



## Statistical Precipitation Downscaling Using Random Forests

- Synthetic experiments over Southeast United States -

Xiaogang He<sup>1</sup>, Nathaniel W. Chaney<sup>1,2</sup>, Justin Sheffield<sup>1</sup>,  
Ming Pan<sup>1</sup>, Eric F. Wood<sup>1</sup>

<sup>1</sup> Department of Civil and Environmental Engineering, Princeton University

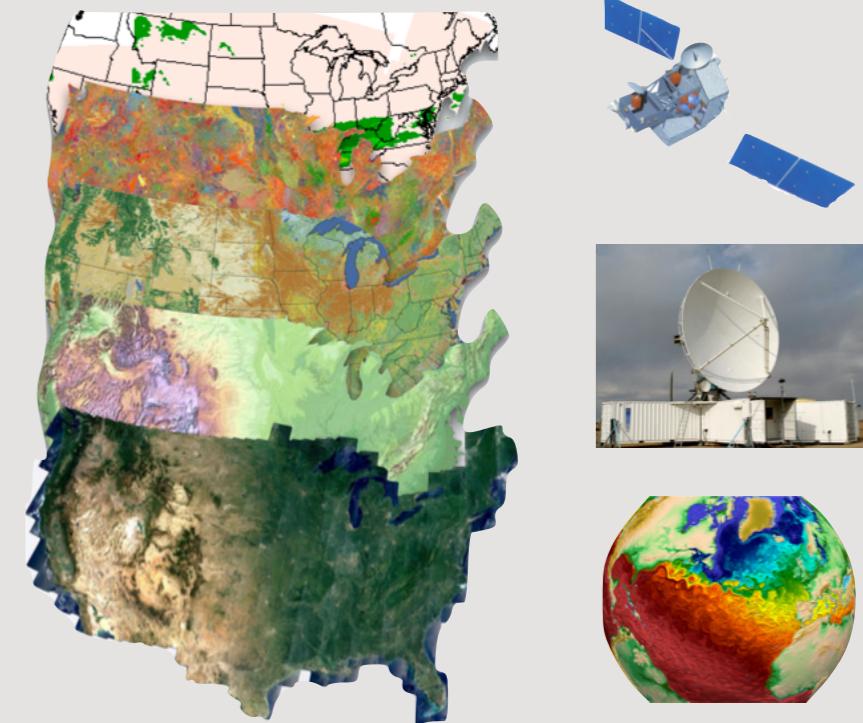
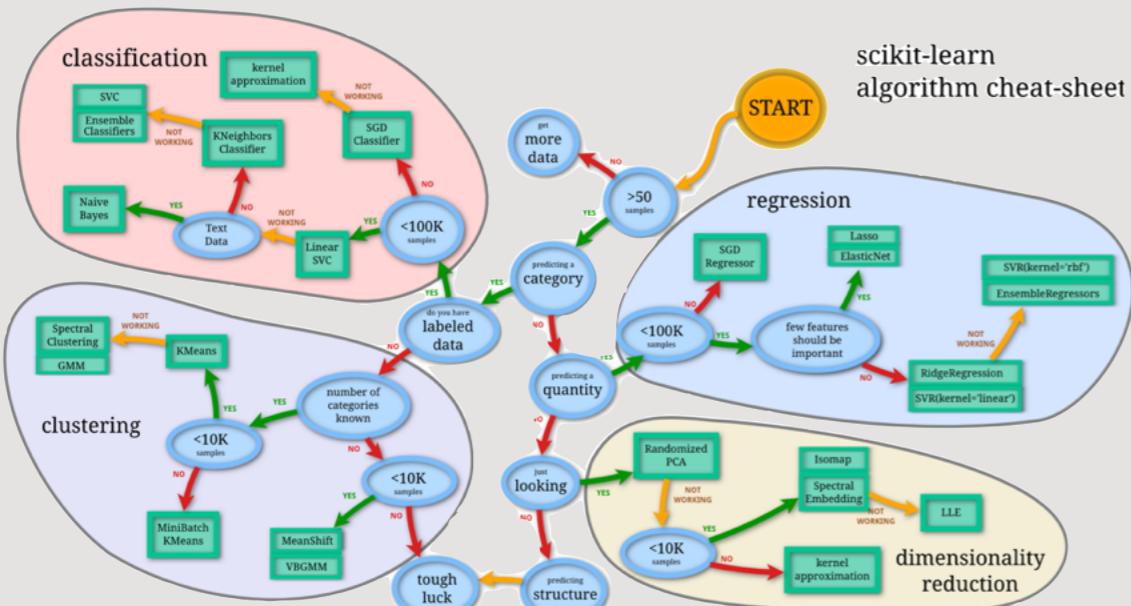
<sup>2</sup> Program of Atmospheric and Oceanic Sciences, Princeton University



# Precipitation downscaling

# Opportunities

## Machine learning approach



Explore and construct complicated relationships



High performance computing

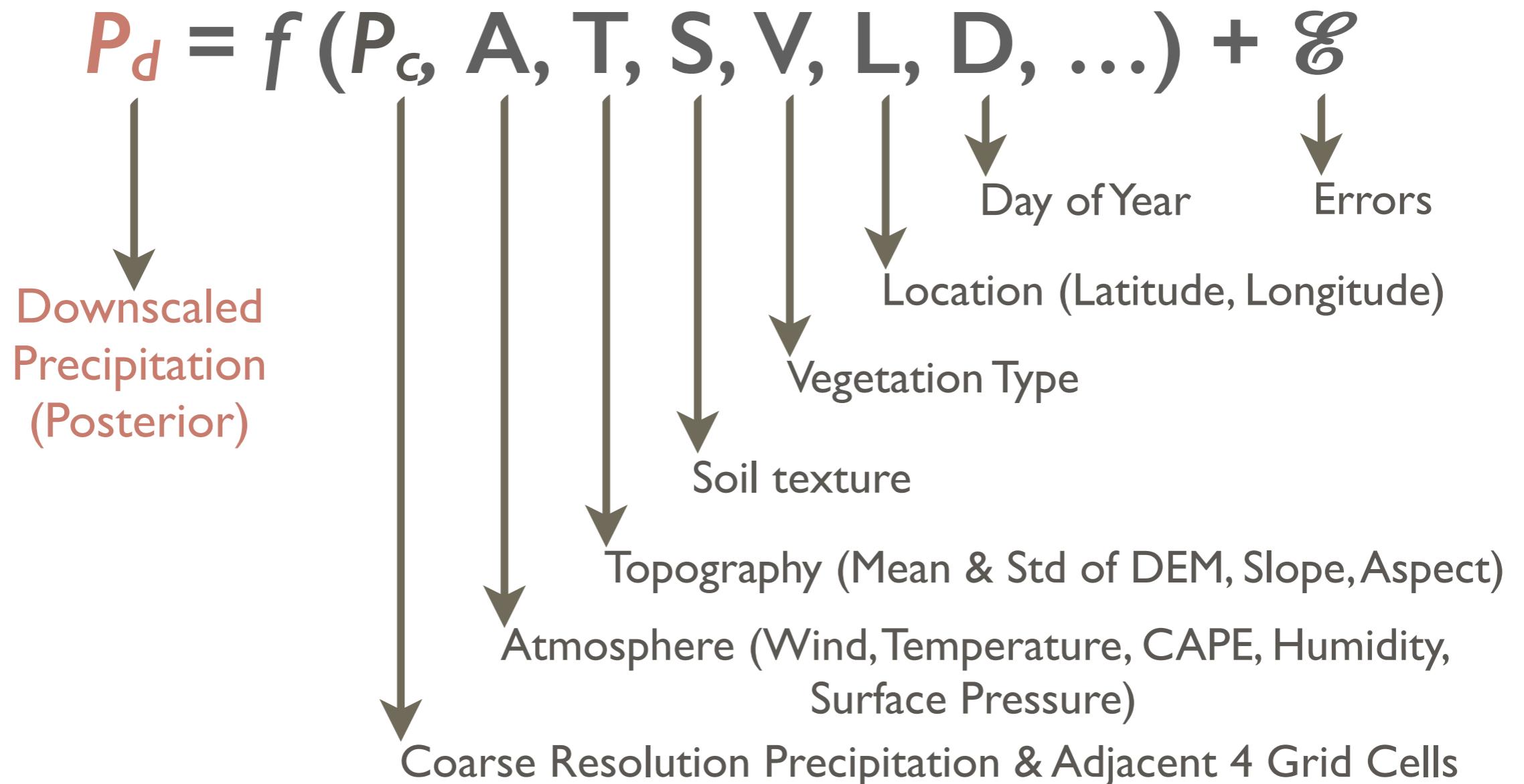


Precipitation  
spatial-temporal  
structures??

Hyperresolution  
precipitation  
downscaling??

# Regression model

# Methodology

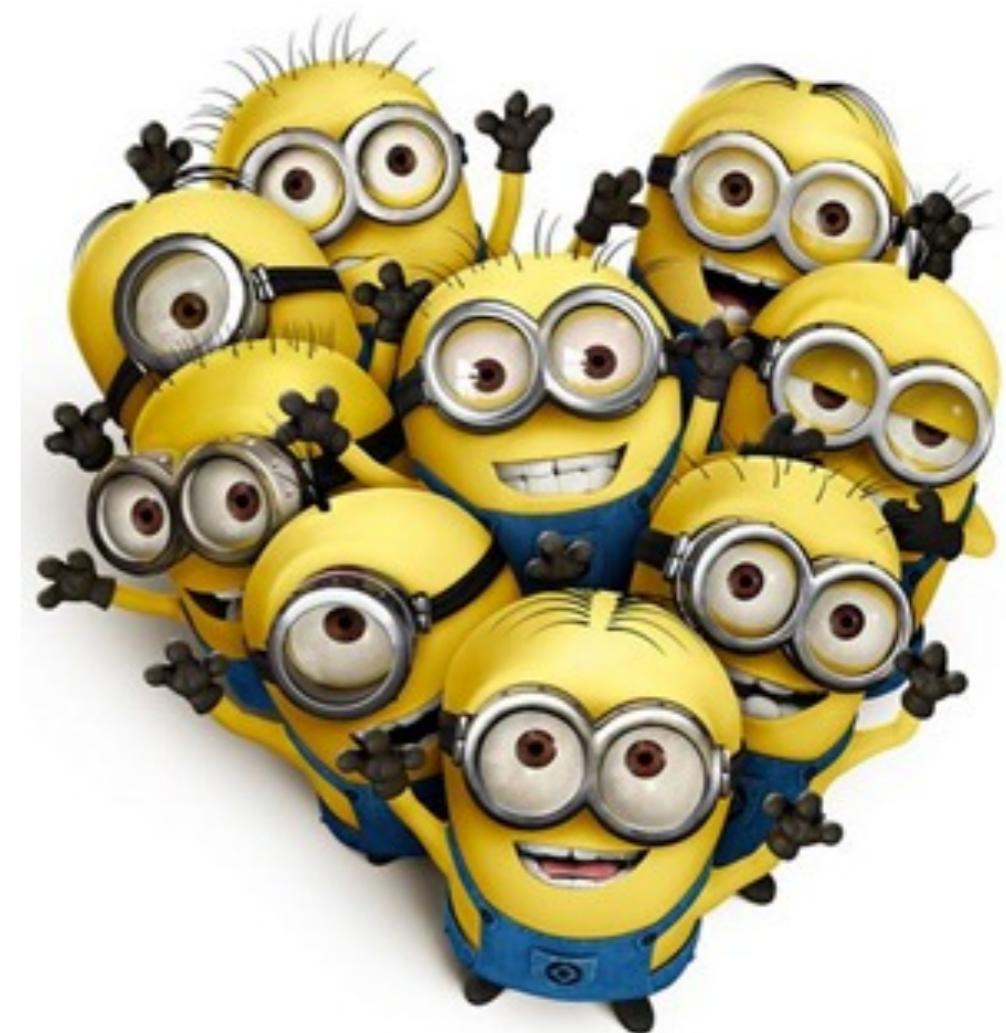


Single learner



VS

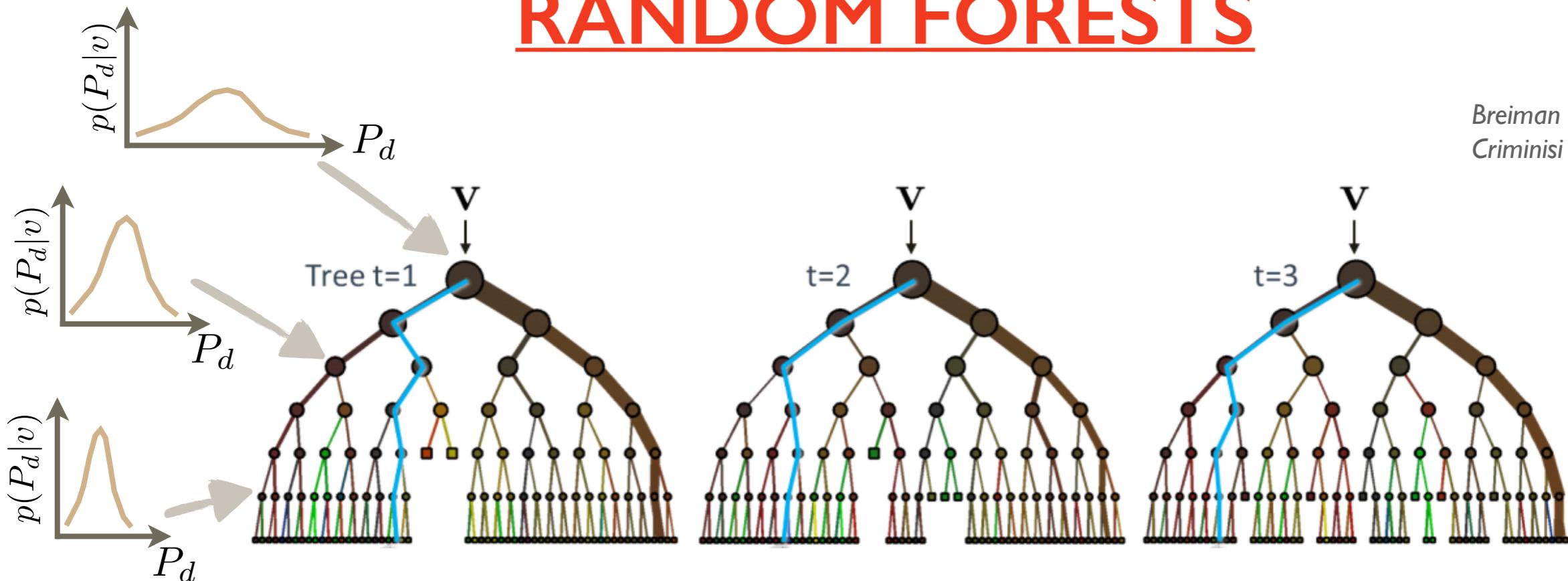
Group of learners



Ensemble methods → Reduce overfitting

# RANDOM FORESTS

Breiman (2001)  
Criminisi et al., (2011)



**Regression forest posterior:**  $p(P_d|v) = \frac{1}{T} \sum_{t=1}^T p_t(P_d|v)$

$v$ : covariates

$P_d$ : predictand (downscaled prec)

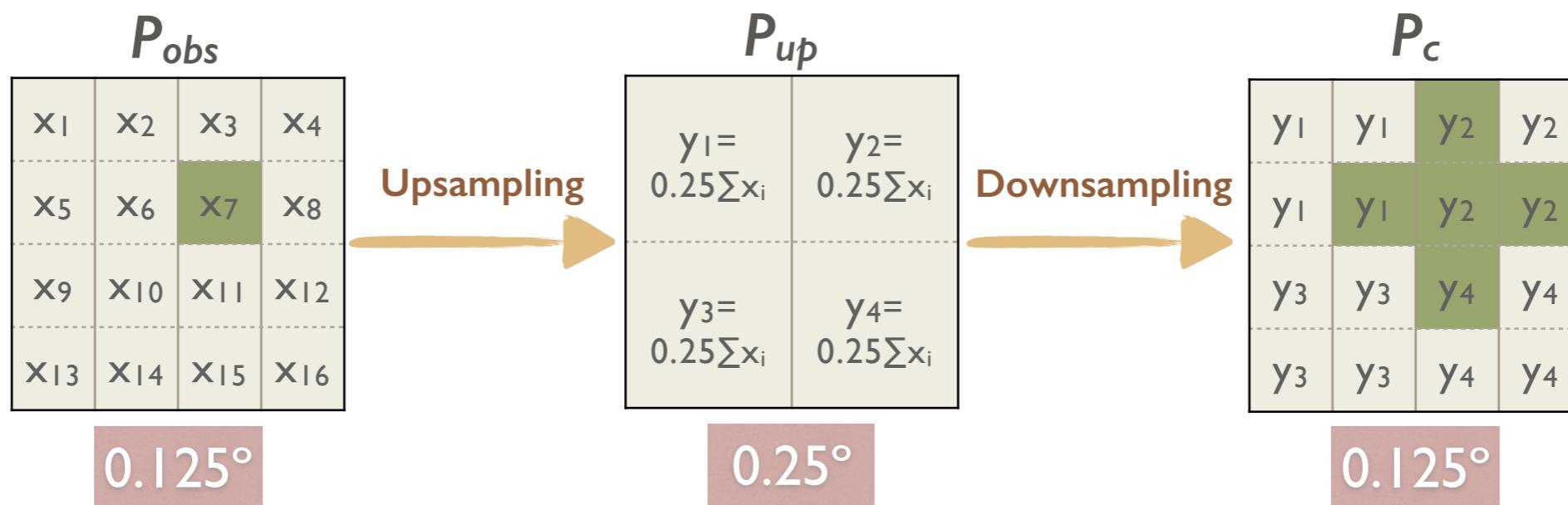
$p_t(P_d|v)$ : individual tree posterior

# Step I: Generate synthetic covariates

# Synthetic Experiment Design

<b>Data:</b>	NLDAS2 <u>North American Land Data Assimilation System 2</u>
<b>Period:</b>	2011.06.01—2011.08.31 (Hourly)
<b>Domain:</b>	<u>Region:</u> Southeast United States <u>Grid:</u> 80×72 (0.125°)

EXP	$P_C$	A
$P_{0.25}A_{0.125}$	0.25°	0.125°
$P_{0.25}A_{0.25}$	0.25°	0.25°
$P_{0.5}A_{0.125}$	0.5°	0.125°
$P_{0.5}A_{0.5}$	0.5°	0.5°
$P_1A_{0.125}$	1°	0.125°
$P_1A_1$	1°	1°

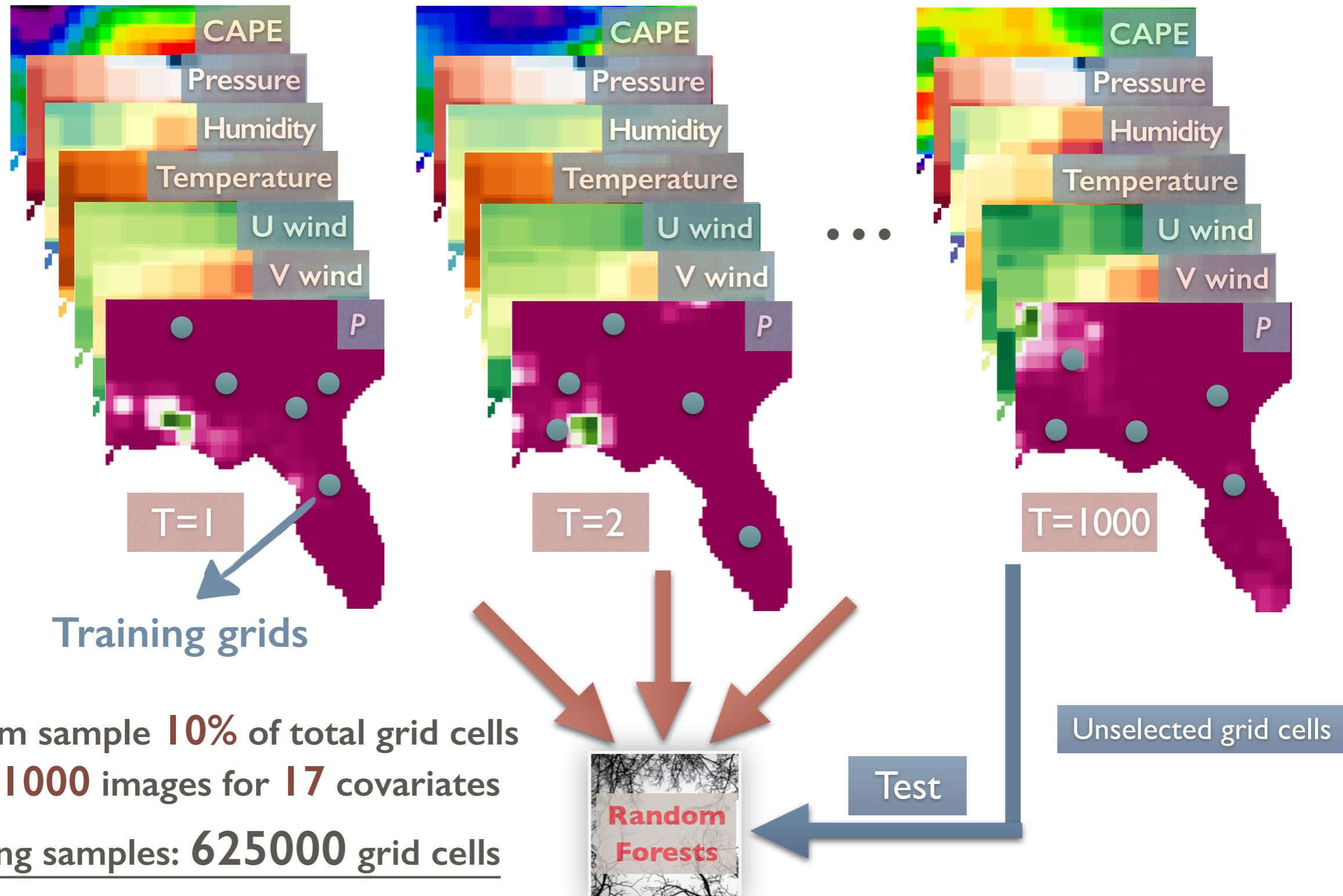


Adjacent grid cells are also considered  
Same procedures for atmospheric covariates

## Step 2: Train and test Random Forests

## Synthetic Experiment Design

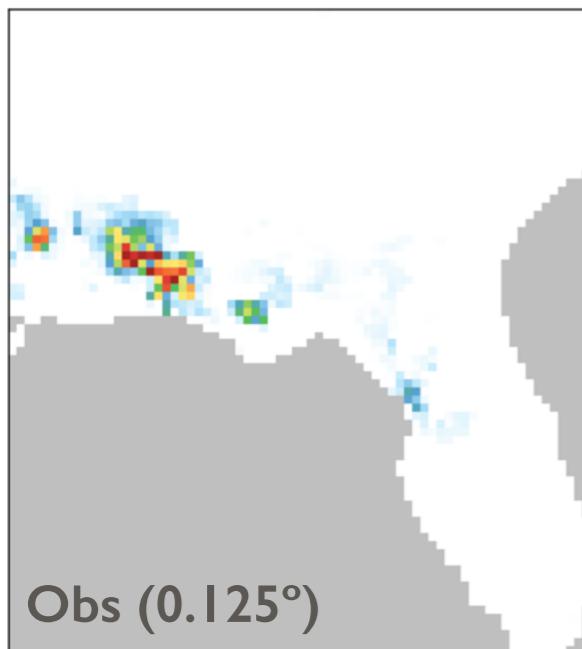
Coarse  $P$  + Dynamic/Fixed Covariates  $\Rightarrow$  Downscaled  $P$



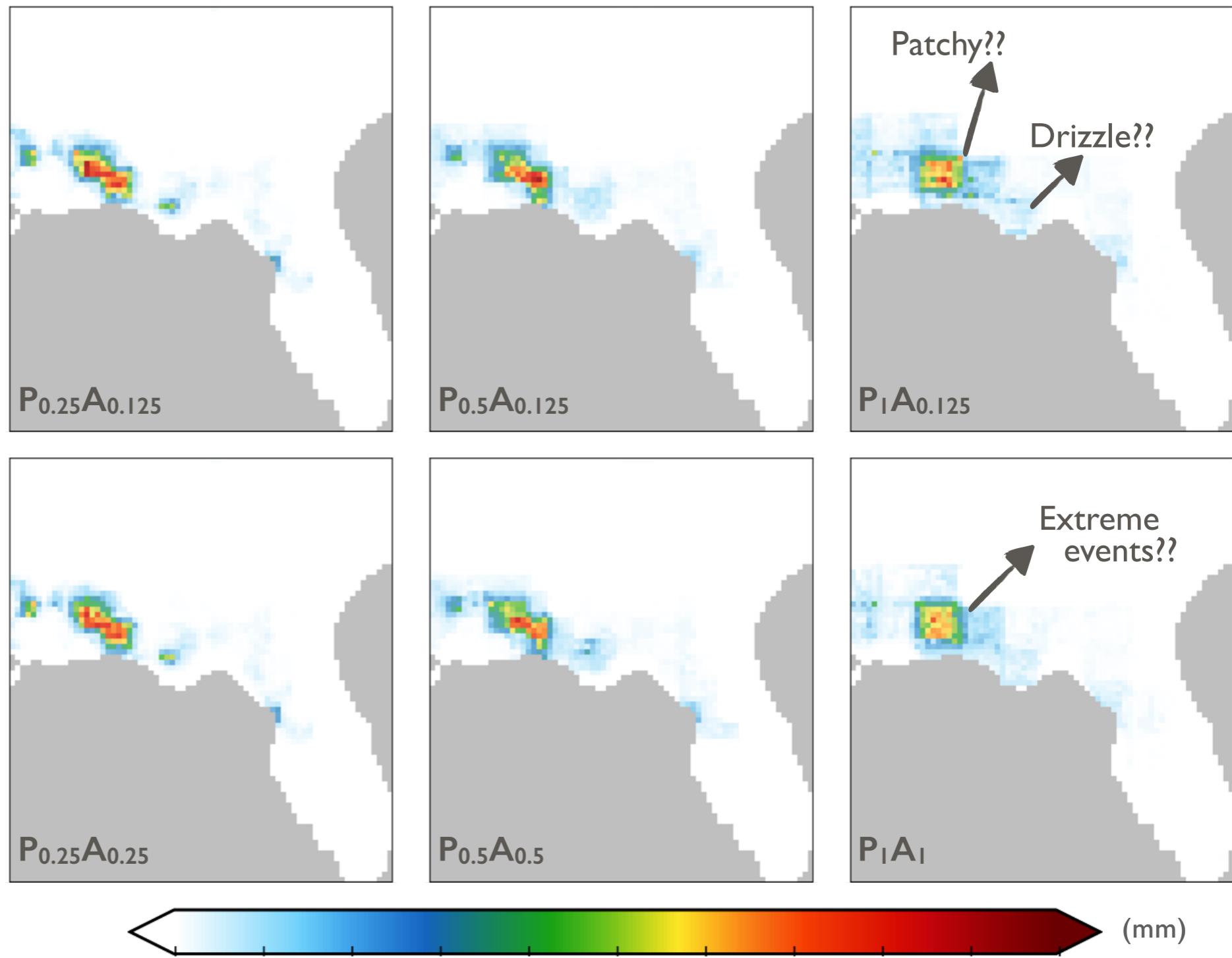
# Spatial pattern

# Results

## Scaling Experiments



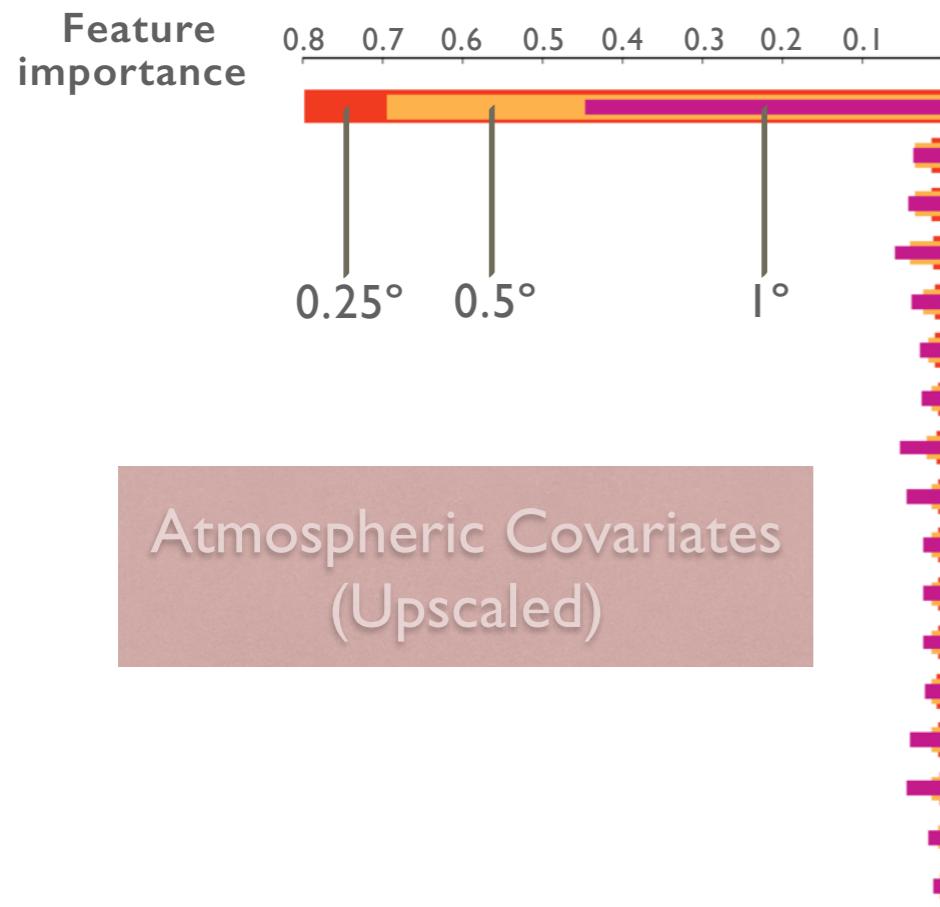
Example:  
2011.06.06.23:00



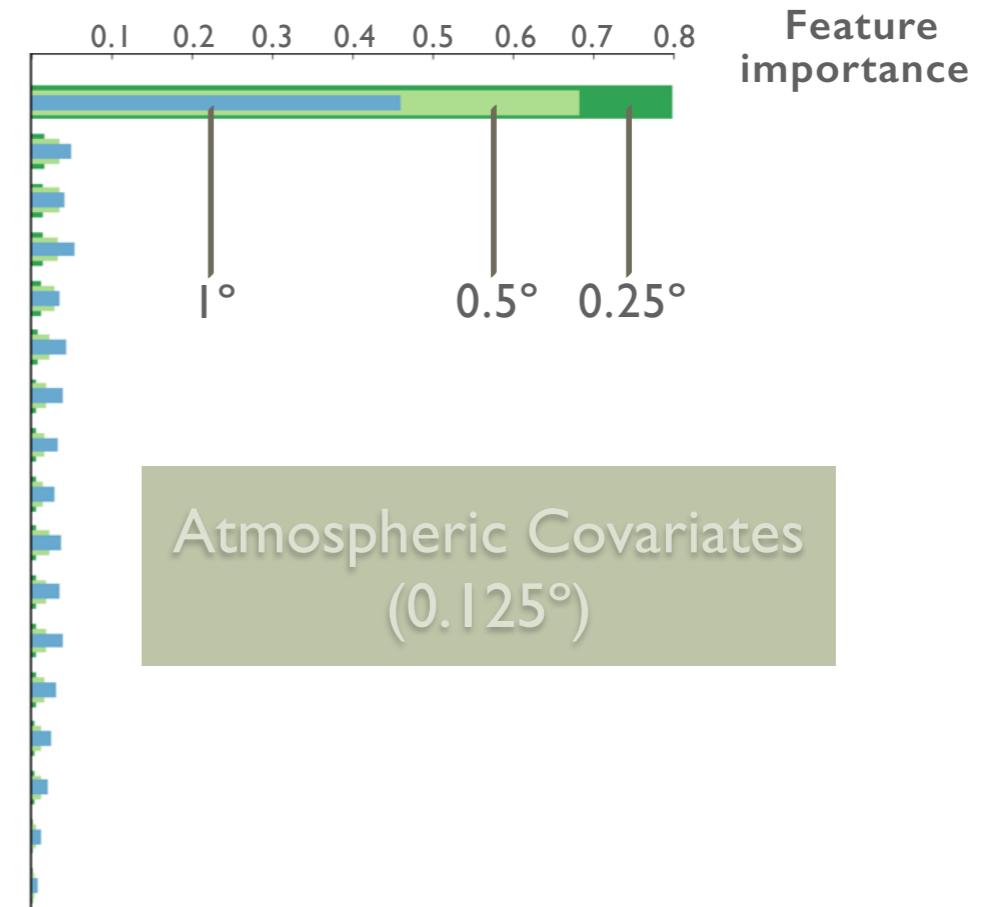
# Feature importance

# Results

***Feature importance*** measures the prediction strength for each covariate



Precipitation (center)  
Precipitation (down)  
Precipitation (up)  
Precipitation (right)  
Precipitation (left)  
Temperature  
Humidity  
Aspect  
Slope  
Meridional wind  
Zonal wind  
CAPE  
Pressure  
Elevation (std)  
Elevation (mean)  
Vegetation Type  
Soil Texture

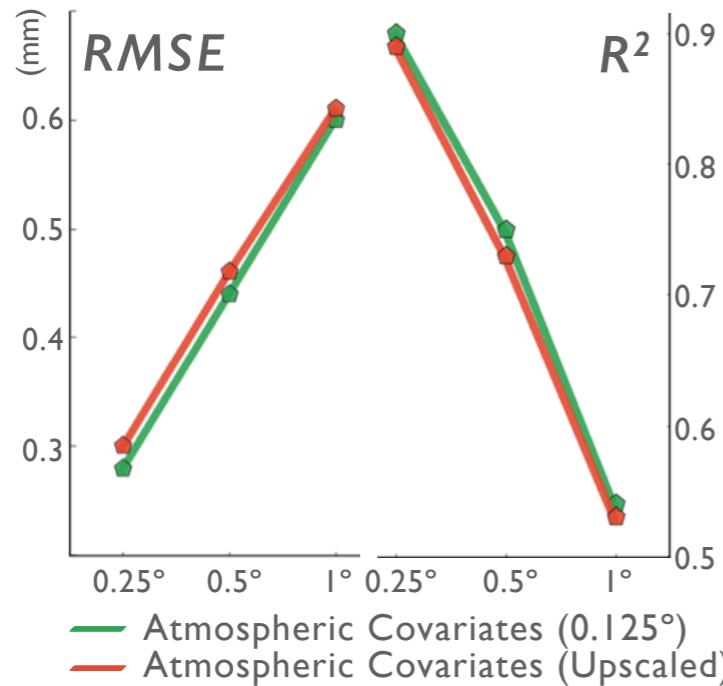


- ★ Central coarse precipitation dominates
- ★ Dynamic fields matter
- ★ Topography matters (e.g., P<sub>I</sub>A<sub>I</sub>)

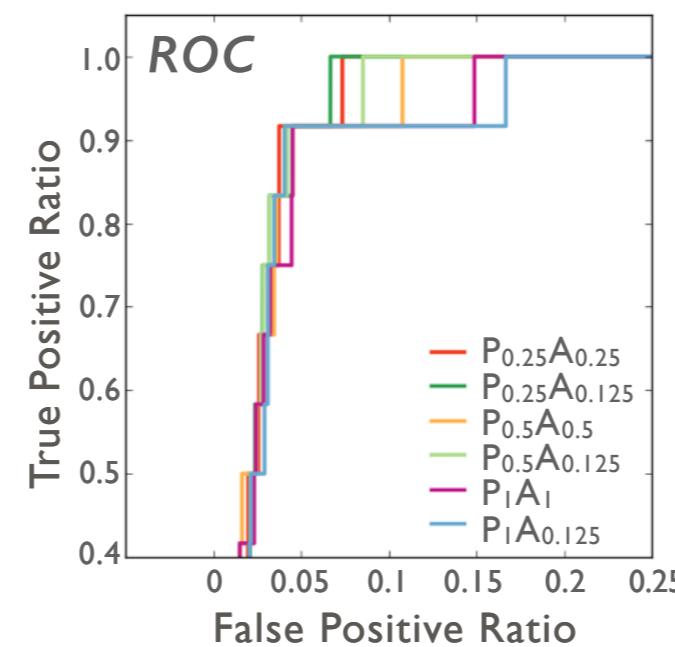
# Downscaling skill

# Results

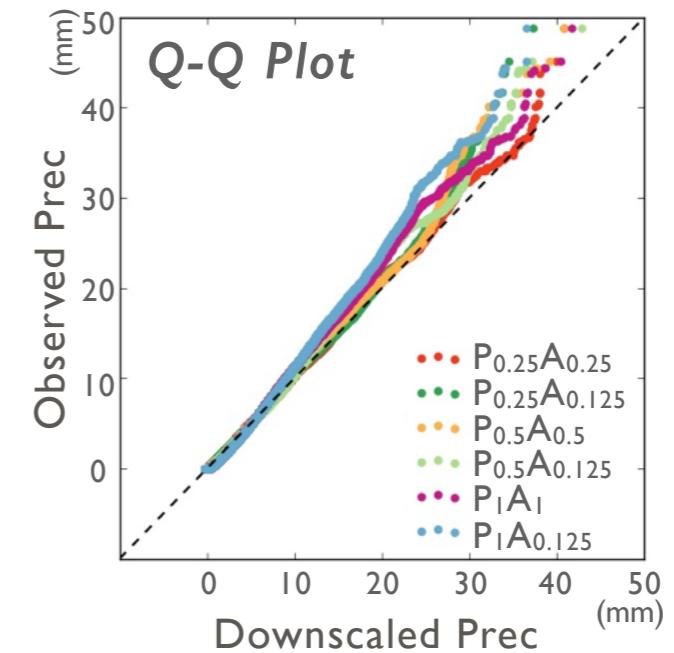
## Goodness-of-fit



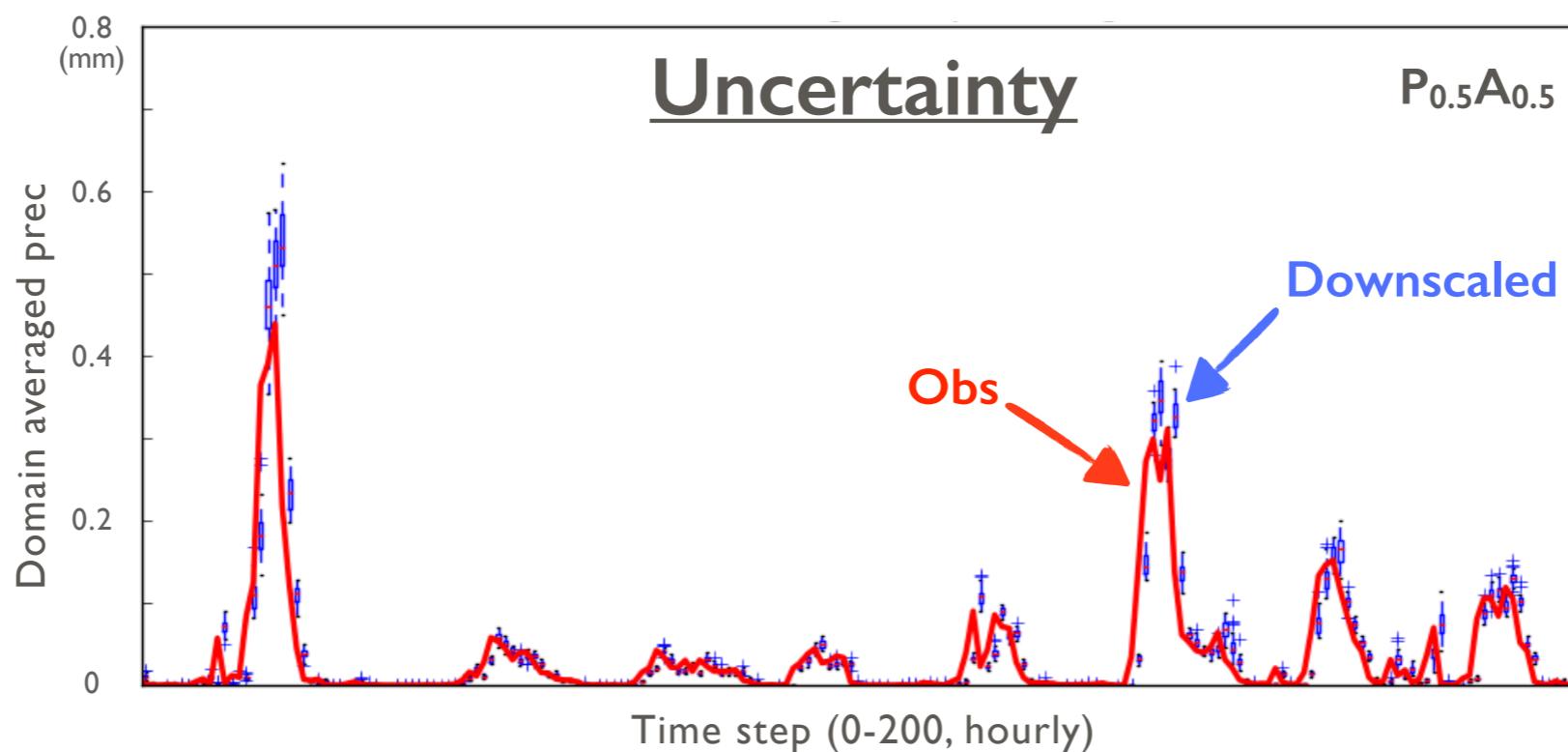
## Classification



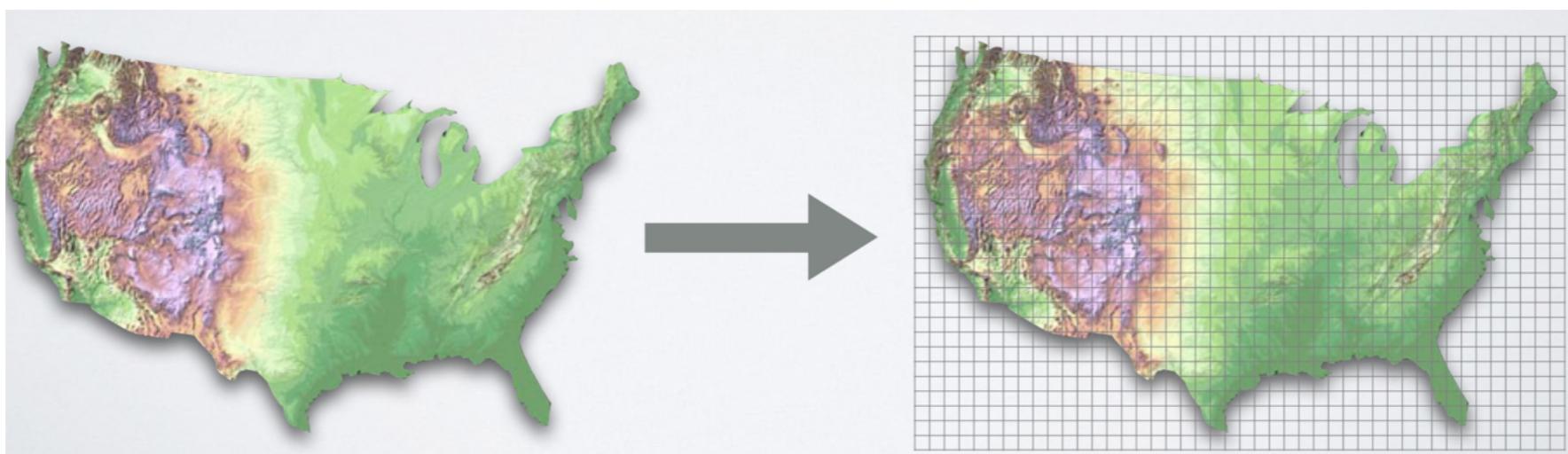
## Distribution



## Uncertainty



- Synthetic experiments → Try other regions
  - Western US (California and mountainous regions)
  - Northeastern climate division
  - Central US
- Real experiments
  - Train StageIV, downscale satellite/reanalysis
- CONUS/Global scale → Moving window approach



*Thanks!!*

**Questions??**