

Master's thesis by
Ingrid Ingemarsson

Retrieving precipitation over Brazil

A Quantile Regression Neural
Networks approach

Intro

Data

Modelling

Results

Intro

Background

Water cycle

Society



Background

Water cycle

Society

Global warming

Extreme weather

Monitoring

nature

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nature > news > article

NEWS | 26 August 2021

Climate change implicated in Germany's deadly floods

Attribution study suggests extreme flood events will become more common in Western Europe as the world warms.

Holly Else



Natten mot onsdag har kraftiga skyfall drabbat Gävleborg och Dalarna. I näheten av Romme Alpin, mellan Bortfänge och Smedjebacken, har en del av en bilväg har rasat. Foto: Ulf Palm/TT

GÄVLEBORG



Kraftiga skyfall och stora översvämnningar i Gävle

NEWS

Home | Coronavirus | Climate | Video | World | UK | Business | Tech | Science | Stories | Entertainment & Arts

Asia | China | India

China floods: Nearly 2 million displaced in Shanxi province

© 11 October



Agência Brasil

Record rainfall caused severe flooding in the city of Jinzhong, in the northern Chinese province of Shanxi, on Saturday, displacing nearly 2 million people. The flooding has been caused by heavy rain and snowmelt from melting snow in the mountains. The government has declared a state of emergency in the area. The flooding has caused widespread damage to infrastructure, including roads, bridges, and buildings. The government is providing aid to affected areas, including food, water, and medical supplies. The flooding has also caused some loss of life. The government is urging people to stay safe and avoid flood-prone areas.

Heavy and prolonged rainfall and storms are further hampering rescue efforts.

Chuvas deixam Amazonas em estado de atenção

Defesa civil diz que 13 cidades decretaram emergência

Available methods

Rain gauges

Ground radars

Satellite remote sensing



Available methods

Rain gauges

Ground radars

Satellite remote sensing



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Satellite remote sensing

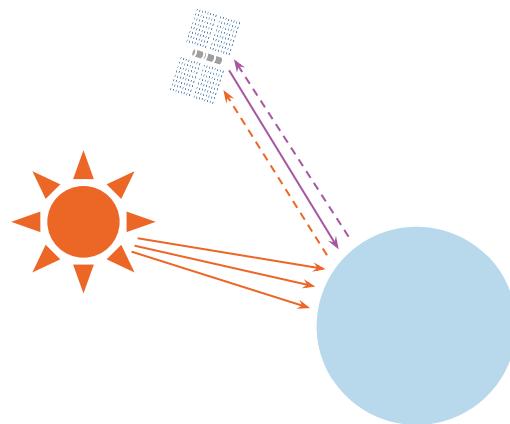


Available methods

Rain gauges

Ground radars

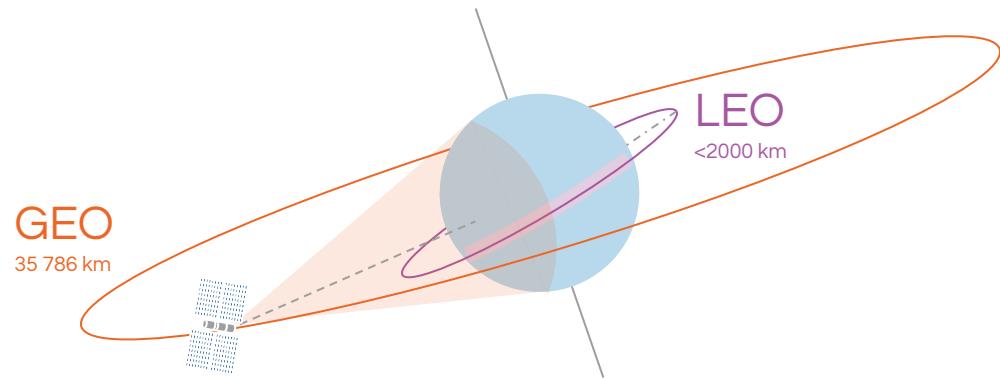
Satellite remote sensing



Orbit type

Geostationary Earth Orbit

Low Earth Orbit



Orbit type

Frequency

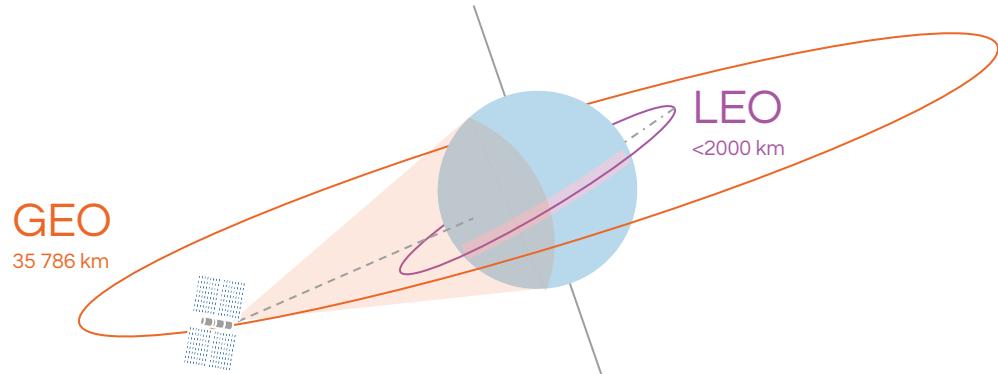
Temporal resolution

Geostationary Earth Orbit

Low Earth Orbit

Microwave
~ Precipitation

Low



Orbit type

Frequency

Temporal resolution

Geostationary Earth Orbit

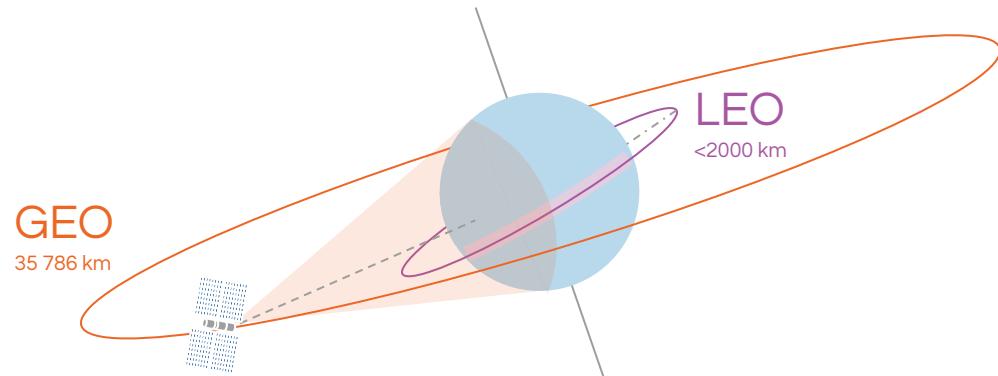
Visible & Infrared
~ Cloud top temperature

High

Low Earth Orbit

Microwave
~ Precipitation rate

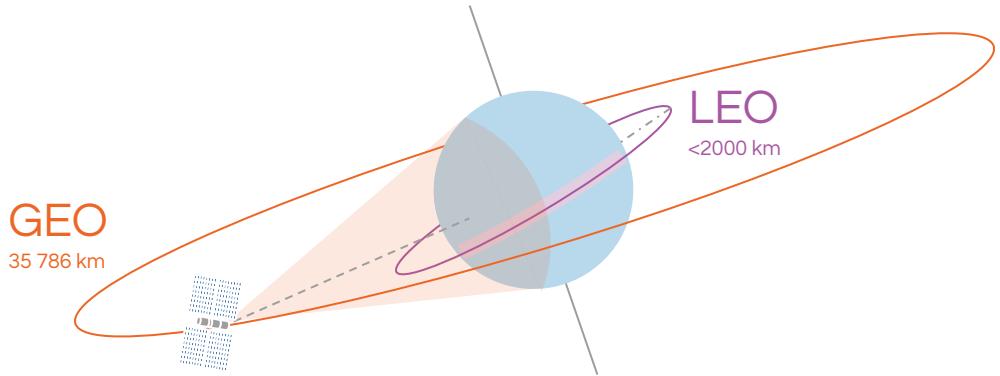
Low



In this thesis

Can we obtain high quality precipitation retrievals from geostationary observations?

→ Combine **GEO** and **LEO** observations



In this thesis

Can we obtain high quality precipitation retrievals from geostationary observations?

- Combine **GEO** and **LEO** observations
- Consider uncertainty

y : cloud top temperature observations
 x : precipitation rate

$$p(x|y)$$

Data

Source

Satellites

GOES-16 (**GEO**)
GPM CO (**LEO**)



Source

Satellites

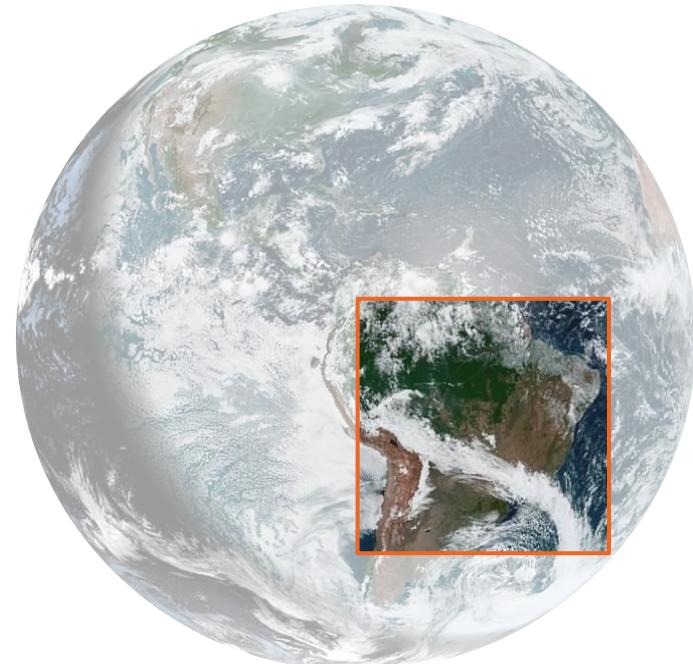
GOES-16 (**GEO**)
GPM CO (**LEO**)

Region

Brazil

Dates

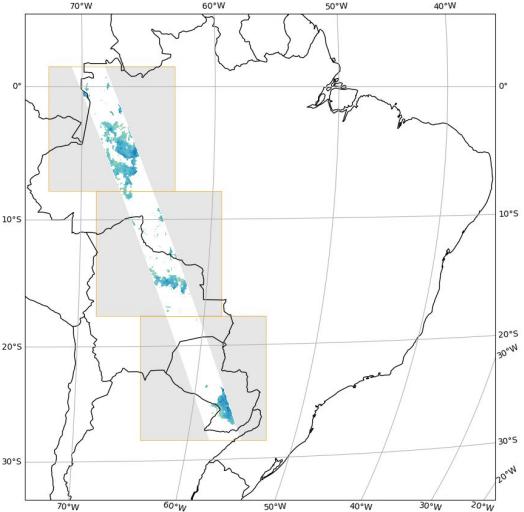
from: 2017 Dec
to: 2021 Mar



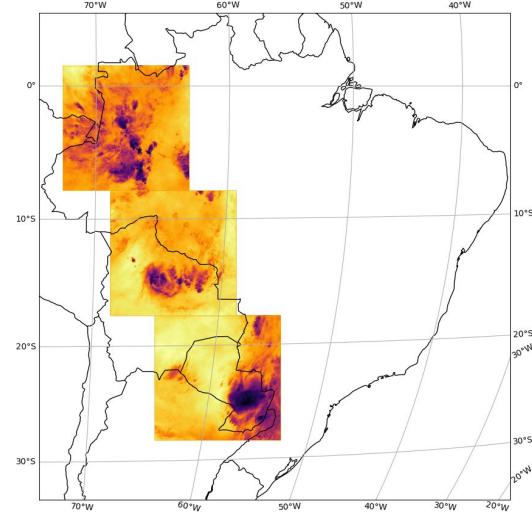
Data processing

Transform label

Match along path



Label
Precipitation rate
(LEO)

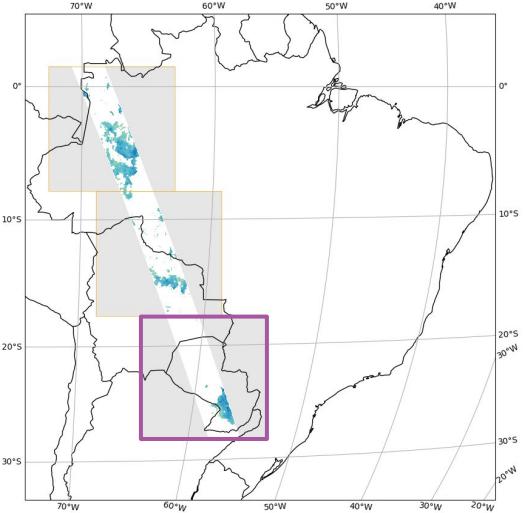


Input channels
Brightness temperature
(GEO)

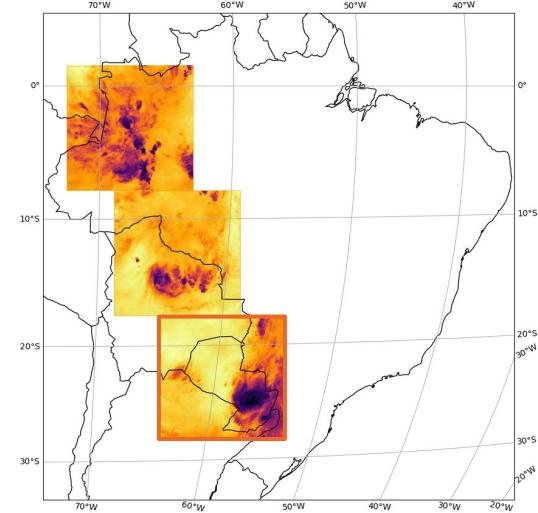
Data processing

Transform label

Match along path



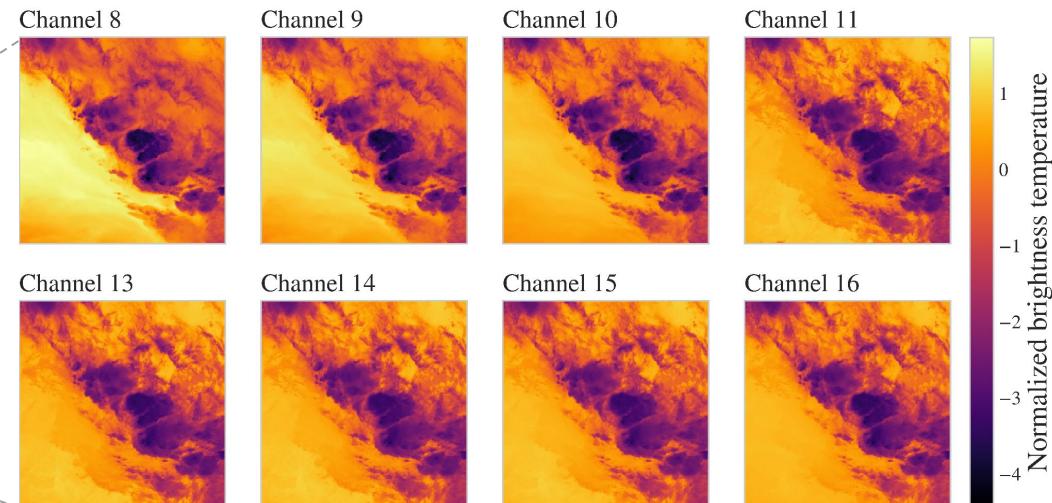
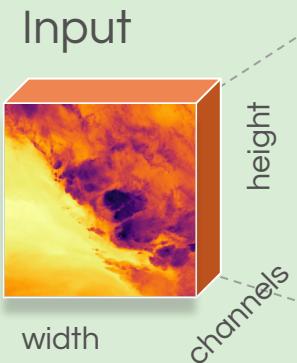
Label
Precipitation rate
(**LEO**)



Input channels
Brightness temperature
(**GEO**)

Input

Channels sensitive
to different radiation
frequencies



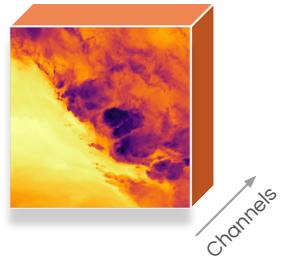
Data split

Split	Period start	Period end	Samples
train	2017 Dec	2020 Mar	5212
validation	2017 Dec	2020 Mar	1354
test	2020 Apr	2021 Mar	2928

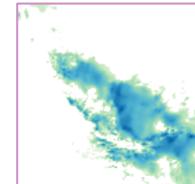
Modelling

Input & Output

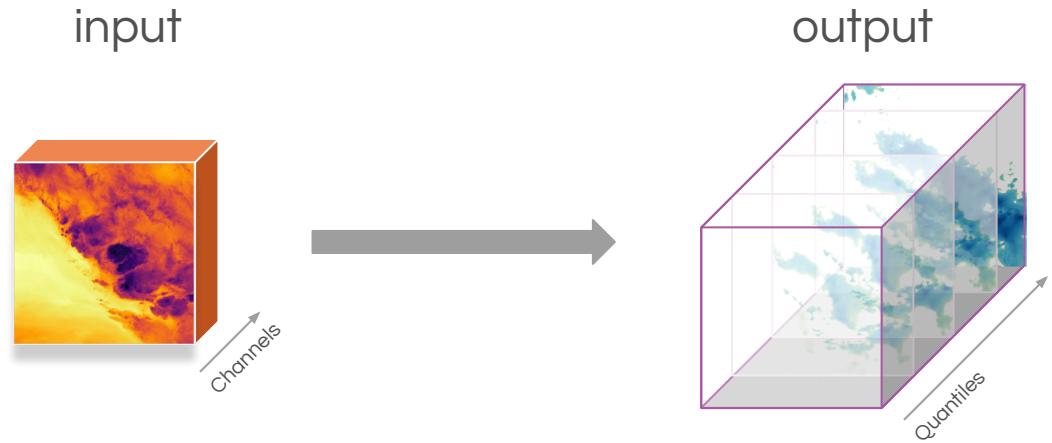
input



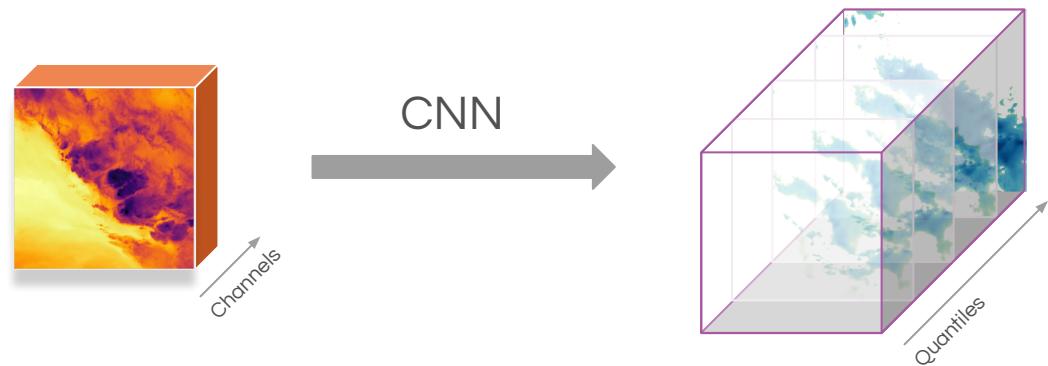
output



Input & Output

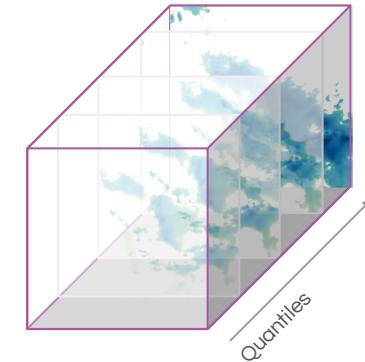
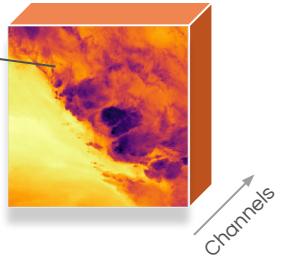
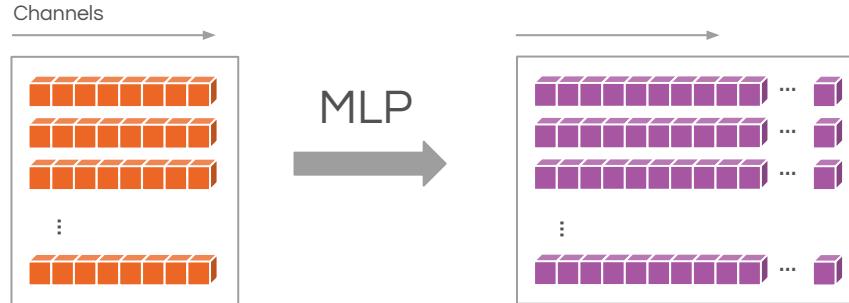


Input & Output



Input & Output

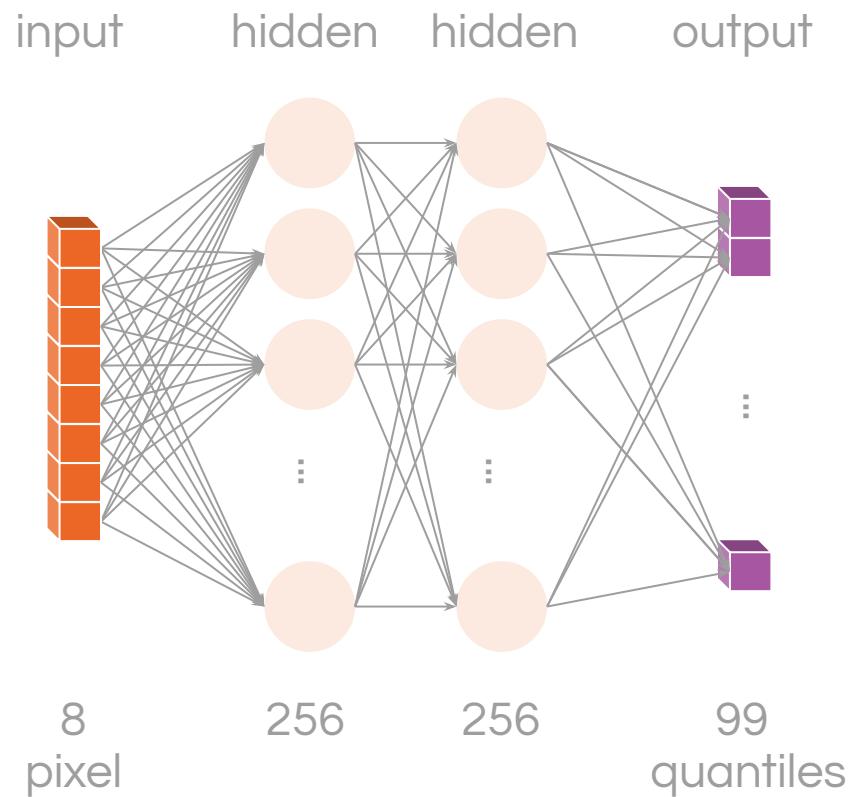
Independent pixels



Multilayer Perceptron

Linear

ReLU activation



Convolutional Neural Network

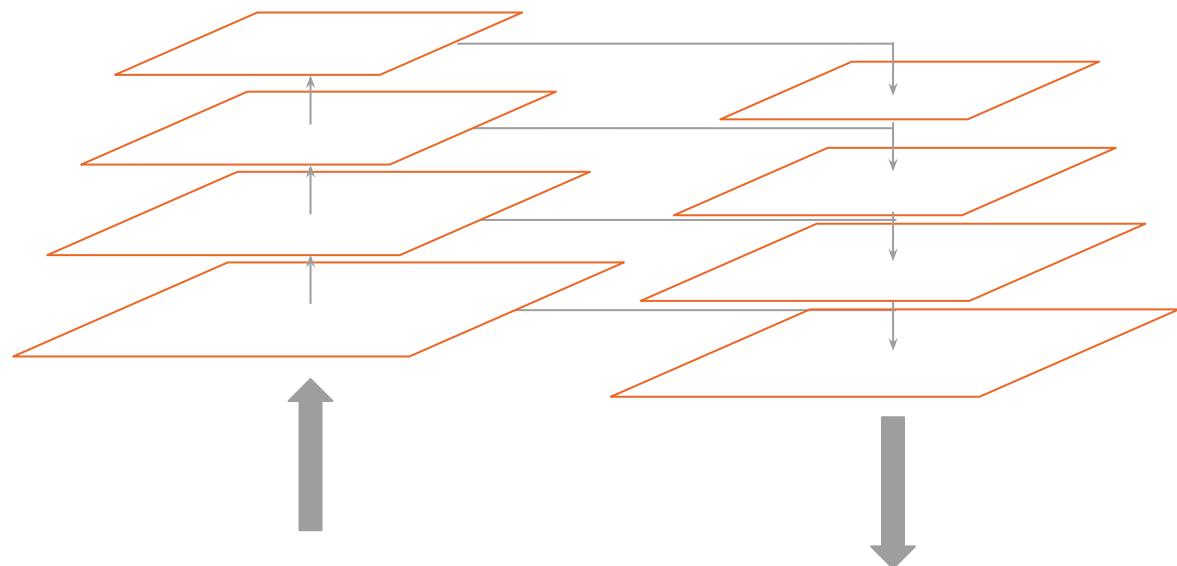
Feature pyramid
network

Depth-wise
Separable
Convolution

Convolutional Neural Network

Feature pyramid
network

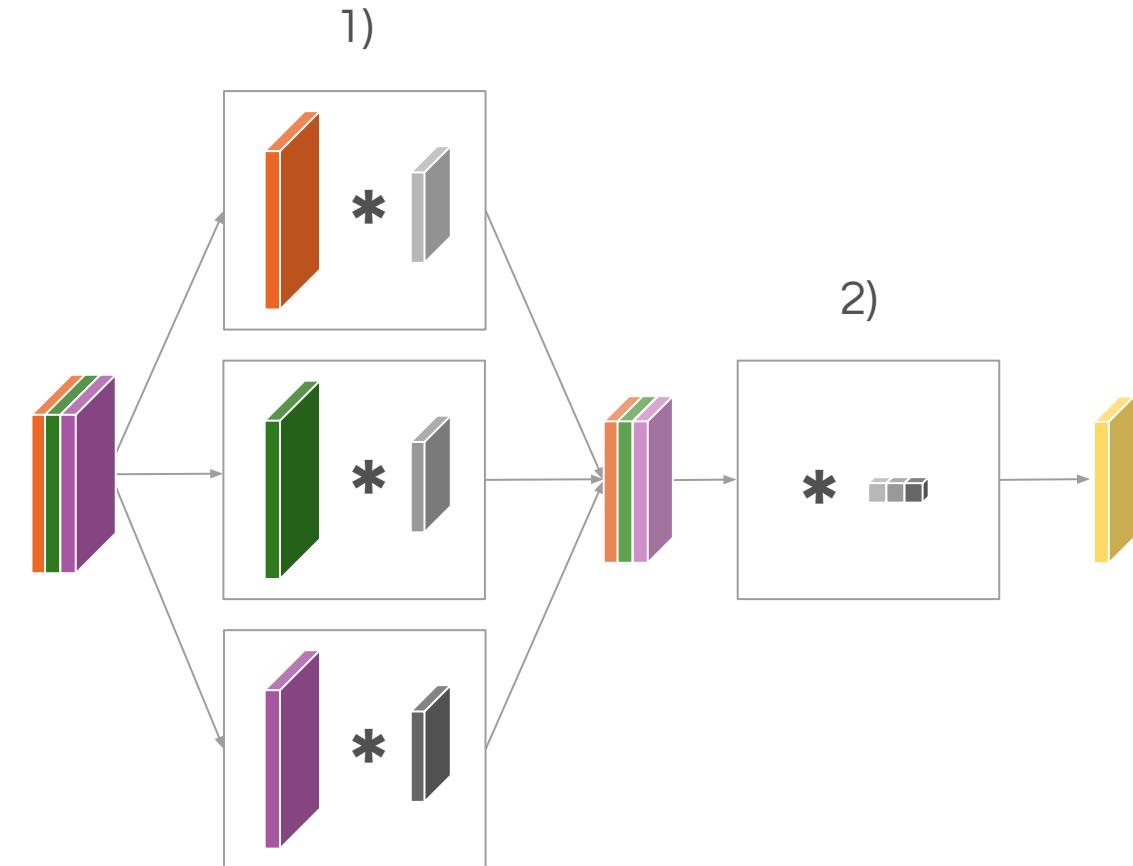
Depth-wise
Separable
Convolution



Convolutional Neural Network

Feature pyramid
network

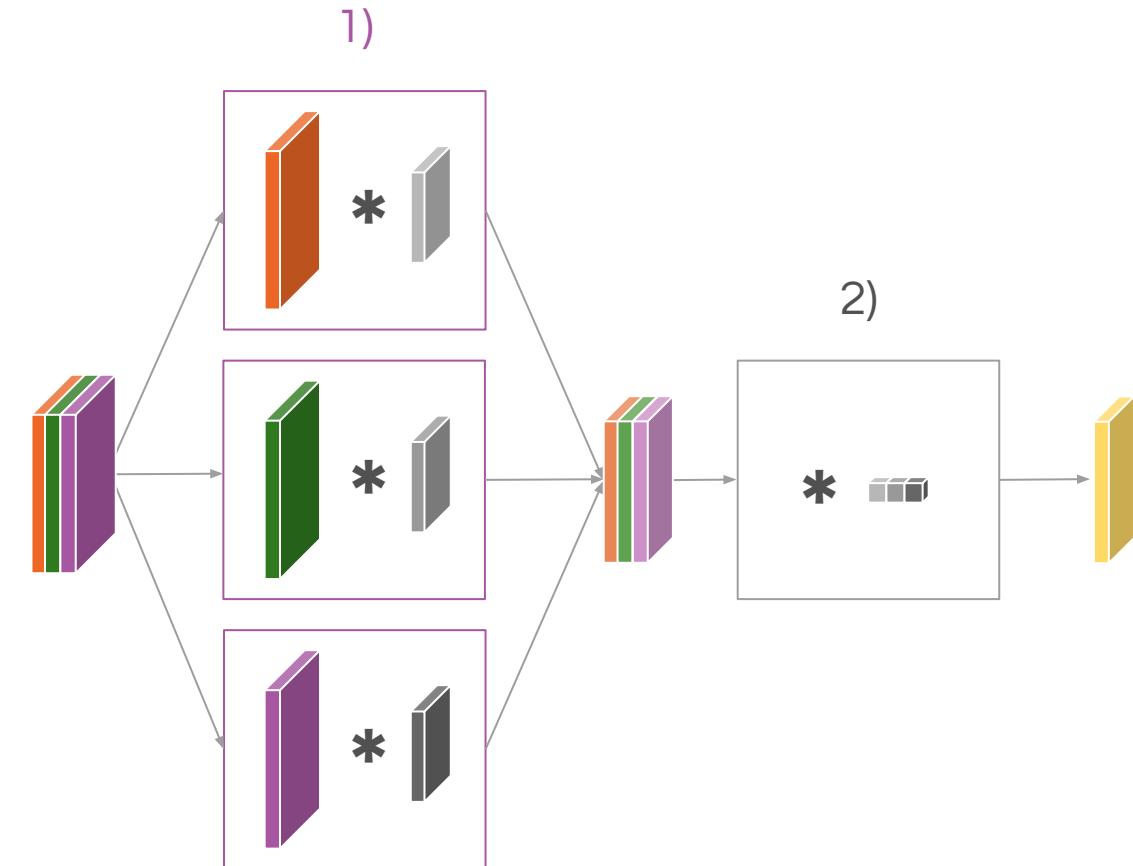
Depth-wise
Separable
Convolution



Convolutional Neural Network

Feature pyramid
network

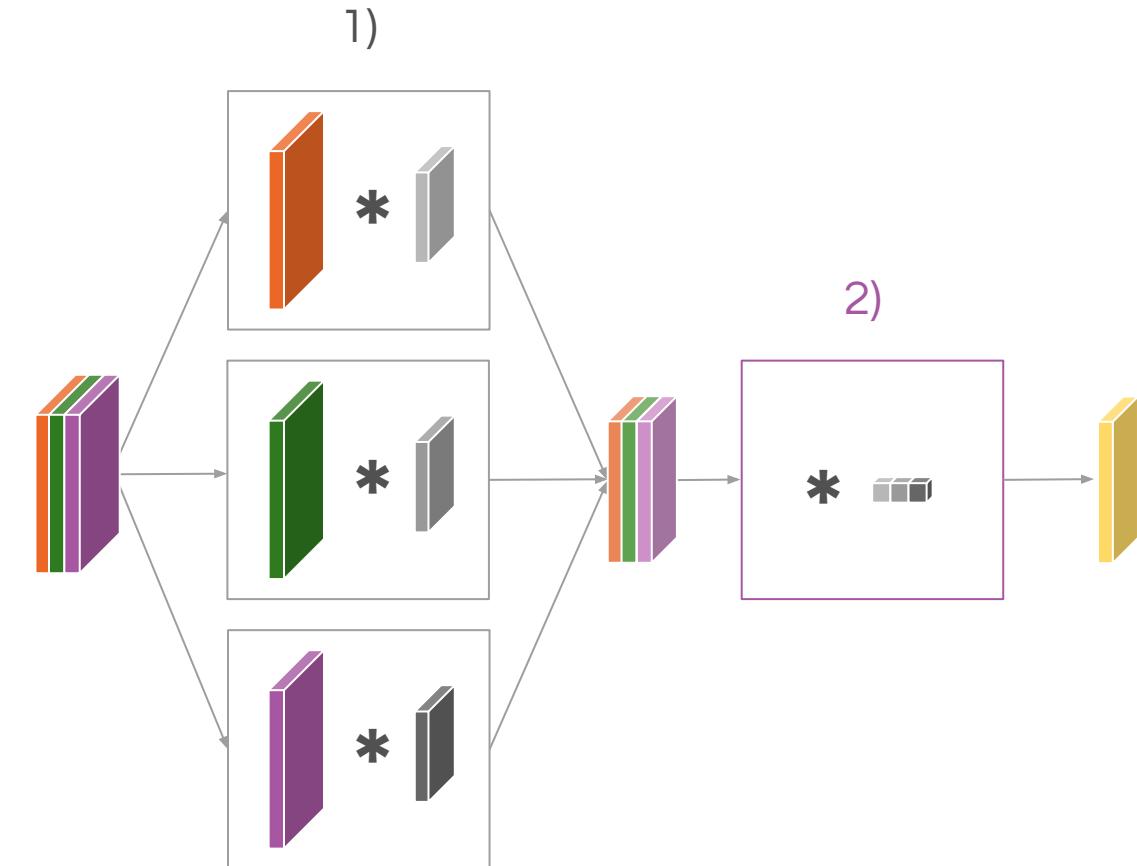
Depth-wise
Separable
Convolution



Convolutional Neural Network

Feature pyramid network

Depth-wise
Separable
Convolution



Quantile regression

Quantile regression

x_τ : τ th quantile

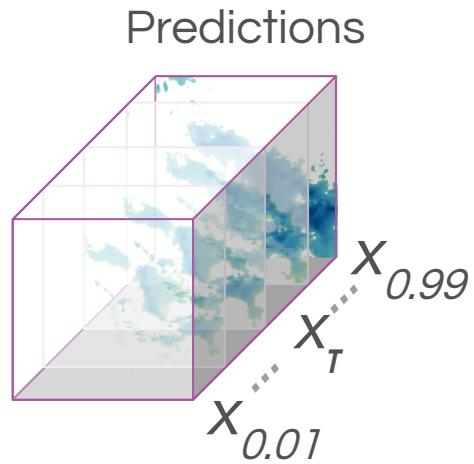
Quantile regression

x_τ : τ th quantile

$$L_\tau(x_\tau, x) = \begin{cases} \tau |x - x_\tau|, & x_\tau < x \\ (1 - \tau) |x - x_\tau|, & x_\tau \geq x \end{cases}$$

Quantile regression

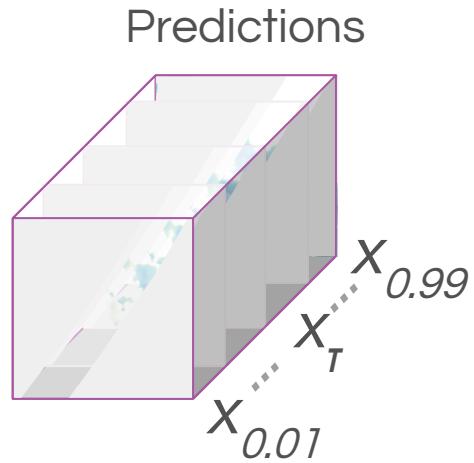
x_τ : τ th quantile



$$L_\tau(x_\tau, x) = \begin{cases} \tau |x - x_\tau|, & x_\tau < x \\ (1 - \tau) |x - x_\tau|, & x_\tau \geq x \end{cases}$$

Quantile regression

x_τ : τ th quantile

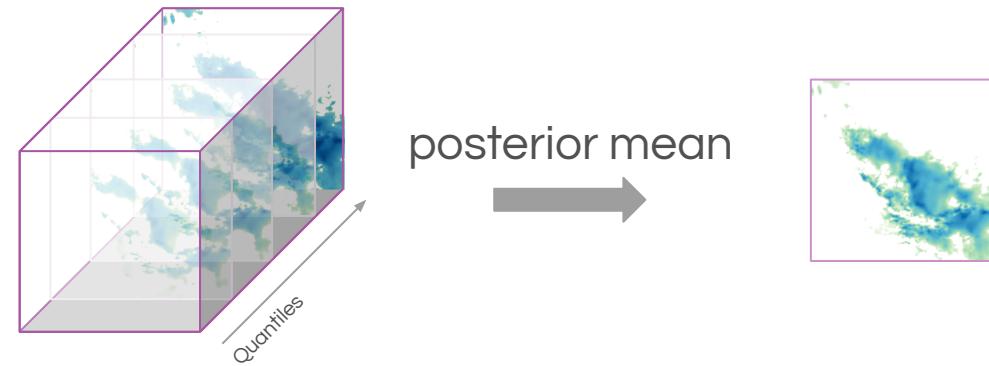


$$L_\tau(x_\tau, x) = \begin{cases} \tau |x - x_\tau|, & x_\tau < x \\ (1 - \tau) |x - x_\tau|, & x_\tau \geq x \end{cases}$$

Results

Evaluation

Posterior mean



Metrics

Regression

Bias

Mean absolute error (MAE)

Mean squared error (MSE)

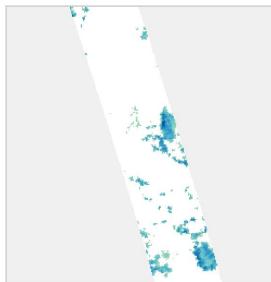
Probabilistic

Loss

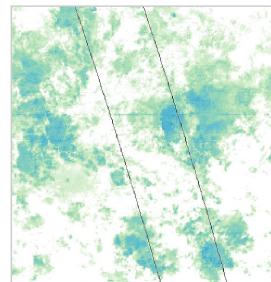
Continuous Ranked Probability Score (CRPS)

Example predictions

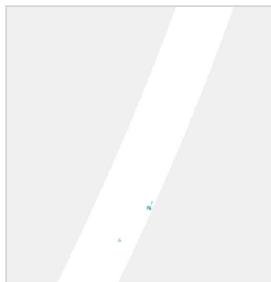
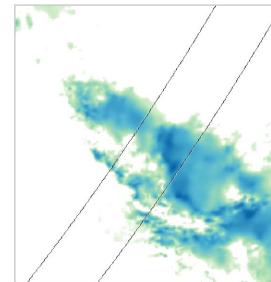
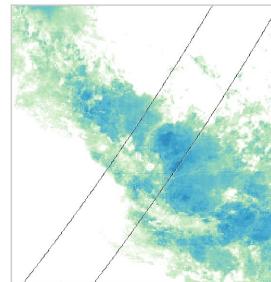
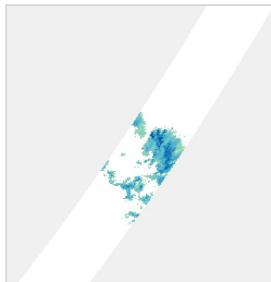
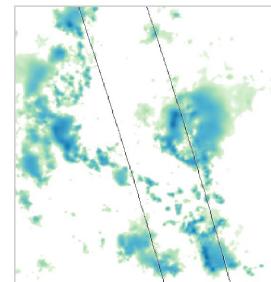
Ground truth



MLP

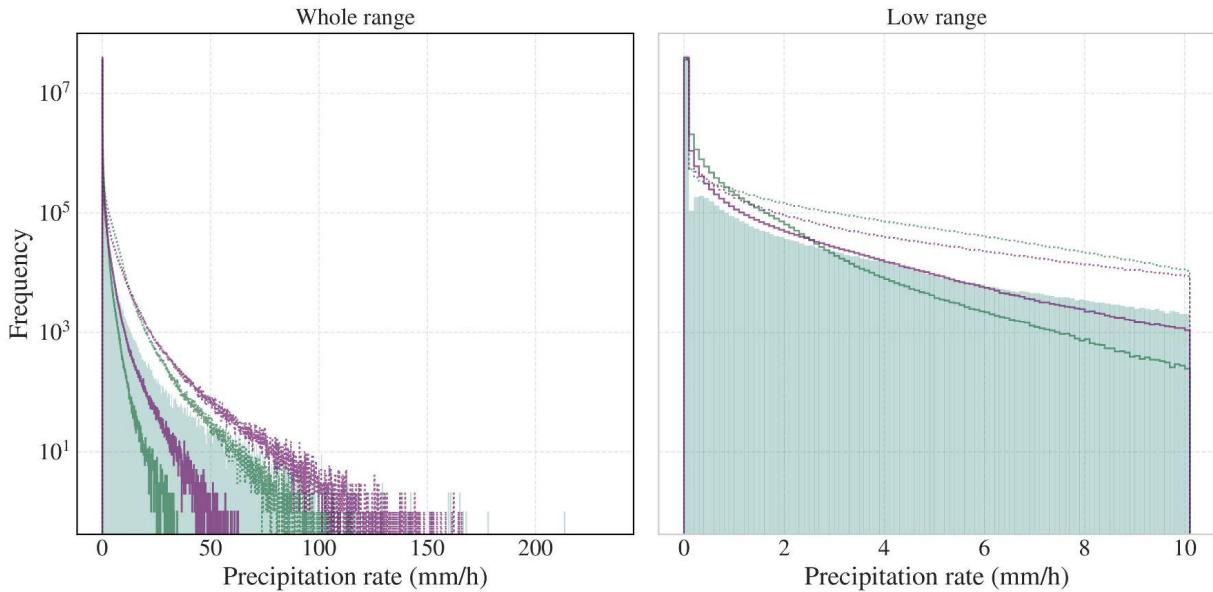


CNN



Distribution

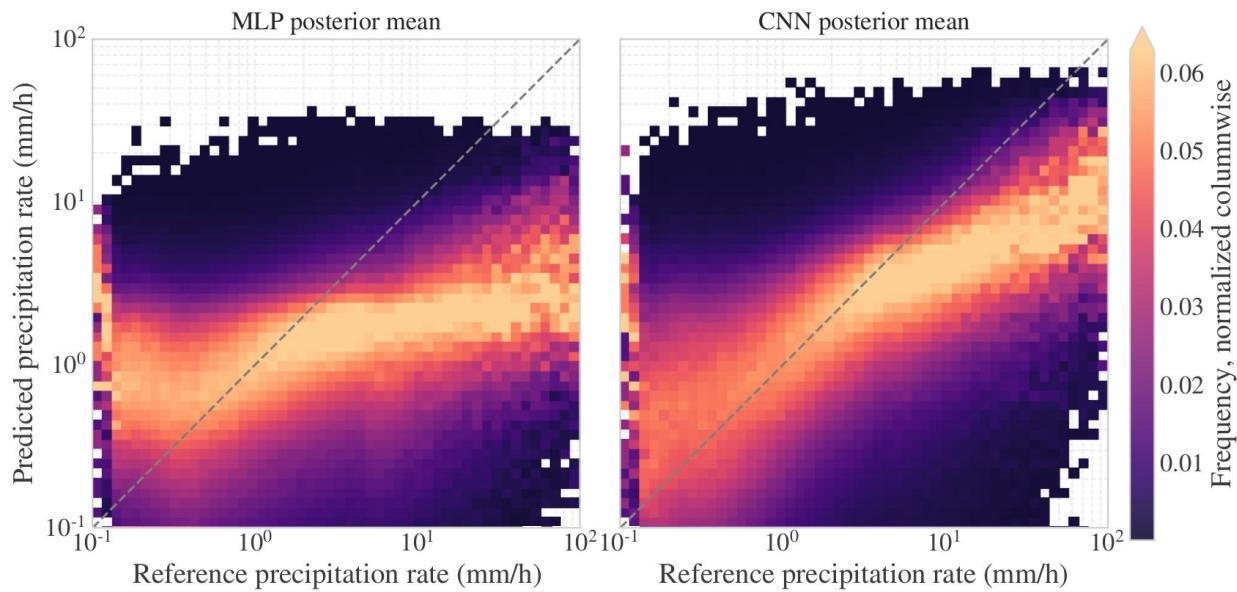
Ground truth MLP posterior mean CNN posterior mean
MLP 95th quantile CNN 95th quantile



Metrics

Metric	MLP	CNN
Bias	-0.00952	0.00980
MAE	0.197	0.148
MSE	1.53	1.23
Mean loss	0.0625	0.0504
Mean CRPS	0.116	0.0945

2D-histogram



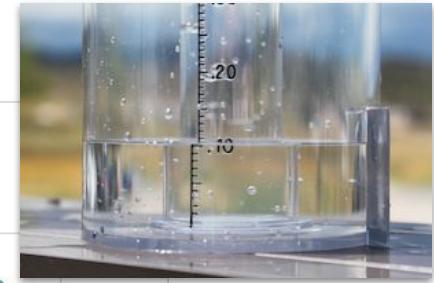
Independent test data

INPE

Rain gauges

Dec 2020

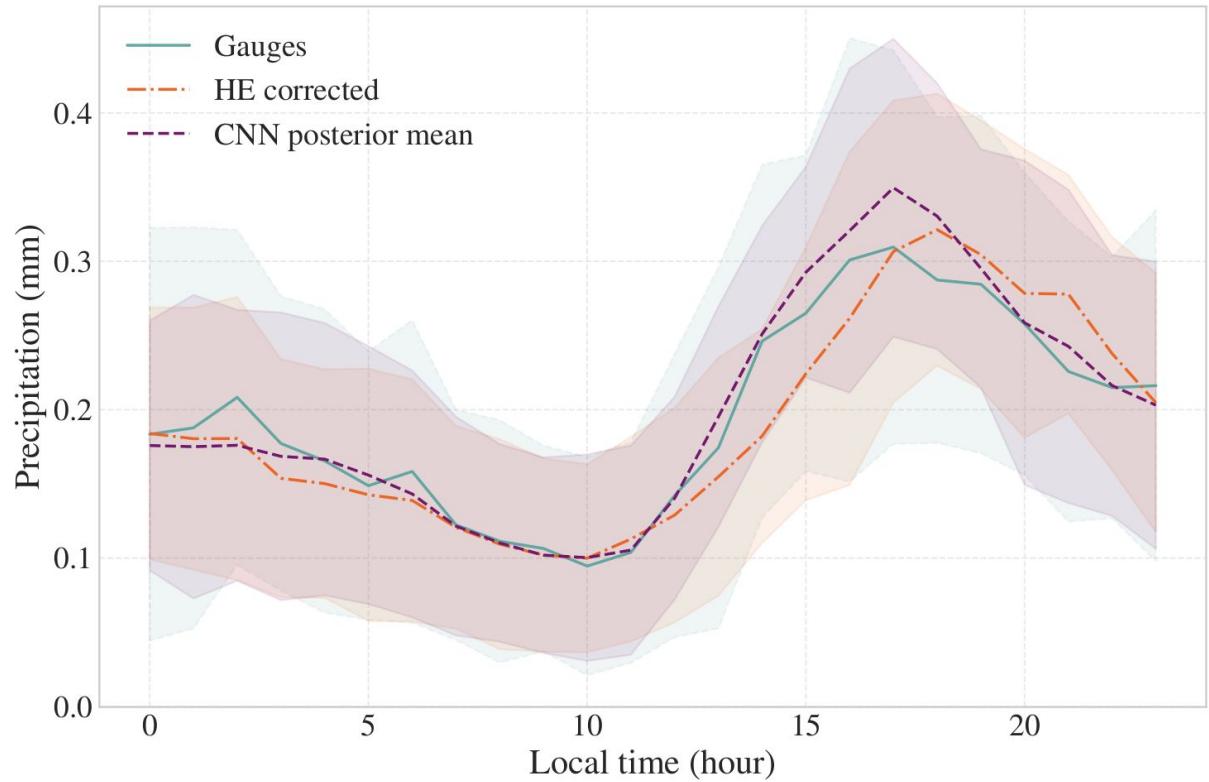
Compare to
Hydro-Estimator



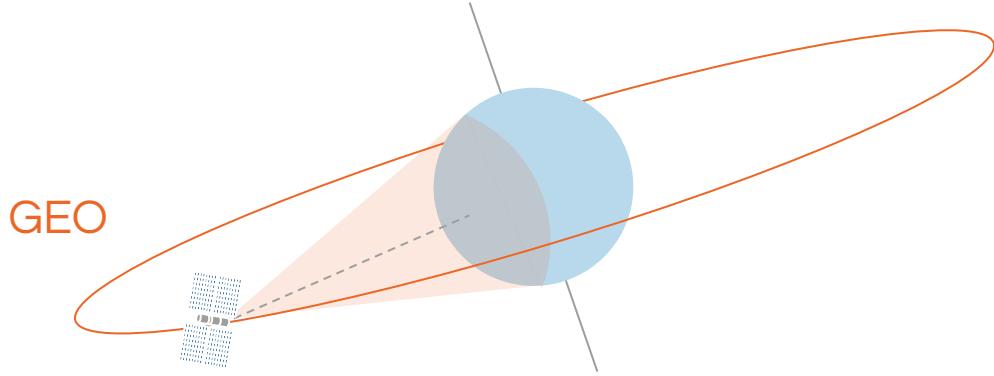
Metrics

Metric	HE	HE corr.	MLP	CNN
Bias	0.104	-0.00655	-0.0213	0.00423
MAE	0.394	0.300	0.265	0.232
MSE	3.94	2.44	2.04	1.70

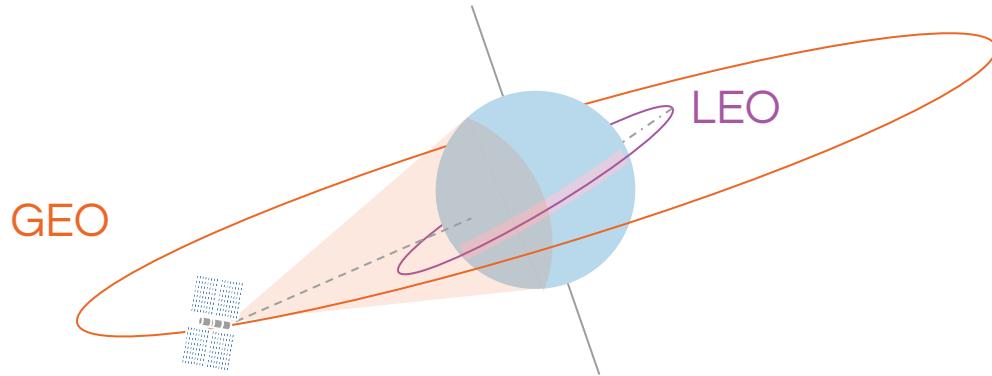
Diurnal cycle



Conclusions



Conclusions



Conclusions

- Spatial info improves the retrieval

Conclusions

- Spatial info improves the retrieval
- QRNN models outperform HE



Thank you for
listening!

Image sources

Background:

<https://unsplash.com/photos/1YHXFeOYpN0>

<https://www.bbc.com/news/world-asia-china-58866854>

<https://www.nature.com/articles/d41586-021-02330-y>

<https://www.svt.se/nyheter/lokalt/gavleborg/stora-oversvamningar-allmanheten-varnas>

<https://agenciabrasil.ebc.com.br/geral/noticia/2021-04/chuvas-deixam-regiao-norte-em-estado-de-atencao>

Available methods:

<https://www.cocorahs.org/>

<http://www.nwclimate.org/guides/weather-radar-websites/>

<https://www.ospo.noaa.gov/Operations/GOES/transition.html>

Source:

https://www.star.nesdis.noaa.gov/GOES/fulldisk_band.php?sat=G16&band=GEOCOLOR&length=24