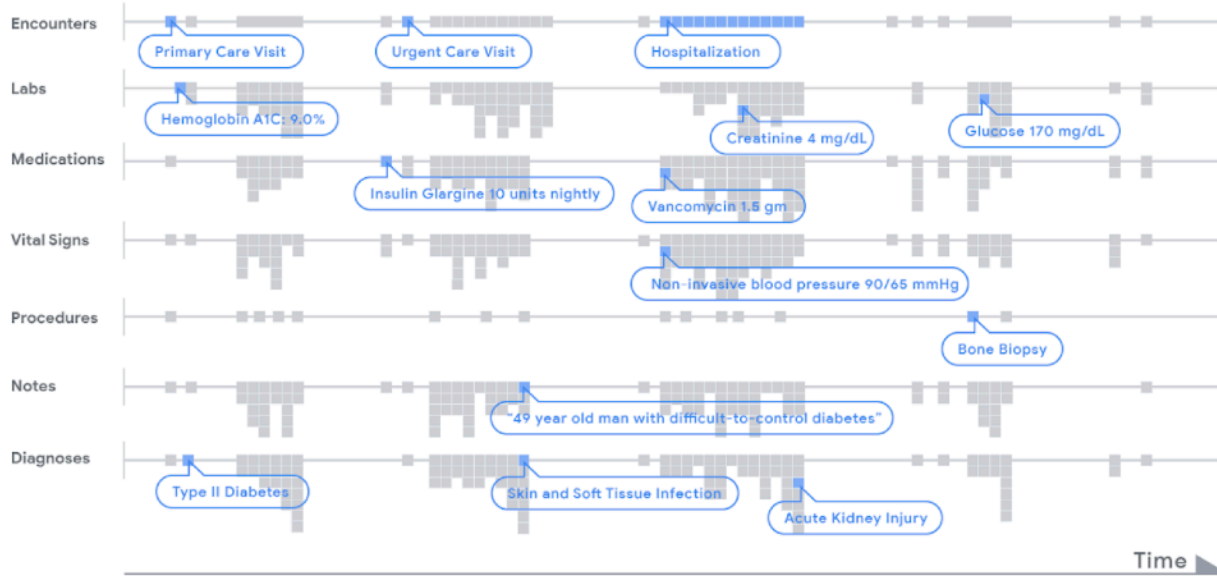
Use to identify examples not represented by the model



# Fairness and Participation

# Medical and other data represent people

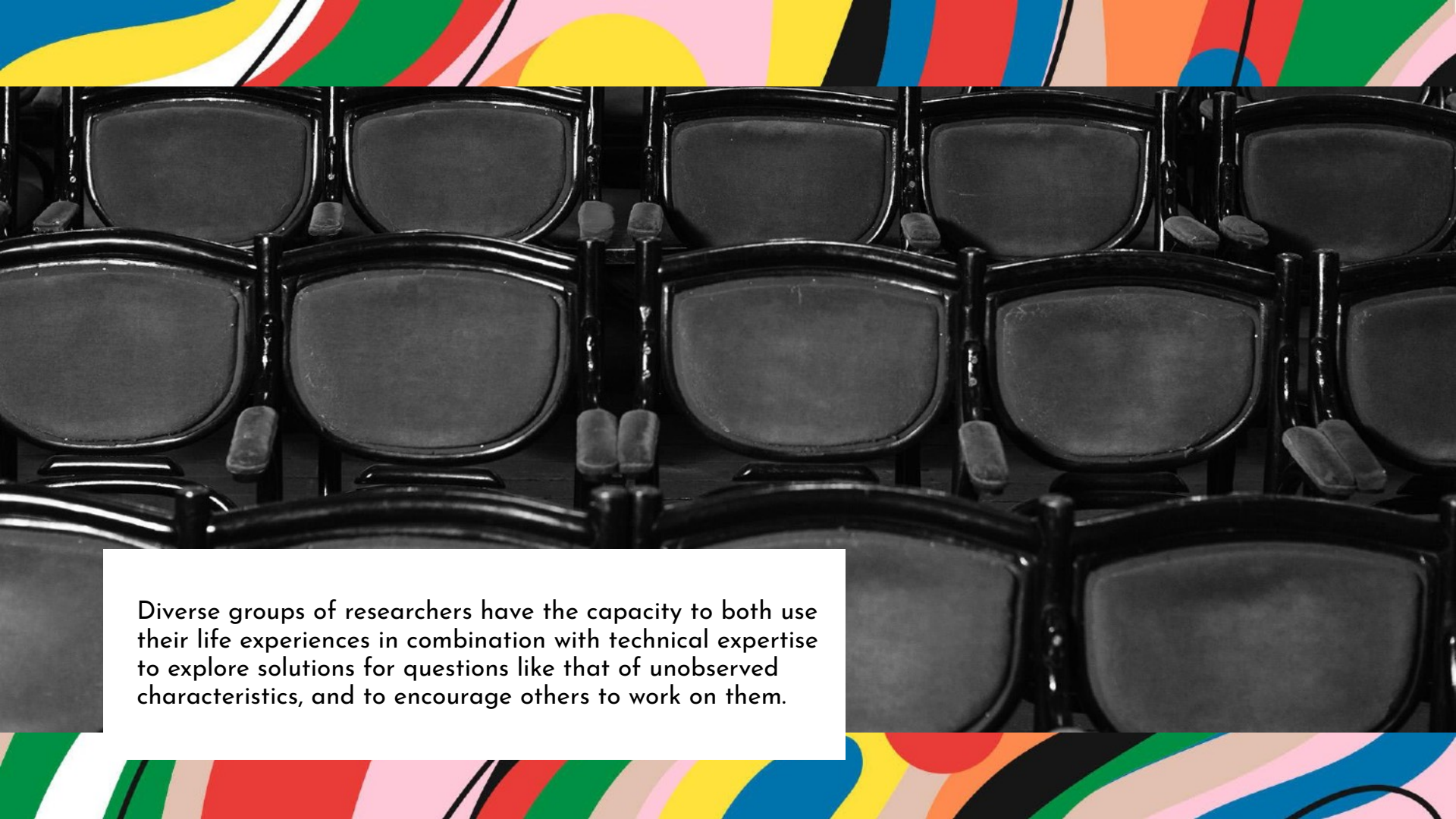
## Patient Timeline



Knowing legal gender or self-identified race or age becomes the basis of fairness analyses.

Paper: Fairness for Unobserved Characteristics: Insight from Impacts on Queer Communities





Diverse groups of researchers have the capacity to both use their life experiences in combination with technical expertise to explore solutions for questions like that of unobserved characteristics, and to encourage others to work on them.

# Queer Fairness

Assessing fairness for unobserved characteristics

## Several Areas of Vulnerability

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Privacy; Censorship; Inclusive language;  
Fighting Online abuse; Health; Mental  
Health; Employment



## REUSABLE METHODOLOGY

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Find ways for different types of communities, those who are marginalised, and those who are most vulnerable, to become part of addressing the problem.

Paper: Fairness for Unobserved Characteristics: Insight from Impacts on Queer Communities



# AI for Everyone?



## INTERCULTURAL ETHICS

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How technology can support society and culture, rather than becoming an instrument of cultural oppression and colonialism.



## POLITICAL COMMUNITY

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Power in strengthening varied forms of political community, who can create new forms on understanding and elevate intercultural dialogue.

Paper: Decolonial Theory as Sociotechnical Foresight in AI

# Deep Learning Indaba



2017, Johannesburg, South Africa

# Deep Learning Indaba



2018, Stellenbisch, South Africa

# Deep Learning Indaba

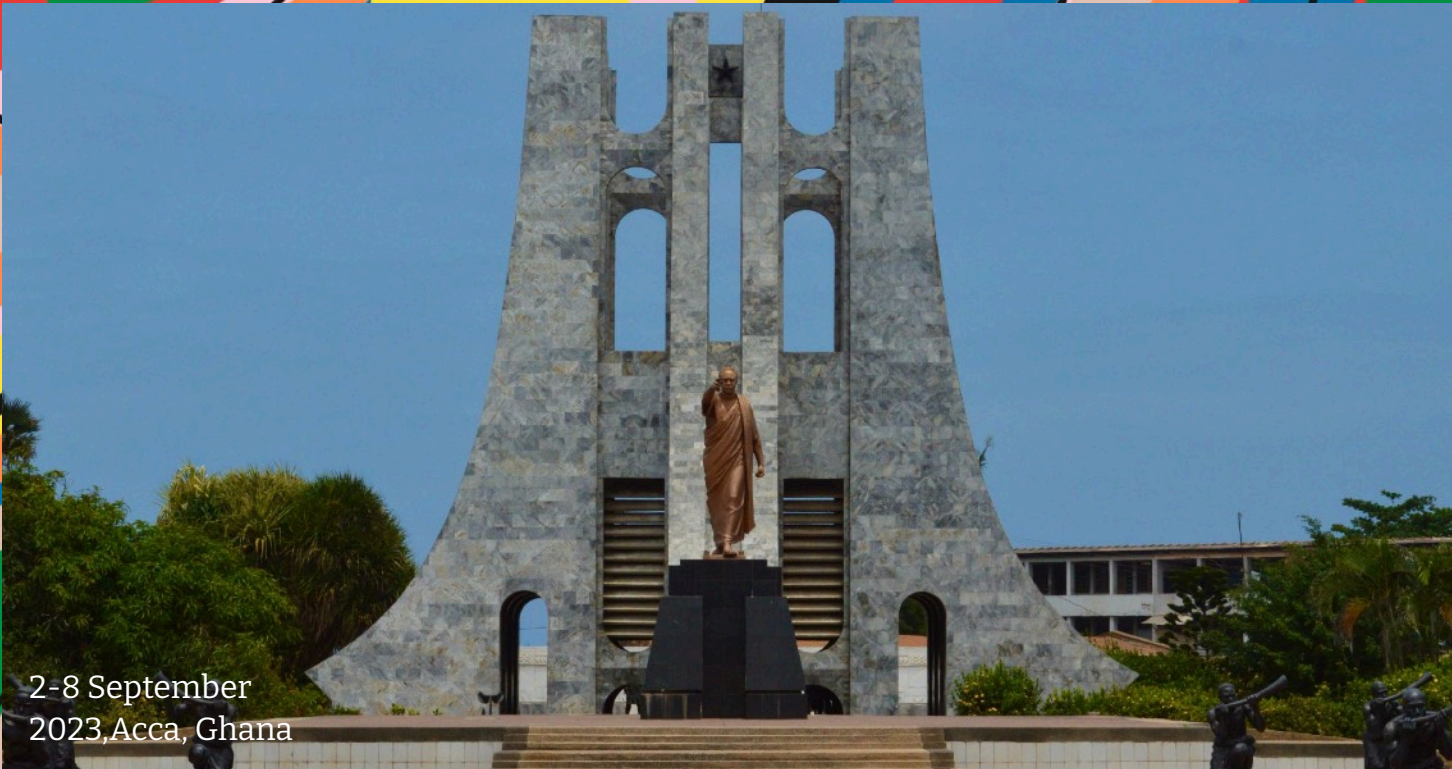


# Deep Learning Indaba



2022, Tunis, Tunisia

# Deep Learning Indaba



2-8 September  
2023, Accra, Ghana



04

WRAP UP



## YOUR SOCIAL PURPOSE

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An expanded view of what is within our responsibilities that infuses our work with social purpose.



## RECLAIM YOUR AGENCY

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Develop a view of the sociotechnical stack, intervene where you best can, and support richer participation in AI.



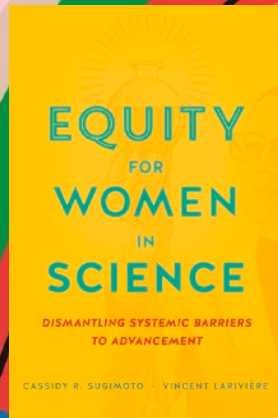
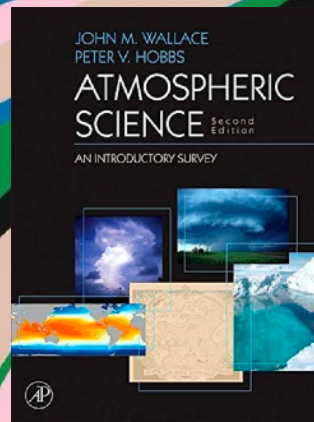
## GLOBAL AI

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Support for grassroots transformation and wider ownership of AI is working. Keep doing more.



# Some Resources



Research & Publications



AI, Labor, and the Economy

### Guidelines for AI and Shared Prosperity

Explore PAI's Guidelines for AI and Shared Prosperity: tools to design and deploy AI systems in service of workers' rights and well-being.

Article | [Open Access](#) | Published: 29 September 2021

### Skilful precipitation nowcasting using deep generative models of radar

Suman Ravuri, Karel Lenc, Matthew Willson, Dmitry Kangin, Remi Lam, Piotr Mirowski, Megan Fitzsimons, Maria Athanasiadou, Sheilem Kashem, Sam Madge, Rachel Prudden, Amol Mandhane, Aidan Clark, Andrew Brock, Karen Simonov, Raia Hadsell, Niall Robinson, Ellen Clancy, Alberto Arribas & Shakir Mohamed

*Nature* **597**, 672–677 (2021) | [Cite this article](#)

### GraphCast: Learning skillful medium-range global weather forecasting

Remi Lam<sup>1,2</sup>, Alvaro Sanchez-Gonzalez<sup>1</sup>, Matthew Willson<sup>1</sup>, Peter Wilmberger<sup>1,3</sup>, Meire Fortunato<sup>1</sup>, Alexander Pritzel<sup>2</sup>, Suman Ravuri<sup>1</sup>, Timo Ewalds<sup>1</sup>, Ferran Alai<sup>1</sup>, Zach Eaton-Rosen<sup>1</sup>, Weihua Hu<sup>1</sup>, Alexander Mersos<sup>2</sup>, Stephan Hoyer<sup>2</sup>, George Holland<sup>1</sup>, Jacklyn Stott<sup>1</sup>, Oriol Vinyals<sup>1</sup>, Shakir Mohamed<sup>1</sup> and Peter Battaglia<sup>1</sup>

<sup>1</sup>equal contribution, <sup>2</sup>DeepMind, <sup>3</sup>Google

We introduce a machine-learning (ML)-based weather simulator—called “GraphCast”—which outperforms the most accurate deterministic operational medium-range weather forecasting system in the

Philosophy & Technology  
<https://doi.org/10.1007/s13347-020-00405-8>

RESEARCH ARTICLE

### Decolonial AI: Decolonial Theory as Sociotechnical Foresight in Artificial Intelligence

Shakir Mohamed<sup>1</sup> · Marie-Therese Png<sup>2</sup> · William Isaac<sup>1</sup>



### Power to the People? Opportunities and Challenges for Participatory AI

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#ICML2023

# Machine Learning with **Social Purpose**

Shakir Mohamed