# Advancing Week-2 Precipitation Prediction Using Convolutional Neural Network

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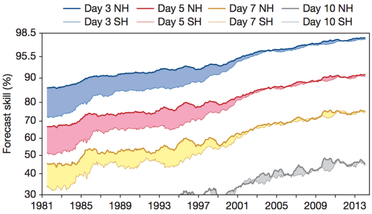
# Introduction

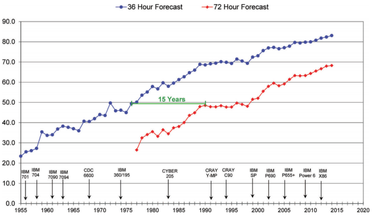
## Evolution of Predictive Skills



### Evolution of Predictive Skills for 500 hpa Geo Potential Height(GPH):




Correlation Coefficient Skill of ECMWF*




Square Error Skill of NCEP for Northern Hemisphere†

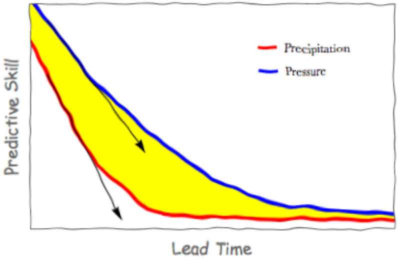
*Frédéric Vitart. Evolution of ECMWF sub-seasonal forecast skill scores. Quarterly Journal of the Royal Meteorological Society, 140(683):1889–1899, 2014.

†National Center for Environmental Prediction, accesses July 20, 2015

# Introduction

## On the Particular Difficulty of Quantitative Precipitation Forecast(QPF)

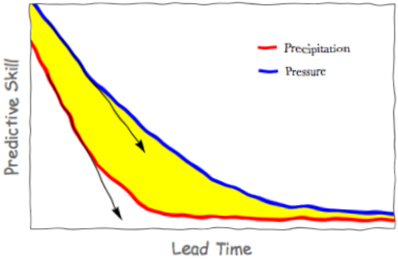




# Introduction

## On the Particular Difficulty of Quantitative Precipitation Forecast(QPF)

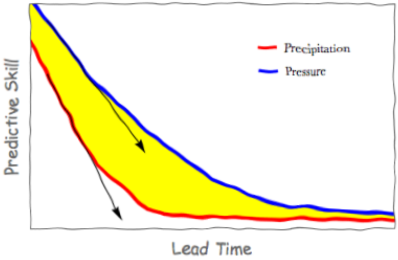





1. Precipitation Predictive Skill $<$ Pressure Predictive Skill
   - Precipitation parameterization introduces significant error.

# Introduction

## On the Particular Difficulty of Quantitative Precipitation Forecast(QPF)




1. Precipitation Predictive Skill $<$ Pressure Predictive Skill
   - Precipitation parameterization introduces significant error.
2. $\left|\frac{\partial(\text{Precipitation Predictive Skill})}{\partial(\text{Lead Time})}\right| > \left|\frac{\partial(\text{Pressure Predictive Skill})}{\partial(\text{Lead Time})}\right|$
   - Parameterization error is sensitive to dynamical deviation.

# Motivation

**On the Difficulty of Long Term QPF:**

1. Dynamical Precipitation forecast assumes statistical connection between atmosphere dynamics and precipitation.
    - The connection is at computing step time scale(minutes).
    - The connection is sensitive to dynamical errors.
2. As dynamical errors increase with forecast lead time, precipitation predictability worsens.

‡ Charles, S. P., I. N. Smith, and J. P. Hughes, 2004: Statistical down- scaling of daily precipitation from observed and modelled atmospheric fields. Hydrol. Processes, 18, 1373–1394.

# Motivation



**On the Difficulty of Long Term QPF:**

1. Dynamical Precipitation forecast assumes statistical connection between atmosphere dynamics and precipitation.
   - The connection is at computing step time scale(minutes).
   - The connection is sensitive to dynamical errors.
2. As dynamical errors increase with forecast lead time, precipitation predictability worsens.

**A Possible Way Out:**

- Is there a more reliable connection between precipitation and atmosphere dynamics at a less-resolved temporal scale?
  - Linear Regression using SLP provides equally competitive mean precipitation estimates at monthly scale[‡].
- Better alternative precipitation estimates can be achieved, provided that model offers more reliable prediction sources.

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[‡] Charles, S. P., I. N. Smith, and J. P. Hughes, 2004: Statistical down- scaling of daily precipitation from observed and modelled atmospheric fields. Hydrol. Processes, 18, 1373–1394.

# Research Question

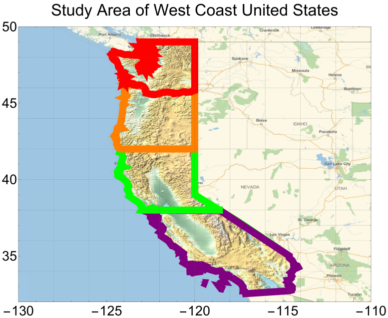


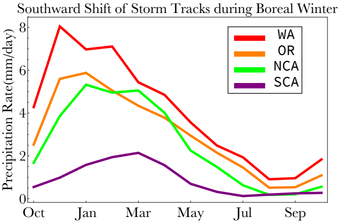
Apply the modern image processing techniques, specifically, **Convolutional Neural Network**, to explore the following questions:

1. Is there more reliable connection between precipitation and circulation at larger temporal scale?
2. Could we apply the connection for long-term precipitation prediction?

# Study Area & Data





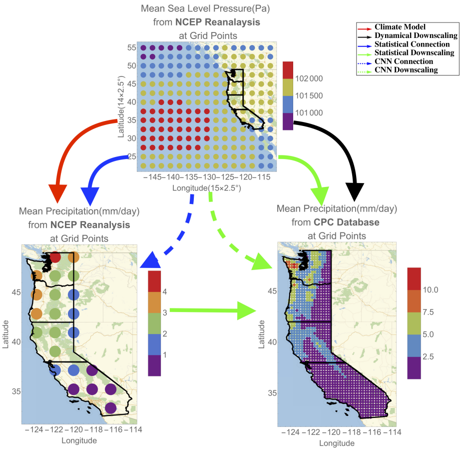




| Source | Variable | Spatial Resolution | Temporal Resolution | Coverage |
|---|---|---|---|---|
| **Reanalysis**(NCEP) | P<br>SLP | $2.5^\circ \times 2.5^\circ$ | 6 hour | 1948-2017 |
| **Observation**(CPC) | P | $0.25^\circ \times 0.25^\circ$ | daily | 1948-2017 |
| **Hindcast**(S2S) | P<br>SLP | $1.5^\circ \times 1.5^\circ$ | daily | **NCEP**:1999-2010<br>**ECMWF**:1995-2016 |

# Methodology



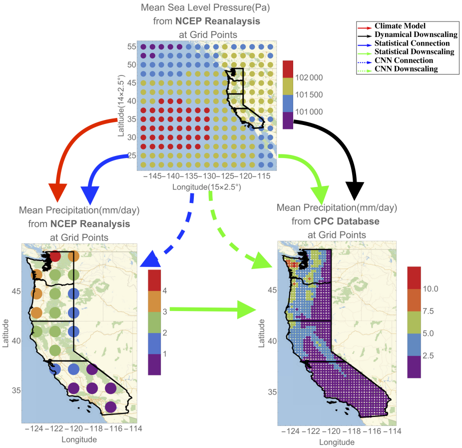
## 1. Construct SLP-P connection using CNN



# Methodology



## 1. Construct SLP-P connection using CNN

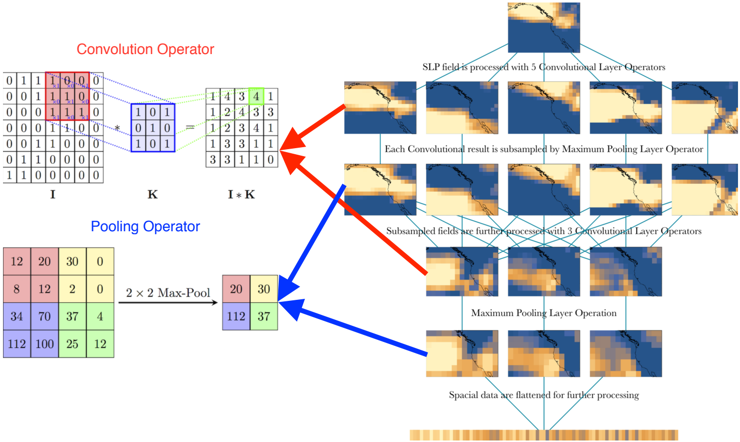



## 2. $\mathbf{SLP}_{\mathbf{forecast}} \xrightarrow{\mathbf{CNN}} \mathbf{P}_{\mathbf{CNN\text{-}forecast}}$

# Construct SLP-P Connection

## Convolutional Neural Network

1. Distill pressure features that influence precipitation.




2. Use these features to estimate precipitation.

# Construct SLP-P Connection

## CNN Architecture



| Layer No. | Layer Type | Hyperparameter |
|---|---|---|
| 1 | Normalization Layer | |
| 2 | Convolution Layer | Kernel Size: $5\times5$ |
| 3 | Pooling Layer | Kernel Size: $2\times2$ |
| 4 | Convolution Layer | Kernel Size: $3\times3$ |
| 5 | Pooling Layer | Kernel Size: $2\times2$ |
| 6 | Flatten Layer | |
| 7 | Dropout Layer | P=0.5 |
| 8 | Linear Layer | |
| 9 | Transform Layer | ReLu |
| 10 | Batch Normalize Layer | |
| 11 | Dropout Layer | P=0.5 |
| 12 | Linear Layer | |
| 13 | Transform Layer | ReLu |
| 14 | Linear Layer | |
| 15 | Batch Normalize Layer | |

With the architecture constructed, parameters were initialized and trained using ADAptive Moment Estimation Method.

# Construct SLP-P Connection

## CNN Architecture



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With the architecture constructed, parameters were initialized and trained using ADAptive Moment Estimation Method.

## Comparison with other Convolution Models

| Model | Kernel | Convolution Window | Dimension | Utility |
|---|---|---|---|---|
| **Fourier Transform** | Fixed(*Sin*,*Cos*) | Fixed($-\infty$ to $\infty$) | usually 1-2D | Periodicity |
| **Wavelet Transform** | Selective(Meyer,Morlet,Mexican hat,etc.) | Tunable | usually 1-2D | Feature extraction |
| **CNN** | Trainable | Tunable | No limitation | Machine learning |

# Construct SLP-P Connection
## Evaluation Scores



$$r = \frac{E[(P_{obser} - \overline{P_{obser}})(P_{simu} - \overline{P_{simu}})]}{\sigma_{P_{obser}} \sigma_{P_{simu}}}$$

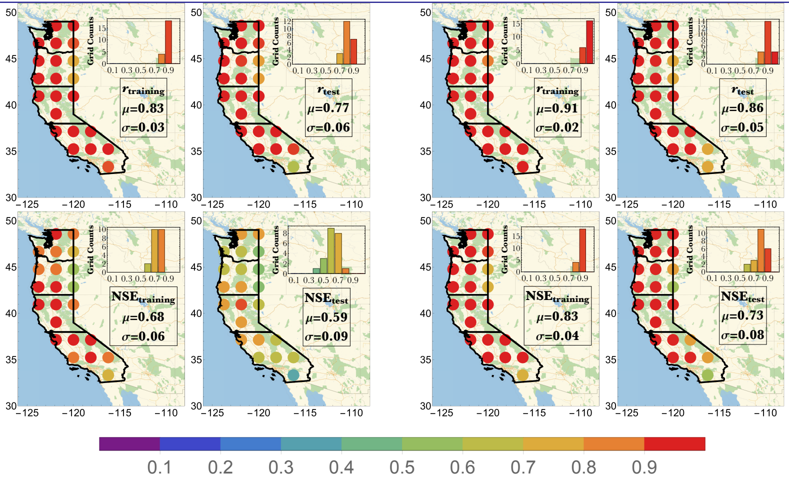
$$NSE = 1 - \frac{\sum (P_{obser} - P_{simu})^2}{\sum (P_{obser} - \overline{P_{obser}})^2}$$

# $SLP_{Reanalysis} \rightarrow P_{Reanalysis}$(R2R)



## Hourly Scale

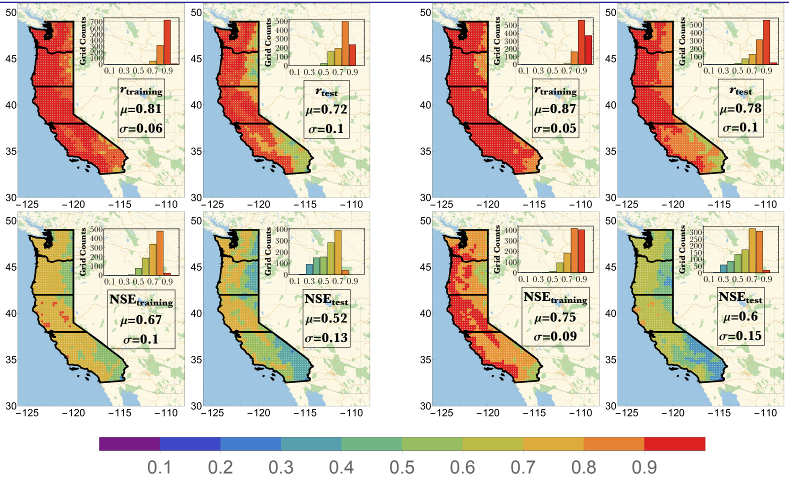
## Weekly Scale



# $SLP_{Reanalysis} \rightarrow P_{Gauge}$(R2O)

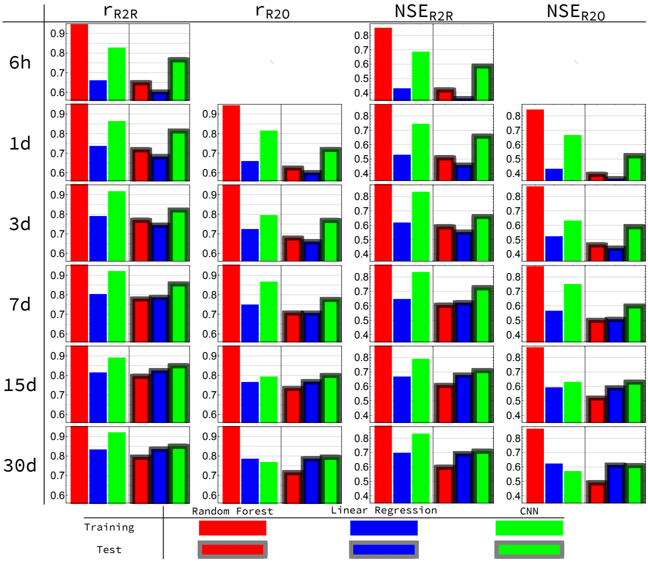


## Daily Scale | Weekly Scale



# SLP-P Connection
## Summary for Different Scales

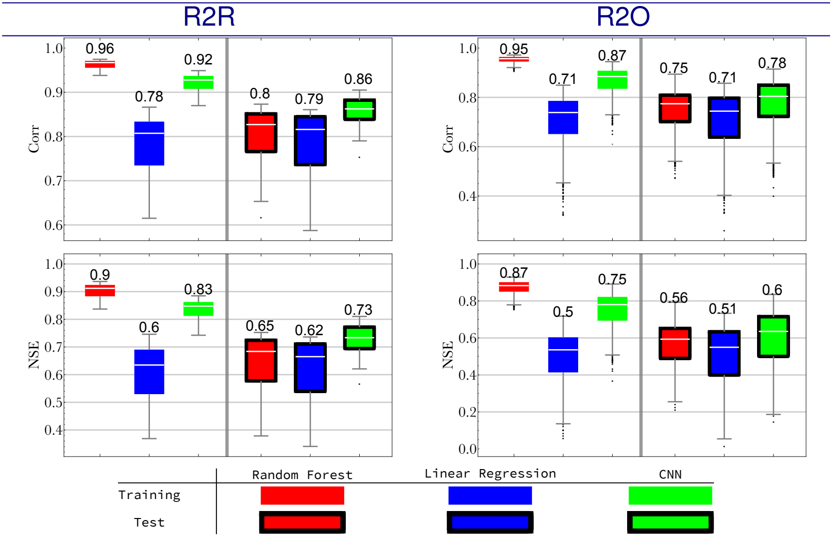




# Week-2 Precipitation Prediction

Statistics at Weekly Scale

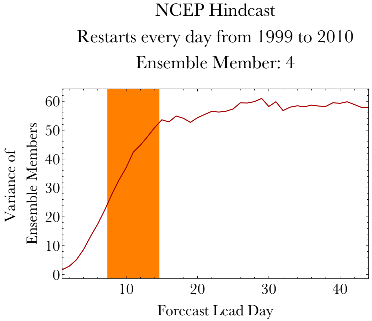


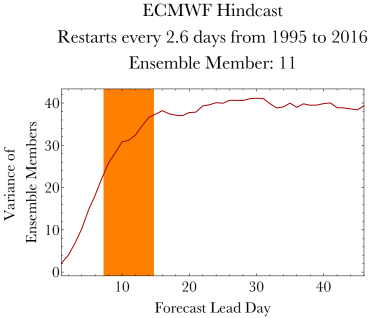


# Week-2 Precipitation Prediction

## Strategy





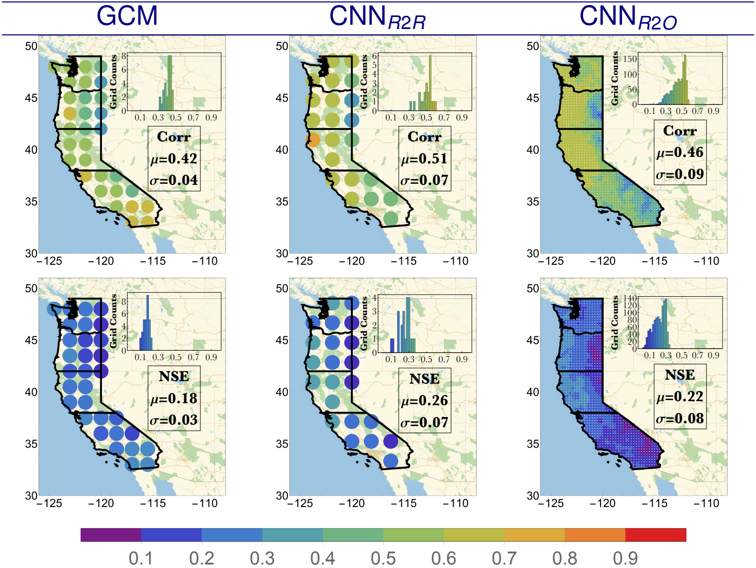




With the connection constructed, now we apply the trained CNN to process GCM SLP hindcasts for alternative precipitation estimates. Results are compared with reanlaysis data and gauge observation data.

# Week-2 Precipitation Prediction

NCEP



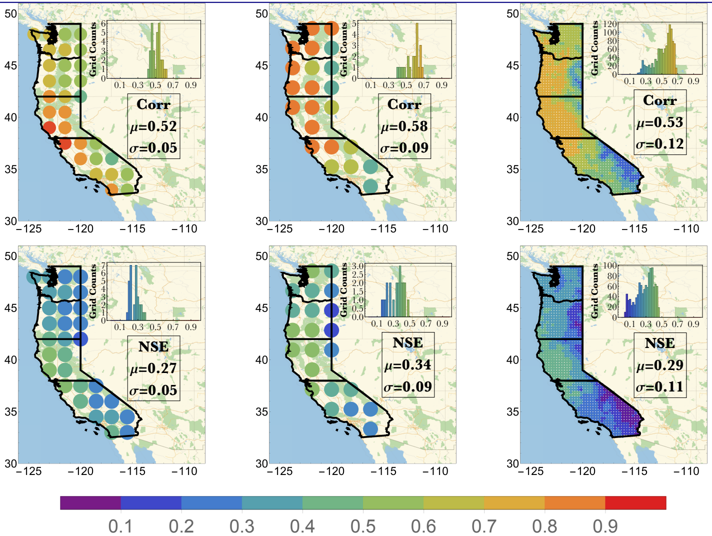


# Week-2 Precipitation Prediction

ECMWF



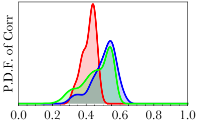
| GCM | $CNN_{R2R}$ | $CNN_{R2O}$ |
|---|---|---|

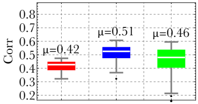


# Week-2 Precipitation Prediction
## Summary



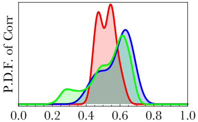
$r_{NCEP}$

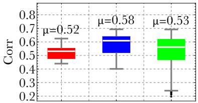



| | GCM | $CNN_{R\to R}$ | $CNN_{R\to O}$ |
|---|---|---|---|
| Max | 0.47 | 0.61 | 0.6 |
| 75% | 0.45 | 0.56 | 0.54 |
| Median | 0.43 | 0.53 | 0.48 |
| 25% | 0.39 | 0.48 | 0.41 |
| Min | 0.32 | 0.32 | 0.16 |

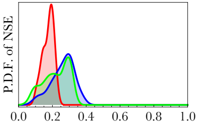
$r_{ECMWF}$

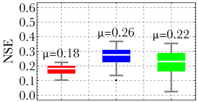



| | GCM | $CNN_{R\to R}$ | $CNN_{R\to O}$ |
|---|---|---|---|
| Max | 0.62 | 0.69 | 0.69 |
| 75% | 0.55 | 0.64 | 0.62 |
| Median | 0.53 | 0.61 | 0.56 |
| 25% | 0.48 | 0.52 | 0.47 |
| Min | 0.44 | 0.4 | 0.2 |

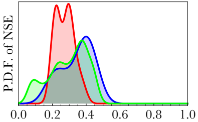
$NSE_{NCEP}$

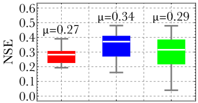



| | GCM | $CNN_{R\to R}$ | $CNN_{R\to O}$ |
|---|---|---|---|
| Max | 0.22 | 0.37 | 0.35 |
| 75% | 0.2 | 0.31 | 0.29 |
| Median | 0.18 | 0.28 | 0.23 |
| 25% | 0.15 | 0.23 | 0.16 |
| Min | 0.1 | 0.1 | 0.02 |

$NSE_{ECMWF}$




| | GCM | $CNN_{R\to R}$ | $CNN_{R\to O}$ |
|---|---|---|---|
| Max | 0.39 | 0.48 | 0.48 |
| 75% | 0.31 | 0.41 | 0.38 |
| Median | 0.28 | 0.37 | 0.32 |
| 25% | 0.23 | 0.27 | 0.22 |
| Min | 0.19 | 0.16 | 0.04 |

# Conclusions



- There is a less-resolved but more stable connection between precipitation and circulation for the West Coast United States.
  - CNN works better at capturing the connection from hourly to weekly scales.
  - The connection transfers from nonlinear to linear as scale expands.
- We can have alternative better Week-2 precipitation estimates(with $r$ and *NSE* improved by 0.1 on average), since model offers more reliable circulation predictions.

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