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Center for
Computational Science

Toward Model Acceleration By ML

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Outline

- ❑ CNN for 3D Precipitation Nowcasting
- ❑ CNN Based Model Acceleration

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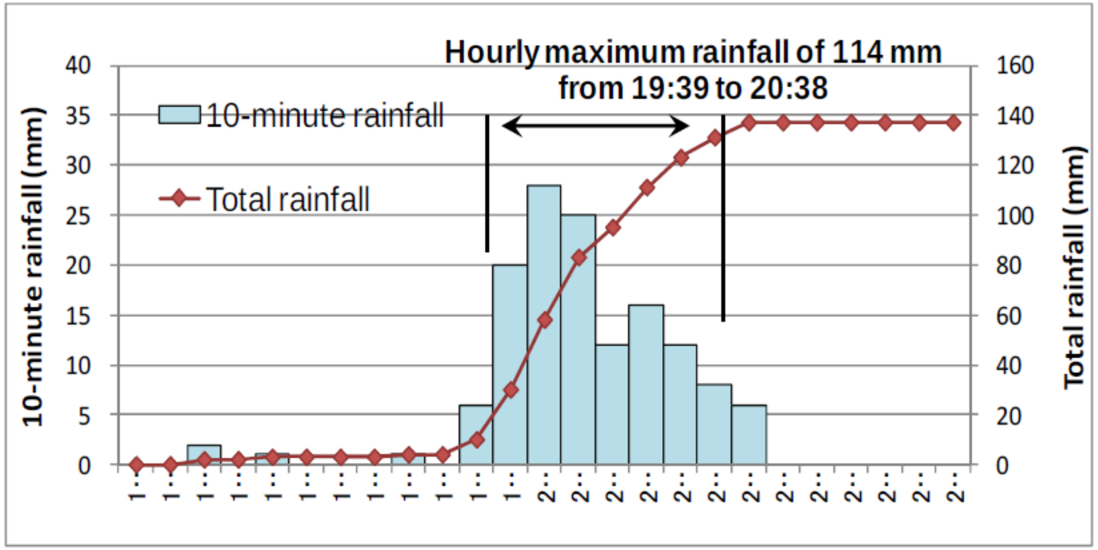
CNN for 3D Precipitation Nowcasting

Introduction

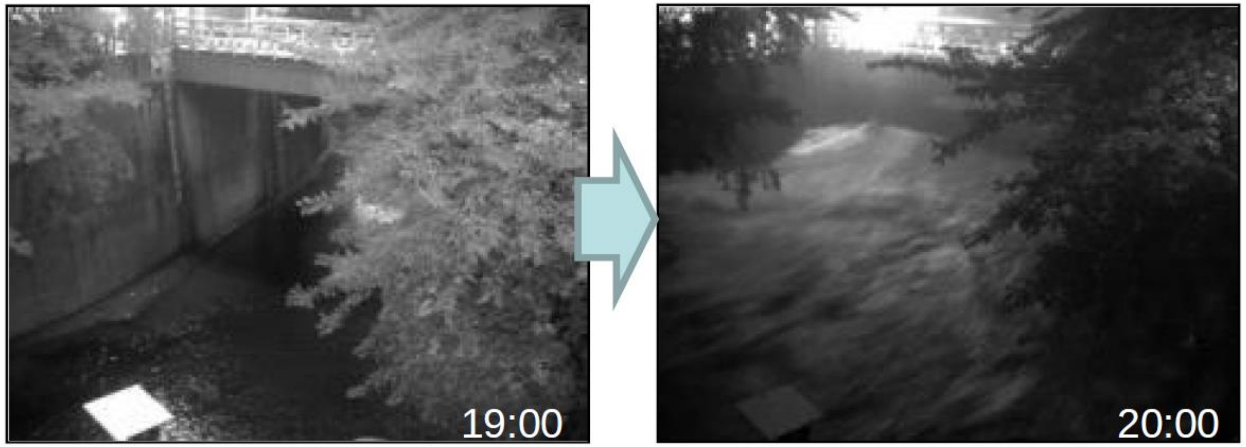
- Precipitation nowcasting:
  - Short-term prediction (10-30mn)
  - Latest observations
- Why nowcasting? -> Disaster prevention
  - Abrupt downpours/hailstorms
  - E.g. Tokyo-Itabashi 05/07/2010

Shakujii River flooded 108 houses

Maximum hourly rainfall of 114 mm



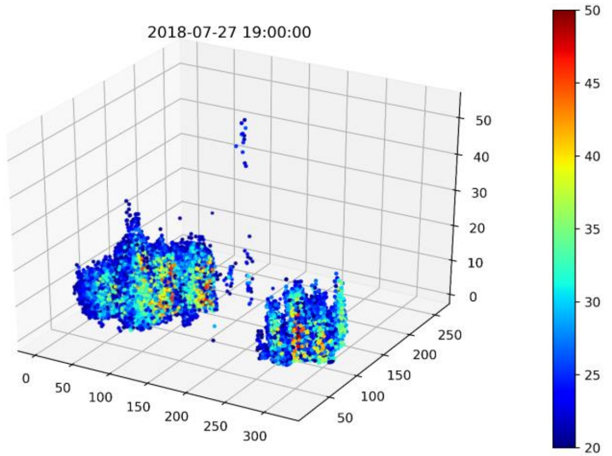
Water level rose by 3.45 m in 10 minutes



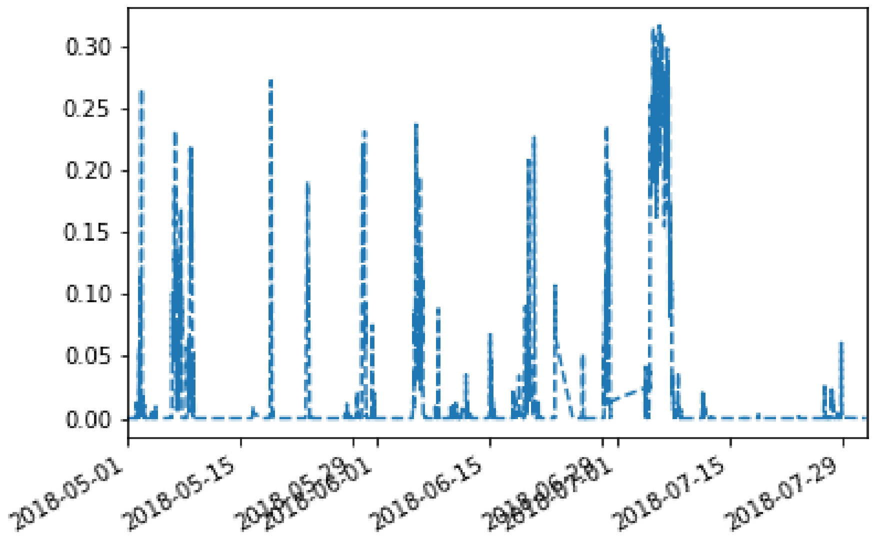
Figures by Koji IKEUCHI, Water and Disaster Management Bureau, MLIT, Japan

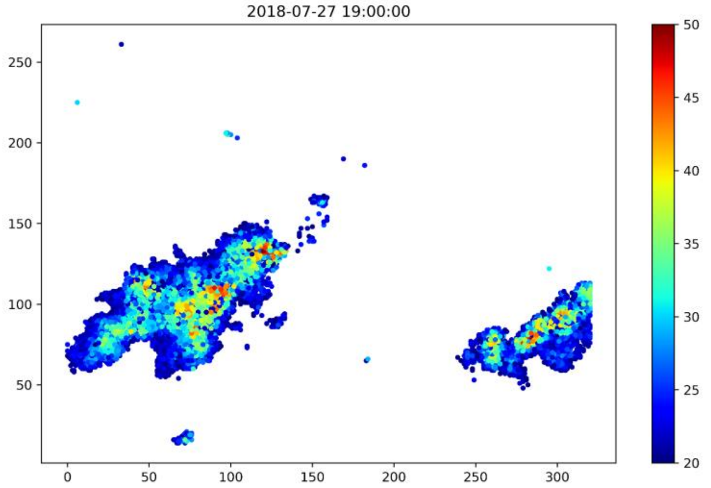
Data Sources

- Phased-Array Weather Radar (PAWR)
- Location: Kobe area
- Range: 01/05/2018 to 31/07/2018
- Image size: 321×321×57 pixels
- Resolution: 250m
- Frequency: 30sec aggregated to 10mn



Rain coverage

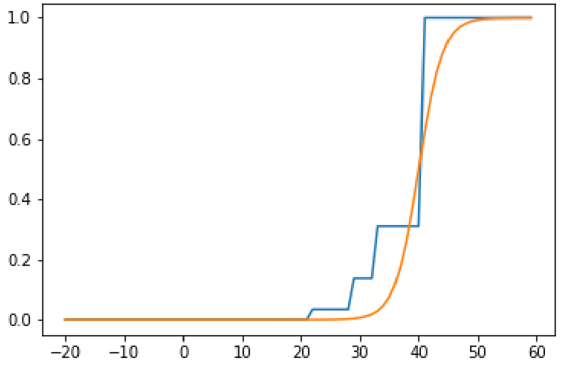




Nowcasting Algorithm

- Convolutional neural network
- Optimizer: ADAM
- Implementation: Tensorflow
- Input: Latest 6 observations
- Output: Next observation estimate

Weight function w



Objective function

$$\text{WMSE}=\frac{1}{N}\sum w(max(x,\hat{x}))\,.\,(x-\hat{x})^2$$

Validation metrics

Rain if > 22dBZ

Predicted

Actual	Rain	No rain
Rain	TP	FN
No rain	FP	TN

T: True, F: False
P: Positive, N: Negative

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \qquad \text{Recall} = \frac{\text{TP}}{\text{TP+FN}}$$

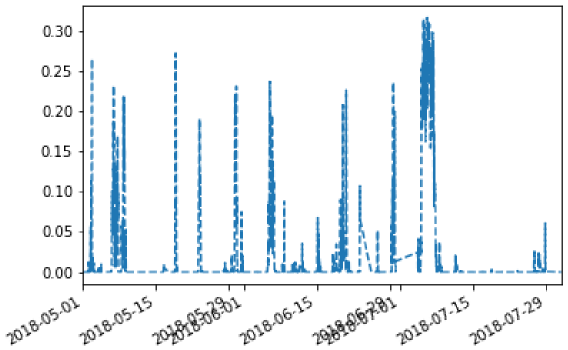
Challenging Points

High dimensional input

- Non-convex objective function
- Large # of local minima
- Convergence to non-optimal solution

Sparsity

- 2% of data contain rain information
- Time and space complexity
- Compression => variable input size Fully convolutional network?



High dimensional output

- Image prediction vs classification
- Wide layers (large # nodes/layer)
- Large memory requirement

Border Effect

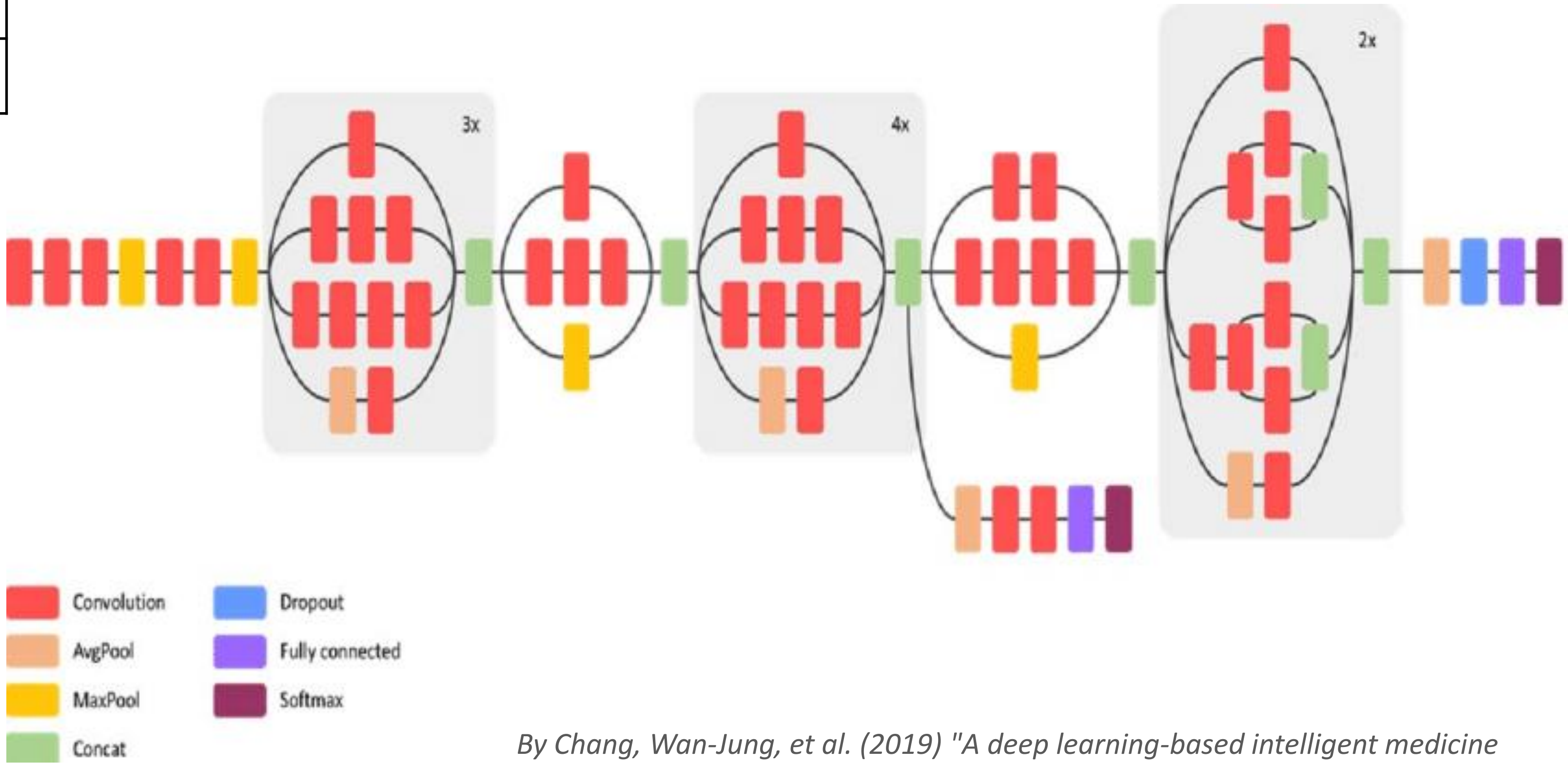
- Few information about pixels in the borders
- Low precision in the borders

Results

Comparison

	CNN	FCN	InceptionV3
Precision	.84	.81	.89
Recall	.82	.85	.89

- CNN: Classical CNN with 1 convolutional layer
- FCN: Fully convolutional network
- InceptionV3: deep CNN

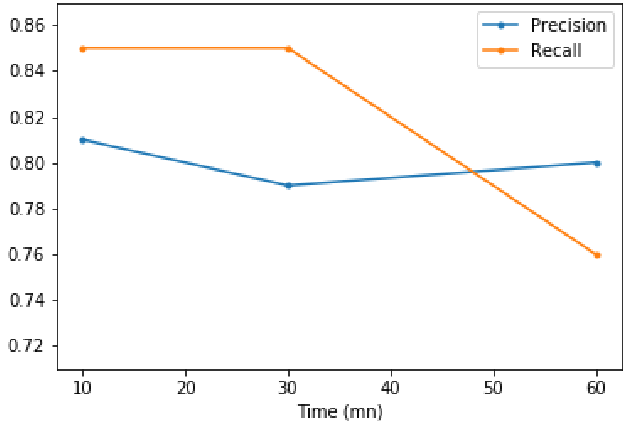


By Chang, Wan-Jung, et al. (2019) "A deep learning-based intelligent medicine recognition system for chronic patients". IEEE Access

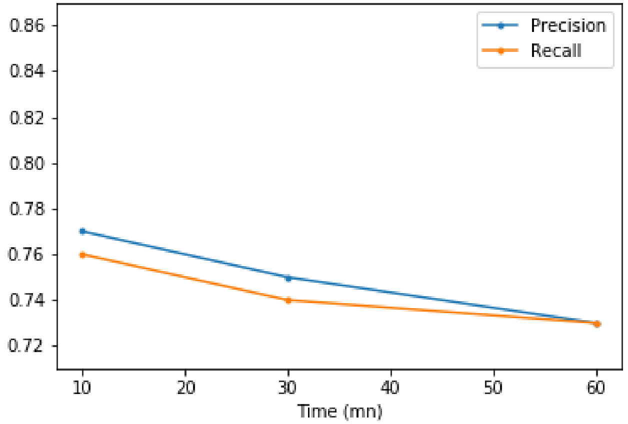
Results

Resolution: FCN Model

HR = 321 x 321 x 20



LR = 160 x 160 x 20



Next Steps

- Larger data set with seasonal variations
- Comparison with ConvLSTM and Reservoir computing
- Comparison with Optical Flow (Dr. Otsuka presentation)

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CNN Based Model Acceleration

Introduction

- Physical models in meteorology are computationally expensive
- Require complex operations: e.g. matrix inversion/multiplication
- Disaster prevention requires near real time predictions.

Objective:

Apply simple physical models (low resolution)
and Infer high resolution results using ML

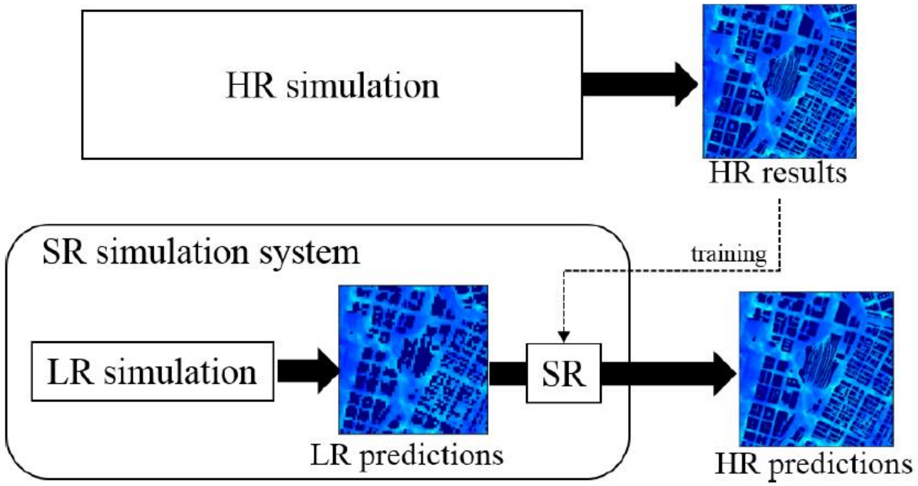
DATA SET

- PRISM Climate Data (PRISM Climate Group)
  http://www.prism.oregonstate.edu/
- Public data sets used by many researchers for validation
- Climate observations: short and long term pattens (since 1895)
- Metrics: temperature, precipitation, vapor pressure deficit

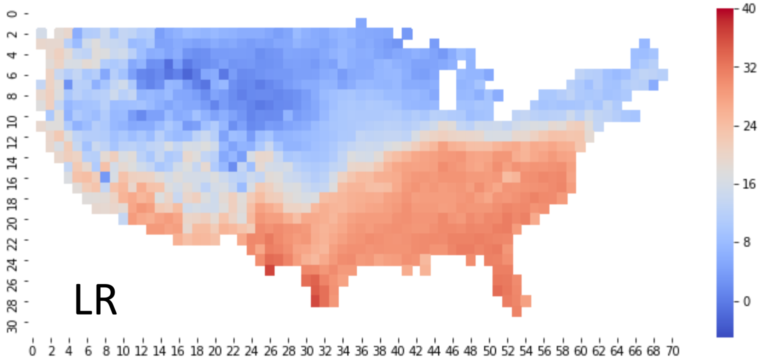
Considered data

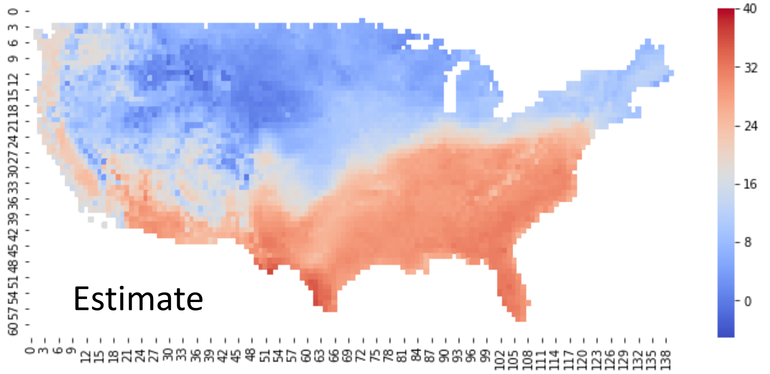
- Metric: max temperature (°F)
- Frequency: daily
- Range: 10/2018 - 11/2019 observations
- HR: 40KM, LR:80KM

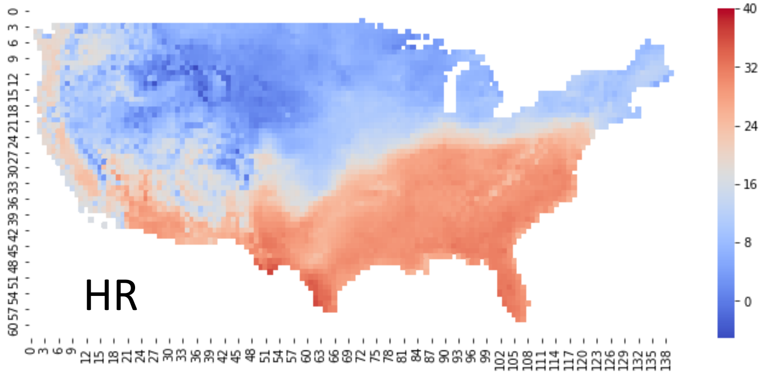
CNN Based Super resolution



by Onishi, R., Sugiyama, D., and Matsuda, K. (2019). "Super-resolution simulation for real-time prediction of urban micrometeorology". *SOLA*.







Training

- Run complex model to create HR images
- Run simple model for LR images
- Train CNN to map LR to HR

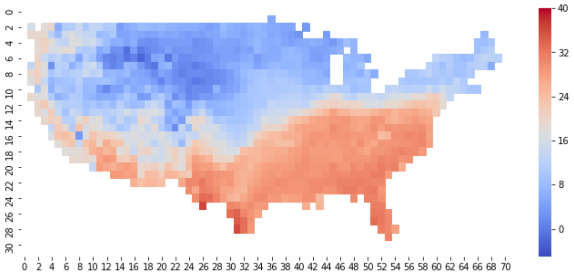
Real time

- Run simple model for LR images
- Map LR to HR using trained model

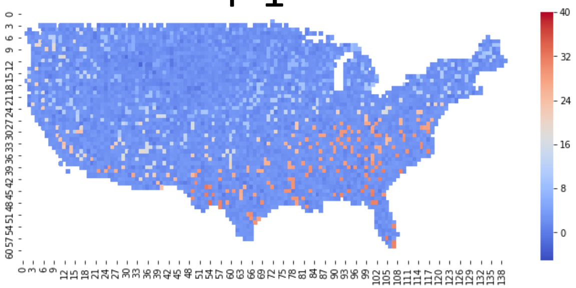
Results: Iterations

- 1 iteration= 14s

LR



i=1



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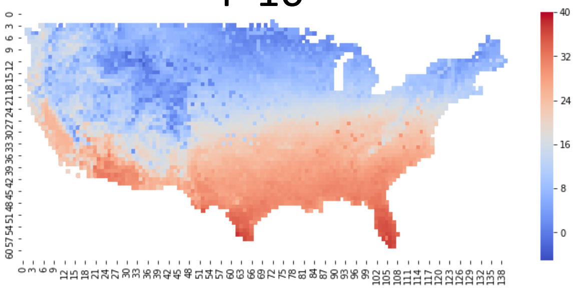
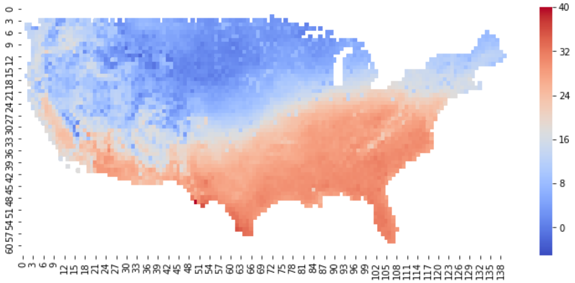
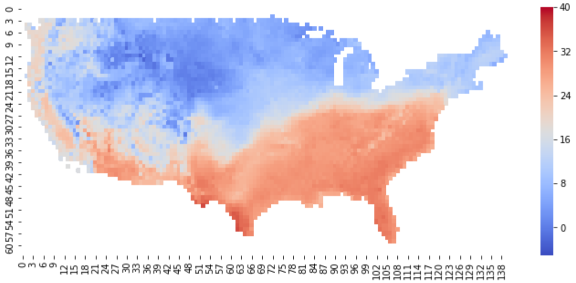


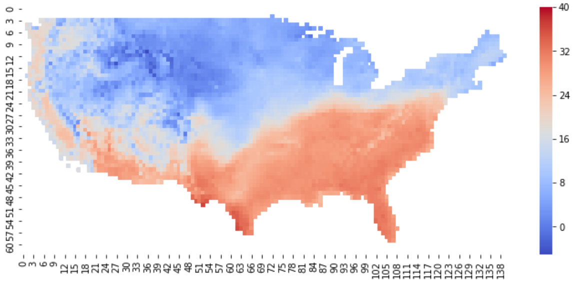
i=100



i=750

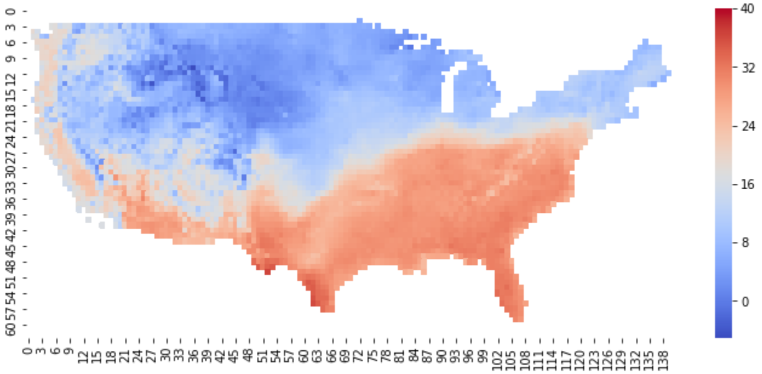


HR

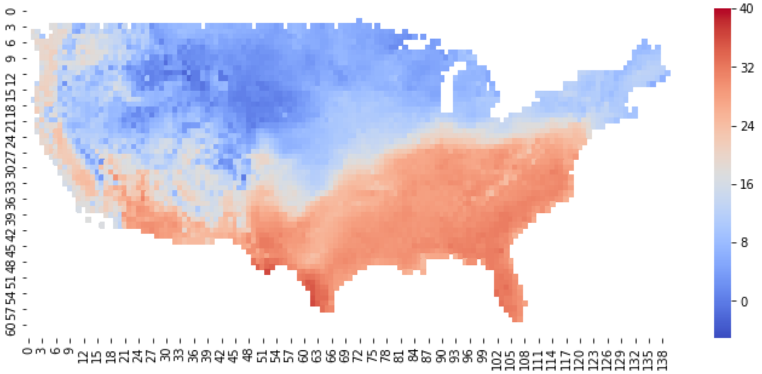


Results: Comparison

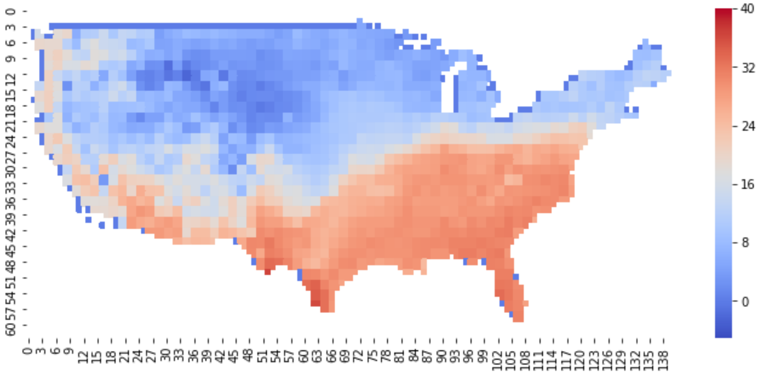
HR



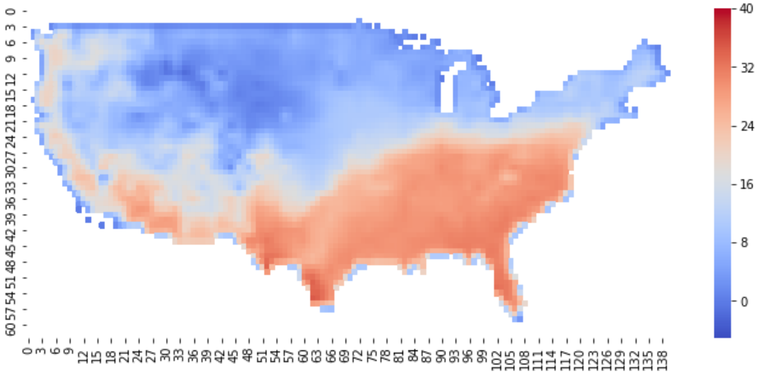
CNN



Nearest Neighbor Interpolation



Bilinear Interpolation



Conclusion

	CNN	NN Interpolation	Bilinear Interpolation
MAE (°F)	0.76	1.07	1.02

Next steps

- Apply SR to data from SCALE model
- Tune CNN for a higher accuracy
- Explore other state of the art solutions and compare