Eric D. Robinson, Robert J. Trapp, Michael E. Baldwin

Regional trends in severe convective weather: a dynamical downscaling approach

Department of Earth and Atmospheric Sciences
Purdue Climate Change Research Center
Purdue University
West Lafayette, Indiana, USA

Goals/Motivation

- Reproduce the distribution of severe thunderstorms over the U.S. using coarse driving data
  - Hail > 25 mm in diameter, Wind > 25 m/s, any tornado
- Examine regional trends in severe convective occurrences
- Connect any changes in thunderstorm activity to changes in large-scale forcing.

Dynamical downscaling/Modeling approach:

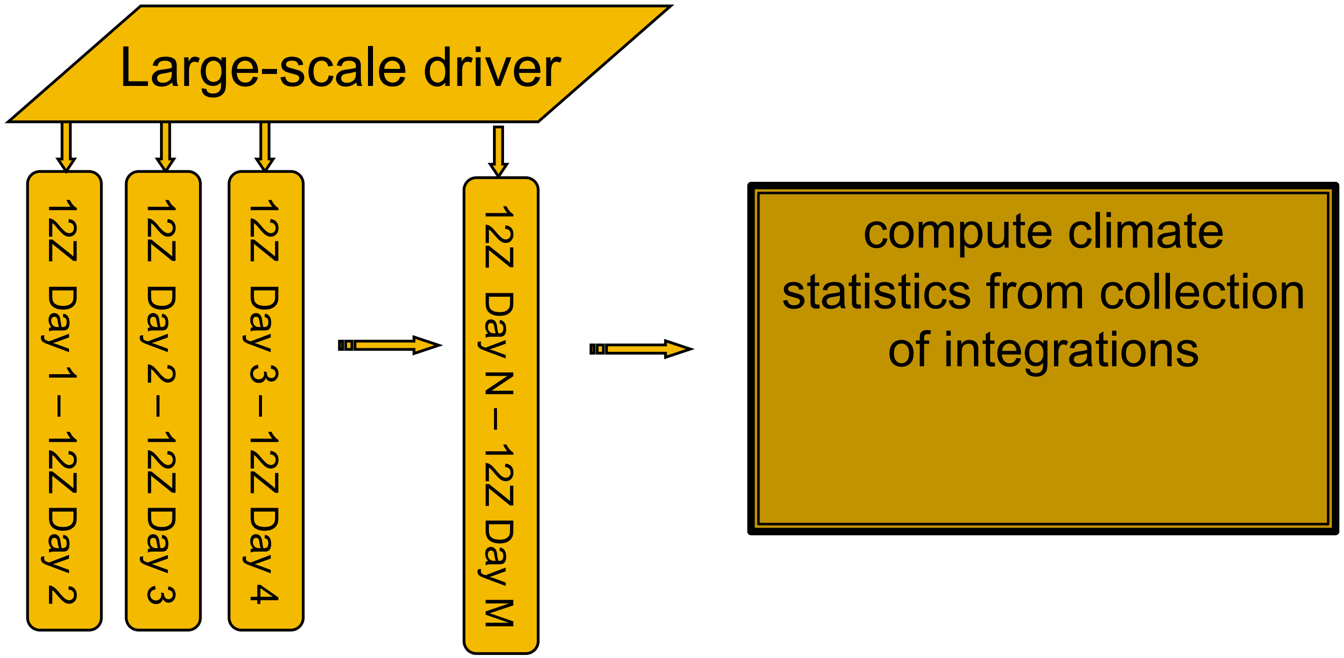
- Computational domain: continental U.S.
- Initial/boundary conditions from:

  NCEP-NCAR Reanalysis Project (R1) global data

- Series of short-term (24-hr) integrations with "advanced research" WRF model, using 4.25-km horizontal gridpoint spacing
  - *convective-storm permitting: no cumulus parameterization*

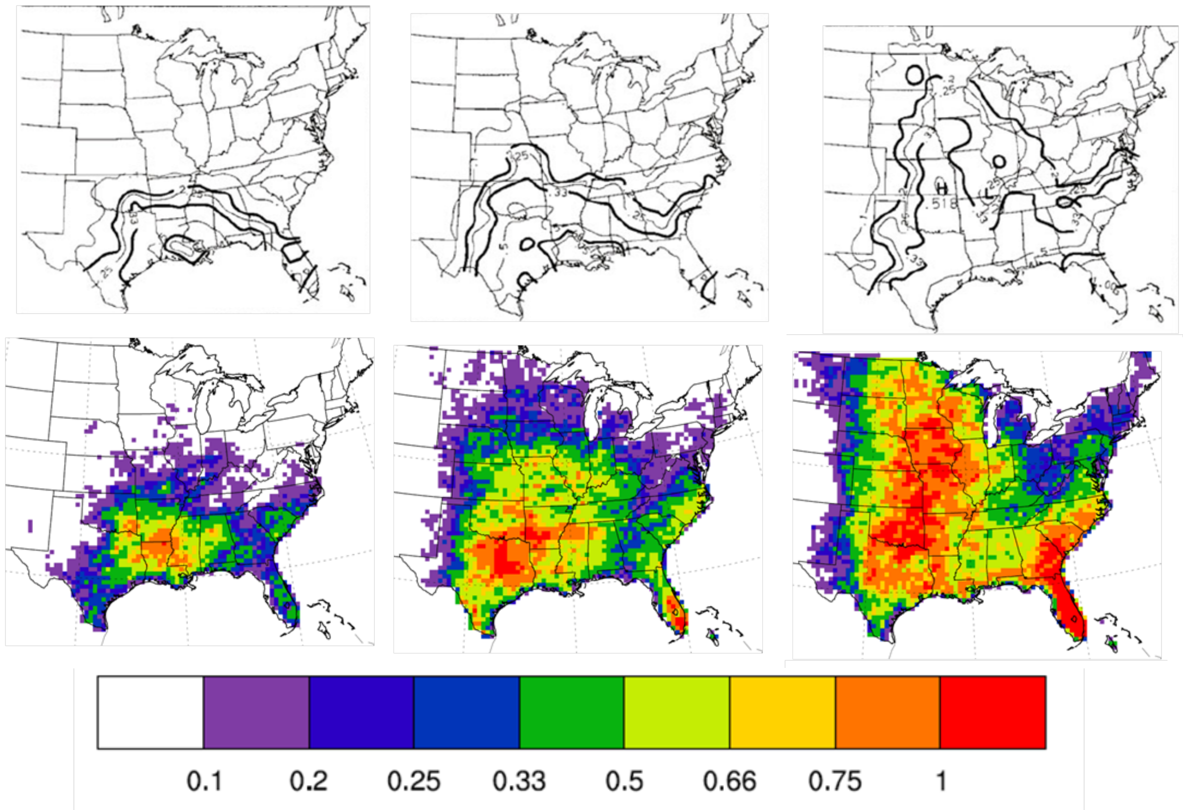
Integration procedure

- *24-h* integrations (12 UTC - 12 UTC) for months of April, May, June, over period 1990-2009
  - daily re-initialization (partly to efficiently use resources)
  - model "spin-up" within ~6 h: diurnal cycle maintained



Results: Heavy Rain Events

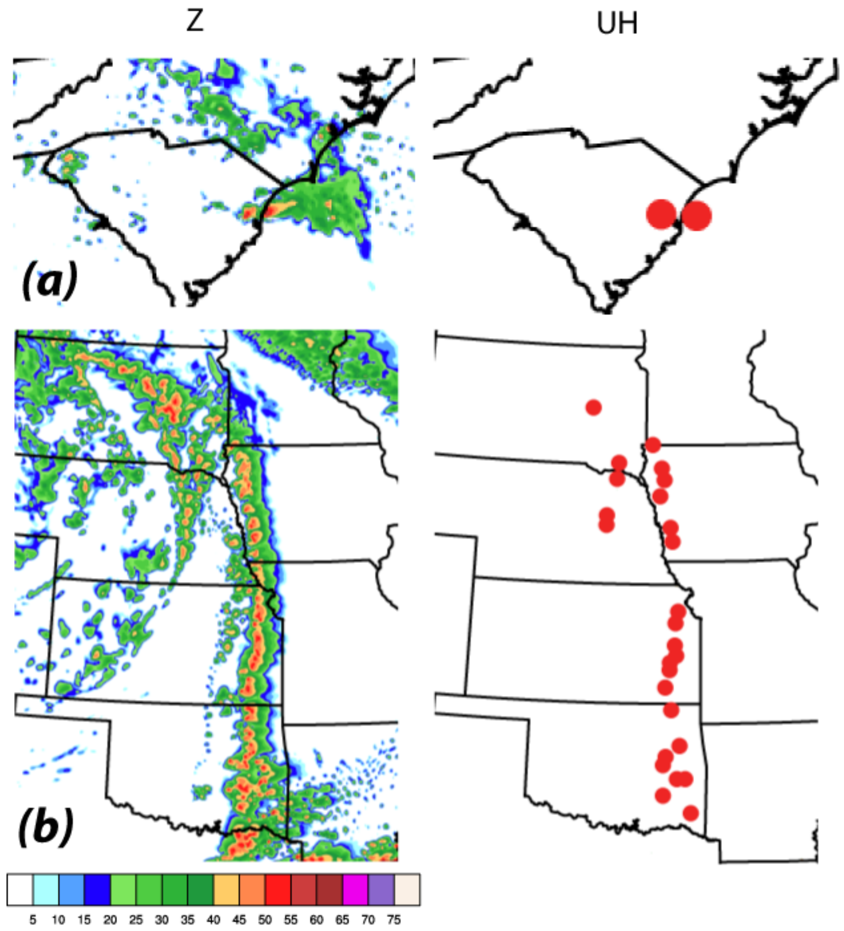
- Directly predicted by the model
- Climatologies over different times
  - But overall spatial coverage looks good
- No access to original data so only subjective conclusions



Frequency of occurrence of rain > 1"/hr from rain gauges (top, Brooks & Stensrud, 2000) and the model (bottom) for April (left), May (middle), and June (right).

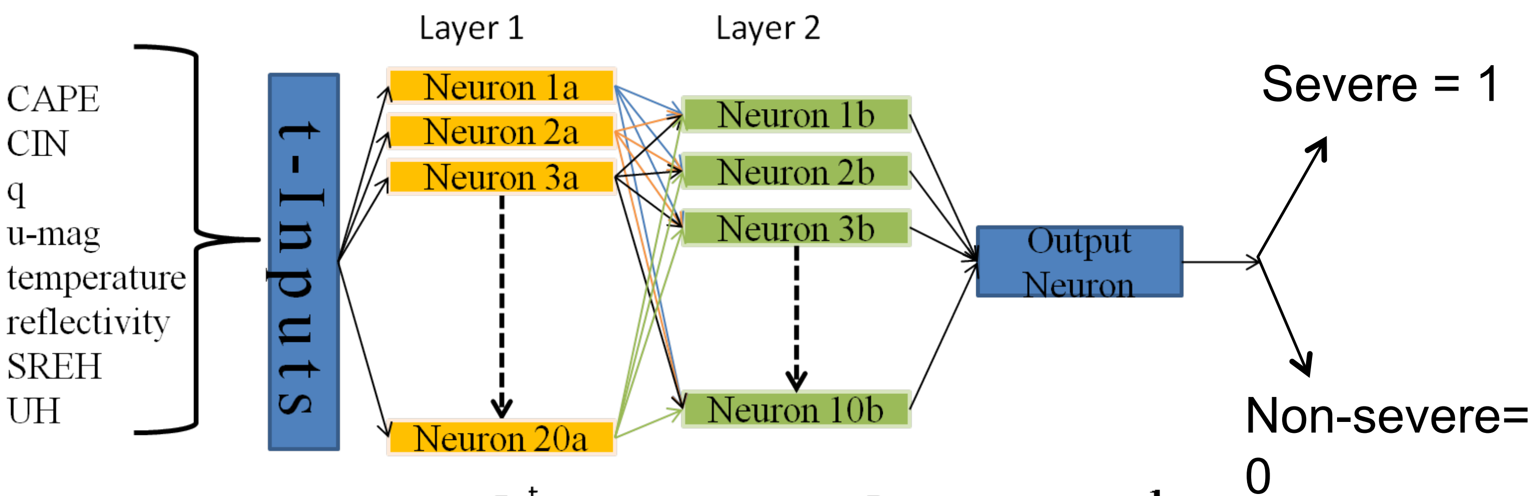
Detecting Modeled Severe Convection

- **When is <u>severe</u> convection occurring in the model?**
  - **Previous work deals mainly with environment, without considering initiation**
  - Tornadoes, strong winds, large hail
  - **Not directly resolved in model output!!**
- How can one differentiate between strong modeled convection and severe modeled convection??
- Develop a storm proxy
  - **Artificial Neural Network (ANN)**



Neural Networks (Supervised Learning)

- Adaptive computational model that can “learn” to recognize severe convection
  - Network must be trained to recognize severe weather

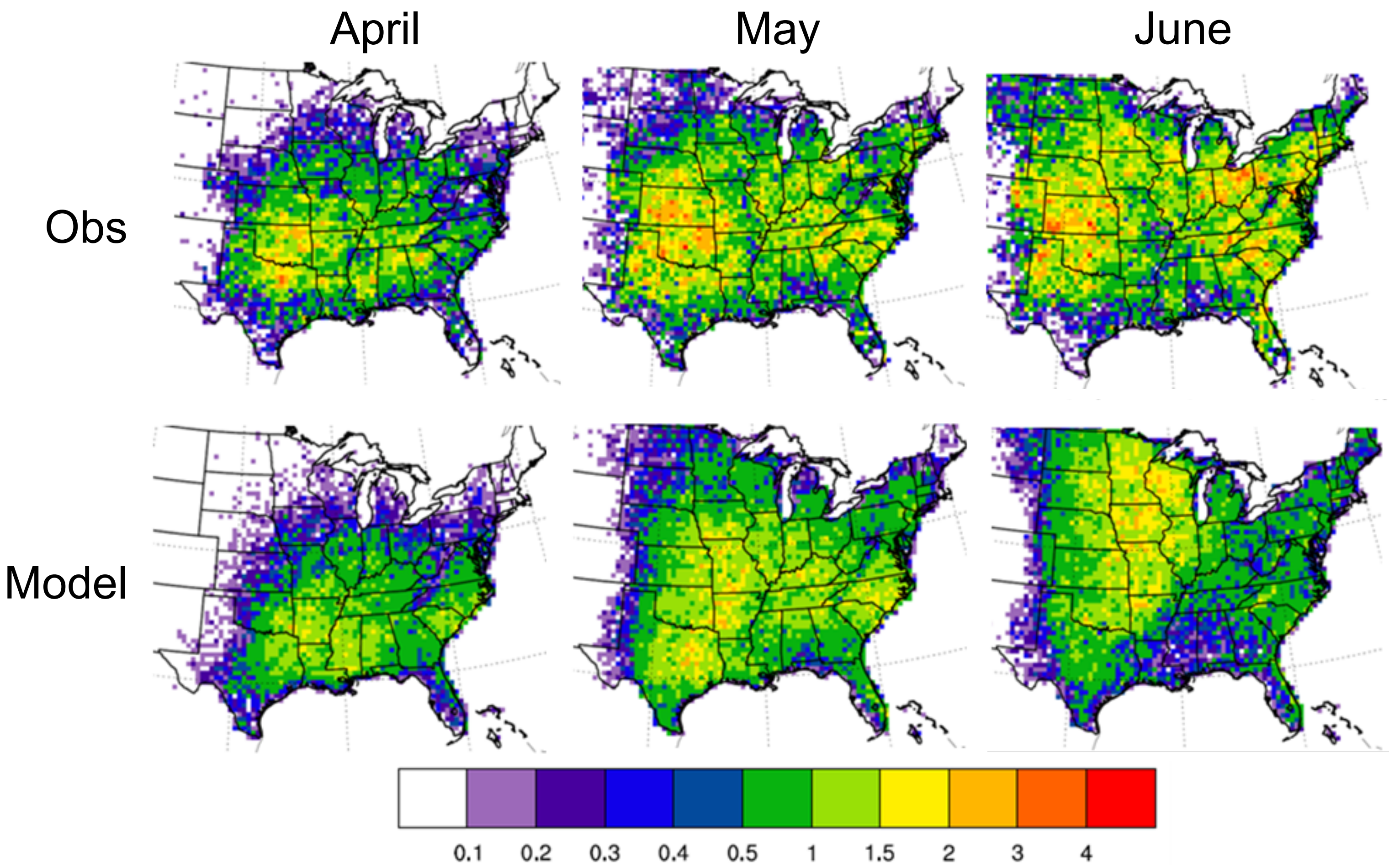


Output 1a = logsig[n] = logsig $\left[\sum_{i}^{t} \text{Input}_i \times \text{Weight } 1a_i \right]$ logsig = $\dfrac{1}{1+e^{-n}}$

Training procedure

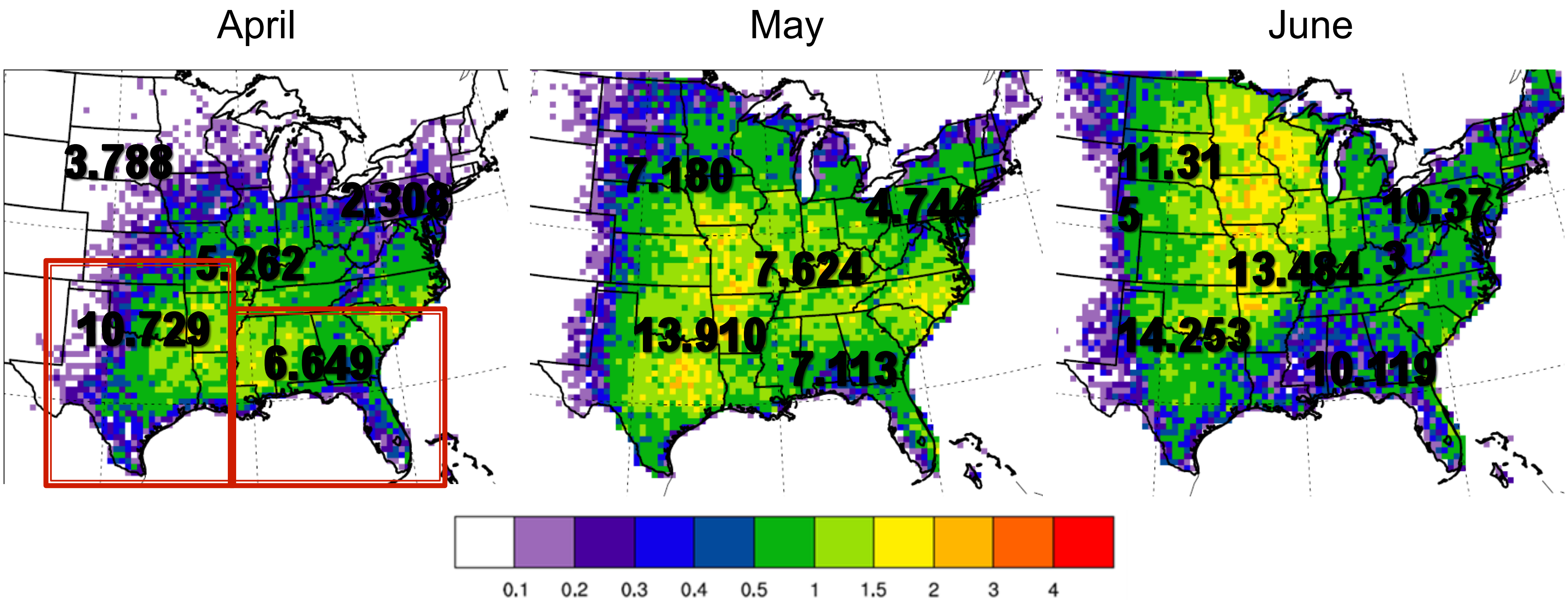
- Example severe and non-severe cases are selected from the observations
- Cases are all submitted to the ANN for classification.
- ANN iteratively classifies the events and modifies itself in order to minimize error (MSE or RMSE)

Avg. Frequency of Occurrence of Severe Convection

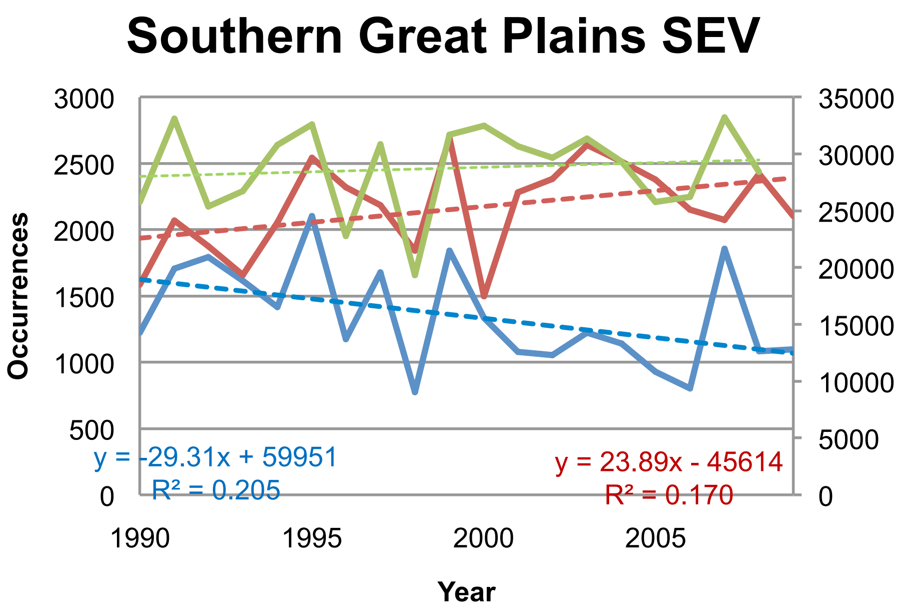


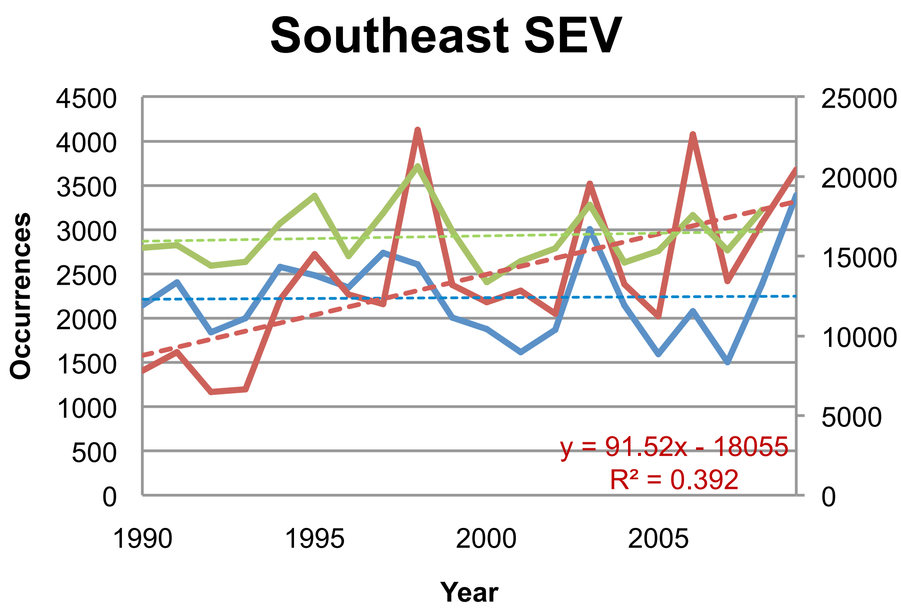
Regional Results - RMSE

Minimum RMSE values for average frequency of occurrence of severe convective hazards over 5 separate regions of the U.S. (1990-2009)



Regional Timeseries of Total Convective Events





- No significant trends in the environmental control
- Increase in reported severe occurrences
- Decrease or no trend in the modeled occurrences
- Good inter-annual agreement

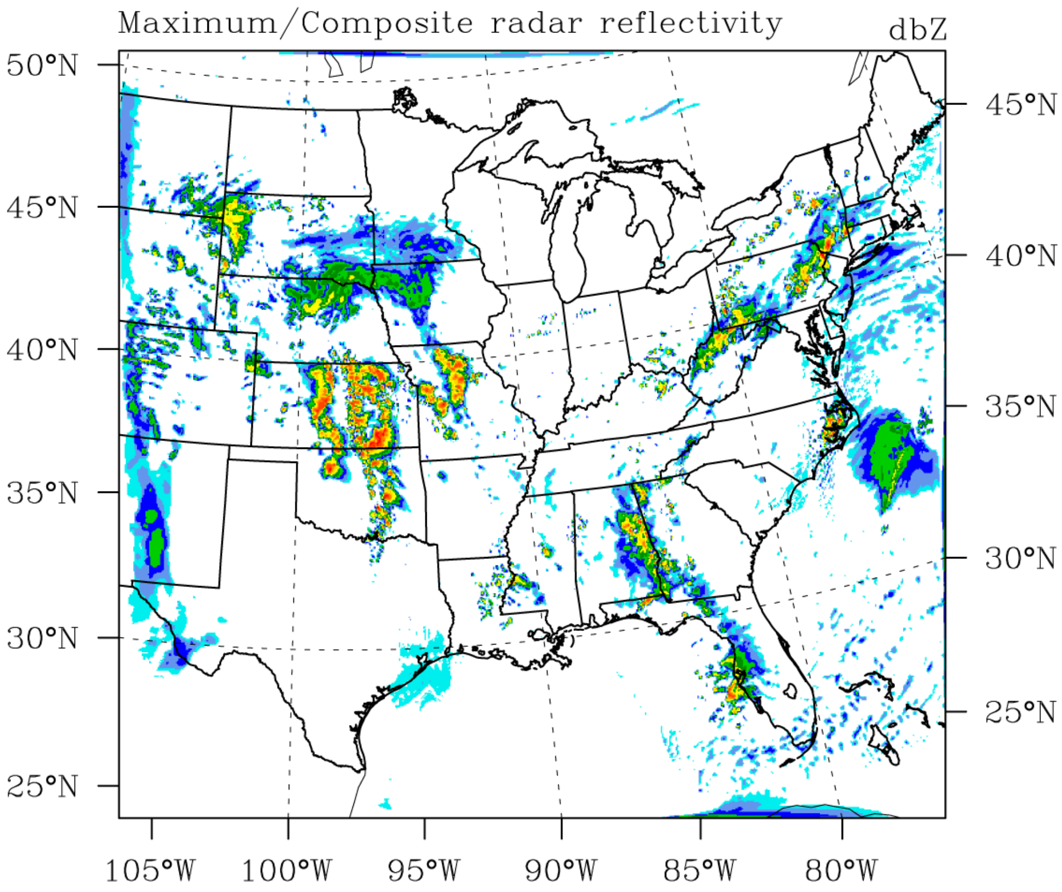
Caveats and Summary

- Single WRF setup, single data source
- Dynamical downscaling is able to recreate heavy rain events and severe convection with some fidelity
- Neural networks can provide assistance in identifying modeled severe storms
- Modeling results suggest a decrease in overall severe activity in the last 20 years over some of the U.S.
  - Bias correction of the observations?

Future Work

- GCM driven runs for future severe weather
- Large-scale connections
  - Are there large-scale indicators of convective activity changes?
- Severe event differentiation

10 April 2099 12Z 14hr Forecast



Questions?

Acknowledgements

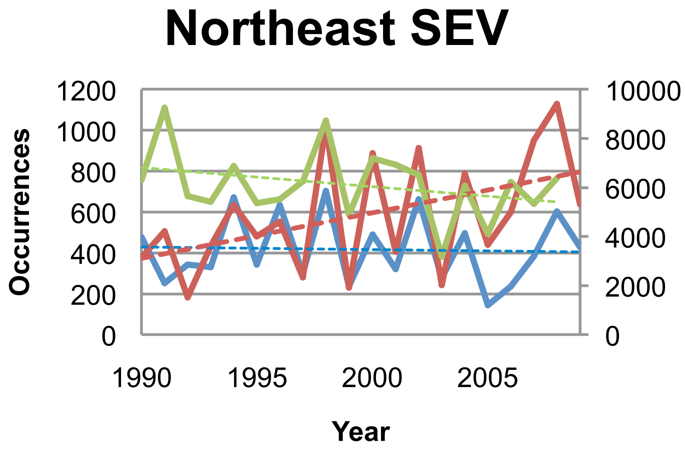
NSF ATM 0541491
NCAR Accelerated Scientific Discovery initiative

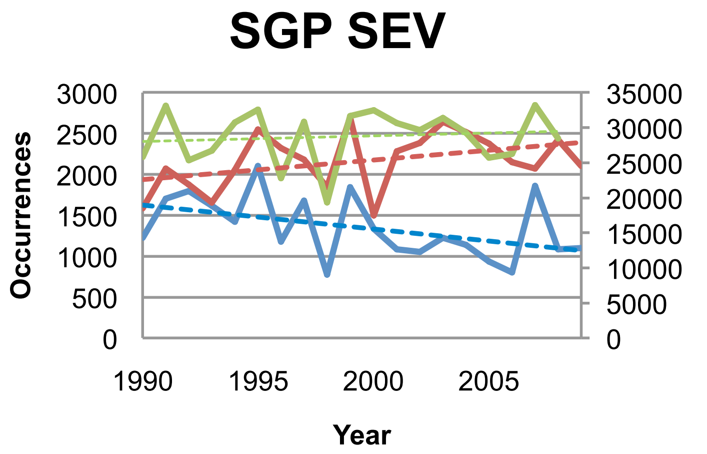
This is part of a larger collaborative effort, advancing Purdue's Climate and Extreme Weather (CLEW) initiative

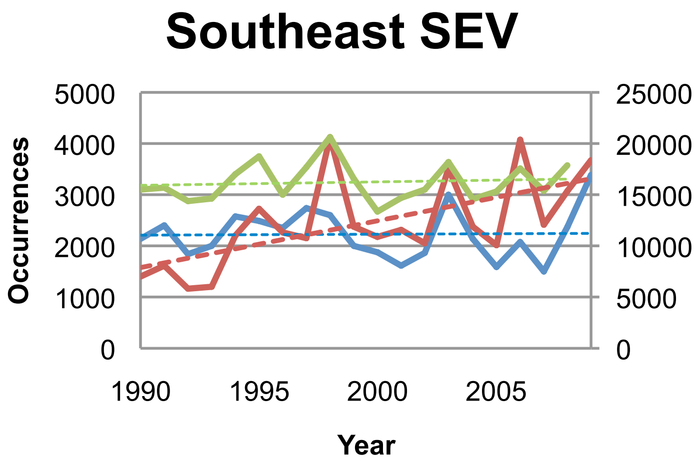
Eric Robinson
edrobins@purdue.edu

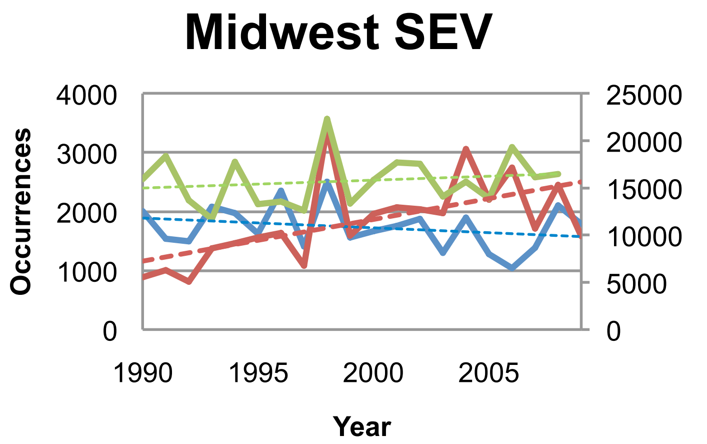
Model setup: similar to forecast-model applications

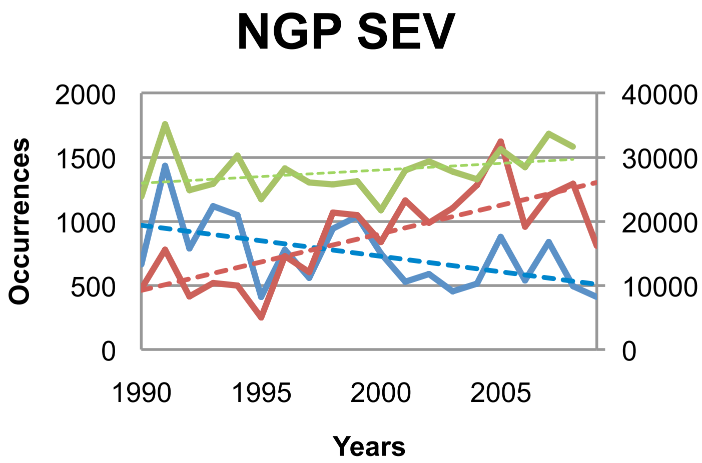
Parameterization	**Scheme**
Microphysics	WSM6
Radiation (SW/LW)	Dudhia / RRTM
Land Surface Model	Noah
Planetary Boundary Layer	MYJ
Model Parameters	
time step	25 s
vertical (Eta) levels	35
horizontal gridpoints	n_x = 790, n_y = 660, $\Delta_{x,y}$ = 4.25 km


Northeast SEV
Occurrences
Year
1200
1000
800
600
400
200
0
10000
8000
6000
4000
2000
0
1990
1995
2000
2005


SGP SEV
Occurrences
Year
3000
2500
2000
1500
1000
500
0
35000
30000
25000
20000
15000
10000
5000
0
1990
1995
2000
2005

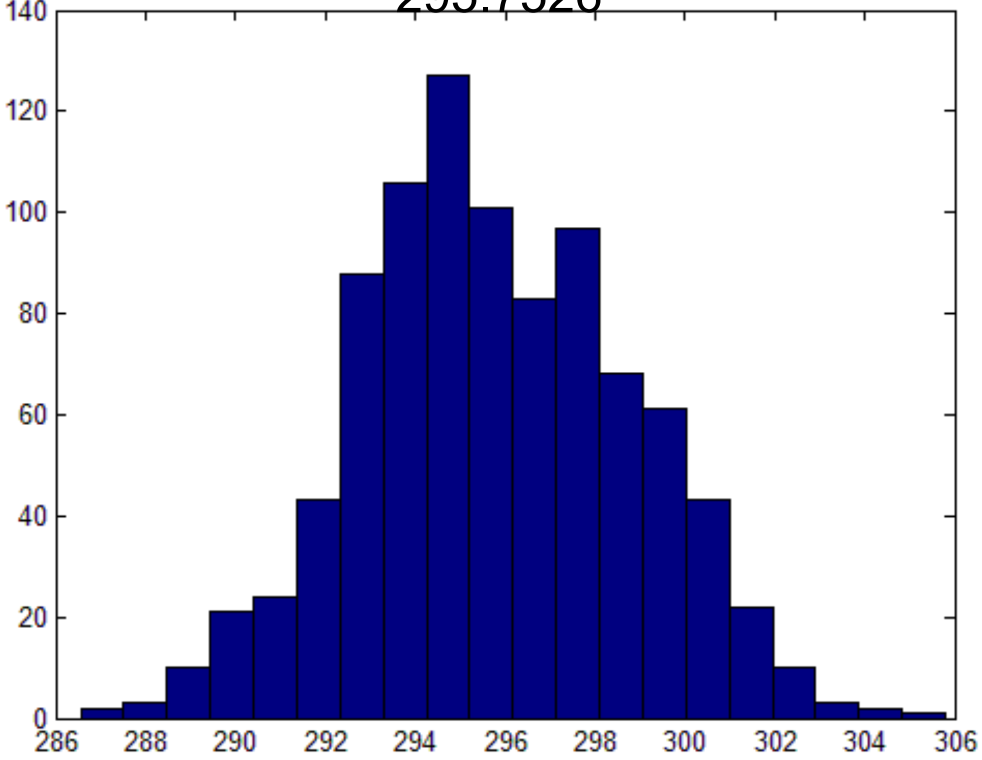

Southeast SEV
Occurrences
Year
5000
4000
3000
2000
1000
0
25000
20000
15000
10000
5000
0
1990
1995
2000
2005


Midwest SEV
Occurrences
Year
4000
3000
2000
1000
0
25000
20000
15000
10000
5000
0
1990
1995
2000
2005

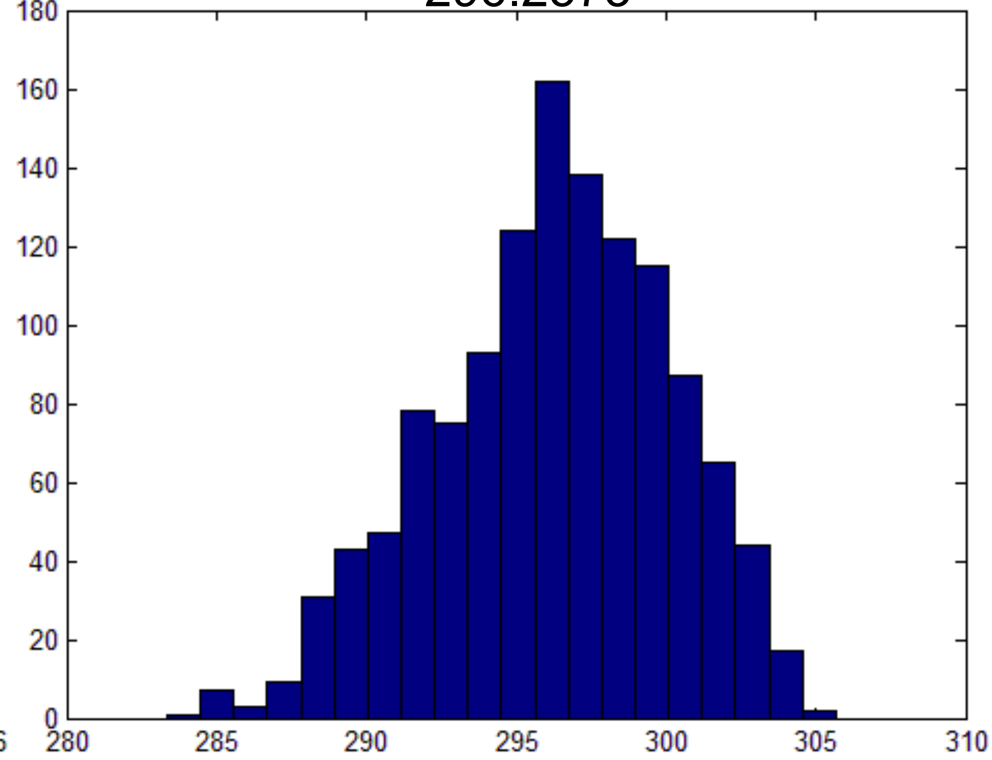

NGP SEV
Occurrences
Years
2000
1500
1000
500
0
40000
30000
20000
10000
0
1990
1995
2000
2005

Temperature

0, mean = 295.7526

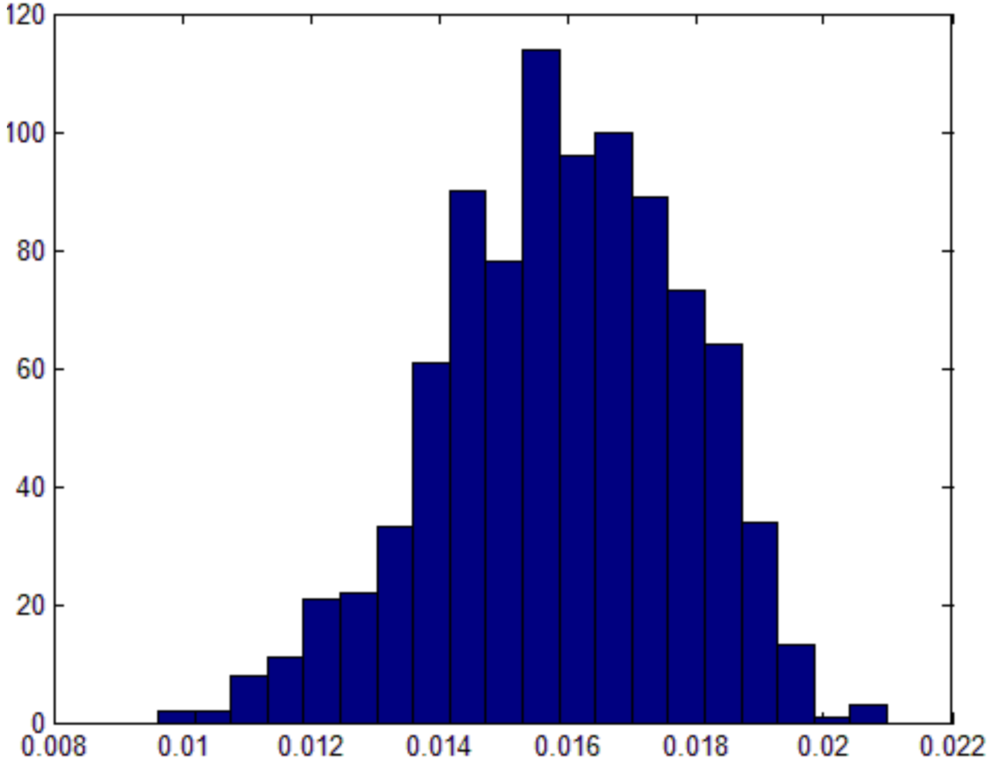


1, mean = 296.2573

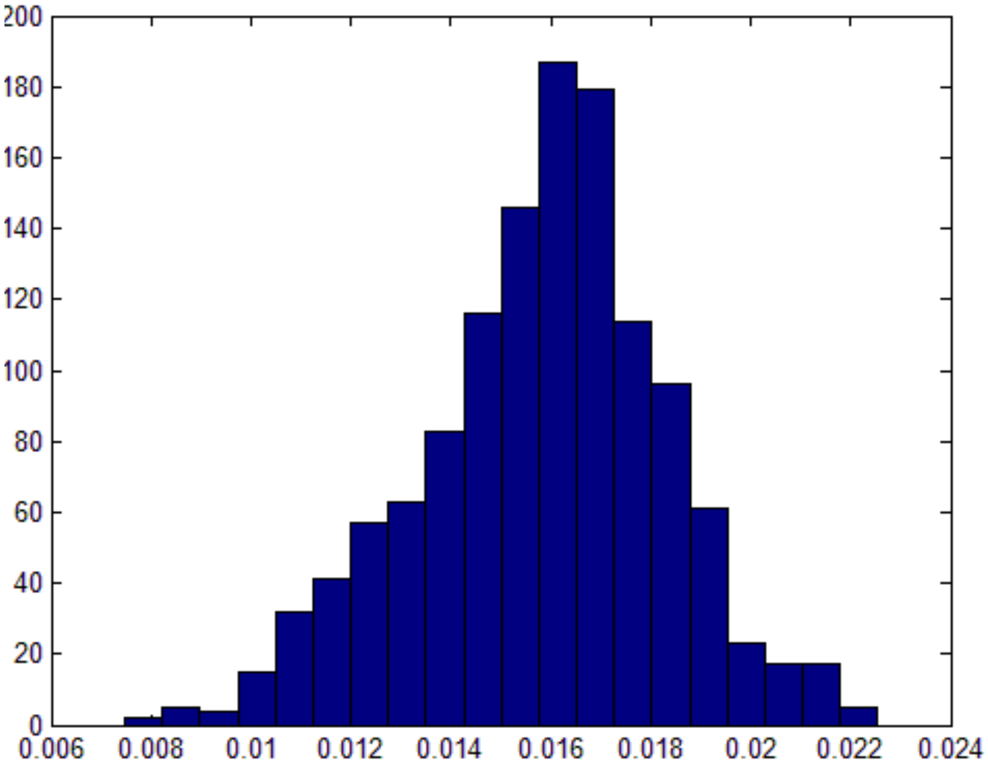


Specific Humidity

0, mean = .0159

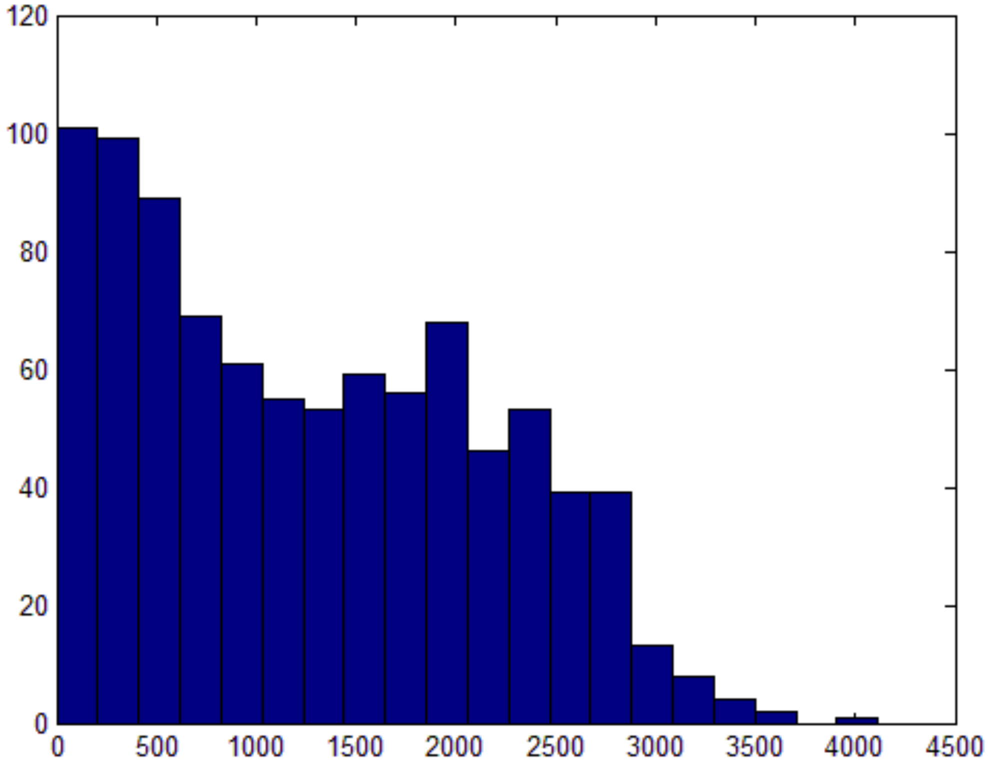


1, mean = .0158

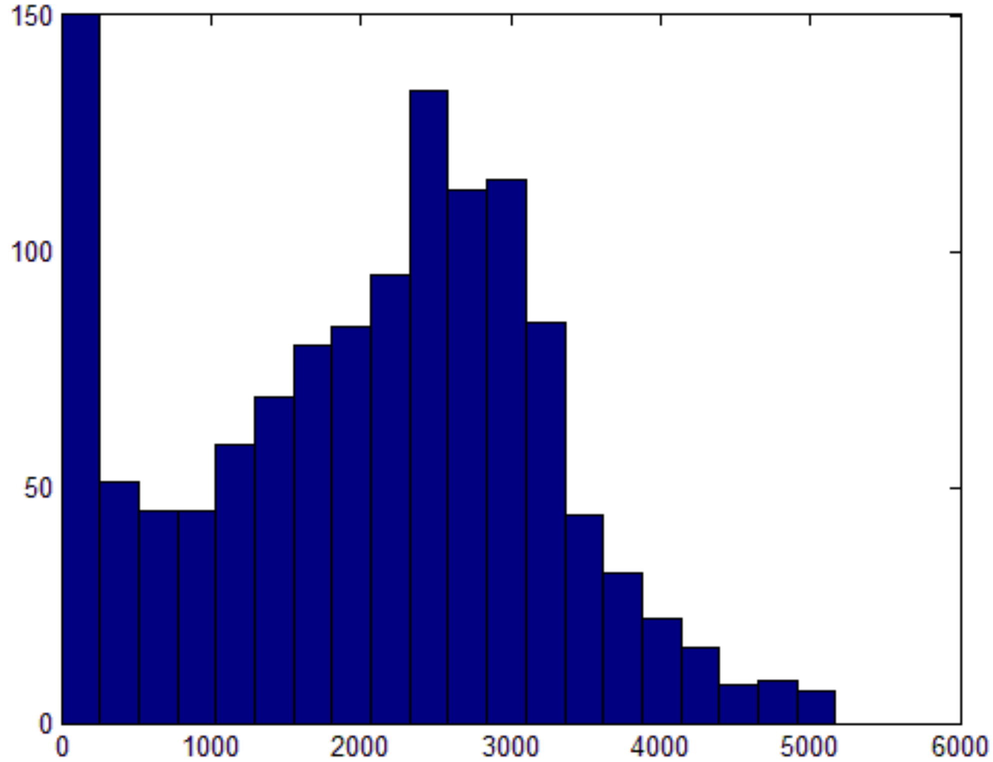


CAPE

0, mean, no zeros = 1273

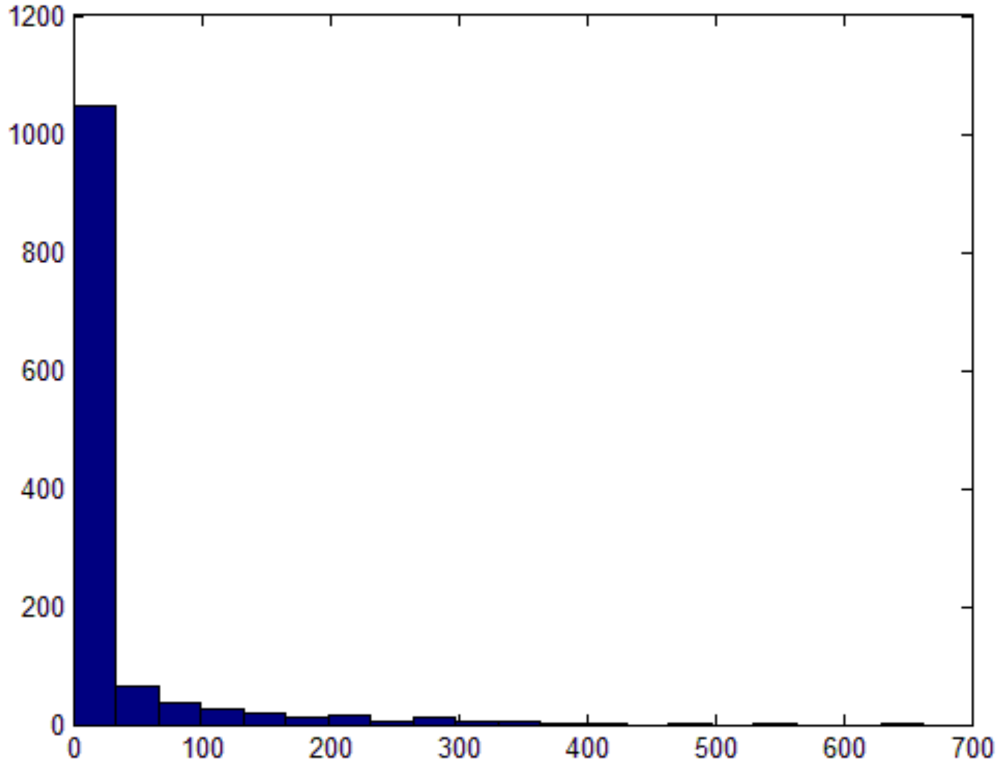


1, mean, no zeros = 2039

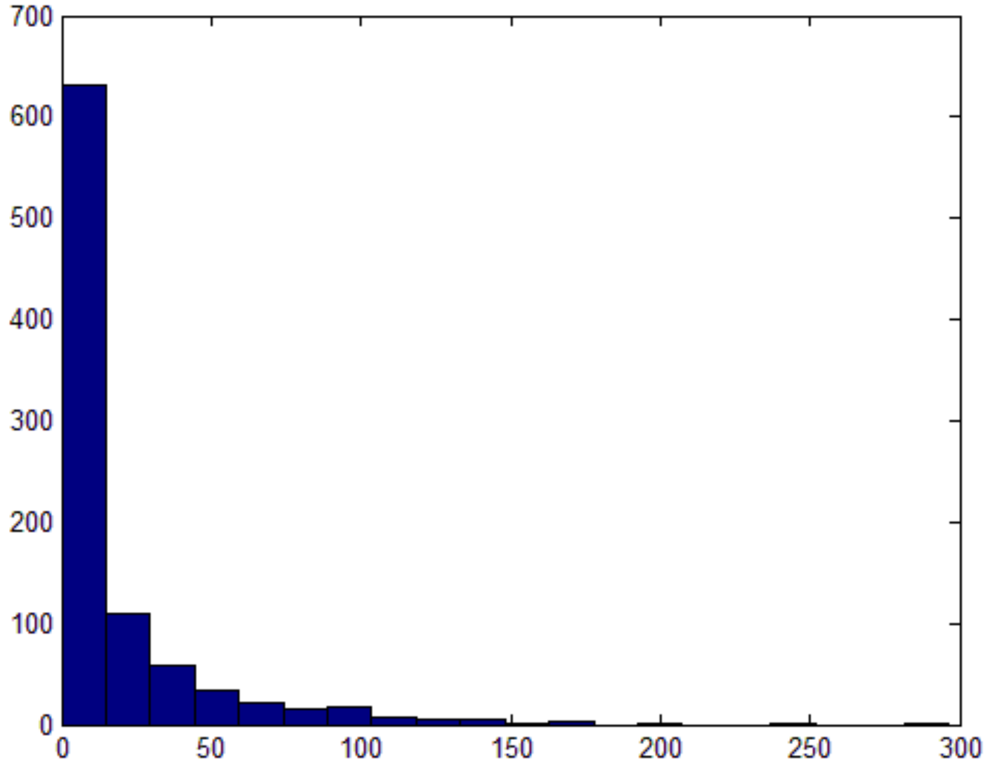


CIN

0, mean, no zeros = 18.4368

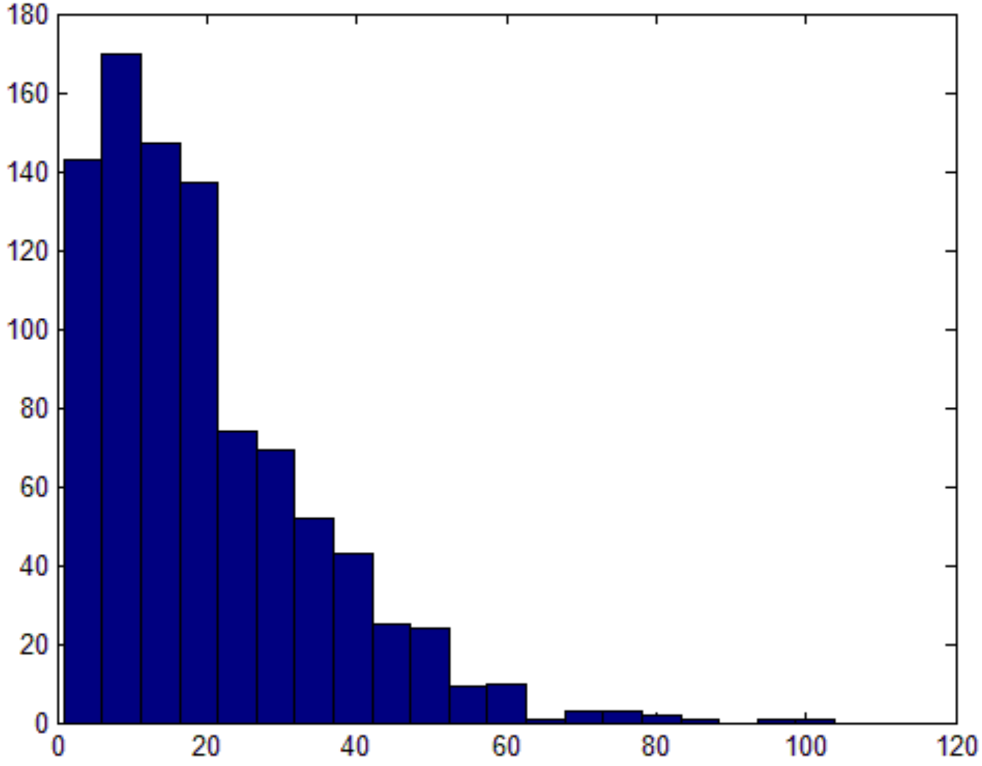


1, mean, no zeros = 29.9099

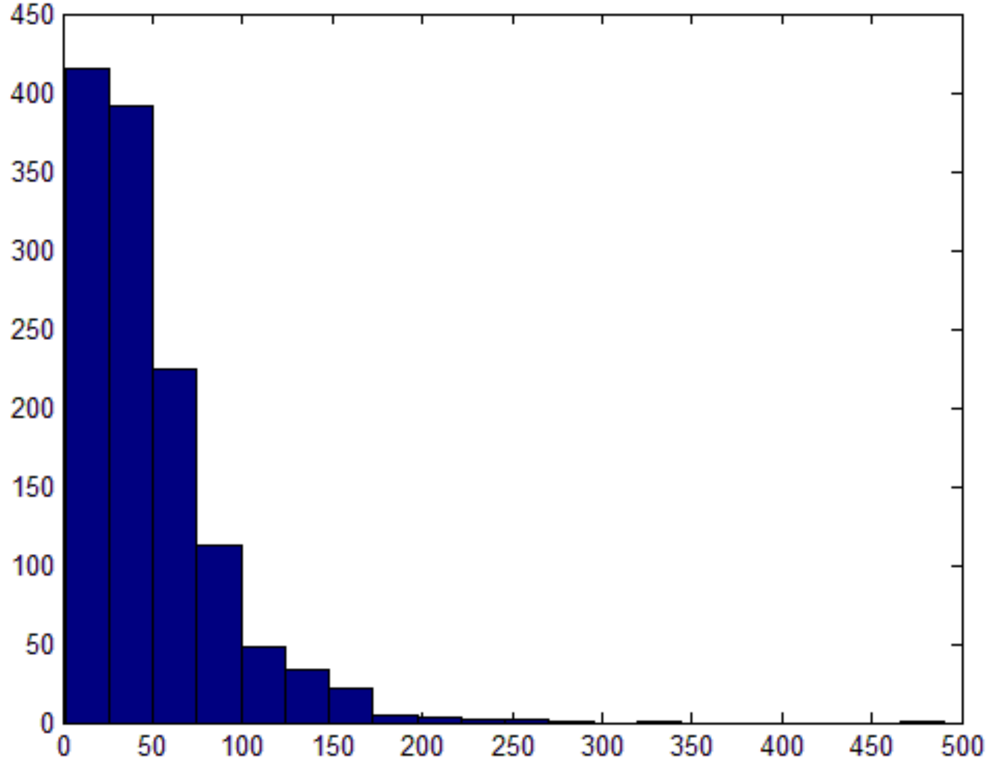


UPHL

0, mean = 19.8887

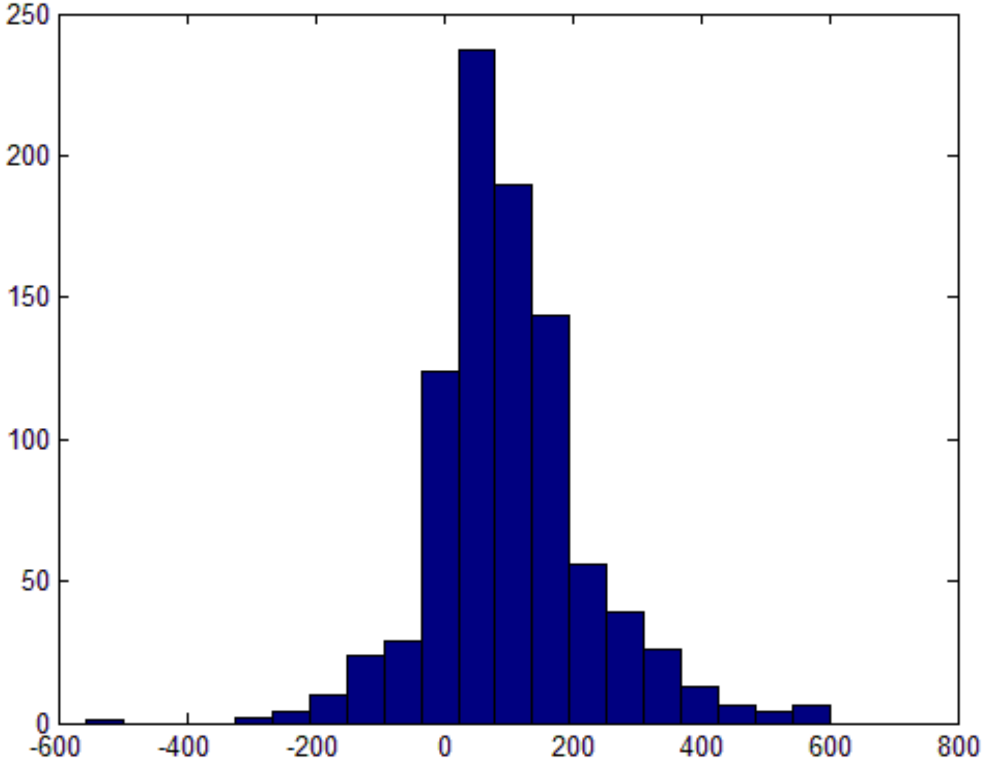


1, mean = 48.6007

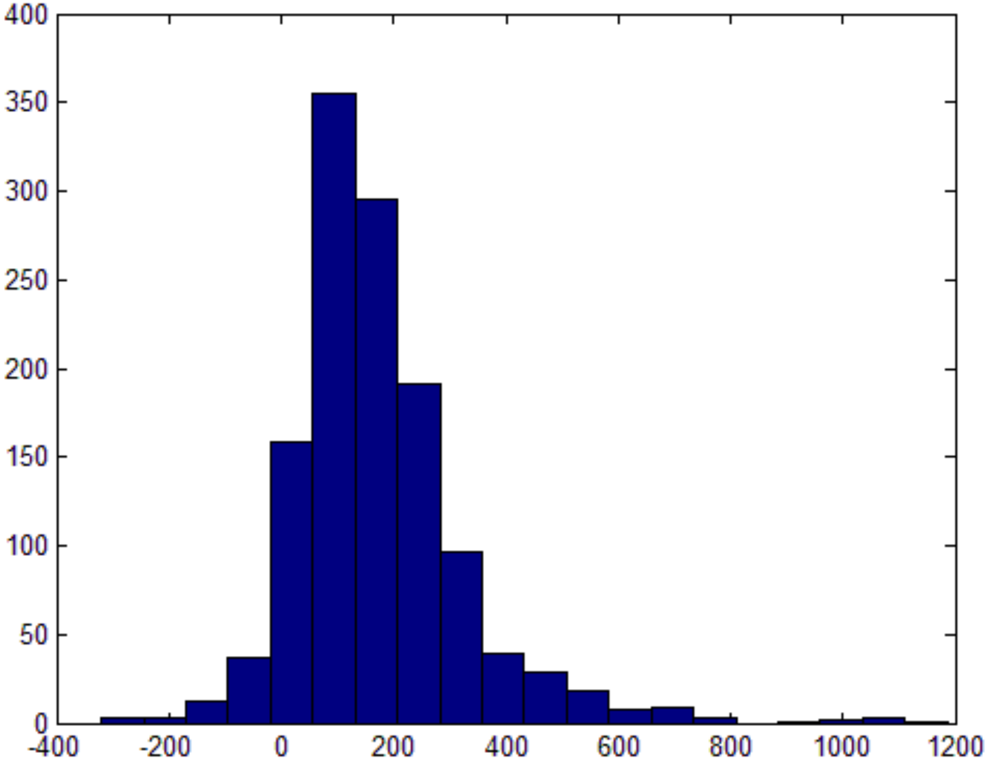


SREH

0, mean =

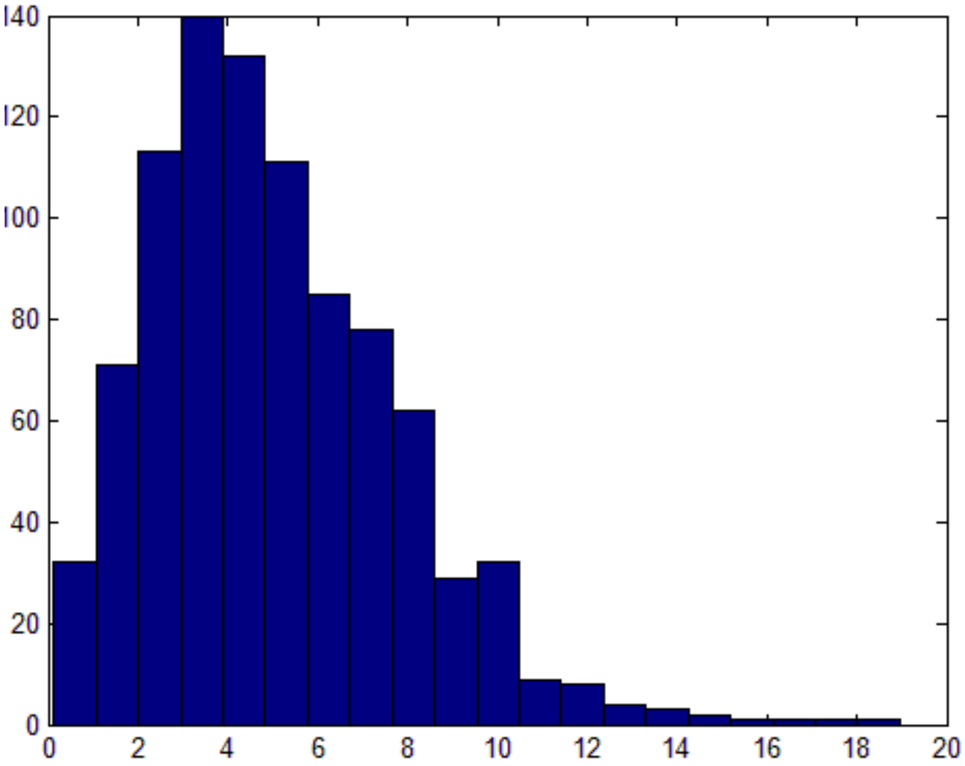


1, mean =



UMAG

0, mean = 5.0342



1, mean = 6.9704