Conditional Generative Adversarial Networks (cGANs) For Near Real-time Precipitation Estimation From Multispectral GOES-16 Satellite Imageries

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Introduction

- One important component to improve the accuracy of satellite-based precipitation estimation products according to Sorooshian et al. (2011) is to making the best use of available and new datasets by taking advantage of any advanced methodology that can extract valuable and useful information related to rainfall.
- A **data-driven and end-to-end precipitation estimation algorithm** is proposed using **multiple sources of information** and **advanced Deep Learning algorithms** in image processing.
- Performance is evaluated using a number of common performance measures, including both R/NR and real-valued precipitation accuracy, and is compared with Precipitation Estimation from Remotely Sensed Information Using Artificial Neural Networks Cloud Classification System (PERSIANN-CCS).

General Flow Diagram

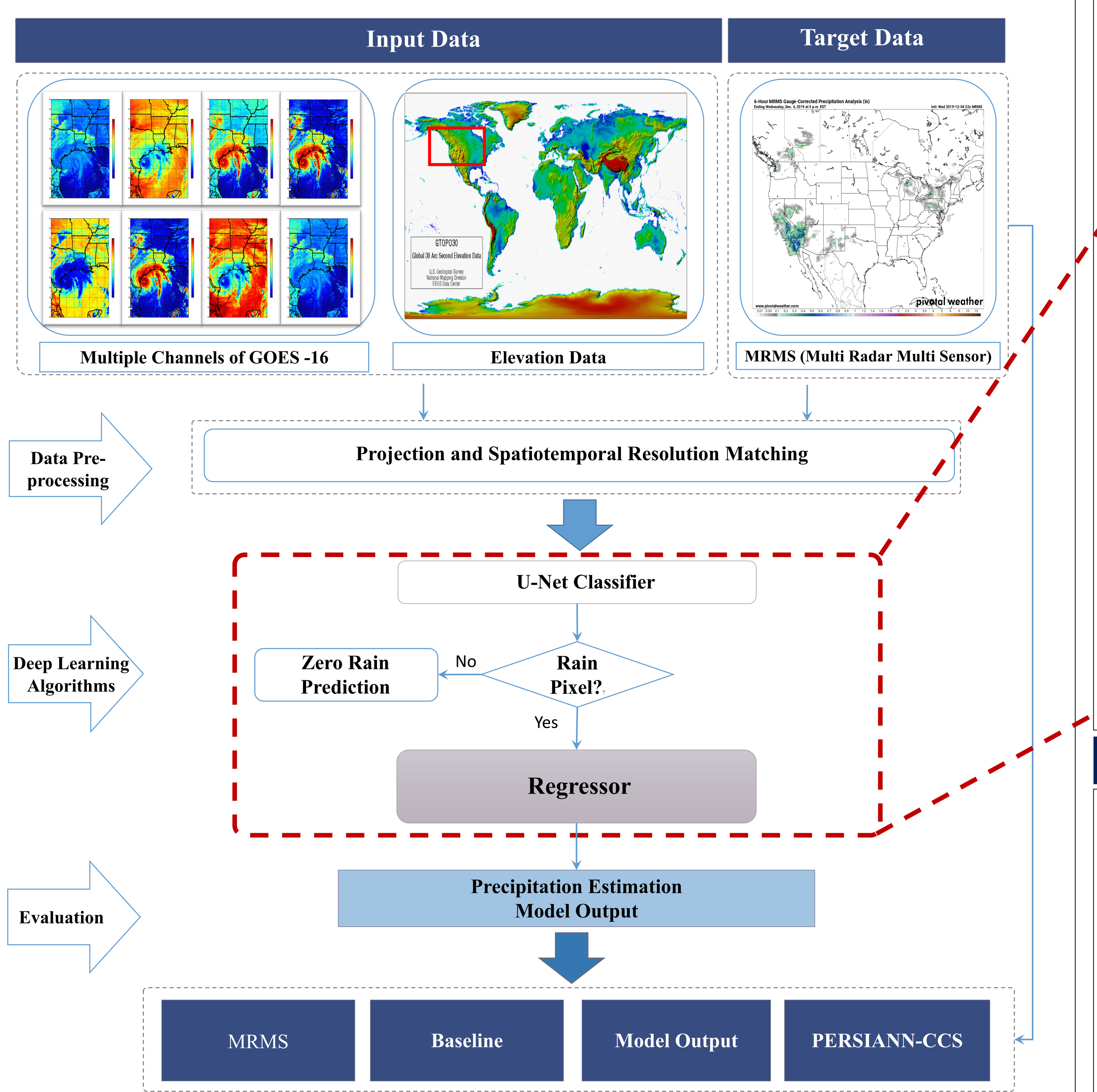

Figure 1. Overview of the model training and verification process.

Datasets and Study Region

- **Datasets:**

- **GOES-16) Advanced Baseline Imager (ABI) -** Emissive Channels of Geostationary Operational Environmental Satellite-R Series. *Obtained from : NOAA CLASS*
- **Elevation data.** *Obtained from : Global 30 Arc-Second Elevation Data Set (GTOPO30) provided by the USGS*
- **MRMS** (Multi Radar Multi Sensor). *Obtained from : GPM Ground Validation Data Archive*
- **PERSIANN-CCS** (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Network- Cloud Classification System). *Obtained from : CHRS Data Portal*

- **Region:** The Contiguous United States.

Methodology – conditional Generative Adversarial Networks(cGAN)

- GAN is defined as zero-sum (Min-max) game with the following objective function and flow diagram. **Pr** is the data distribution over real sample (x and y).

$$\text{Objective function} = \min_G \max_D \underbrace{\mathbb{E}_{x,y\sim \mathbf{P_r}}[\log D(x,y)] + \mathbb{E}_{x\sim \mathbf{P_r}}[\log(1-D(x,G(x)))]}_{\text{Discriminator Term}} + \mathbb{E}_{x,y\sim \mathbf{P_r}}[\|y-G(x)\|^2]$$

Generator Term: $\mathbb{E}_{x\sim \mathbf{P_r}}[\log(1-D(x,G(x)))] + \mathbb{E}_{x,y\sim \mathbf{P_r}}[\|y-G(x)\|^2]$

* Parameters are described in the figure below.

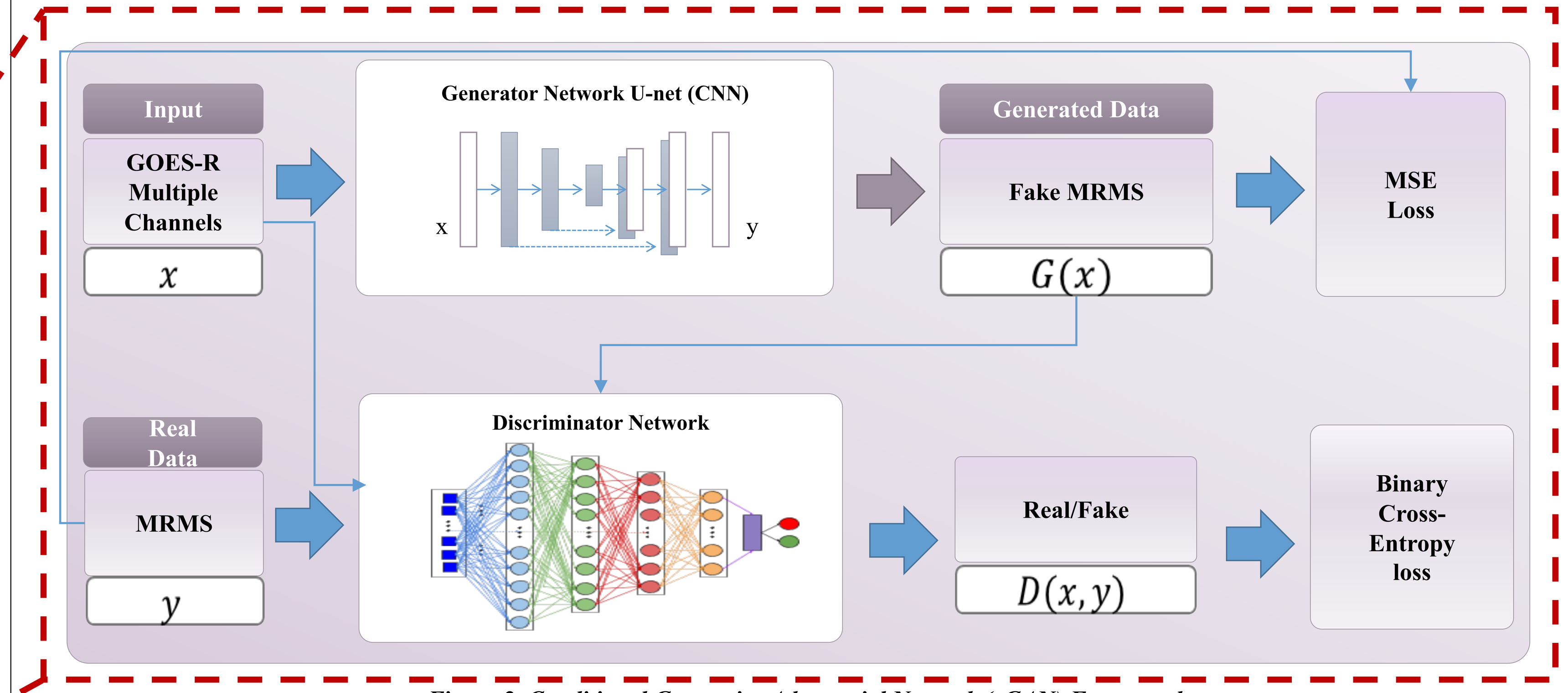

Figure 2. Conditional Generative Adversarial Network (cGAN) Framework

Statistical Evaluations

Table 1. Validation Metrics for Different Scenarios

cGAN Model Output - Single Spectral Bands													
Sc.	Band number & Wavelength (µm)	Without Elevation						With Elevation					
		MSE	COR	BIAS	POD	FAR	CSI	MSE	COR	BIAS	POD	FAR	CSI
1	8 (6.2 µm)	1.410	0.270	-0.030	0.356	0.734	0.174	**1.096**	**0.311**	**-0.017**	**0.363**	**0.726**	**0.180**
2	9 (6.9 µm)	1.452	0.271	-0.044	0.371	0.725	0.182	**1.107**	**0.317**	**-0.032**	**0.428**	**0.736**	**0.190**
3	10 (7.3 µm)	1.536	0.281	-0.090	0.474	0.755	0.188	**1.105**	**0.313**	**-0.037**	**0.450**	**0.727**	**0.200**
4	11 (8.4 µm)	1.310	0.271	-0.034	0.507	0.714	0.219	**1.053**	**0.326**	**-0.047**	**0.599**	**0.726**	**0.229**
5	13 (10.3 µm)	1.351	0.262	-0.041	0.518	0.718	0.220	**1.037**	**0.323**	**-0.039**	**0.594**	**0.731**	**0.224**

cGAN Model Output - Multiple Spectral Bands							
Sc.	Band number & Wavelength (µm)	MSE	COR	BIAS	POD	FAR	CSI
1	8 (6.2 µm), 9 (6.9 µm), 10 (7.3 µm), 11 (8.4 µm)	1.170	0.319	-0.064	0.601	0.658	0.275
2	8 (6.2 µm), 9 (6.9 µm), 10 (7.3 µm), 13 (10.3 µm)	1.258	0.317	-0.077	0.594	0.655	0.274
3	8 (6.2 µm), 9 (6.9 µm), 10 (7.3 µm),11 (8.4 µm), 12 (9.6 µm),13 (10.3 µm), 14 (11.2 µm)	1.178	0.359	-0.086	0.706	0.681	0.278

PERSIANN-CCS							
Sc.	Band Wavelength (µm)	MSE	COR	BIAS	POD	FAR	CSI
1	10.8 µm	2.174	0.220	-0.046	0.284	0.622	0.193

- Infusion of **elevation data along with each channel of GOES-16 satellite** is showing performance enhancement in precipitation retrieval task.
- The metric evaluations are presenting the **effectiveness of implementing all emissive channels** to improve the near real-time precipitation retrieval task.

Results Visualization

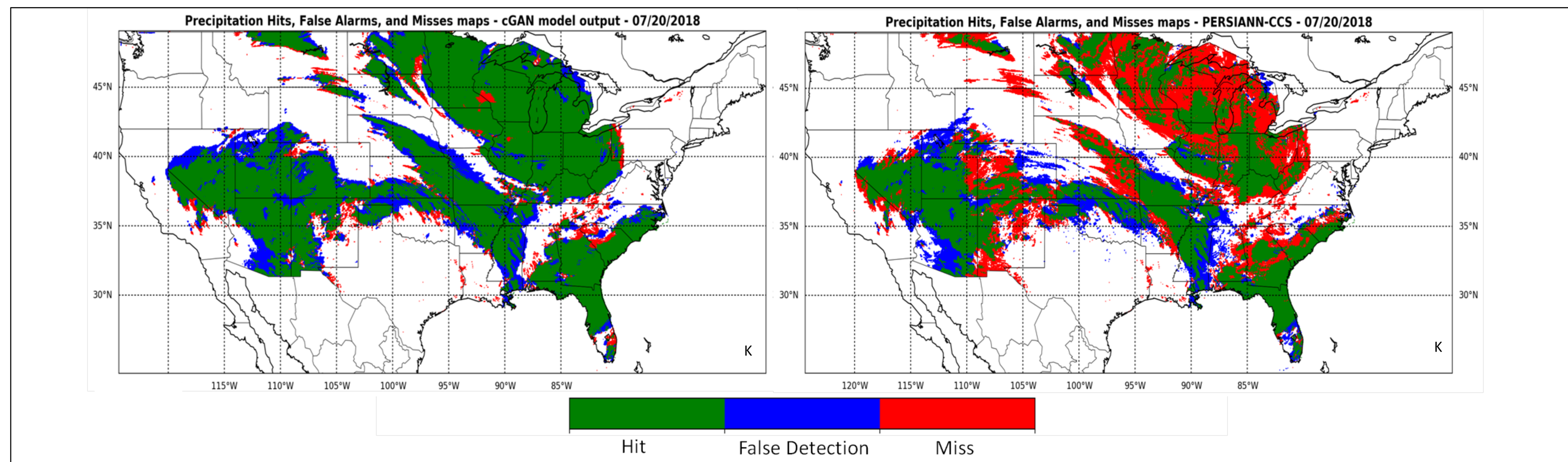

Figure 3. Precipitation Identification Performance – 20th of July, 2018

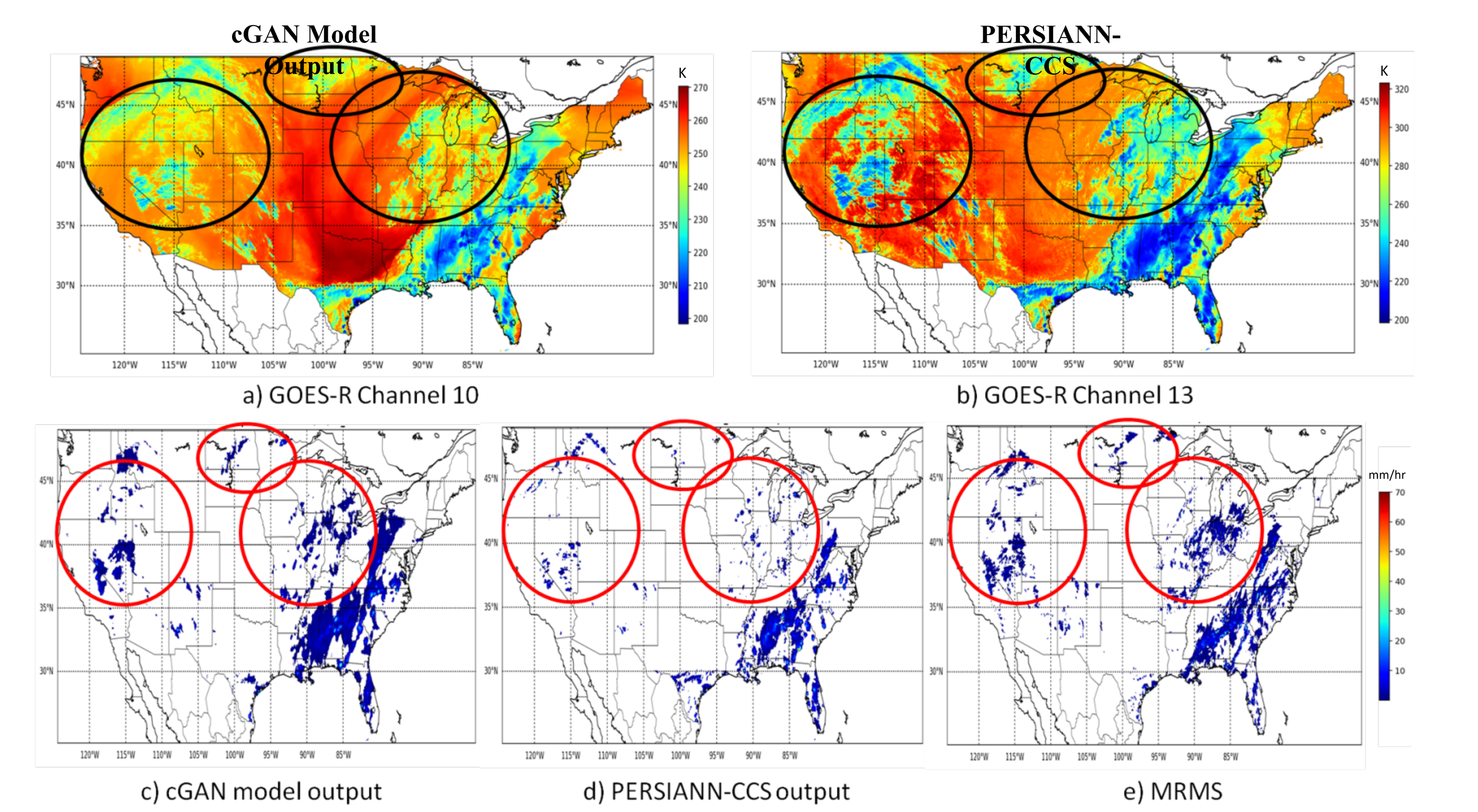

Fig4: a) Channel 10 and b) Channel 13 from ABI GOES-16 imagery, c) cGAN model half hourly, d) PERSIANN-CCS half hourly precipitation values, and e) The MRMS data - July 31st, 2018 at 22:00 UTC

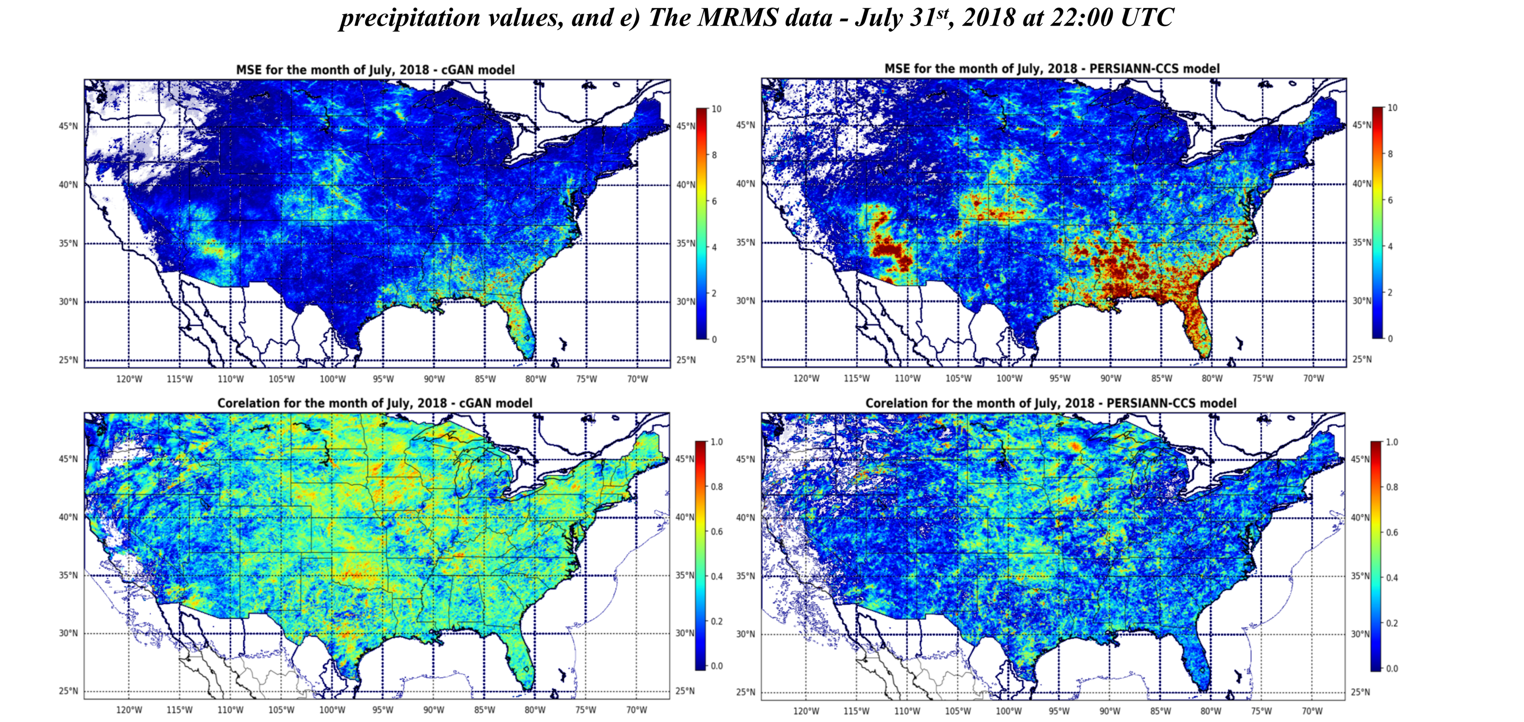

Fig 5: The Correlation and MSE (mm h⁻¹)² values for the cGAN and PERSIANN-CCS model during the validation period (month of July 2018).

Conclusion

- Application of a two-stage framework using a more complex objective function to train a Convolutional Neural Networks (CNNs) such as U-Net as the building block in the architecture of Generative models increase the accuracy to capture the complex properties of precipitation.
- Generative models help to better match the distribution of the generated precipitation from the observed data, and help to relax the strict assumptions of the traditional and conventional loss functions such as RMSE.
- Infusion of multiple channels of data as well as topography map as an auxiliary source of information helps to improve and better generalize the precipitation estimates on a larger scale.

Acknowledgement

Financial supports of this research are from U.S. Department of Energy (DOE Prime Award # DE-IA0000018). California Energy Commission (CEC Award # 300-15-005), MASEEH fellowship. NASA – Jet Propulsion Laboratory (JPL) Grant (Award # 1619578).

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