

Data-driving modelling of natural processes and beyond

I Li-Pen Wang (lpwang@ntu.edu.tw)

I feat. Wang Up team

Li-Pen Wang, PhD

Education

PhD in Civil & Environmental Engineering, Imperial College London
MSc in Computer Aided Engineering, National Taiwan University
BSc in Civil Engineering, National Taiwan University

Professional Experiences

Assistant Professor, National Taiwan University (current)
Postdoc Researcher, Imperial College London, KU Leuven
Head of CAT unit, Microinsurance Catastrophe Risk Organisation
Founder/Director/Hydrometeorologist, Rain++ Ltd.

Research Areas

Hydrometeorology,
Remote Sensing
Computational Statistics



RAIN++

miCRO



Honours, Awards & Services

2024- IMF expert roster (climate change)
2023-27 ICL Honorary Research Associate
2021-22, 2023-24 Dissertation Supervisor Award
2021-22 Outstanding teaching award
2019- CoC of EGU session: Precipitation and Urban Hydrology





WangUp

NTU Computational Hydrometeorology Lab

In NTU Computational Hydrometeorology Lab (NTU HydroMet Lab), we research on hydrometeorological process modelling and prediction based upon advanced statistical theories and AI



wangup.caece.net



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Modelling convective cell life cycles with a copula-based approach

Chien-Yu Tseng¹, Li-Pei Wang^{1,2}, and Christian Onof¹

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Modelling rainfall with a Bartlett-Lewis process: pyBL (v1.0.0), a
fun software package and an application with short records

What do we do in the Wang Up team?

We develop innovative solutions and apply cutting-edge technology to tackling hydrometeorological & environmental challenges.



What do we do in the Wang Up team?

We develop **innovative solutions** and apply cutting-edge technology to tackling hydrometeorological & environmental challenges.

You are **encouraged** to think and be creative!



What do we do in the Wang Up team?

We develop innovative solutions and apply **cutting-edge technology** to tackling hydrometeorological & environmental challenges.

You will be properly **trained**.



What do we do in the Wang Up team?

We develop innovative solutions and apply cutting-edge technology to tackling **hydrometeorological** & environmental challenges.

hydrometeorology noun

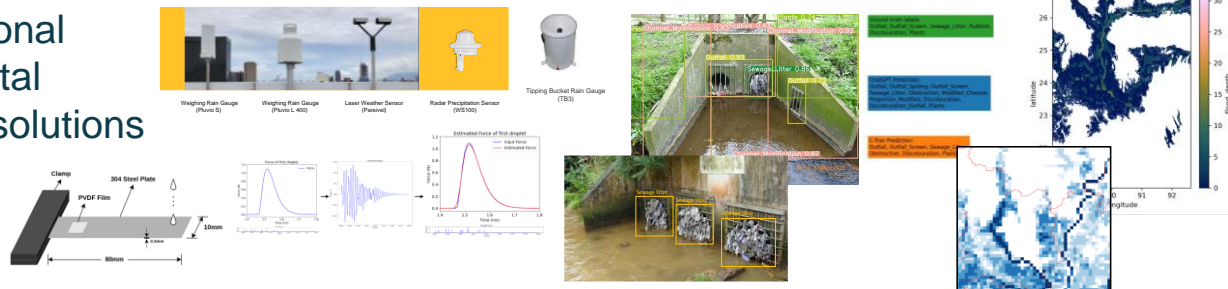
hy·dro·me·te·o·rol·o·gy (,hī-drō-,mē-tē-ə-'rā-lə-jē ◀▶)

: a branch of meteorology that deals with water in the atmosphere especially as precipitation

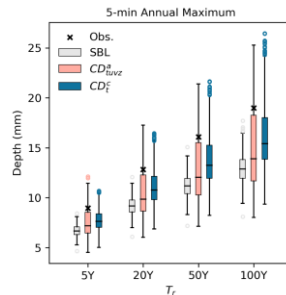
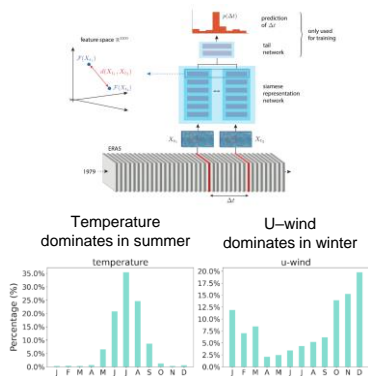


So, what exactly do we do?

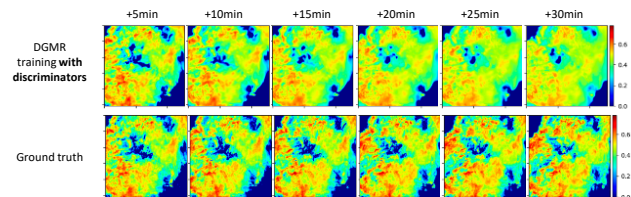
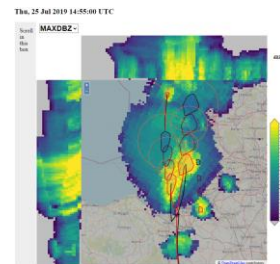
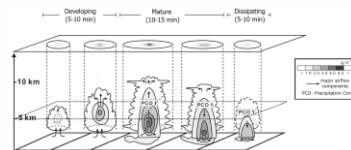
Unconventional environmental monitoring solutions



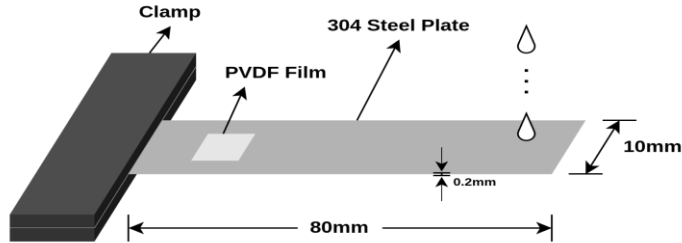
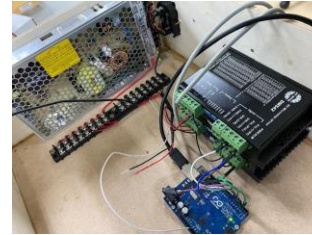
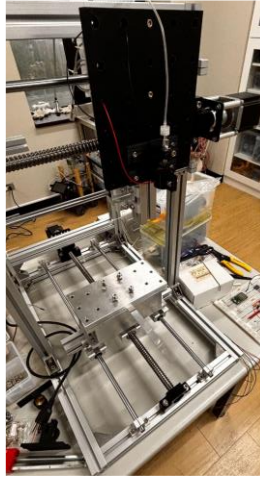
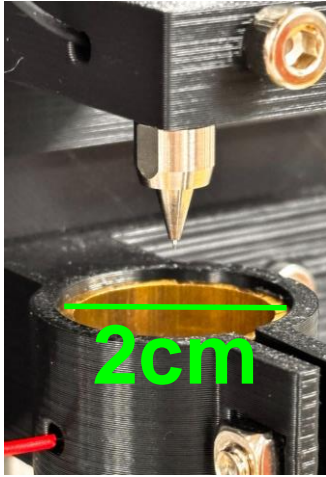
Incorporating impact of climate changes to local rainfall modelling



Convective storm nowcasting & modelling



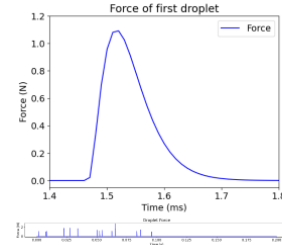
Development of a low-cost rain drop sensor



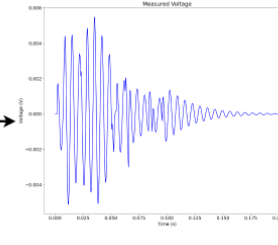
$$YI \frac{\partial^4 w(x,t)}{\partial x^4} + c_a I \frac{\partial^2 w(x,t)}{\partial x^2 \partial t} + c_a w(x,t) + m \frac{\partial^2 w(x,t)}{\partial t^2} + \theta v_{out}(t) \left(\frac{dw(x)}{dx} - \frac{dw(x-L)}{dx} \right) = F_{impact}(t) \delta(x - (L - l_0))$$

$$A \cdot v''(t) + B \cdot v'(t) + C \cdot v(t) + D \cdot \int v(t) dt = F(t)$$

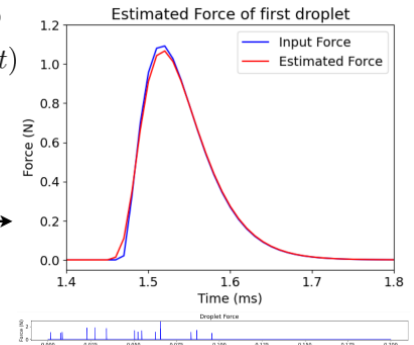
(a) Steel plate governing equation



(b) The input shape of first droplet



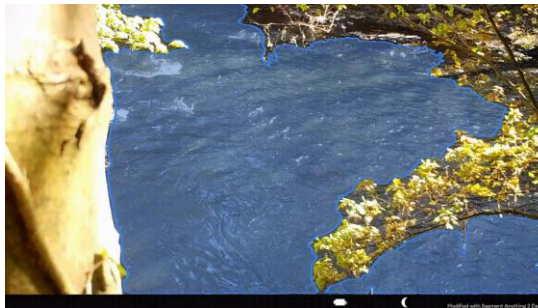
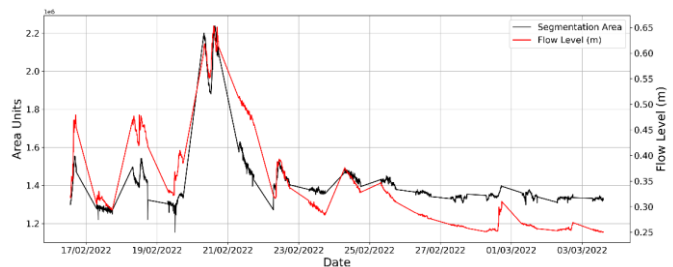
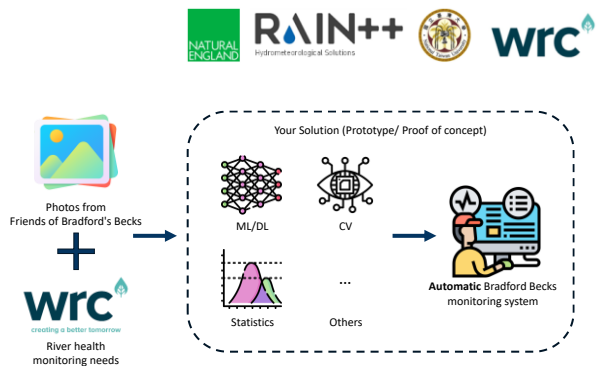
(c) Voltage generated by the PVDF



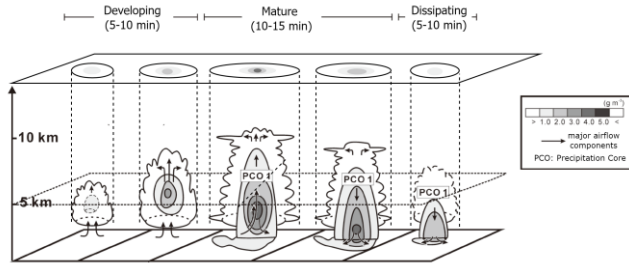
(d) Estimated input force and real input force

Creative solutions to monitoring river with help from AI and Citizen Science

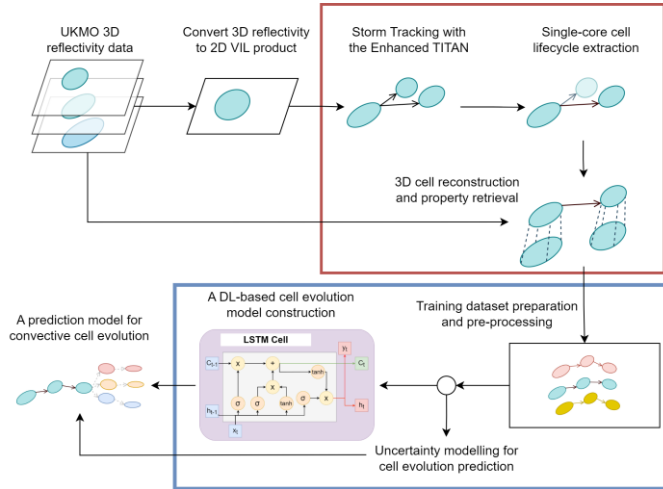
Eyes on the Water



Predicting thunderstorms with help from deep learning



Adopted from Kim et al., 2012



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Exploring the use of 3D radar measurements in predicting the evolution of single-core convective cells

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^c Met Office, Exeter, United Kingdom

ABSTRACT

Object-based radar rainfall nowcasting is a widely used technique for convective storm prediction. Currently, most existing object-based nowcasting methods primarily focus on predicting cell movements, neglecting the temporal evolution of cell properties such as size, shape, and intensity. Incorporating this evolution is critical for improving predictability in convective storms. While previous studies have used three-dimensional (3D) radar observations to capture vertical changes during convective cell formation, these efforts often analyse or reconstruct specific convective events. Integrating 3D radar information into operational object-based radar rainfall nowcasting remains an open challenge. This research addresses this challenge using deep learning (DL) techniques. More specifically, a DL-based prediction model is developed, which uses 2D and 3D cells' properties retrieved from 3D radar reflectivity data at the current time and across the past 15 min to predict the evolution of these properties over the next 15 min. This model could eventually be integrated into existing object-based nowcasting models. A total of 4708 cell lifecycles, extracted from high-resolution (5-min, 1-km, 24 levels at 0.5 km intervals) 3D radar data across the UK, are used to train the model, and a total of 1177 lifecycles are used for testing. The proposed model is shown to predict the evolution of single-core convective cells effectively, including changes in 2D projected geometry and mean 2D and 3D reflectivity. In particular, by incorporating information on the vertical evolution of convective cores, the prediction errors of mean reflectivity (in both 2D and 3D) can be reduced by approximately 50% at 15-min forecast lead time, as compared to a persistence forecast. **Keywords:** radar, tracking, convective cell, nowcasting, 3D, deep learning, lstm.

1. Introduction

Climate change has reportedly altered global precipitation patterns, leading, amongst other things, to the intensification of short-duration rainfall extremes (Trenberth et al., 2003; Lenderink et al., 2017; Liu et al., 2009). This has increased the frequency and severity of flood events worldwide, particularly in urban areas where ongoing urbanisation exacerbates both likelihood and impacts (Guhathakurta et al., 2011; Huong and Pathirana, 2013; Willems, 2013; Miller and Hutchins, 2017; Guerreiro et al., 2018; Tabari, 2020; Fowler et al., 2021a, 2021b).

Despite ongoing investment in structural flood mitigation (e.g. improved drainage – both traditional and sustainable – and flood defences) (Zhou et al., 2019; Ghodsi et al., 2020; Hobbie and Grimm, 2020; Pour et al., 2020), it is virtually impossible – as well as economically and environmentally unsustainable – to eliminate the hazard (Webber et al., 2020; Cristiano et al., 2023). Instead, non-structural measures aimed at enabling optimisation of existing drainage systems and improving res.

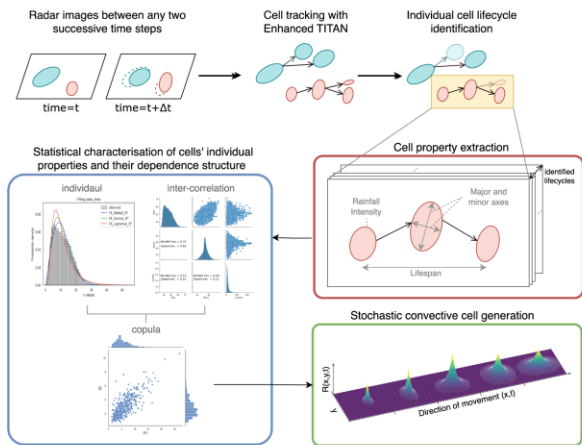
successful implementation of said non-structural measures relies greatly upon good-quality short-term rainfall forecasts, which can be used as input to optimisation, flood forecasting and warning systems (Hajuar-achehi et al., 2011; Tingsanchai, 2012).

There are two main sources of short-term rainfall forecasts for use in such operational systems: n and radar-based rainfall n Bowler et al., 2006; Schei Casagrande et al., 2017). D last 40 years (Bauer et al., short lead times (0–5 h) is sti period required for a comj results in relatively low pr et al., 2005).



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A copula-based convective cell lifecycle generator



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Modelling convective cell life cycles with a copula-based approach

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²Imperial College London, London, SW7 2AZ, United Kingdom

Correspondence: Li-Pen Wang (lpwang@ntu.edu.tw)

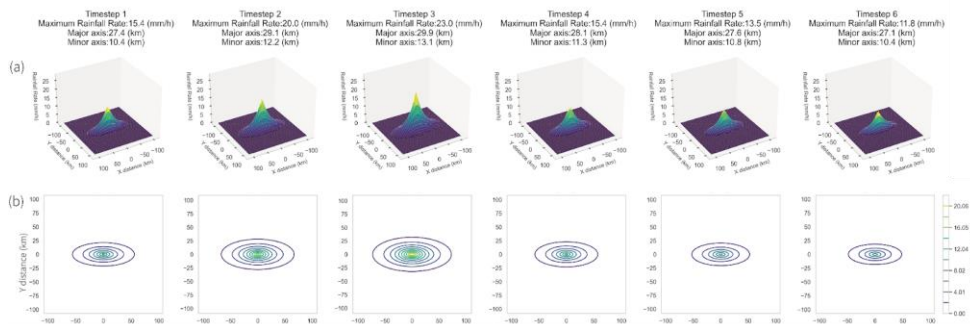
Received: 23 May 2024 – Discussion started: 30 May 2024

Revised: 5 November 2024 – Accepted: 6 November 2024 – Published: 3 January 2025

Abstract. This study proposes an algorithm designed to model convective cell life cycles, for the purpose of improving the representation of convective storms in rainfall modelling and forecasting. We propose to explicitly model cell property inter-dependence and temporal evolution. To develop the algorithm, 165 effective convective storm events occurring between 2005 and 2017 in Birmingham, UK, were selected. A state-of-the-art storm tracking algorithm was employed to reconstruct convective cell life cycles within each selected event. The investigation of these cell life cycles proceeded in three stages. The initial stage involved statistically characterising individual properties of convective cells, including rainfall intensity, spatial extent at peaks and lifespan. Subsequently, an examination of the inter-correlations amongst these properties was conducted. In the final stage, the focus was on examining the evolution of these cell properties during their lifetimes. We found that the growth and decay rates of cell properties are correlated with the cell properties themselves, hence the need to incorporate this correlation

1 Introduction

Climate change has emerged as an urgent environmental concern, driving non-negligible changes in global weather patterns, particularly the frequency and intensity of extreme events (Trenberth et al., 2003; Liu et al., 2009; Guhathakurta et al., 2011). A notable trend linked to this phenomenon is the intensification of localised, short-duration rainfall extremes, often attributed to severe convective systems (Guerreiro et al., 2018; Fowler et al., 2021b, a; Lenderink et al., 2021). This trend highlights the need to enhance the modelling of convective storm models and to better account for their subsequent hydrological applications. Accurate models in climate research (Trapp et al., 2020; Prein et al., 2020; Halladay et al., 2024). Despite of ex



Understanding the key challenges and opportunities in creating climate transition pathways

Gap to be filled



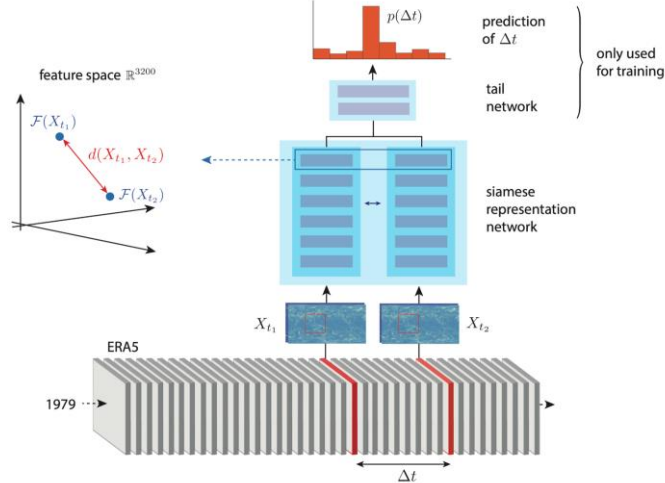
	CATASTROPHE MODELS	CLIMATE MODELS	TRANSITION RISK MODELS
USE	To measure the impact or financial loss from physical risks and catastrophic events.	To understand the evolution of the system over different time scales (past, present and future).	To inform economic risks arising from the transition to a zero carbon economy.
INPUTS	Historical statistical distributions that describe physical hazards; do not explicitly consider future climate considerations.	Physical models that represent the Earth system and help to understand the evolution of the system over different time scales (past, present and future); do not measure the financial or economic impact of climate events.	Incorporates two different types of information: climate data that don't measure the financial and economic impacts of climate events, and economic data that leverage historical patterns to predict a future that will look different due to intensifying climate change impacts.
BENEFITS	Provides probabilities of extreme event occurrence assuming current climate conditions.	Can produce realistic future climate conditions.	Portrays plausible scenarios or pathways to transition the economy from a predominantly fossil fuel energy perspective to one incorporating new types of fuel sources.
LIMITATIONS	Only well developed for geographic areas and hazards where a large percentage of the population is insured against that hazard. They are less developed in geographies with a low amount of insurance coverage that could be susceptible to climate change.	Struggles to predict many of the extreme events that most impact the insurance industry (such as hurricanes and wildfires). These events occur on spatial scales that are too small to be "seen" in most climate models.	Risk of misinterpreting the output of the models when making portfolio-level decisions due to the highly simplified and backward looking representation of physical hazard impacts on the economy.

ClimaDist

- Dataset

ERA5 1940 – 2009

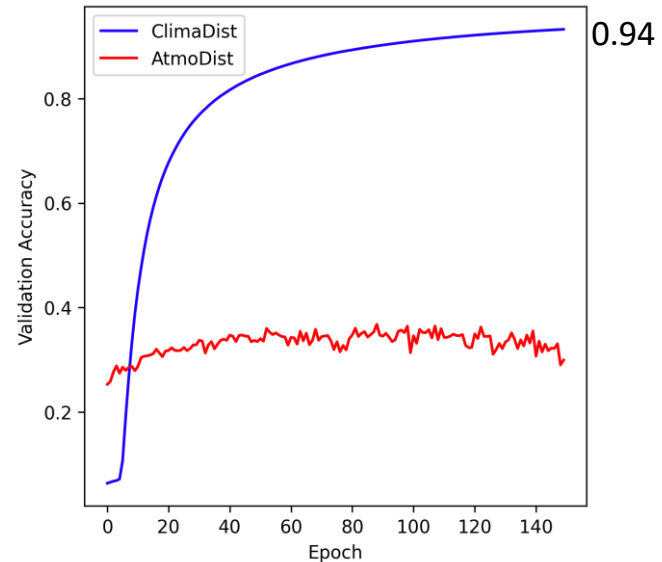
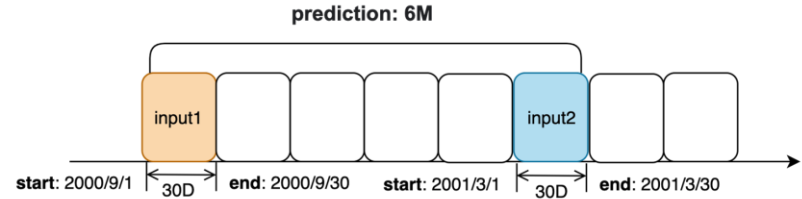
Climate variates: Temperature, U and V-component of wind, Geopotential



(AtmoDist - Hoffmann and Lessig, 2022)

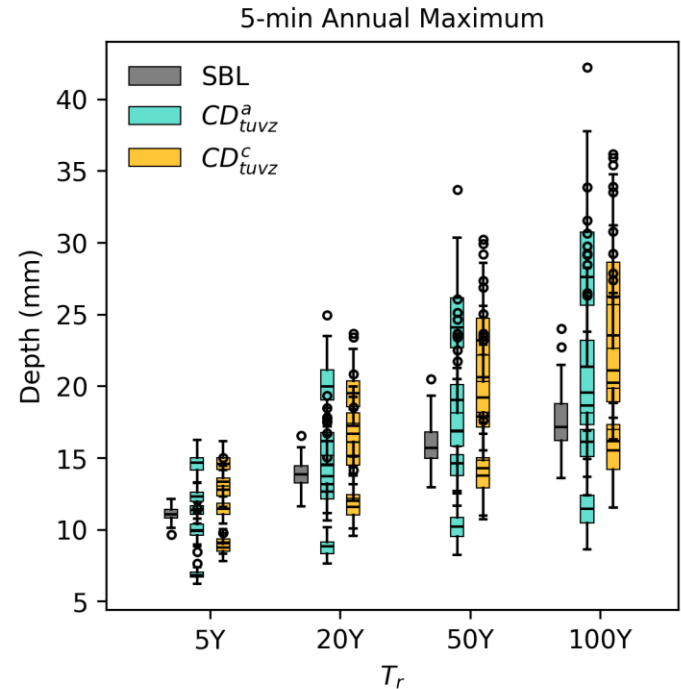
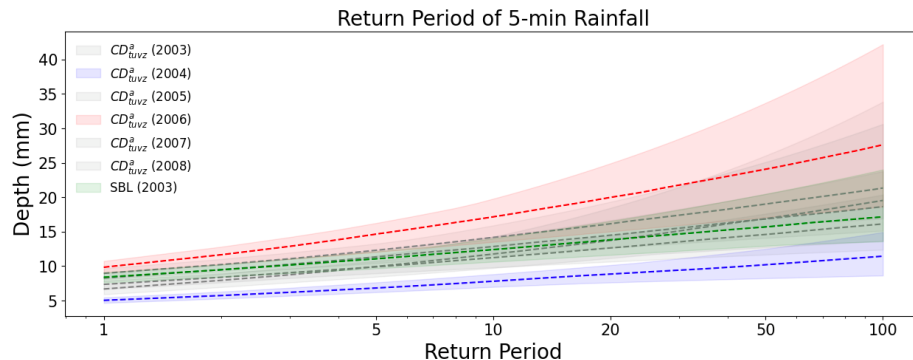
A deep-learning model (CNN) proposed to capture weather dynamics, without the labelling needs.

ClimaDist can predict the time difference between weather variables from any two time points.



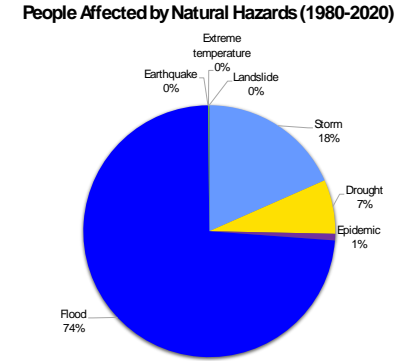
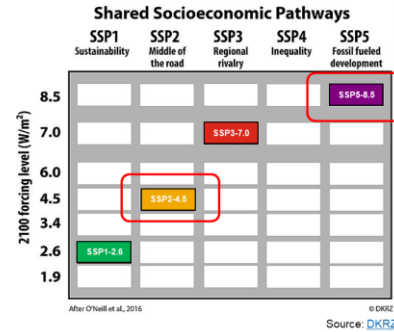
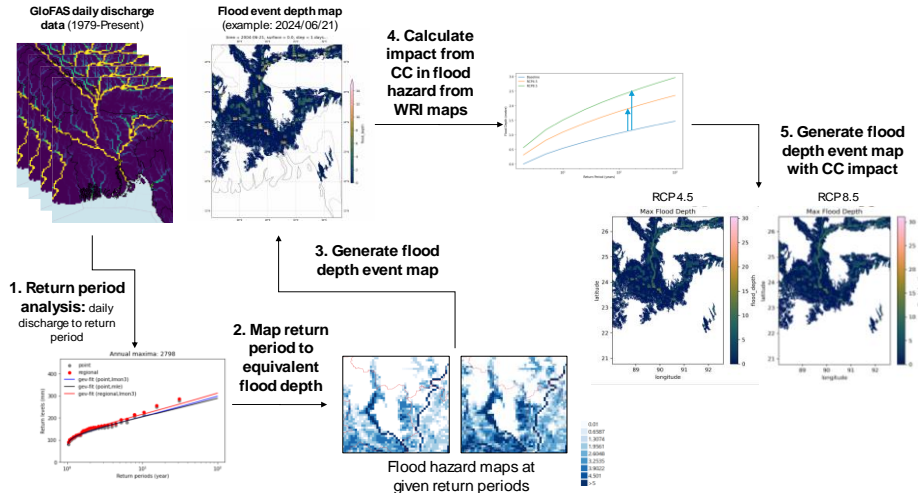
Application – the impact of climate dynamics propagates to rainfall extremes

The original ‘stationary’ rainfall model (SBL) fails to account for the variation in rainfall properties between years, which causes an underestimation of rainfall extremes and their estimation uncertainty.

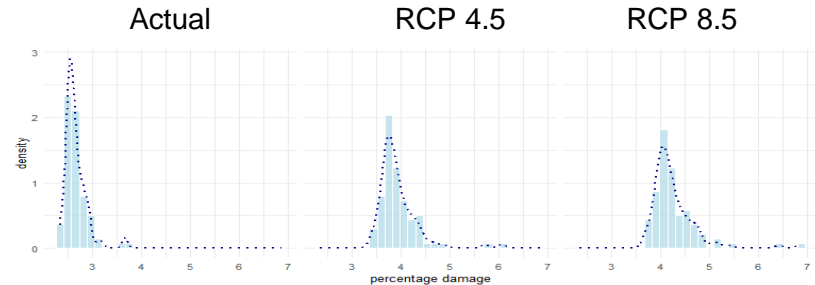


What if 2004 flood event happens again under RCP8.5 CC scenario?

- We helped IMF and local agency identify critical natural hazards and co-design CC scenarios.
- We delivered the first ever flood hazard estimation mission for IMF fully based on public datasets.



Damage estimation



We are looking for...

- Someone who is interested in developing (ML/DL-based) algorithms that enable best use of our massive weather data collection.
- Someone who is interested in applying cutting-edge AI or Stats techniques to climate risk modelling.
- Someone who is interested in doing something I don't know.
- Someone who wants to make impacts.



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