Downscaling CHIRPS precipitation data: an artificial neural network modelling approach

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Introduction:

· The main aim of this article is to propose a novel downscaling method in order to attain high resolution (1km x 1km) precipitation datasets, by correlating the CHIRPS dataset with altitude information and the normalized difference vegetation index from satellite images at 1km x 1km, utilizing artificial neural network models.

Data and methods:

· CHIRPS is a high-resolution (0.05° x 0.05°) land-only climatic database of precipitation.

· SPOT Vegetation NDVI data (the synthesized pre-processed S10 NDVI product, which is a geometrically and radiometrically corrected 10 day composite image).

· Digital elevation model (50km).

· Cyprus Department of Meteotology (136 meteorological stations).

· MLP ANN. *(It has been shown that ANNs with two input layers may sufficiently represent complex physical systems[Lippmann, 1987].)*

· January 1999 to December 2012 (70% train, 15% validation, 15% test).

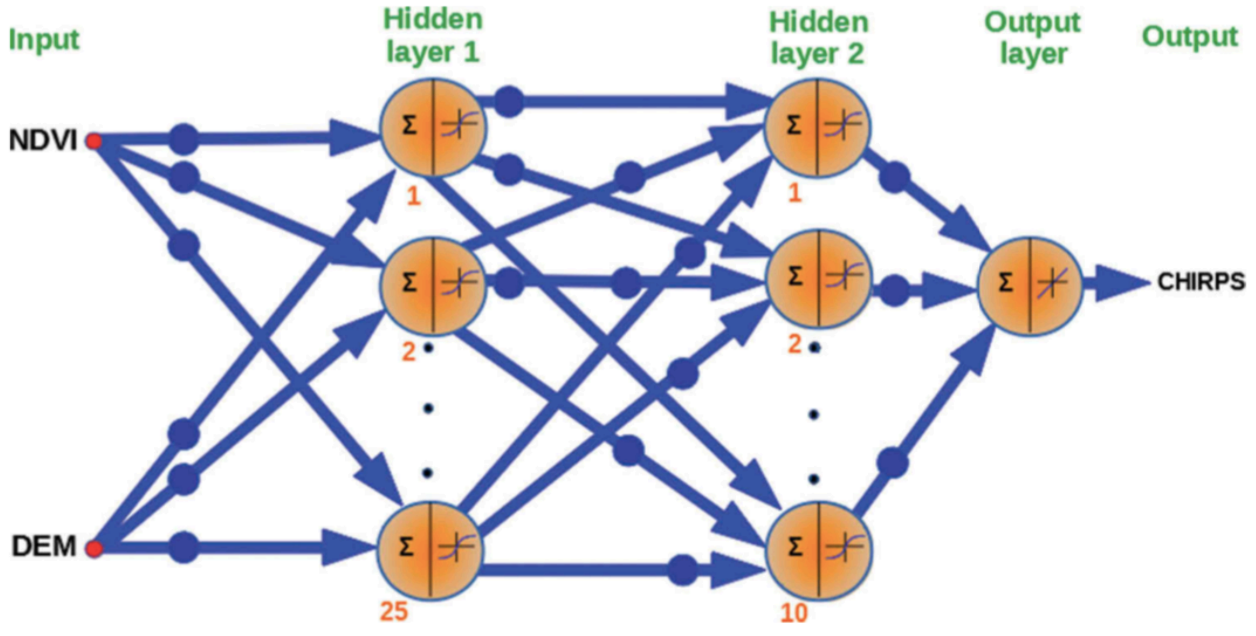

Figure 1. Multi-layer Perceptron for the ANN model 7. Nodes in each hidden layer are numbered in red. The weights are denoted by blue knots. The biases related to each node are exclusively defined but are not shown. The linear activation in each node is denoted by Σ, whereas, the sigmoidal and linear activation functions are graphically shown, accordingly.

Table 1. Neural network architectures tested.

Neural network	1	2	3	4	5	6	7
Number of neurons of hidden layer 1	5	8	10	15	20	20	25
Number of neurons of hidden layer 2	3	4	5	5	5	10	10

The simplest model, namely model 1, the actual subsets for training, validation and testing are small and the regression results are the worst.

For the months with high rainfall amounts, model 4 seems to perform better.

This supports the argument that no universal strategy exists for building ANNs and each paradigm should be investigated separately with all the possible variations under consideration.

Table 3. Performance metrics of annual ANN estimations.

	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
IA	0.93	0.88	0.86	0.96	0.97	0.89	0.98	0.91	0.93	0.94	0.94	0.93	0.90	0.89
RMSE	106.19	106.40	131.52	110.29	89.83	209.90	79.06	97.12	117.65	84.05	210.44	132.41	138.52	235.48
ME	−64.59	41.05	−22.02	−44.93	11.30	−179.93	−34.81	−7.51	−27.17	8.38	−90.35	−102.51	74.18	80.71
MAE	86.21	79.32	98.18	91.59	70.94	184.11	65.43	78.61	96.32	69.91	160.35	111.46	109.88	192.15

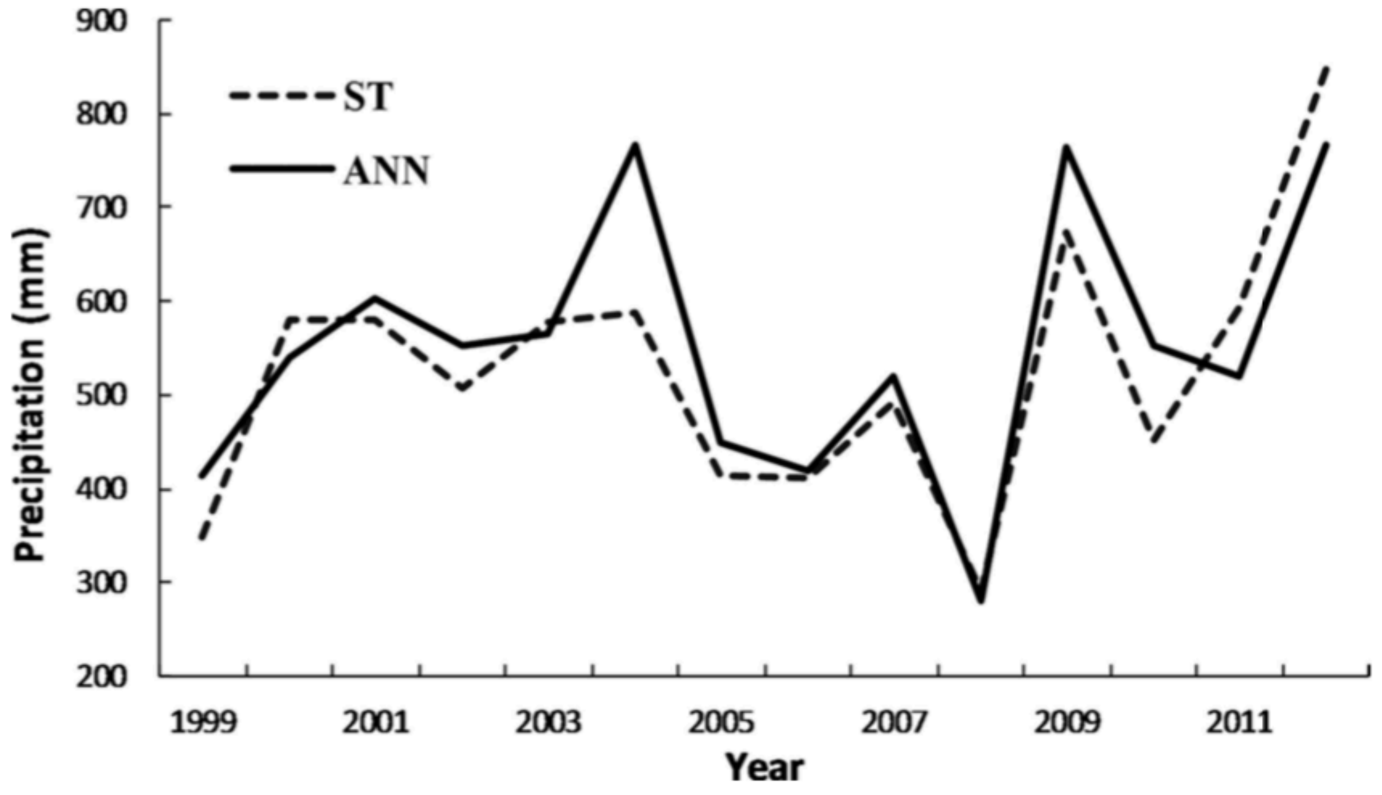

Figure 2. Mean annual (1999–2012) ANN estimated (ANN) and station measured (ST) precipitation.

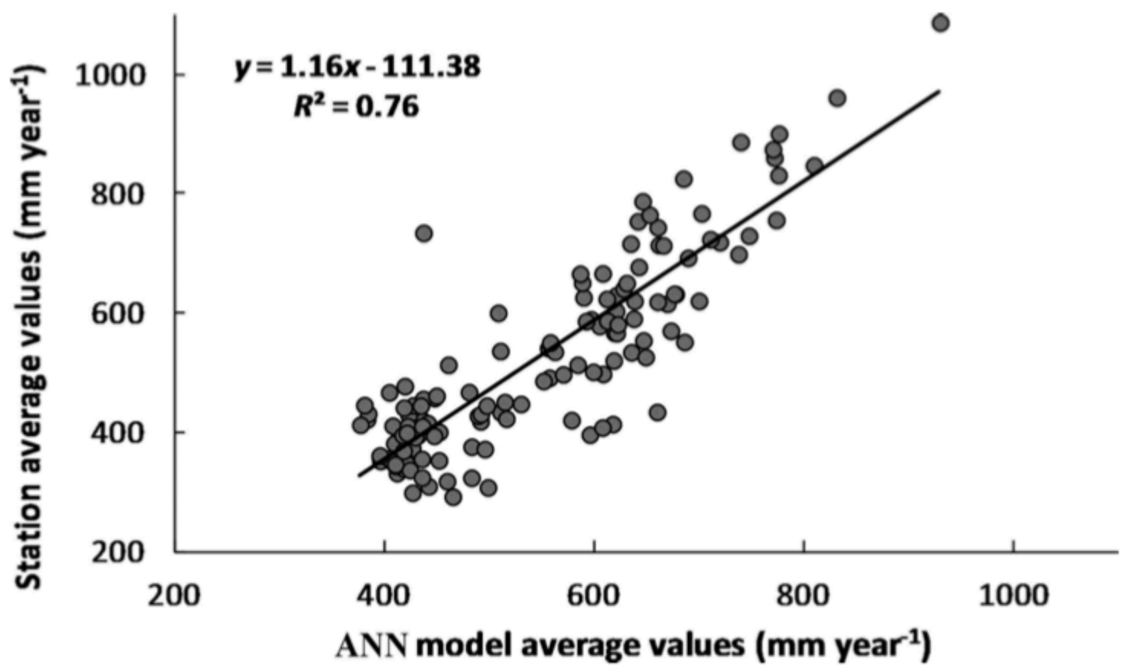

Figure 3. Regression analysis between mean annual (1999–2012) ANN estimated (ANN) and station measured (ST) precipitation.

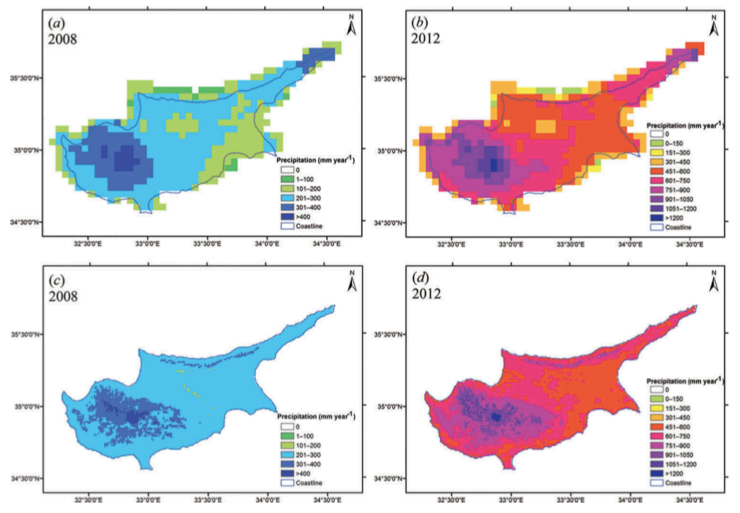

Figure 5. CHIRPS precipitation maps at nominal resolution of 0.05° for: (*a*) the driest year (2008), and (*b*) the wettest year (2012). Downscaled precipitation maps at 1 km resolution for: (*c*) the driest year (2008), and (*d*) the wettest year (2012).

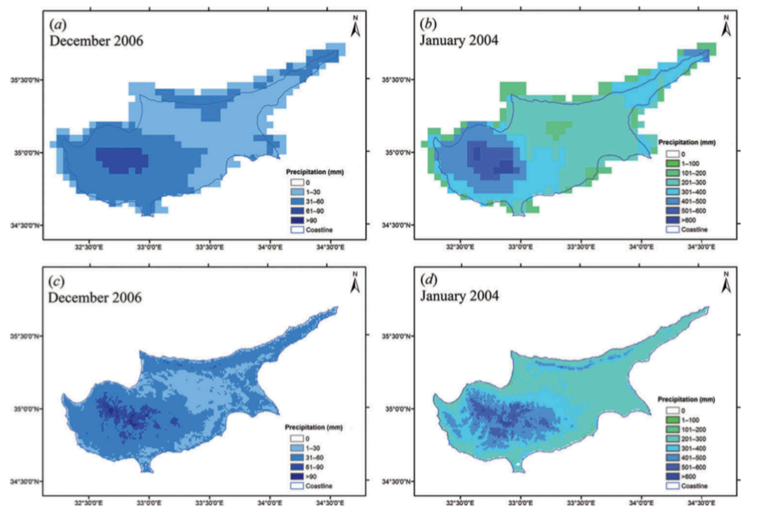

Figure 6. CHIRPS precipitation maps at nominal resolution of 0.05° for: (*a*) the driest month (December 2006), and (*b*) the wettest month (January 2004). Downscaled precipitation maps at 1 km resolution for: (*c*) the driest month (December 2006), and (*d*) the wettest month (January 2004).

Conclusions:

· Results indicated that the new product is able to capture the spatial precipitation varibility, especially in the mountainous areas.

· Regarding the annual estimates, IA is relatively high, while RSME, ME and MAE values are also depicting a similar to IA trend. For monthly estimates, IA is very high for all months with the exception of January, while high RMSE, ME and MAE values are noticed for the rainy months, these could be attributed to the possible overestimation of CHIRPS precipitation.

· The methodology can easily be applied to other geographical regions.

Report

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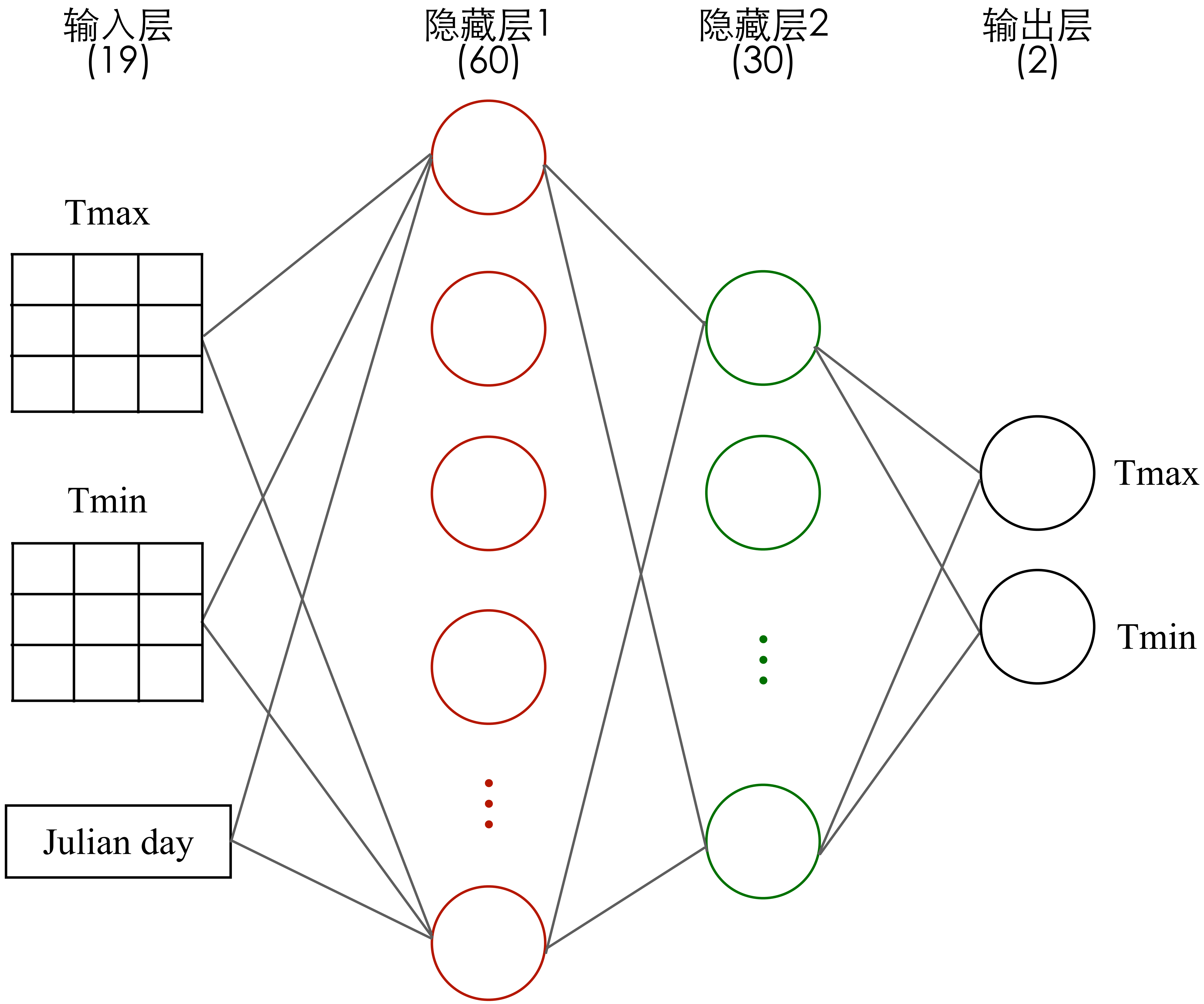
输入层
(19)
隐藏层1
(60)
隐藏层2
(30)
输出层
(2)
Tmax
Tmin
Julian day
Tmax
Tmin


Correlation Coefficient
Standard Deviation
RMSD
Ref
ANN(9-julian)
ANN(1-julian)
ANN(9-non)
ANN(1-non)
Linear
CCSM
ANN(9-julian)
ANN(1-julian)
ANN(9-non)
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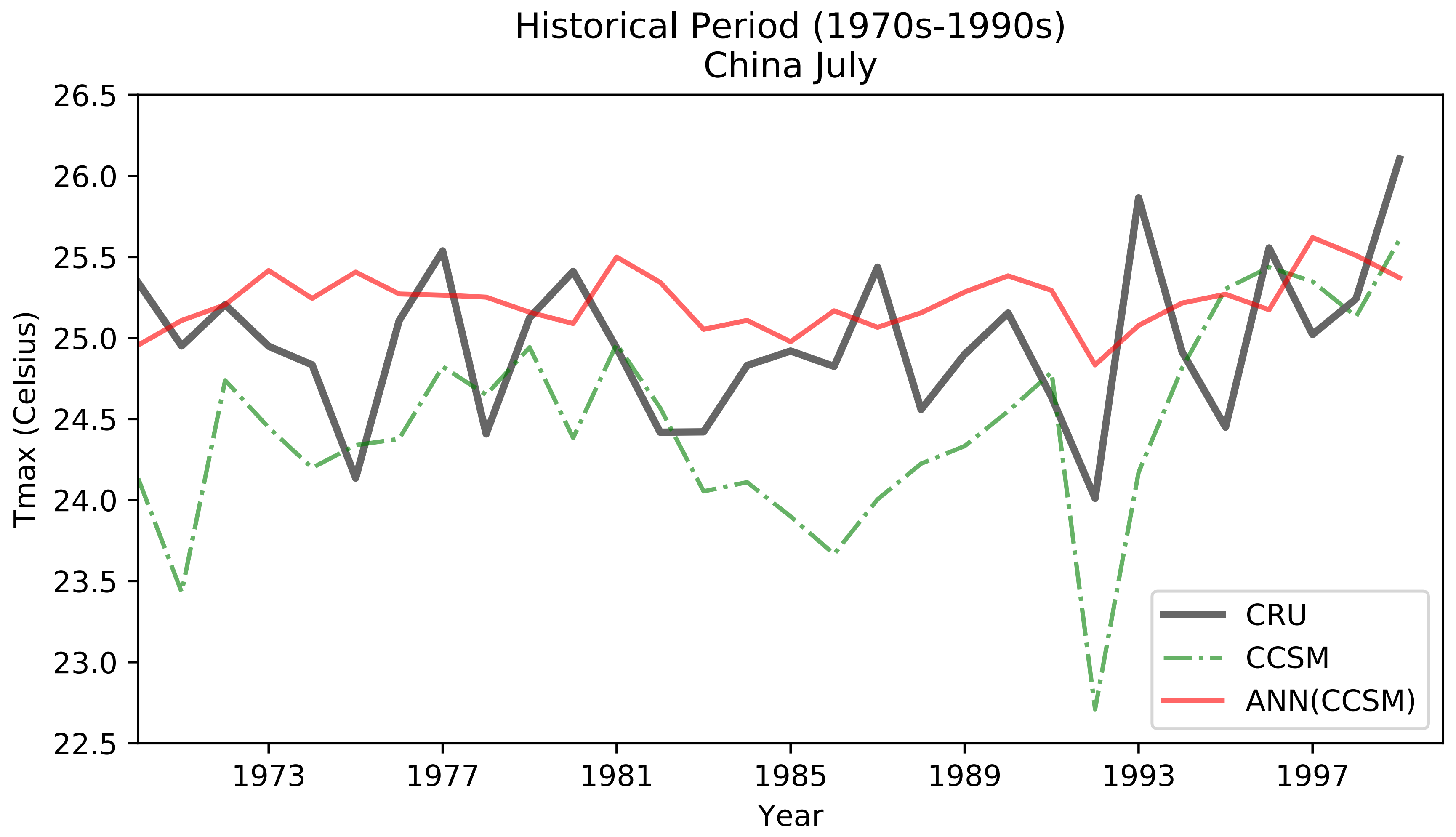
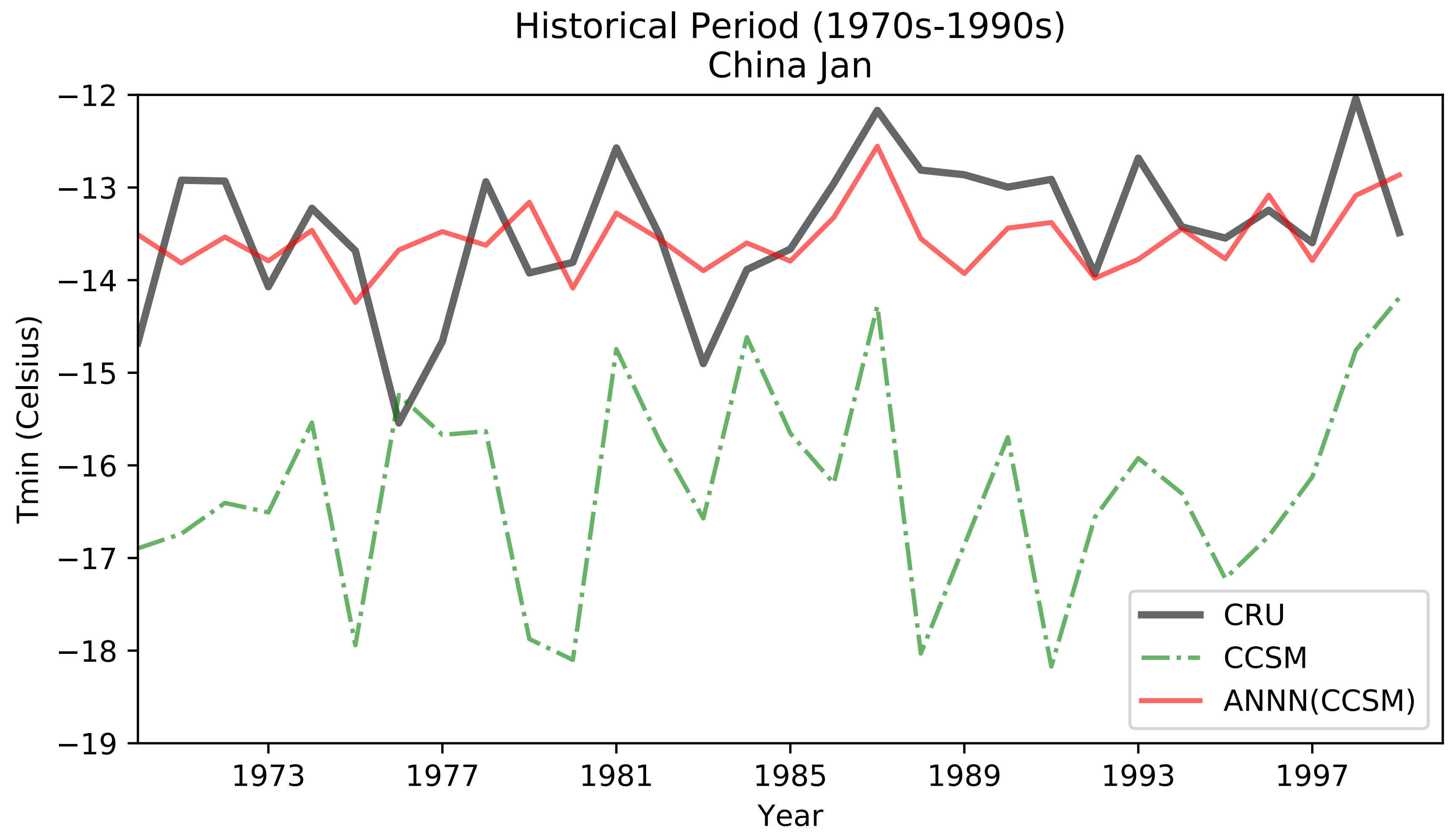
Standard Deviation
RMSD
Ref



Historical Period (1970s-1990s)
China July
Tmax (Celsius)
Year
CRU
CCSM
ANN(CCSM)



Historical Period (1970s-1990s)
China Jan
Tmin (Celsius)
Year
CRU
CCSM
ANNN(CCSM)

谢谢

Train

	Tmax			Tmin		
	obs	ccsm	ANN	obs	ccsm	ANN
mean						
std						
r^2						
RMSE						

Validation

	Tmax			Tmin		
	obs	ccsm	ANN	obs	ccsm	ANN
mean						
std						
r^2						
RMSE						