APEC Climate Symposium 2009

Climate prediction and applications: Relevance for climate adaptation strategies

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Statistical Downscaling: Downscaling in space

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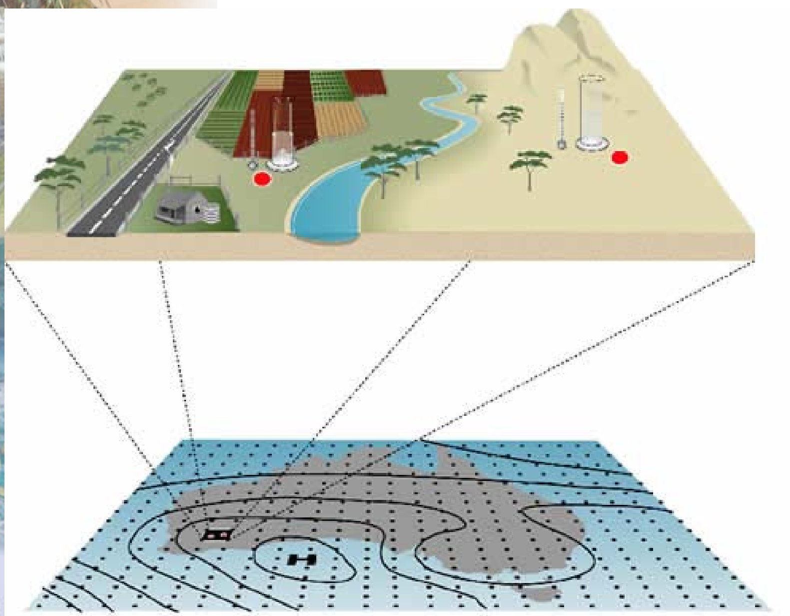
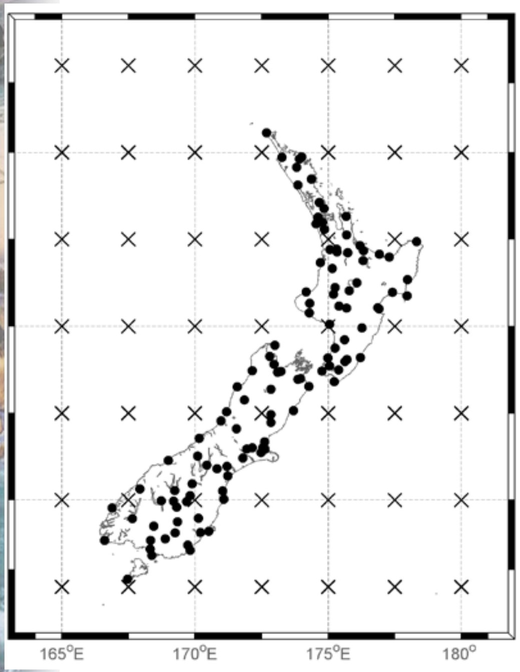
Downscaling

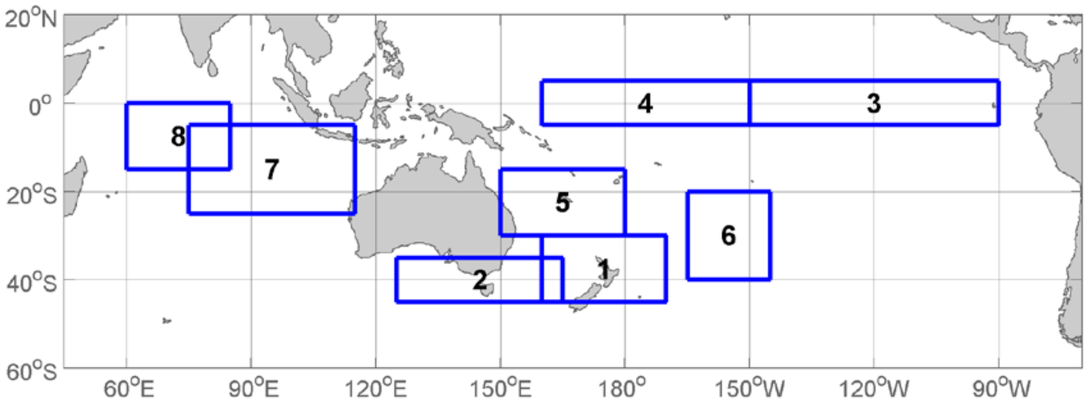


- "Zoom in" to below grid scale
- Used in weather prediction for decades
- Two techniques:
  - Run high-resolution climate model over location of interest, forced by GCM, or…
  - Use statistical relationships to infer local detail
- Very important for New Zealand
  - Usually <10 grid points in GCMs
  - Little clue about mountain effects etc
  - Very skilful because of strong orographic forcing

Statistical Downscaling



- How to get from large scale to station scale?
- Develop a statistical relationship
  - Lagged
  - Contemporary
- Define a relationship between large and local scales



Downscaling methods

- Relationships developed between…
  - large-scale climate indices (predictors)
  - local climate anomalies (predictands)
- Multiple linear regression
- Canonical Correlation Analysis (CCA) or Maximum Covariance Analysis (MCA)
  - a.k.a Singular Value Decomposition Analysis (SVDA)
- Analogue methods
- Neural nets

Less linear – Will not discuss

Regression

- Predictors X (*p* columns): set of time series
- Predictand Y (single column): single time series
- Both defined at *n* times

$$X = \begin{pmatrix} x_{11} & x_{12} & \dots & x_{1p} \\ x_{21} & x_{22} & \dots & x_{2p} \\ \dots & & & \\ \dots & & & \\ x_{n1} & x_{n2} & \dots & x_{np} \end{pmatrix} \qquad y = \begin{pmatrix} y_1 \\ y_2 \\ \dots \\ \dots \\ y_n \end{pmatrix}$$

Fit: $y = a + b_1x_1 + b_2x_2 + \dots + b_px_p$

$$Y = Xb$$

$$b = (X^TX)^{-1} X^TY$$

CCA/MCA/SVDA

- Two fields, X defined at *p* points, Y defined at *q* points, both at *n* times:

$$X = \begin{pmatrix} x_{11}\ x_{12}\ \dots\ x_{1p} \\ x_{21}\ x_{22}\ \dots\ x_{2p} \\ \dots \\ \dots \\ x_{n1}\ x_{n2}\ \dots\ x_{np} \end{pmatrix} \qquad Y = \begin{pmatrix} y_{11}\ y_{12}\ \dots\ y_{1q} \\ y_{21}\ y_{22}\ \dots\ y_{2q} \\ \dots \\ \dots \\ y_{n1}\ y_{n2}\ \dots\ y_{nq} \end{pmatrix}$$

SVDA definition

- Cross-covariance matrix C:

$$C = \frac{1}{n} X^T Y$$

$$C = USV^T$$

- U & V orthonormal matrices: left & right singular vectors
  - $\boldsymbol{u}_1$, $\boldsymbol{u}_2$, etc the spatial patterns of field X
  - $\boldsymbol{v}_1$, $\boldsymbol{v}_2$, etc the spatial patterns of field Y
  - Time series of ($\boldsymbol{u}_1$,$\boldsymbol{v}_1$) the linear combination with maximum covariance

- S is a diagonal matrix of singular values
  - s_1^2, s_2^2, etc indicate amount of squared covariance accounted for

SVDA definition

- Amplitude time series Z, Q

$$Z = XU, \;\; \Rightarrow X = ZU^T$$

$$Q = YV, \;\; \Rightarrow Y = QV^T$$

- Re-expression of X & Y in terms of (U,Z) and (V,Q)
- A different space-time decomposition
  - Equivalent to a simultaneous rotation of axes

SVDA: Significance

- Similar situation to EOFs
  - Squared covariance fraction (squared singular values) can be treated like eigenvalues
    - Spectral plot, error estimates
  - More of an art than a science…
- Rotation possible, as for EOFs
  - Done simultaneously, a double-varimax procedure

CCA definition

- Scaled cross-covariance matrix Ĉ:

$$\hat{C} = C_{xx}^{-1/2}\left(\frac{1}{n}X^{T}Y\right)C_{yy}^{-1/2}$$

$$\hat{C} = USV^{T}$$

- U & V orthonormal matrices as for SVDA
- Vectors (spatial patterns) defined as
  - $w_i = C_{xx}^{-1/2}u_i$ & $t_i = C_{xx}^{-1/2}v_i$
  - Time series of ($\boldsymbol{w_1}$,$\boldsymbol{t_1}$) the linear combination with maximum correlation

- S is a diagonal matrix of singular values: the "canonical correlations"

CCA definition

- Amplitude time series Z, Q

$$Z = XC_{xx}^{-½}U = XW, \; \Rightarrow \; X = ZW^{T}$$

$$Q = YC_{yy}^{-½}V = YT, \; \Rightarrow \; Y = QT^{T}$$

- Re-expression of X & Y in terms of (W,Z) and (T,Q)
- A different space-time decomposition
  - Equivalent to a simultaneous rotation of axes

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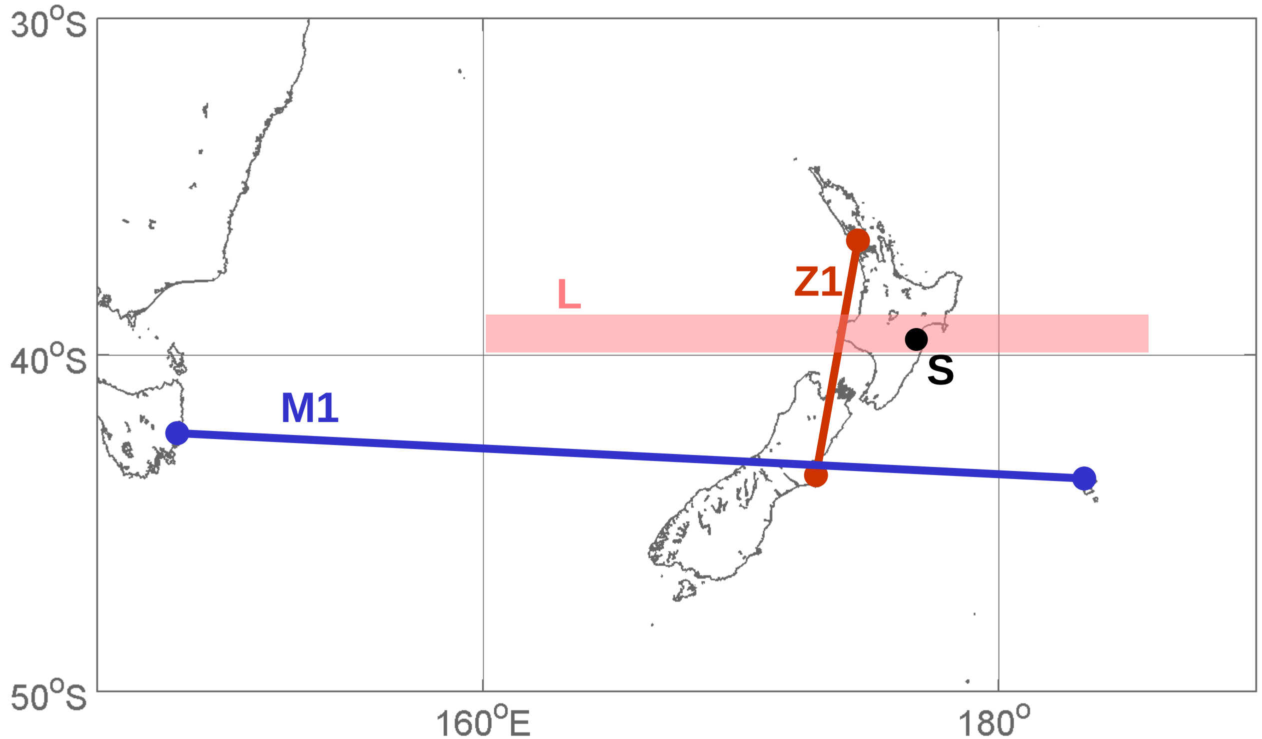
Regression example

- Downscaling climate change for New Zealand
  - GCM output to station data
- Define relationships between observed variables, then substitute GCM values
- Large-scale forcing
  - Zonal-average temperature anomaly
  - Zonal-average precipitation anomaly
  - Zonal and meridional wind indices
    - MSLP differences in New Zealand region
- Deliberately simple statistical model

Regression downscaling: GCM input

- "AR4" GCM output from PCMDI
  - B2, A1B, A2 SRES scenarios
    - 20 models
  - Validate control simulations
    - 12 models retained

Regression Downscaling: approach



- $S - L = a + bZ1 + cM1$ (observed)
- ➔ $S' = L' + a + bZ1' + c\,M1'$ (model)

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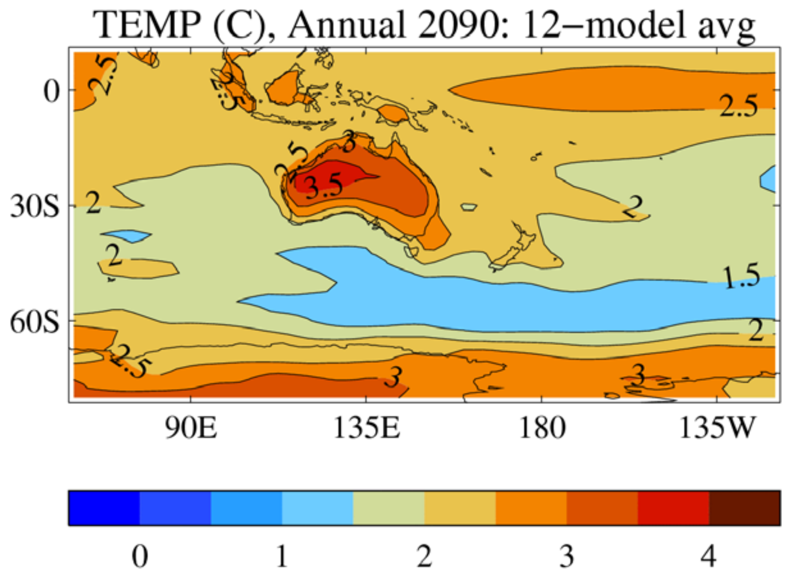
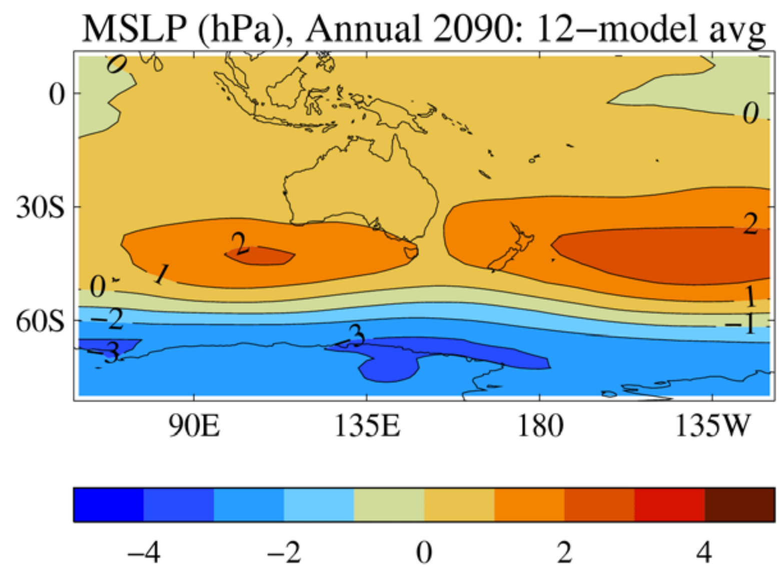
Projections – South Pacific/Australasia



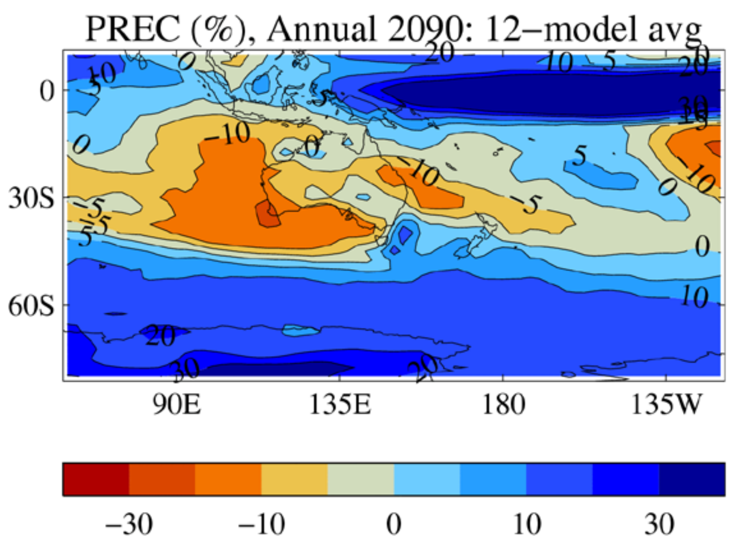


Annual mean changes for A1B scenario:

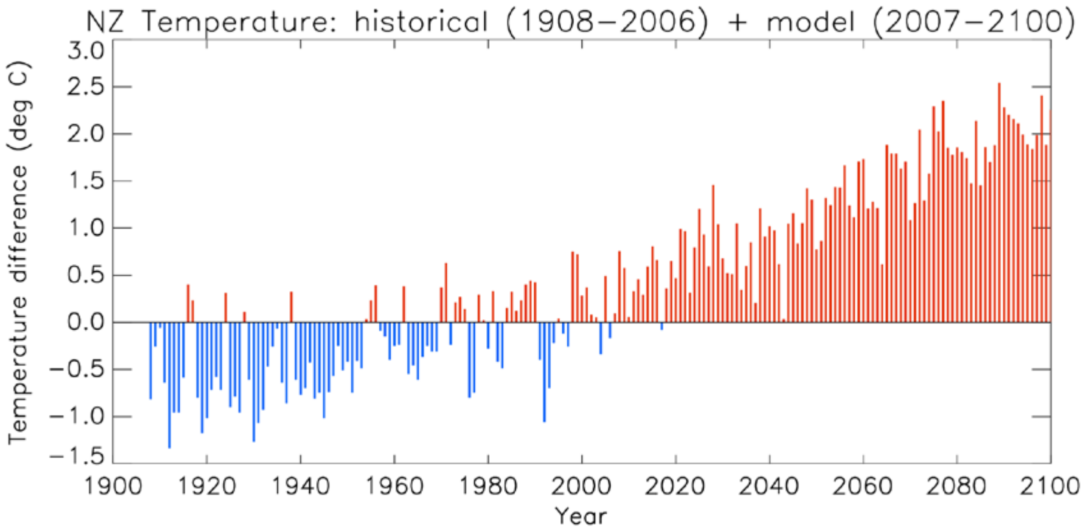
1) NZ temperature increase smaller than Australia (& 75% of global rate)

2) Higher pressures across N. Is. & increased westerlies across S. Is

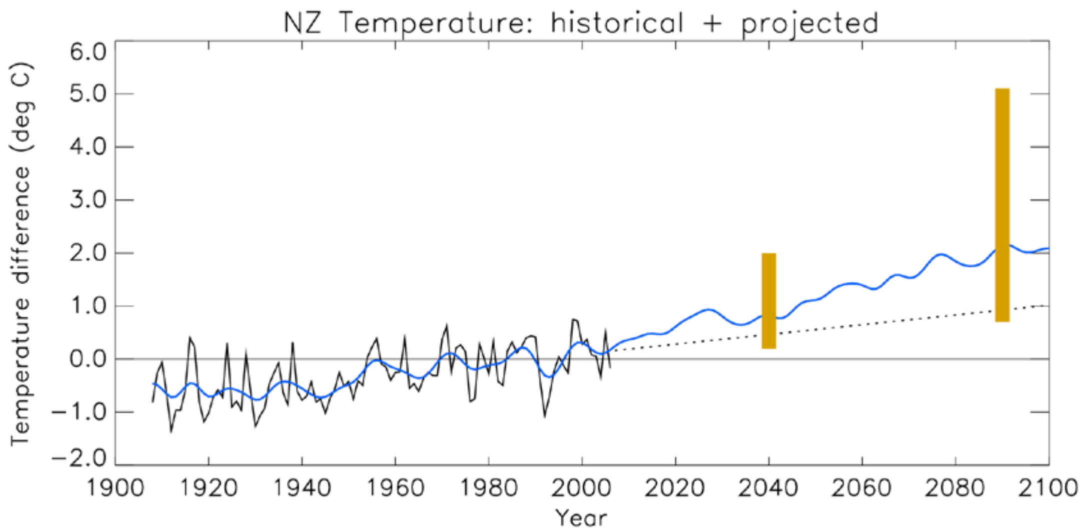
3) Drier over N. Is. & wetter over S. Is. (at model grid-scale)



NZ Temperature Projection



Example of projection for 1 model with A1B scenario



Projected range at 2040 and 2090 over all 6 SRES marker emission scenarios

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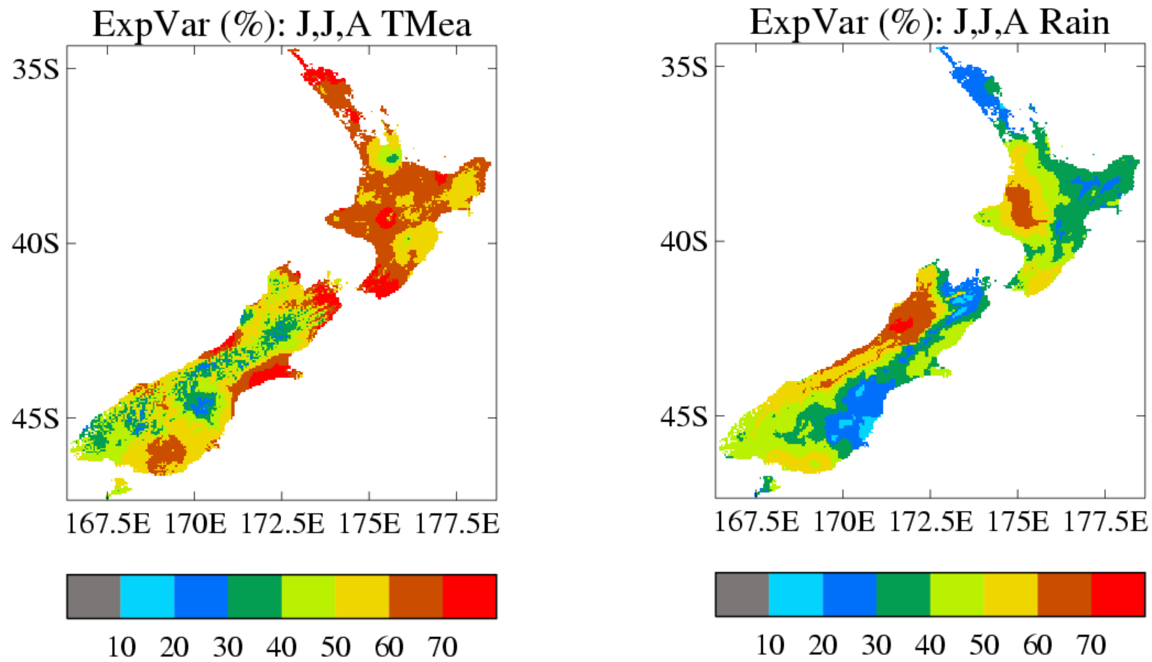
Regression downscaling



- Explained variance, JJA downscaling regression
  - mean monthly temperature (TMea, left)
  - monthly precipitation (Rain, right)
- Defaults to GCM estimate if explained variance near zero

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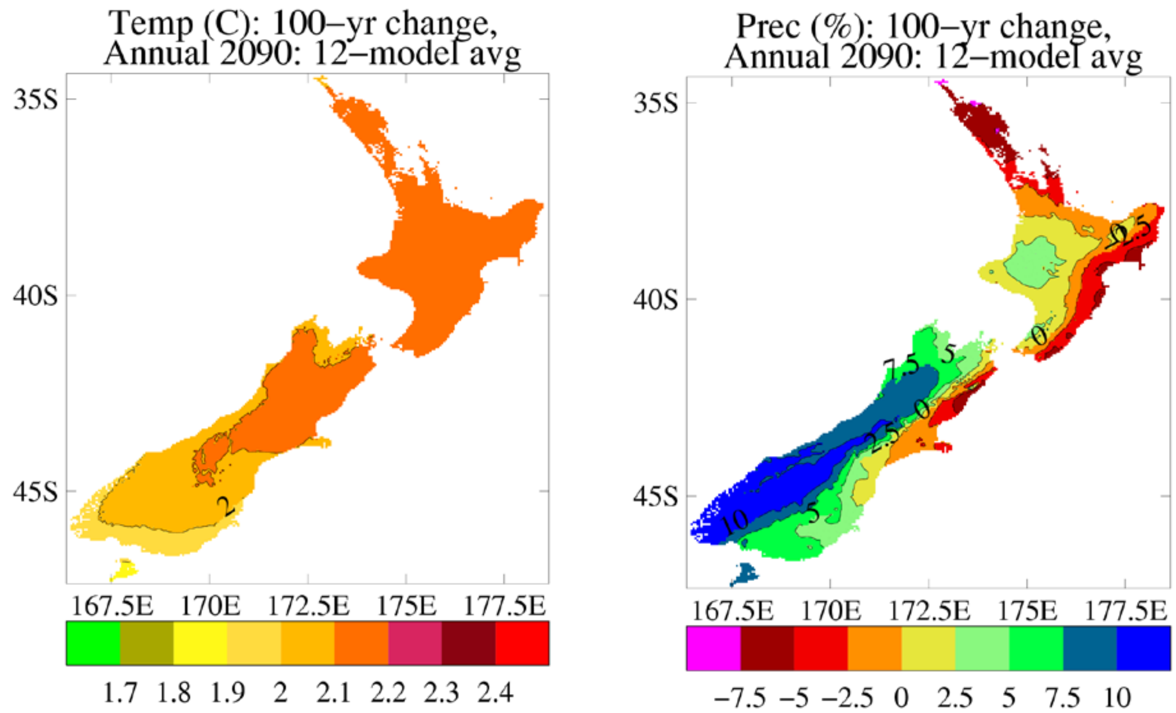
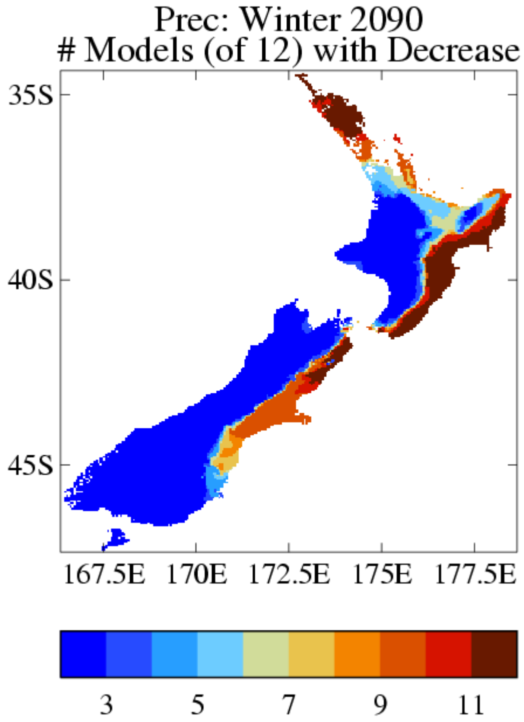
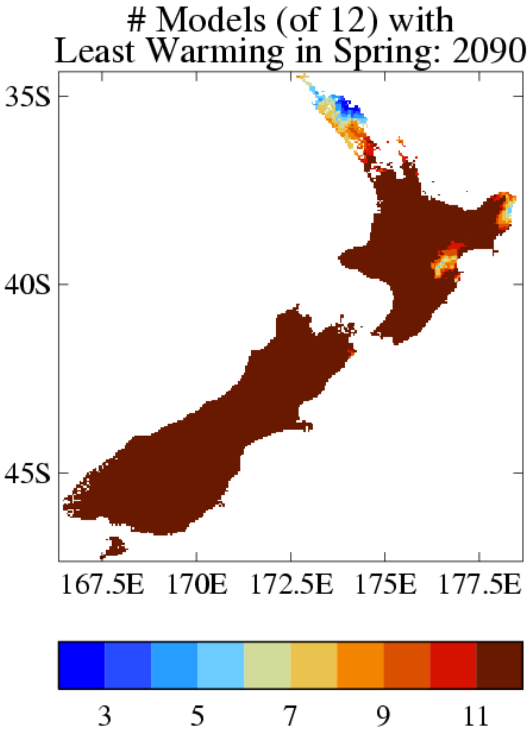
Projections – New Zealand



- Projected changes, 2090 relative to 1990
  - annual mean temperature (°C, left)
  - annual mean rainfall (%, right)
- Average over 12 GCMs for A1B emission scenario

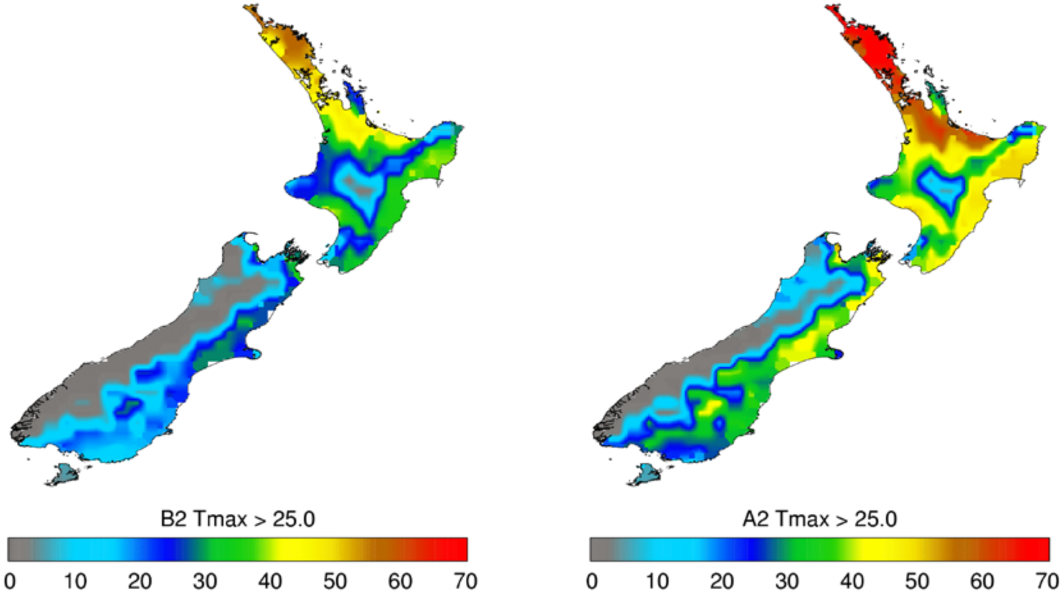
Model Confidence





- Level of agreement between models, changes to 2090
  - Left: number of models (of 12) with decreased winter precip
  - Right: number of models (of 12) showing least warming in spring

Dynamical downscaling



- Change to 2090 in number of days per year with extreme temperatures above 25°C
  - B2 (left) and A2 (right) scenarios
- Ability to assess changes in distributions, not just means
- Use this to improve statistical downscaling

Statistical and dynamical downscaling

Statistical Downscaling	***Dynamical Downscaling***
• Lots of models & scenarios - cheap • Monthly Temperature & Rainfall • Daily projections possible (weather generators, offsets to observed data) • Projections at observed data resolution (~5km)	• Limited model/scenario choice - expensive • Lots of climate fields, daily & monthly • Projections at RCM resolution (~30km?)

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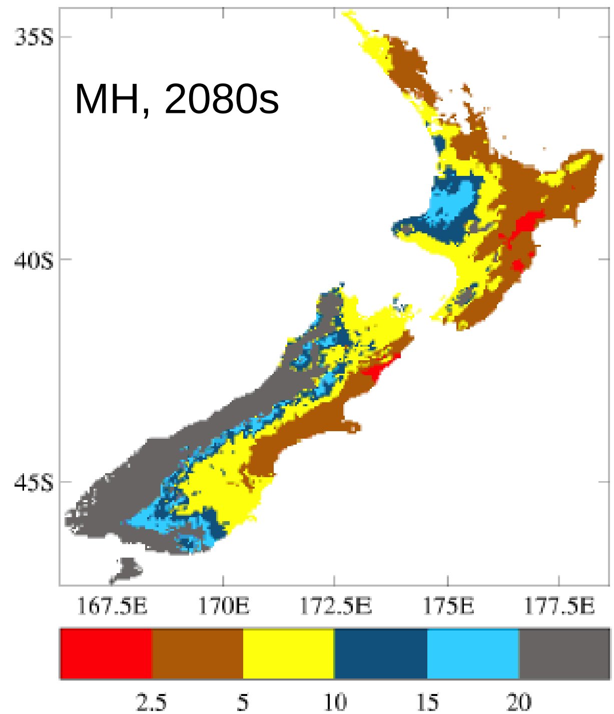
Impacts - Increased Drought Risk

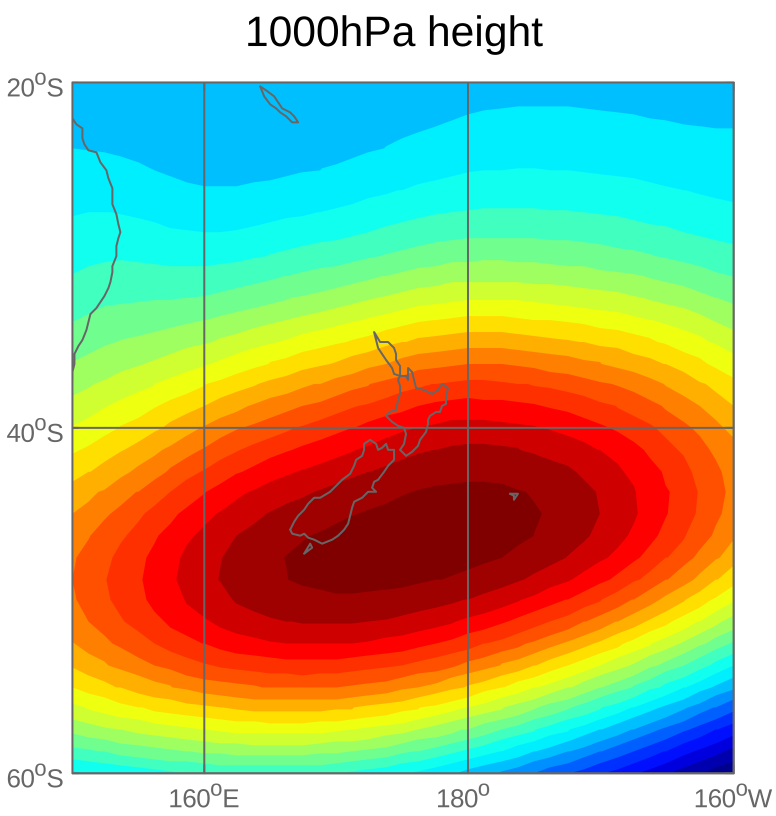
Evening Post

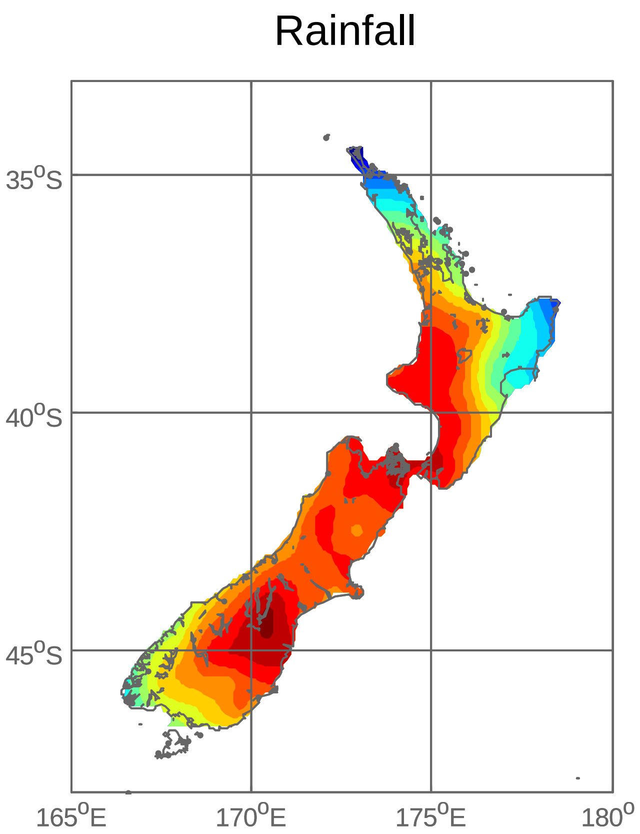


Predicted average recurrence interval (years) in 2080s for driest conditions that currently occur on average once every 20 years (Medium-High scenario)

http://www.climatechange.govt.nz/resources/reports/drought-risk-may05/drought-risk-climate-change-may05.pdf

SVDA example

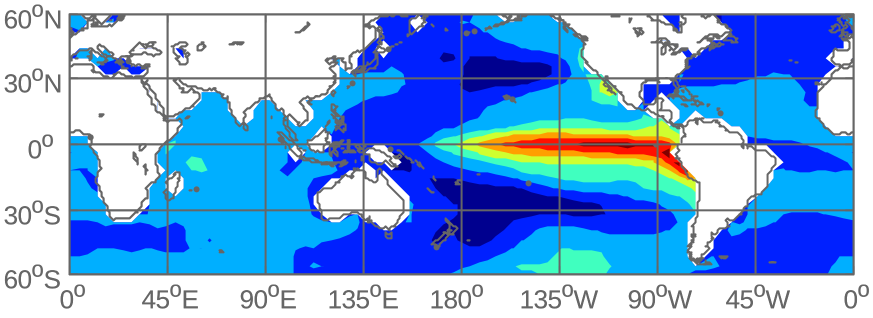




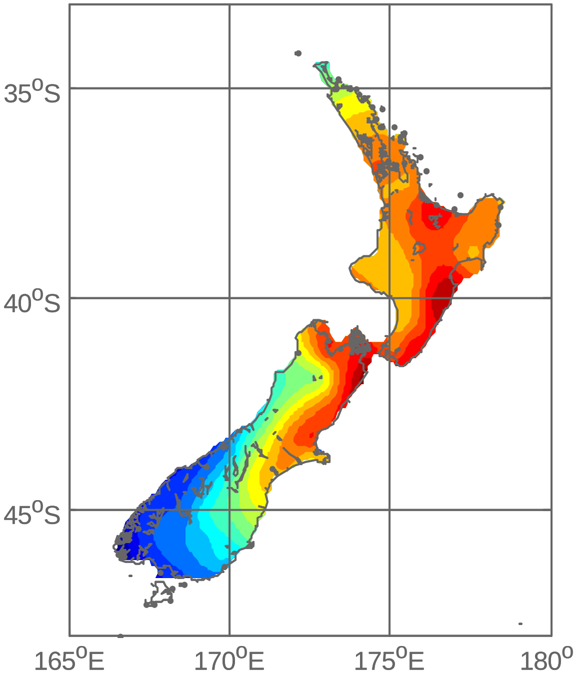
SVDA mode 1: SCF 48%, Corr 0.54, EV 35/30

SVDA example

SST

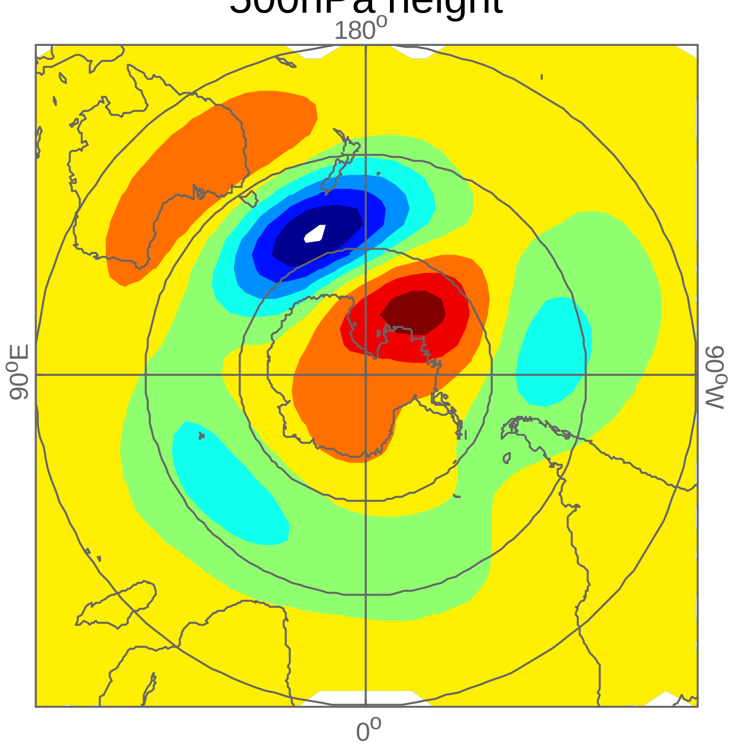


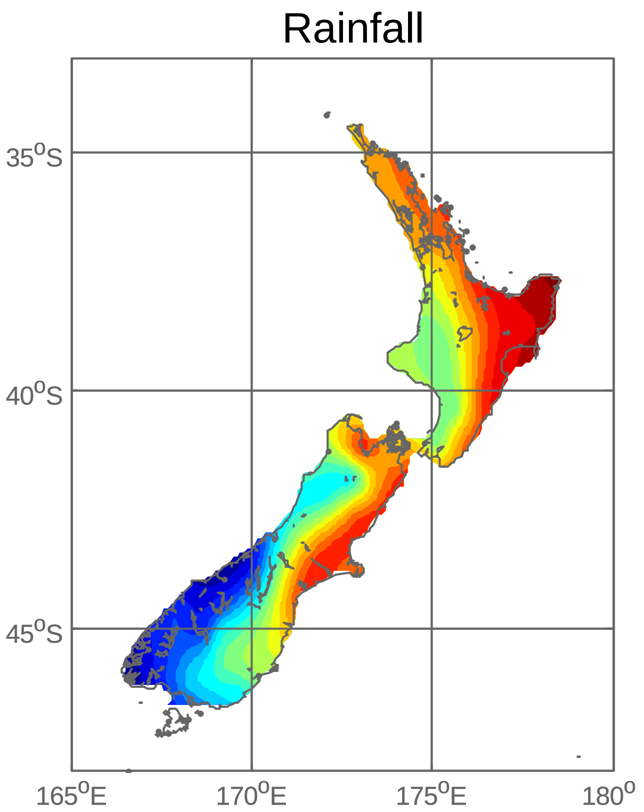
Rainfall



SVDA mode 1: SCF 41%, Corr 0.25, EV 17/27

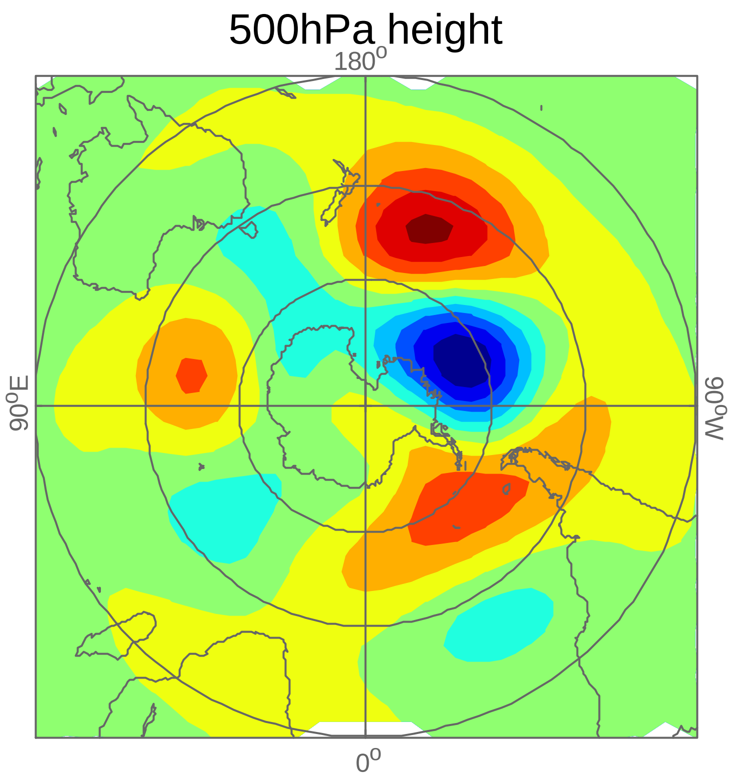
CCA example

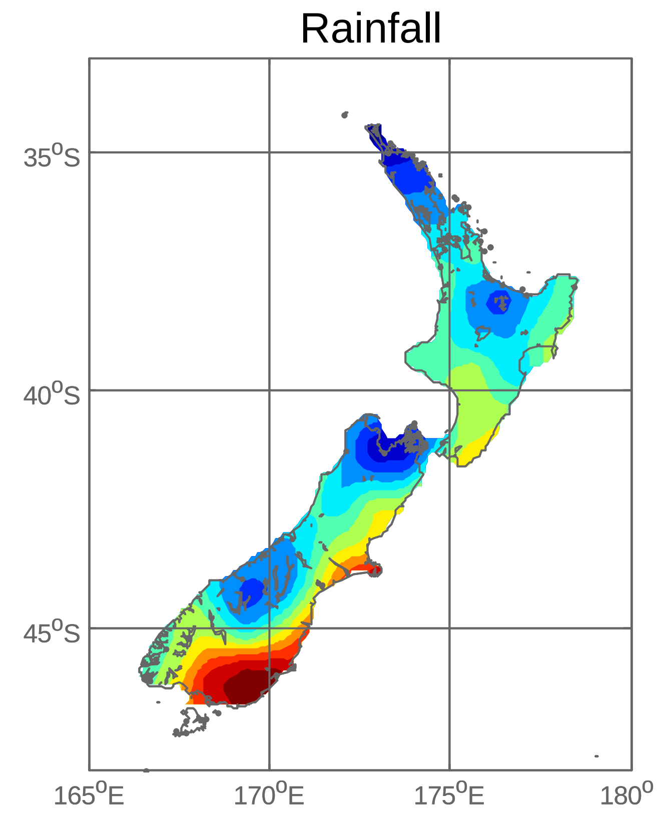




CCA mode 1: SCF 27%, Corr 0.63, EV 3/11

CCA example





CCA mode 2: SCF 13%, Corr 0.42, EV 4/12

Summary

- Often strong relationships between large and local scale climate
  - Statistical downscaling can work well
  - Simple models most reliable?
  - Westerly wind variations a key for NZ
- A number of statistical methods available
  - Generally linear
- Combination of dynamical and statistical methods most powerful?

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