Master’s thesis by
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Retrieving precipitation over Brazil

A Quantile Regression Neural Networks approach

Intro

Data

Modelling

Results

Intro

Background

Water cycle

Society

Background

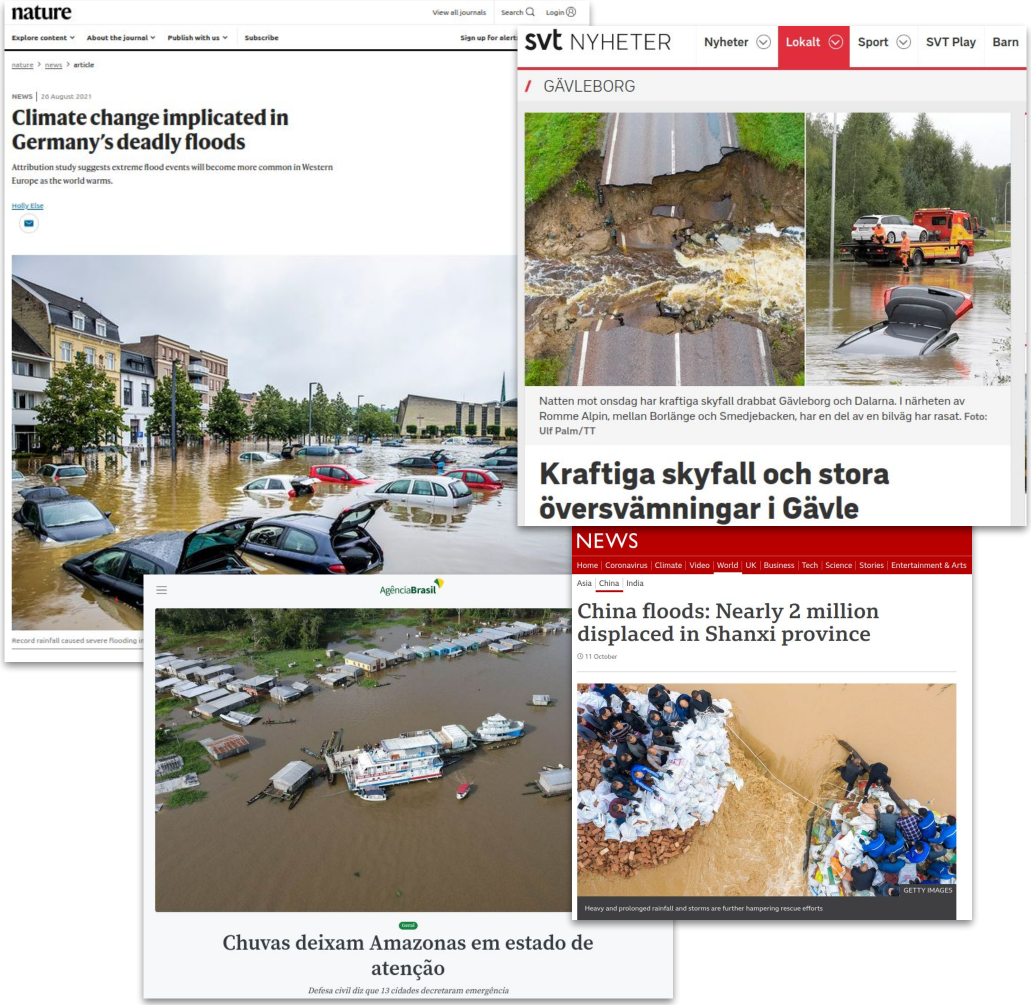
Water cycle

Society

Global warming

Extreme weather

Monitoring

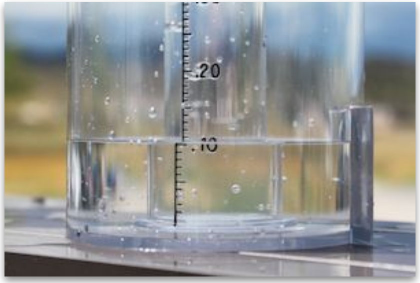


Available methods

Rain gauges

Ground radars

Satellite remote sensing



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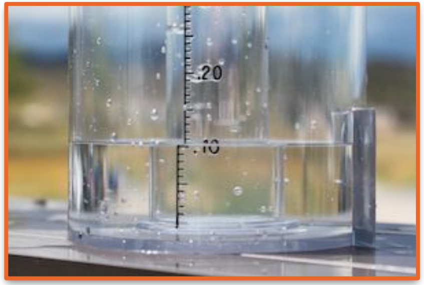

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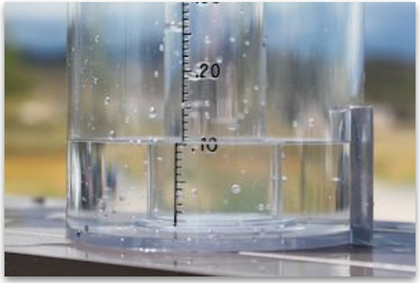

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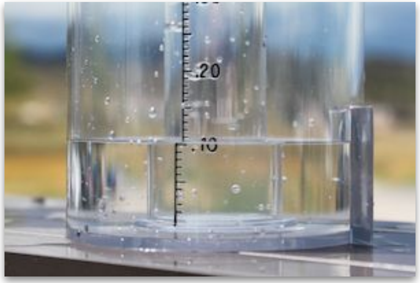

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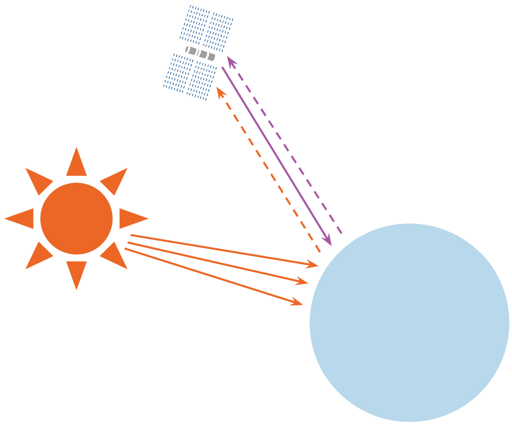
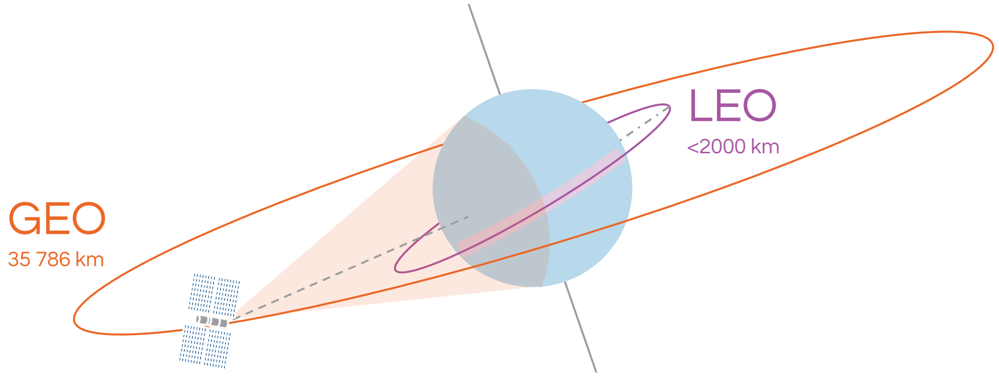


Orbit type

Geostationary Earth Orbit

Low Earth Orbit



Orbit type

Frequency

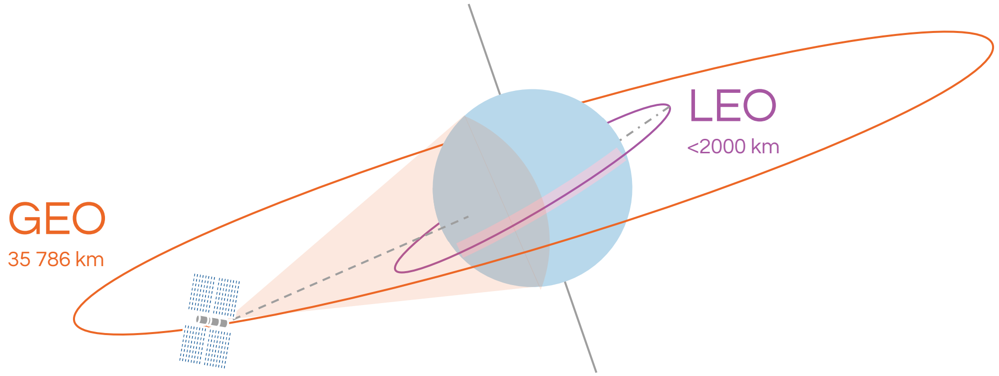
Temporal resolution

Geostationary Earth Orbit

Low Earth Orbit

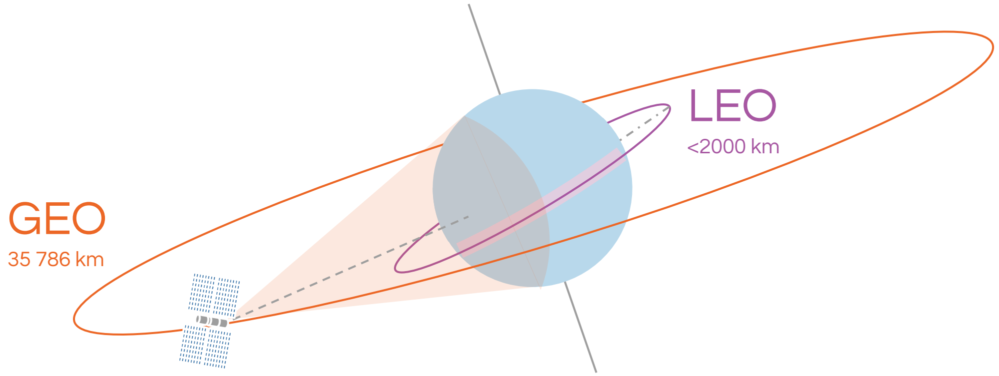
Microwave
~ Precipitation

Low



Orbit type

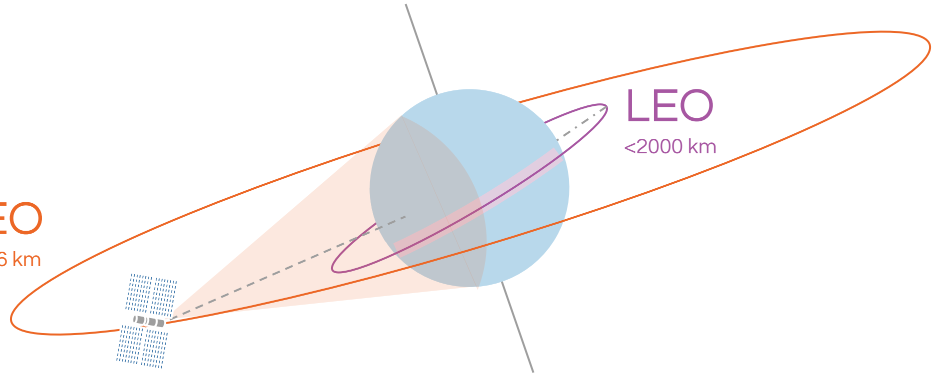
	Geostationary Earth Orbit	Low Earth Orbit
Frequency	Visible & Infrared ~ Cloud top temperature	Microwave ~ Precipitation rate
Temporal resolution	High	Low



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

$\boldsymbol{y}$: cloud top temperature observations
x: precipitation rate

$$p(x \mid \boldsymbol{y})$$

Data

Source

Satellites

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

Source

Satellites

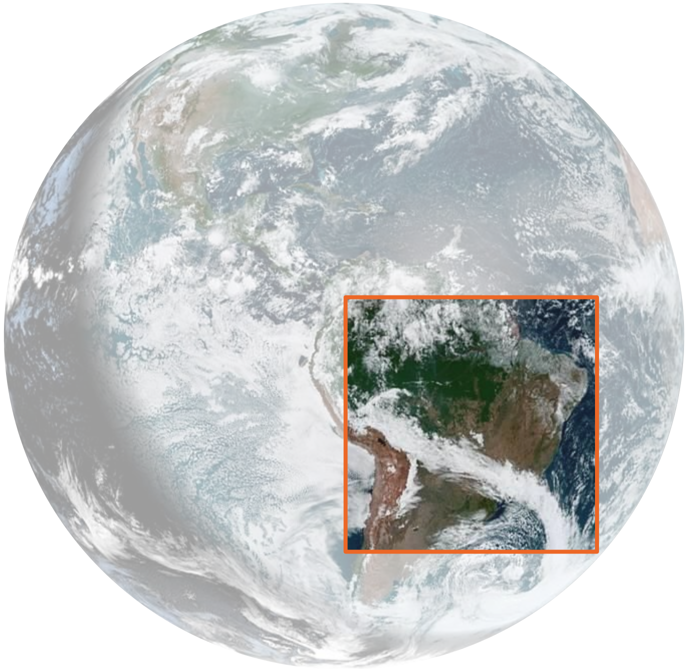
GOES-16 (GEO)
GPM *CO* (LEO)

Region

Brazil

Dates

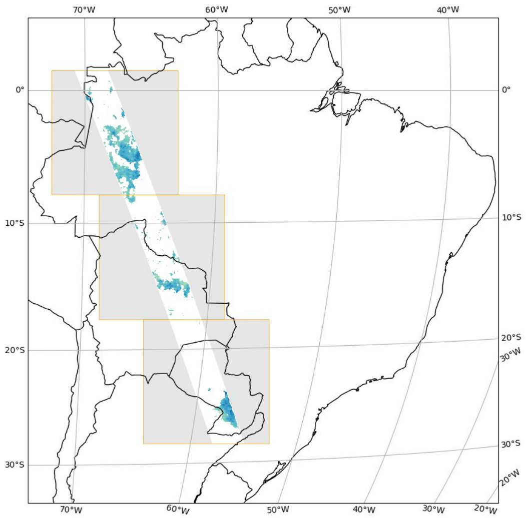
from: 2017 Dec
to: 2021 Mar

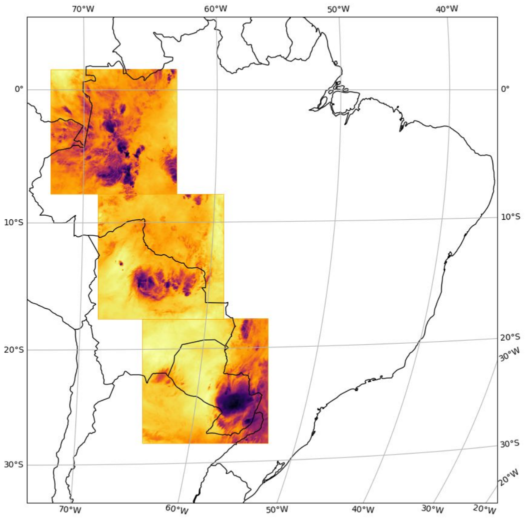


Data processing

Transform label

Match along path





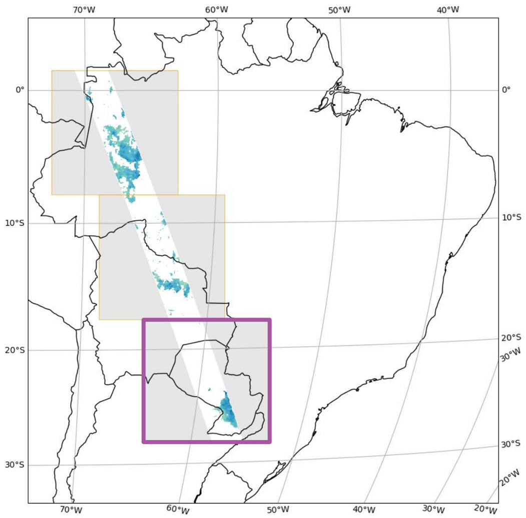
Label
Precipitation rate
(LEO)

Input channels
Brightness temperature
(GEO)

Data processing

Transform label

Match along path



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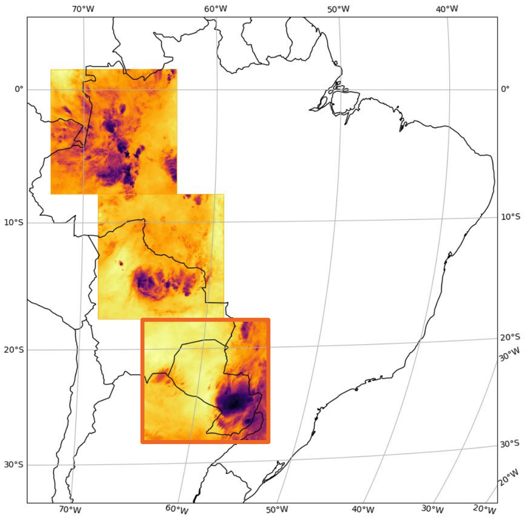
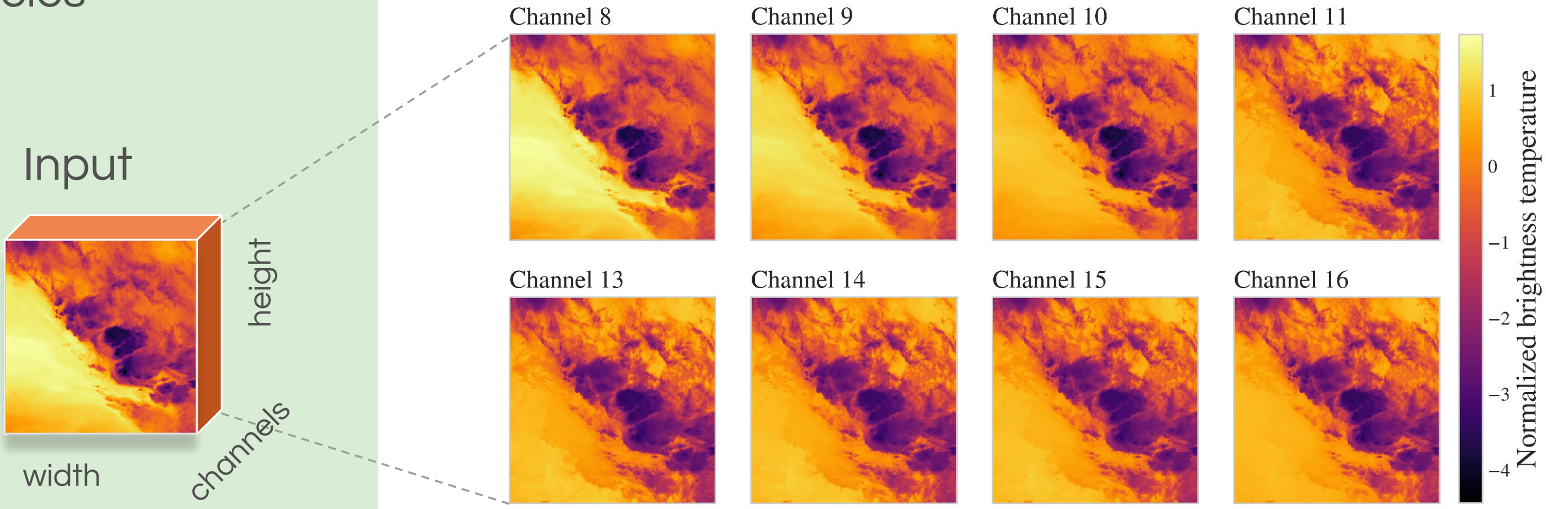


Input channels
Brightness temperature
(GEO)

Input

Channels sensitive to different radiation frequencies



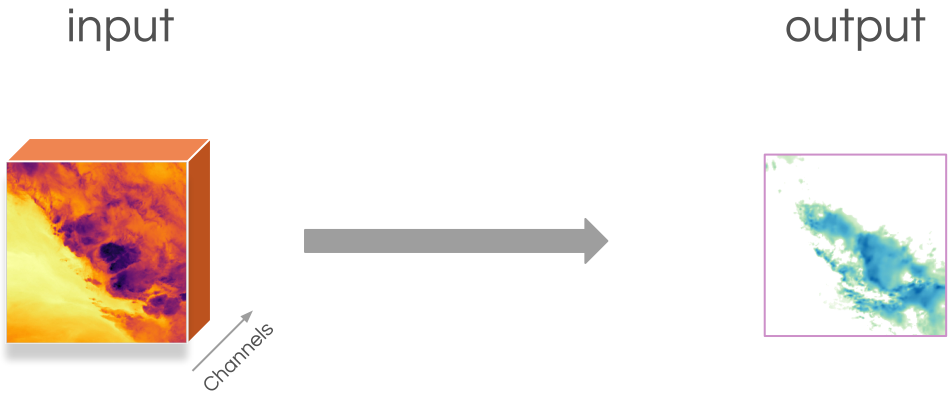
Normalized GOES-16 ABI channels

Data split

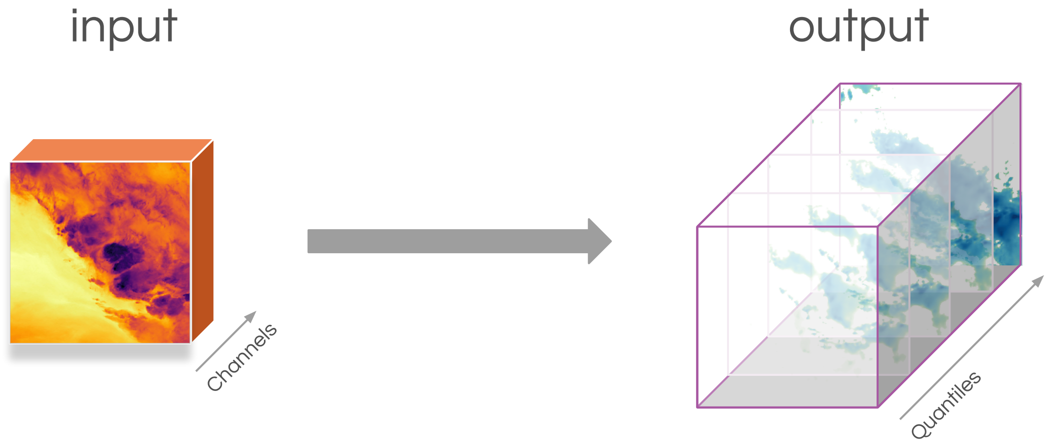
Split	Period start	Period end	Samples
train	2017 Dec	2020 Mar	5212
validation	2017 Dec	2020 Mar	1354
test	2020 Apr	2021 Mar	2928

Modelling

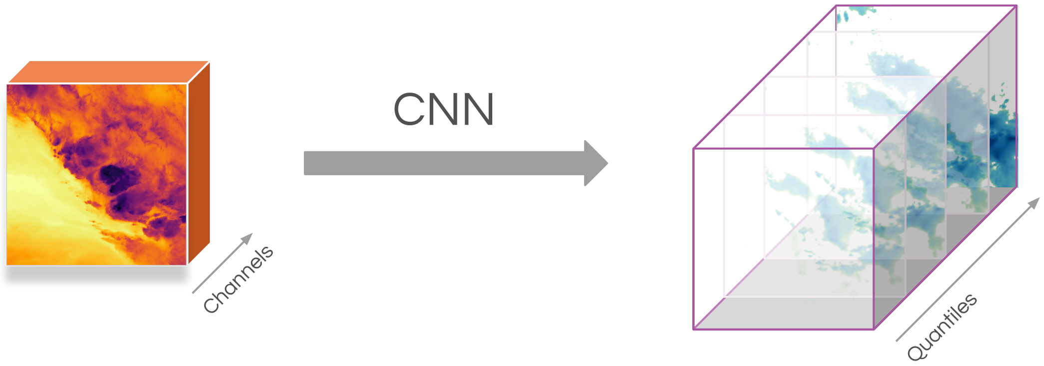
Input & Output



Input & Output

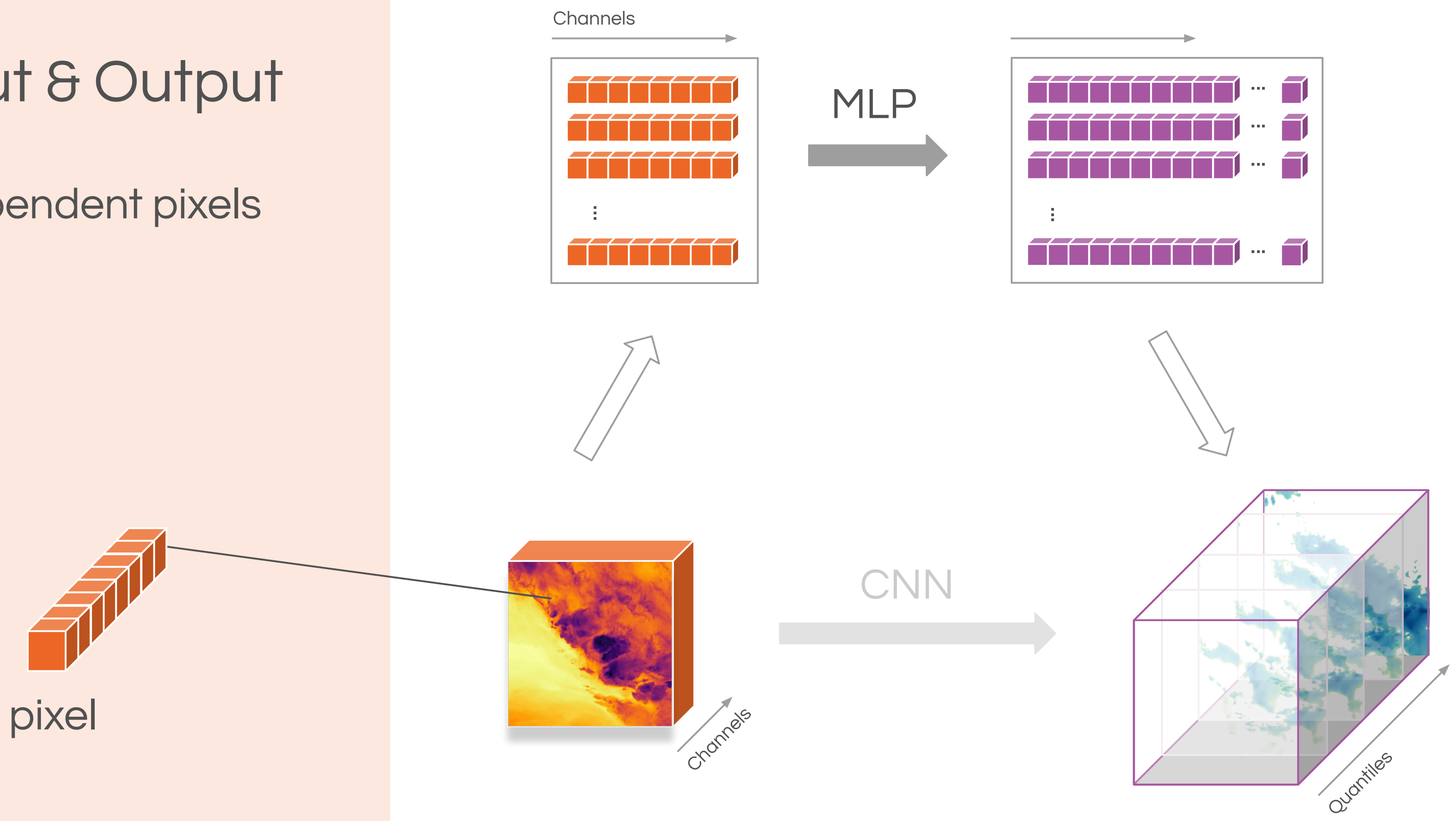


Input & Output



Input & Output

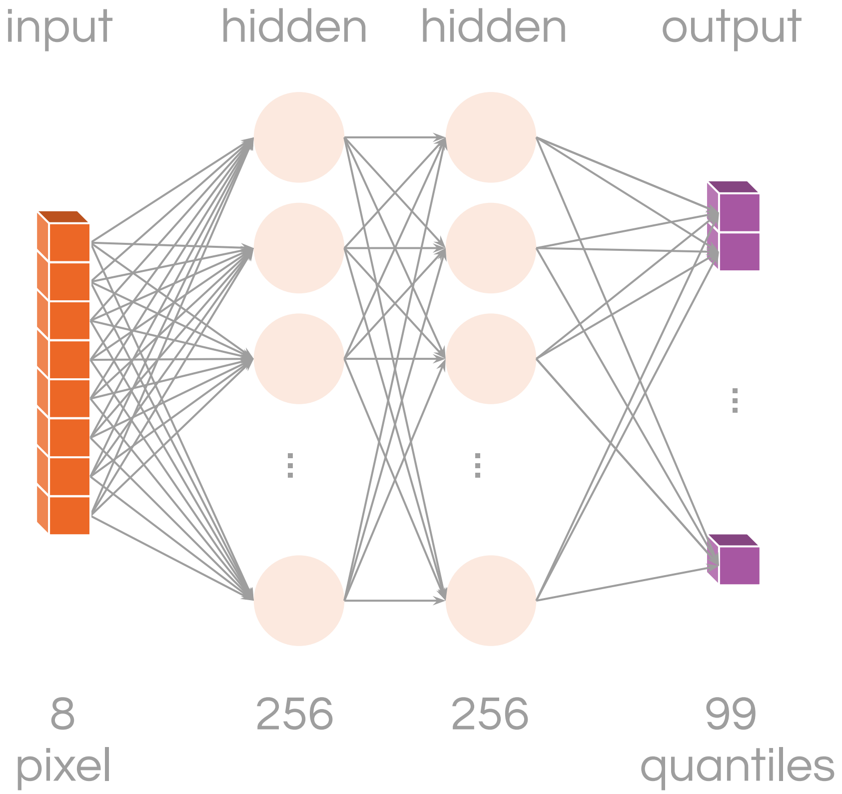
Independent pixels



Multilayer Perceptron

Linear

ReLU activation



Convolutional Neural Network

Feature pyramid network

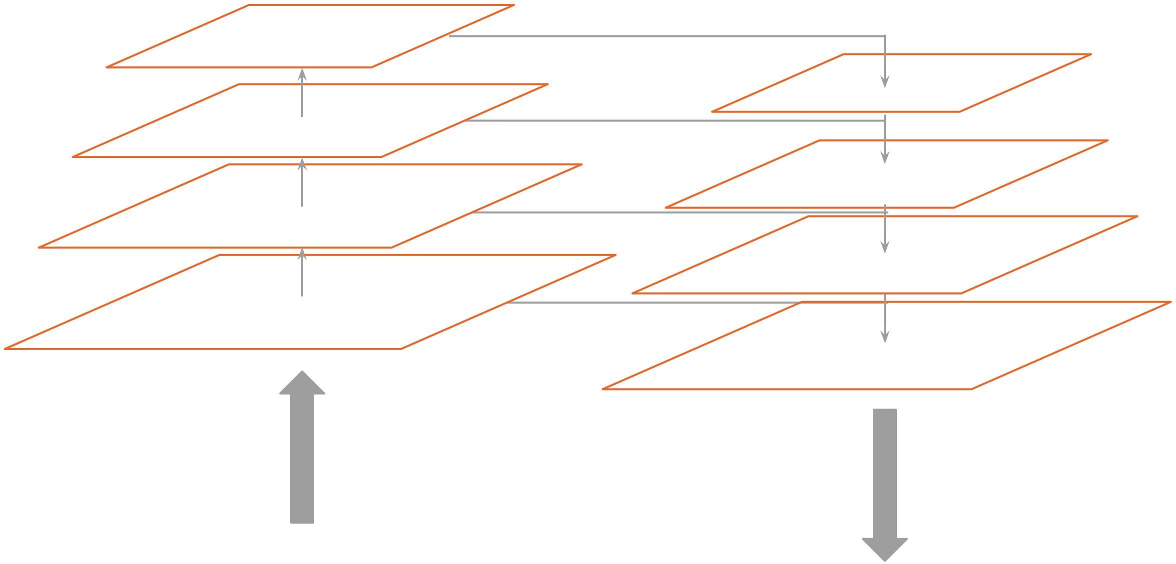
Depth-wise Separable Convolution

Pfreundschuh. (2021). XceptionFPN - quantnn library.

Convolutional Neural Network

Feature pyramid network

Depth-wise Separable Convolution

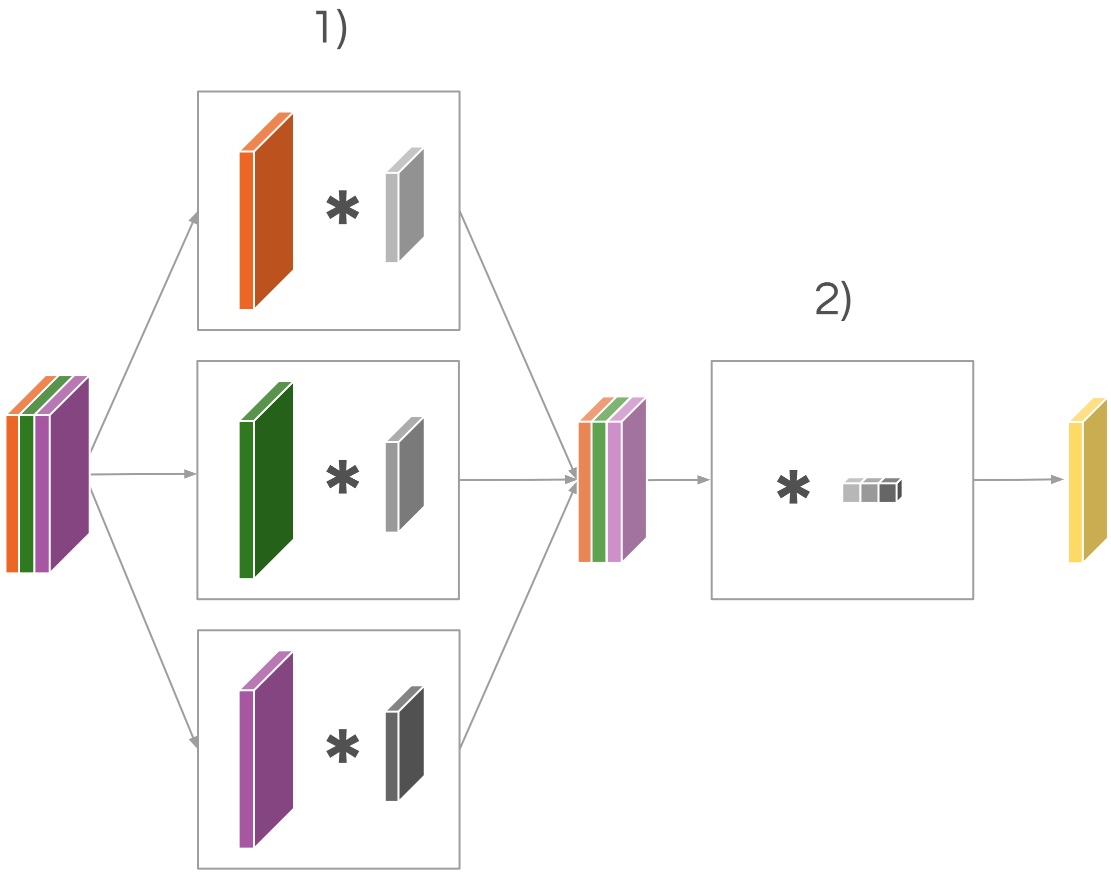


Lin et al. (2017). Feature Pyramid Networks for Object Detection.

Convolutional Neural Network

Feature pyramid network

Depth-wise Separable Convolution

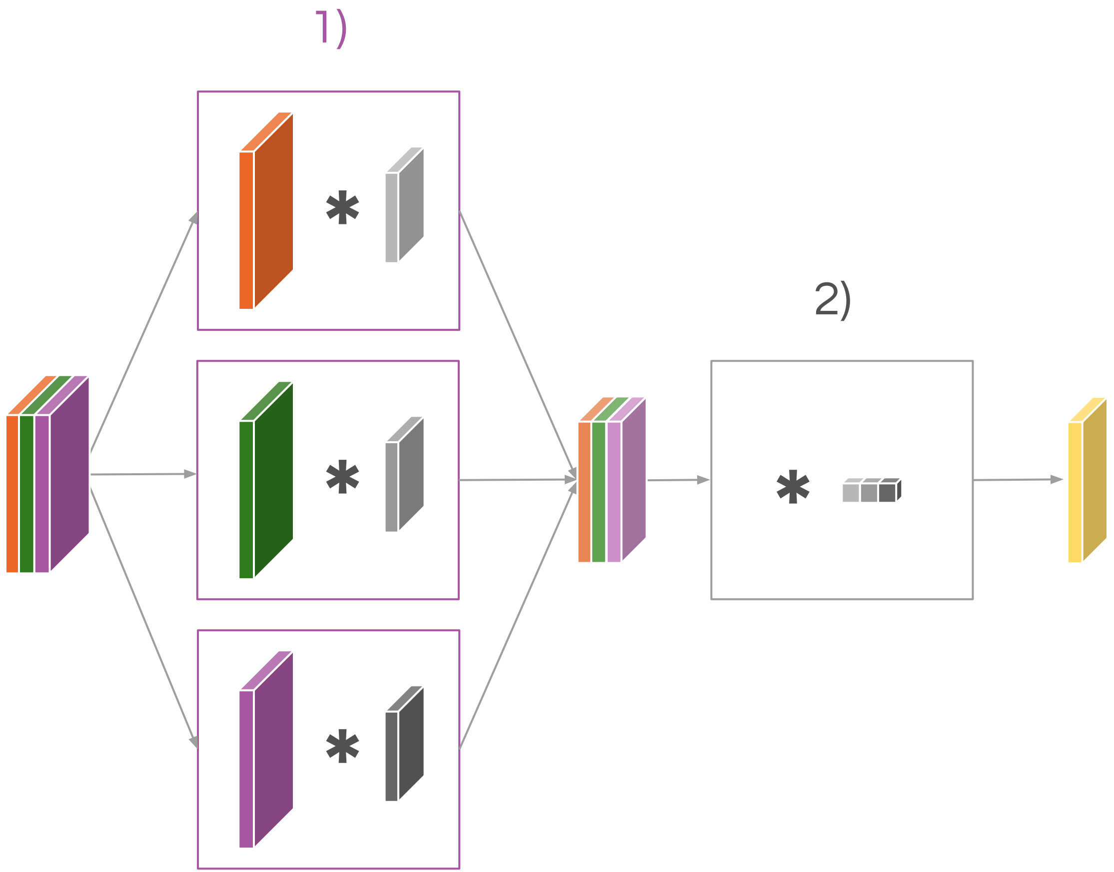


Chollet. (2017). Xception: Deep Learning with Depthwise Separable Convolutions

Convolutional Neural Network

Feature pyramid network

Depth-wise Separable Convolution



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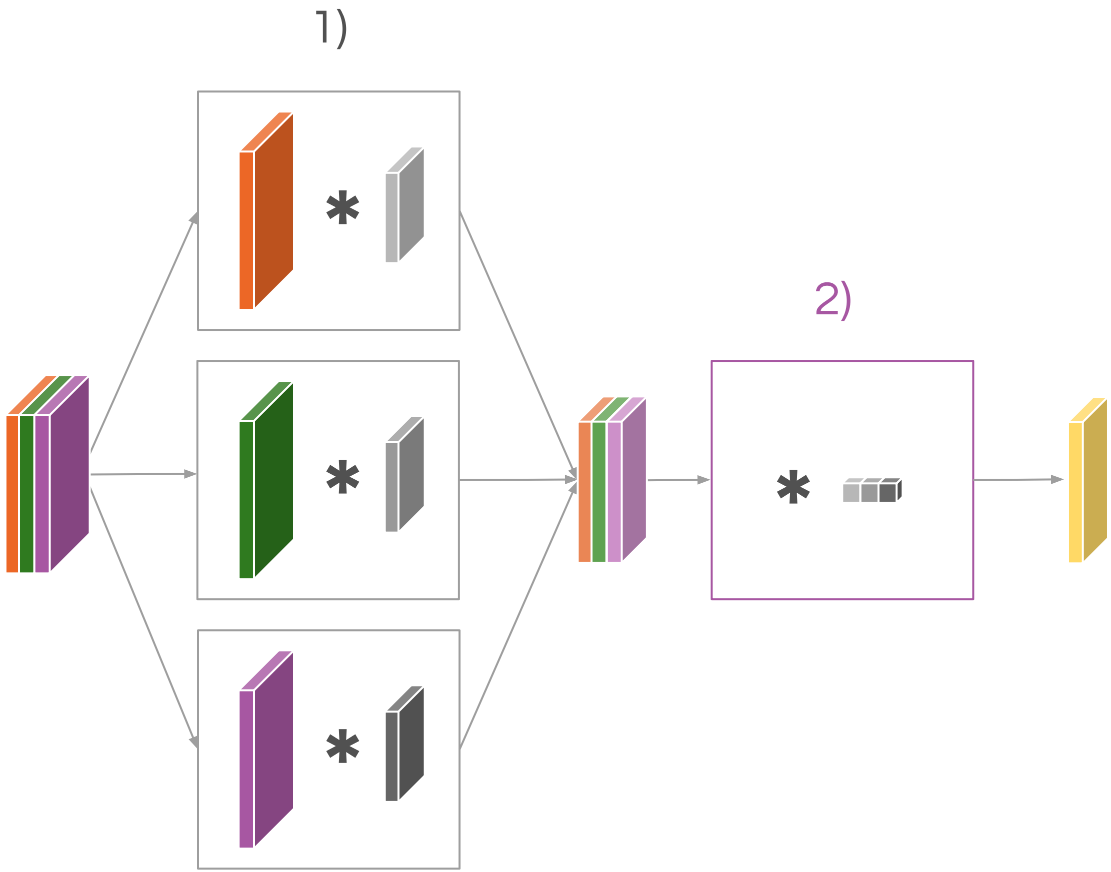

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Quantile regression

Quantile regression

x_τ: τth quantile

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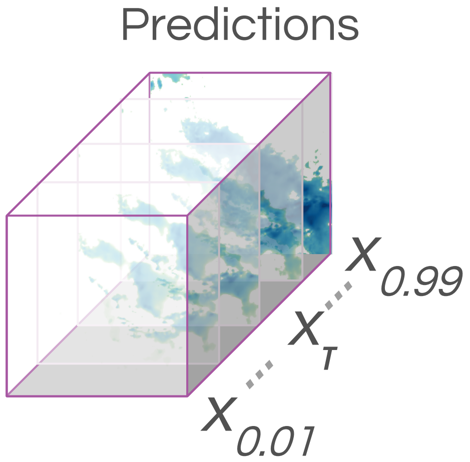
x_τ: τth quantile

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

Quantile regression

x_τ: τth quantile



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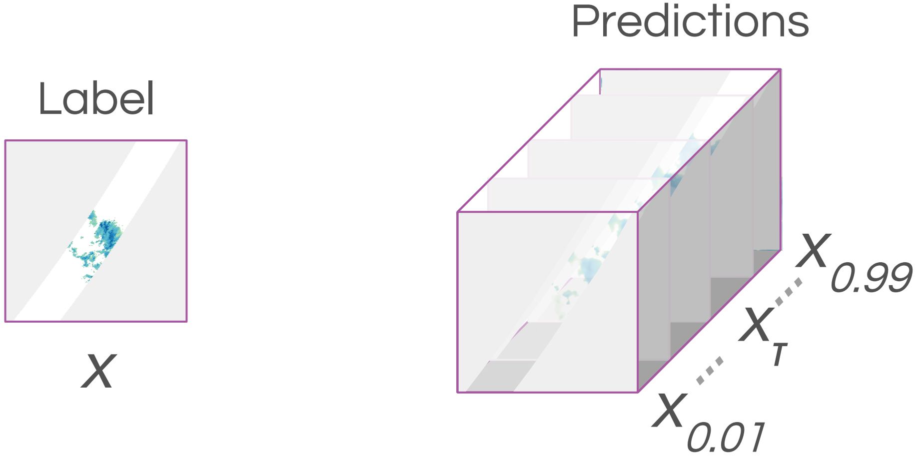

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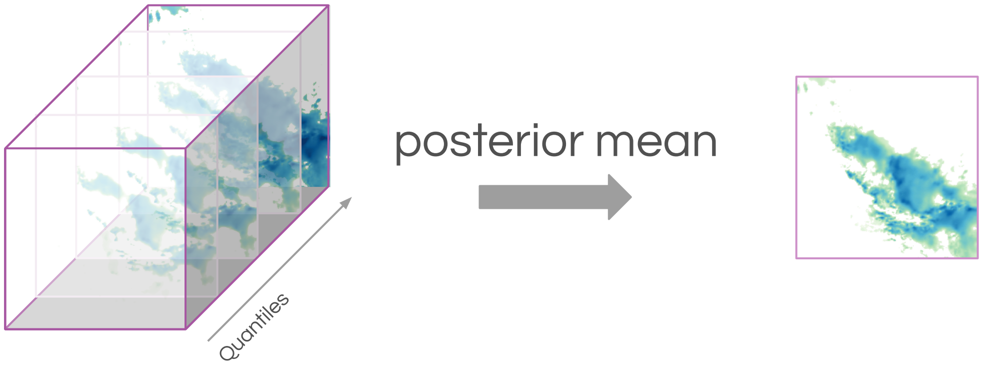
Results

Evaluation

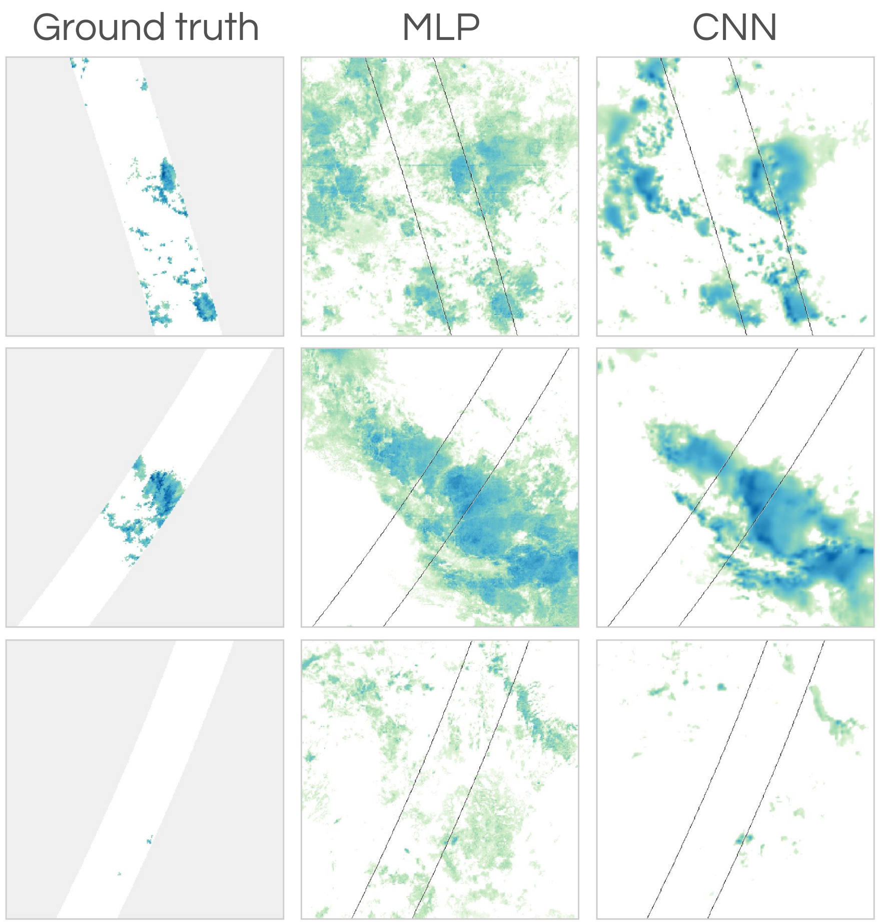
Posterior mean



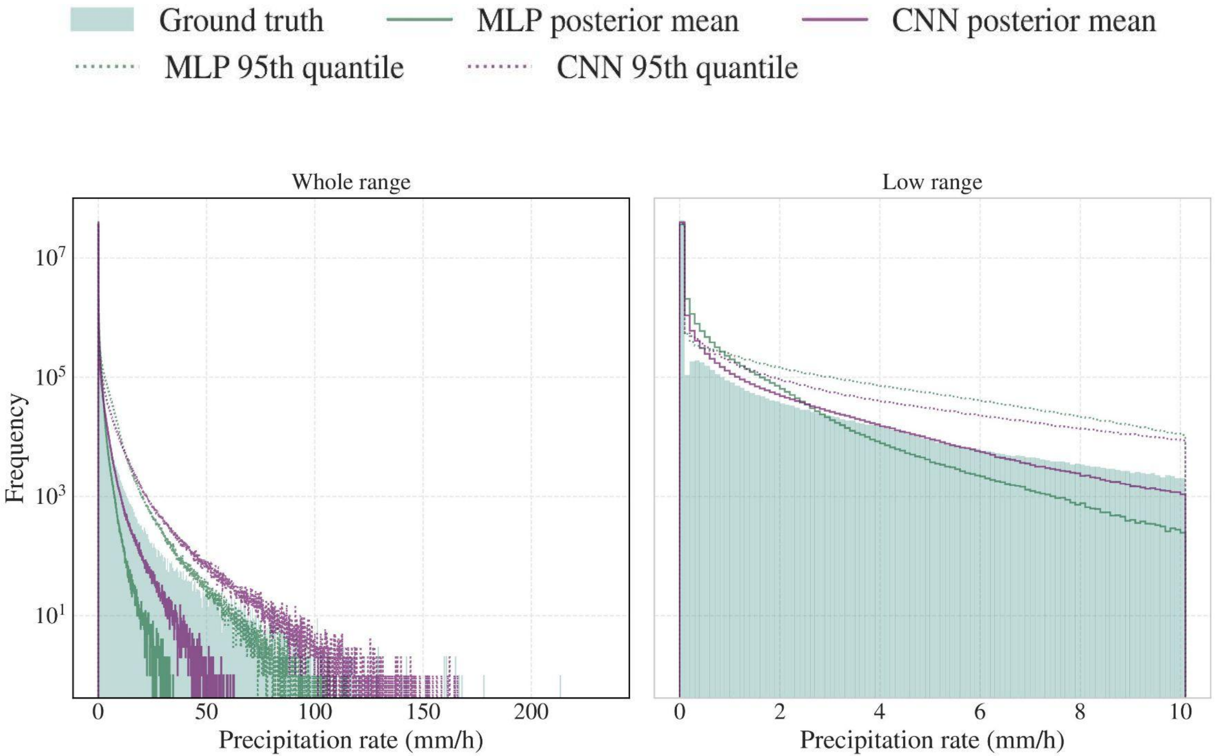
Metrics

Regression	Bias Mean absolute error (MAE) Mean squared error (MSE)
Probabilistic	Loss Continuous Ranked Probability Score (CRPS)

Example predictions



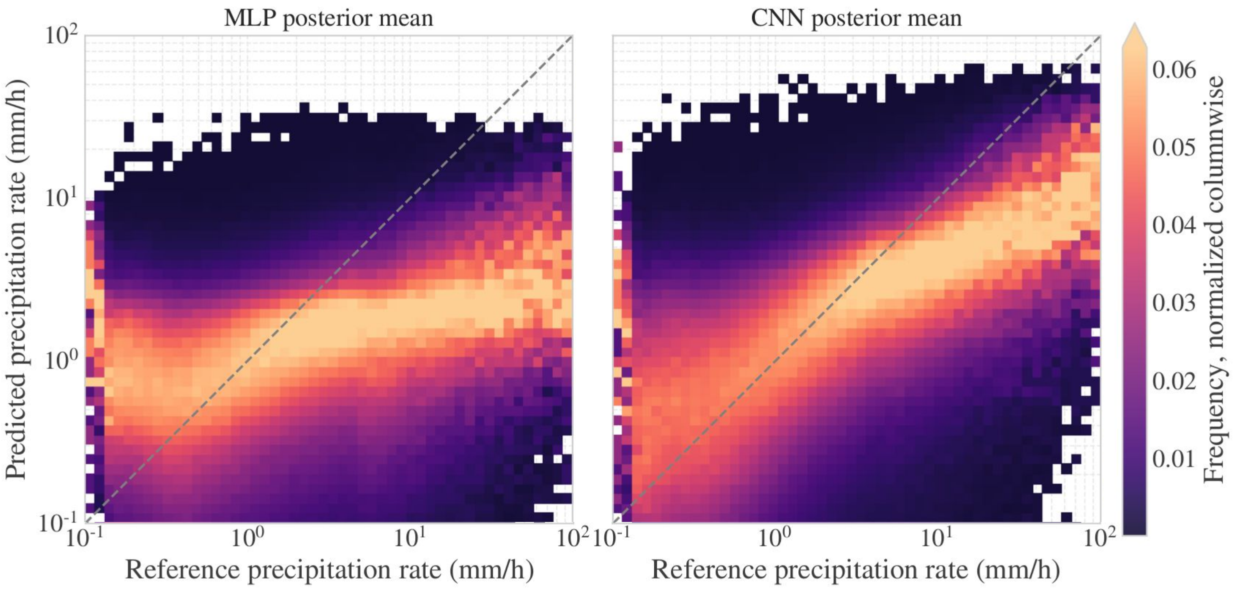
Distribution



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



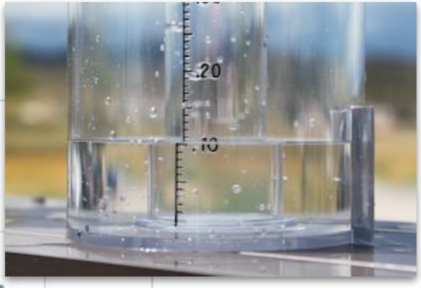
Independent test data

INPE

Rain gauges

Dec 2020

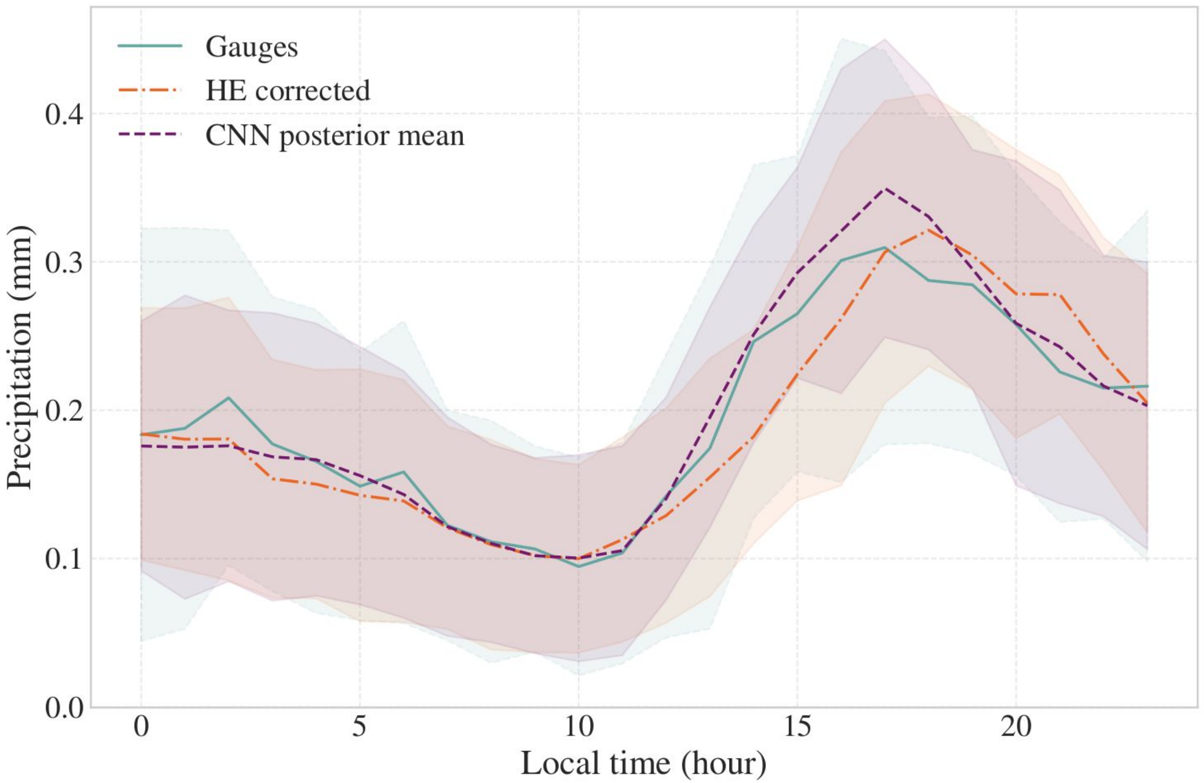
Compare to Hydro-Estimator



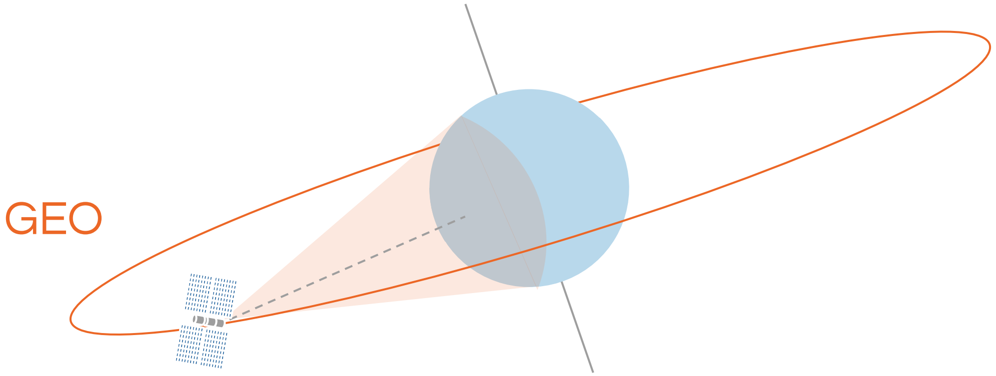
Metrics

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



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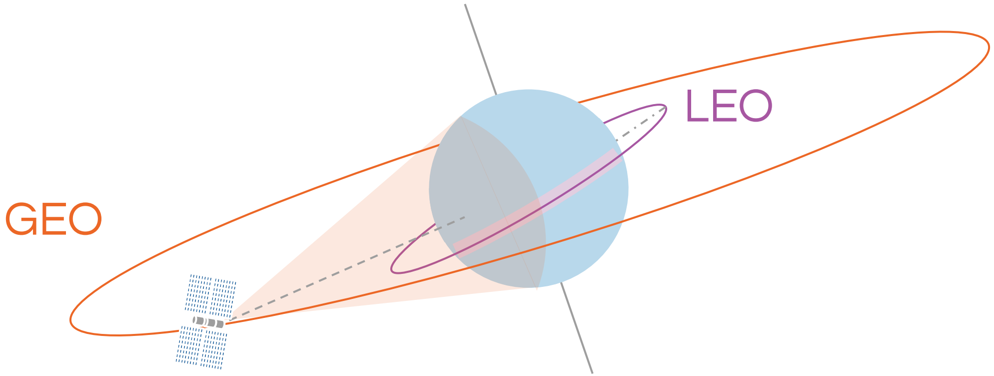

Conclusions

→ 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