WHAT IS IT GOING TO BE ABOUT?

- goal: to stimulate discussion

IS STATISTICAL DOWNSCALING CONDEMNED TO DEATH?

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OUTLINE

1. Historical parallel
2. Main paradox of downscaling – and ways out of it
3. Criteria of validation
4. Statistical vs. dynamical downscaling
5. Nonlinear methods – my own experience
6. Recommendations

HISTORICAL PARALLEL

- beginnings: 1950's – pioneering work by W.H. Klein
- weather prediction
- 'specification' of sfc. weather from large-scale circulation
- NWP in similar state to present climate modelling – unable to provide regional / local details
- but now – NWP models **are** able …
- so – what's 'our' future?

HISTORICAL PARALLEL

- NWP still needs (and will need forever) statistical postprocessing methods
  - to de-bias forecasts
  - e.g. precipitation, extreme temperatures
    - ç imperfections in model physics
    - ç incomplete description of physical processes
- similar will likely hold for climate models
- statistical downscalers (= we) are not bound to become extinct

PARADOX OF STAT. DOWNSCALING

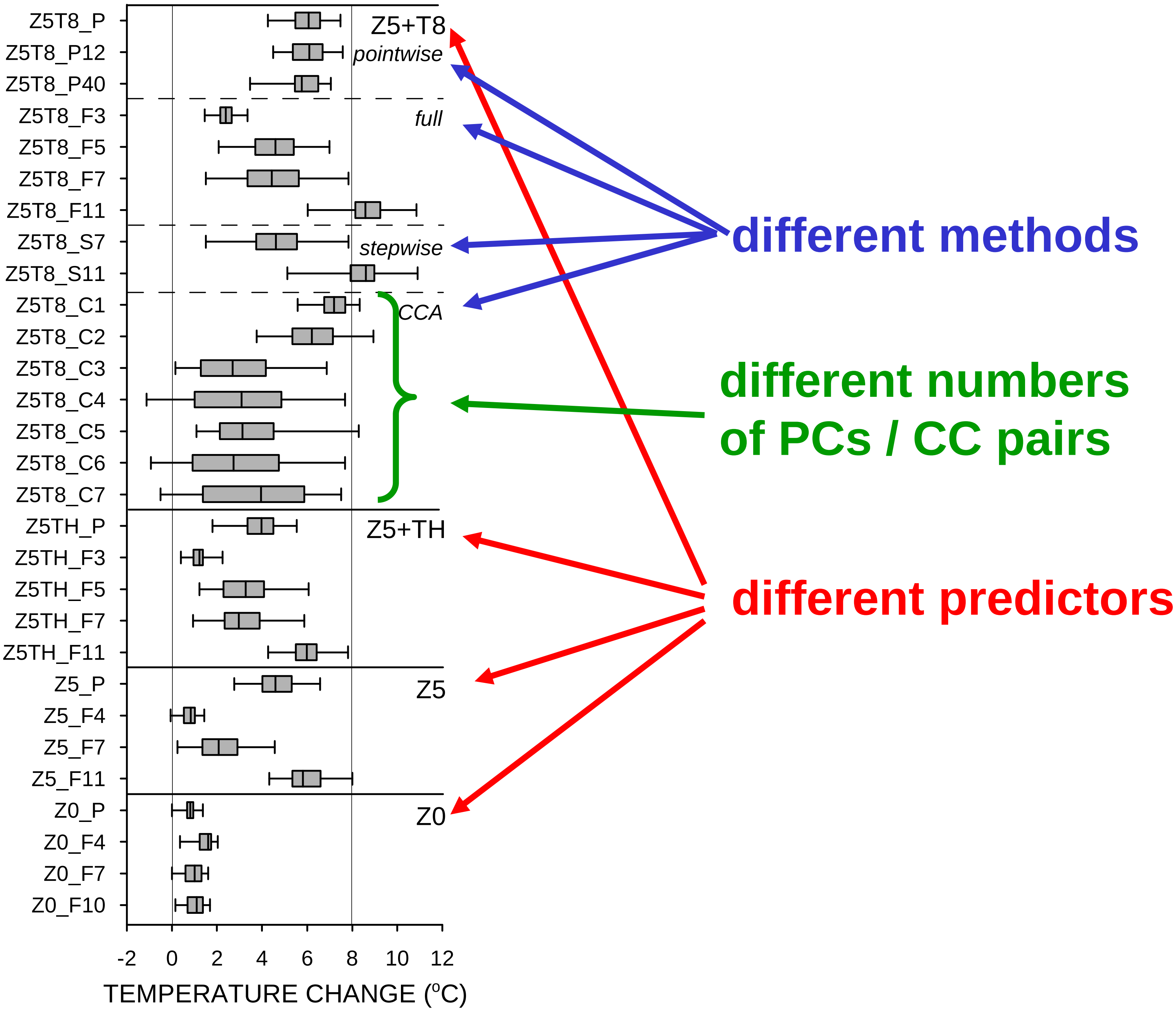
- in application to scenario construction
- problem: extremely high sensitivity to
  - method
  - predictors
  - parameters (no. of PCs, canonical pairs,…)

DATASETS

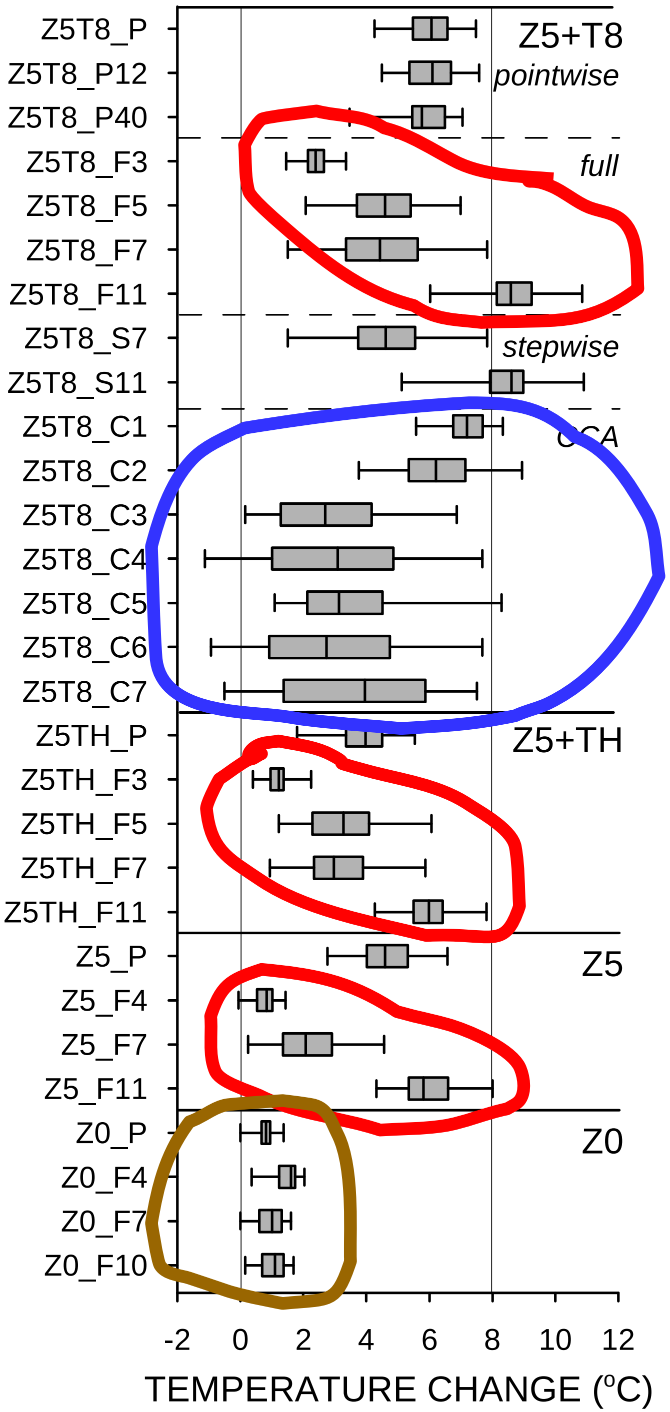
- 39 European stations
- DJF
- 1982/83 – 1989/90
- daily mean temperature
- predictors:
  - 500, 1000 hPa heights
  - 850 hPa temperature
  - 1000/500 hPa thickness

DATASETS

- observed relationships applied to CCCM2 GCM



Z5T8_P
Z5T8_P12
Z5T8_P40
Z5T8_F3
Z5T8_F5
Z5T8_F7
Z5T8_F11
Z5T8_S7
Z5T8_S11
Z5T8_C1
Z5T8_C2
Z5T8_C3
Z5T8_C4
Z5T8_C5
Z5T8_C6
Z5T8_C7
Z5TH_P
Z5TH_F3
Z5TH_F5
Z5TH_F7
Z5TH_F11
Z5_P
Z5_F4
Z5_F7
Z5_F11
Z0_P
Z0_F4
Z0_F7
Z0_F10
Z5+T8
pointwise
full
stepwise
CCA
Z5+TH
Z5
Z0
-2 0 2 4 6 8 10 12
TEMPERATURE CHANGE (°C)
different methods
different numbers of PCs / CC pairs
different predictors

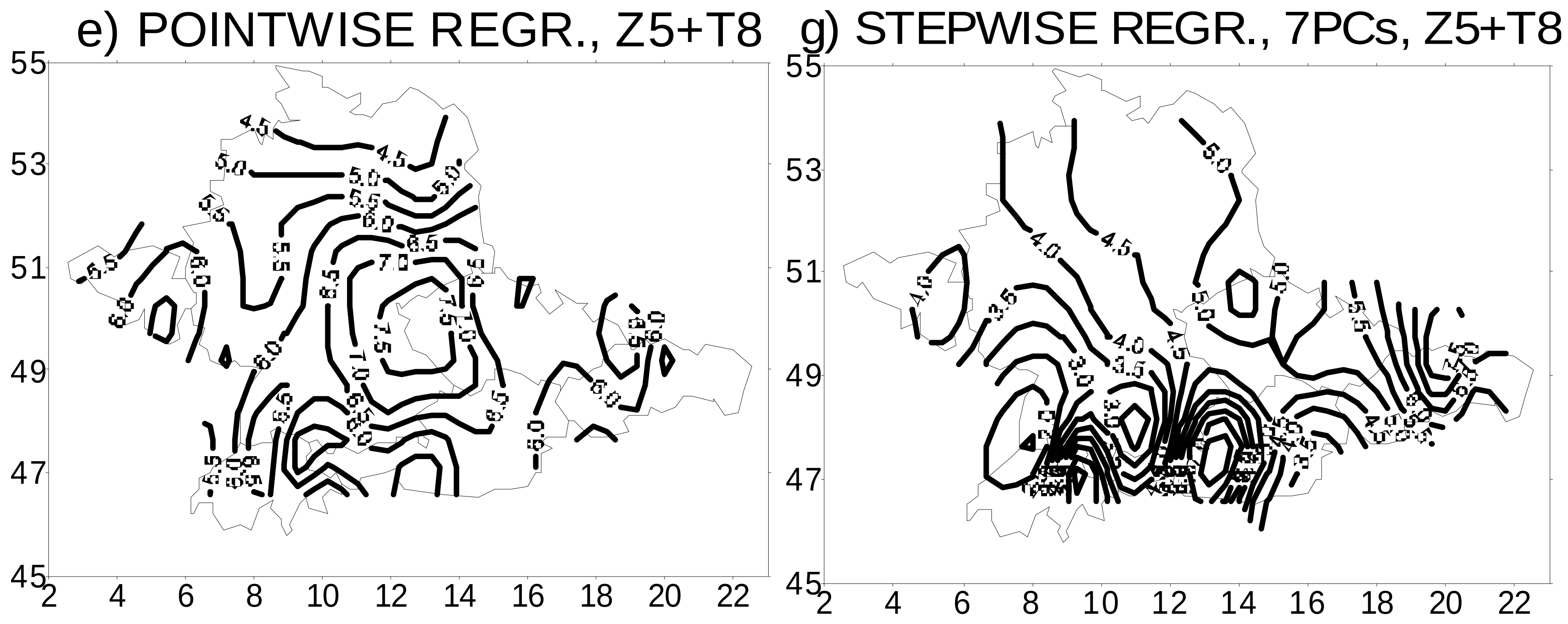


dT increases with increasing number of PCs

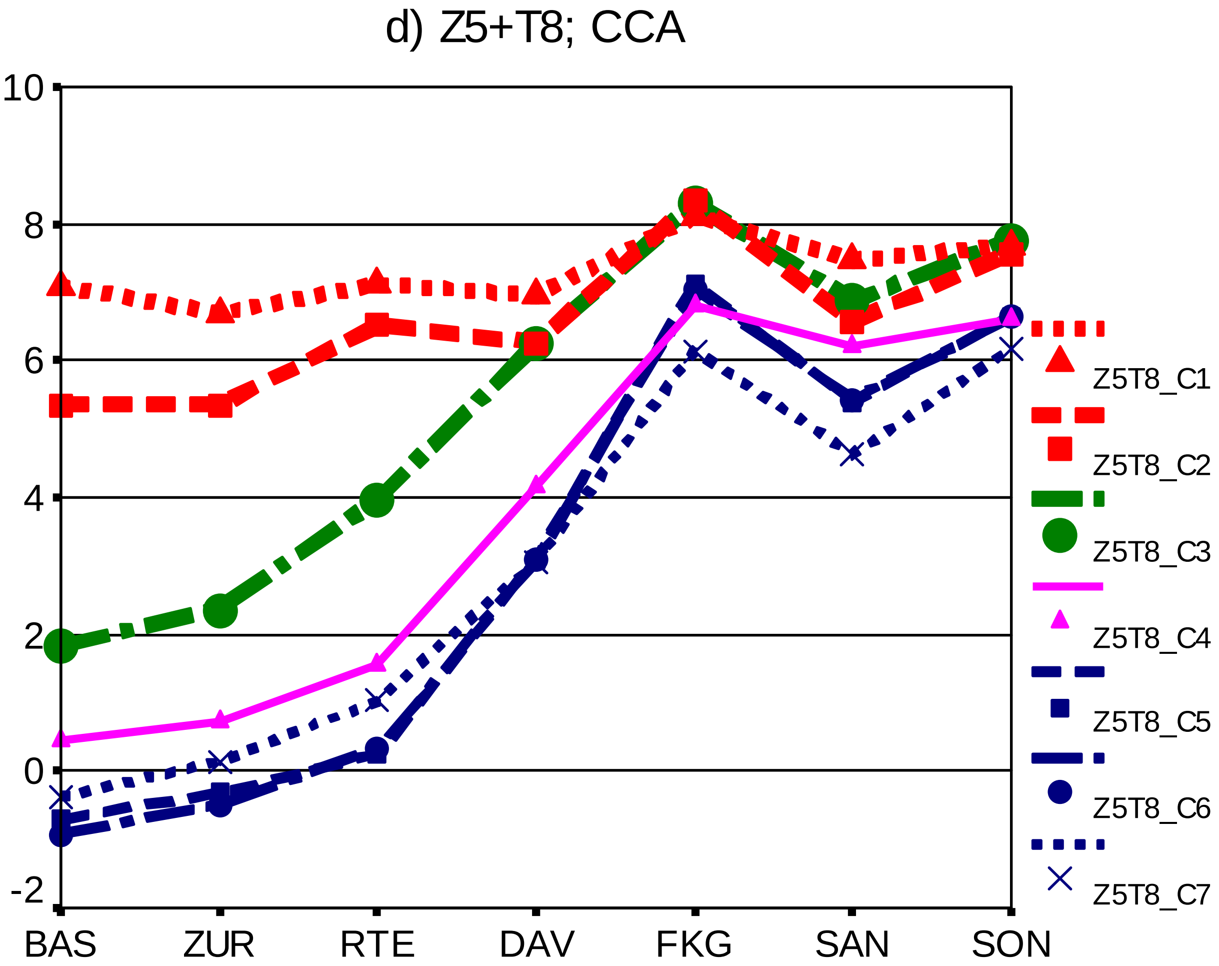
dT changes with changing number of canonical pairs

1000 hPa heights as only predictor lead to negligibly low dT

- not only amplitude of temperature change differs
- also spatial patterns



- not only amplitude of temperature change differs
- also elevation dependence



WHY DEPENDENCE ON PREDICTORS?

area averaged change in predictors,
$2xCO_2$ – control

predictor	absolute change	relative change
Z1000	-13.4 m	-13.7
Z500	64.7 m	67.5
1000/500 thickness	78.1 m	70.1
T850	3.68 °C	98.4

WHY DEPENDENCE ON PREDICTORS?

- natural consequence of radiative heating of troposphere

WHY DEPENDENCE ON PC NUMBER?

For most PCs:

regression coefficients

and

change (2xCO_2 – control) in PC scores

have the same sign

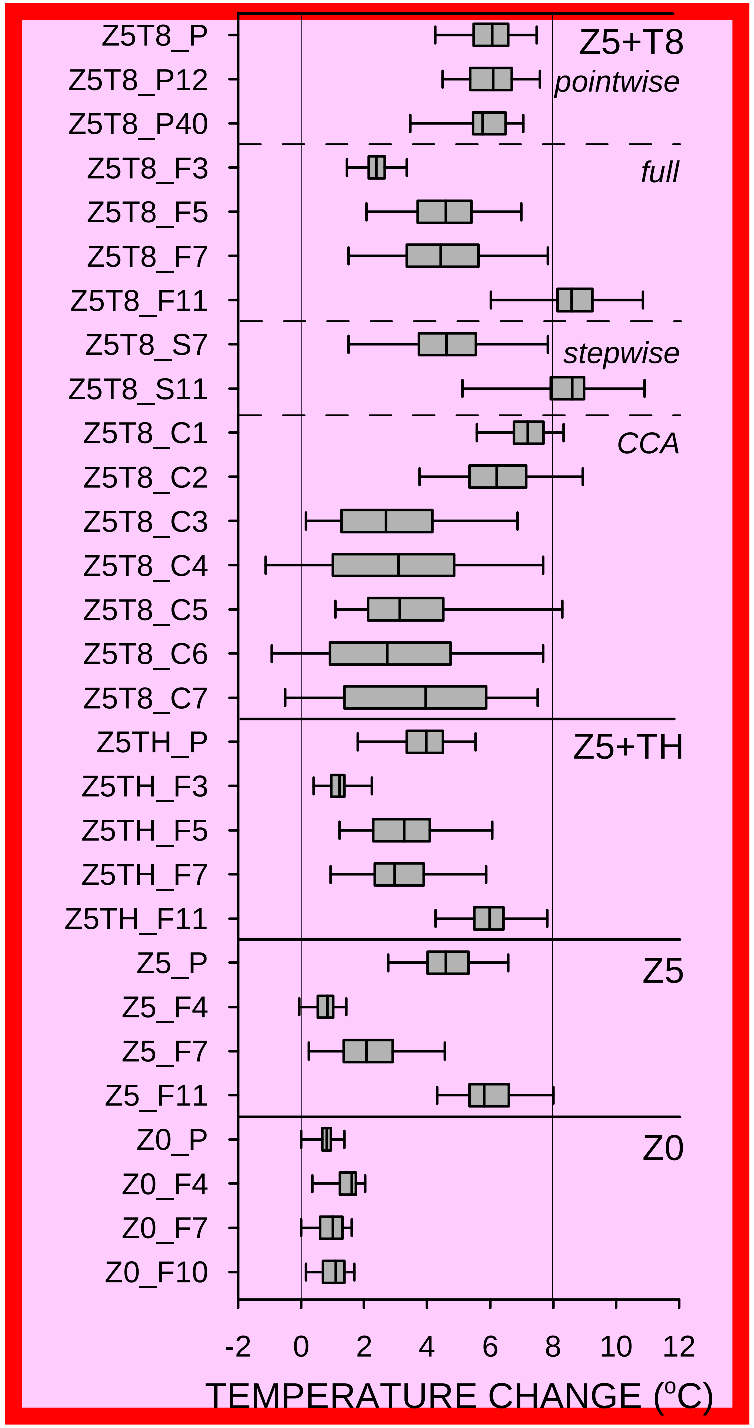
Ł contribute to **warming**

mode	regr. coeff. (averaged over stations)	PC score change (2xCO_2 – control)
1	-59	-0.47
2	-24	0.15
3	18	0.01
4	-14	-0.58
5	11	1.69
6	16	0.06
7	0	1.50
8	13	1.11
9	11	3.36
10	5	0.03
11	3	1.01

mode	regr. coeff. (averaged over stations)	PC score change (2xCO_2 – control)	result
1	-59	-0.47	W
2	-24	0.15	C
3	18	0.01	w
4	-14	-0.58	W
5	11	1.69	W
6	16	0.06	w
7	0	1.50	-
8	13	1.11	W
9	11	3.36	W
10	5	0.03	w
11	3	1.01	W

SENSITIVITY TO DS. MODEL

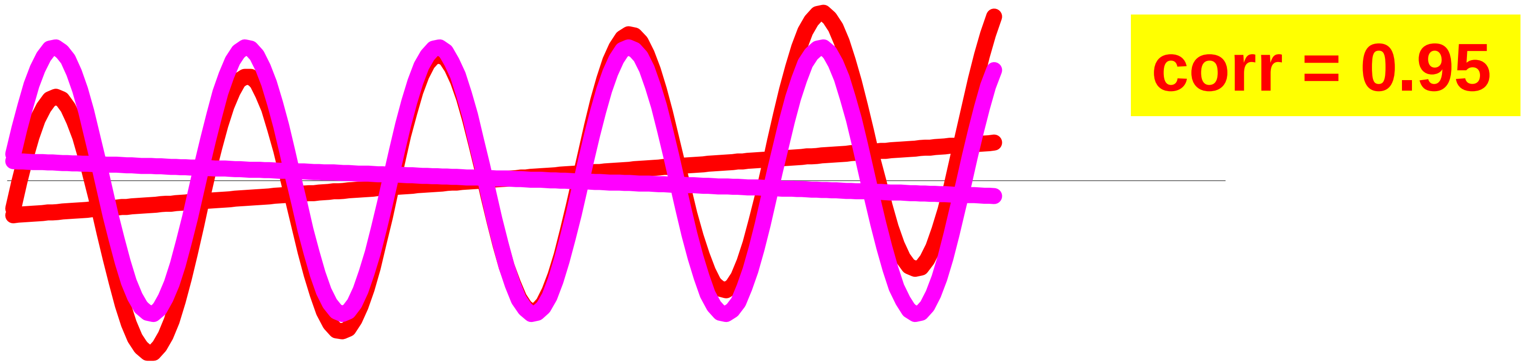
- sensitivity to the number of PCs
  - can be explained in physical (meteorological) terms
  - matter of fact, not fictitious
- similarly for
  - other methods (e.g., CCA)
  - sensitivity to predictors
  - etc.



- all models are good in terms of rmse
- mean temperature change varies from +0.5 to +8.5 deg. C
- other aspects also vary widely
- **so how to decide which model to prefer???**

WHICH MODEL?

- one clear fact: degree of fit with observed data (whatever measure is used) cannot be the only criterion!!!



PRINCIPAL PROBLEM (PARADOX) of statistical downscaling

Models are fitted to variability on time scales much shorter than on which climatic change proceeds

REMEDY for the PARADOX

- possible REMEDY – 2 ways:
  - validation: use appropriate criteria
  - a priori selection of predictors

REMEDY – VALIDATION

- validate trends (but recent and future trends may result from different mechanisms!)
- check ability to simulate contrasting climatic states (cold / warm; dry / wet years) (similar objection)
- verify consistency with driving GCM (but GCM may be wrong!)

REMEDY – PREDICTOR(s) SELECTION

- (1) use predictors reflecting radiative heating of atmosphere (temperature, thickness, mid-tropospheric heights)
- **BUT:**
  - this may work for temperature; what about other variables (precip, cloudiness, …) ?
  - circulation changes may also contribute Ł circulation-only predictors cannot be ruled out a priori
  - impossible to decide a priori how to mix ‘radiative’ and ‘circulation’ predictors

REMEDY – PREDICTOR(s) SELECTION

- (2) use the same variable as predictand

  Ł downscaling reduces to interpolation

- **BUT:**
  - can it work for highly spatially variable quantities with short autocorrelation distance (precipitation) ?
  - does it meet basic requirements of downscaling?
    - well simulated by GCM
    - explains large portions of variance

REMEDY – PREDICTOR(s) SELECTION

- (2) use the same variable as predictand
  - Ł downscaling reduces to interpolation
- **BUT (cont.):**
  - – predictor x predictand relation is purely statistical; if predictor is different, ‘physical’ relationships are implicitly included

CRITERIA OF VALIDATION

- majority of studies: only fit to observed data
  - rmse, correlation
- mean, std.deviation – easy to reproduce by definition (in most cases) – unnecessary to validate

CRITERIA OF VALIDATION

- seldom, but potentially important in various applications
  - higher-order statistical moments, extreme values, distribution tails
  - time structure
  - spatial structure
  - intervariable relationships
  - trends / contrasting climatic states

STATISTICAL vs. DYNAMICAL DOWNSCALING

- statistical downscaling – tendency to be viewed as inferior, simplistic
  - *(example – ENSEMBLES project where it is an appendix of RCM efforts)*
- but: the few comparison studies Ł statist. and dynam. downscaling have similar performance

STATISTICAL vs. DYNAMICAL DOWNSCALING

- **+** of downscaling:
  - computationally simple
  - provides local information
- **+** of RCMs:
  - physical consistency among variables

STATISTICAL vs. DYNAMICAL DOWNSCALING

- not competing, but complementary techniques
- both have caveats that are frequently
  - not admitted
  - not reconciled

NONLINEAR METHODS

- different ways of introducing nonlinearity
  - nonlinear transfer functions
    - usually neural networks
    - others – used scarcely
  - data stratification, application of separate transfer functions in different classes

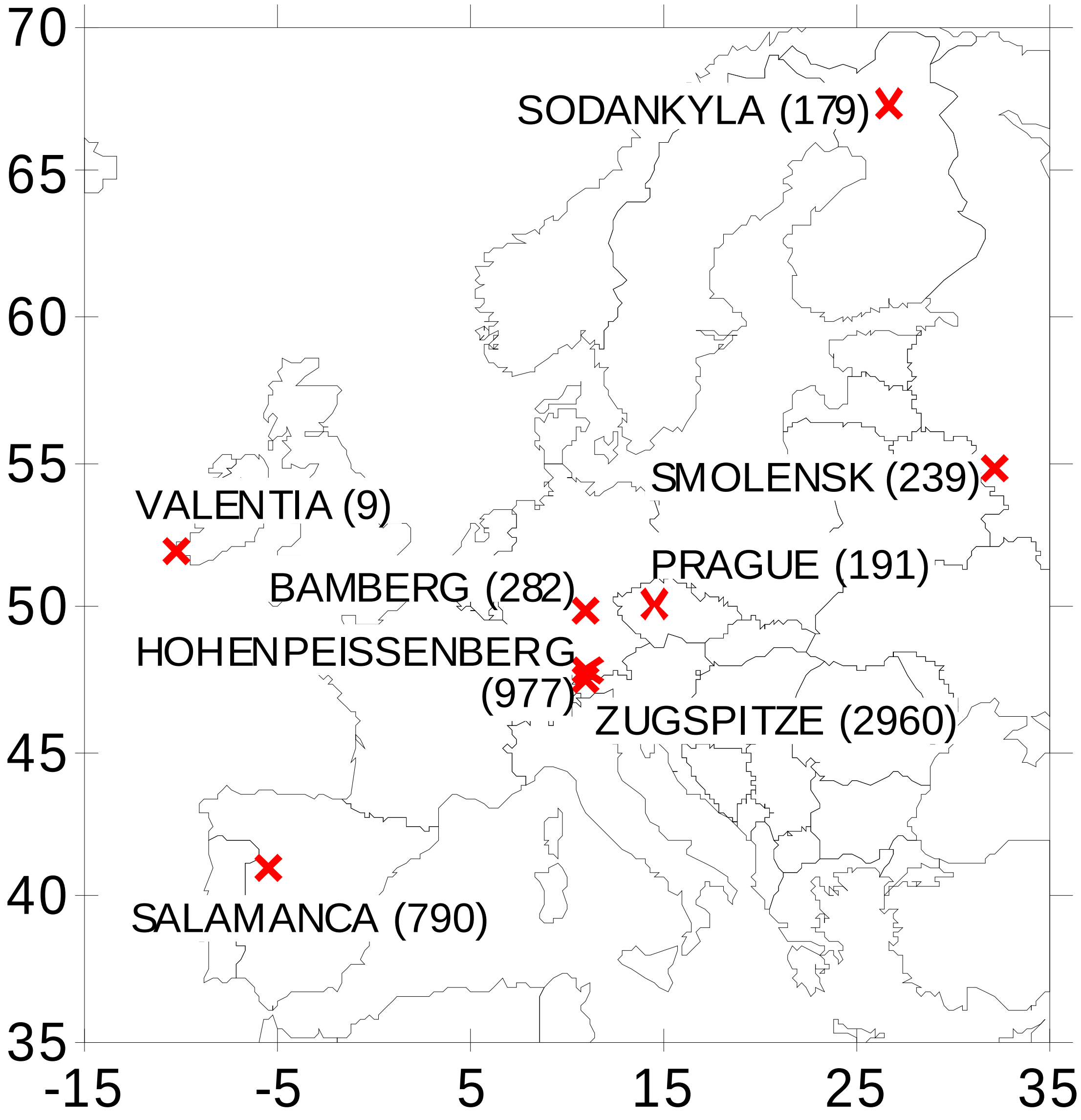
NONLINEAR METHODS

- comparisons linear x nonlinear
  - very rare
  - ambiguous results
    - superiority of nonlinear methods
    - similar performance
    - superiority of linear methods

NONLINEAR METHODS - DATA

- winter season (DJF)
- 35 winters: 1958/59 – 1992/93
- predictand
  - daily max temperature
  - 8 stations across Europe
- predictors
  - 500 hPa heights + 850 hPa temperature
  - NCEP reanalyses, 5 x 5 deg. grid
  - large window: 25N – 80N / 50W – 55E

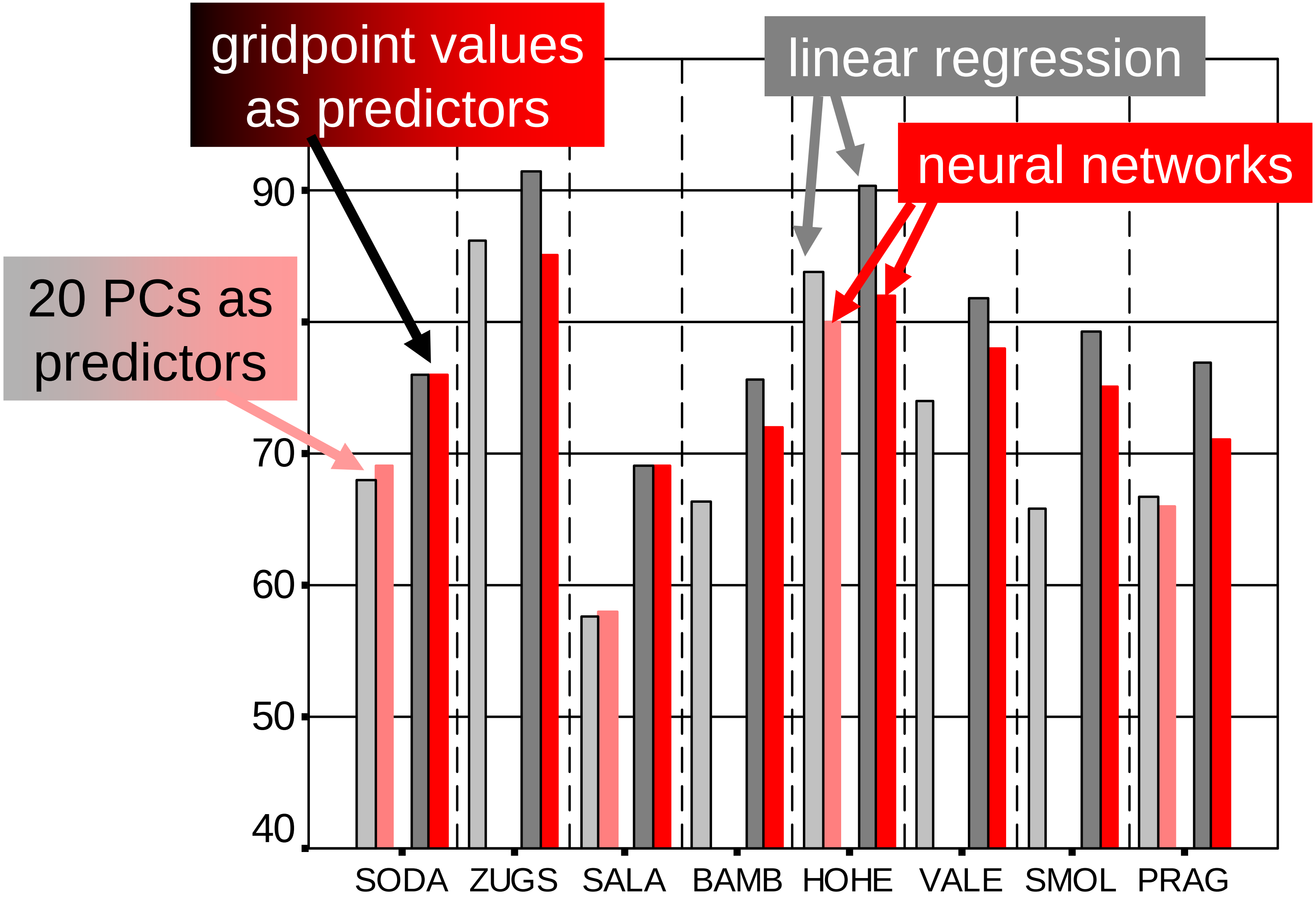
NONLINEAR METHODS - DATA



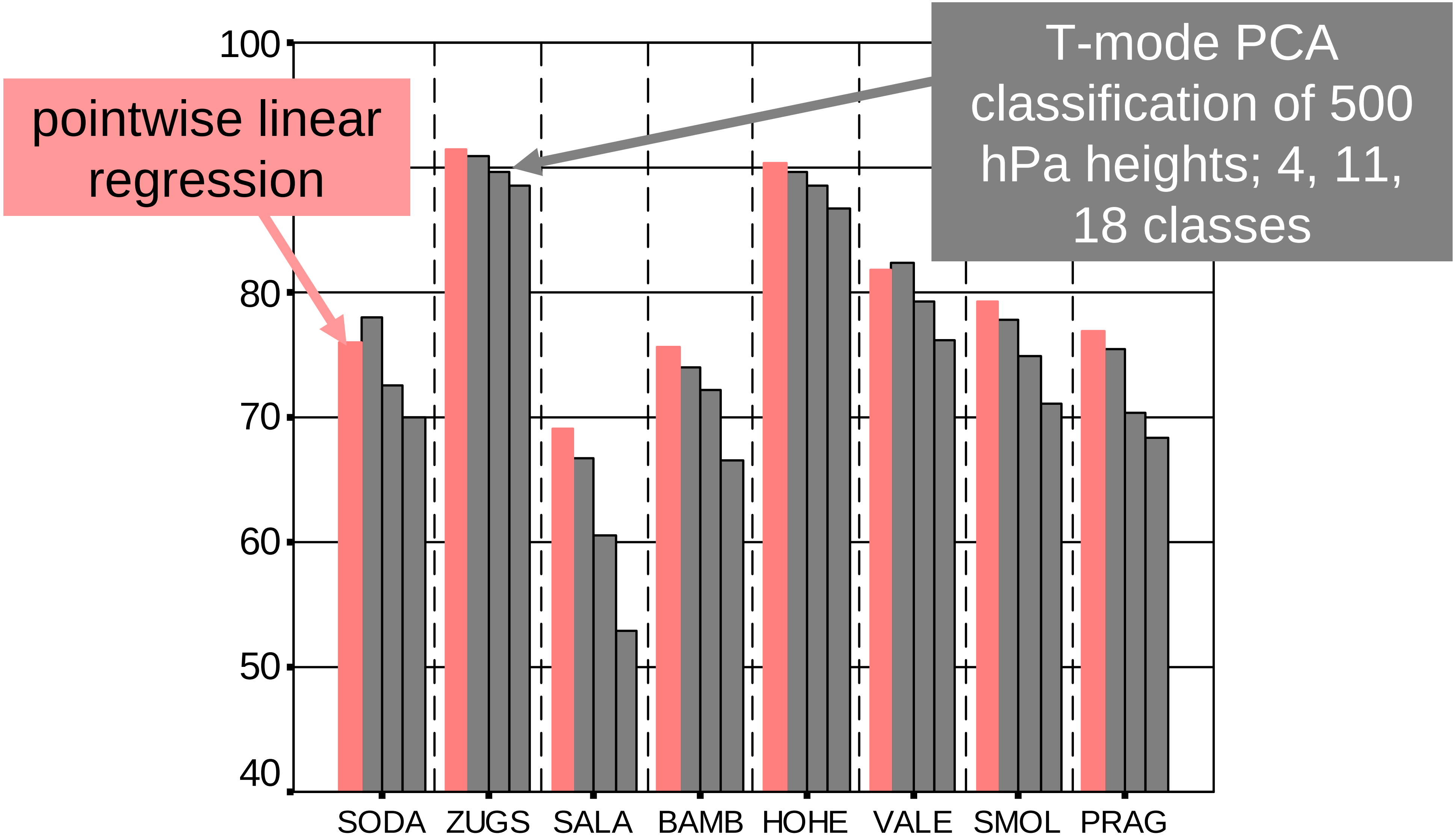
NONLINEAR METHODS - VALIDATION

- cross-validation
  - 1 season held out
  - models built on remaining 34 seasons
  - repeated 35 times
- accuracy in terms of correlation coefficient
  - other measures (rmse, mae) yield similar results

Results – neural networks



Results – classification



NONLINEAR METHODS – SUMMARY OF RESULTS

- linear AND nonlinear methods – pointwise regression better than regression of PCs
- pointwise models: linear methods superior
- stratified data (use of classification)
  - slightly worse than unstratified data
  - increasing number of classes degrades the fit
  - similar for 1000 hPa heights, k-means clustering method
- Tmin – similar to Tmax

Why are nonlinear methods inferior?

- neural networks: too many parameters to determine
- classifications:
  - gain by better fit in subsamples
  - more than compensated for
  - by loss due to smaller sample sizes

Is linear downscaling really the best?

- indication, not proof
- pointwise linear regression of Z500+T850 – best of examined methods

  (incl. CCA, SVD, and other height + thermal predictors)
- is it best of all methods?
- NNs can surpass linear methods ç Ł the best linear method is simple (has small number of individual predictors)
- other variables – potentially a different outcome

WHAT DO I MISS IN (many) DOWNSCALING STUDIES

- comparisons with older / simpler methods
- verification whether assumptions of statistical downscaling are met
- broader validation driven by impact researchers' demands
- recognition of sensitivity of climate change estimates to the methodology

MY STRONGEST RECOMMENDATION

- include the ability to simulate recent trends / contrasting climate states among the necessary requirements posed on downscaling methods

IS STATISTICAL DOWNSCALING CONDEMNED TO DEATH?

I believe NOT.