2020/11/17

Use of bias correction techniques to improve seasonal forecasts for reservoirs — A case-study in northwestern Mediterranean

The Science of the total environment
10.1016/j.scitotenv.2017.08.010

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Introduction:

· Although near-term meteorological forecasts are the most used , the seasonal forecast horizon holds the largest potential, for having information months ahead can substantially increase the resilience of the forecast users.

· It is important to explore new ways to improve seasonal dynamical forecasts and give new insights in their usefulness to provide end-users with the adequate information to decide the best choice for their water management strategies.

· This issue is specially harsh in the Mediterranean where the water deficits of dry summers are often unresolved in the wet season, leading to recurrent drought situations.

· The raw forecasts from dynamical systems show biases in comparison to the reference datasets. These biases are the consequence of the inherent limitations of the physical models related to parameterizations, equation simplification and uncertainties in the initialization procedure.

· However the identification of the best techniques it is not straight-forward and might depend on the domain and variable considered as well as in the nature of the bias correction technique itself.

Data and methods:

· The Muga River basin (flood lamination, irrigation, urban water supply and electricity production)

· E-OBS v8.0 (European Observational dataset)

· European Center for Medium-range Weather Forecasting System 4 (S4)

· MOS-analog

· Linear regression

· Mean bias correction

$$Y = bX.$$

$$ME = \frac{1}{n}\sum_{k=1}^{n}(f_k - o_k)$$

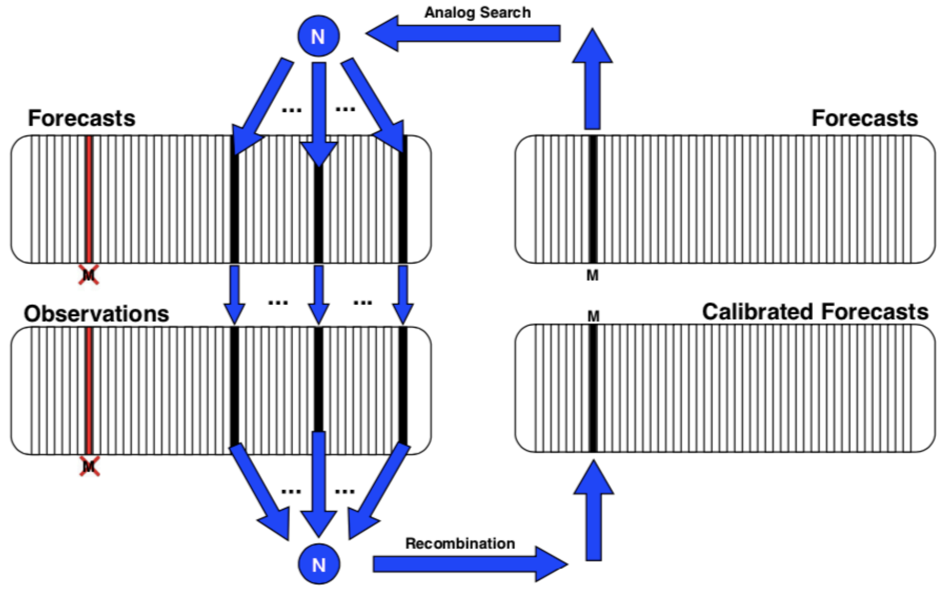


Fig. 3. MOS-analog bias correction scheme. For each lead, ensemble member, variable and forecast month we search the *N* analogs in the analog pool formed by the same month forecasts taken from the hindcast (excluding the forecast month that we want to calibrate). Afterwards, we take the *N* observation fields corresponding to the *N* analogs and average them to form a single output that will become our bias corrected forecast.

Verification:

Deterministic:

· Climatology

· Persistence (consider the forecast as the observed value of the n-preceding month, where n is the horizon of the forecast[eg. the lead 1 forecast for June will be the observed value in May].)

Probabilistic:

· dBSS (discrete Brier Skill Score)

· EVA (Economic Value Area)

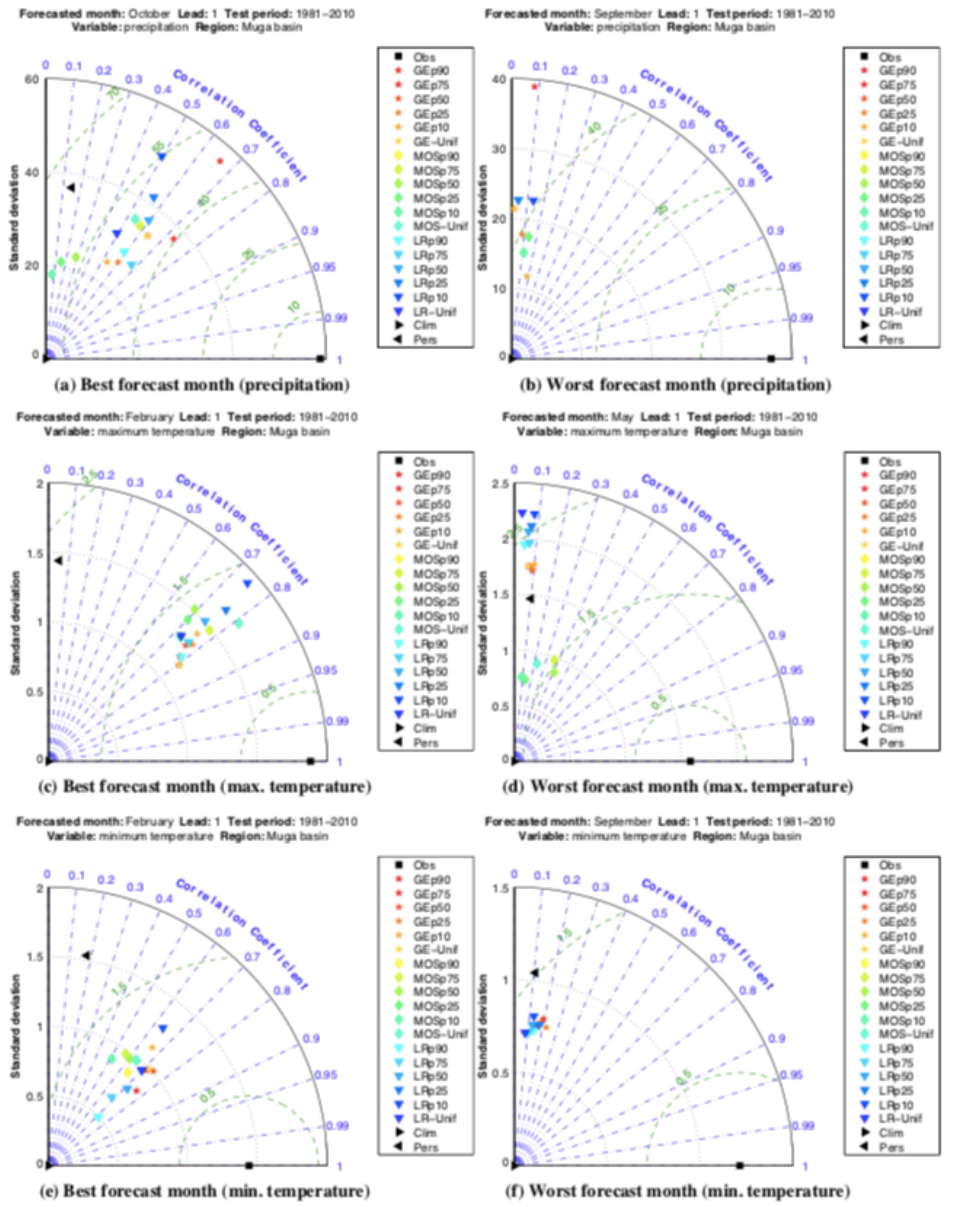


Fig. 4. Muga basin's Taylor diagrams at lead one for the best and worst performing months. Each diagram contains the GE for raw S4 forecasts, MOS-analog and MOS-LR S4 bias corrections, their unified deterministic forecast as well as persistence and climatological controls. The period of study is 1981–2010 (a) The best performing month (precipitation): October (b) The worst performing month (precipitation): September (c) The best performing month (max. temperature): February (d) The worst performing month (max. temperature): May (e) The best performing month (min. temperature): February (f) The worst performing month (min. temperature): September.

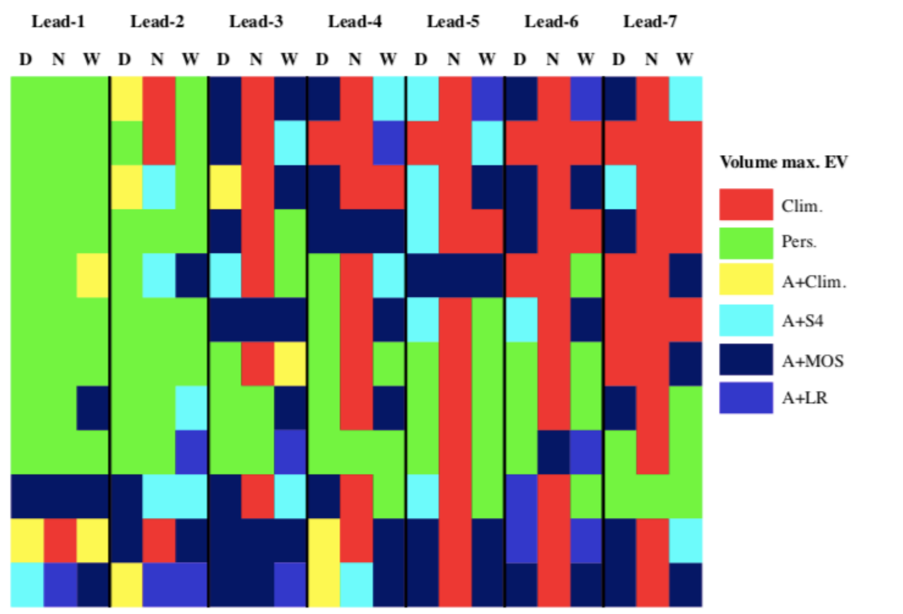


Fig. 6. Volume forecast strategy with the largest Economic Value Area (EVA) for each month, forecast horizon and climatic conditions (**D** -lower tercile-, **N** -middle tercile-, and **W** -upper tercile-) at the Boadella reservoir. The six forecast systems considered are: climatology (Clim.), persistence (Pers.), antecedent observation combined with climatological values (A + Clim.), antecedent observations combined with mean bias corrected S4 (A + S4), antecedent observations combined with MOS-analog bias corrected S4 (A + MOS) and antecedent observations combined with S4 bias corrected with a linear regression procedure (A + LR). Note that forecast strategies different from climatology only appear in the table if they have a minimum EV Area of 0.10.

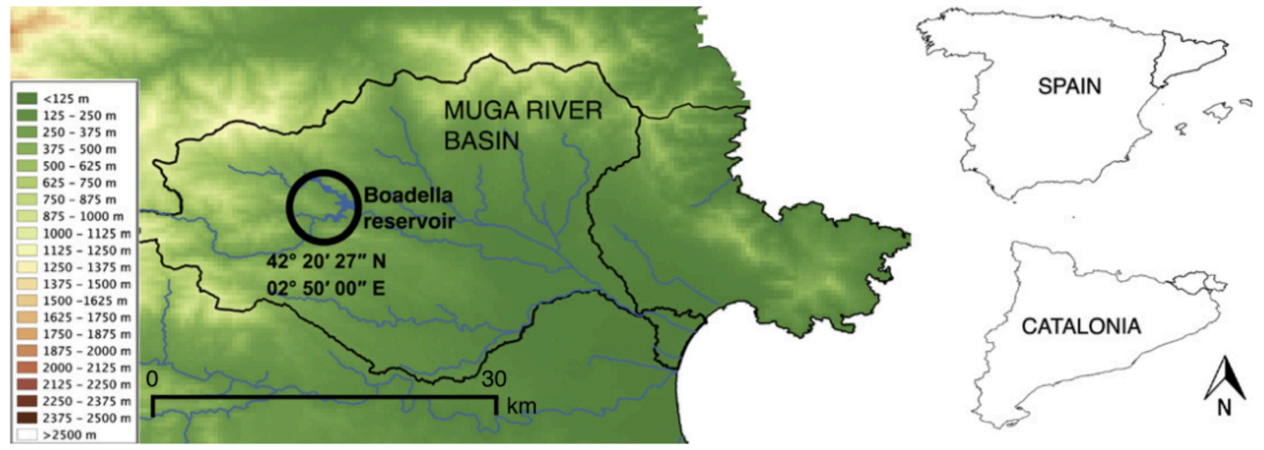
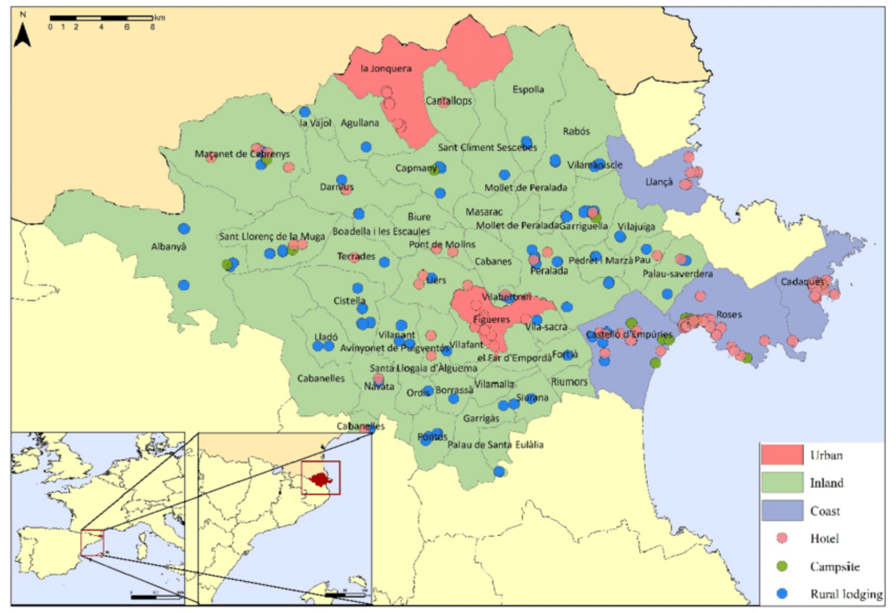


Fig. 1. Boadella reservoir's location in the Muga River basin (Catalonia, north-eastern Spain). Elaborated from GMTED2010 (Danielson and Gesch, 2011) and Spanish river cover from the *Ministerio de Agricultura, Alimentación y Medio Ambiente*.



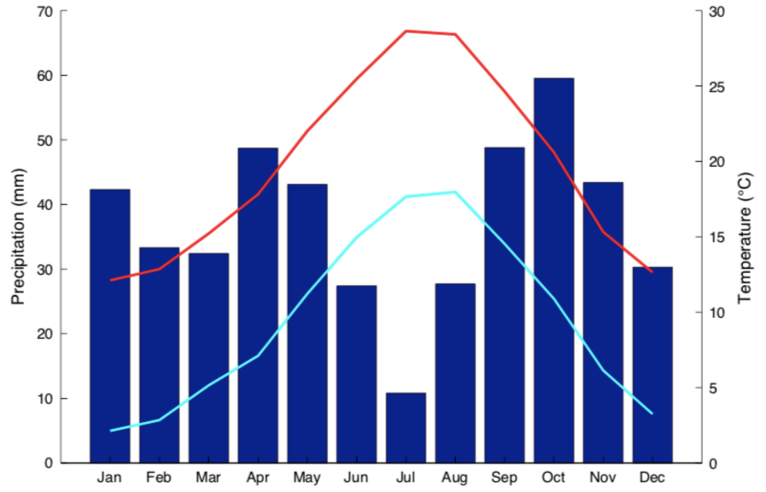


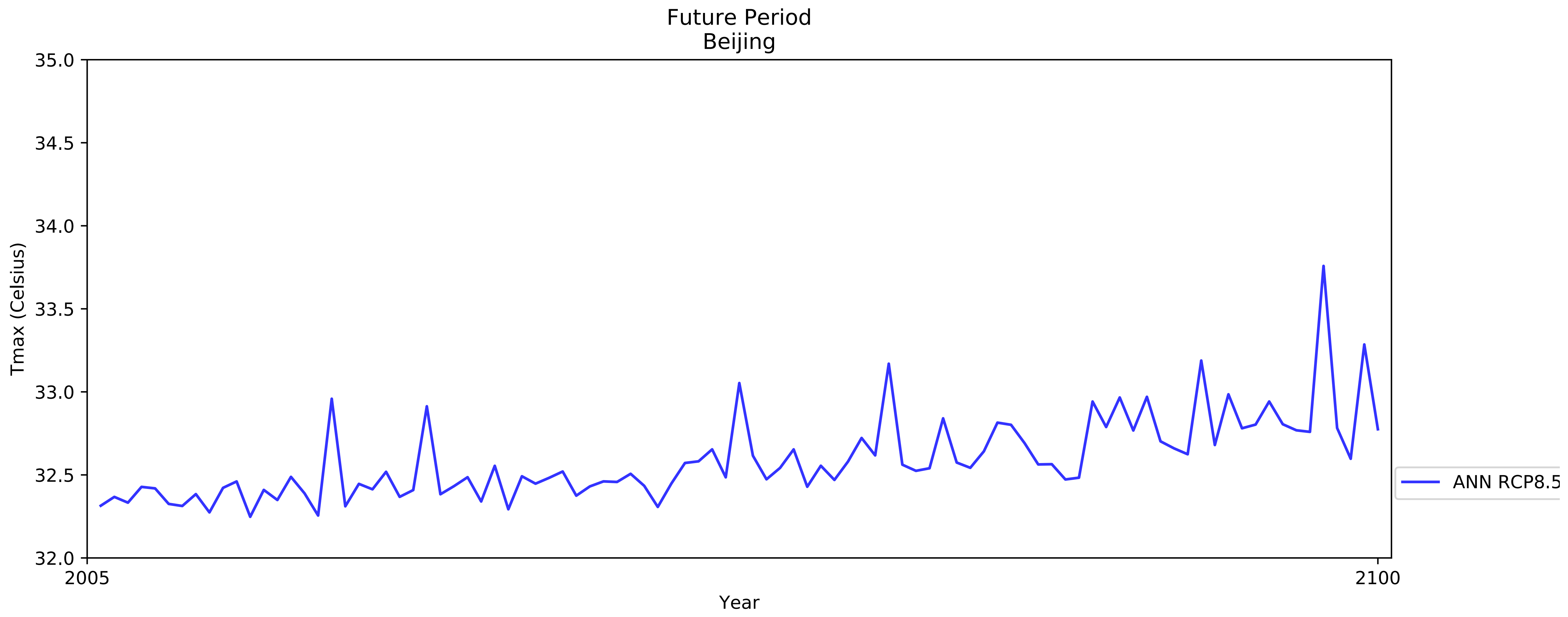
Fig. 2. Muga basin's climogram. Blue bars refer to monthly rainfall; red line is for monthly maximum temperatures; and cyan, for monthly minimum temperatures. Elaborated from E-OBS v8.0.

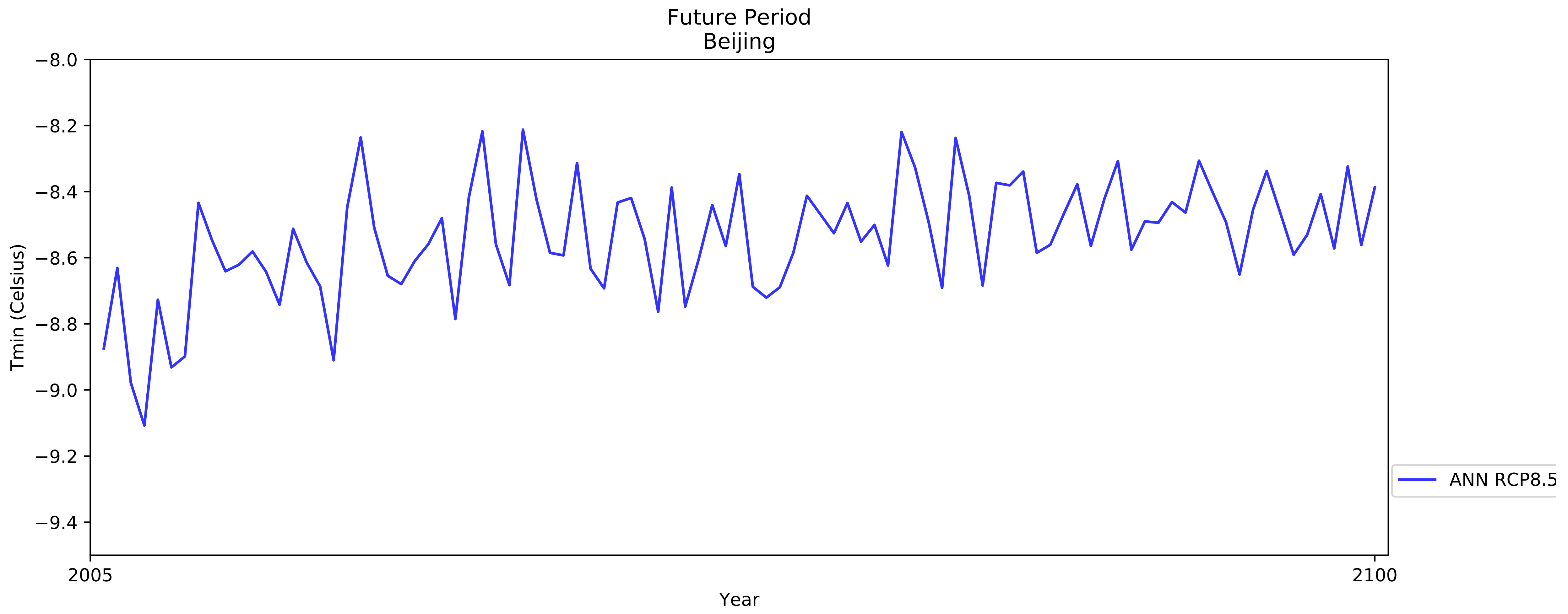
Report

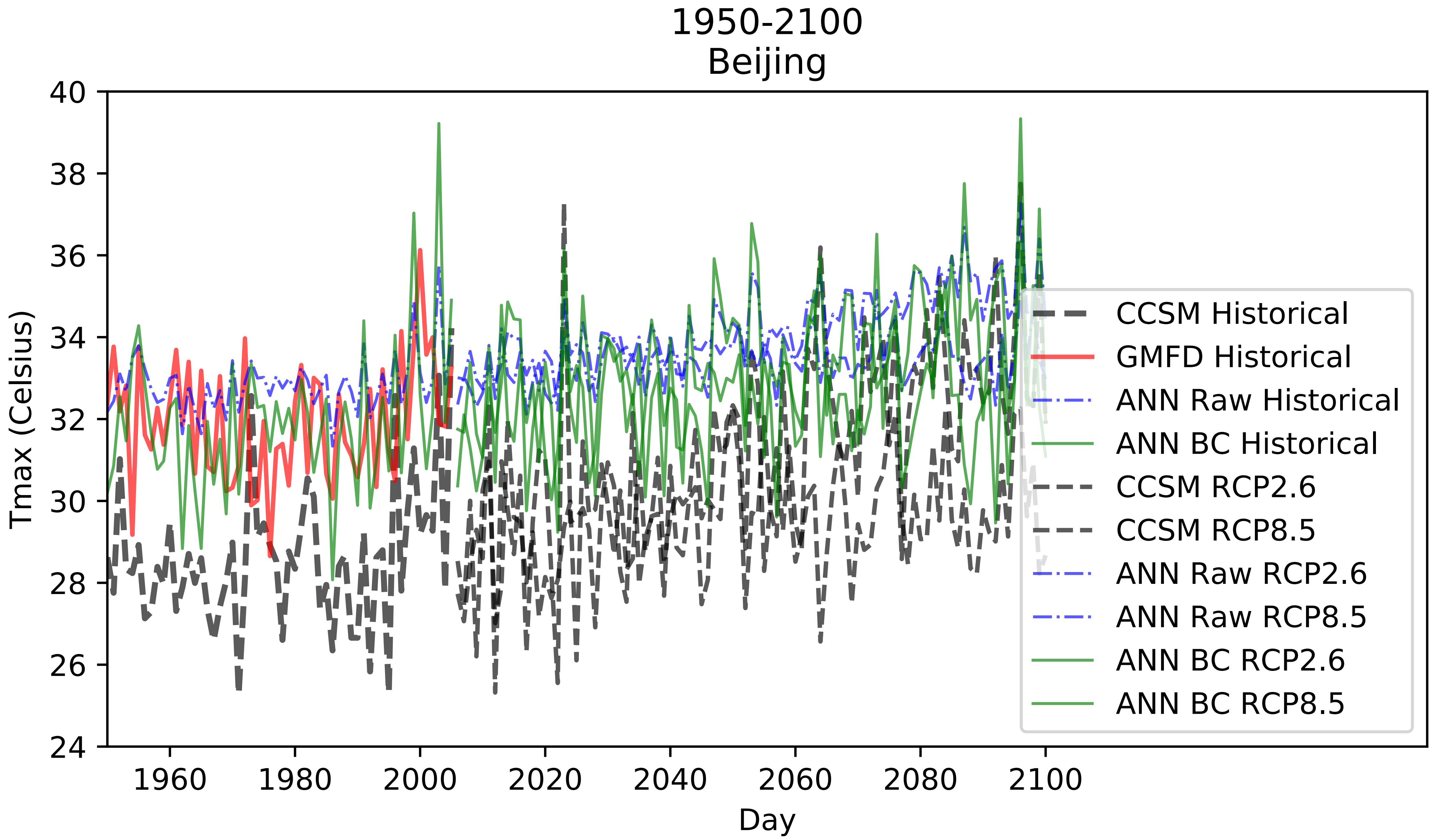
2020.11.18

張慕琪

关于Future predict无法捕捉气候变暖pattern的调查







（无）

关于Future predict无法捕捉气候变暖pattern的调查：

· 回顾了一下之前成功数据的各个代码，经调查：Bias Correction、加权平均两个后处理都没有问题；

· 那么问题只可能产生于ANN原始数据的代码。

与成功数据的ANN predict相比较（进行了多组对比实验进行排除法），一共有两点区别：

1. 在对input做有偏归一化时使用的mean和var的数据从train变成了trian+vali
2. 加入了julian day

于是，开始思考为什么这两个改变都会导致结果错误？

关于第一点（input改变了数据集）：ANN已经fit好…… (ANN is an idiot.)

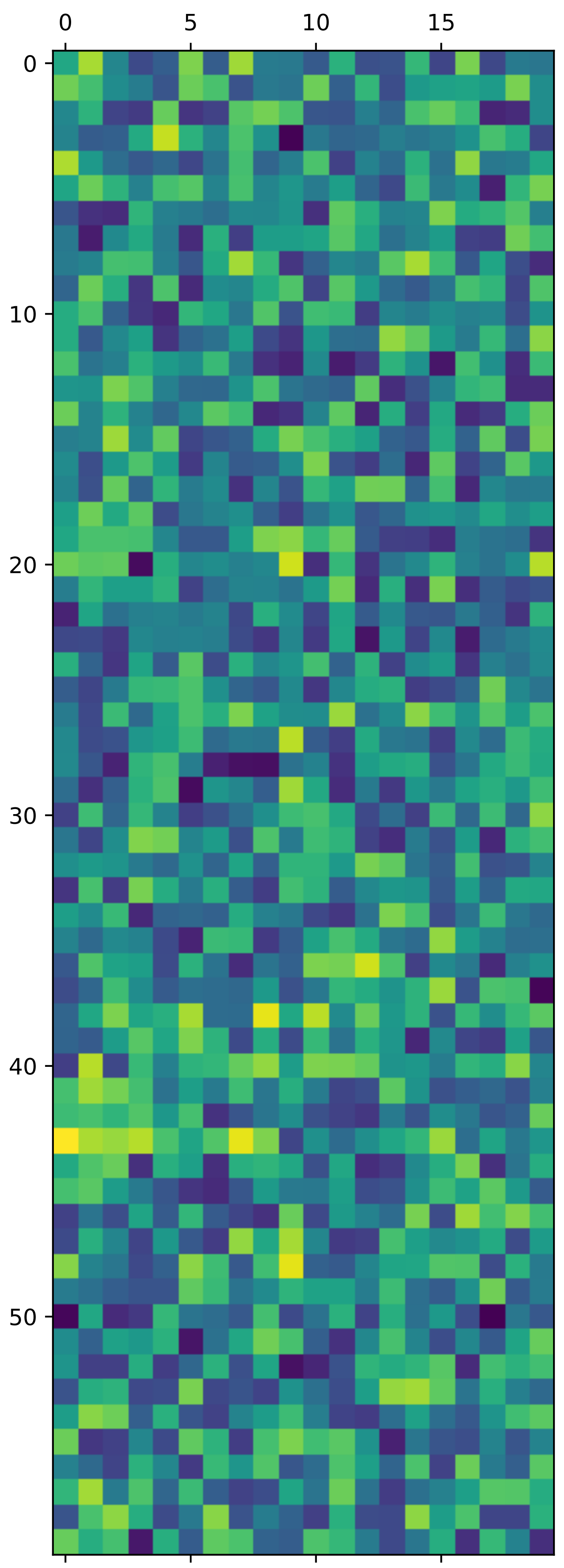
关于第二点（Julian day），未完待续……

关于julian day（猜想1）：

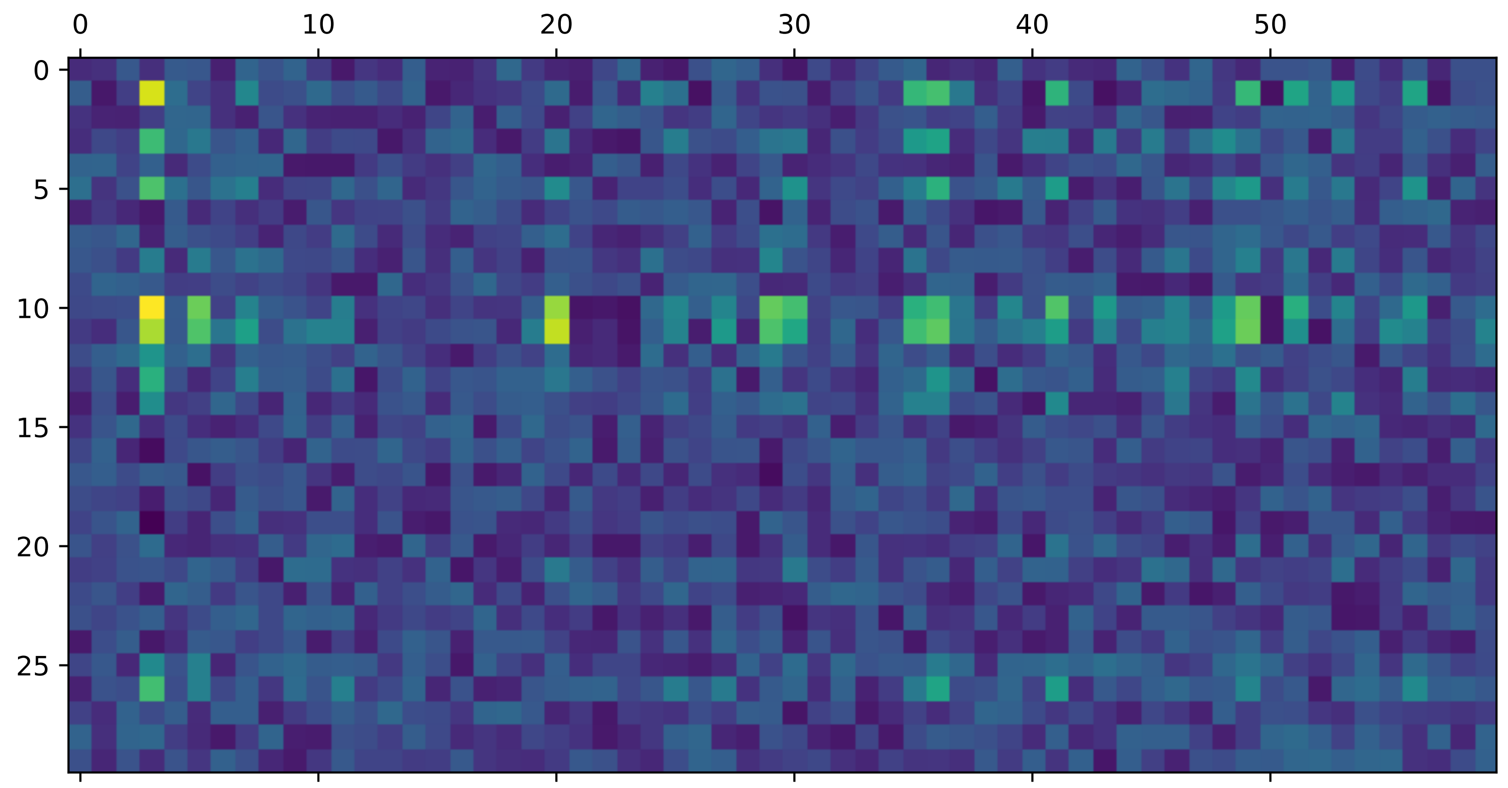
Julian day是无偏的波 (mean=0)，和有偏的温度波形叠加会影响结果。

Julian day的权重太大？ —> No.

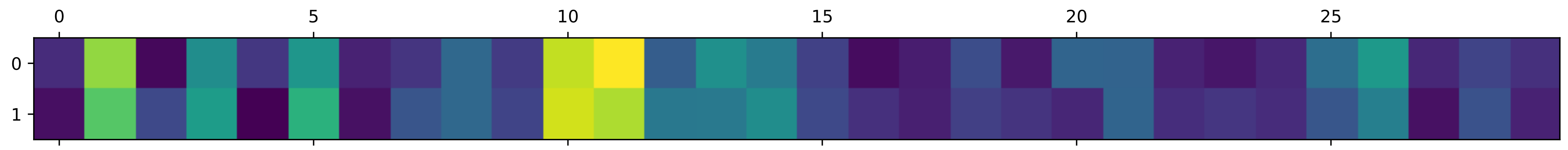
20 x 60



60 x 30

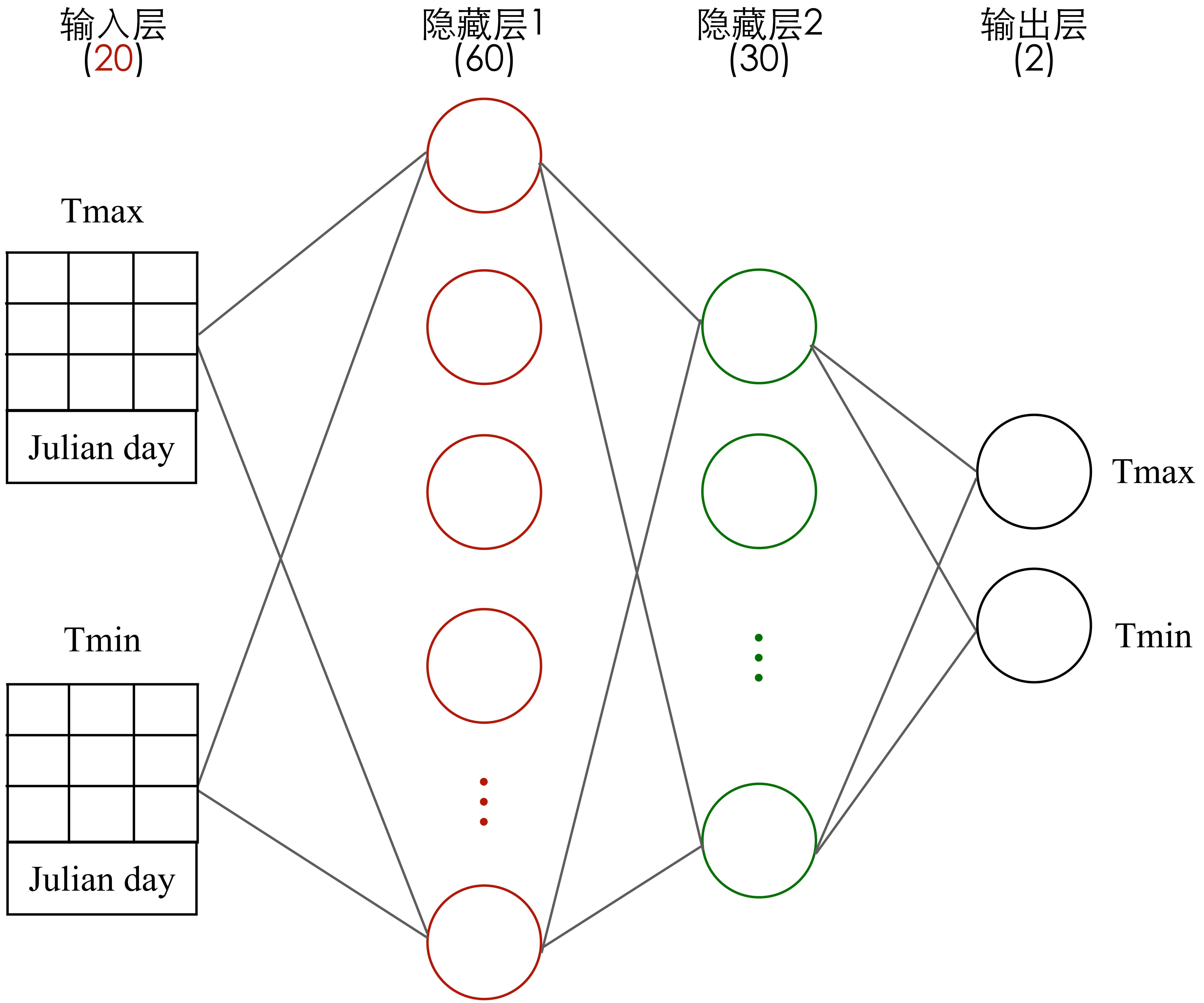


30 x 2



关于julian day（猜想2）：

Julian day加入的位置、Normalization对于julian day的处理



改进：

PlanA: Tmax, Tmin, Julian day三个元素分别做Normalization

Plan B: Tmax, Tmin做Normalization但是Julian day不做

时间缘故，待验证

谢谢