Regional mean sea level anomalies from tide gauges using the neural network approach

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neural network - general

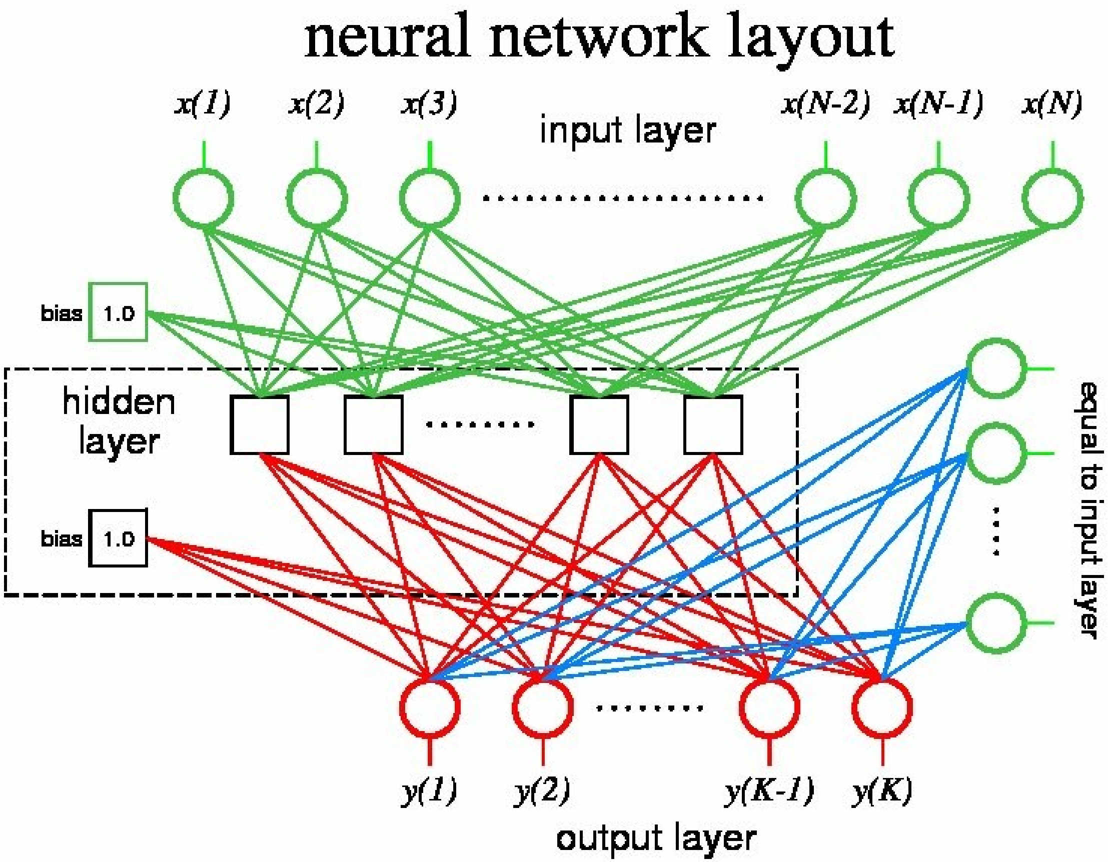
- A neural network is an artificial neural system, a computational model inspired by the notion of neurophysical processes
- It consists of several processing elements called neurons, which are interconnected with each other exchanging information
- The single types of networks differ in the way the neurons are interconnected and in how the single neurons behave

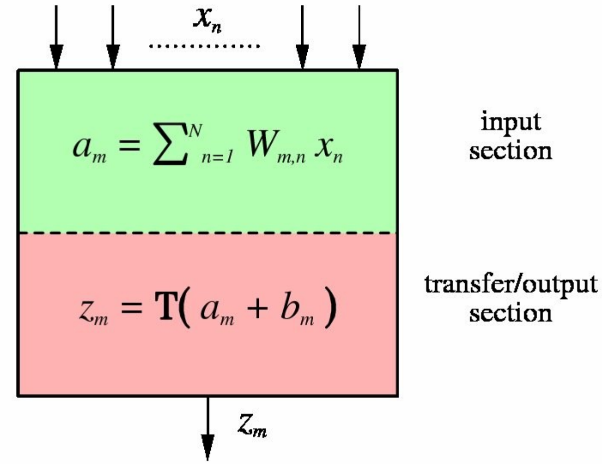
One example is the ***Backpropagation Network*** that will be used here

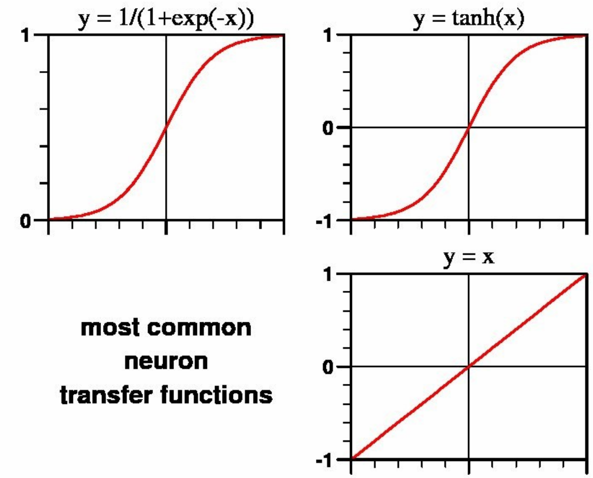
main applications in oceanography and meteorology:

- data processing/analysis (Stogryn et al 1994; Gross et al 1999; Müller et al 2003)
- prediction (Wenzel 1993; Tangang et al 1998; Lee and Jeng 2002)

Backpropagation Neural Network







neural network: training

total network equation:

$$\vec{y} = \vec{b_O} + \mathbf{W}_{IO} \cdot \vec{x} + \mathbf{W}_{HO} \cdot \tanh\{\vec{b_H} + \mathbf{W}_{IH} \cdot \vec{x}\}$$

with unknown parameters: $\vec{b_O}$; $\mathbf{W}_{IO}$; $\mathbf{W}_{HO}$; $\vec{b_H}$; $\mathbf{W}_{IH}$

the network learns from known training vector pairs $\{\vec{x}_m^{dat}, \vec{y}_m^{dat}\}$,
i.e. input and associated output vectors (target values)

cost function:

$$E = \frac{1}{2} \sum_{m=1}^{M} \sum_{k=1}^{K} \left(y_k(\vec{x}_m^{dat}) - y_{k,m}^{dat} \right)^2$$

additional penalty term

to force unimportant weights to approach zero (auto pruning, ridge regression):

$$R = \frac{1}{2} \left[C_{IO} \sum w_{IO}^2 + C_{IH} \sum w_{IH}^2 + C_{HO} \sum w_{HO}^2 \right]$$

with positive constant factors C_{IO}, C_{IH} and C_{HO}.

$$C_j = C_r \cdot K \cdot M / N_j$$

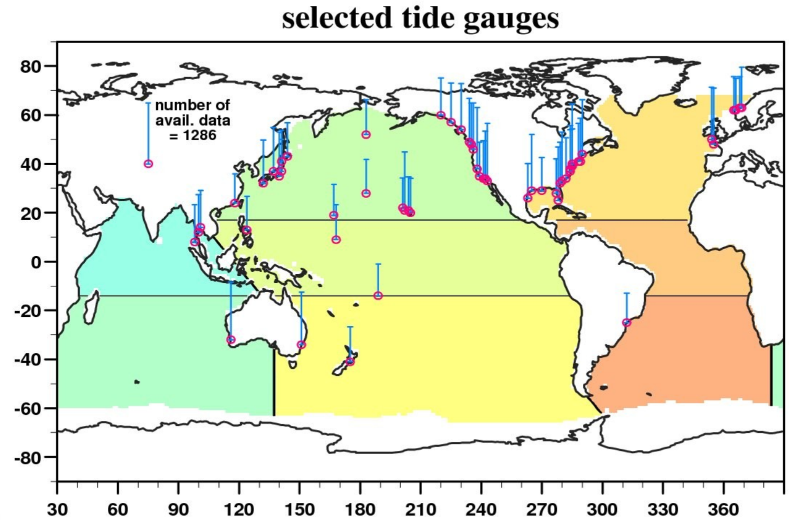
selecting tide gauges

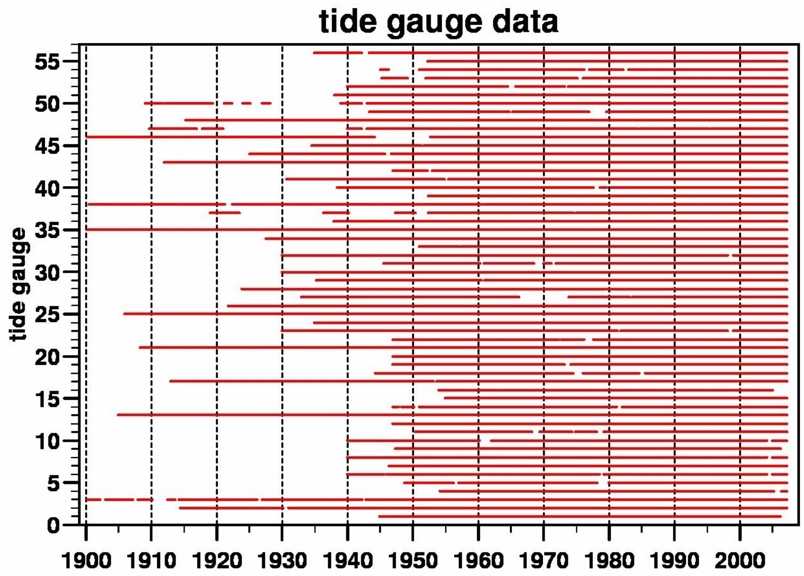
tide gauge data from: PSMSL monthly data

selection criteria:

- more than 11 annual mean values are given in [1993,2005]
- more than 50 annual mean values are given in [1990,2007]
- the tide gauges are neighboured by at least one ocen point of the 1°x1° land-sea mask in the altimetry product (excluding the Mediterranean)

NOTE: *all following computations will be done in the space of temporal derivatives, i.e monthly differences, to avoid possible problems with different local reference frames for the tide gauges !!!*





filling data gaps - 1

FCnet

forecast the values at all tide gauge positions for timestep (n+1) from all values at the steps (n-1) and (n)

BCnet

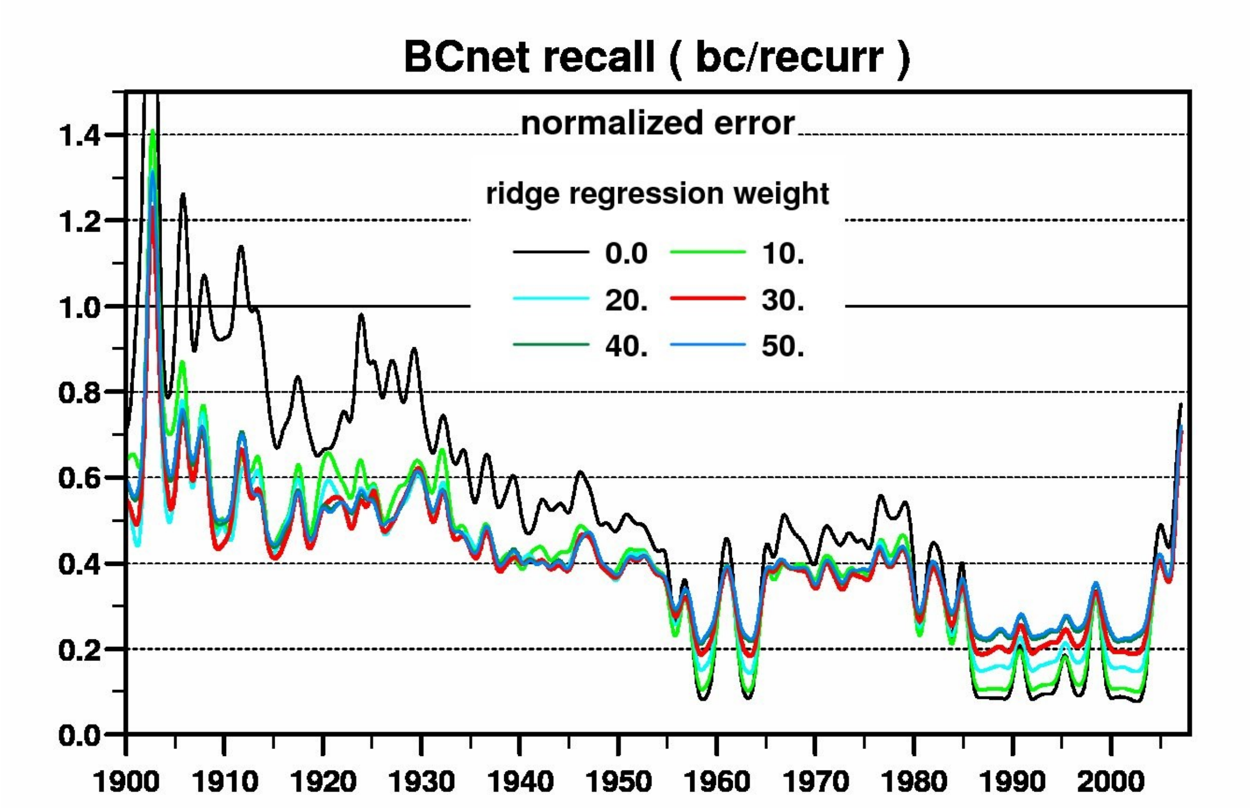
backcast the values at all tide gauge positions for timestep (n-1) from all values at the steps (n+1) and (n)

network design

input neurons:	2 * 56	unknows:	20 524
hidden neurons:	84	training pairs:	297 (*4)
output neurons:	56		

ridge regression C_r : 0; 10; 20; **30**; 40; 50

filling data gaps - 2

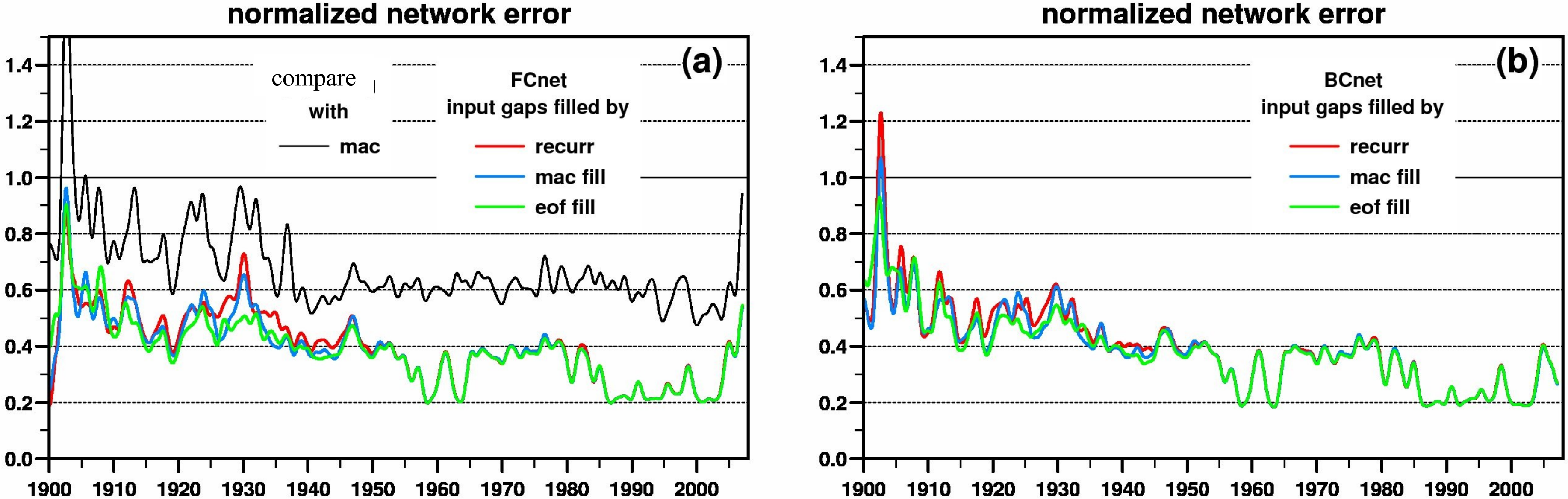


RMS error of the resulting recurrent backcast recall as compared with existing tidegauge values in dependence of the chosen ridge regression weight C_r *. At each timestep the RMS values are normalized with the standard deviation of the corresponding known values, i.e.*

$$Y = \left[\sum(y_k^{net} - y_k^{dat})^2 / \sum(y_k^{dat} - \overline{y^{dat}})^2\right]^{1/2}.$$

For better readability all curve are filtered to exclude the annual cycle.

filling data gaps - 3



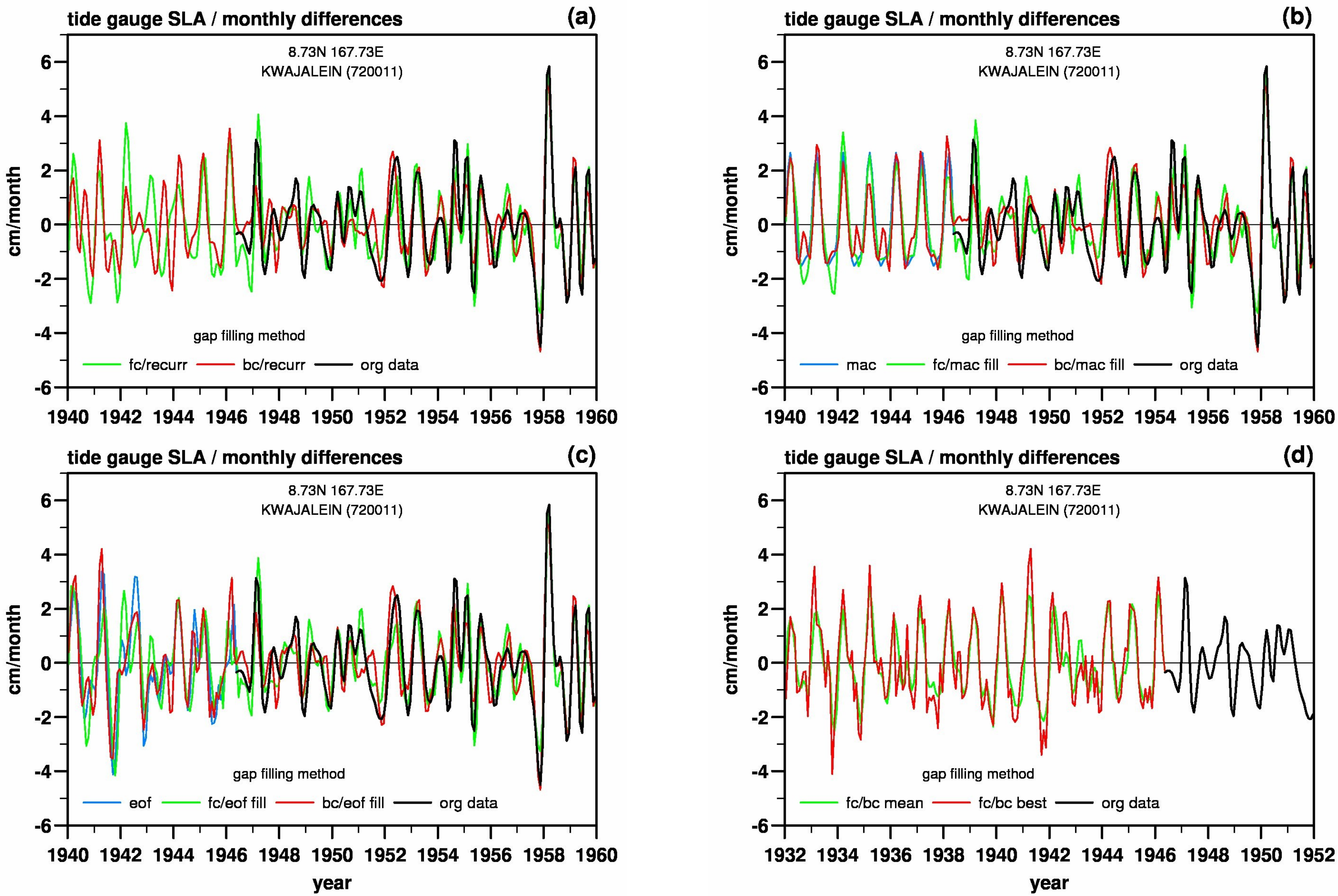
RMS error of the resulting (a) forecast and (b) backcast (C_r=30.0) as compared with existing tidegauge values. The error resulting from comparing the tide gauge data to the values from the mean annual cycle are included in (a).

At each timestep the RMS values are normalized with the standard deviation of the corresponding known values, i.e. $Y = [\ \Sigma(y^{net}_k - y^{dat}_k)^2 \,/\, \Sigma(y^{dat}_k - \mathbf{y}^{dat})^2\ ]^{½}$.
For better readability all curve are filtered to exclude the annual cycle.

gap filling methods used for the tide gauges

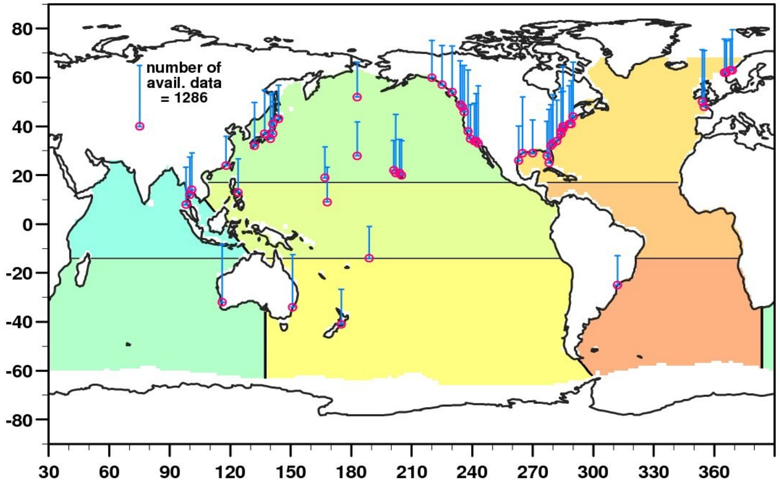
	acronym	method	% timesteps
1	**mac**	mean annual cycle (MAC)	
2	**eof**	EOF reconstruction (EOFR)	
3	**fc/recurr**	FCnet recurrent ; reset input to known values	8.6
4	**fc/mac fill**	FCnet ; input gaps filled by MAC	10.8
5	**fc/eof fill**	FCnet ; input gaps filled by EOFR	29.2
6	**bc/recurr**	BCnet recurrent ; reset input to known values	7.9
7	**bc/mac fill**	BCnet ; input gaps filled by MAC	9.3
8	**bc/eof fill**	BCnet ; input gaps filled by EOFR	34.2
9	**fc/bc best**	best of 3 to 8 (min. fore-/backcast error at known values)	
10	**fc/bc mean**	error weighted mean of 3 to 8	

Example for the resulting gap filling Kwajalein (8.73N 167.73E, code 720011)



from tide gauges to regional mean sea level anomaly (RMSLA)
- network design -

selected tide gauges



- one input neuron for each of the tide gauges
- one output neuron for each of the eight ocean regions

there is no extra output neuron for the global ocean!!

Instead, the training/costfunction includes a constraint to minimize the difference between the area weighted mean of the eight regional values from the neuro network and the given global.

the misfit at the output neurons will be weighted according to the error in the target data !

network design

input neurons:	56	unknows:	7 736		
hidden neurons:	112		**GFZ**	**CSIRO**	**CSIRO+GFZ**
output neurons:	8	training pairs:	148 (*4)	148 (*4)	296 (*4)

ridge regression C_r= 0 ; 15 ; 30 ; 50 ; 75

from tide gauges to regional mean sea level anomaly (RMSLA)
- target data -

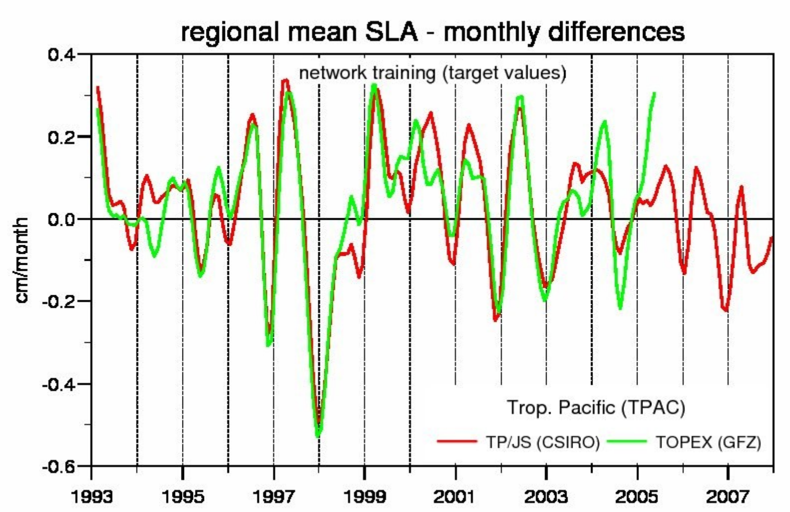
regional mean sea level estimated from satellite altimetry data (monthly, 1° x 1° grid)

- from **GFZ** Potsdam

  TOPEX/Poseidon (Jan.1993 - Jun.2005)

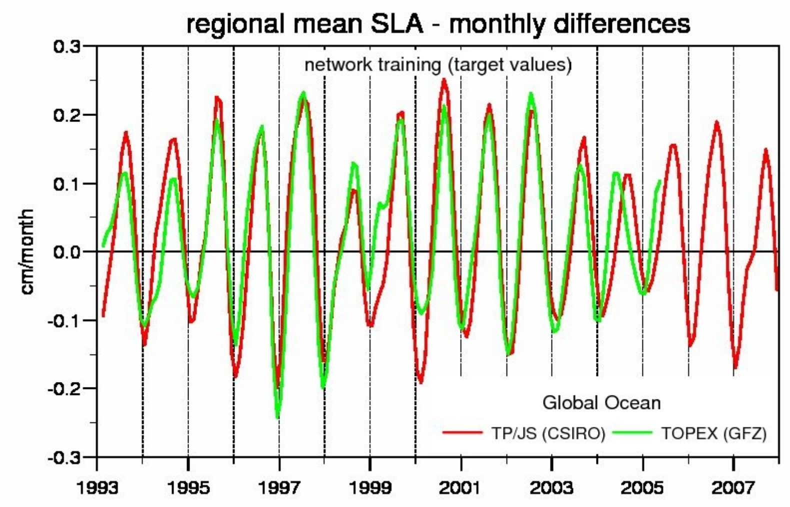
- or/and from **CSIRO** sea level web page

  combined TOPEX and JASON (Jan.1993 - Apr.2008)



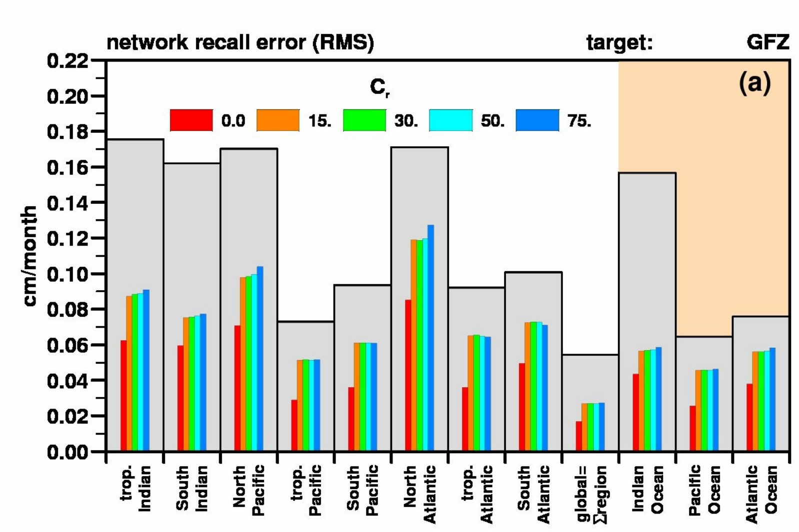
dataset / signal RMS [cm/month]

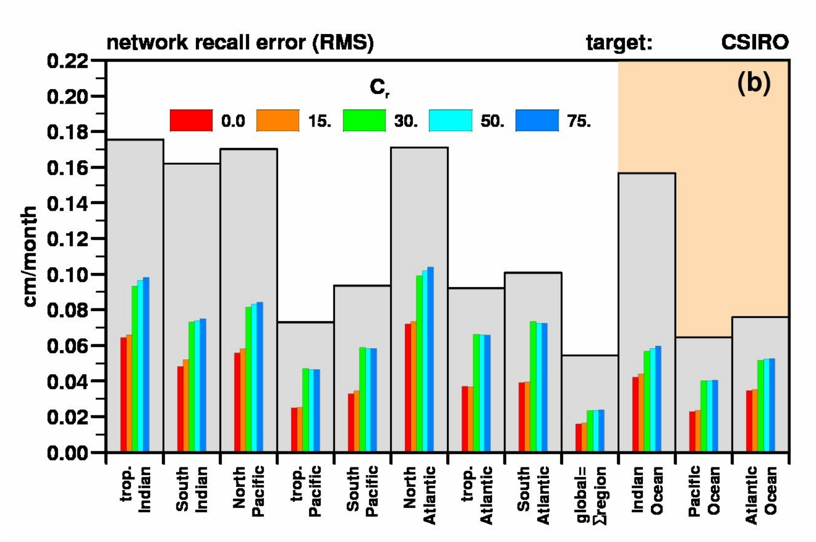
region		GFZ	CSIRO	½(GFZ+CSIRO)	CSIRO-GFZ
trop.	Indian	0.310	0.248	0.280	0.175
South		0.493	0.504	0.499	0.162
North	Pacific	1.033	1.037	1.035	0.170
trop.		0.162	0.159	0.161	0.073
South		0.474	0.455	0.464	0.094
North	Atlantic	1.250	1.240	1.245	0.171
trop.		0.272	0.243	0.258	0.092
South		0.529	0.532	0.532	0.101
global ocean		0.108	0.118	0.113	0.054

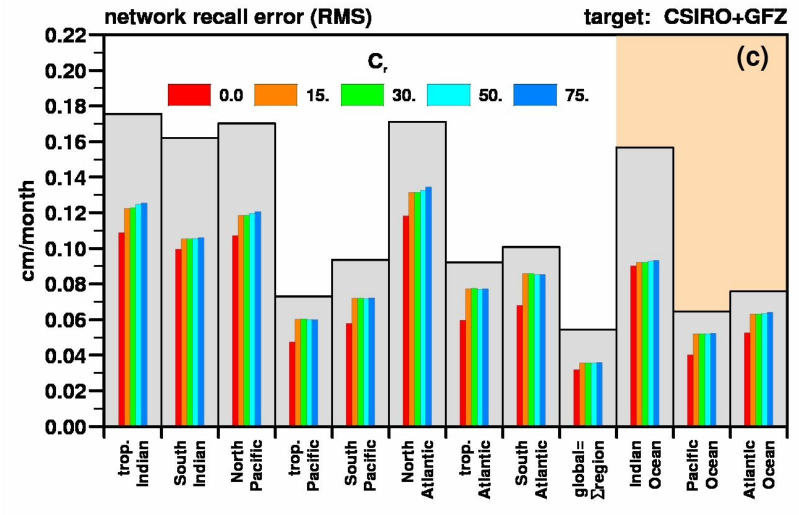


from tide gauges to regional mean sea level anomaly (RMSLA)

- training -



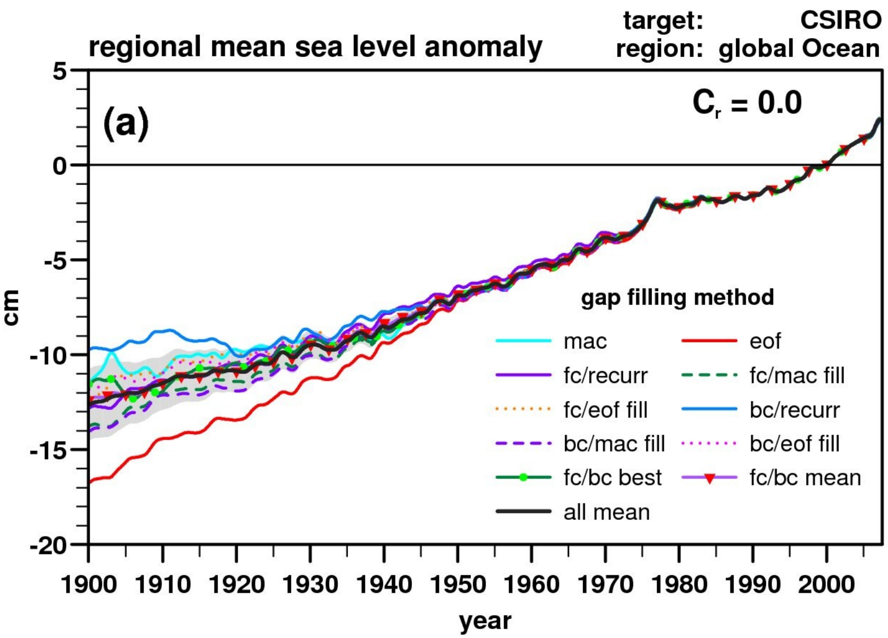


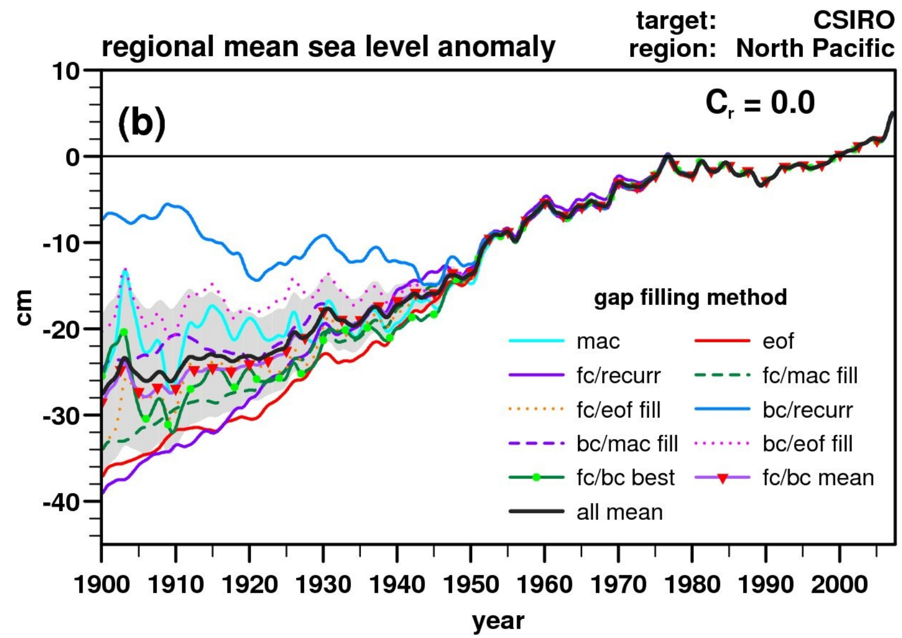


recall error of the trained neural network in dependence of the chosen ridge regression weight C_r for the (a) GFZ, (b) CSIRO and (c) the CSIRO+GFZ target dataset.
The grey shading gives the assumed RMS error of the corresponding target data.

NOTE: the three complete ocean basins (with orange background shading) are not used as a constraint during the network training!

reconstructed regional mean sea level - 1

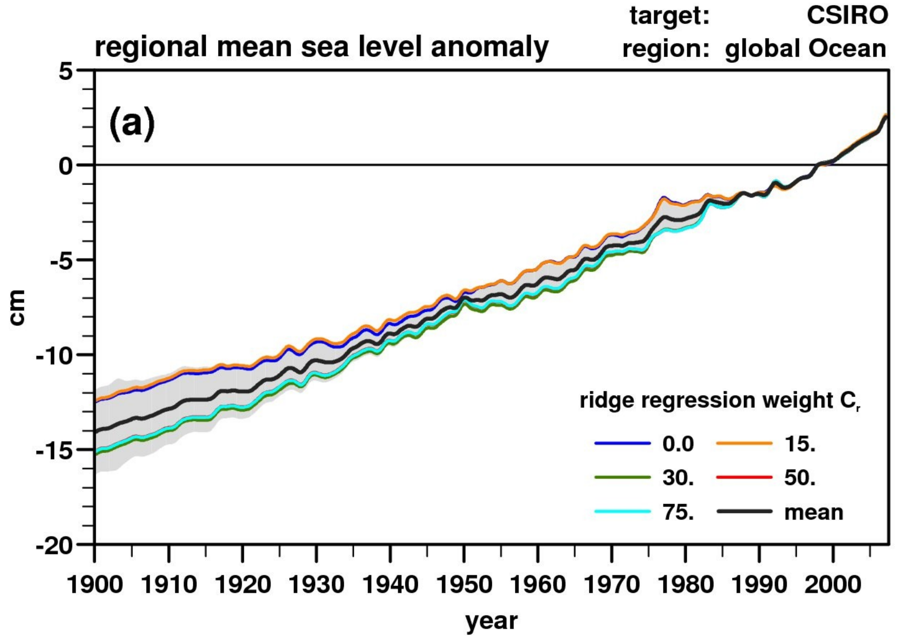


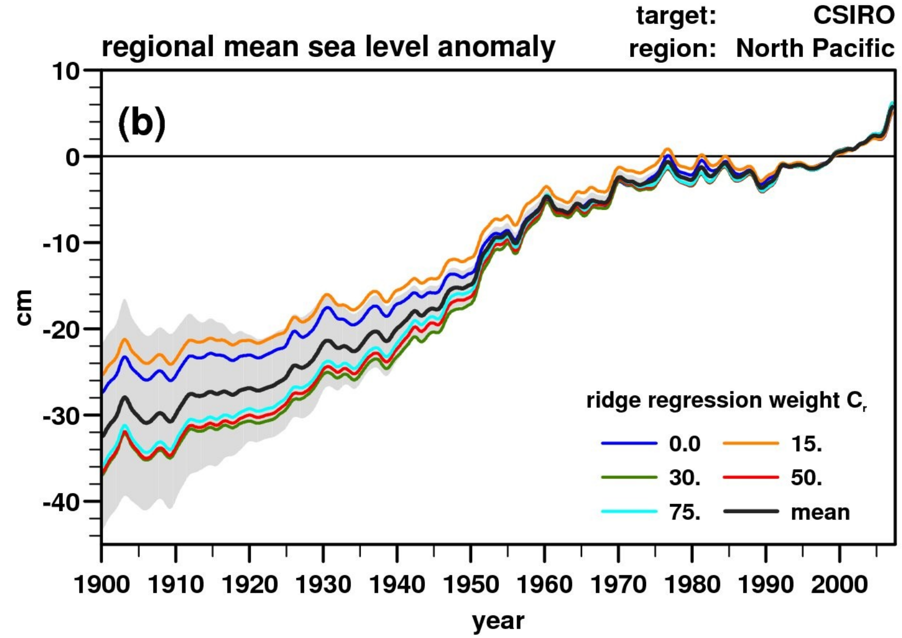


RMSLA for the global ocean (a) and the North Pacific (b) resulting from the network trained with "CSIRO" target data and C_r=0.0. The result for all tide gauge gap filling cases are shown. The black line and the grey shading give the corresponding ensemble mean and standard deviation, respectively.

NOTE: All curves are smoothed before plotting to eliminate the annual cycle!

reconstructed regional mean sea level - 2

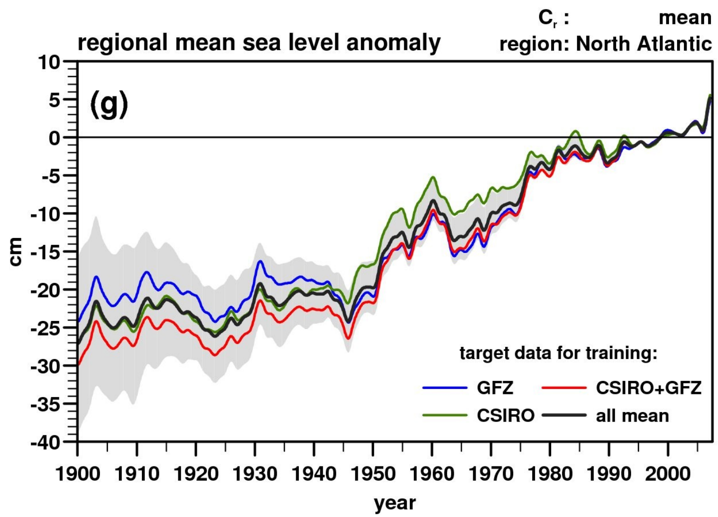


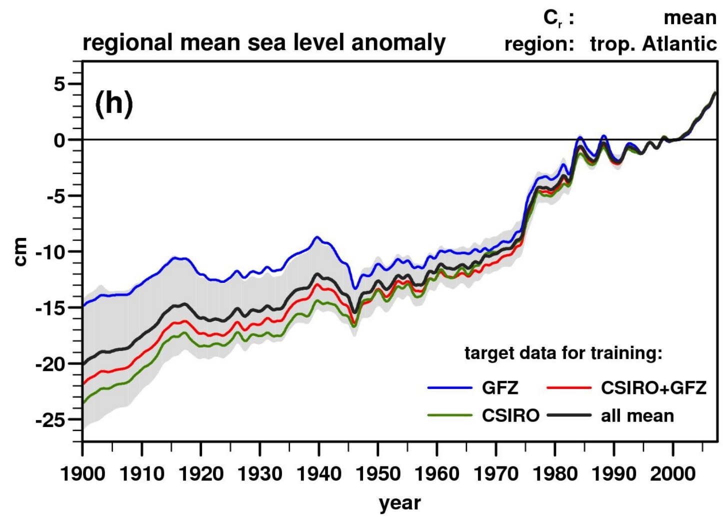


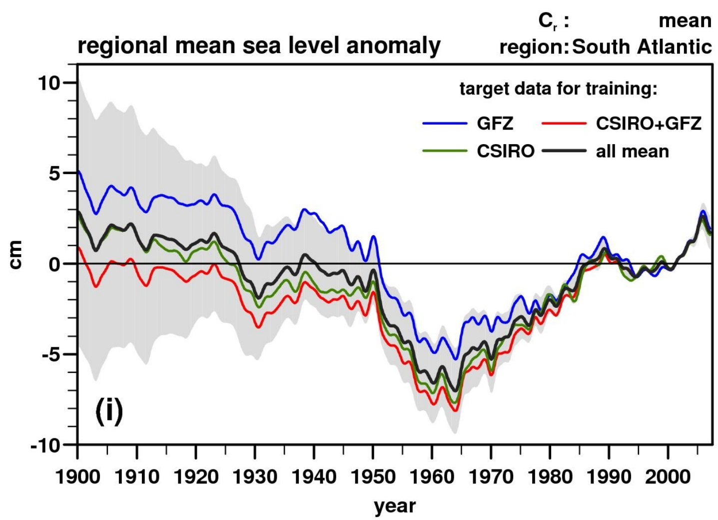
RMSLA for the global ocean (a) and the North Pacific (b) resulting from the network trained with "CSIRO" target data in dependence of C_r. For each C_r value the mean of the corresponding RMSLA sub-ensemble (=10 tide gauge gap filling cases) is shown. The black line and grey shading give the mean and standard deviation, respectively,computed from the enlarged ensemble (50 members).

NOTE: All curves are smoothed before plotting to eliminate the annual cycle!

reconstructed regional mean sea level
- Atlantic Ocean -



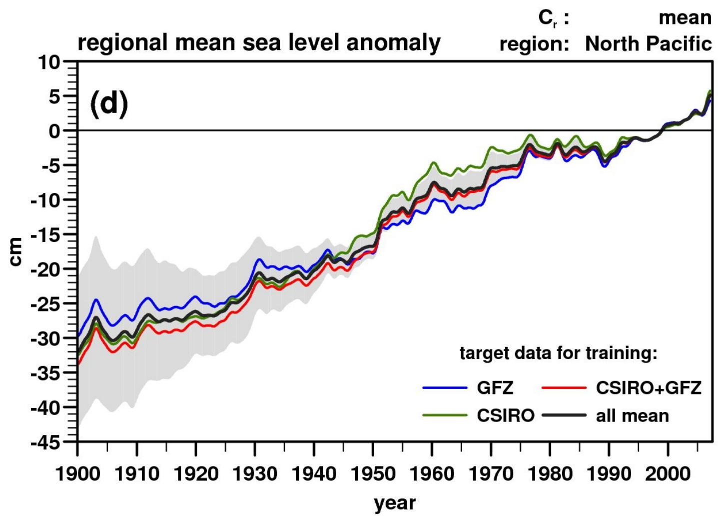


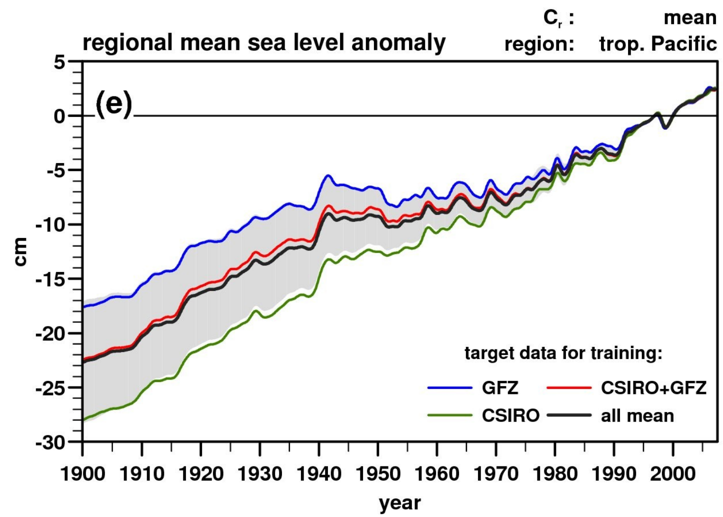


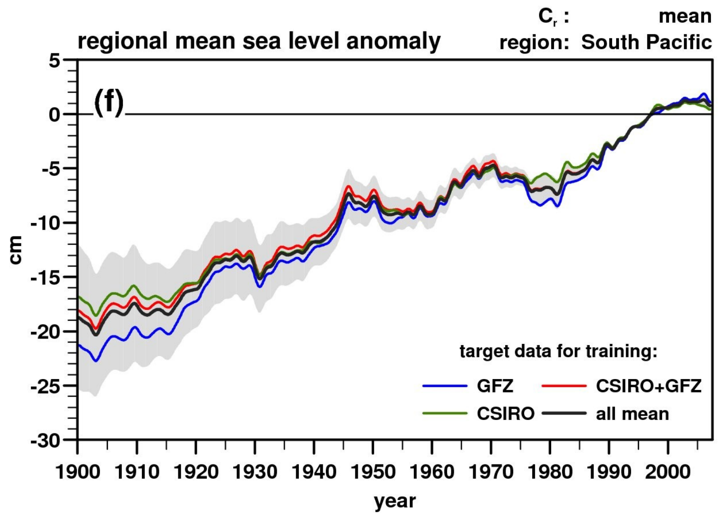
regional mean sea level trend: 1900-2006
[mm/year]

	North	trop.	South
GfZ	2.49 ± 0.99	1.46 ± 0.41	-0.50 ± 0.57
CSIRO	3.02 ± 0.88	2.34 ± 0.35	-0.22 ± 0.65
CSIRO+GfZ	3.18 ± 0.91	2.16 ± 0.33	-0.04 ± 0.66
mean	2.89 ± 0.97	1.99 ± 0.53	-0.26 ± 0.65

reconstructed regional mean sea level
- Pacific Ocean -



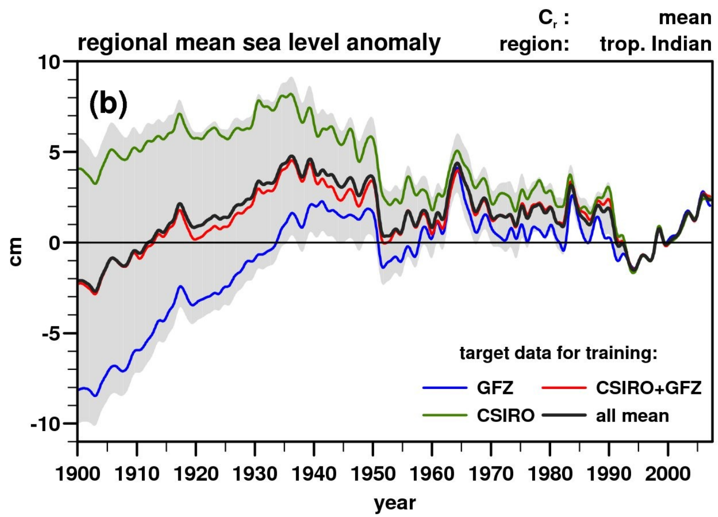


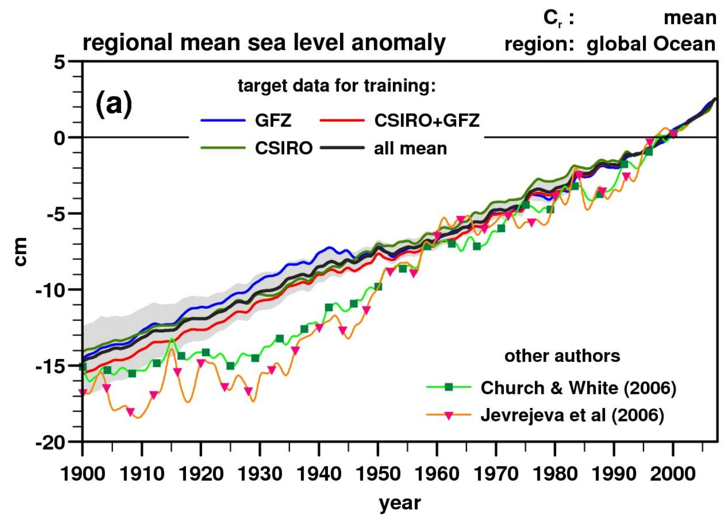


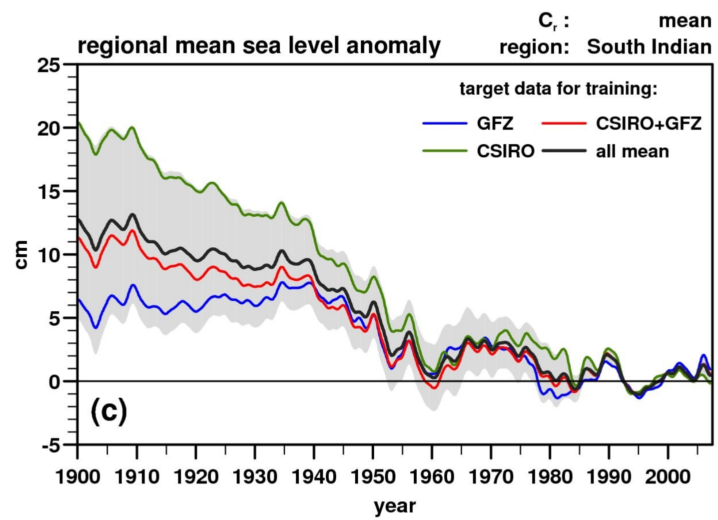
regional mean sea level trend: 1900-2006
[mm/year]

	North	trop.	South
GfZ	3.08 ± 1.06	1.53 ± 0.48	2.09 ± 0.66
CSIRO	3.56 ± 1.02	2.74 ± 0.32	1.79 ± 0.44
CSIRO+GfZ	3.59 ± 0.96	2.04 ± 0.27	1.83 ± 0.52
mean	3.41 ± 1.04	2.10 ± 0.61	1.90 ± 0.56

reconstructed regional mean sea level
- Indian Ocean / Global Ocean-







regional mean sea level trend: 1900-2006
[mm/year]

	Indian Ocean trop.	Indian Ocean South	global Ocean
GfZ	0.63 ± 0.37	-0.78 ± 0.37	1.39 ± 0.23
CSIRO	-0.58 ± 0.79	-2.10 ± 0.63	1.48 ± 0.19
CSIRO+GfZ	0.11 ± 0.30	-1.19 ± 0.49	1.56 ± 0.17
mean	0.05 ± 0.73	-1.35 ± 0.75	1.47 ± 0.21

Summary / Conclusion

neural network

+ easy to use, fast computations

± not very flexible, i.e. once the net is trained you are fixed to the chosen input / output configuration

± it's hard to impossible to learn from the network about e.g. the physics

data gaps

+ neural networks appear to be applicable to fill data gaps in the tide gauge time series

regional mean SLA

+ it is relatively insensitive to the tide gauge reconstruction as long as the amount of gaps is less than 20% (noise level)

± in unknown environment, i.e. outside the training period, it is sensitive to the way the network is trained (e.g. target data and/or value of C_r used)

➔ more reasonable results are achieved by taking the ensemble means from different tide gauge reconstructions, differently trained networks