Downscaling heavy precipitation over the UK: a comparison of dynamical and statistical methods and their future scenarios

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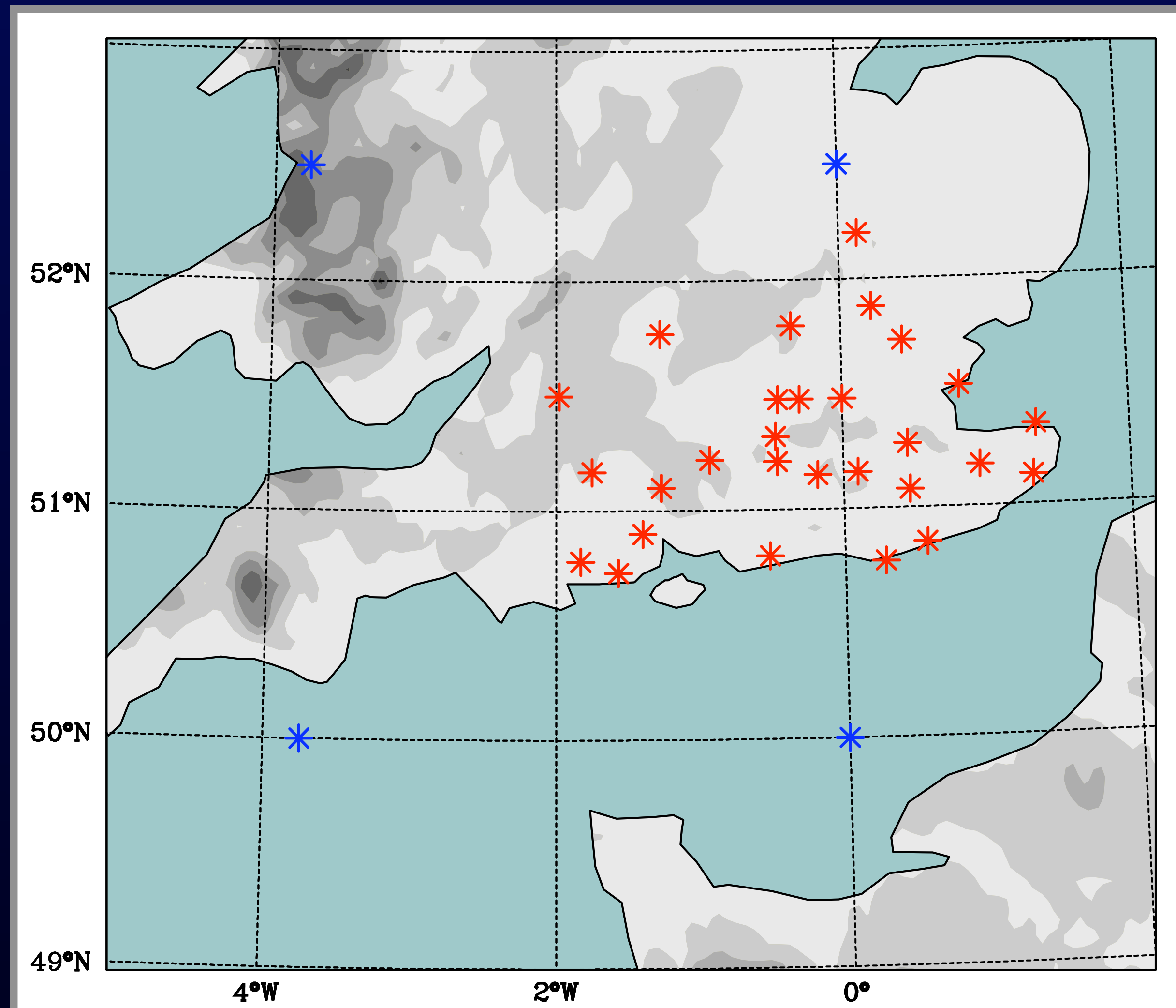
Overview

- Introduction to downscaling
- Data and methodology
- Downscaling models
- Validation of downscaling models
- Scenarios of extreme precipitation
- Conclusion

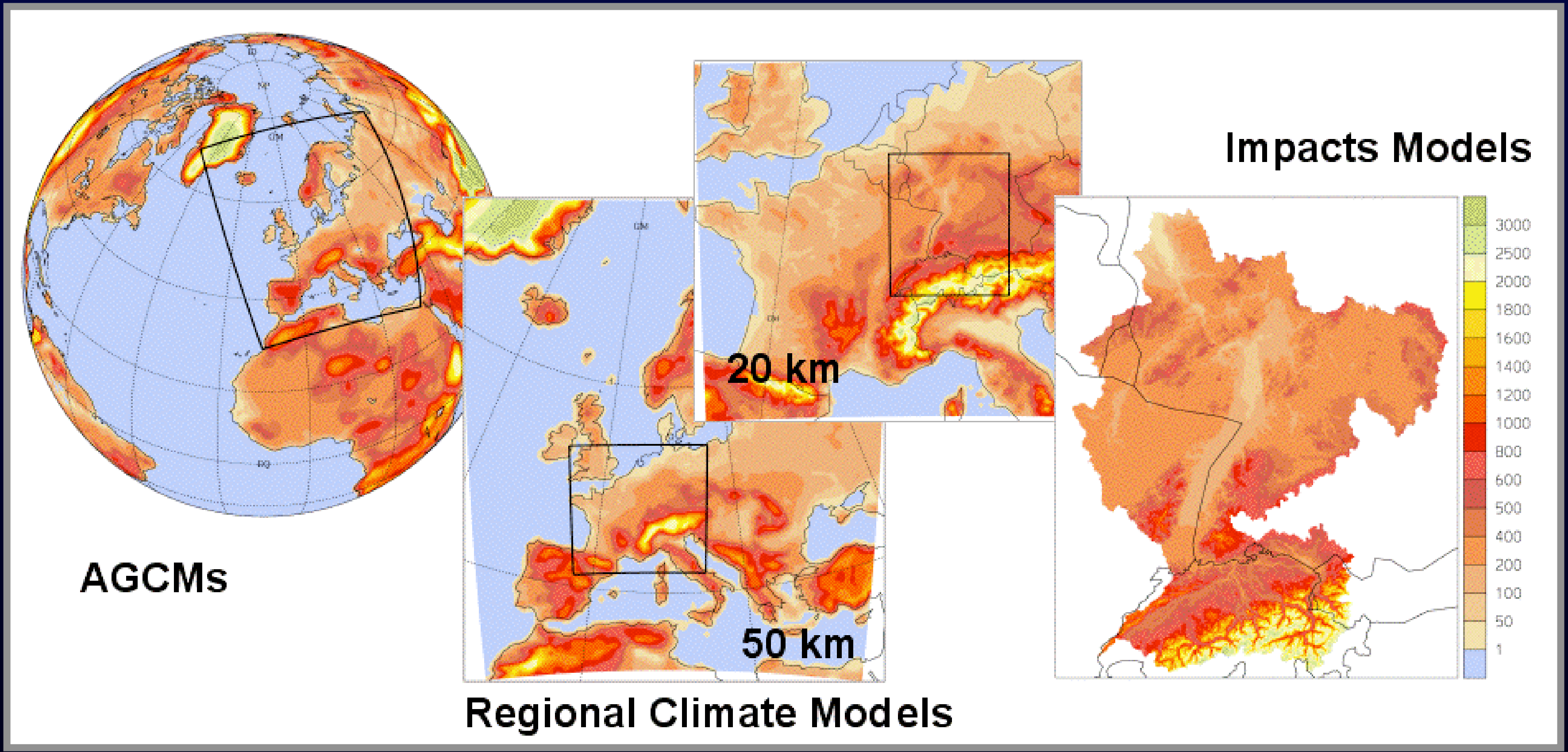
Why Downscale?

- GCMs
  - area-averages
  - smooth topography
  - poorly simulated rainfall
- Need
  - point or catchment scale



Downscaling Methods

- Dynamical downscaling
  - Regional Climate Models



Downscaling Methods

- Statistical Downscaling
  - Empirically relate large-scale GCM fields to local-scale
  - Three types
    - Regression models

      linear - Multiple Linear Regression

      non-linear - Artificial Neural Network
    - Weather pattern approaches

      condition local parameters on circulation type
    - Stochastic weather generators

      Markov models of precipitation
    - Single-site and multi-site

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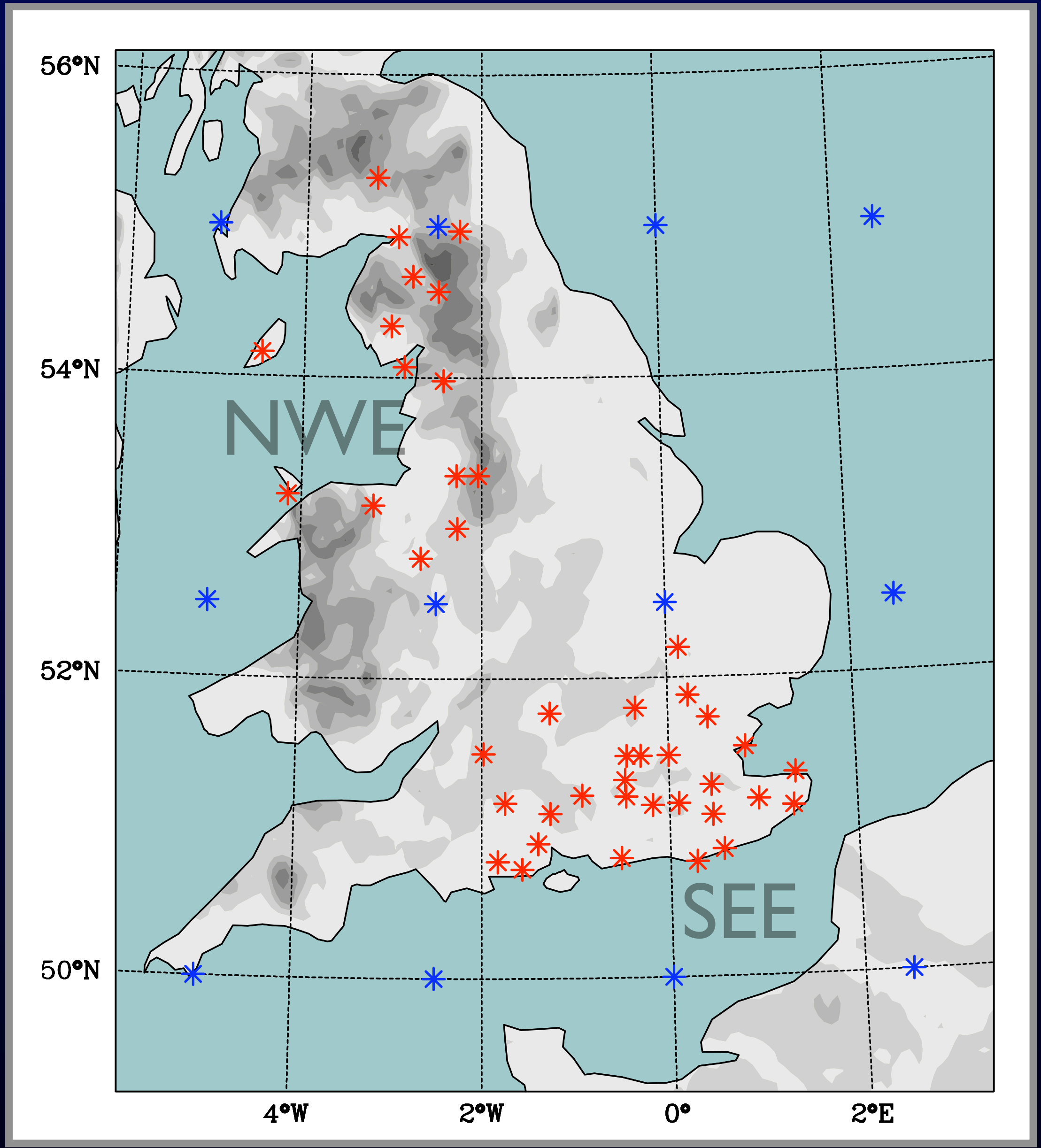
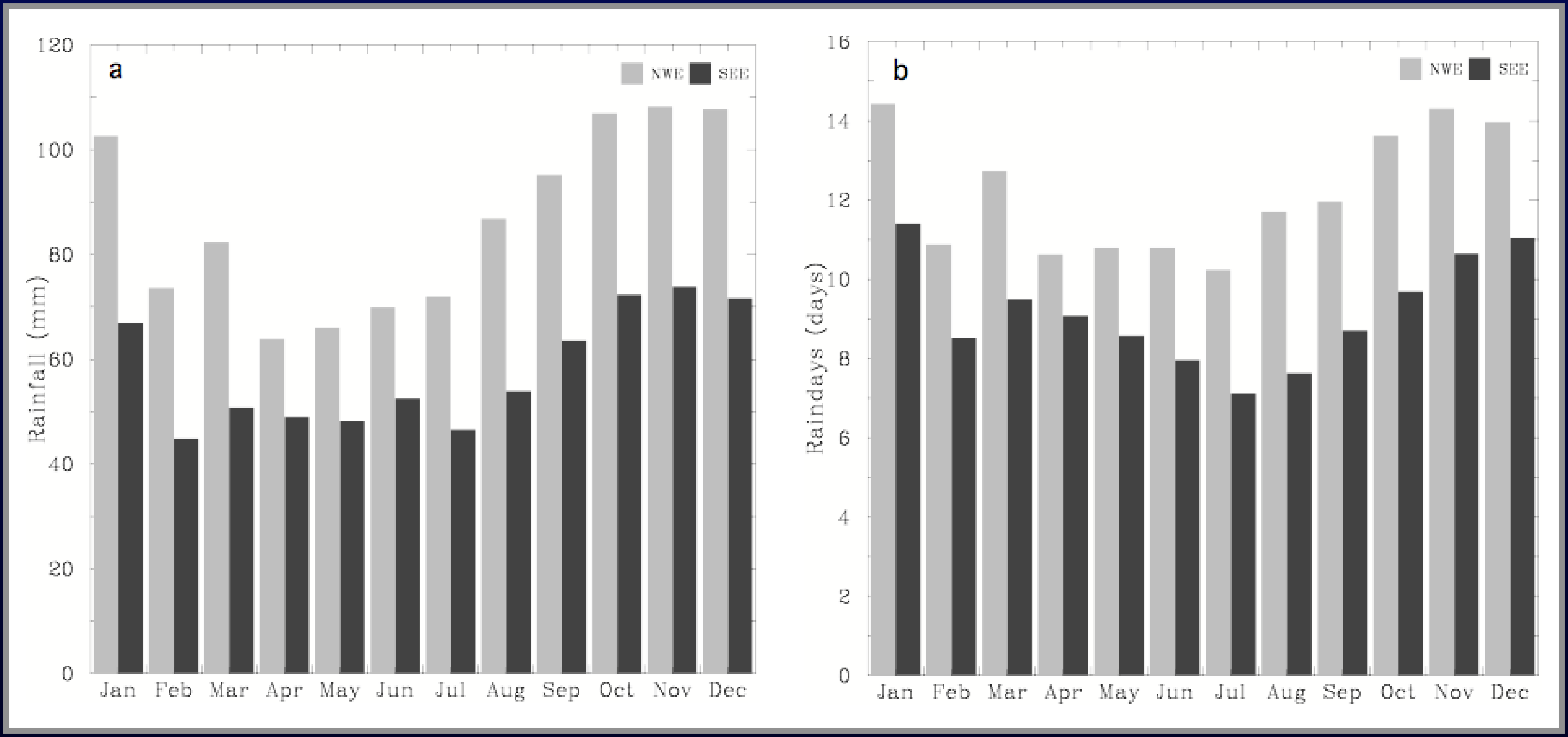
STARDEX Objectives

- To rigorously and systematically inter-compare and evaluate statistical, dynamical and statistical-dynamical downscaling methods for the reconstruction of observed extremes and the construction of scenarios of extremes for selected European regions
- To identify the more robust downscaling techniques and to apply them to provide reliable and plausible future scenarios of temperature and precipitation-based extremes for selected european regions

Two Regions



“Contrasting” Regions



Indices of “Extremes”

Index	Name	Description
pav	mean precipitation	average precipitation on all days
pint	precipitation intensity	average precipitation on days with >1mm
pq90	Precipitation 90th percentile	90th percentile of precipitation on days with >1mm
px5d	maximum 5-day precipitation	maximum precipitation from any 5 consecutive days
pxcdd	maximum consecutive dry days	maximum number of consecutive days with < 1mm
pfl90	fraction of total from heavy events	fraction of total precipitation from events > long-term 90th percentile
pnl90	number of heavy events	number of events > long-term 90th percentile

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Downscaling Models

- Statistical
  - Direct
    - Regression
      CCA
  - Indirect
    - Regression
      MLPS, MLPK, RBF
    - Regression/Resampling
      MLPR, SDSM
- Dynamical
  - HadRM3
  - CHRM

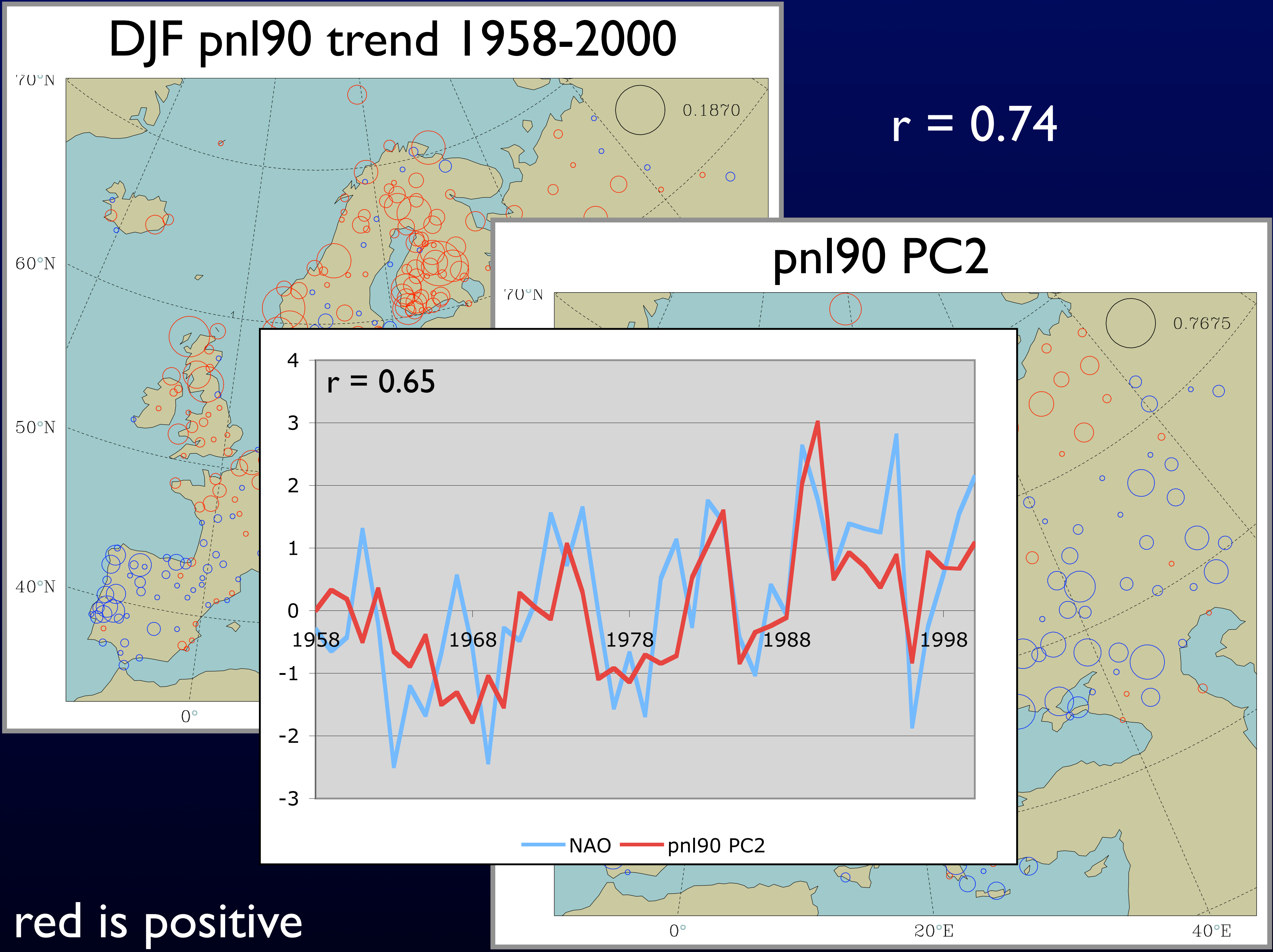
Multi-site methods
- maintain covariance

SDSM

- Two-step conditional resampling
  - downscales area-average daily precipitation using a combination of regression methods and a stochastic weather generator
    - multi-site method
  - stations resampled depending on area average
    - can’t exceed max one-day total
- Grid point predictors of 26 surface and upper air variables at several grid points for two time lags
  - over 200 predictors

CCA

- Downscales seasonal indices of extremes directly using variability of large-scale circulation
- Canonical correlation analysis of indices with MSLP and 700hPa temperature and humidity
- Best combination of predictors chosen using cross validation in training period
- Multi-site method

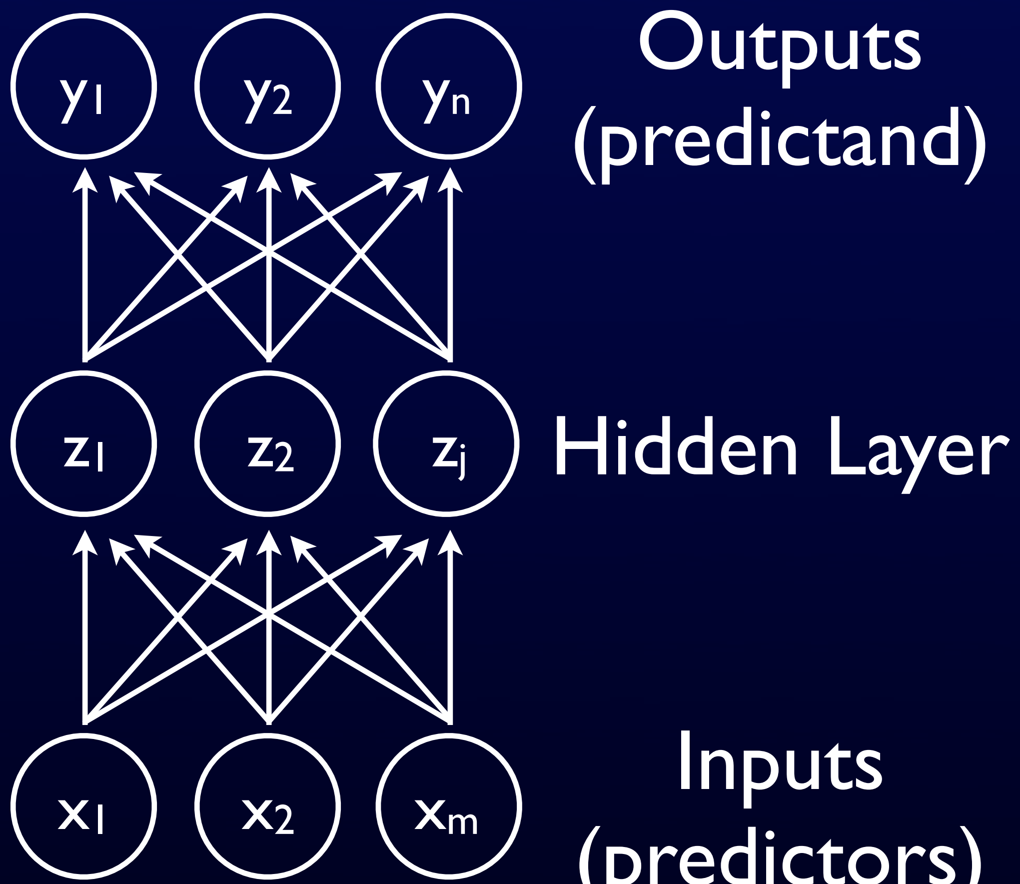


r = 0.74

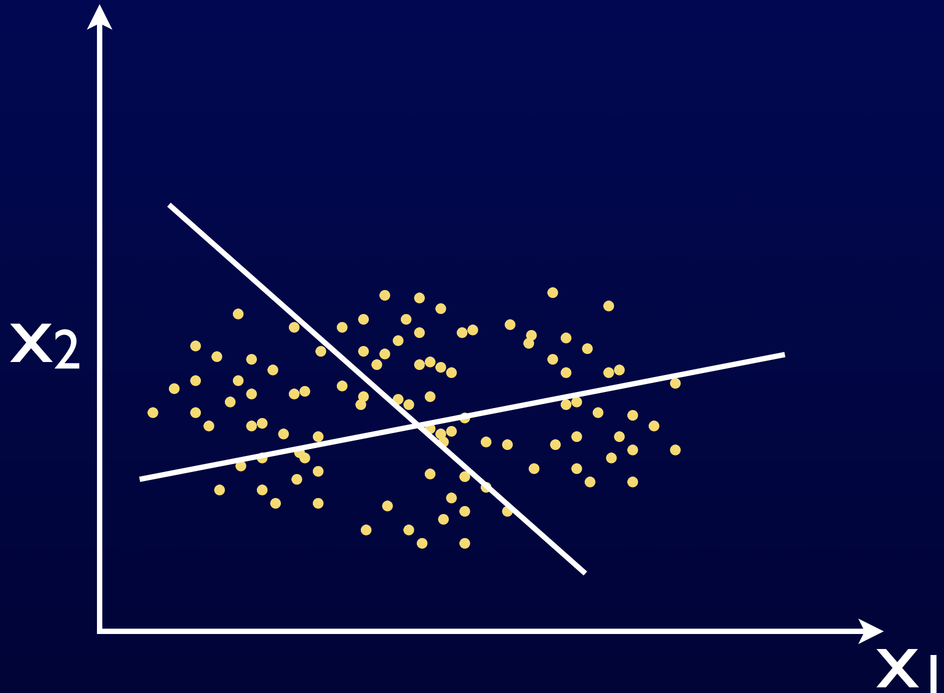
red is positive

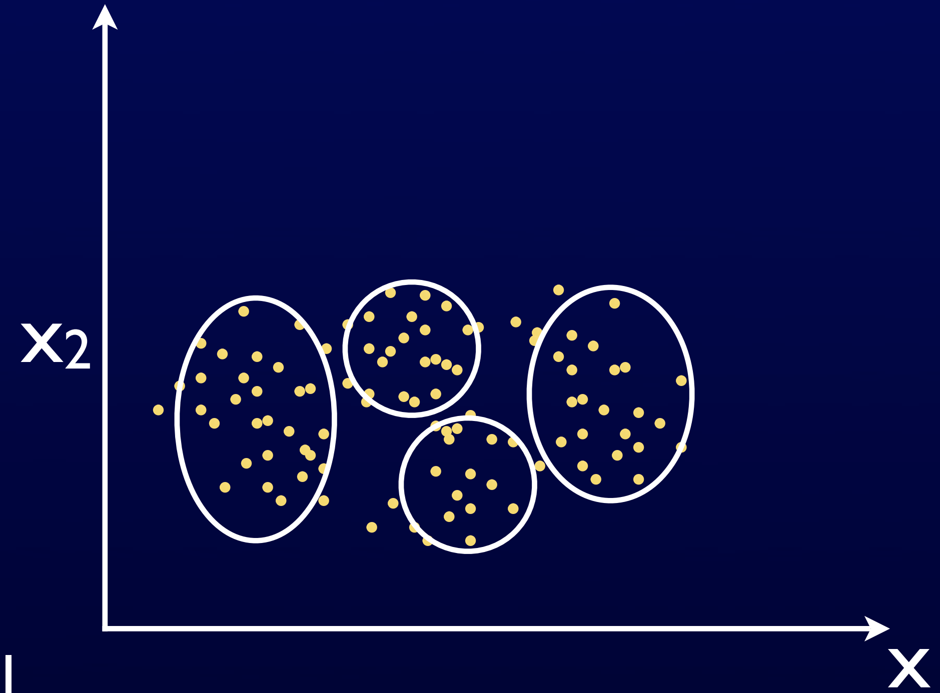
Artificial Neural Networks

- non linear mapping of a set of inputs to a set of outputs via hidden layer nodes
- arbitrary number of hidden layers with an arbitrary number of nodes
- this comparison used a single hidden layer with ~10-20 nodes



Types of ANNs





Multi Layer Perceptron	Radial Basis Function
Optimises network according to inputs and outputs	Optimises network according to inputs only
Slower	Faster but requires estimation of number of clusters

ANNs in this study

- SDSM predictors
- MLPK and RBF
  - MLP and RBF with predictors chosen by MLR
  - sum-of-squares error metric
- MLPS and MLPR
  - MLP with predictors chosen by Automatic Relevance Determination
  - gamma-function error metric
  - probabilistic output of P(rain) and gamma α and β
    - MLPS uses expected rainfall = $P\alpha\beta$
    - MLPR uses Monte Carlo resampling

Dynamical downscaling

- HadRM3
  - Hadley Centre 3rd generation RCM
  - 19 levels + 4 soil, 50km x 50km resolution
  - comprehensive atmospheric and land surface physics
- CHRM
  - adaption of HRM - the operational forecasting model of the German and Swiss met. services
  - 20 levels + 3 soil, 55km x 55km
  - full physics

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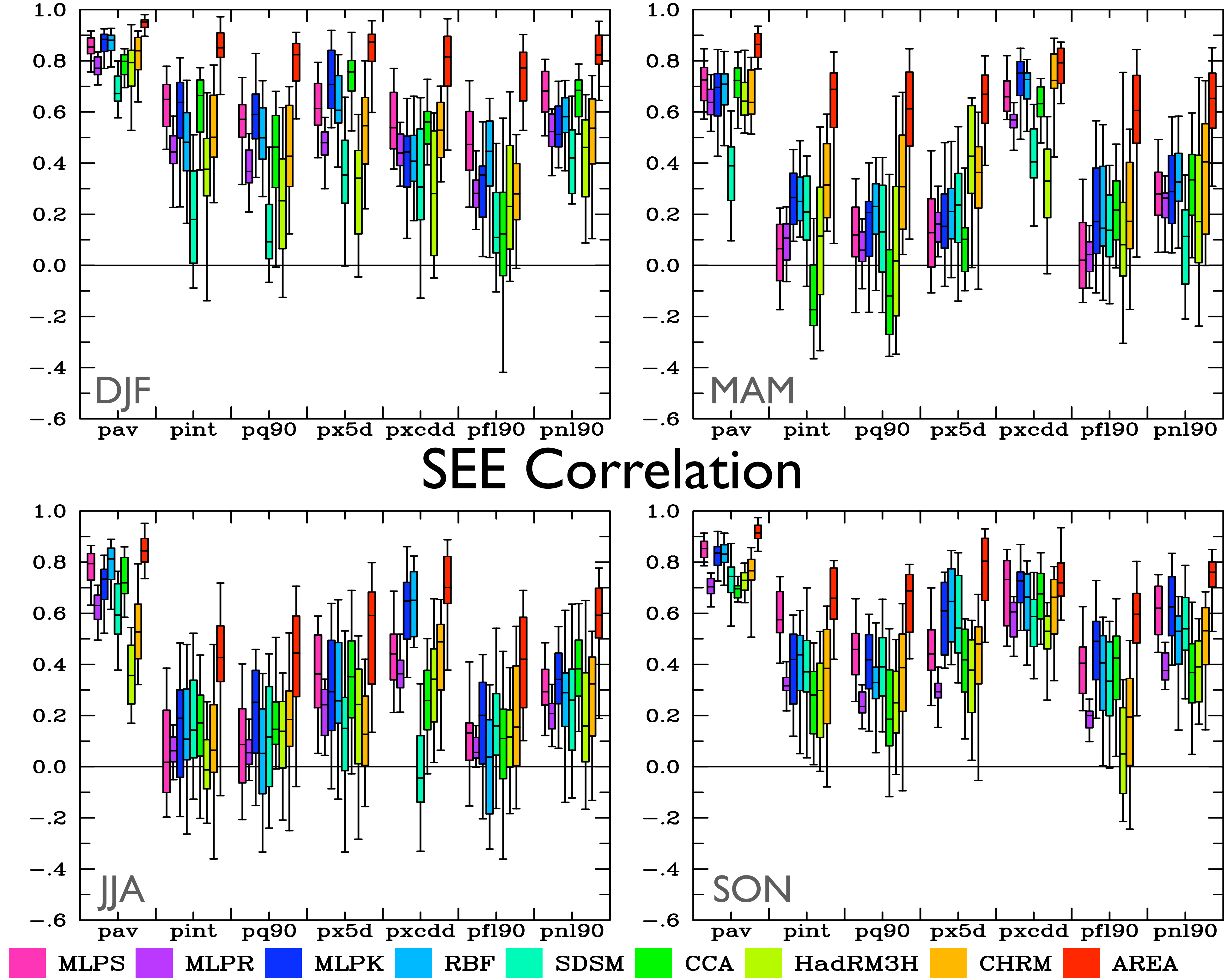
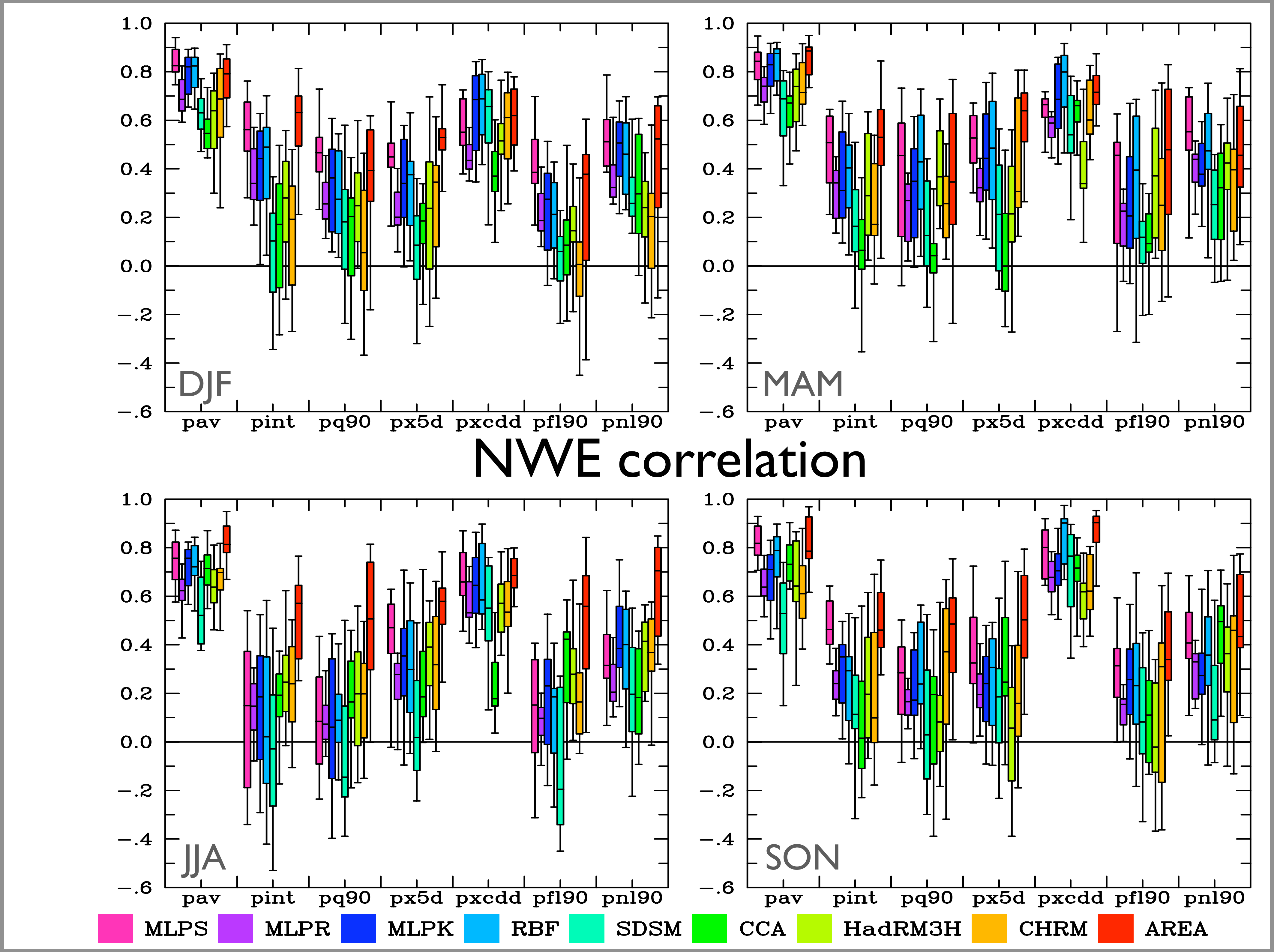
Training and Validation

- Statistical models trained 1958-1978 and 1994-2000 using NCEP data
- Validated 1979-1993 to match ERA-15 nested RCMs
- Compared observed and downscaled indices over validation period

Skill Scores

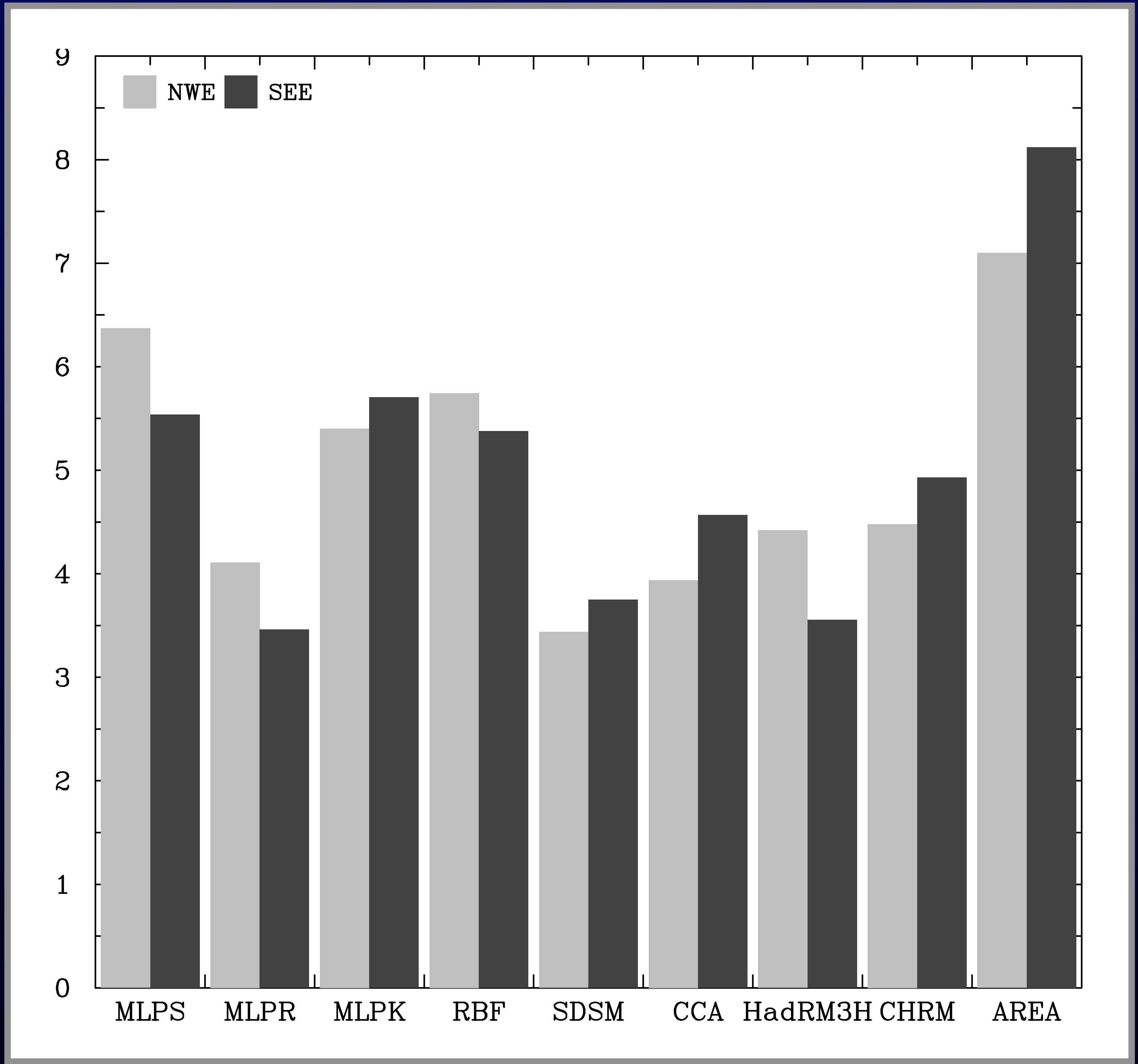
- Spearman Correlation
  - validates inter-annual variability independent of bias or incorrect variance
  - shows how successfully capturing predictor-predictand relationship
- Bias
  - important but some models explicitly model bias
- Debiased RMSE
  - validates inter-annual variability, including variance, independent of bias


SEE Correlation
DJF
MAM
JJA
SON
1.0
0.8
0.6
0.4
0.2
0.0
−.2
−.4
−.6
pav
pint
pq90
px5d
pxcdd
pfl90
pnl90
MLPS
MLPR
MLPK
RBF
SDSM
CCA
HadRM3H
CHRM
AREA

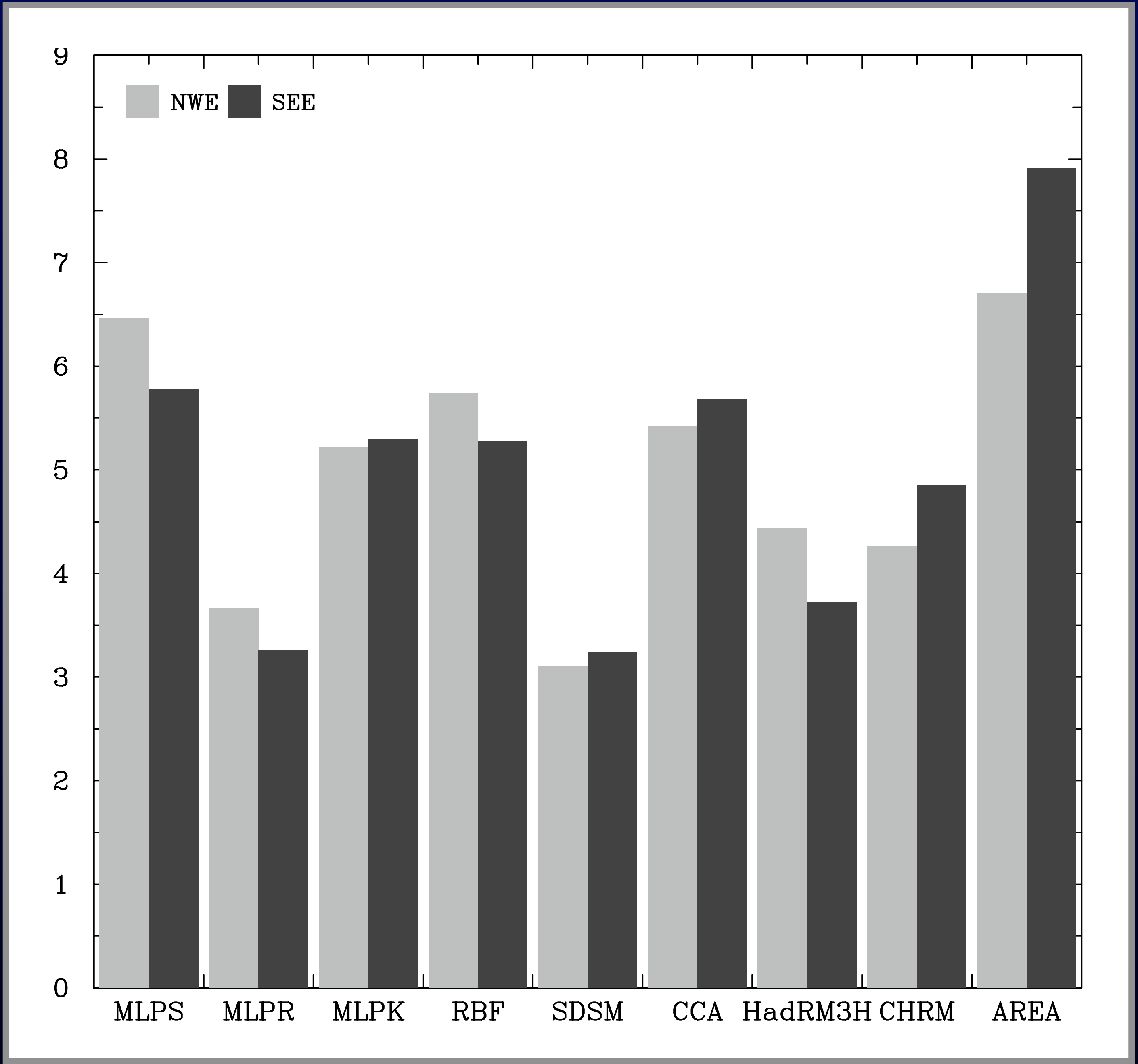


NWE correlation
DJF
MAM
JJA
SON
1.0
0.8
0.6
0.4
0.2
0.0
−.2
−.4
−.6
pav
pint
pq90
px5d
pxcdd
pfl90
pnl90
MLPS
MLPR
MLPK
RBF
SDSM
CCA
HadRM3H
CHRM
AREA

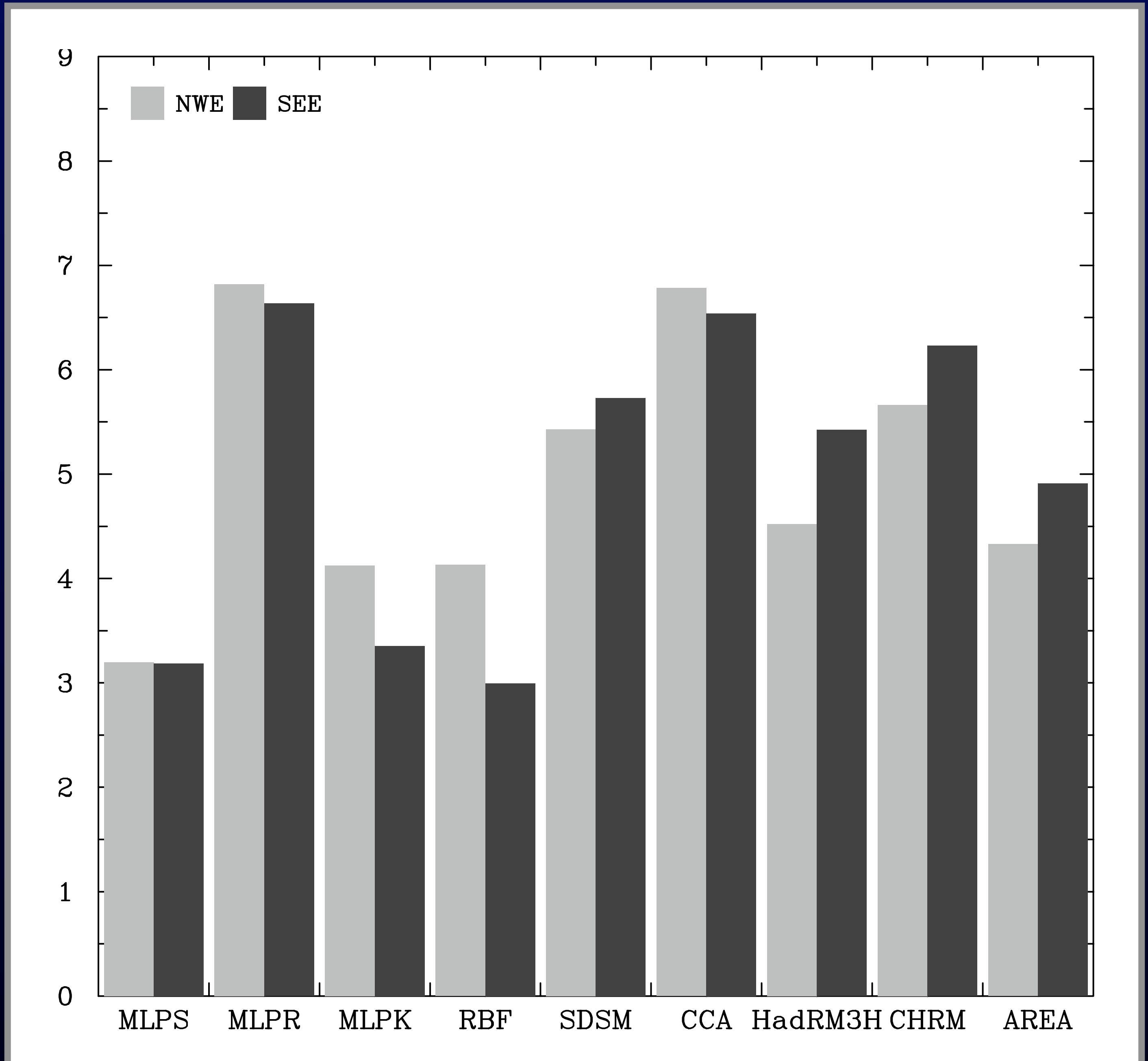
Average Correlation Rank



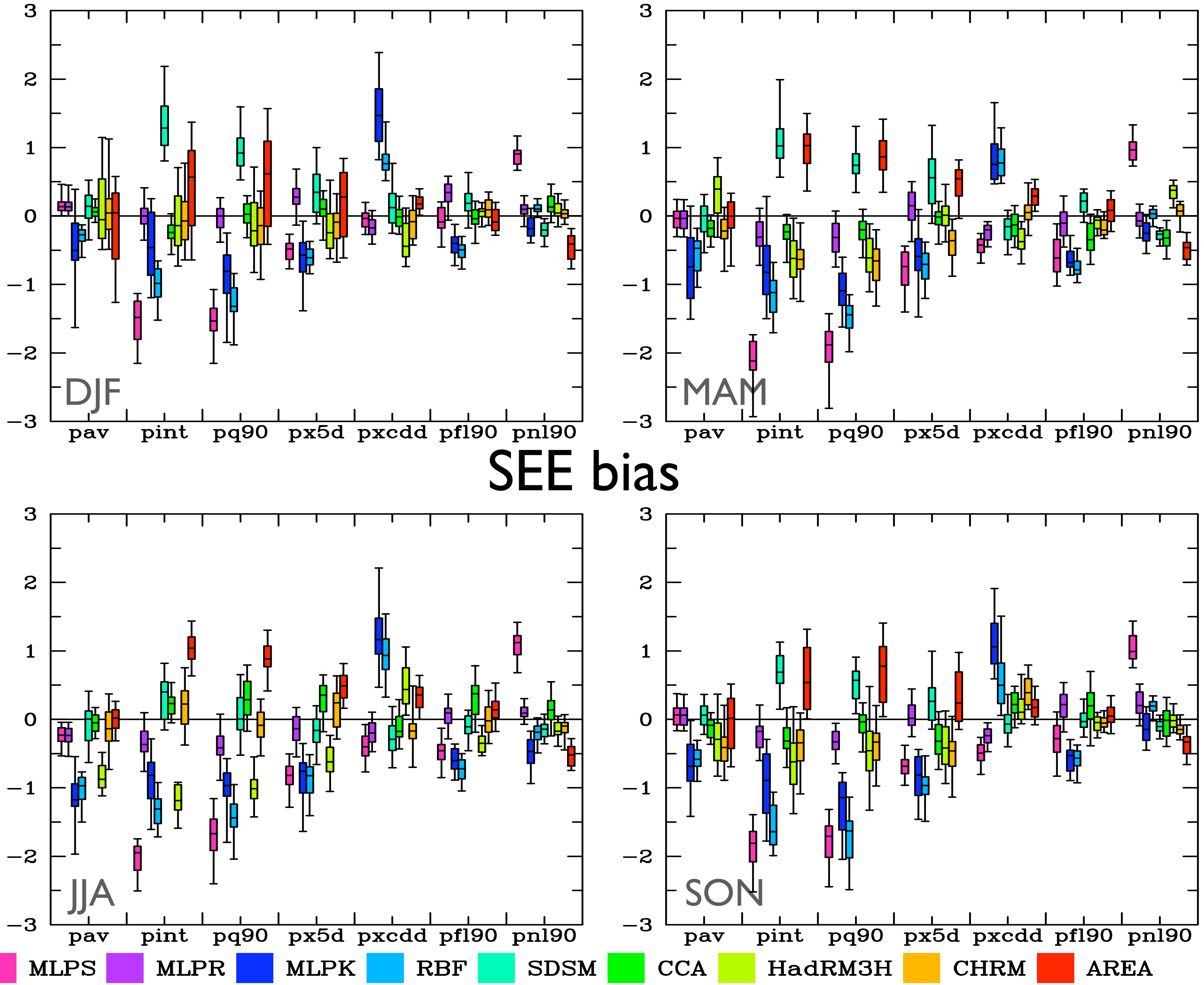
Average RMSE Rank



Average Bias Rank



SEE bias



DJF
MAM
JJA
SON
3
2
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0
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−2
−3
pav
pint
pq90
px5d
pxcdd
pfl90
pnl90
MLPS
MLPR
MLPK
RBF
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AREA

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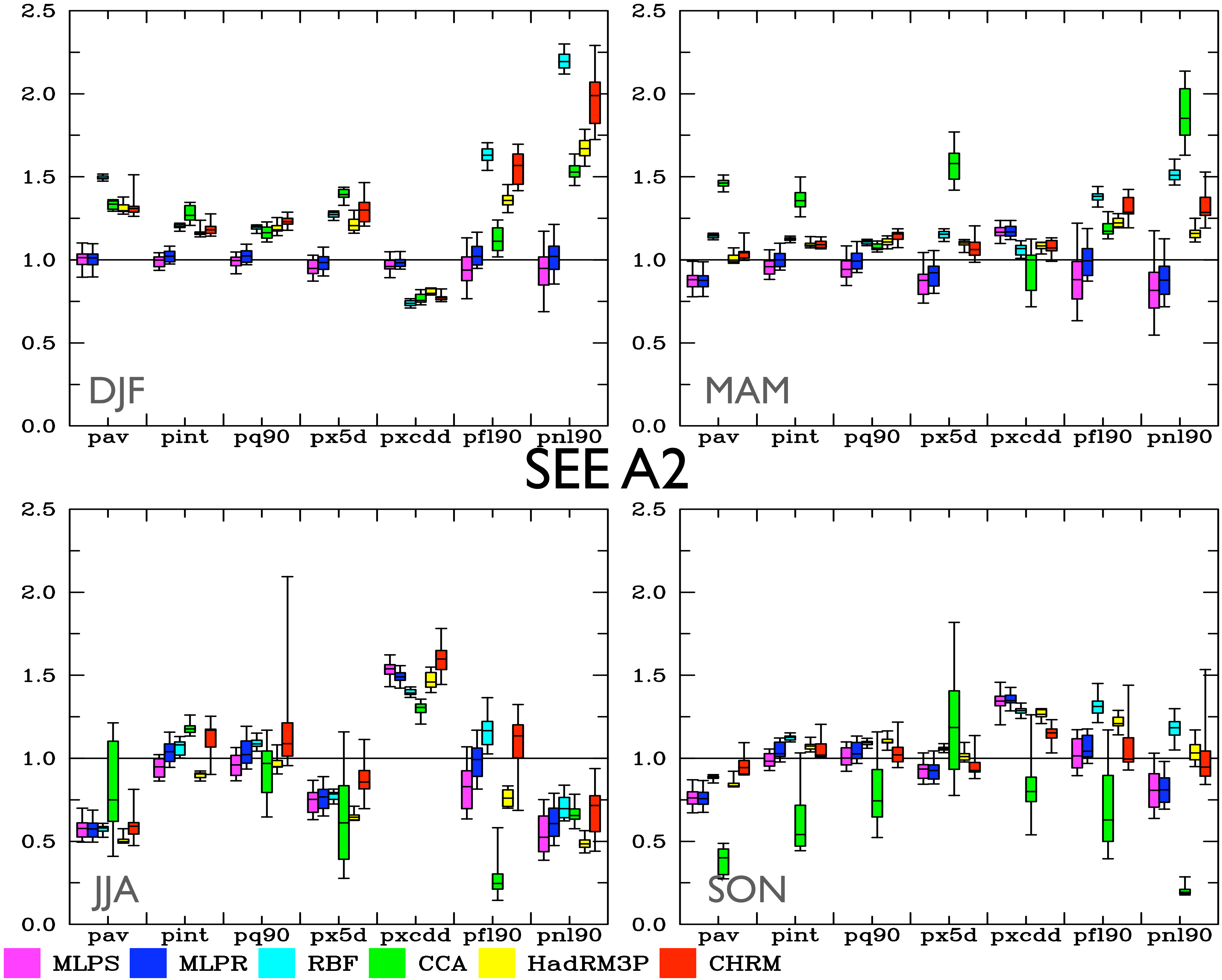
Scenarios

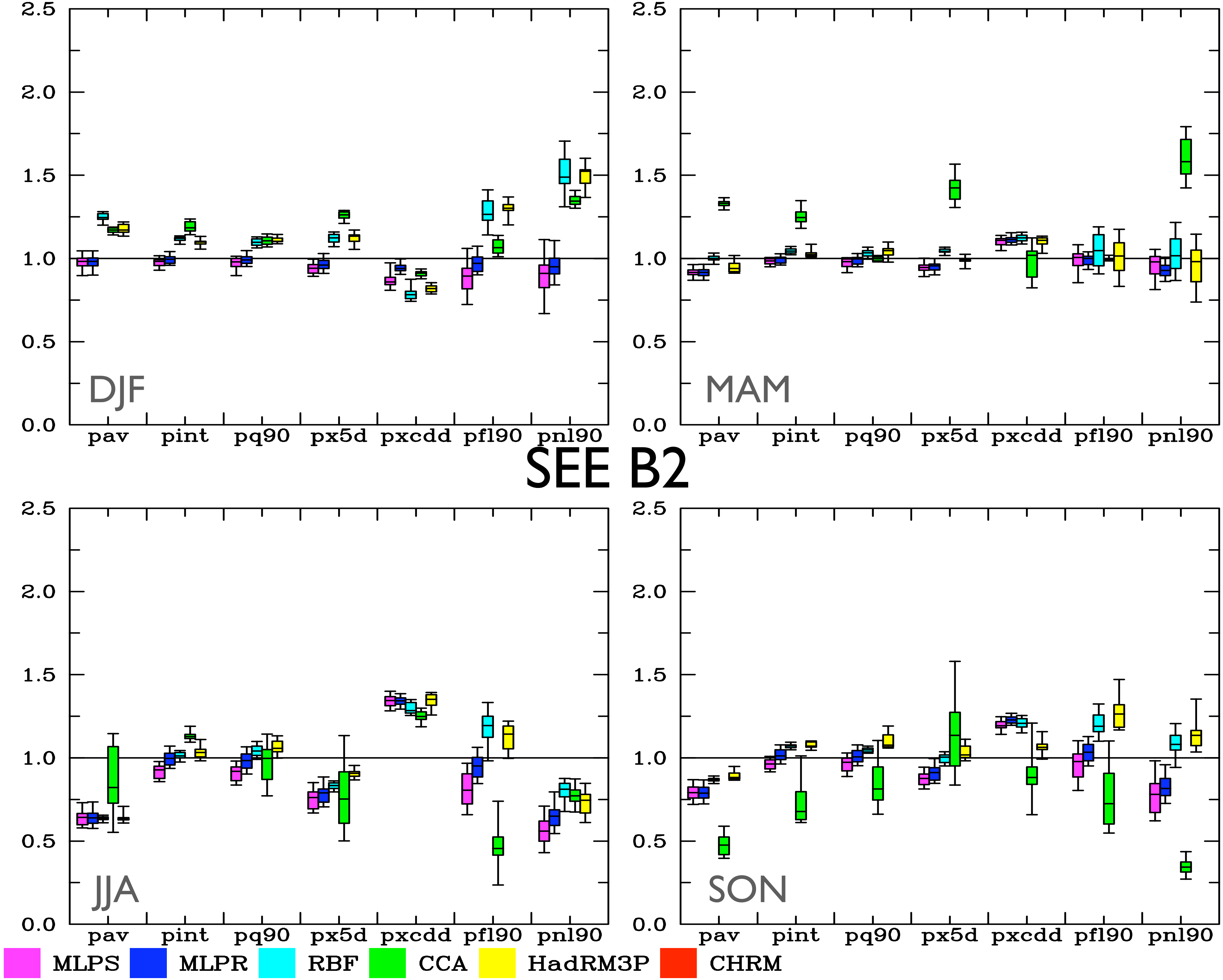
- Models run with HadAM3P data
- HadAM3P regridded to match NCEP
- Grid point mean and standard deviation of data adjusted to match NCEP and same scale factors applied to scenario.
- Indices for 2071-2100 compared with 1961-1990
  - 3 A2 ensemble members
  - 1 B2 member

SEE A2



DJF
MAM
JJA
SON
0.0
0.5
1.0
1.5
2.0
2.5
pav
pint
pq90
px5d
pxcdd
pfl90
pnl90
MLPS
MLPR
RBF
CCA
HadRM3P
CHRM

SEE B2



DJF
MAM
JJA
SON
2.5
2.0
1.5
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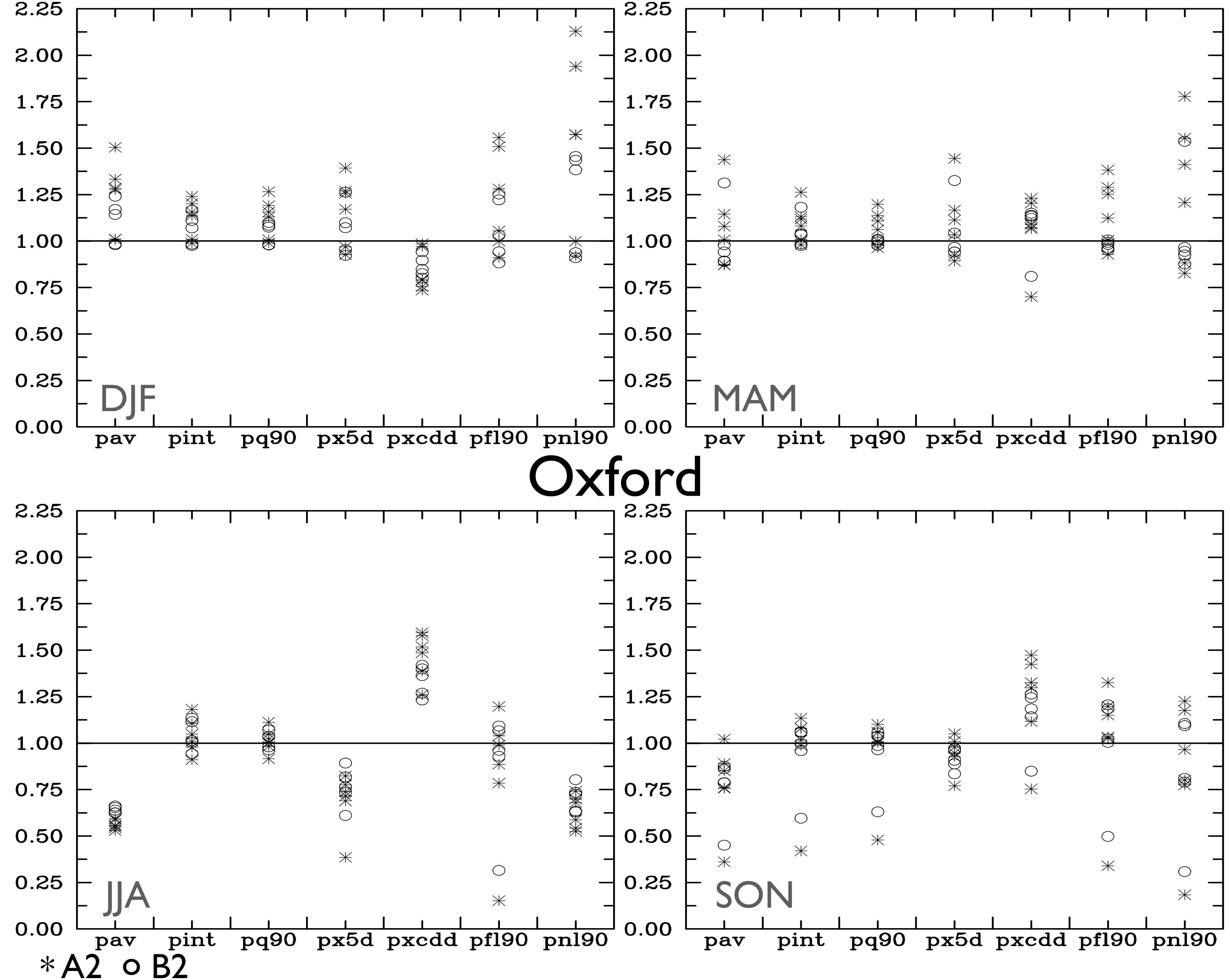
0.5
0.0
pav pint pq90 px5d pxcdd pfl90 pnl90
MLPS MLPR RBF CCA HadRM3P CHRM



Oxford
DJF
MAM
JJA
SON
pav
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pq90
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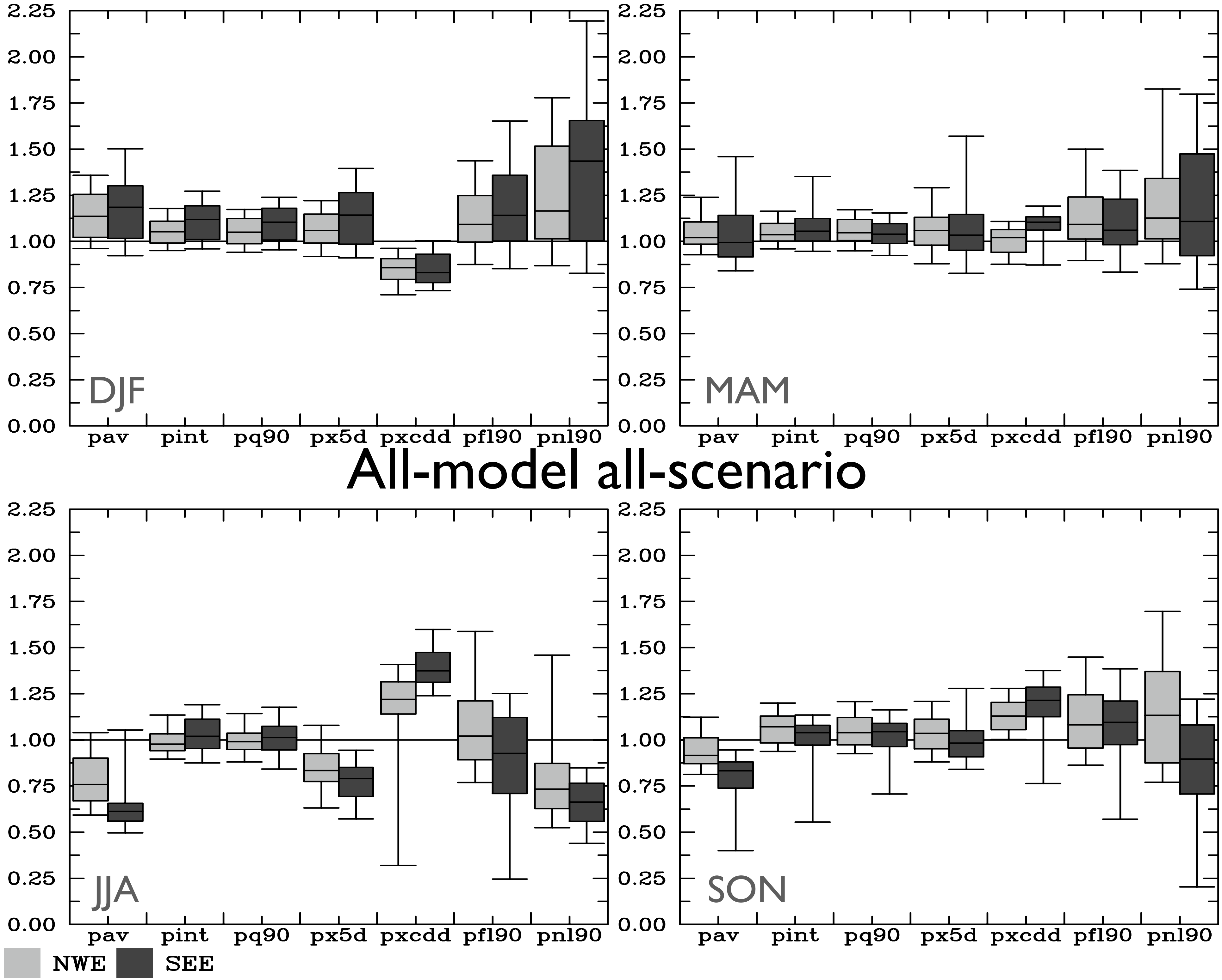
pxcdd
pfl90
pnl90
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
2.25
* A2 o B2



2.25
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
DJF
MAM
JJA
SON
pav
pint
pq90
px5d
pxcdd
pfl90
pnl90
All-model all-scenario
NWE
SEE

Conclusion

- Compared six statistical and two dynamical downscaling models in their ability to downscale seasonal indices of precipitation
- Validation
  - Deterministic models had large negative biases due to tendency towards conditional mean daily rainfall
  - Stochastic models reduced the bias but also reduced correlation skill
  - Skill of models highest for indices and seasons with highest spatial coherence

Conclusion

- Validation
  - ANNs best at modeling inter-annual variability
  - Better performance of models in DJF
  - Rainfall occurrence better downscaled than intensity
- Scenarios
  - Wetter in winter, drier in summer
  - Inter-model differences in scenario changes at least as large as differences between scenarios
    - caution when using one type of model
- Probabilistic output of models is of great benefit for uncertainty estimates and reducing model bias
- Largest source of uncertainty not addressed: GCM