Predictability of Summer Extreme Maximum Temperatures over Taiwan by using NOAA NCEP GEFSv12 Reforecast Products

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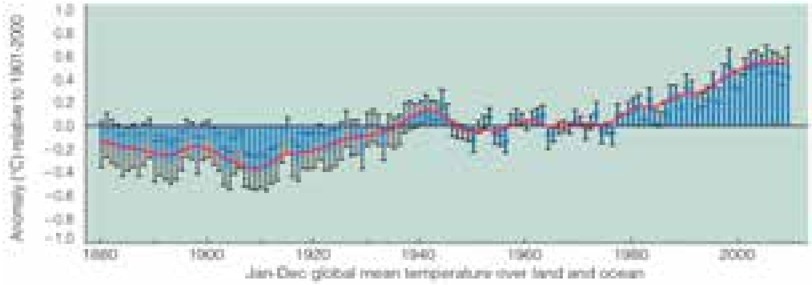
Background and Motivation:

- The human-induced changes in climate are not only increasing the global average temperature (~0.85 °C), but are also increasing the frequency and intensity of extreme weather and climate events over various parts of the globe.

- The last three decades have been successively warmer on the Earth's surface than any preceding decade since 1850 (IPCC 2014). The increase in temperature and its IAV causes to increase the temperature extremes.



- **The increased extreme weather events have serious societal, agricultural, economic, and ecological impacts across the globe.**

- **Taiwan is a sub-tropical island in Asia, and the increase in air temperature (~1.4 °C) in Taiwan is twice that in the N.H (~0.7 °C) from 1911 to 2005 (IPCC 2007).**

- **An accurate Extended range (ERF) Tmax forecast over Taiwan is crucial. It is a difficult time range for weather forecasting because much of the memory of the initial atmospheric conditions on this time scale is lost, affecting the forecast prediction skill.**

- **In Sep. 2020, NOAA NCEP implemented GEFSv12 to support stakeholders for sub-seasonal forecasts and hydrological applications. Consistent GEFSv12 reforecast data for 2000-2019 are initialized at 00 UTC once per day out to 16 days with 5 ensembles except on Wednesdays when the integration extended to 35 days with 11 members.**

- **It is well known that the GCMs raw products are not skillful, particularly on the ERF time scale, and suitable statistical post-processing techniques are highly required for skillful forecast guidance and to increase its usability.**

Data Used

Model : GEFSv12 (Zhou et al. 2019; 2021)

The period used : 2000-2019

Horizontal Resolution: 0.25° X 0.25° for Day-1 to 10 and 0.5° X 0.5° for Day-11 to 35. The entire data is interpolated by using bilinear interpolation over Taiwan with 0.25° X 0.25°

Members used : 5 members (c00, p01, p02, p03, and p04) based on every day 00 UTC initial conditions.

Reference data set used : ERA5 Tmax

Mean Bias (MB) -remove technique (U)

MB is defined as the climatological mean difference between model and observation:

$$b_t = \overline{Y} - \overline{\overline{F}}_t$$

For each day, this difference (b_t) is calculated in the leave-one-out cross-validation manner and adds this mean bias in the 'test' (t) day's model forecast.

$$U_t = F_t + b_t$$

Multiple linear Regression (MLR)

In this method, SVD has been employed for the computation of the regression coefficients (β_0 , β_1, β_2, ... β_p). The advantage of this method is it removes the singular matrix problem while calculating covariance among ensemble members, which can't be entirely solved with the Gauss-Jordan elimination method.

$$E(y) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p$$

Quintile Mapping Method (Q)

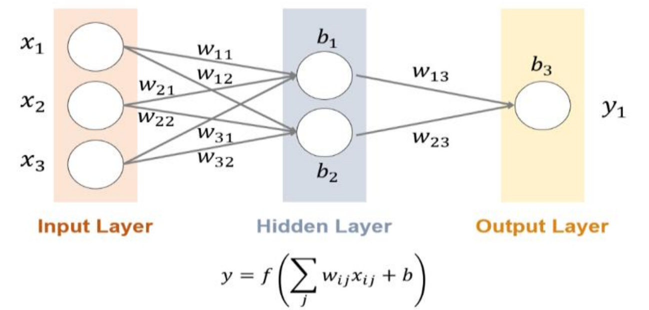
- This technique is mainly used to correct the model predicted Tmax distribution by mapping it onto the observed Tmax distribution. The process is also referred to as 'histogram equalization and/or 'rank matching'.
- In the QQ method, the bias is not calculated explicitly. Suppose CDFs, F_Y for observed data, and $F_{\bar{F}}$ for ensemble mean of model forecast are known. For $\bar{F}_i$ the bias-corrected value Q will then be as follows:

$$Q = F_{Obs}^{-1}\left(F_{\bar{F}}\left(\bar{F}_i\right)\right)$$

Here, F^{-1} is an inverse of CDF. Thus, the quantile mapping procedure is a transformation between two CDFs. The whole procedure is implemented in the leave-one-out cross-validation way.

Artificial Neural Network (ANN)

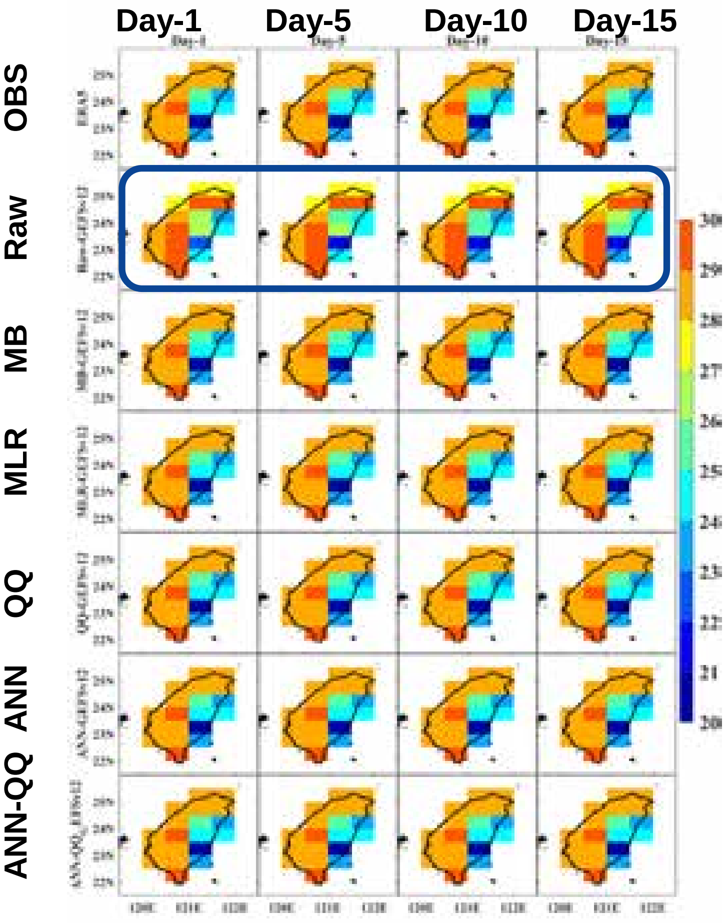
Artificial neural networks are forecasting methods that are based on simple mathematical models of the brain. They allow complex nonlinear relationships between the response variable and its predictors



The following are considered to develop a simple ANN model in the present preliminary study to improve the GEFSv12 prediction skill in depicting Heat waves over Taiwan :

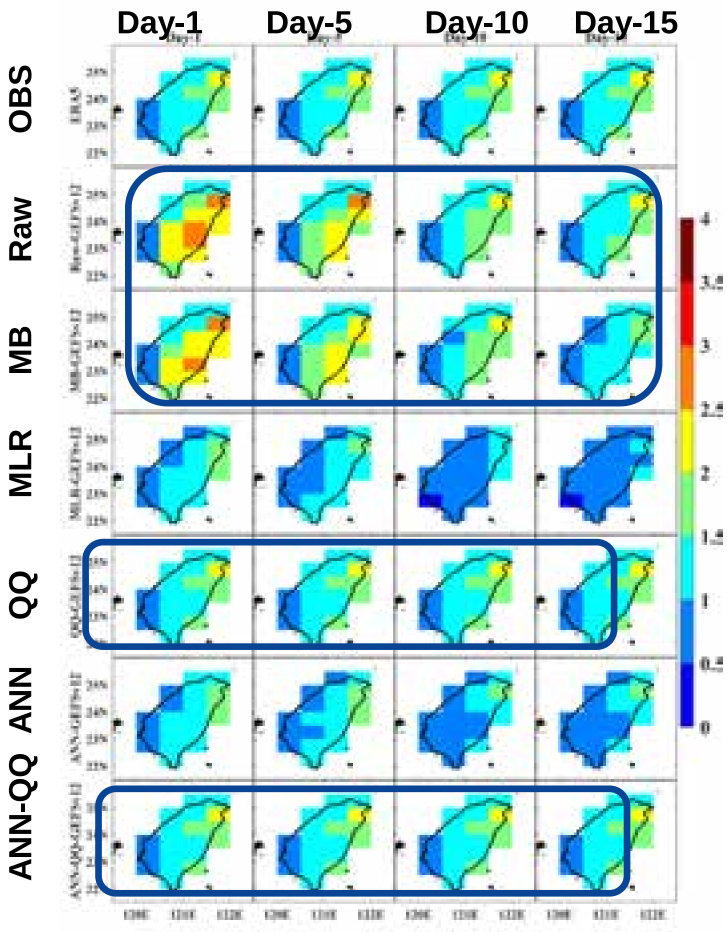
No. Hidden layers :	: 1
No. of nodes/neurons in the hidden layer	: 3
Neural Network used	: Feedforward network
Neural Network Processing Functions:	: Map matrix row minimum and maximum values to [-1 1]
Data divided function	: 70% data for training and 30% data for validation
Learning rate	: 0.001
Max number of iterations/epochs used	: 1000
Error tolerance for stopping criterion	: 1e-14
Training function used	: Supervised weight/bias training function with Sequential order weight/bias training (trains)
Neural Network Performance Functions used	: Mean squared error performance function

Spatial pattern of JJAS Tmax (◦C)



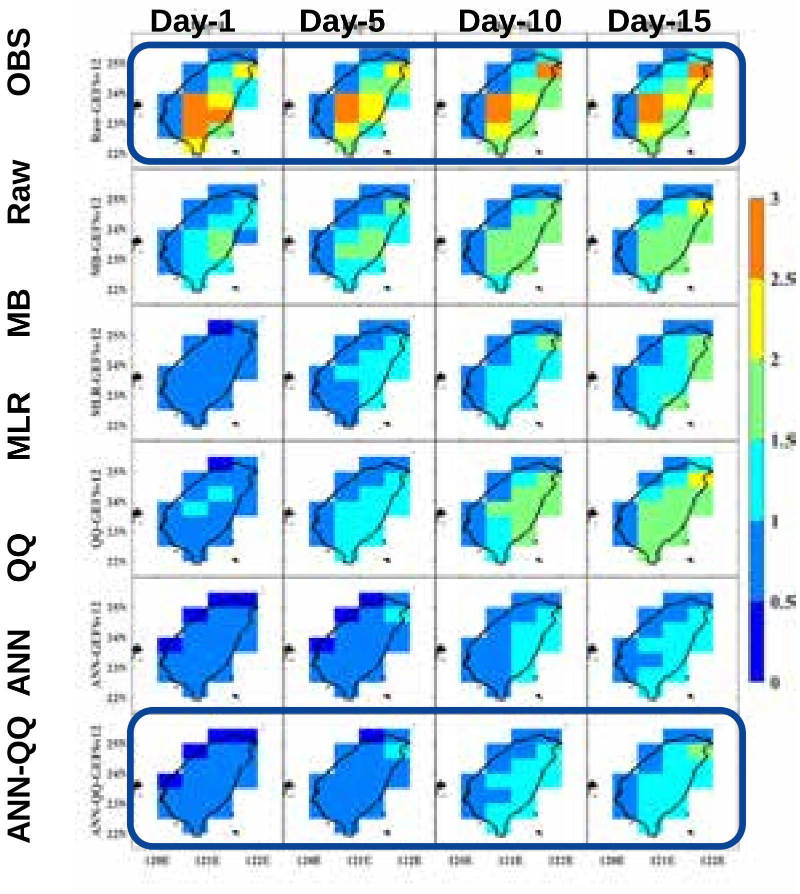
- The GEFSv12 is able to capture the Tmax patterns with all lead time forecasts.
- The Raw-GEFSv12 has a large warm bias over the south and middle part of Taiwan for all the lead time forecasts.
- However, a slight cold bias over the eastern and western parts of Taiwan.
- All the calibration methods remarkably reduced the warm/cold bias for all the lead time forecasts.

IAV of JJAS Tmax (◦C)



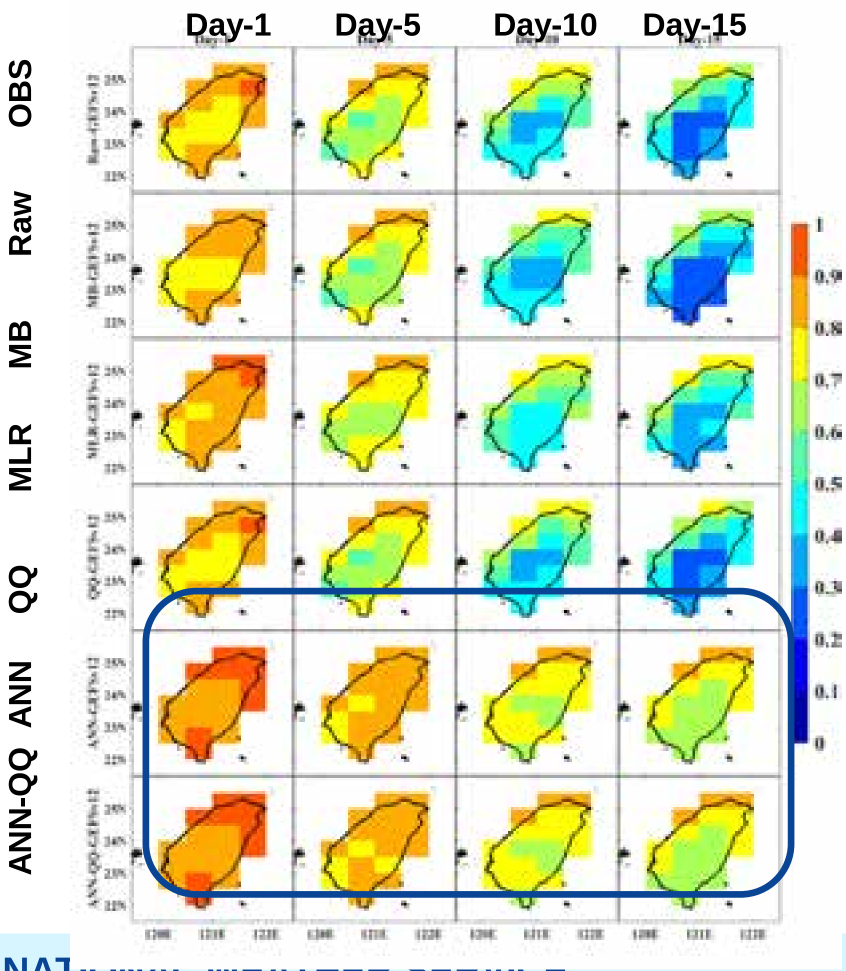
- The Raw and MB-GEFSv12 methods have an overestimation in the IAV of Tmax, while the MLR and ANN-GEFSv12 have a large underestimation in the IAV of Tmax in most parts of Taiwan.
- However, the IAV of Tmax from QQ and ANN-QQ-GEFSv12 are very similar to the ERA5 in most parts of Taiwan

RMSE

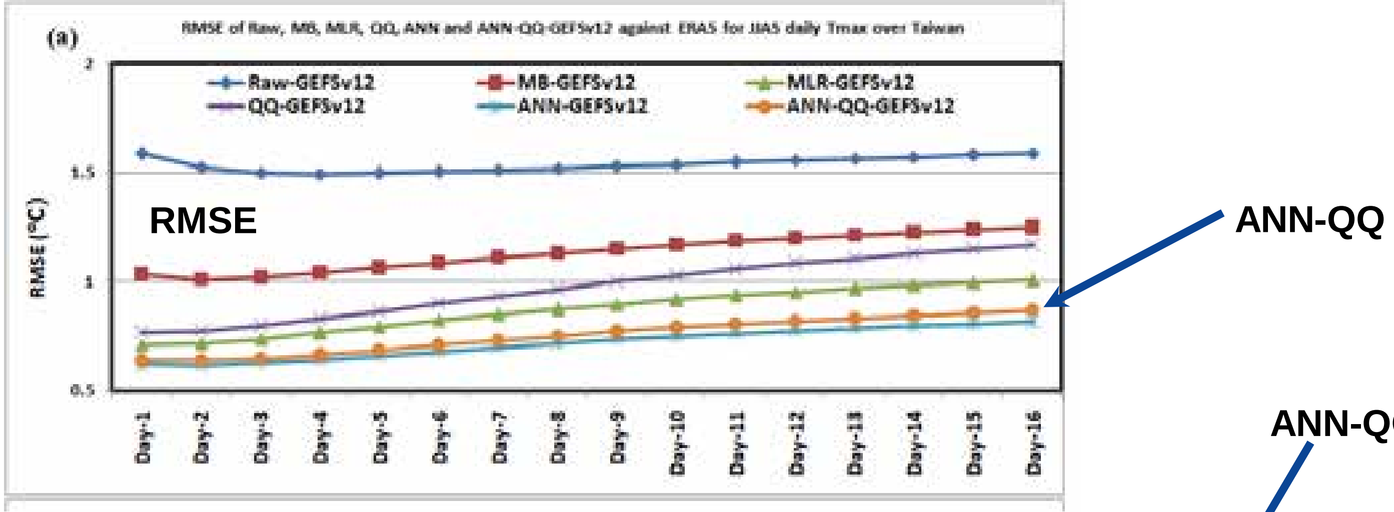


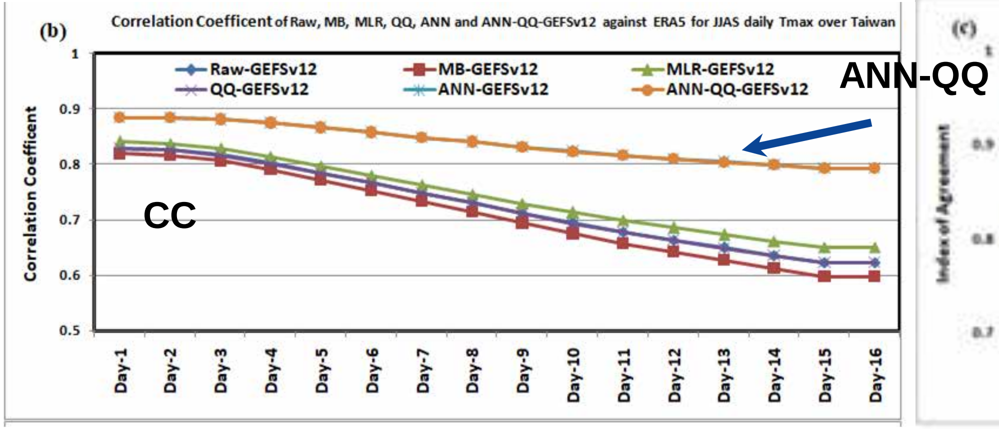
- **The Raw-GEFSv12 has a large RMSE error over the south and middle part of Taiwan for all the lead time forecasts, while it is less over the east and western parts of Taiwan.**
- **All the calibration methods remarkably reduced the RMSE error for all the lead time forecasts.**
- **However, The ANN and ANN-QQ methods have less RMSE in most parts of Taiwan than the other calibration methods.**

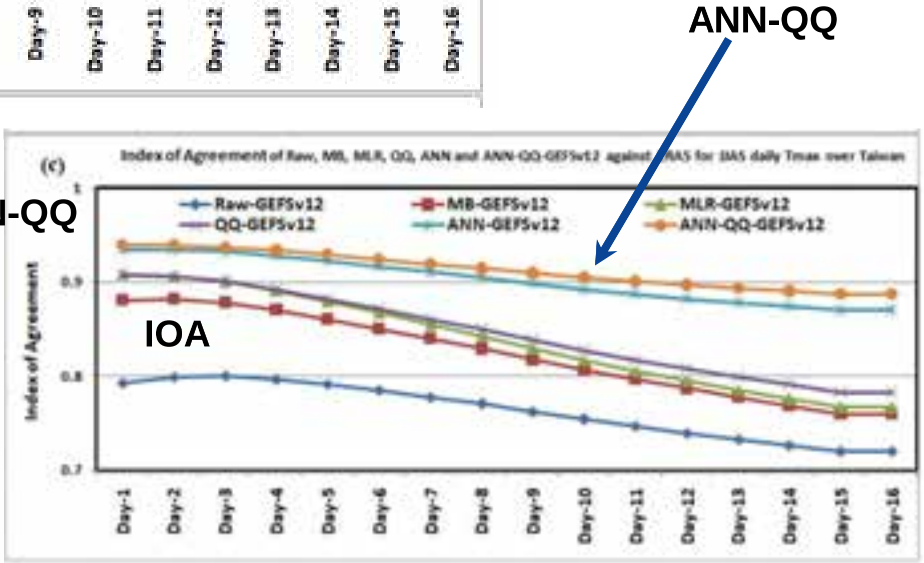
Correlation Coefficient



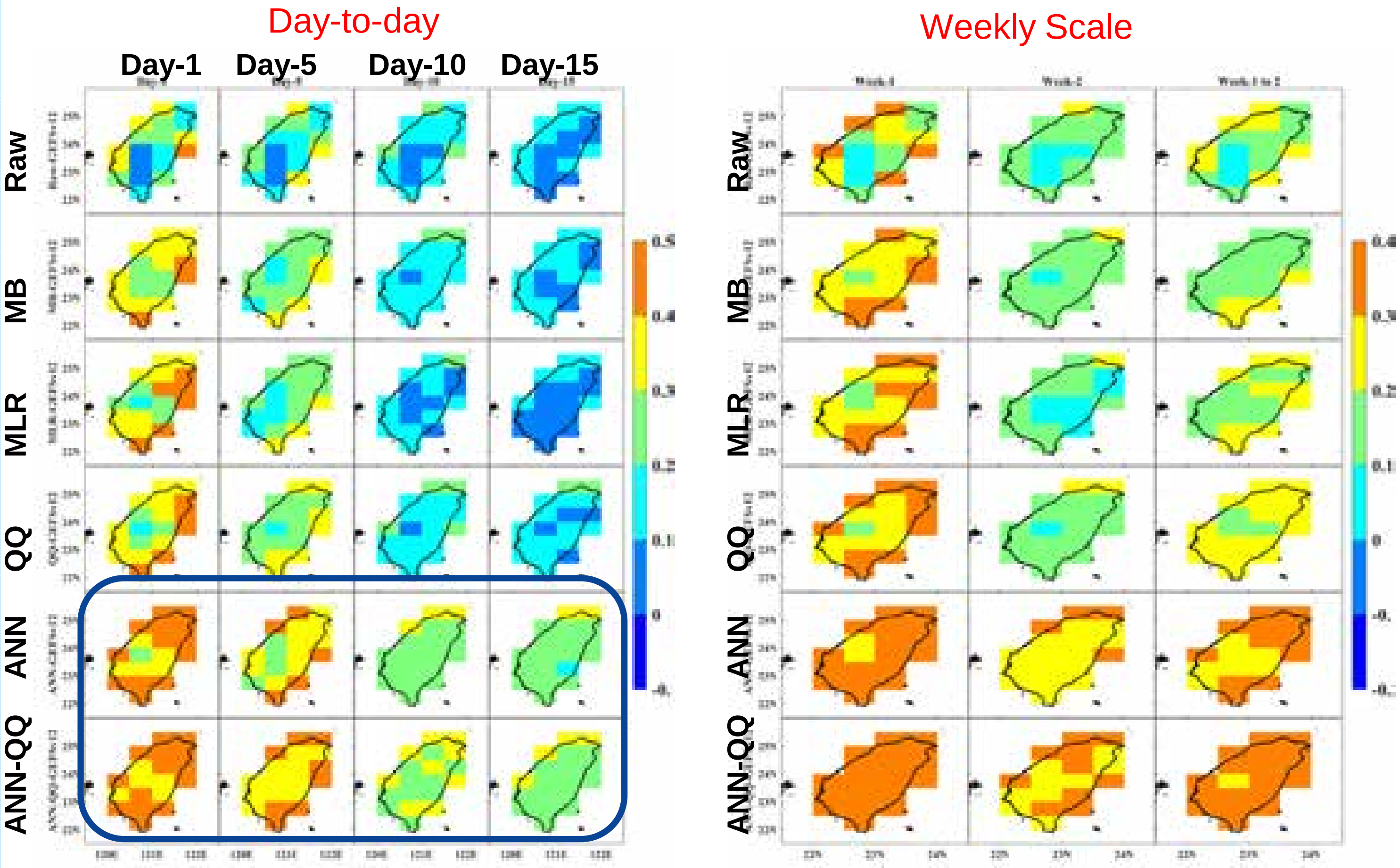
- The CC of Raw, MB, MLR, QQ, ANN, ANN-QQ-GEFSv12 for Tmax is decreased with lead time in most parts of Taiwan.
- The CC for the Day-1 forecast is significantly high (~0.8) from Raw and all calibration methods.
- It is interesting to notice that the ANN and ANN-QQ calibration methods remarkably improved the CC in most parts of Taiwan for all lead time forecasts while a slight improvement from MLR.
- There are no remarkable changes from MB and QQ methods.


(a)
RMSE of Raw, MB, MLR, QQ, ANN and ANN-QQ-GEFSv12 against ERA5 for JJAS daily Tmax over Taiwan
Raw-GEFSv12
MB-GEFSv12
MLR-GEFSv12
QQ-GEFSv12
ANN-GEFSv12
ANN-QQ-GEFSv12
RMSE
RMSE (°C)
2
1.5
1
0.5
Day-1
Day-2
Day-3
Day-4
Day-5
Day-6
Day-7
Day-8
Day-9
Day-10
Day-11
Day-12
Day-13
Day-14
Day-15
Day-16
ANN-QQ

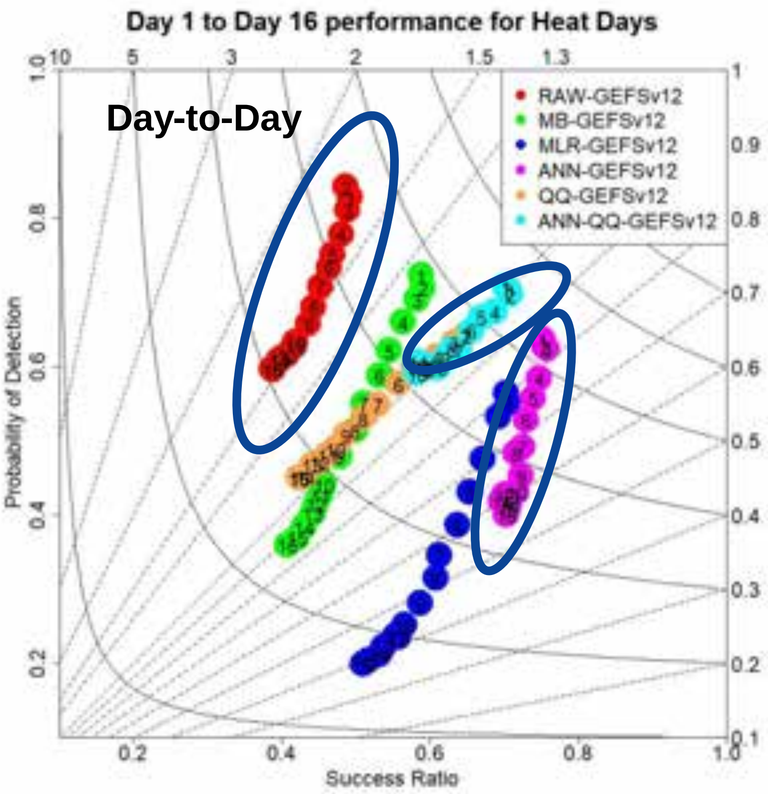

(b)
Correlation Coefficent of Raw, MB, MLR, QQ, ANN and ANN-QQ-GEFSv12 against ERA5 for JJAS daily Tmax over Taiwan
Raw-GEFSv12
MB-GEFSv12
MLR-GEFSv12
QQ-GEFSv12
ANN-GEFSv12
ANN-QQ-GEFSv12
ANN-QQ
CC
Correlation Coefficent
1
0.9
0.8
0.7
0.6
0.5
Day-1
Day-2
Day-3
Day-4
Day-5
Day-6
Day-7
Day-8
Day-9
Day-10
Day-11
Day-12
Day-13
Day-14
Day-15
Day-16

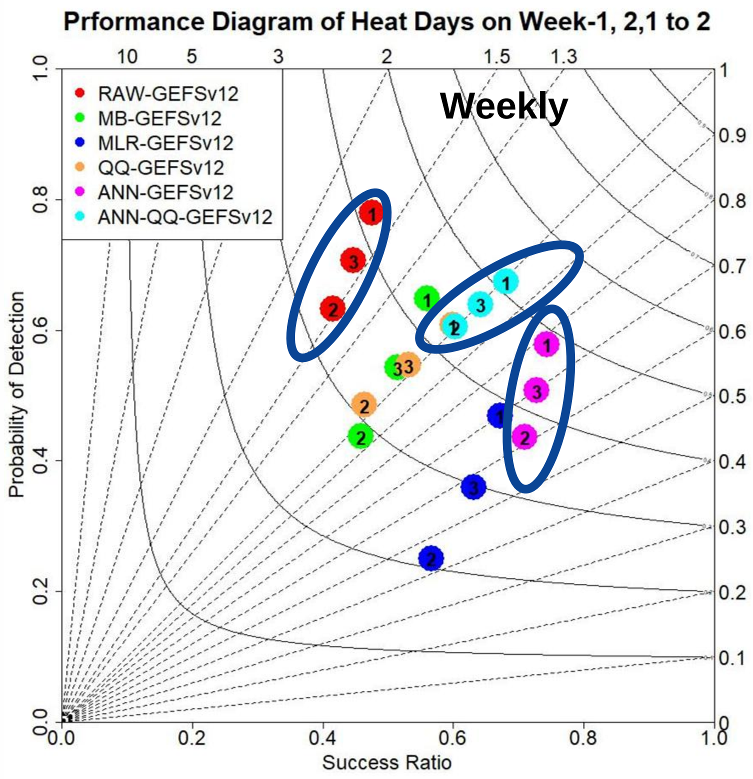

ANN-QQ
(c)
Raw-GEFSv12
MB-GEFSv12
MLR-GEFSv12
QQ-GEFSv12
ANN-GEFSv12
ANN-QQ-GEFSv12
IOA
Index of Agreement
1
0.9
0.8
0.7
Day-1
Day-2
Day-3
Day-4
Day-5
Day-6
Day-7
Day-8
Day-9
Day-10
Day-11
Day-12
Day-13
Day-14
Day-15
Day-16

ETS for Heat wave days from Raw, MB, MLR, QQ, ANN and ANN-QQ



- The ETS of GEFSv12 is relatively better for shorter lead times forecasts.
- The ANN and ANN-QQ notably increase the ETS in all lead time forecasts.
- The ETS from ANN is relatively better in all lead time forecasts than the MLR.





- **The performance diagram depicts that the ANN-QQ is relatively better than other traditional methods as well as ANN.**

Summary & Conclusions

- The GEFSv12 is able to capture the Tmax over Taiwan with all lead time forecasts. However, it has a large warm bias and also an overestimation of the IAV of Tmax in the south and interior parts of Taiwan. The prediction skill (CC and IOA) of GEFSv12 is decreased with a lead time.
- ANN remarkably reduced the warm bias, similar to other traditional calibration methods. The prediction skill (CC and IOA) improvement from the ANN is relatively higher.
- The GEFSv12 has a large overestimation of Heatwave days over Taiwan. All calibration methods remarkably reduced the overestimation HWs.
- The statistical categorical skill scores (ETS, TS, SR, and Frequency Bias) for HWs are relatively higher from ANN than the other methods. However, there is an underestimation of heat wave days from ANN.
- After incorporation of the QQ method on ANN outputs, the ANN-QQ is relatively outperforming (relatively higher statistical and categorical skill scores) for Tmax as well as its extremes than the other methods.
- The incorporation of auxiliary variables along with targeted variables as input of ANN may further improve the prediction skill.

Thank You