

# Deep learning for bias correction of satellite retrievals of orographic precipitation

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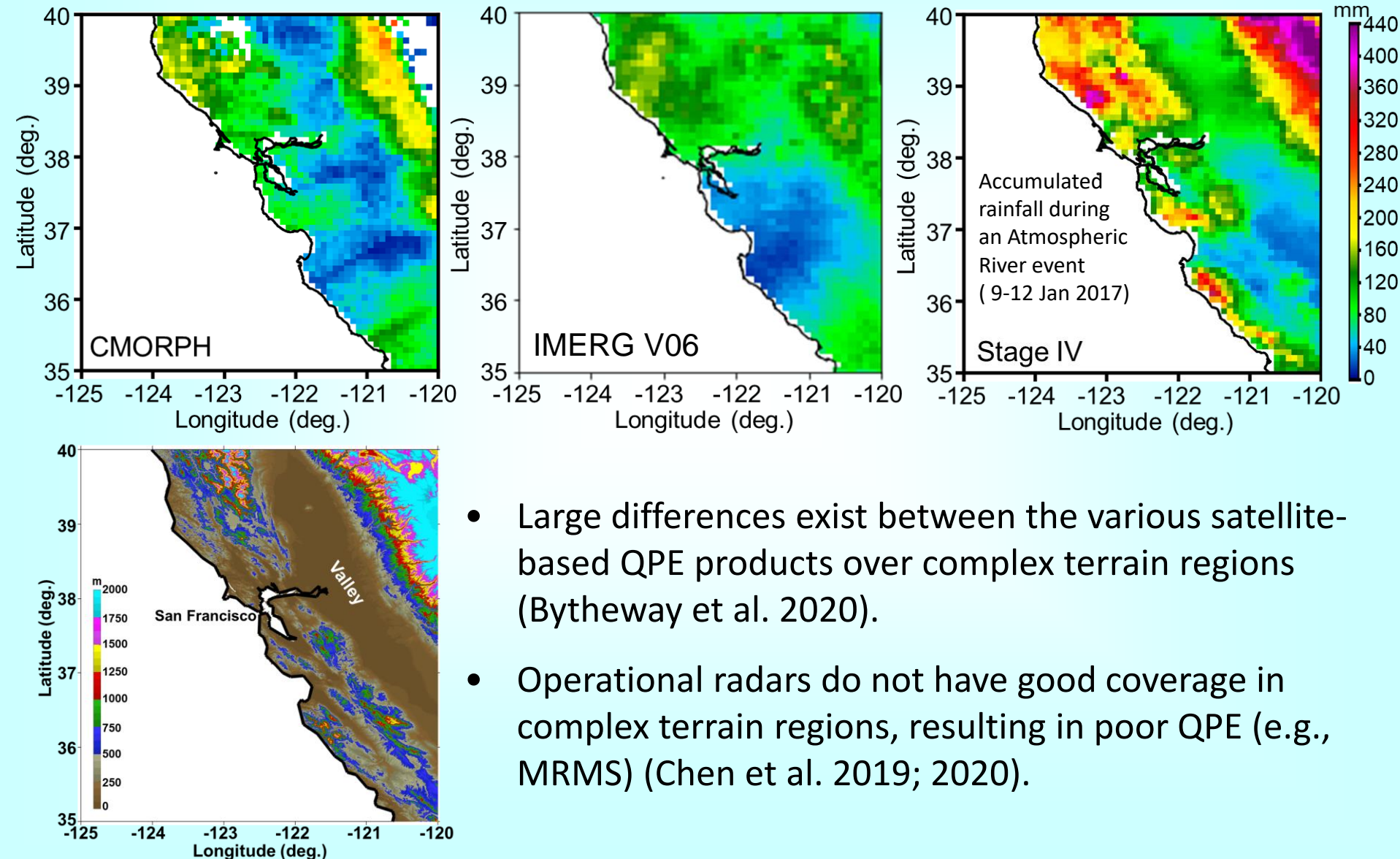
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# Motivations

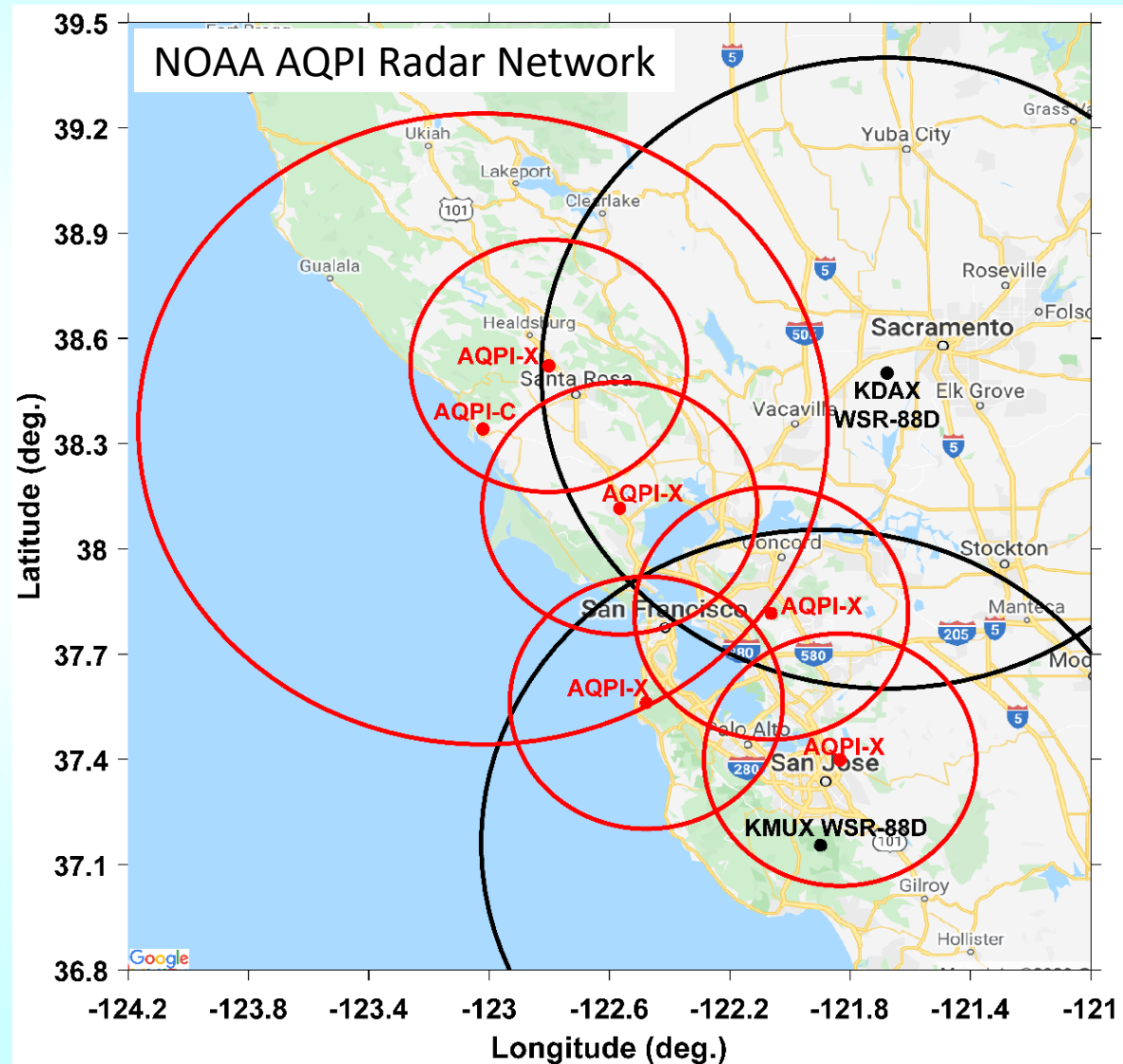


- Large differences exist between the various satellite-based QPE products over complex terrain regions (Bytheway et al. 2020).
- Operational radars do not have good coverage in complex terrain regions, resulting in poor QPE (e.g., MRMS) (Chen et al. 2019; 2020).

# Objective

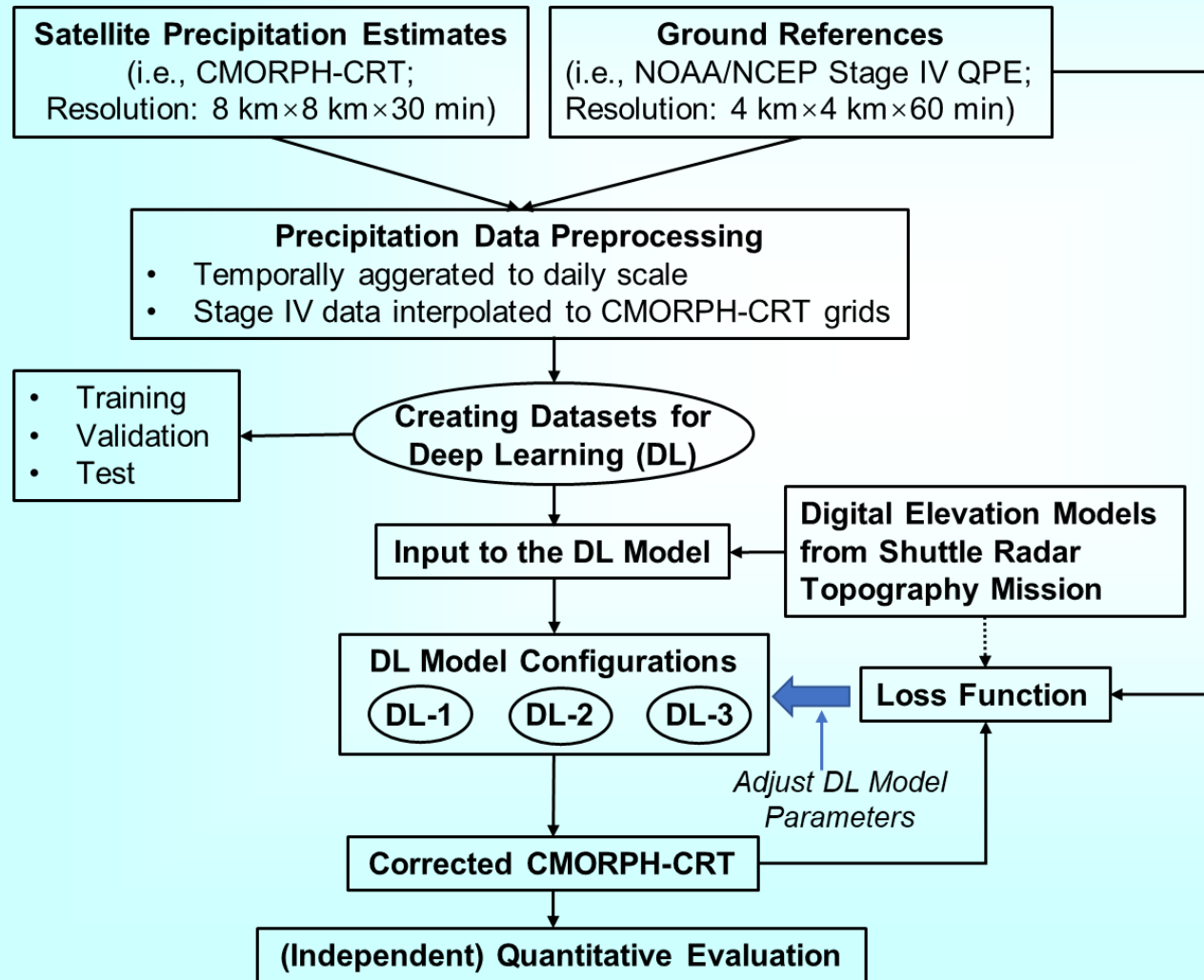
**Develop a deep learning framework for bias correction of satellite retrievals of coastal orographic precipitation.**

- Start from CMORPH, but the framework is applicable to other satellite precipitation products such as IMERG.
- Use Stage IV QPE as references in training the machine learning model and evaluating the bias correction performance.



# Bias Correction of Satellite Retrievals of Orographic Precipitation

## Conceptual diagram of the bias correction framework



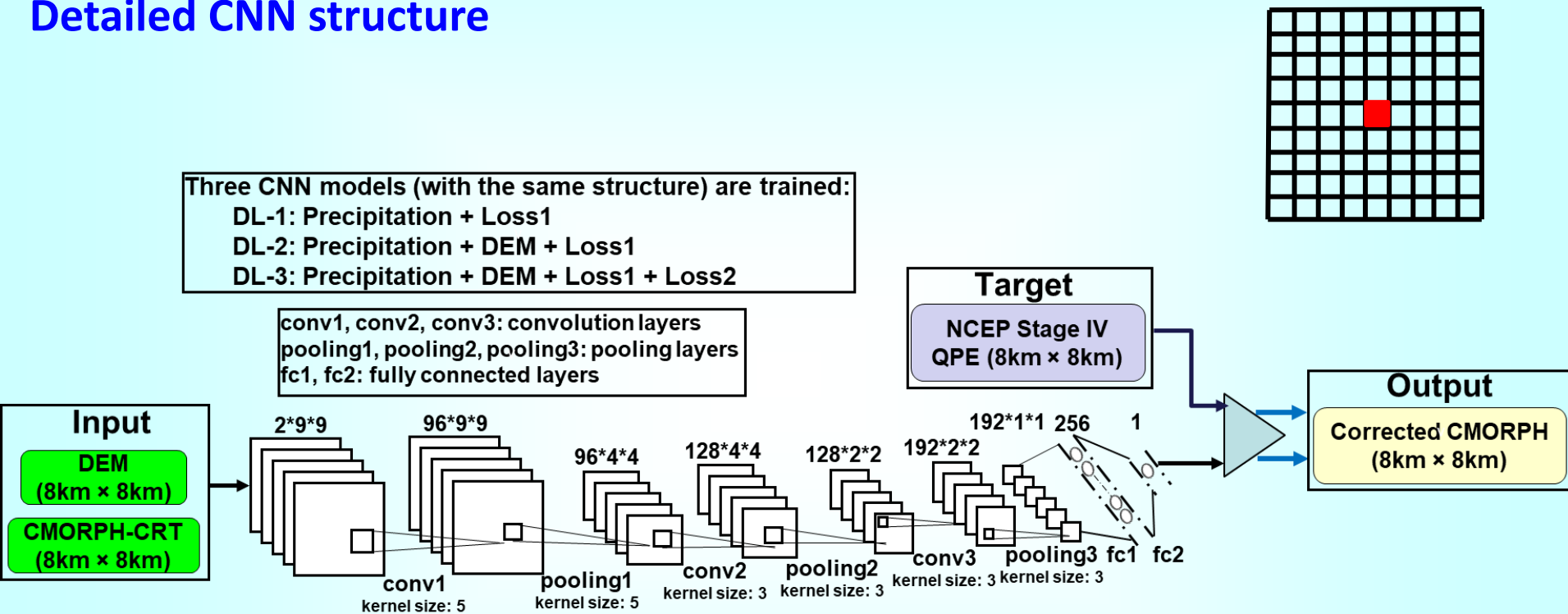
- Spatial and temporal alignment between CMORPH and State IV QPE

- Stage IV QPE remapped to CMORPH grids
- Correction is performed at daily scale

- We will quantify the impact of terrain on satellite QPE through different model configurations.

# Bias Correction of Satellite Retrievals of Orographic Precipitation

## Detailed CNN structure



- Paddings for conv1, conv2, and conv3 are 2, 2, and 1, respectively.
- Strides in conv1, conv2, and conv3 are 2, 1, and 1, respectively.
- Paddings for pooling1, pooling2, and pooling3 are 1, 0, and 1, respectively.
- Stride is 2 for all the pooling layers.

# Bias Correction of Satellite Retrievals of Orographic Precipitation

## Detailed CNN structure: Loss functions for DL-1, DL-2, and DL-33

### Loss functions

DL-1:  $W1 \cdot \text{MSE}(\text{Precipitation})$

DL-2:  $W1 \cdot \text{MSE}(\text{Precipitation})$

DL-3:  $W1 \cdot \text{MSE}(\text{Precipitation}) + W2 \cdot \text{MSE}(\text{DEM} / 25)$

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (X_L - X_{DL})^2 \quad W1 = \begin{cases} 2, & 0 < x \leq 20 \\ 5, & 20 < x \leq 40 \\ 10, & 40 < x \leq 60 \\ 20, & 60 < x \leq 80 \\ 30, & x > 80 \end{cases} \quad W2 = \begin{cases} 2, & 0 < x \leq 500 \\ 3, & 500 < x \leq 1000 \\ 4, & 1000 < x \leq 1500 \\ 5, & 1500 < x \leq 2000 \\ 6, & x > 2000 \end{cases}$$

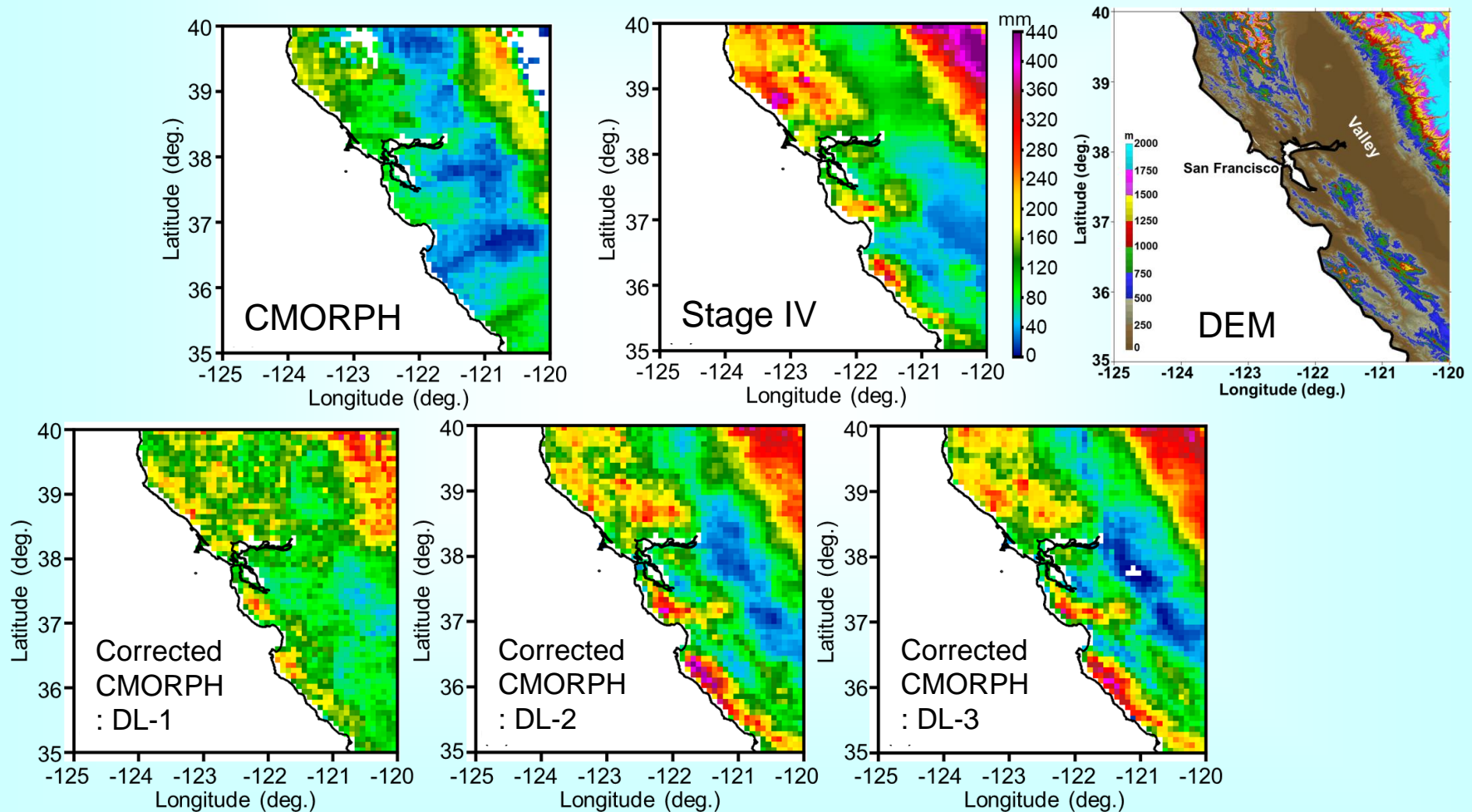
### Model Training, Validation, and Test

- Ten-month data: January - February (2016-2019), March (2018, 2019)
- The total number of precipitation samples is 90,448, which is divided into training (90%) and validation (10%) subsets.
- Four precipitation events are excluded from the dataset for independent test: 9-12 January 2017, 21-23 March 2018, 13-16 February 2019, 25-28 February 2019.



# Bias Correction of Satellite Retrievals of Orographic Precipitation

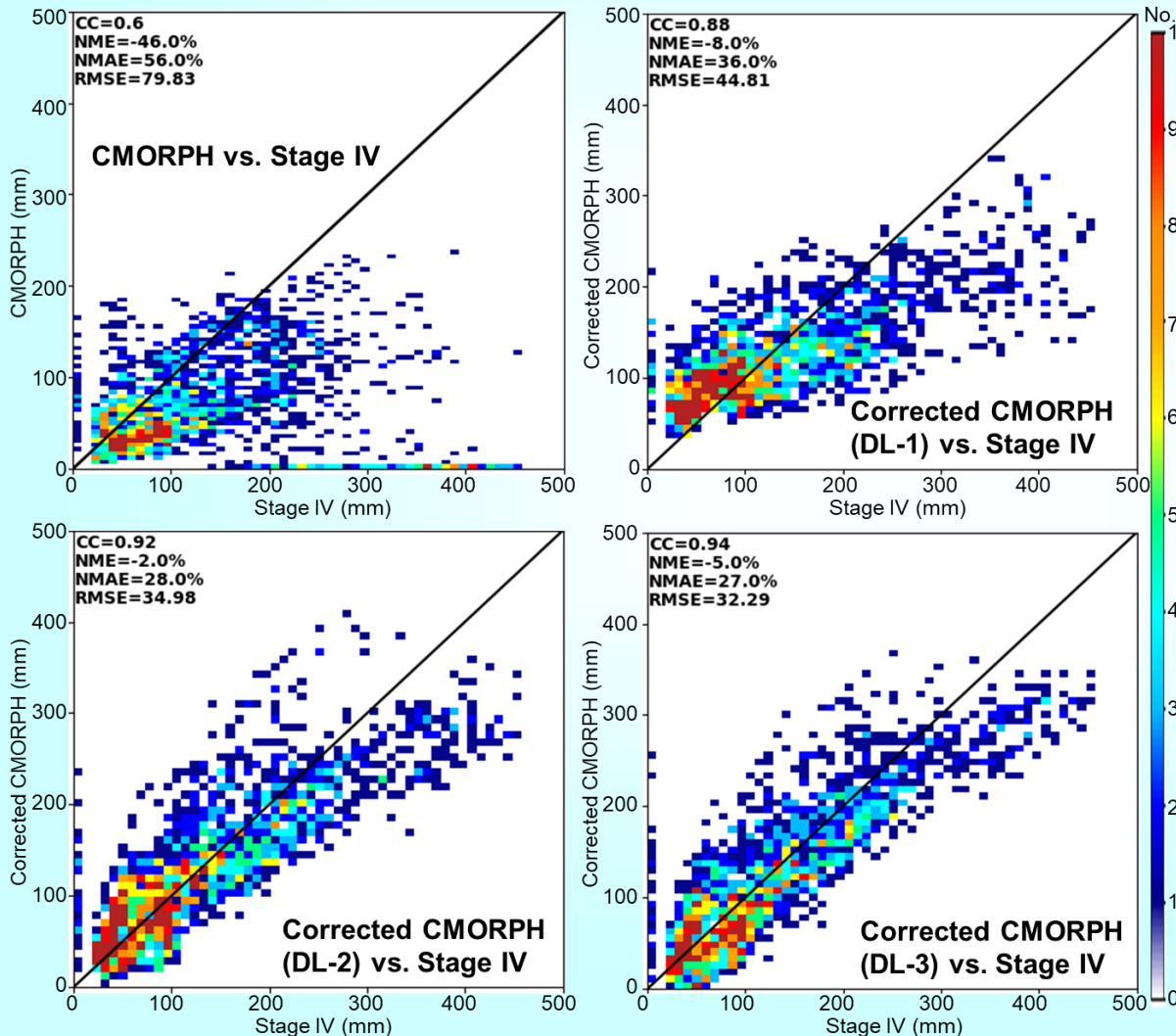
Case studies: 9-12 January 2017



Precipitation accumulations during 9-12 January 2017

# Bias Correction of Satellite Retrievals of Orographic Precipitation

## Case studies: Precipitation accumulations during 9-12 January 2017



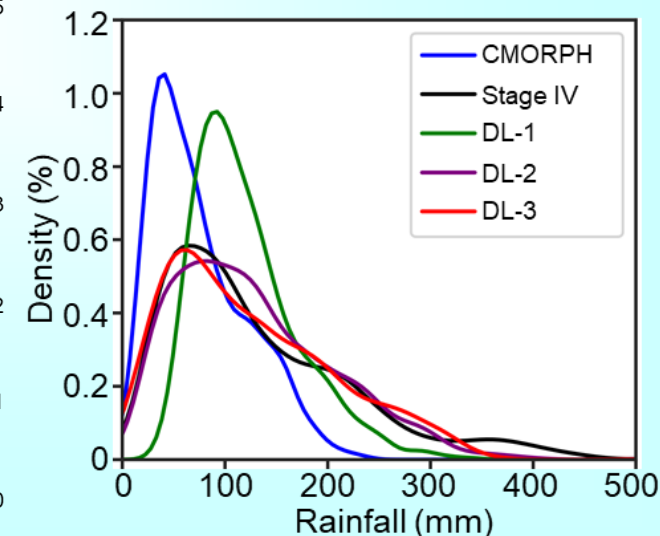
$$CC = \frac{\sum[(R_S - \langle R_S \rangle)(R_G - \langle R_G \rangle)]}{\sqrt{\sum(R_S - \langle R_S \rangle)^2} \sqrt{\sum(R_G - \langle R_G \rangle)^2}}$$

$$NME = \frac{\langle R_S - R_G \rangle}{\langle R_G \rangle}$$

$$NMAE = \frac{\langle |R_S - R_G| \rangle}{\langle R_G \rangle}$$

$$RMSE = \sqrt{\langle (R_S - R_G)^2 \rangle}$$

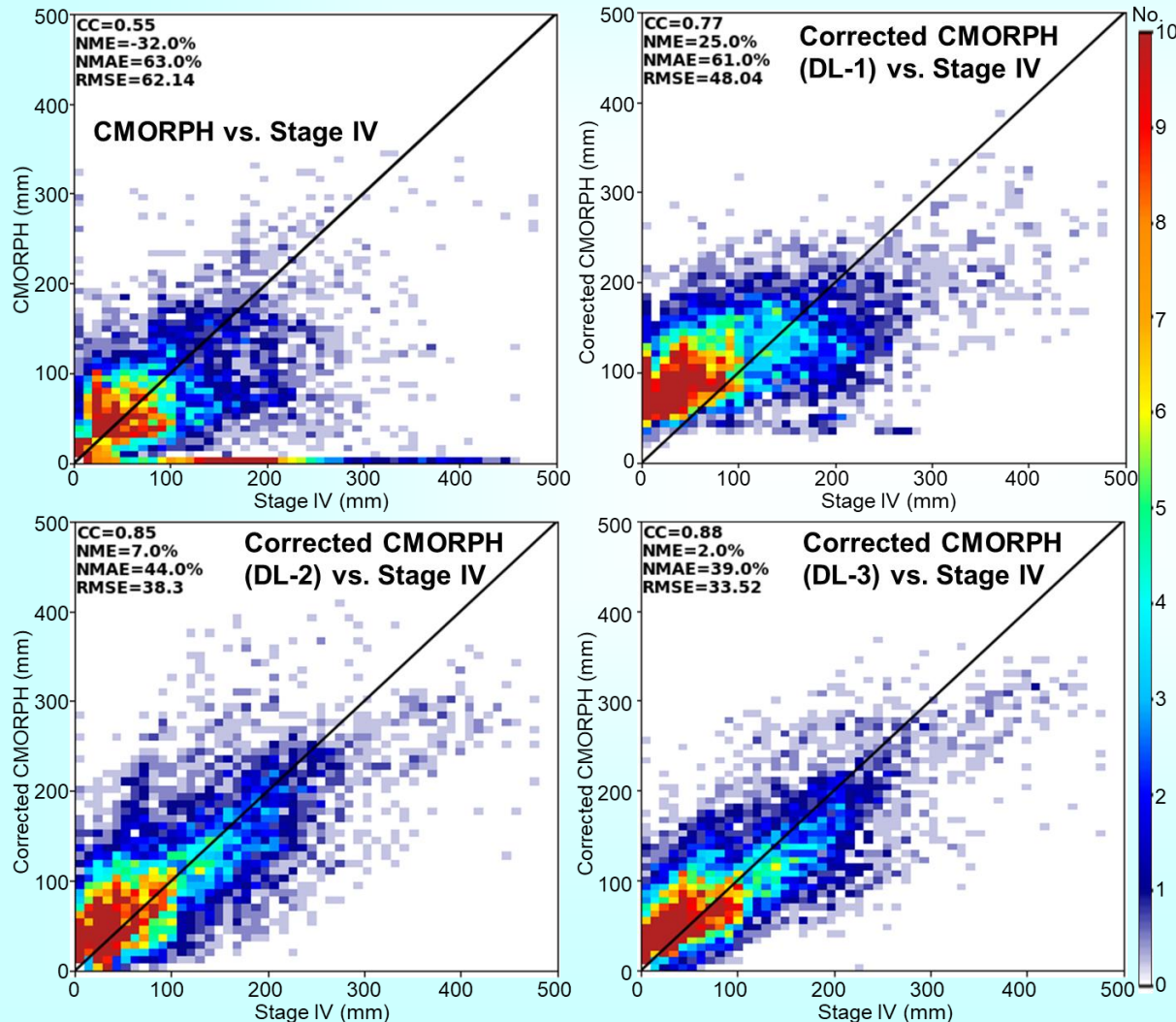
where the angle brackets stand for sample average;  $R_S$  and  $R_G$  denote the estimated rainfall using CMORPH and Stage IV, respectively.





# Bias Correction of Satellite Retrievals of Orographic Precipitation

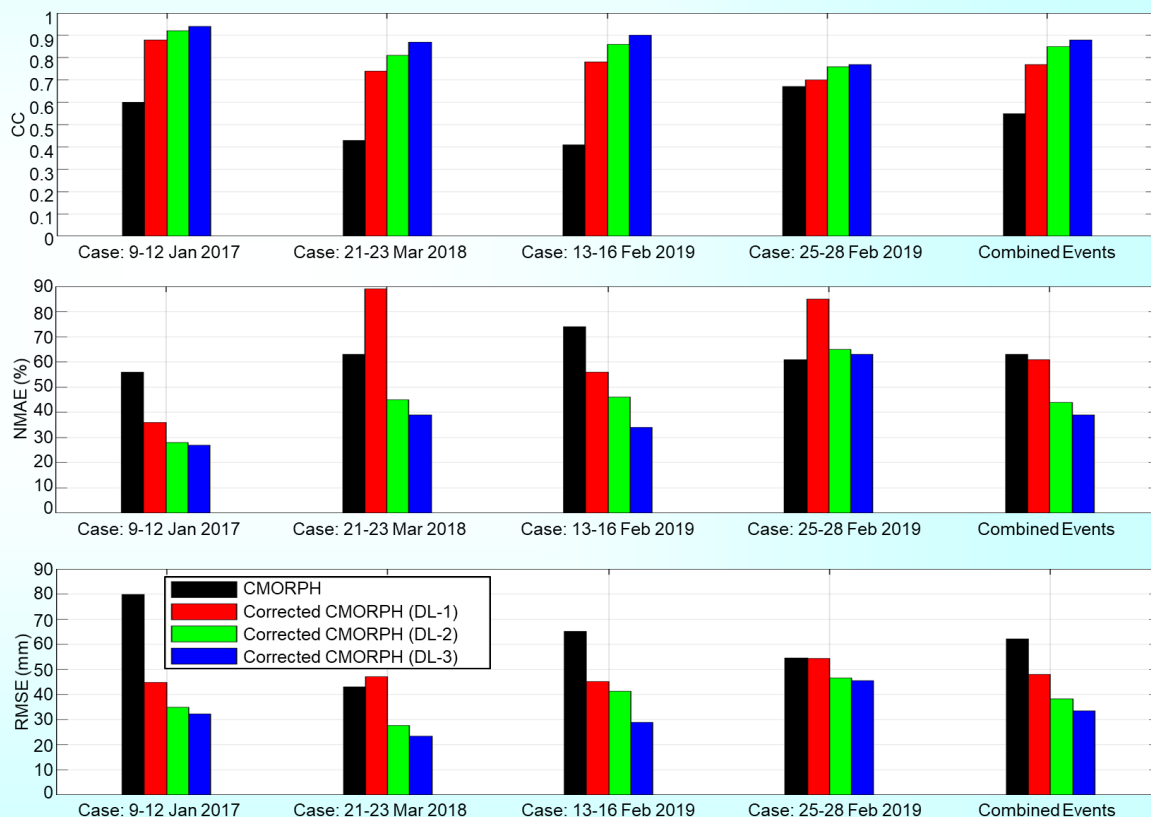
Case studies: 2017/1/9-12, 2018/03/21-23, 2019/2/13-16, 2019/2/25-28



Scatter plots of CMORPH vs. Stage IV QPE during the four independent test events

# Summary

- Satellite retrieval of orographic precipitation remains a formidable challenge, especially during shallow precipitation processes.
- This study has developed a machine learning framework to characterize and correct the biases associated with satellite precipitation product, with an emphasis on quantifying the impact of orographic enhancement.
- Case studies in coastal mountain regions in Northern California demonstrated the great performance of the bias correction scheme.
- Future work will focus on the generalization capability of this DL-based bias correction approach (in different regimes and for enhancing other products such as IMERG).



# Thank you for your attention!

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**Chen, H.,** L. Sun, R. Cifelli, and P. Xie, 2021: Deep learning for bias correction of satellite retrievals of orographic precipitation. *Transactions on Geoscience and Remote Sensing*, (under review)