



ENHANCING TROPICAL CYCLONE RAINFALL FORECASTS FOR ANTICIPATORY HUMANITARIAN ACTION USING DEEP LEARNING

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MOTIVATION

- Tropical Cyclones (TCs) lead to several hazards that cause significant impacts
- Over the past 50 years, TC-related disasters killed >779k people and caused US\$ 1408 billion in economic losses – an average of 43 deaths and US\$ 78 million in damages every day (WMO, 2020)



Flooded Houses in Buzi, Mozambique, after Cyclone Idai's landfall, 18 March 2019 (Credits: INGC, FATHUM)

The use of TC rainfall and flood forecasts for anticipatory action is hampered by forecast skill, as errors are large for decision-making and limit the actionable lead times



Can we improve the skill of forecasts of TC rainfall, both severity and location, via Machine Learning (ML)?

DATASETS

Observations:

- **IBTrACS**: global TC tracks, with >73k time steps between 1996 and 2020 (resampled at 6h)
- **Multi-source observational dataset (MSWEP)** as precipitation ground truth
 - Temporal resolution: 3h
 - Spatial resolution: 0.1°
 - Period: 1980-present

Forecasts:

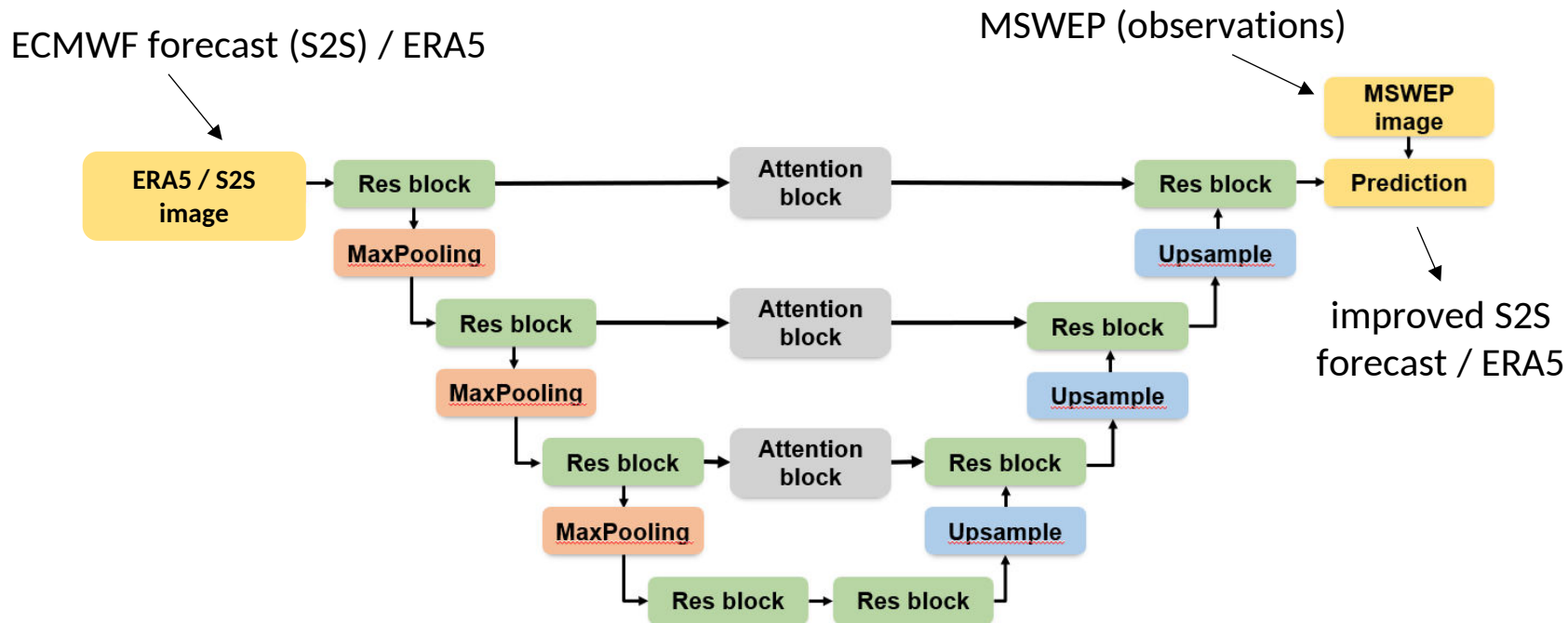
- **S2S precipitation (P) forecasts by ECMWF** (*results for now only for ENS control member*)
 - Temporal resolution: 6h
 - Spatial resolution: 0.125°
 - Period: 20 years hindcasts, twice weekly from 2016 to 2023 (first hindcast year: 1996)

Reanalysis:

- ERA5 precipitation reanalysis (*used to set up the methodology, results not shown here*)
 - Temporal resolution: 1h
 - Spatial resolution: 0.25°
 - Period: 1979-present

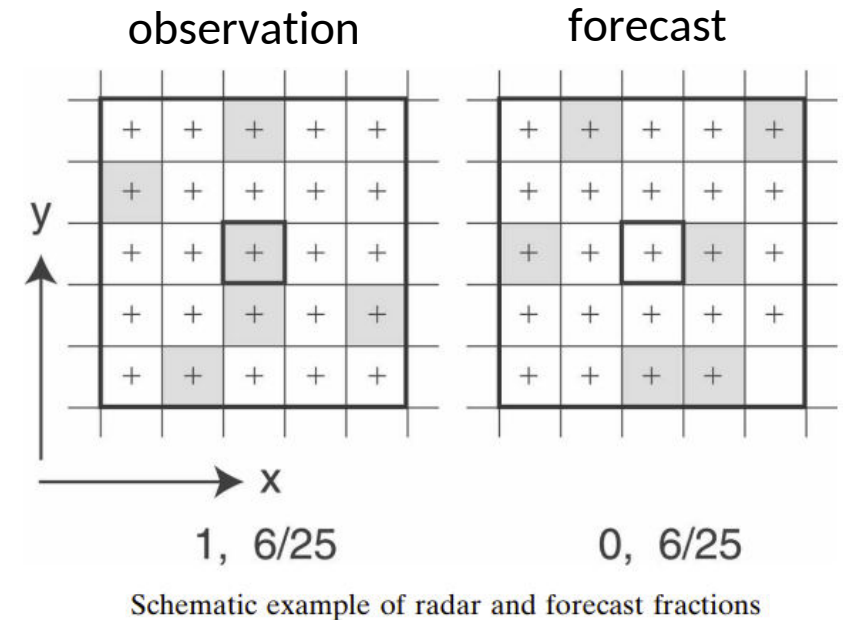
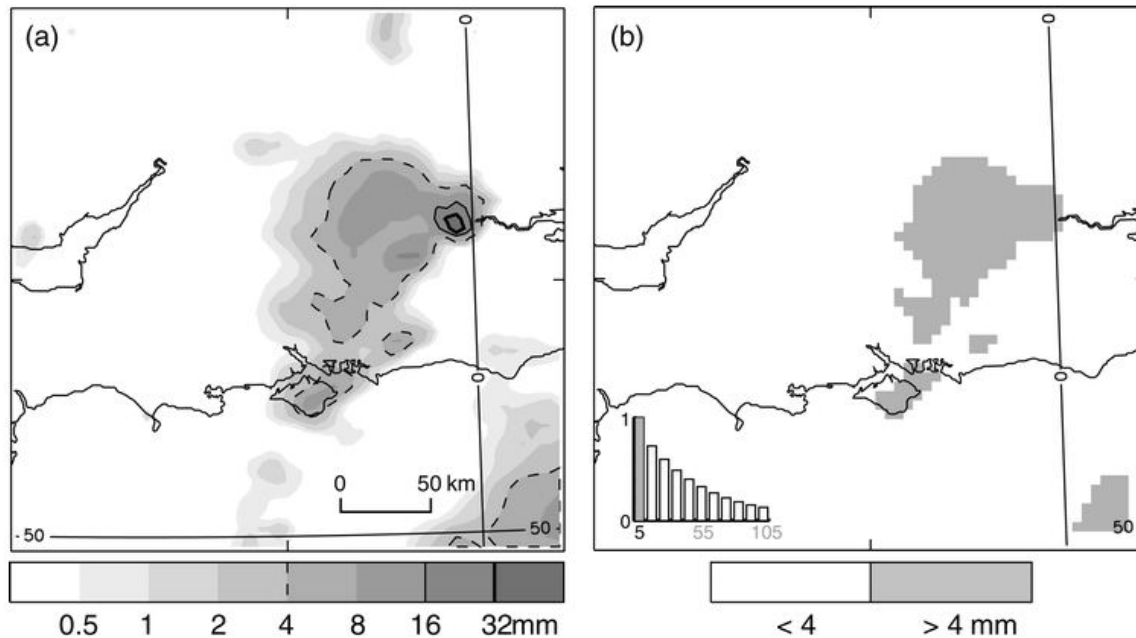
METHODS: DEEP LEARNING

- We post-process precipitation (P) forecasts based on a **deep-learning algorithm (ARU-Net)** to adjust both local biases and spatial distribution of rainfall
- We train the model on a **large sample from global TC events**, using a multi-source observational dataset (MSWEP) as ground truth
- We use a **composite loss function to train the model**, based on the combination of Mean Squared Error (MSE) and Fractions Skill Score (FSS)



METHODS: SPATIAL ACCURACY SCORE

- We adapted the Fractions Skill Score, FSS (Roberts and Lean, 2007) to be used as loss function (replaced hard threshold with tanh, then Gauss filter and normalised to range [0, 1])
- FSS takes values between 0 (no match) and 1 (perfect match) – our modified FSS is inverted
- Two key parameters: Q (intensity threshold) and N (patch size)
- We selected Q = [80th, 95th, 99th] percentile & N=15 grid cells



Adapted from Roberts and Lean (2007)

METHODS: ACTION-RELEVANT SCORES

- For forecast evaluation, we use action-relevant scores for humanitarians, False Alarm Ratios & Hit Rates (target levels: FAR < 0.5 & HR > 0.5), modified using an effective action scale
- Action scale: effective spatial scale of a warning to trigger useful actions based on the level of 'acceptable' forecast error in the Mozambique Red Cross' Early Action Protocol (EAP) for TCs

“Activation of the EAP is based on the forecast information

- We distributed at least 72 hours before landfall. At this point, the margin of error is approximately 240 km”

Red Cross EAP for TC in Mozambique



EAP APPROVED March 2019	Population to be assisted 1500 HH	EAP timeframe 5 Years
EAP NUMBER EAP2019MZ01	Budget: 249,390 Swiss francs	Early action timeframe 1 Month

The IFRC's Programme and Operations Division has approved the EAP for the Mozambique Red Cross on Cyclones with a timeframe of five years and a budget of CHF 249,390, consisting of CHF 145,906 for readiness and pre-positioning and CHF 103,484 for early action.

The EAP shall be funded from the IFRC's Forecast based Action by the DREF where allocations shall be drawn on annual basis to cover readiness costs, a one-off pre-positioning cost the first year followed by a one-off sum to implement early actions upon a forecast reaching the trigger.

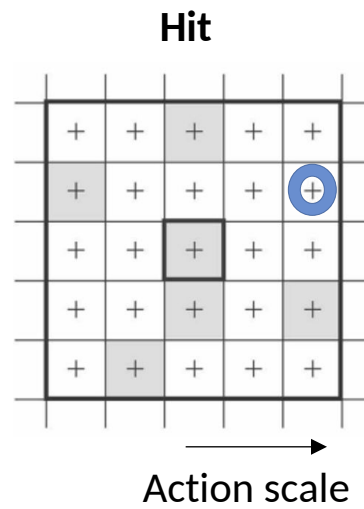
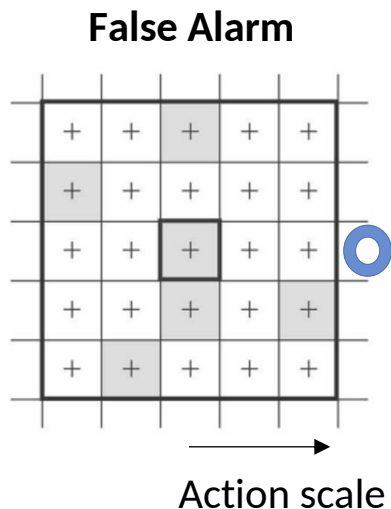
SUMMARY OF THE EARLY ACTION PROTOCOL

Mozambique is the third most-vulnerable country to extreme weather events in Africa and the tenth in the world (PDRR, 2017). Mozambique's excessive vulnerability is associated with its geographic location, as its coastline (2700km) borders one of the most active cyclonic zones in the southwest Indian Ocean. Tropical storms and cyclones occur frequently during the October to March rainy/cyclone season and CVM has ample experience engaging in preparedness, mitigation, and response activities related to these hazards. In the period 1984 to 2017 at least 13 cyclones with wind speeds above 120 km/h reached the Mozambican coast.

Mozambique is also one of the poorest countries in the world and is at the bottom of the table in terms of the Global Development Indexes such as the Gross Domestic Product (GDP) per capita (position 221 out of 228 countries) and the Human Development Index (position 181 in a universe of 188 countries), placing the population in a situation of great vulnerability (CIA 2018, UNDP 2018).



Due in part to general levels of poverty, the majority of the population lives in precarious housing. According to National Statistics (2007), constructions in Mozambique are classified as Conventional, Huts (Palhotas), Mixed and Improvised housing. Approximately 90% of the Mozambican population live in huts (a house where the building material is essentially of natural and vegetable origin, i.e. adobe, grass, bamboo, straw, etc.), contributing to their vulnerability.



+ Forecast event (yes)

○ Observed event (yes)

Action scale < 240 km

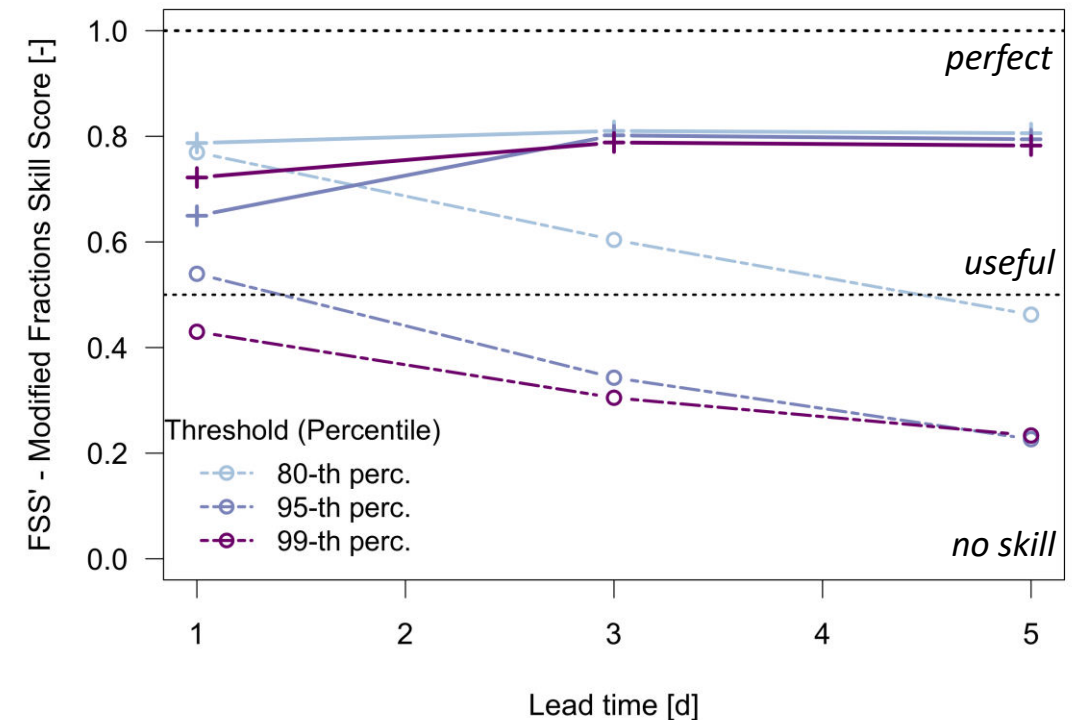
RESULTS: BIAS AND SPATIAL ACCURACY

- Results were analyzed both over **training + validation** and **test** sets
- The ML-based model **improves substantially overall rainfall biases and spatial accuracy**

MSE [(mm/6h)^2] - training + validation		
Lead time	Original S2S forecast	Improved forecast
1 day	28.68	25.20
3 days	42.42	31.56
5 days	52.25	36.12

Spatial accuracy (FSS') - training + validation

original forecast (o) vs. improved forecast (+)

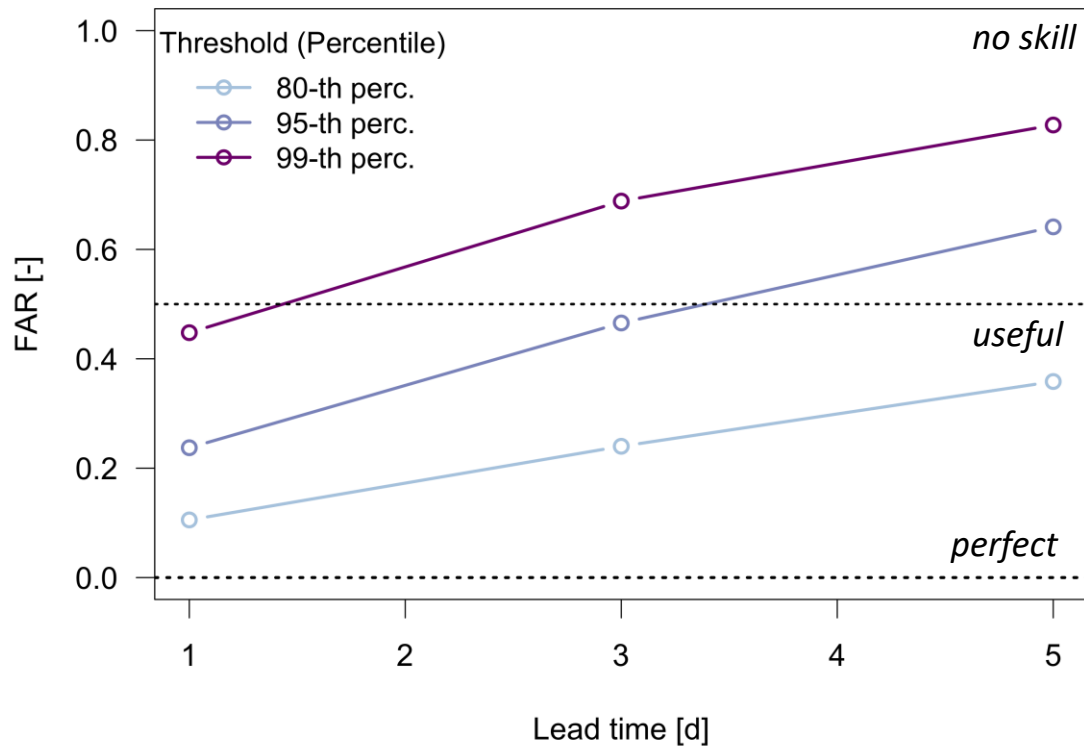


RESULTS: FAR (ORIGINAL S2S, TEST SET)

- False Alarm Ratios (FAR) increase with lead time and with rainfall intensity
- Marked improvement in skill for early action by enlarging the action scale from 50 to 100 km

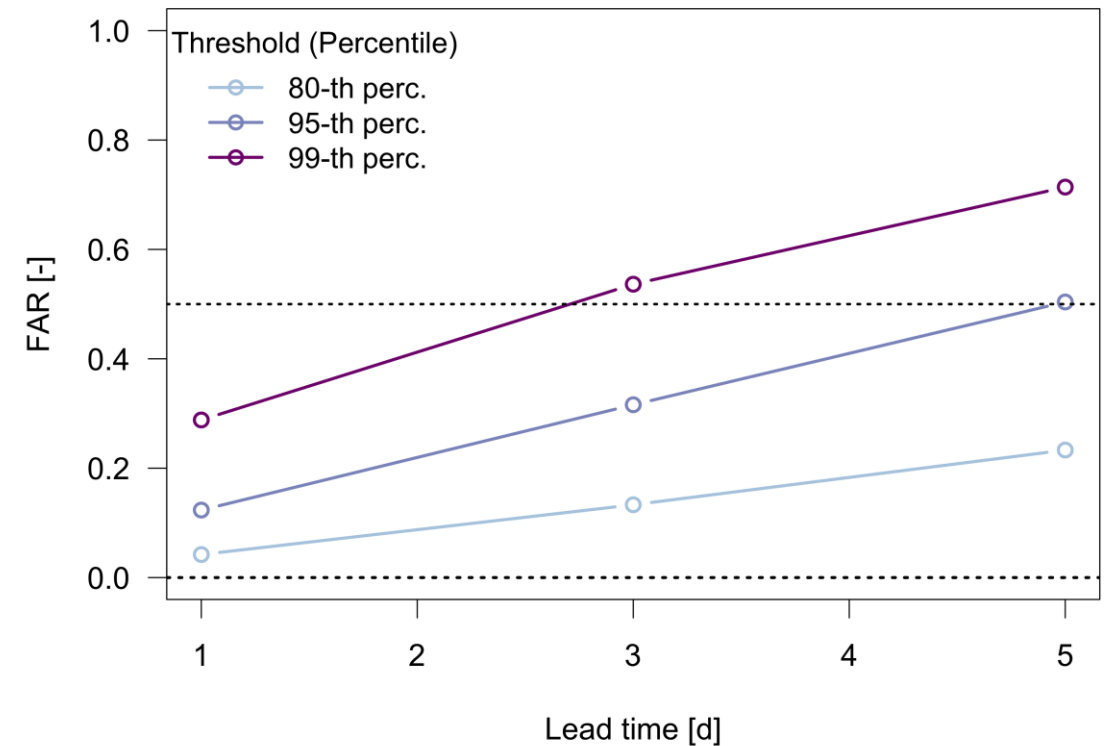
FAR with 50-km action scale

original forecast (o)



FAR with 100-km action scale

original forecast (o)

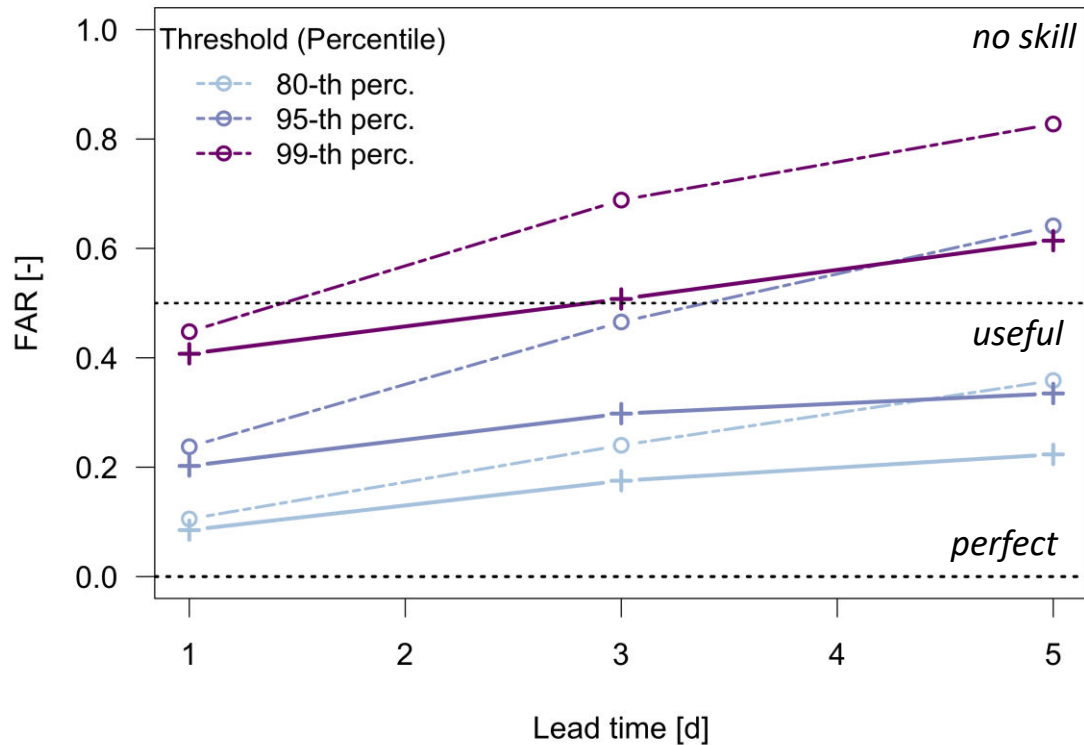


RESULTS: FAR (ADJUSTED S2S, TEST SET)

- Our ML-based post-processing **reduces substantially false alarms, at lead times ≥ 3 days**
- Our ML adjustments can bring skill closer to (or satisfy) target levels (FAR<0.5) for higher thresholds

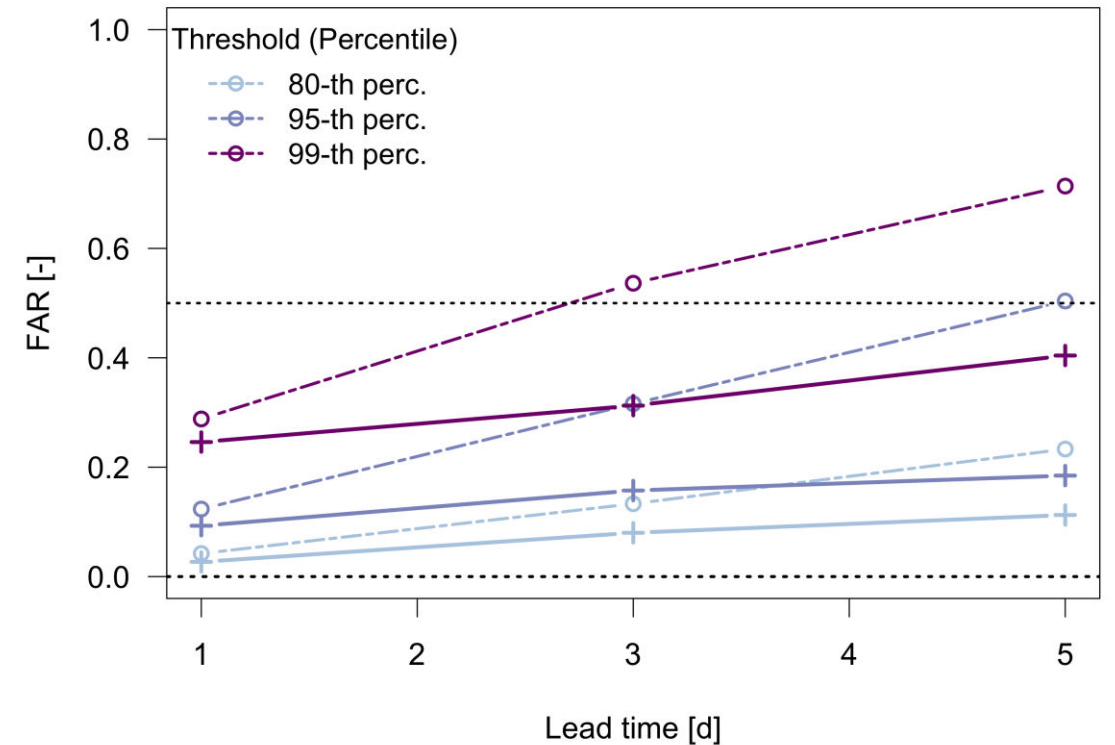
FAR with 50-km action scale

improved forecast (+) vs. original forecast (o)



FAR with 100-km action scale

improved forecast (+) vs. original forecast (o)

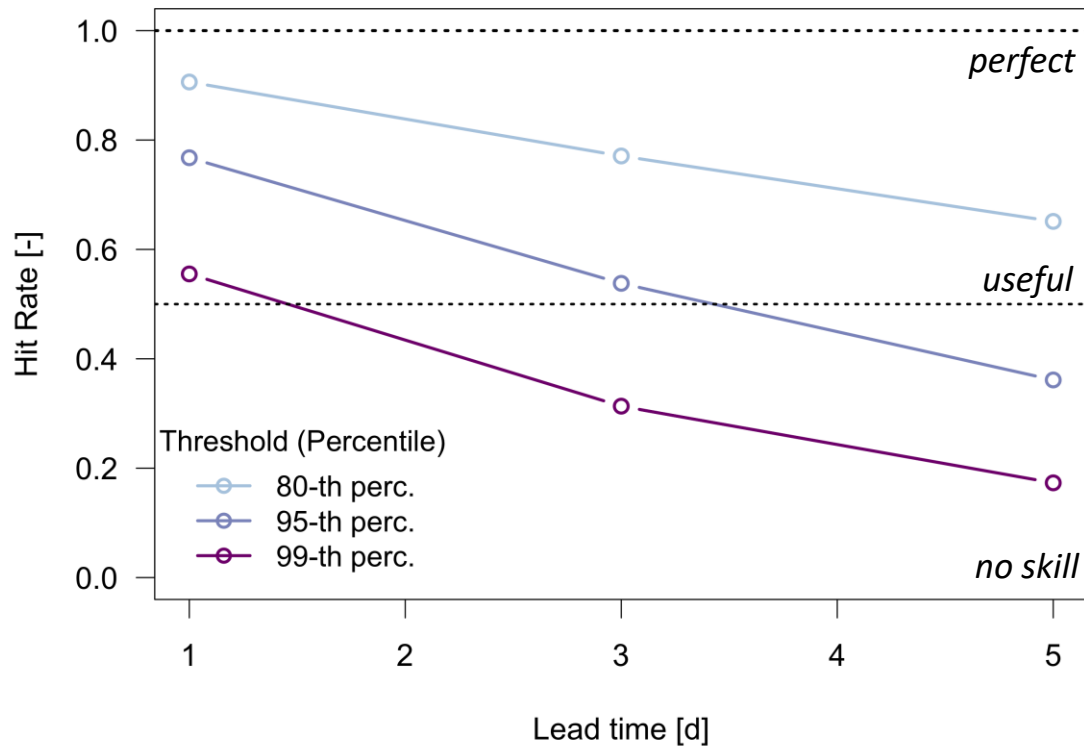


RESULTS: HR (ORIGINAL S2S, TEST SET)

- Hit Rates (HR) decrease with lead time and with rainfall intensity
- Marked improvement in skill for early action by enlarging the action scale from 50 to 100 km

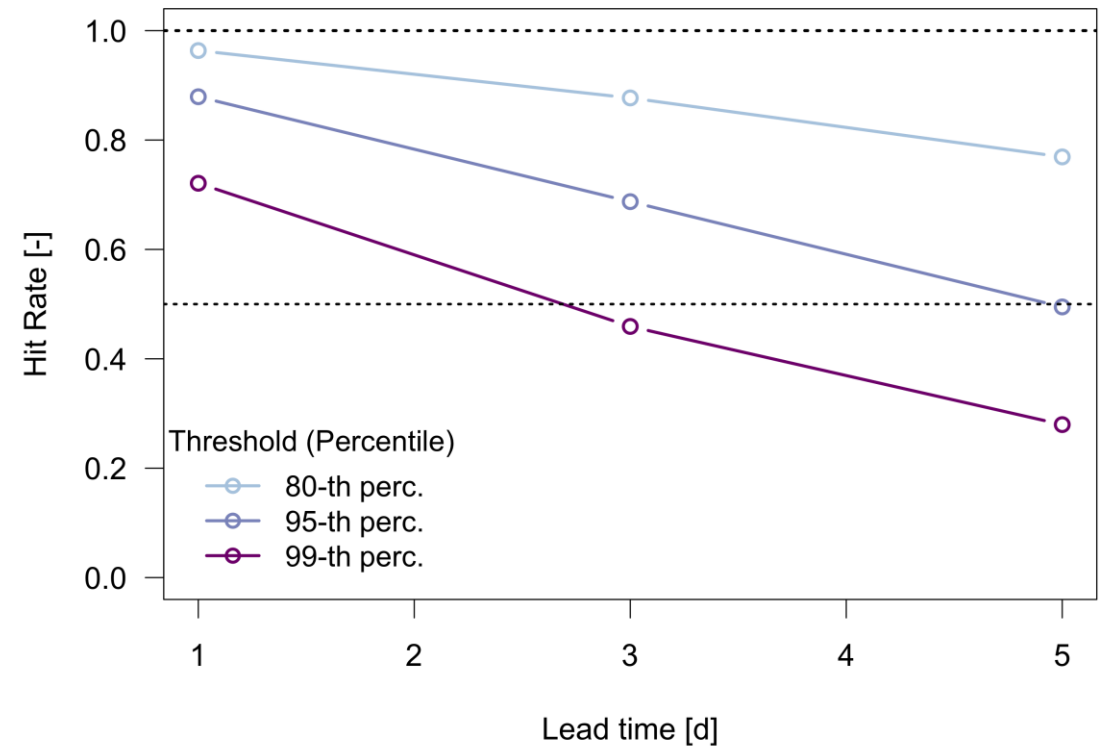
Hit Rate with 50-km action scale

original forecast (o)



Hit Rate with 100-km action scale

original forecast (o)

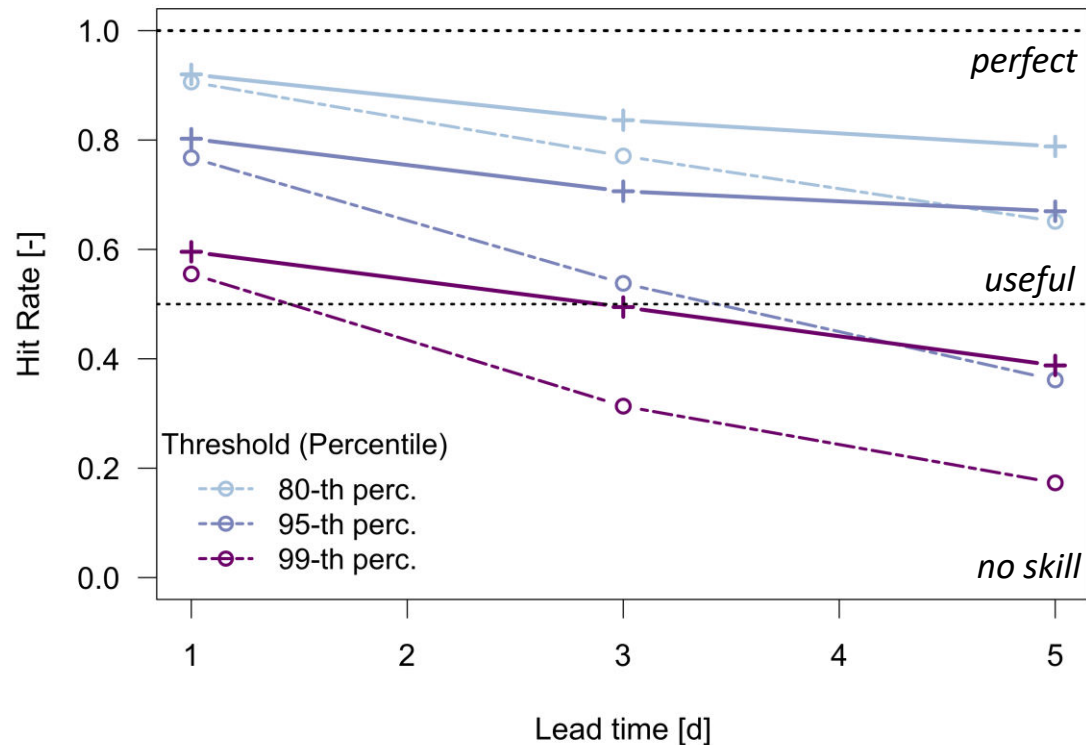


RESULTS: HR (ADJUSTED S2S, TEST SET)

- The ML-based post-processing **increases substantially Hit Rates (HR) at lead times ≥ 3 days**
- Our ML adjustments **bring forecast skill closer to/above target levels (HR >0.5)** for higher thresholds at 5 days lead time

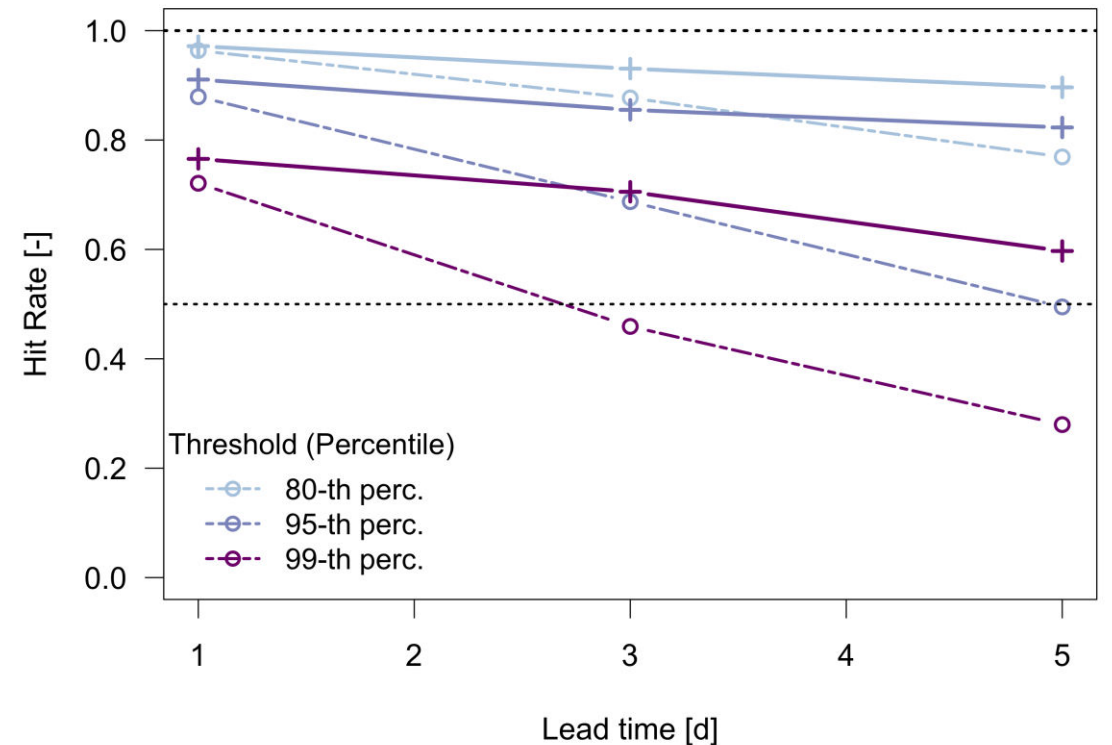
Hit Rate with 50-km action scale

improved forecast (+) vs. original forecast (o)



Hit Rate with 100-km action scale

improved forecast (+) vs. original forecast (o)



CONCLUSIONS

Takeaways

- We proposed a **ML-based post-processing model** (ARU-Net) that **improves substantially the spatial accuracy and skill** of medium-range rainfall forecasts (1-5 days Lead Times)
- Forecast skill varies substantially with the **action scale** and **rainfall intensity threshold**
- Our ML post-processing makes TC rainfall forecasts (at 3-5d LT) **more skillful for early action**

Next steps

- **Lead Time extension:** extending the tests beyond 5 days, up to 15 days (ongoing)
- **Ensemble:**
 - (i) **test the model over the whole S2S Ensemble**, using ARU-Net trained on the control member & validating over all ENS members (or retraining for ENS over shorter period)
 - (ii) **evaluate the action-relevant scores for different trigger probabilities**, and the spread-error relationship

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