Enhancing Precipitation Nowcasting in West Africa through IR-Integrated Deep Generative Models

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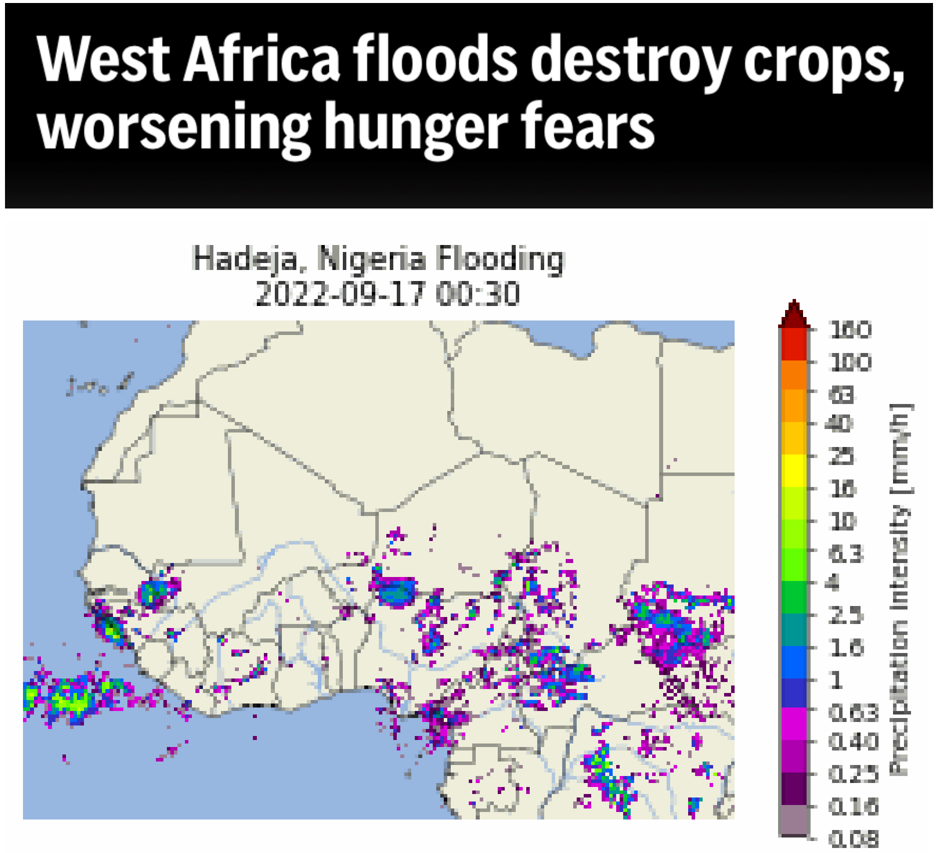
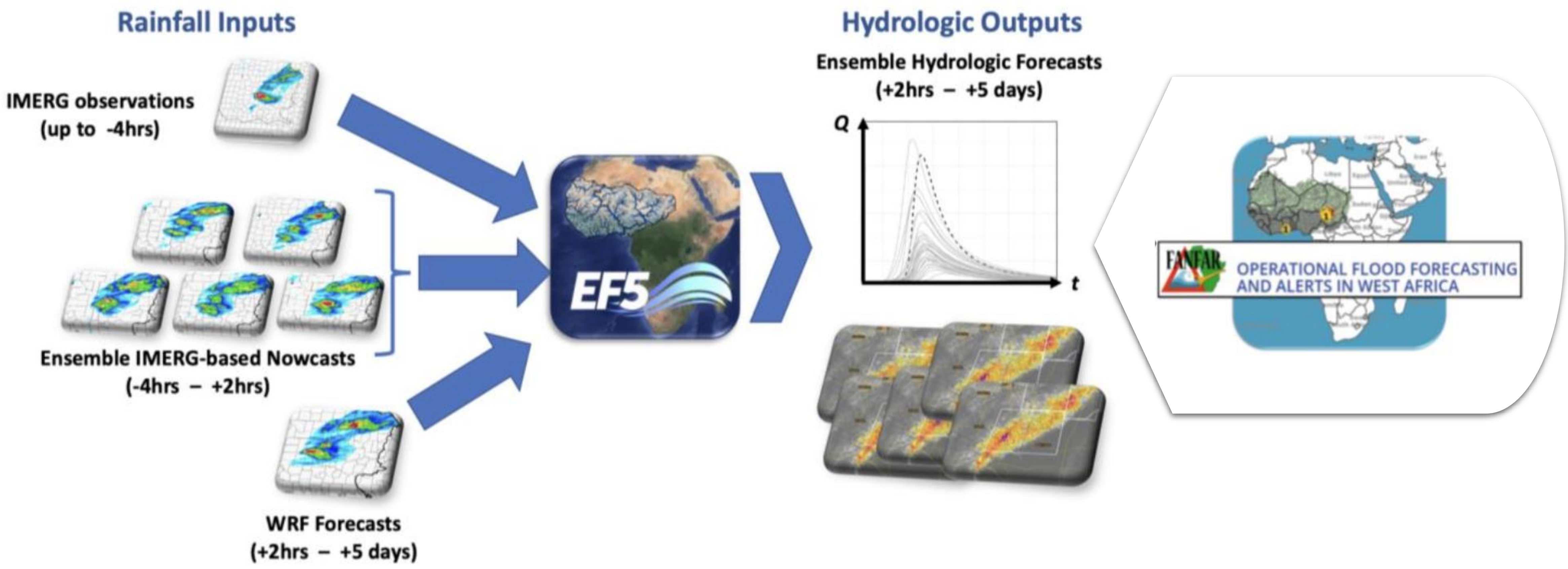
Introduction

- Precipitation over West Africa is governed by wide range of temporal and spatial variability [1].
- Per USAID, this has exposed increasingly large population to the consequences of flash floods leading to humanitarian crises [2].
- To equip institutional stakeholders with capacity to prepare for these extreme floods,
  - Existing riverine flash flood forecasting systems need to be provided with accurate precipitation nowcasts.
  - Precipitation nowcasting models should be designed to overcome the lack of radar-based imagery in West Africa by adequately using relevant sensor information.



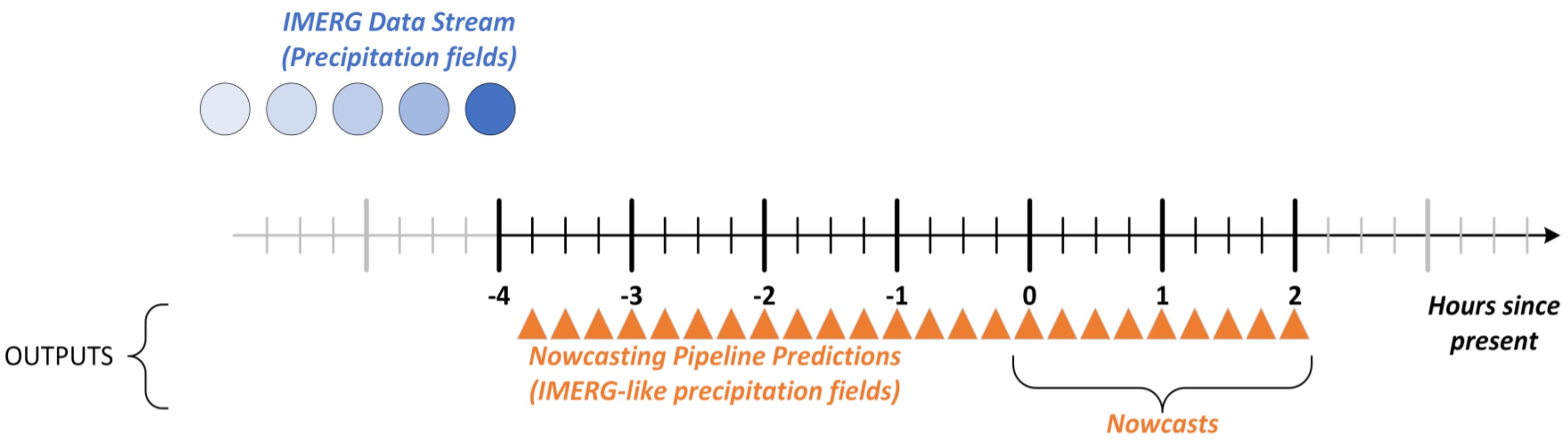
Precipitation recorded during flooding event [3]

Ensemble Flash Flood Forecasting System



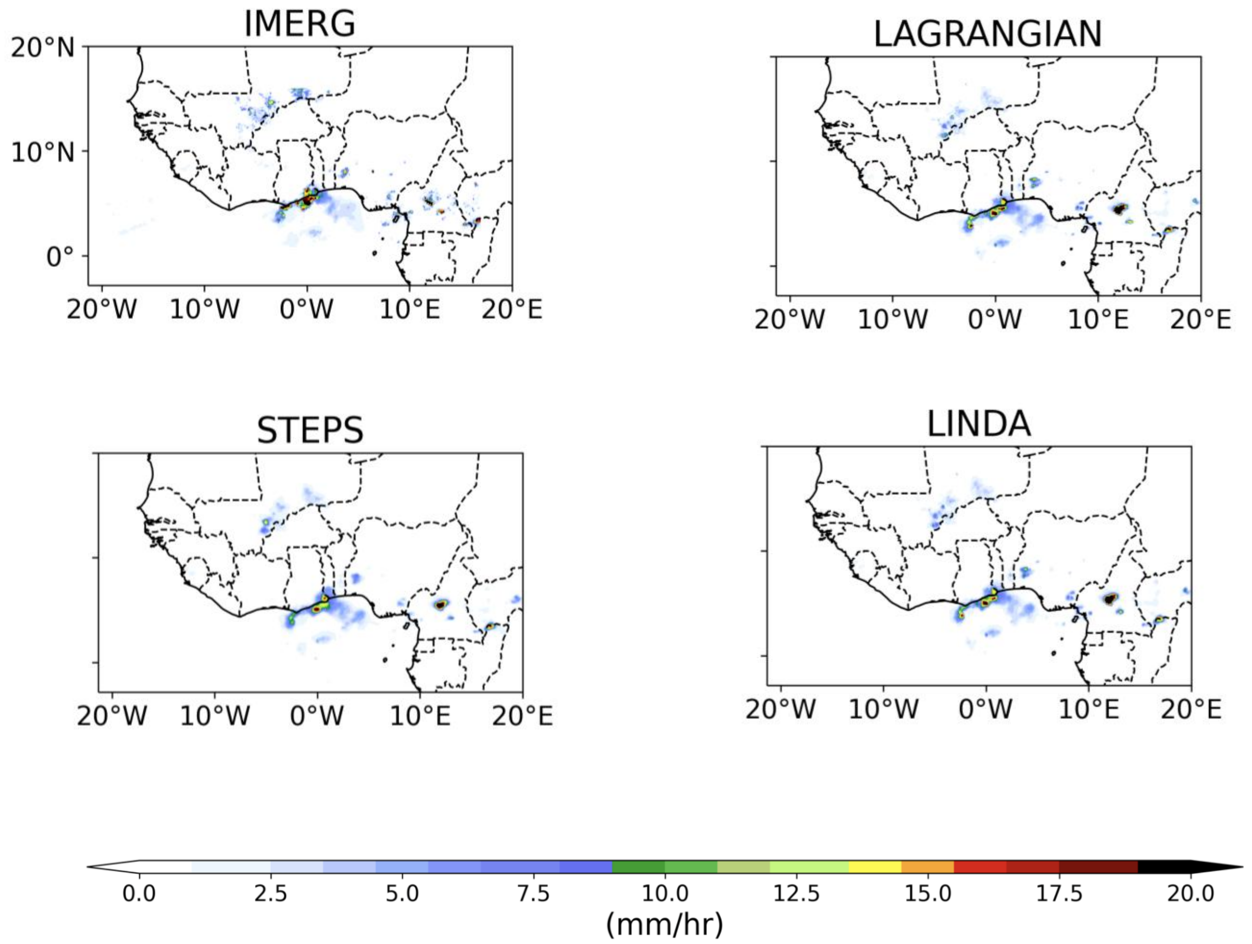
The Challenge at Hand

- In the absence of radar data over West Africa, we must depend on satellite-based products such as NASA IMERG Early Run v6 for real-time production systems [4]
- IMERG Early Run data is produced at a latency of 4 hours at a rate of one image per 30 minutes.
- We need to predict 6 hours ahead to produce nowcasts of 2 hours ahead.



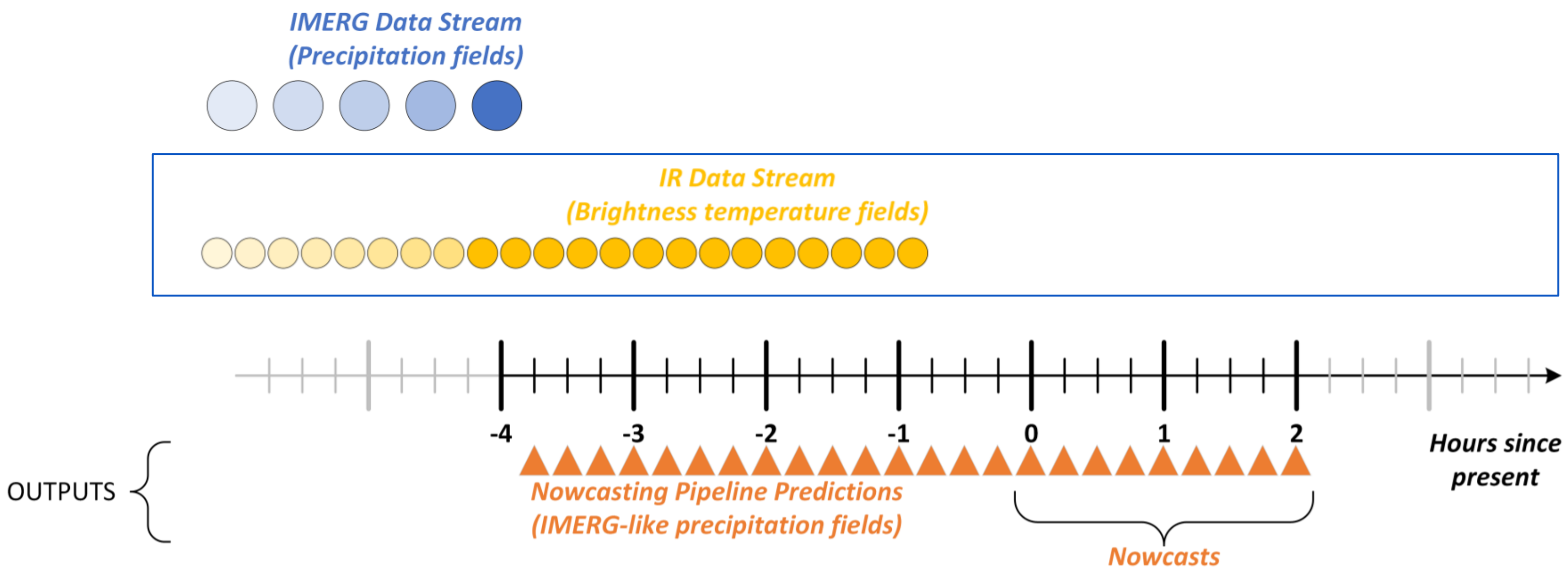
Nowcasting Methods

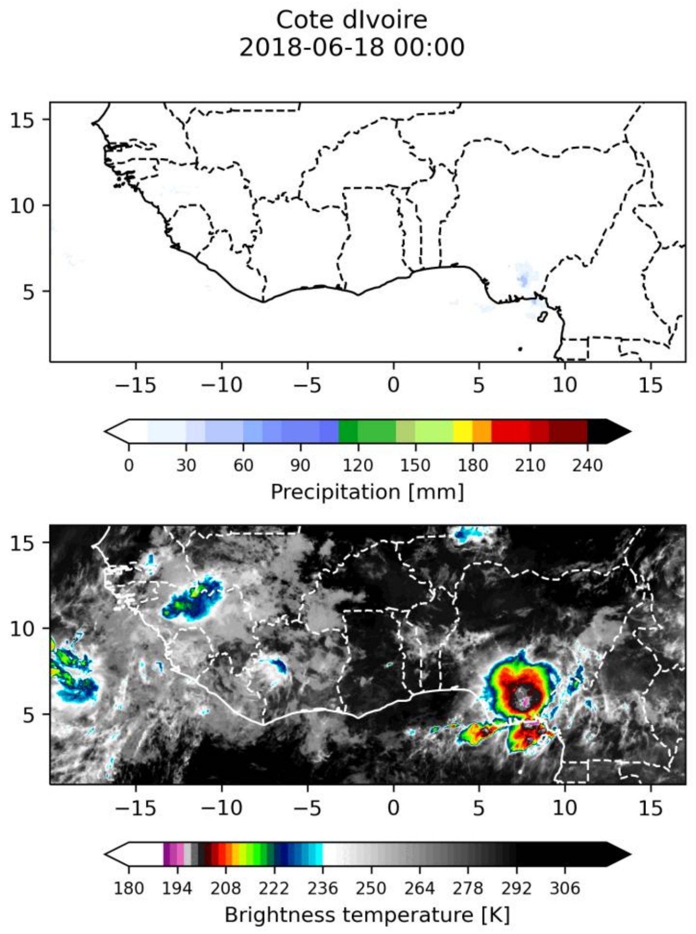
- Numerical Weather Prediction (NWP) based methods.
  - Model precipitation using the advection equation.
  - Able to produce ensembles to account for uncertainty.
  - Examples include pySTEPS, LINDA and Lagrangian Persistence.
  - Incorporating other data sources is not straightforward
  - Obey (some) atmospheric physics laws.
- Neural-based methods
  - Deep learning-based methods do not directly rely on advection equations.
  - Can account for non-linear evolution, which may not observe conservation laws.



Bridging the Latency Gap

- High Rate (15min) Infra-Red (IR) data [5], which capture rapid cooling rates at cloud tops — an established indicator of impending precipitation events [6].





Our Goal

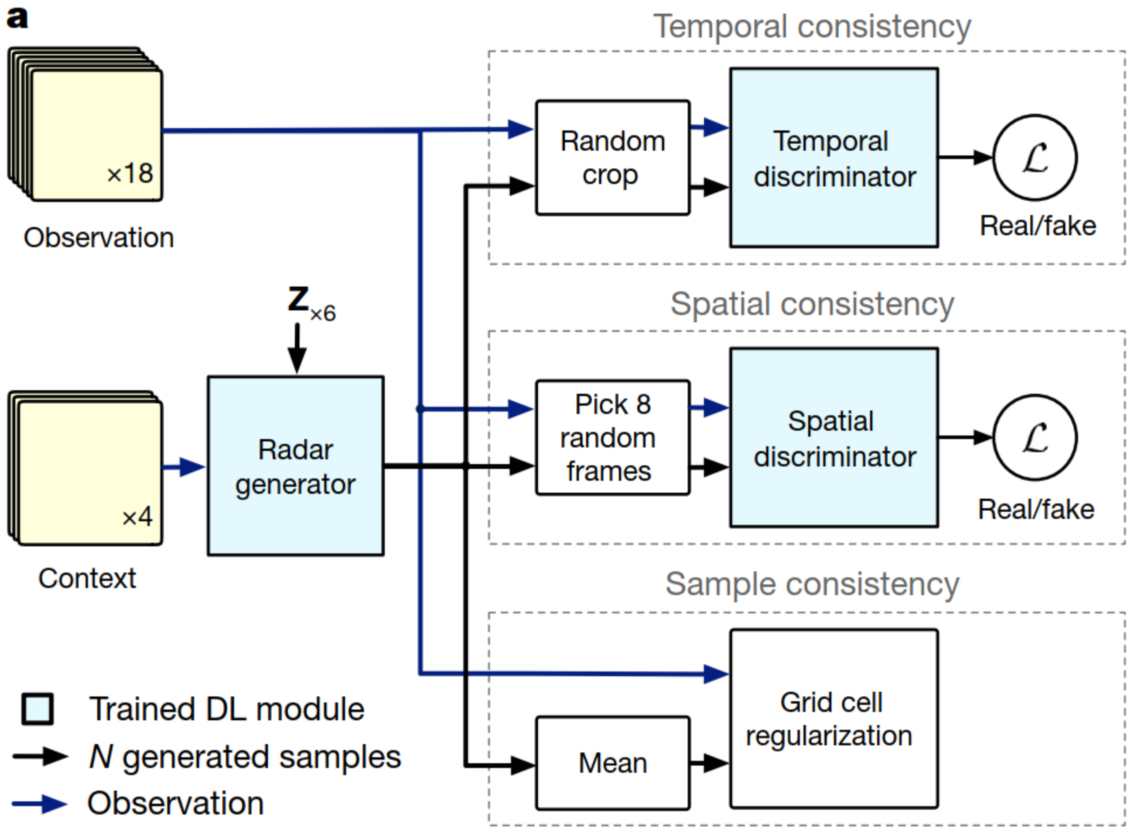
- Produce a precipitation nowcasting ensemble that
  - Is up to 2 hours ahead.
  - In addition to IMERG, also leverages IR imagery.
  - Is, hopefully, more skillful than considering IMERG only.
  - Takes advantage of recent, successful deep generative learning approaches in fore/nowcasting.

Deep Generative Models

- Deep Generative Models
  - Aim at learning data distributions.
  - Accomplished by learning transformations of random variables stemming from a known, reference distribution.
  - Enable sampling from these distributions.
- How they learn
  - Traditional estimation (maximum likelihood and variations thereof)
    - Typically, intractable for deep generative models.
  - Score matching
  - Adversarial learning, e.g., as employed by Generative Adversarial Networks (GANs)
- Of Interest: Deep Generative Model for Radar (DGMR).
  - DGMR [8] appeared in 2021.
  - Showcased skillful precipitation nowcasting up to 2 hours ahead over the UK based on Radar imagery.

DGMR for IMERG/IR Precipitation Nowcasting

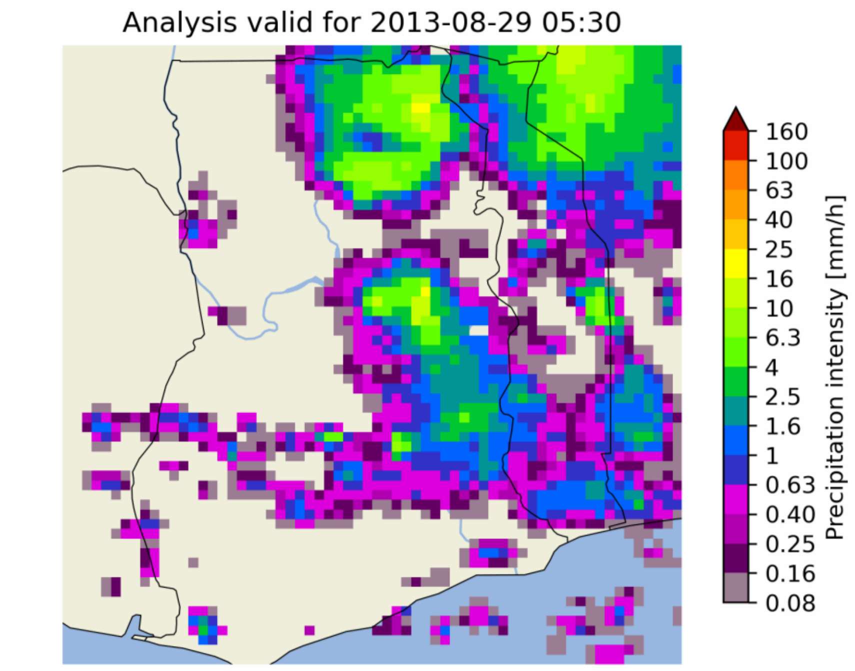
- DGMR architecture
  - A conditioning stack provides context at four different time/space scales.
  - Conditioning stack representations inform the outputs of recurrent networks, one for each nowcast.
- DGMR architecture for our purposes
  - Radar images are replaced by IMERG imagery.
  - The conditioning stack is expanded to include IR data.



Overview of DGMR architecture [8].

Training & Evaluation

- As a proof-of-concept, we chose to train and evaluate our model over Ghana, which has seen several flash flood events over the last decade.
- Specifically, we chose the month of October which falls in end of the rainy season in Ghana [7].
- We trained the models with precipitation from October of 2010 to 2018. With 2019 – 2022 used for evaluation.
- Training input images were of size 64x64 were obtained from IMERG samples.
- IR images were obtained from EUMETSAT (High Rate SEVIRI Level 1.5)
- Evaluation metrics
  - Critical Success Index (CSI)
  - Radially Averaged Power Spectral Density (RAPSD)



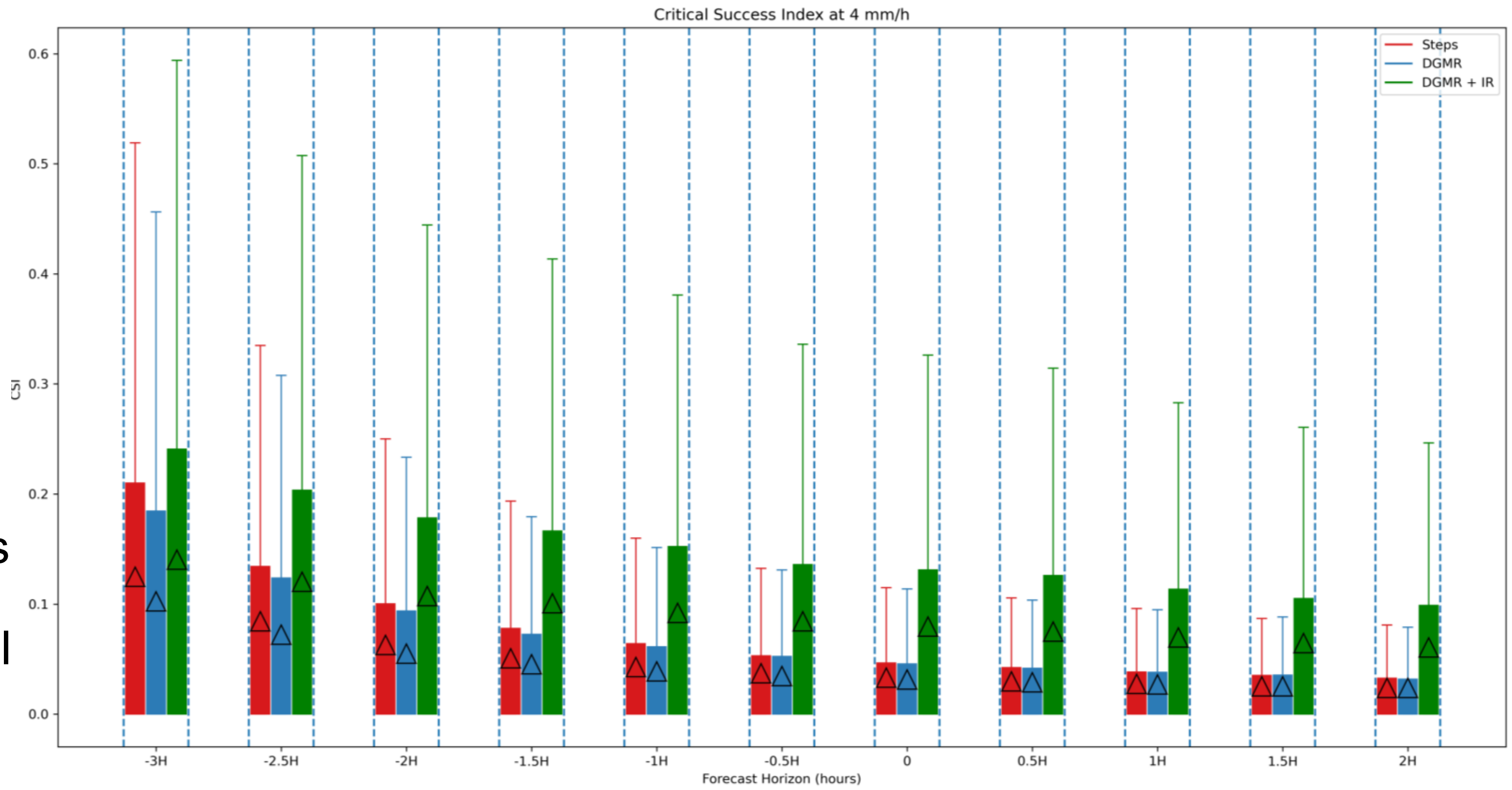
Results: CSI

CSI (Critical Success Index)

- For a given threshold, It is the ratio of hits to the sum of hits, false alarms and misses.
- It provides a balanced estimate of the quality of the forecasts.
- 1 indicates a perfect forecast

Observations

- Results indicate that for 4mm/h, the IMERG + IR model performs significantly better than both PySteps and IMERG only model for all time steps.
- In the absence of IR data, DGMR performs slightly worse than PySteps for all time steps.



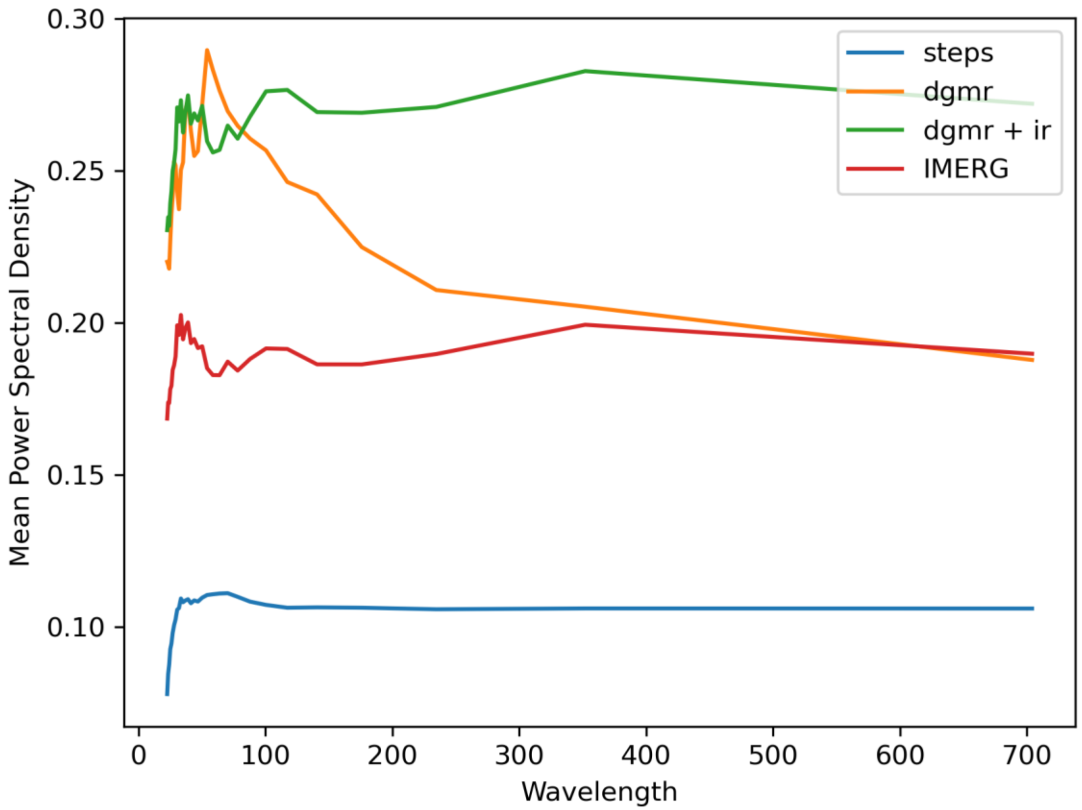
Results: RAPSD

Power Spectral Density

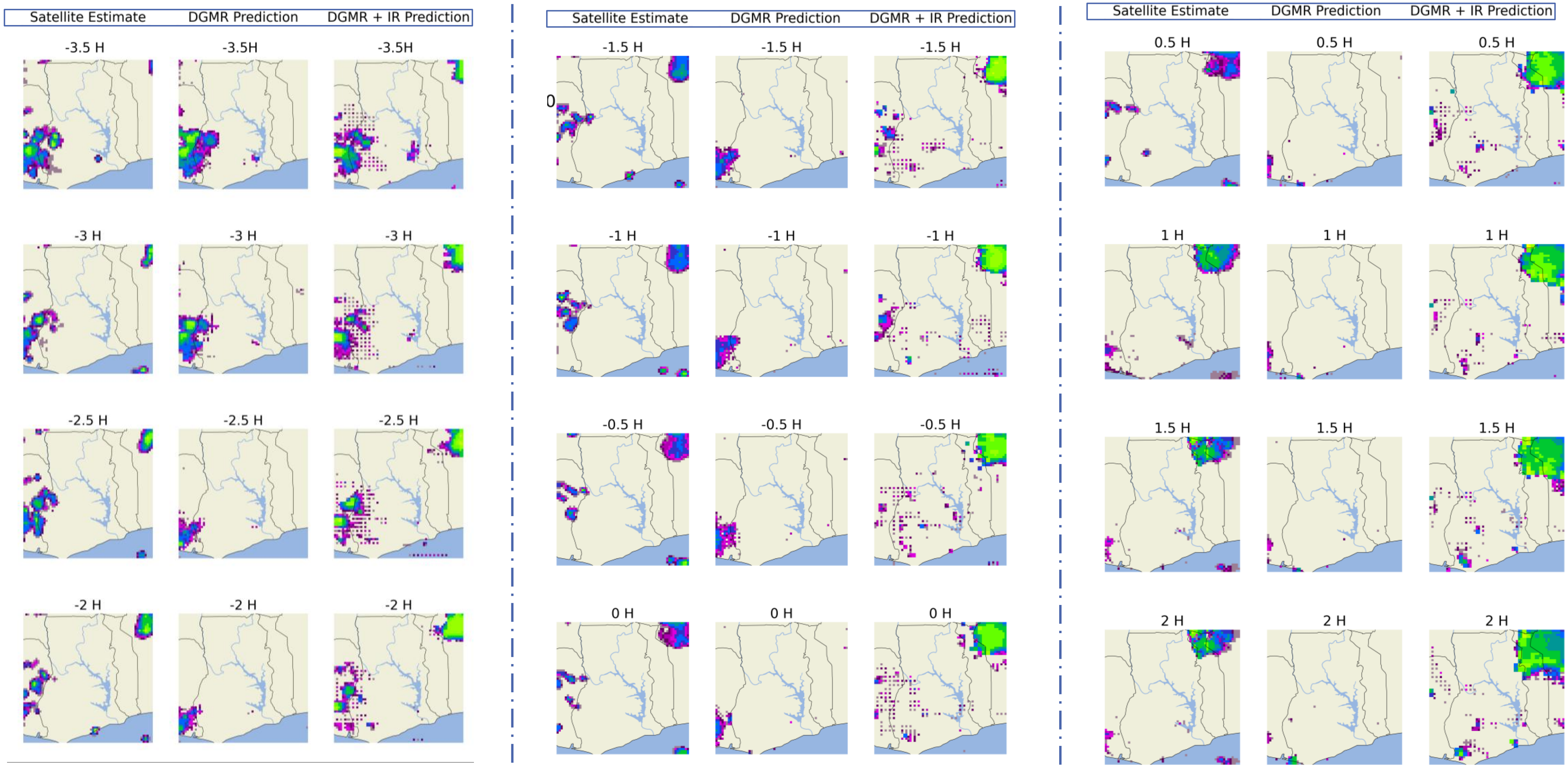
- Used to compare the power spectrum of the true and predicted image.
- The model for whom the curve is closer to the true output is determined to the better model

Observations

- DGMR aligns more with the IMERG for true IMERG outputs for later wavelengths.
- DGMR + IR aligns more with IMERG for earlier wavelengths but deviates for higher wavelengths.



Results: Precipitation Visualization



Main Takeaways

- DGMR can be a viable architecture for precipitation nowcasting exhibiting more skill than traditional alternatives.
- Our preliminary results reveal a tangible promise
    - Despite the significant data latency.
    - Especially, when incorporating IR imagery in precipitation nowcasting.
- This raises the question whether additional meteorological fields may aid the nowcasting task even further.
- Nevertheless, the adversarial training of DGMRs may pose significant challenges – beyond the heavy computational burden – in terms of training convergence/stability.
- Therefore, it may be fruitful to investigate alternatives (e.g., score-based diffusion models).

Thank you!

We will be happy to entertain a few questions now.

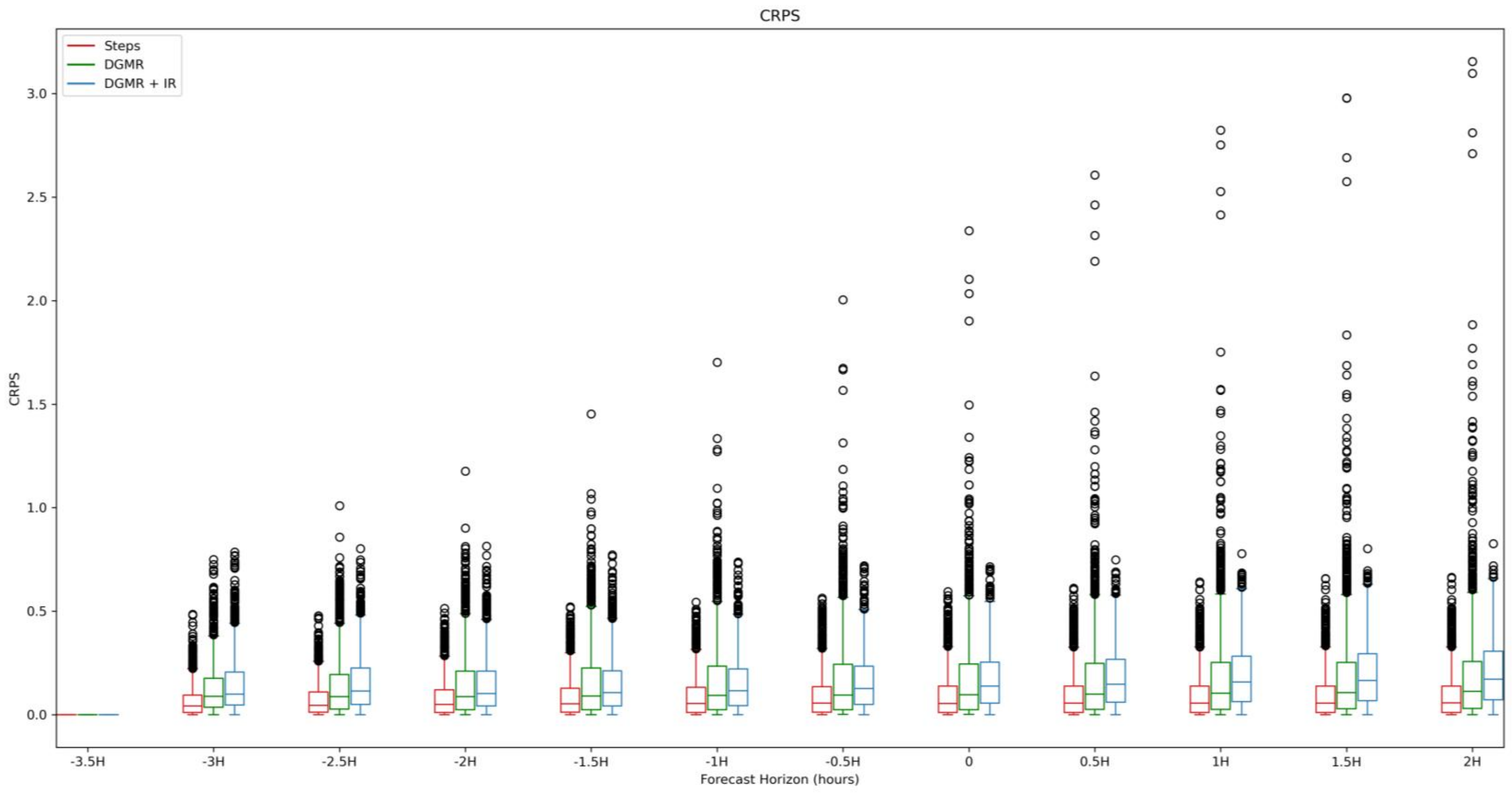
Results: CRPS

Continuous Ranked Probability Score

- Used to measure prediction ensembles.
- Compares the cumulative distribution functions
- The lower the CRPS, lower the difference between the distributions.

Observations

- PySteps in general has a lower CRPS compared to both DGMR and DGMR + IR.



Cited References

[1] Nouaceur, Z., & Murarescu, O. (2020). Rainfall Variability and Trend Analysis of Rainfall in West Africa (Senegal, Mauritania, Burkina Faso). Water, *12*(6), 1754. [DOI]

[2] Power, S. Historic Flooding in West and Central Africa Leaves Communities in Urgent Need. USAID/USAFID (n.d.). [URL]

[3] Asadu, C. (2022, October 22). West Africa floods destroy crops, worsening hunger fears. AP News. [URL]

[4] NASA. IMERG V06 Technical Documentation. (n.d.). [URL]

[5] EuMetSat product navigator. (n.d.). [URL]

[6] Ombadi, M., Nguyen, P., Sorooshian, S., and Hsu, K.-L. (2021). How much information on precipitation is contained in satellite infrared imagery? Atmospheric Research, 256, 105578. [DOI]

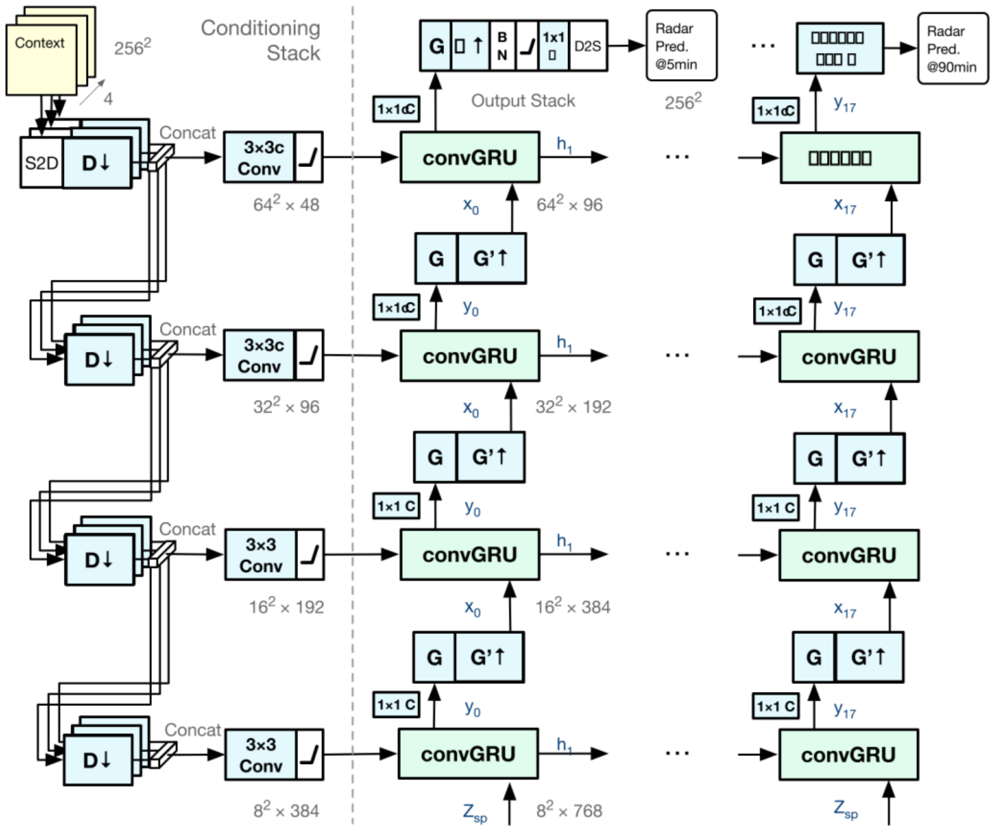
[7] *Undp climate change country profile: Ghana*. UNDP Climate Change Country Profile: Ghana | UNDP NCSP. (n.d.). [URL]

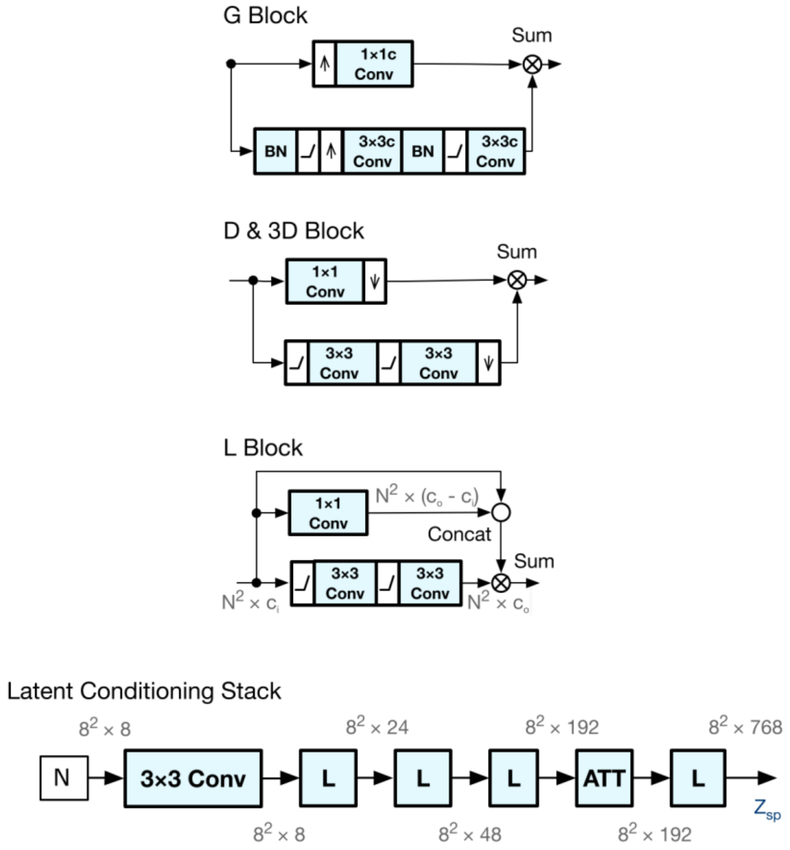
[8] Ravuri, S., Lenc, K., Willson, M., Kangin, D., Lam, R., Mirowski, P., Fitzsimons, M., Athanassiadou, M., Kashem, S., Madge, S., Prudden, R., Mandhane, A., Clark, A., Brock, A., Simonyan, K., Hadsell, R., Robinson, N., Clancy, E., Arribas, A. and Mohamed, S. (2021). Skilful precipitation nowcasting using deep generative models of radar. Nature volume 597, pages672–677. [DOI]

Backup Slides

DGMR Architecture

- Generator Architecture Closeup [8]





DGMR Architecture

- Discriminator Architecture Closeup [8]