交通部中央氣象局委託研究計畫成果報告

台灣梅雨季節 superensemble 及 downscaling 統計之應用

計畫類別：☐國內　　∨國外

計畫編號：MOTC-CWB-98- 3M-02

執行期間：98 年 02 月 27 日至 98 年 12 月 31 日

計畫主持人：　T.N. Krishnamurti

執行單位：　T.N. Krishnamurti

中華民國　98　年　12　月

交通部中央氣象局98年度政府部門科技計畫期末摘要報告

計畫名稱：台灣梅雨季節 superensemble 及 downscaling 統計之應用

審議編號：	X	部會署原計畫編號：	MOTC-CWB-98-3M-02
主管機關：	中央氣象局	執行單位：	T.N. Krishnamurti
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期程：	98年 2月 27 日至 98 年 12 月 31 日		
經費：(全程)	930 仟元	經費(年度)	930 仟元

執行情形：

1.執行進度：

	預定（％）	實際（％）	比較（％）
當年	100	100	0
全程	100	100	0

2.經費支用：

	預定	實際	支用率（％）
當年	100	100	
全程	100	100	

3.主要執行成果：

(1) 蒐集雷達,衛星及雨量計觀測之降雨資料，並且內插到1.2公里的解析度。

(2) 備妥台灣地區1.2公里解析度網格日降雨觀測資料於2006年和2007年5，6月及2008年6月訓練期間。

(3) 蒐集多重大尺度模式之降雨預報。

(4) 使用2所得之觀測資料來 statistically downscale 多重大尺度模式5天預報，其中包含每個模式在整個 domain 訓練期間內(如2中) downscale slope 和 intercept coefficients 的計算。

(5) 使用 downscale 的資料來執行 superensemble 的訓練，以使獲得每個模式在 superensemble 預報之加權。

(6) 使用 downscale slope 和 intercept coefficients(如4) 來 downscale 每個大尺度模式之預報期間(2008年6月)。

(7) 使用訓練期間所得之加權及預報期間多重模式 downscale 之結果來做5天 superensemble 降雨預報。

(8) 對台灣預報期間(2008 年 6 月)的每個降雨預報做技術評估。

4.計畫變更說明：None

5.落後原因：None

6.主管機關之因應對策（檢討與建議)：

台灣梅雨季節 superensemble 及 downscaling 統計之應用

1. Introduction

This is a summary of our consulting project with the CWB in Taiwan. It entails a demonstration on the workings of the FSU downscaled superensemble for high resolution precipitation forecasts over the Taiwan Region for June 2008. This work is based on our recent work :

Krishnamurti, T.N., A.K. Mishra, A. Chakraborty, and M. Rajeevan, 2009: Improving Global Model Precipitation Forecasts over India Using Downscaling and the FSU Superensemble. Part I: 1–5-Day Forecasts. /Mon. Wea. Rev./, *137*, 2713–2735.

This work carries eight components:

a) Collecting radar /satellite based rainfall and interpolate, where necessary, all to a 1.2km resolution.

b) Prepare high resolution gridded rainfall files for the Taiwan region at 1.2 km covering the months May and June of the years 2006 and 2007 and for June 2008 . Interval of rainfall totals 24 hourly per day.

c) Collect large scale multimodel forecasts from a suite of operational models.

d) Downscale all multimodel forecasts using the observed radar/satellite based rains covering each model and each day of forecasts through day 5.Obtain the downscaling slope and intercept coefficients for each model over entire domain for the training period.

e) Carry out multimodel superensemble using the downscaled supereensemble methodology during training phase to obtain weights for the forecast superensemble.

f) From the member model forecasts during the forecast phase first carry out the downscaling of member model forecasts for each model using the slope and intercept coefficients of step d.

g) Using the weights of the downscaled multimodel superensemble carry out multimodel superensemble forecasts from the entire suite of models through day 5 of forecasts.

h) Apply skill metrics to evaluate each forecast over the Taiwan Domain .

We shall be presenting these results here and we are willing to demonstrate this work in detail. These are for the year 2008.

The following Tables and appendices are provided here:

Table 1 List of member Models.

Appendix 1 Superensemble Methodology

Appendix 2 Downscaling Algorithm

Appendix 3. Skill score METRICS

2. Rainfall data sets.

Taiwan CWB provided the radar data sets that carried rainfall at a resolution of 1.2km over Taiwan. Our computational Taiwan domain is somewhat bigger, it covers 21.5N to 26N and 118E to 123.5 E . To cover the oceans around Taiwan we have incorporated the TRMM 3B42 data sets and merged the two data sets. The TRMM data sets are available for download from their web site easily on a 3 hourly basis at 25 km horizontal resolution. Radar data takes precedence over TRMM where radar data are available. The TRMM data is simply linearly interpolated to the 1.2km resolution and all final observed rain is at the 1.2 km resolution. This data sets covers, for training, daily totals for May and June of the years 2006 and 2007 and for the forecast phase it covers the month of June for the year 2008 . Sample rainfall illustrations are provided in the illustrations to follow.

3. Forecast results over the Taiwan Area during June 2008.

The training phase consisted of 5 day daily forecasts from the downscaled superenesmble over the Taiwan area covering the periods May, June for the years 2006 and 2007. This 4 months of training provided robust results for the superensemble weights. Minimally 120 days of training days seem to equilibrate the training weights. The downscaled resolution is 1.2 km. the model resolutions are provided in Table 1. We shall sequentially describe the forecast phase results, this phase covered the entire month of June 2008.

Figs 1 and 2 show the equitable threat scores and the bias scores(See appendix 2) respectively for day 1 of forecasts for this entire month. This includes the suite of models shown in Table 1. The abscissa of Fig 1 are the thresholds, i.e. 25 mm/day or above carries the highest equitable threat score in this one day forecast from the multimodel downscaled superensemble. Over all the multimodel superensemble carries the best forecast. The best single model of this suite is the UK Met model. The improvements from the downscaled multimodel superensemble are very significant. For low rain rates, i.e. less than 5 mm/day, the improvement over the best model is small, same is true for very high rain rates above 50mm/day. For moderate rain rates, such as 25mm/day, which is still quite heavy rain, the improvements are very large. This was a consistent result and this can be easily implemented by the Taiwan CWB for their interests. The bias score is illustrated in Fig 2. As seen in appendix 2, a bias score of 1.0 is considered the best forecast. As can be seen in Fig 2 the best bias scores are carried by the multimodel for all rain rate thresholds. The abscissa of Fig 2 carries these thresholds and the ordinate denotes the bias scores. Most models carry very large bias errors, such as the GFS which has bias errors around 4 for moderate rains..This is another significant contribution of the downscaled multimodel superensemble for day 1 of forecast. For day 3 of forecasts shown in figs 3 and 4 the ETS scores and their bias scores respectively, The results again confirm essentially the same superiority of the skill of precipitation forecasts for the downscaled multimodel superensemble as compared to all member models. The ETS scores on day 3 are in fact quite a bit higher compared to day 1 of forecasts. This has to do with the member model spin up of precipitation. The bias scores on day 3 are a bit less for the downscaled superensemble, being closer to 2.0 as against day 1 of forecast when they were closer to 1.0. Nevertheless the downscale superensemble carries the best bias scores compared to all member models in a rather consistent manner for days 1 through 3 of forecasts. What this means is that CWB can issue a downscaled forecast for precipitation at 1.2km resolution that would be consistently superior to the forecast provided by the best model available to them.

In figs 5 we show the entire month June 2008, rainfall totals from day 1 of forecasts. and the area averaged skills. The total area averaged rain is shown on top inset in each diagram, the bottom insets include the rms errors and the spatial correlations. The bottom scores and the details of patterns are most important. The pattern of details on mesoscale are best seen from the superensemble that carries the least rms errors and the highest spatial correlations as compared to all member models. The JMA model carries a spatial correlation of 0.09 whereas using the downscaled superensemble it is possible to improve that to 0.93. This is what the downscaled superensemble is all about. This also captures many details on the high resolution.

In figures 6 through 13 we present several sample forecasts of day 1 of forecasts. These show the rainfall patterns and the rms/pattern correlation skills for each of many days during June 2008 . The downscaled superensemble clearly carries mesoscale details that are not present in the results of forecasts of the large scale member models, nor are they seen in their ensemble mean. Almost every single downscaled superensemble forecast shows the lowest rms forecast skill and the highest value for the spatial correlation. In this sense these forecasts from the downscaled superenesmble forecasts are very consistent .They nearly always perform better than all member models. The mesoscale precipitation forecast details are very impressive for the Taiwan region, that was the goal of this study.

Similar high skills were noted for days 2 and 3 of forecasts But the skills seem to slowly decrease by day 5 of forecasts. Sample day 5 of forecasts are illustrated in figures 14 through 16.Even though the forecasts skills had gone lower by day 5 of forecasts, those from the downscaled multimodel superensemble were still somewhat better than those of the best model. .ECMWF did carry high forecast skills, but theirs were large scale rainfall patterns, the downscaled superenesemble carried mesoscale rainfall patterns with a skills comparable or higher than those of ECMWF for day 5 of precipitation forecasts. Most models carried very low skills at day 5. Having the ECMWF in this suite of models for this longer range day 5 of forecast was very helpful. Our recommendation to CWB is that they include ECMEF model in their multimodel suite if they wish to go as long as day 5 of forecasts.

In figures 17 through 21 we show maps of temporal correlatioons for the forecasts for the entire month June 2008. This includes forecasts for days 1, 2,3 and 5. We show these results for 5 best models, the ensemble mean, the bias corrected ensemble mean and the downscaled multimodel superensemble. Overall again the results seem to confirm that the overall temporal correlations for the Taiwan Domain are best provided by the downscalled multimodel superensemble as comapred to all member models and the ensemble mean ensemble mean. We also show a bias corrected ensemble mean here, whose performance was close to that of the multimodel downscaled superensemble. Overall the results do degrade by day 5 of forecasts but the results from the downscaled multimodel superensemble defines the current state of the art.

Table 1 TIGGE Models

Center	Ensemble members	Model resolution (lon×lat)	Forecast length
ECMWF	51	N200 (Reduced Gaussian)	10 d
ECMWF	51	N128 (Reduced Gaussian)	10–15 d
UKMO	24	$1.25^\circ \times 0.83^\circ$	15 d
JMA	51	$1.25^\circ \times 1.25^\circ$	9 d
NCEP	21	$1.00^\circ \times 1.00^\circ$	16 d
CMA	15	$0.56^\circ \times 0.56^\circ$	10 d
CMC	21	$1.00^\circ \times 1.00^\circ$	16 d
BOM	33	$1.50^\circ \times 1.50^\circ$	10 d
MF	11	$1.50^\circ \times 1.50^\circ$	2.5 d
KMA	17	$1.00^\circ \times 1.00^\circ$	10 d
CPTEC	15	$1.00^\circ \times 1.00^\circ$	15 d

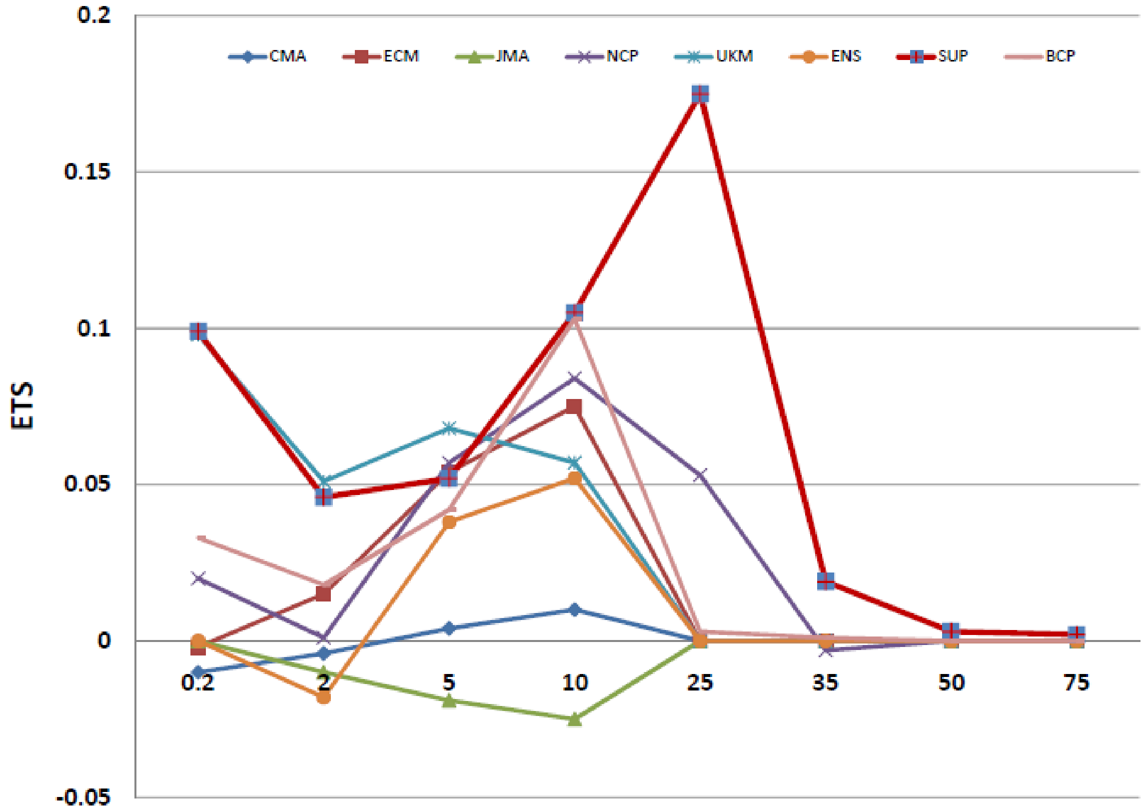

Figure 1:

Equitable Threat Score for different thresholds (x-axis in mm/day) on Day 1 Multimodel Forecasts for June 2008

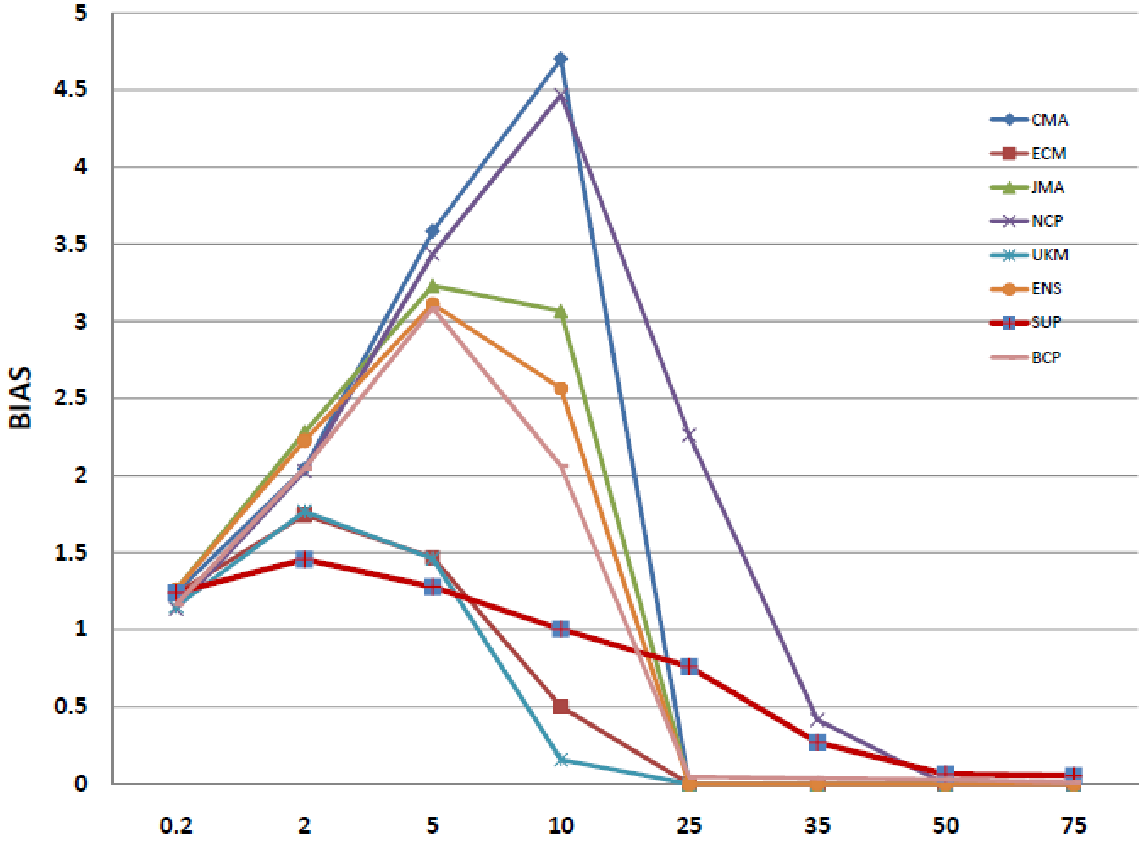

Figure 2:

BIAS Score on Day 1 Multimodel Forecasts for June 2008

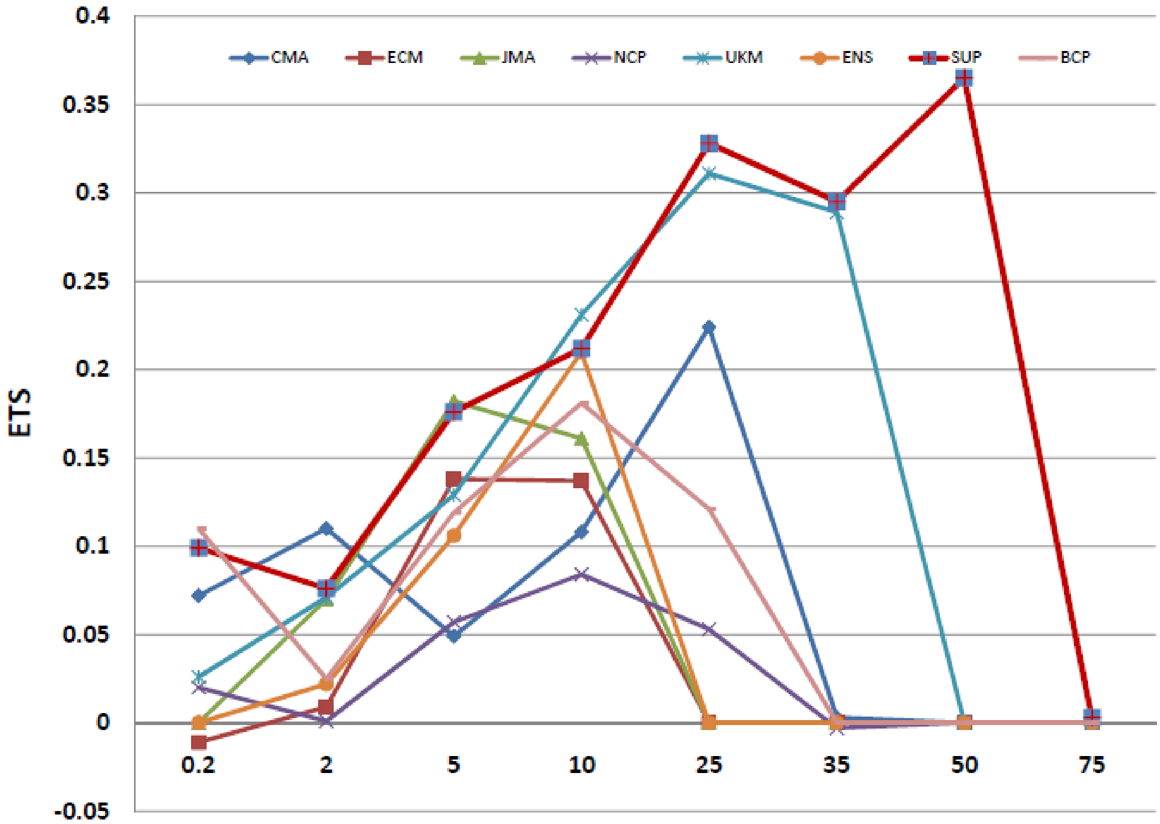

Figure 3:

Equitable Threat Score for different thresholds (x-axis in mm/day) on Day 3 Multimodel Forecasts for June 2008

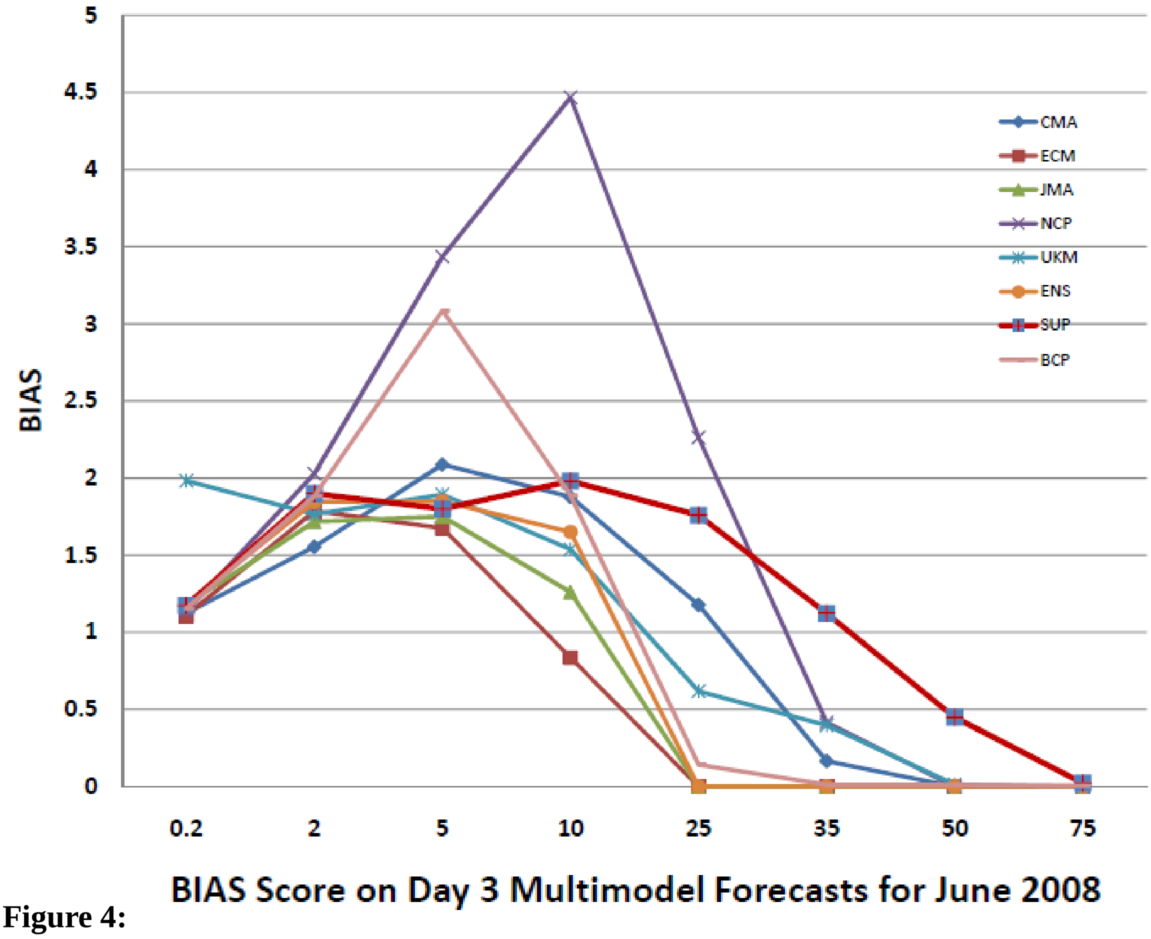
5
4.5
4
3.5
3
2.5
2
1.5
1
0.5
0
BIAS
0.2
2
5
10
25
35
50
75
CMA
ECM
JMA
NCP
UKM
ENS
SUP
BCP
BIAS Score on Day 3 Multimodel Forecasts for June 2008

Figure 4:

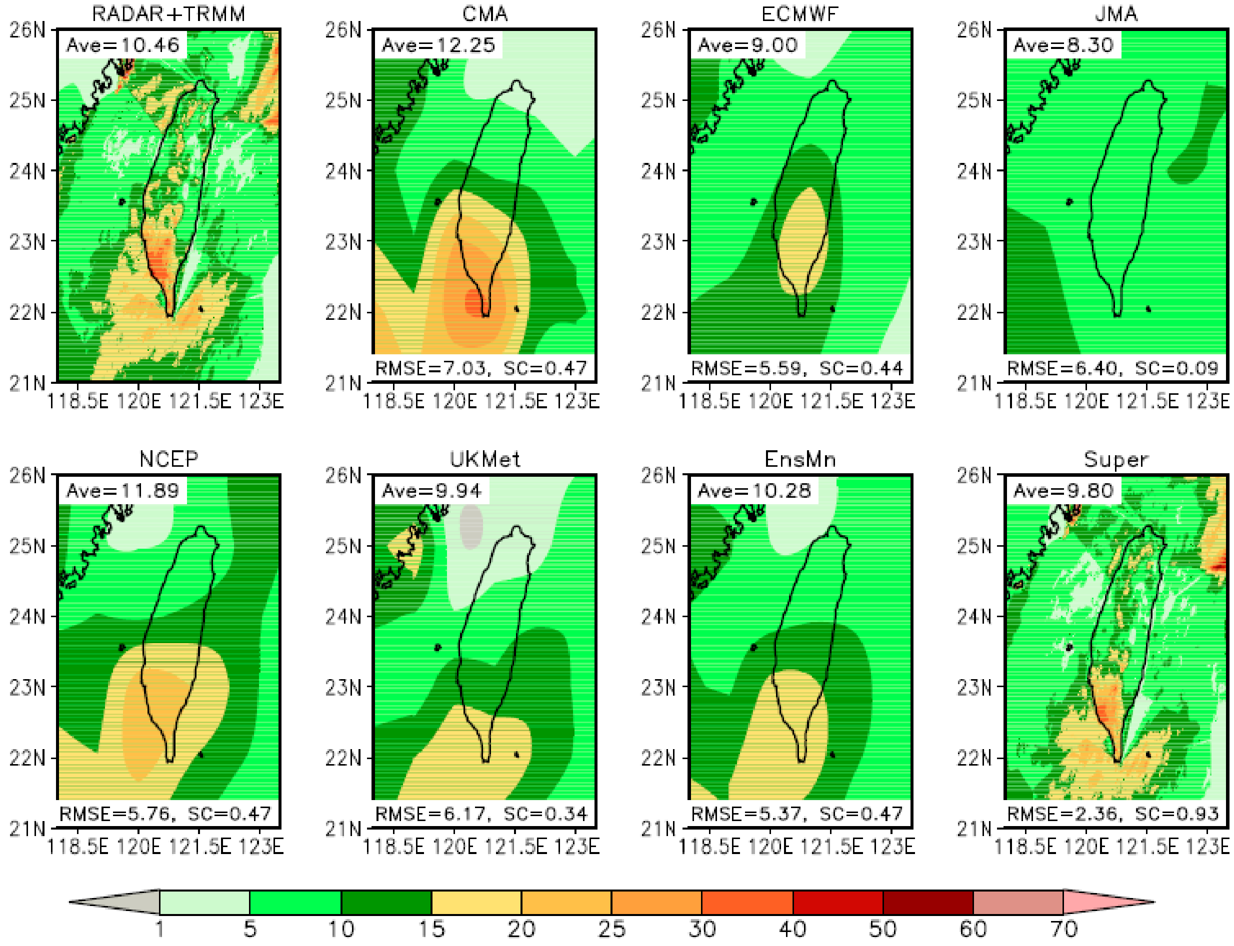

Figure 5:

Skills for Day1 Multimodels forecasts during June 2008

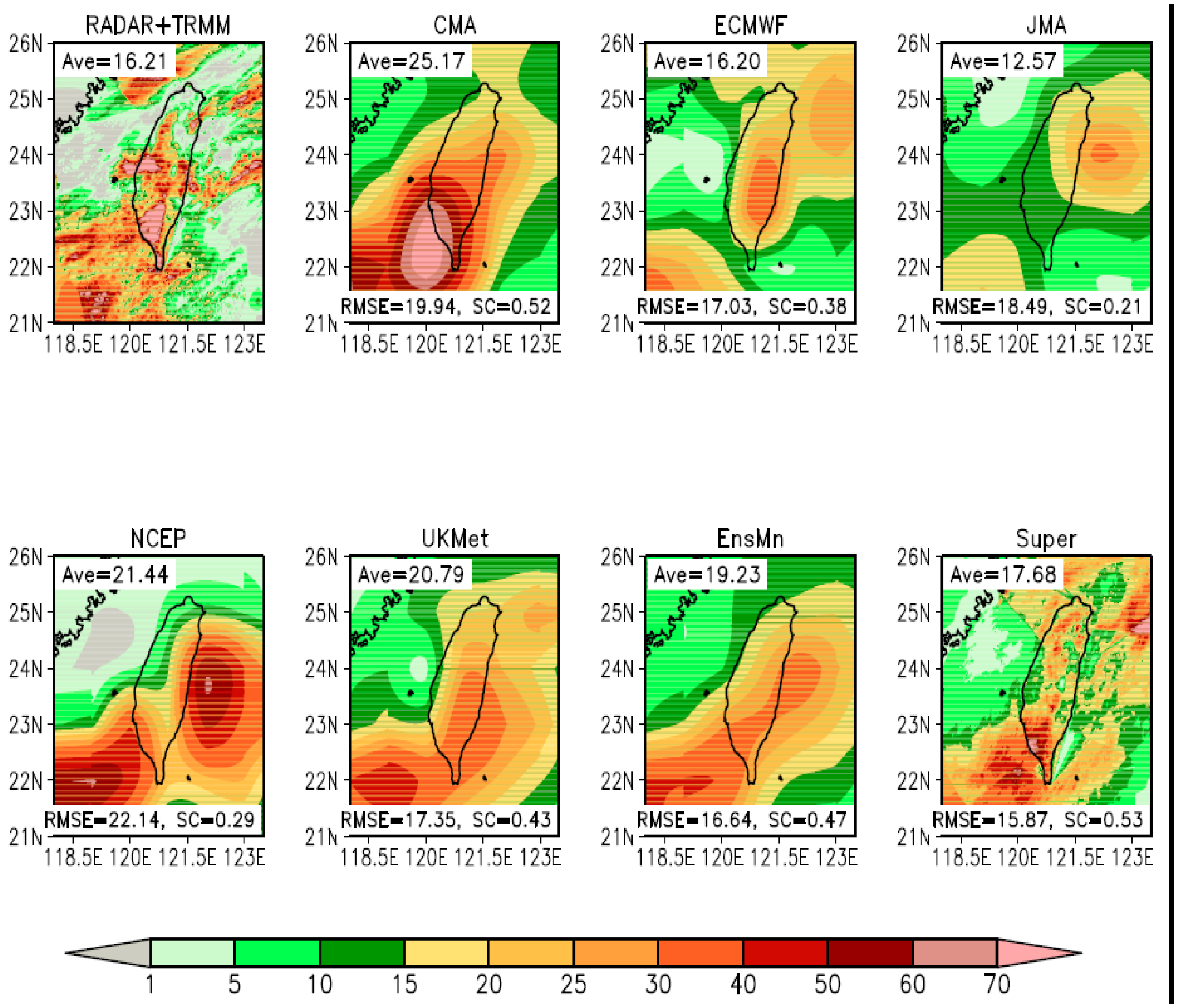

Figure 6:

Skills for Day1 Multimodels forecasts issued on 1st June 2008

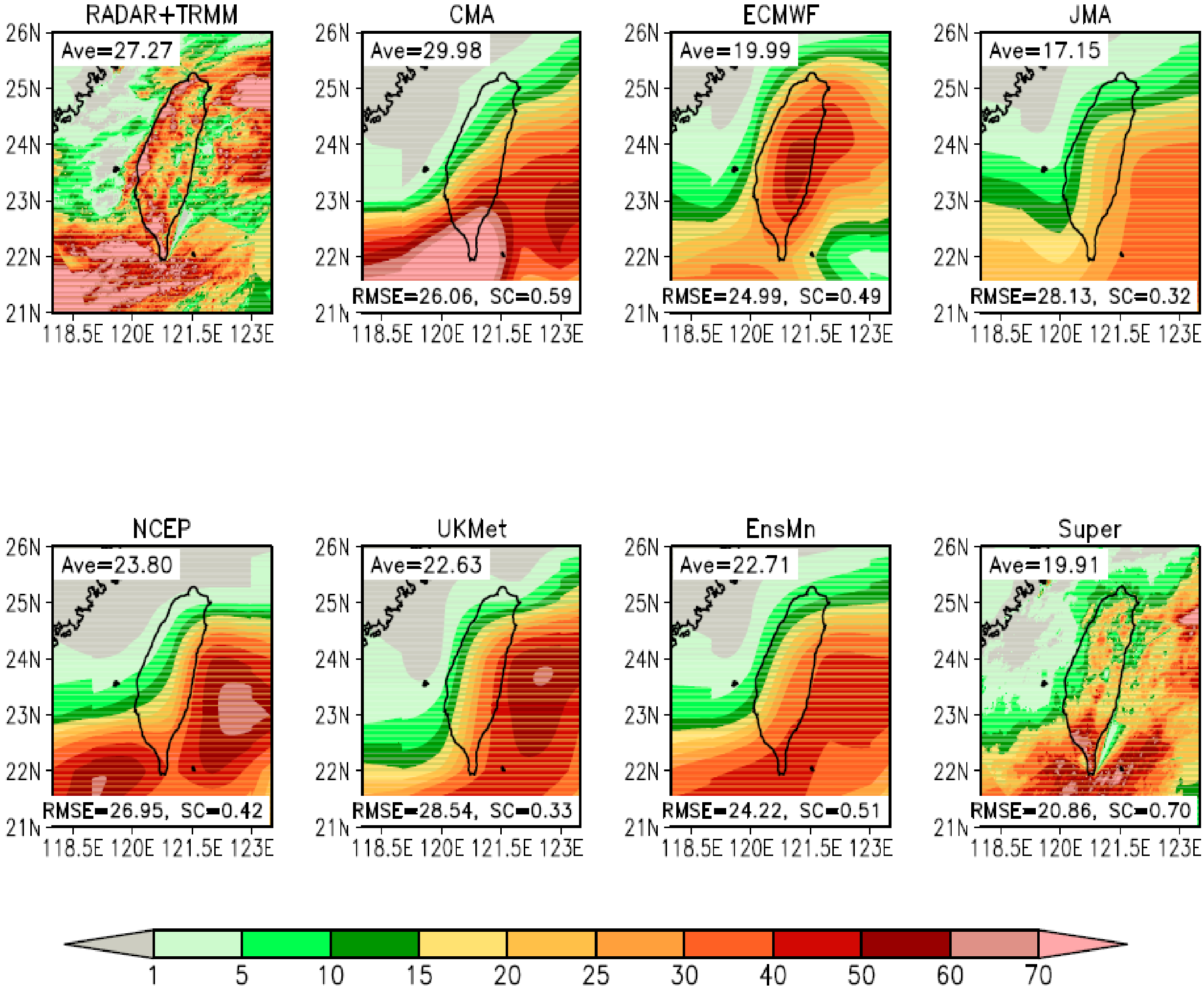

Figure 7:

Skills for Day1 Multimodels forecasts issued on 2nd June 2008

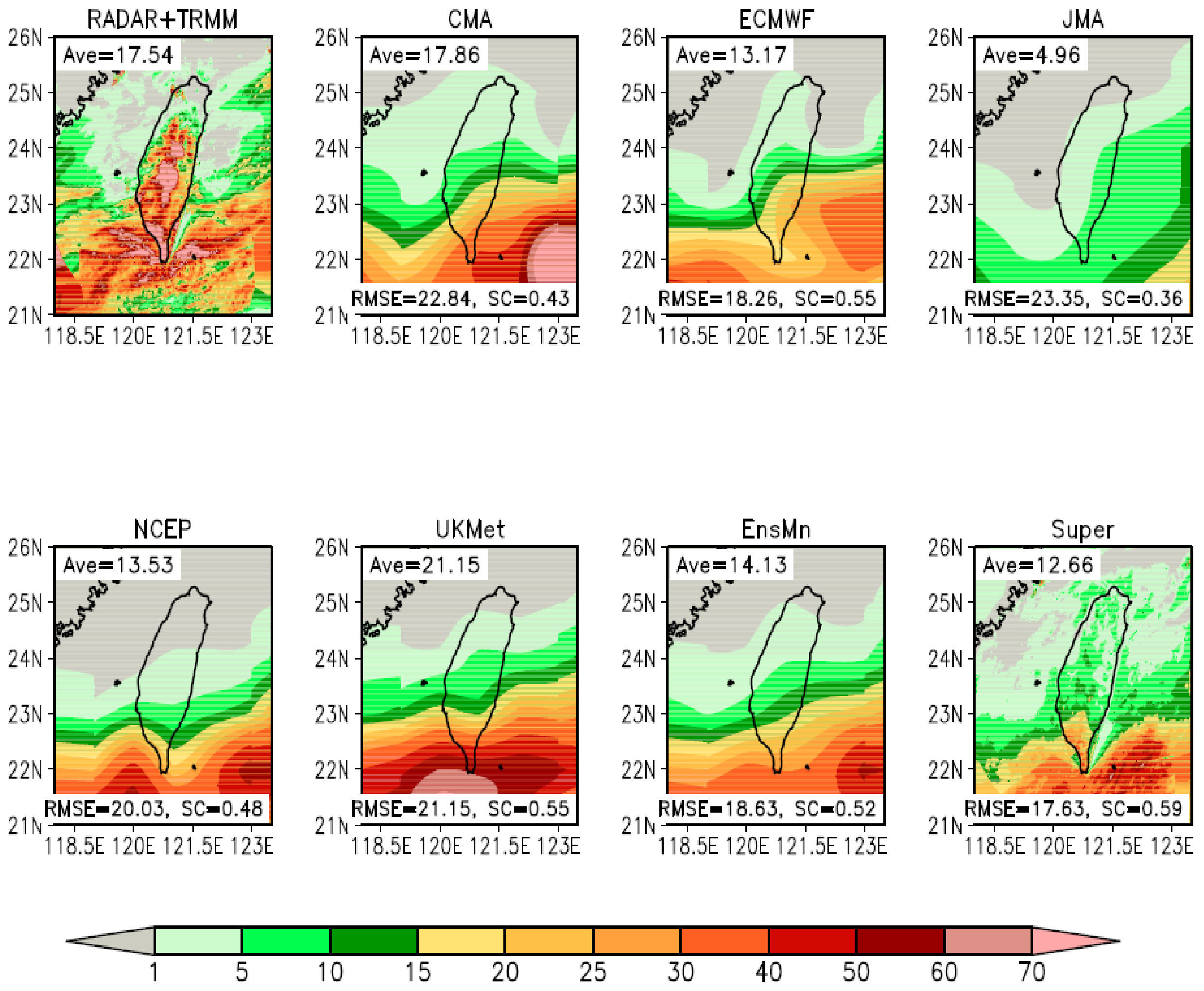

Figure 8:

Skills for Day1 Multimodels forecasts issued on 3rd June 2008

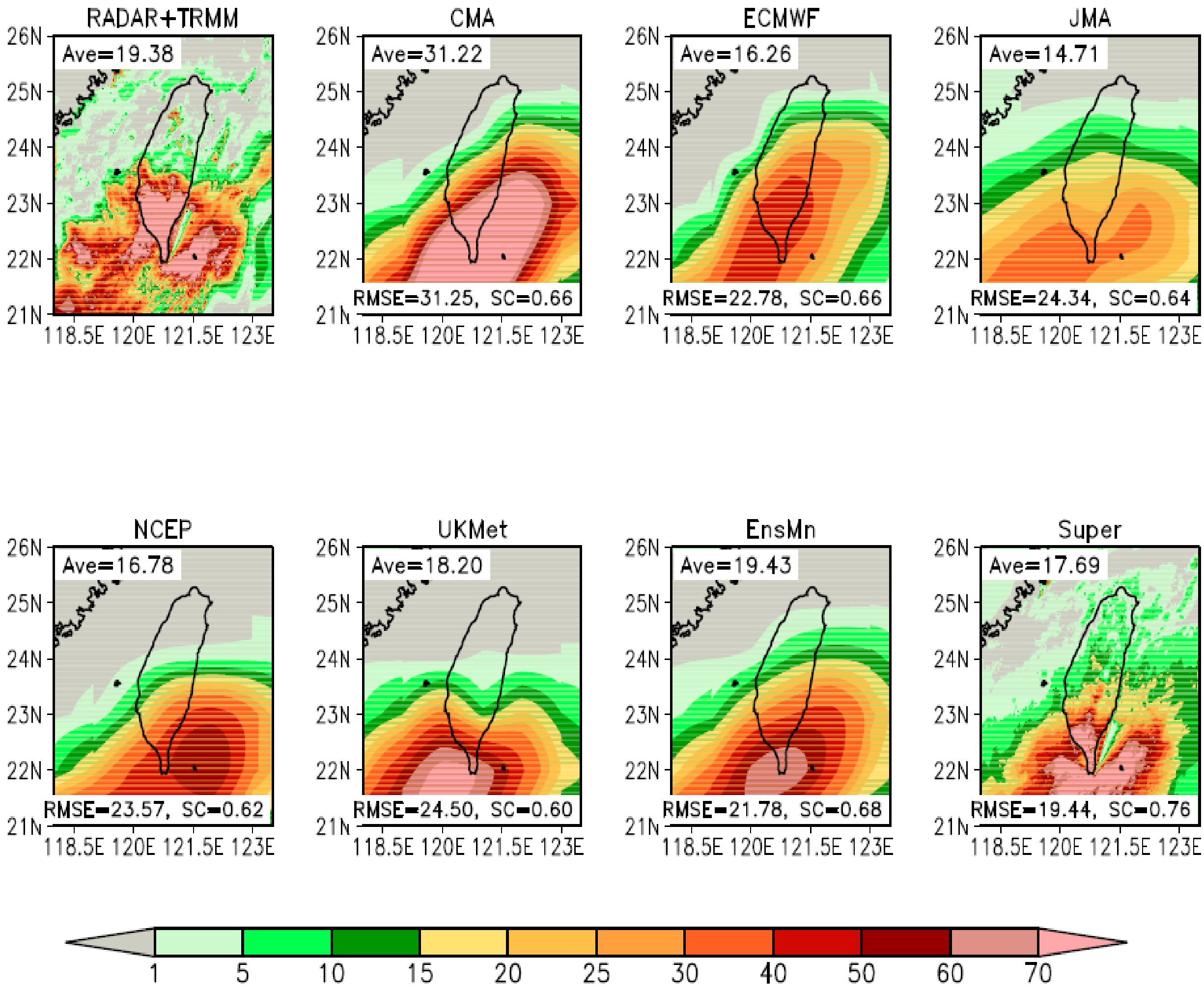

Figure 9:

Skills for Day1 Multimodels forecasts issued on 4th June 2008

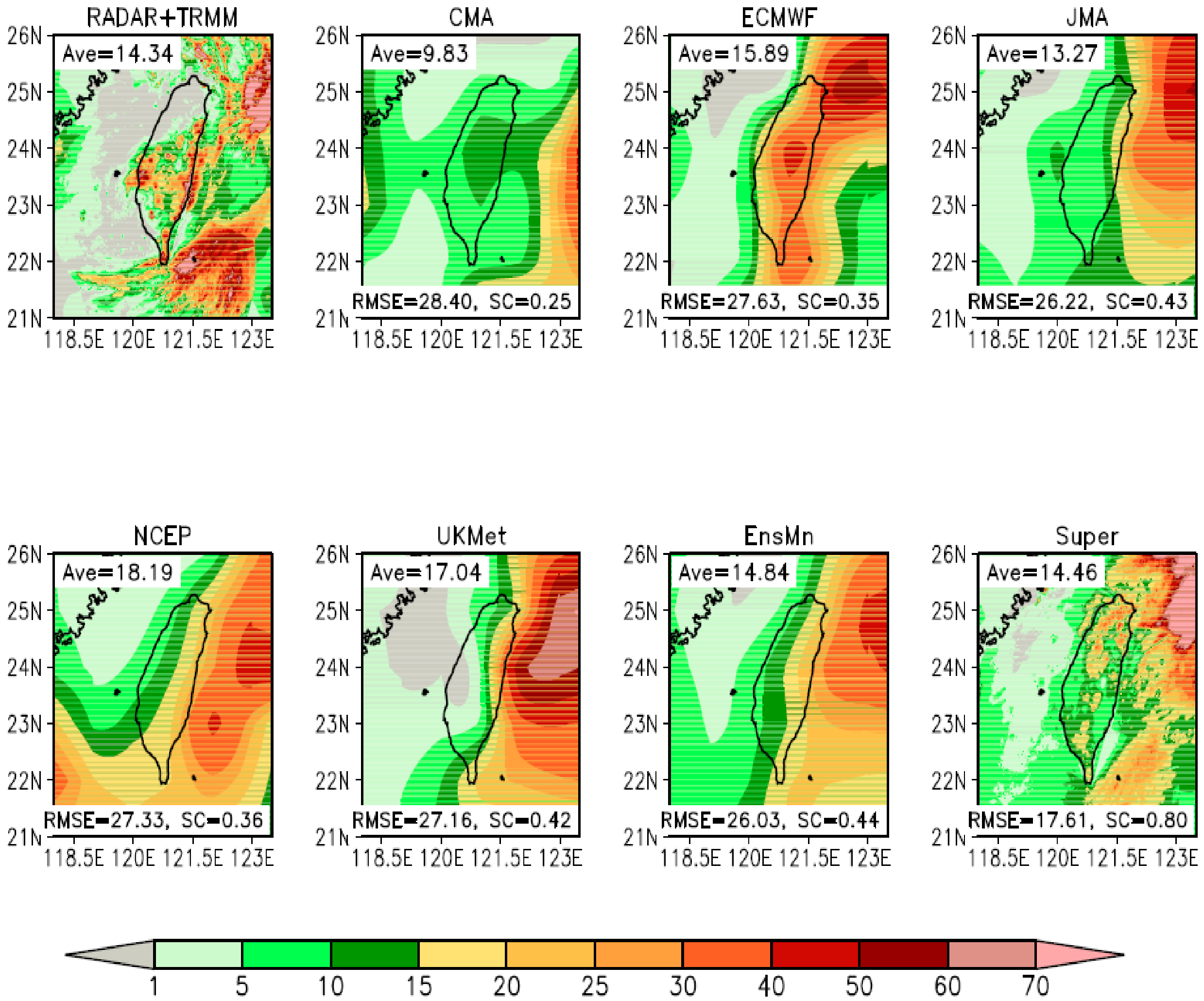

Figure 10:

Skills for Day1 Multimodels forecasts issued on 5th June 2008

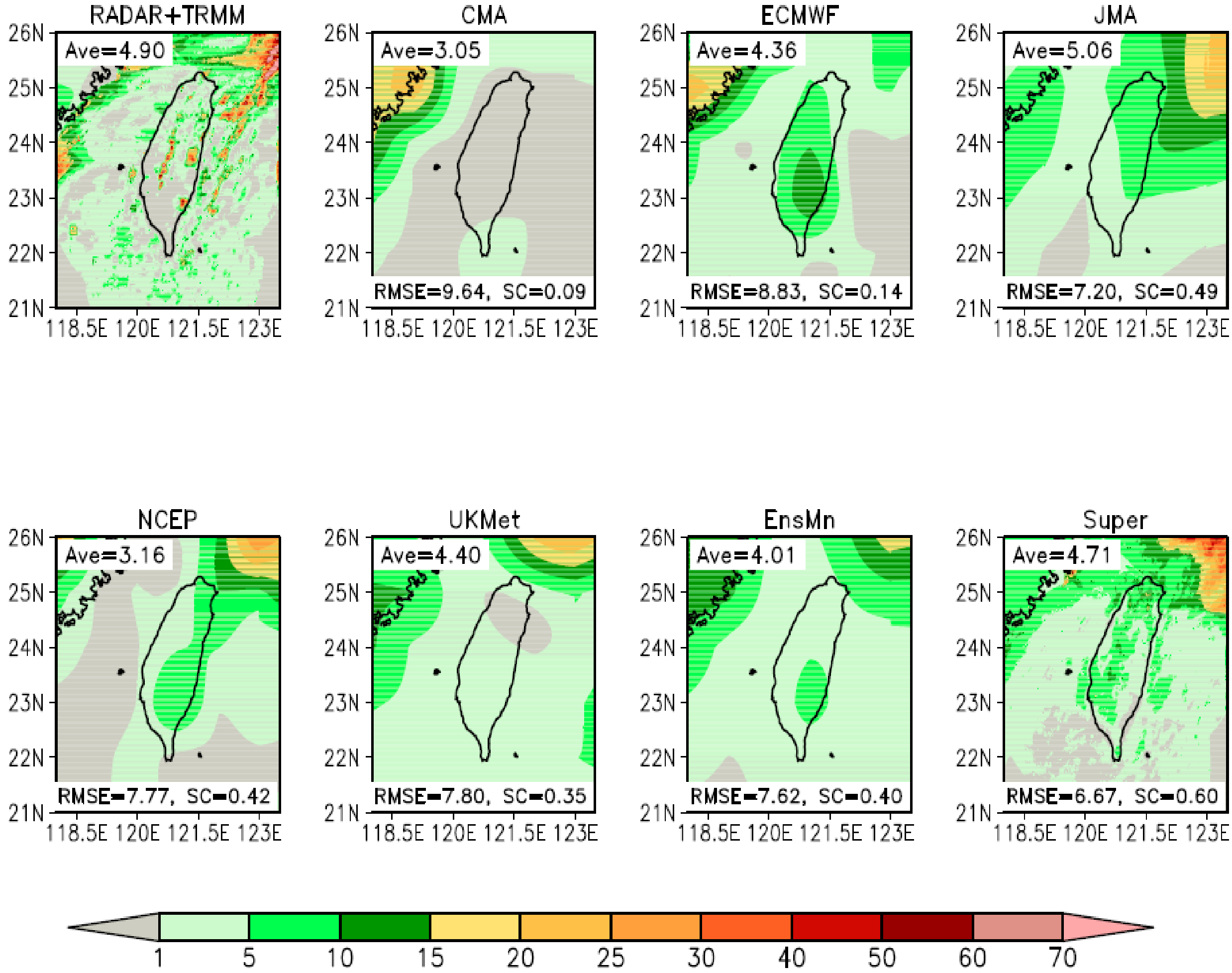

Figure 11:

Skills for Day1 Multimodels forecasts issued on 7th June 2008

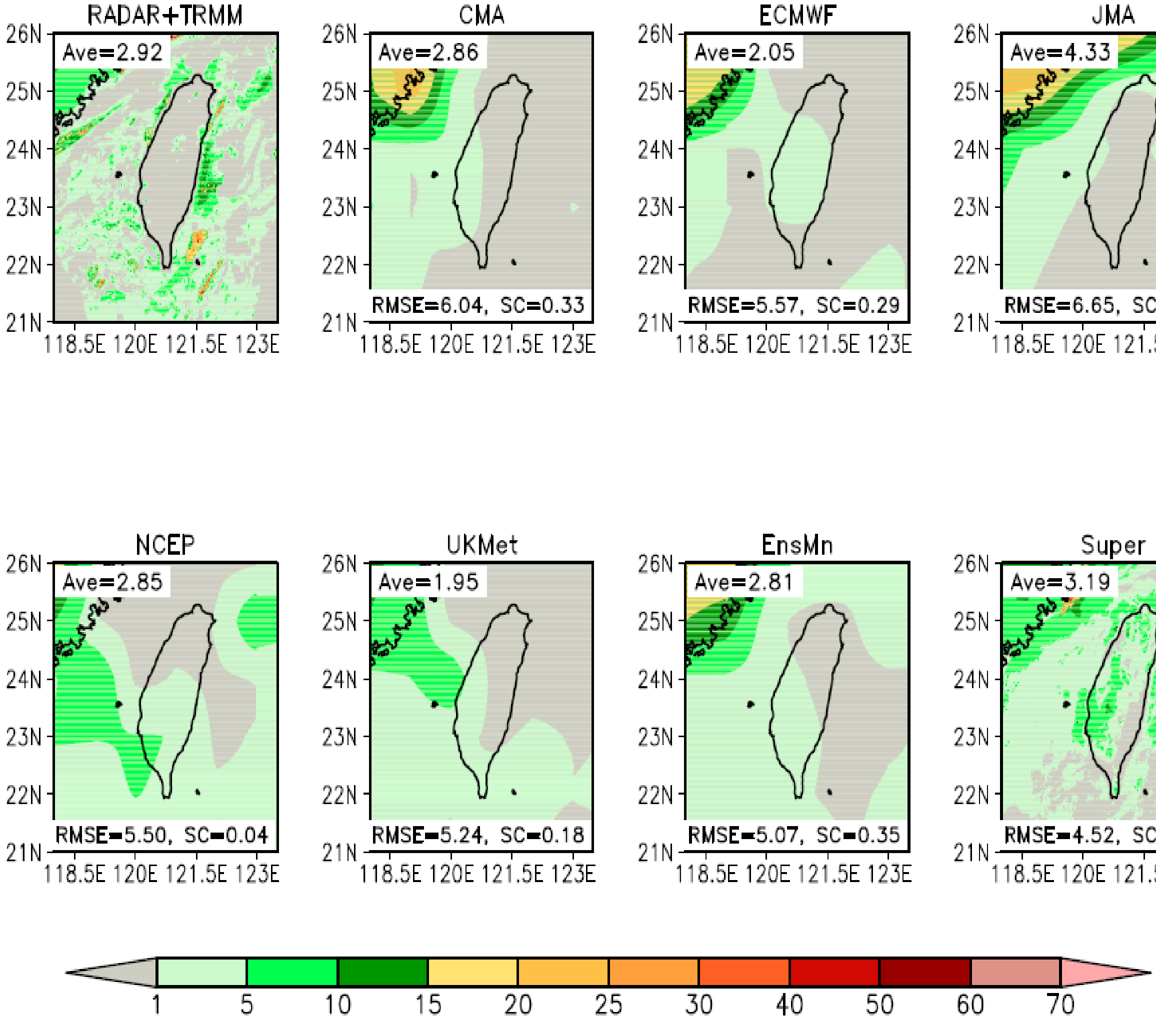

Figure 12:

Skills for Day1 Multimodels forecasts issued on 10th June 2008

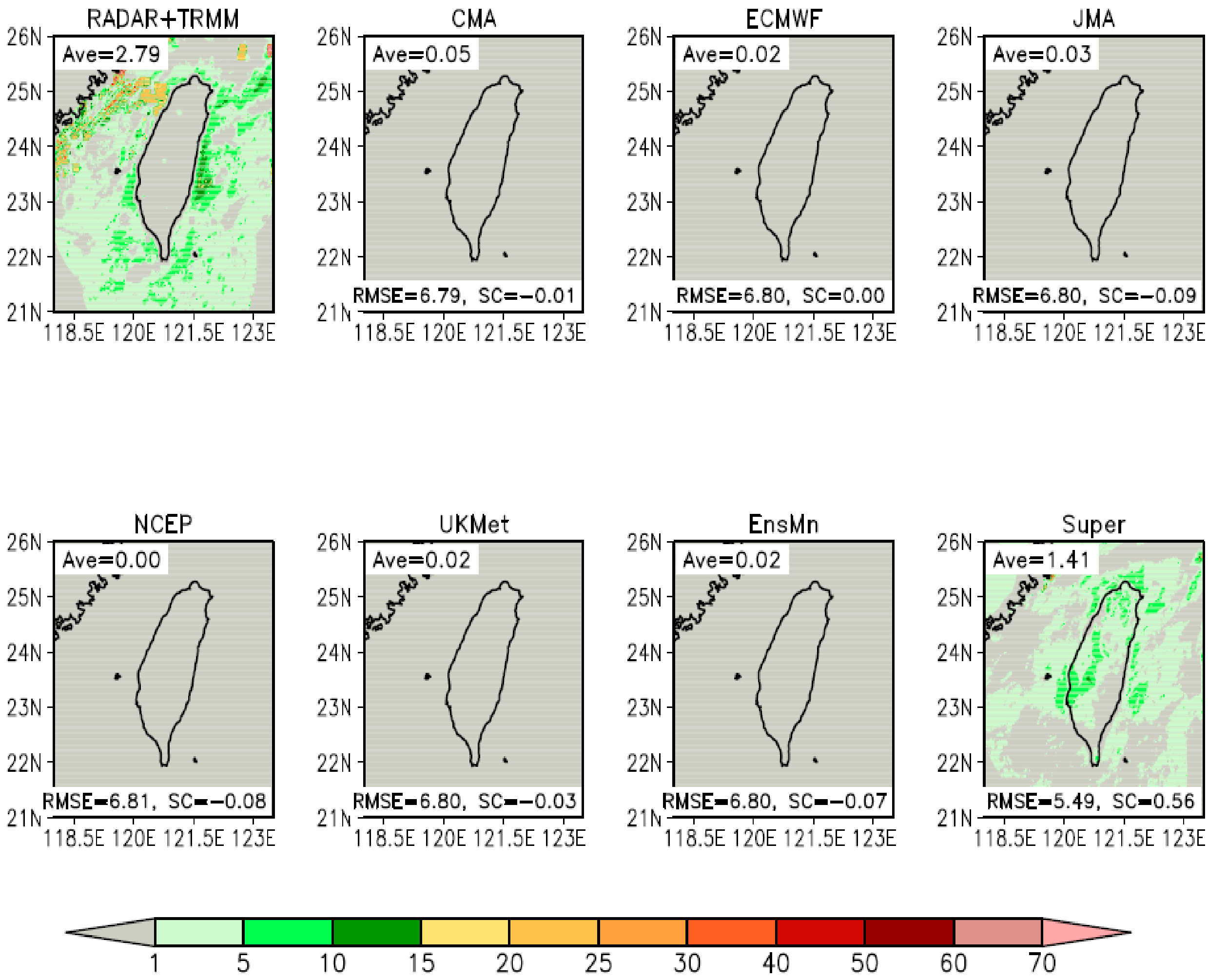

Figure 13:

Skills for Day1 Multimodels forecasts issued on 20th June 2008

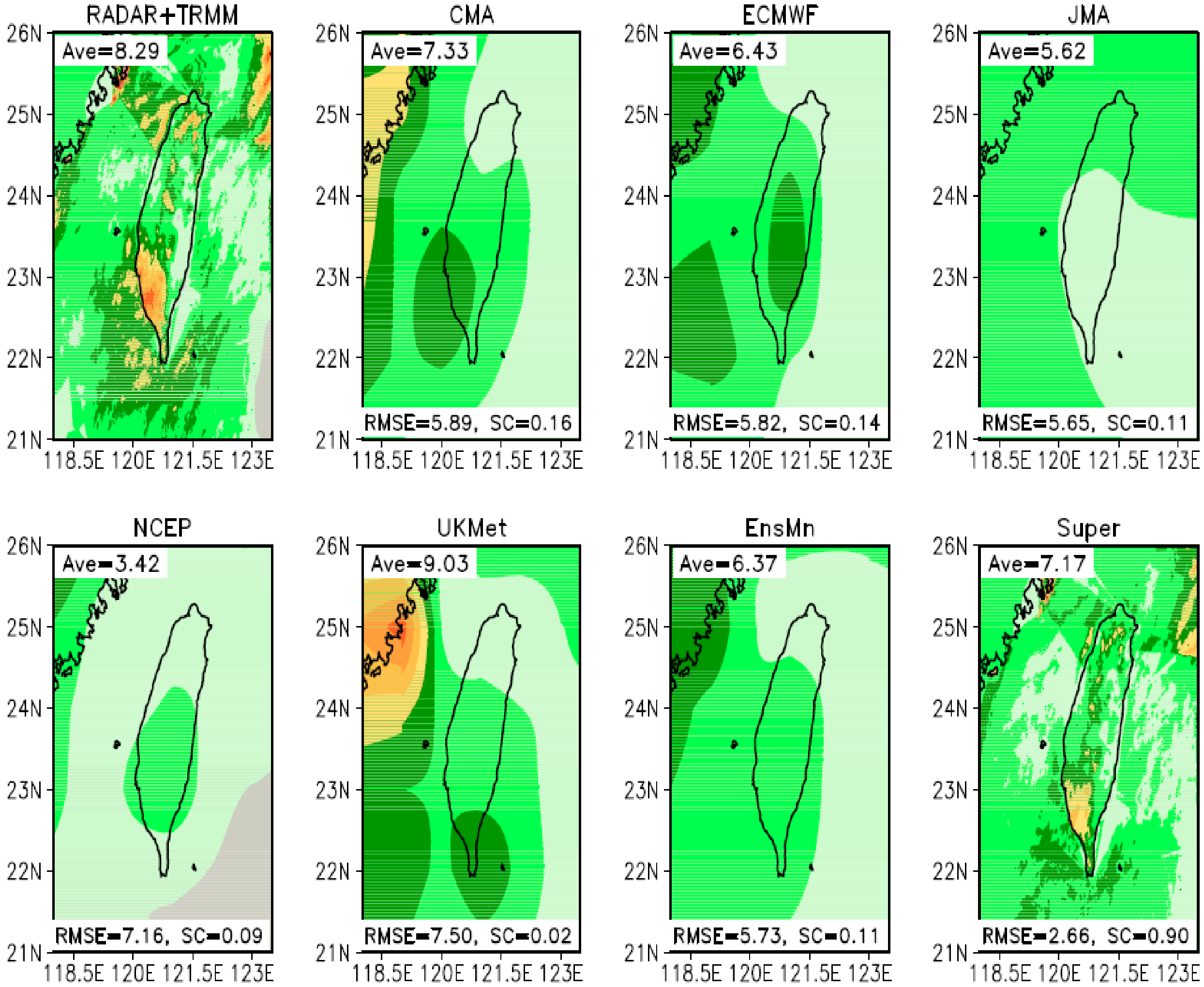

Figure 14:

Skills for Day5 Multimodels forecasts during June 2008

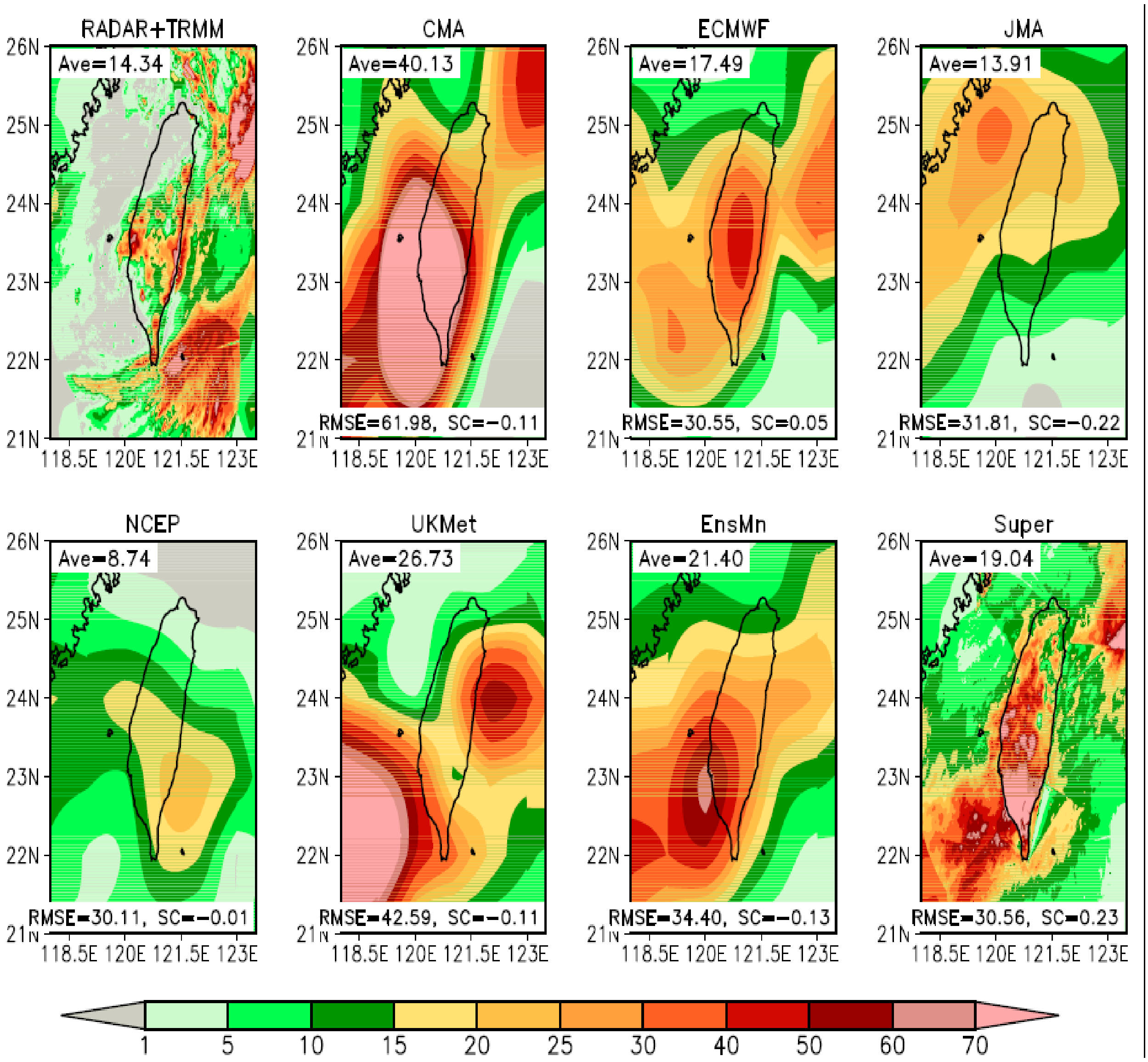

Figure 15:

Skills for Day5 Multimodels forecasts issued on 2nd June 2008

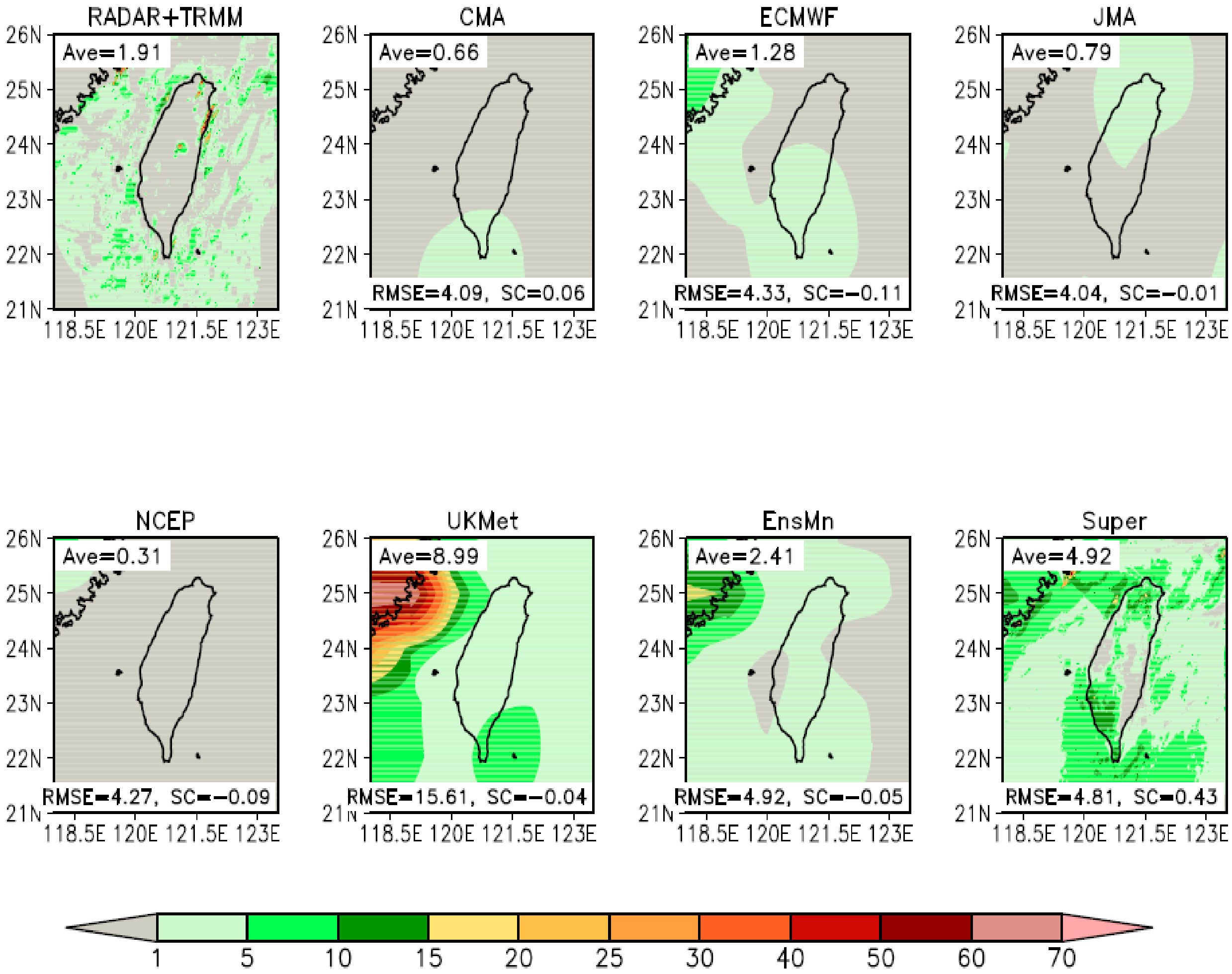

Figure 16:

Skills for Day5 Multimodels forecasts issued on 5th June 2008

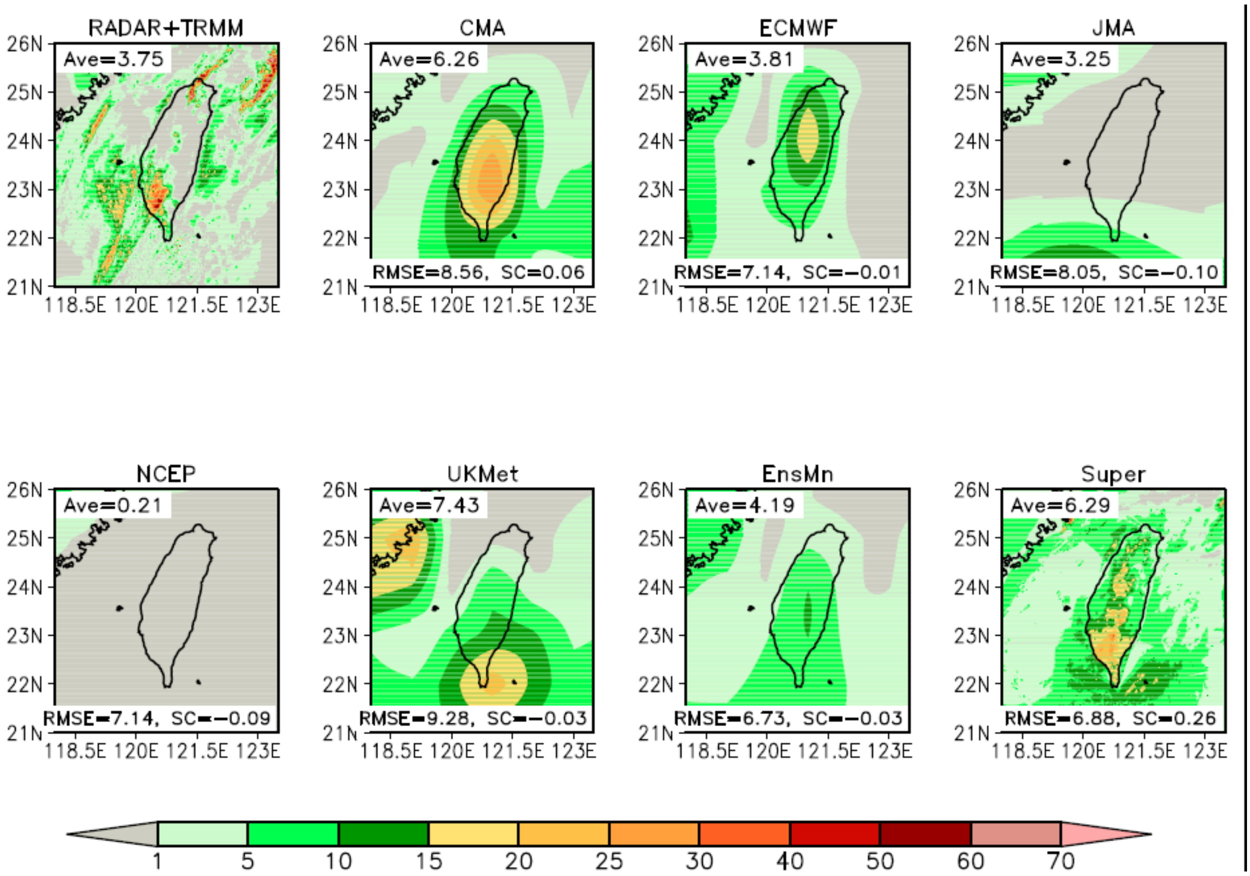

Figure 17:

Skills for Day5 Multimodels forecasts issued on 20th June 2008

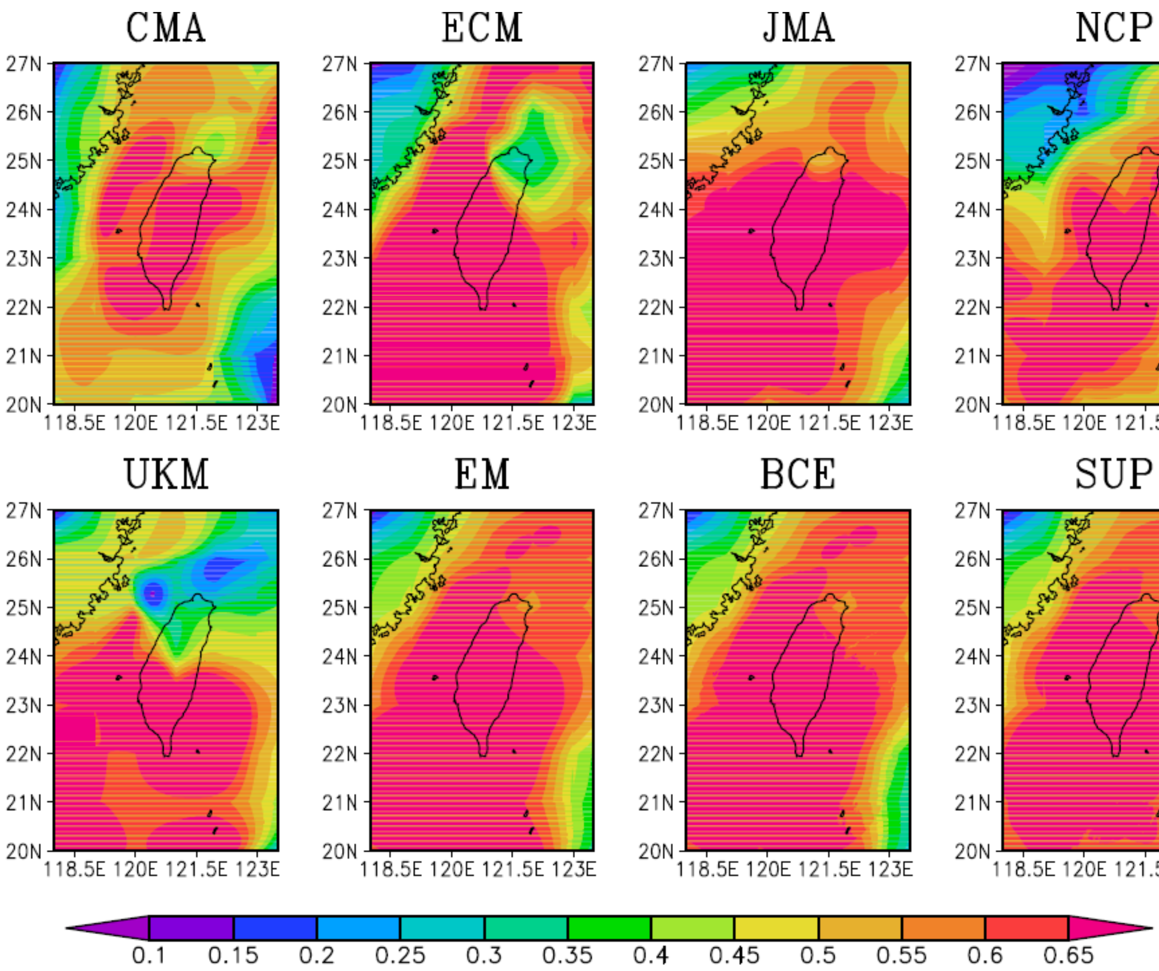

Figure 18:

Temporal Correlation for Multimodels Day 1 forecasts during June 2008

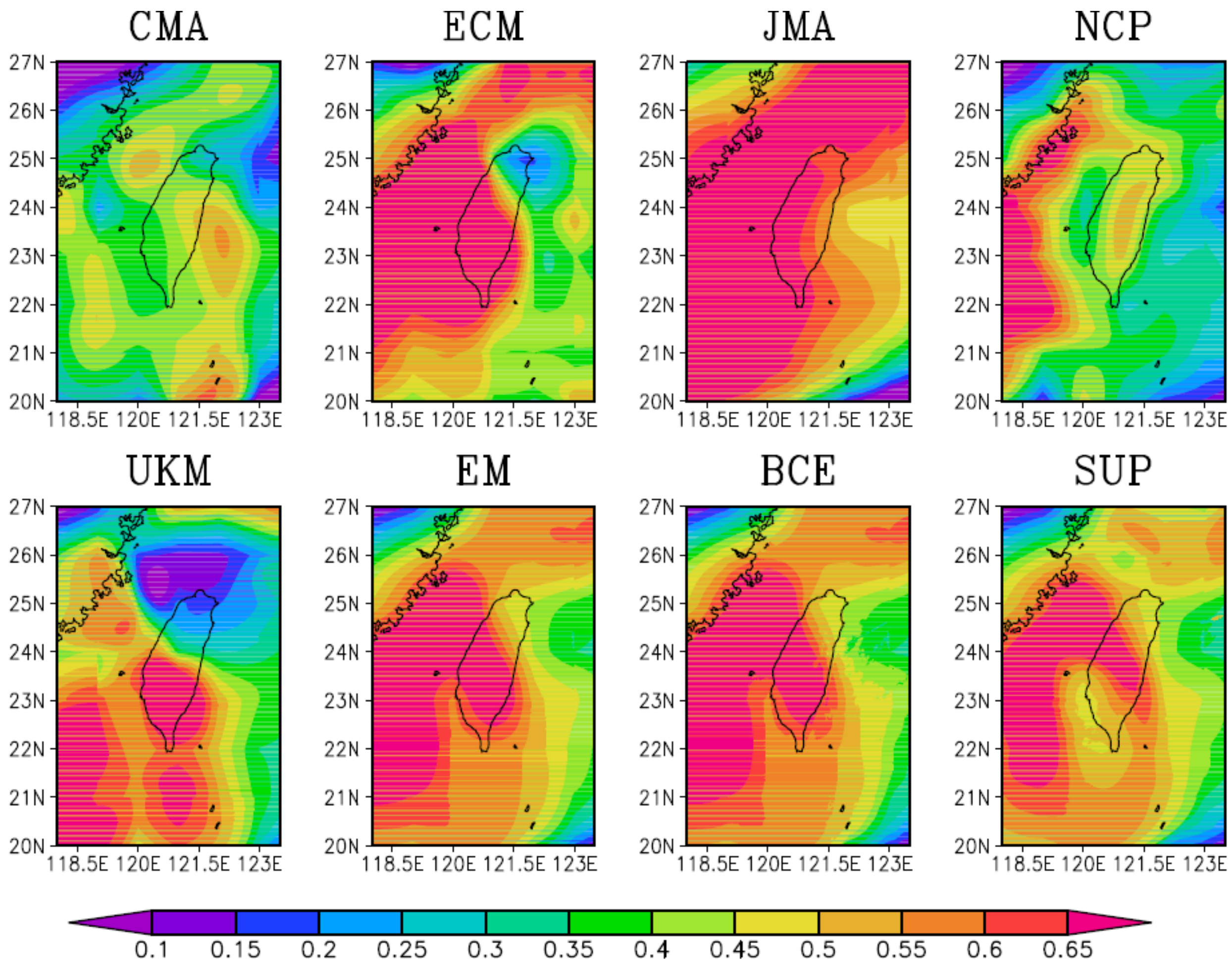

Figure 19:

Temporal Correlation for Day2 Multimodels forecasts during June 2008

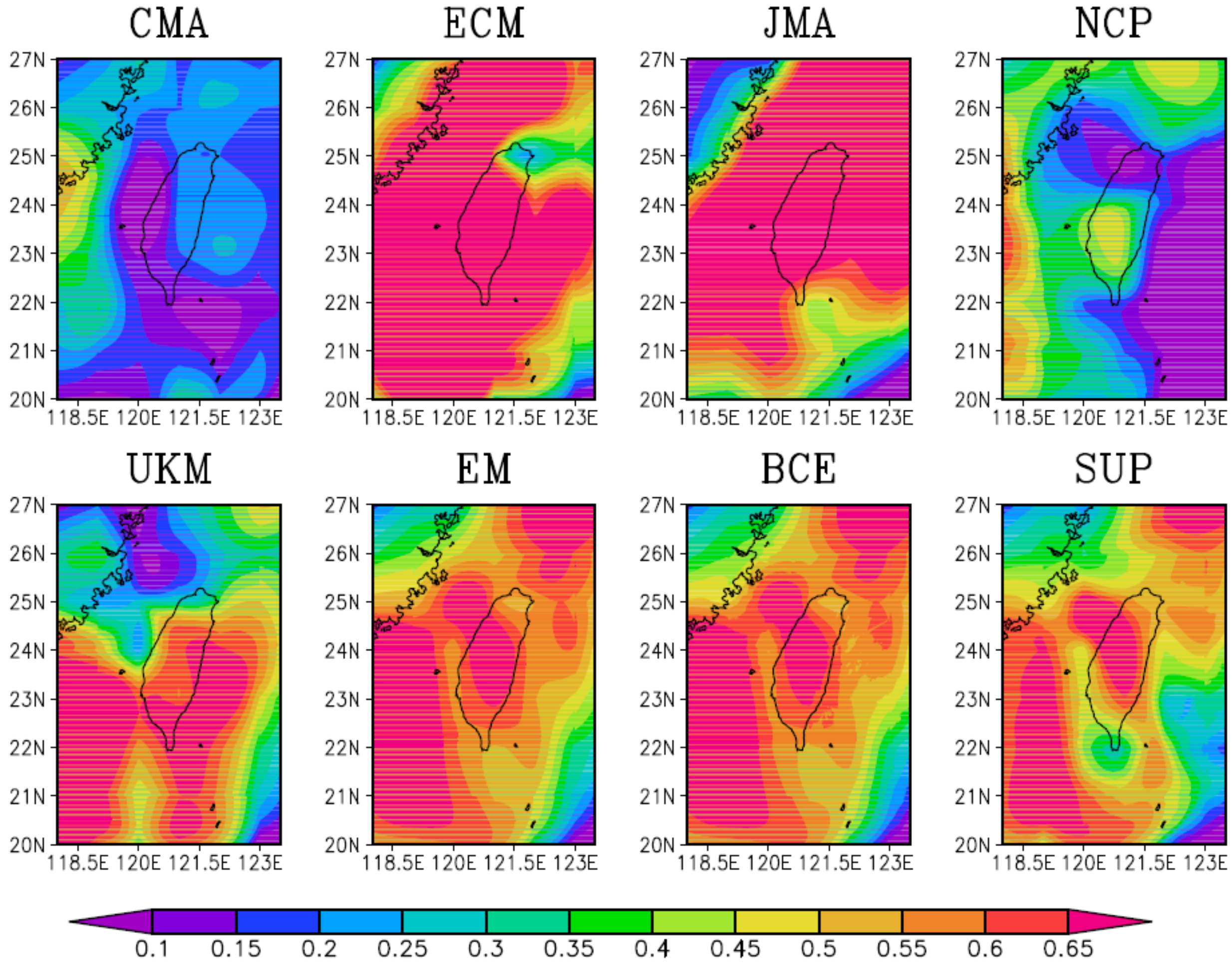

Figure 20:

Temporal Correlation for Day3 Multimodels forecasts during June 2008

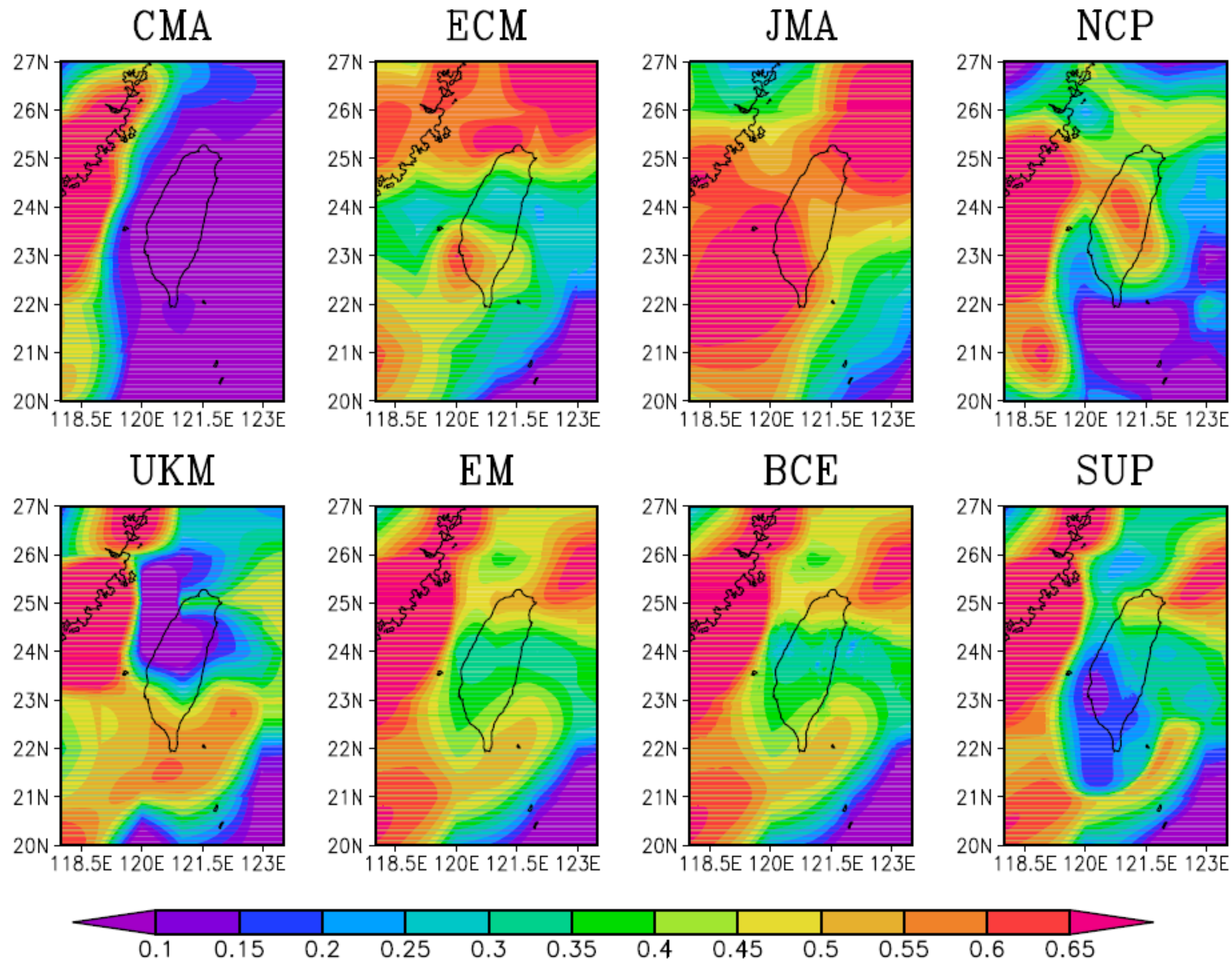

Figure 21:

Temporal Correlation for Day5 Multimodels forecasts during June 2008

APPENDIX-1

Multimodel conventional superensemble

The notion of the multimodel superensemble for weather and seasonal forecasts was first proposed by Krishnamurti et al. (1999). This method is based on producing a weighted average of model forecasts to construct a superensemble forecast. This procedure carries two phases: training and prediction. During the training phase past forecasts from a number of member models and the corresponding observed (analyzed) fields are used. The training entails determining statistical weights for each grid location in the horizontal, at all vertical levels, for all variables, for each day of forecasts and for each of the member models.

The constructed forecast is

$$S = \overline{O} + \sum_{i=1}^{N} a_i (F_i - \overline{F_i})$$

where S is superensemble prediction, $\overline{O}$ is the observed climatology; a_i is the weight for the i^{th} member in the ensemble; and F_i and $\overline{F}_i$ are the forecasts and forecast climatological values for the training period, respectively, for the i^{th} model's forecast. The summation is taken over the N member models of the ensemble.

The weight a_i are obtained by minimizing the error term G, written as

$$G = \sum_{i=1}^{N_{train}} (S_t^{'} - O_t^{'})^2$$

where N_{train} is the number of time samples in the training phase, $S_t^{'}$ and $O_t^{'}$ are the superensemble and observed field anomalies, respectively, at training time t.

Following is the illustration

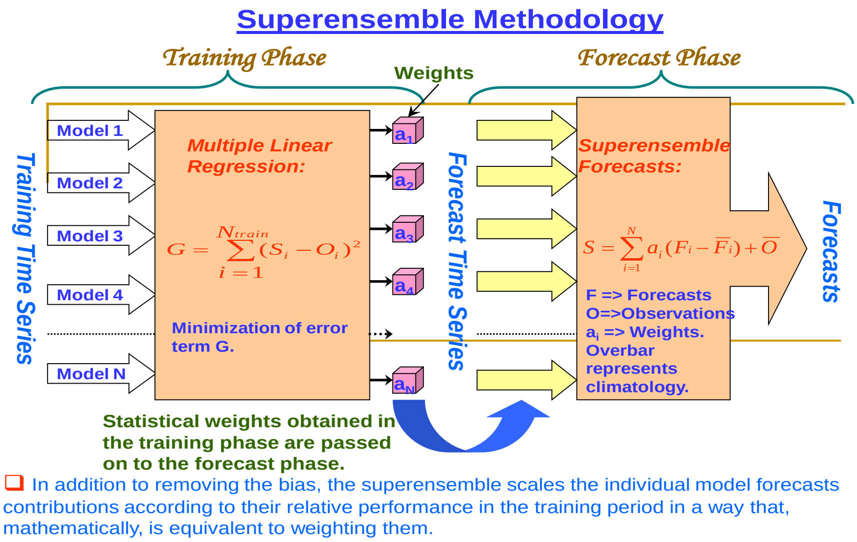
Superensemble Methodology
Training Phase
Forecast Phase
Weights
Training Time Series
Model 1
Model 2
Model 3
Model 4
Model N
Multiple Linear Regression:
$G = \sum_{i=1}^{N_{train}} (S_i - O_i)^2$
Minimization of error term G.
a_1 a_2 a_3 a_4 a_N
Forecast Time Series
Superensemble Forecasts:
$S = \sum_{i=1}^{N} a_i (F_i - \overline{F_i}) + \overline{O}$
F => Forecasts
O=>Observations
a_i => Weights.
Overbar represents climatology.
Forecasts
Statistical weights obtained in the training phase are passed on to the forecast phase.
In addition to removing the bias, the superensemble scales the individual model forecasts contributions according to their relative performance in the training period in a way that, mathematically, is equivalent to weighting them.

Figure A1

Appendix-2

Statistical downscaling

Given the forecasts of precipitation from a number of forecast models, our downscaling for model precipitation follows three steps.

1) Coarse resolution precipitation data from various models are bi-linearly interpolated to the grid resolution of the observed datasets. This is done for each day of forecast for each model. Where ‘‘daily rain’’ refers to 24-h precipitation accumulation between 1200 and 1200 UTC the next day.

2) A time series of the interpolated rain is made for each model at every grid point and for each day of forecast separately (i.e., the string of day-1 forecasts). The same procedure is followed to generate strings for the day-2, -3, -4, and -5 forecasts. For each forecast lead time we have a string of high resolution, rain gauge–based rainfall observations. This provides an observational string.

3) The downscaling strategy involves a linear regression of the time series of the data at each grid point:

$$Y_i = aX_i + b$$

Where X_i are the rainfall forecasts (separately handled for each day and that had been subjected to bilinear interpolation), Y_i are the observed counterparts, a is slope and b is intercept.

Appendix-3

$$\text{RMS error} = \left[\frac{1}{N}\sum_{n=1}^{N}(f_n - o_n)^2\right]^{1/2}.$$

$$\text{Systematic error (Bias)} = \frac{1}{N}\sum_{n=1}^{N}(f_n - o_n).$$

Anomaly correlation

$$= \frac{\sum_{n=1}^{N}[(f_n - c_n)(o_n - c_n)]}{\left[\sum_{n=1}^{N}(f_n - c_n)^2 \sum_{n=1}^{N}(o_n - c_n)^2\right]^{1/2}}$$

(AC>0.6 for useful forecast skill).

Correlation coefficient

$$= \frac{\sum_{n=1}^{N}[(f_n - \bar{f})(o_n - \bar{o})]}{\left[\sum_{n=1}^{N}(f_n - \bar{f})^2 \sum_{n=1}^{N}(o_n - \bar{o})^2\right]^{1/2}}$$

$(-1 \leq \mathrm{c} \leq 1)$.

$$\text{Equitable threat score} = \frac{H - \left(F \times \frac{O}{N}\right)}{F + O - H - \left(F \times \frac{O}{N}\right)}$$

$(0 \leq \mathrm{ETS} \leq 1)$.

$$\text{Bias} = \frac{N_f}{N_o}.$$

In these expressions:

N = number of grid points
f_n = forecast value at grid point n
o_n = observed value at grid point n
c_n = climatological (mean) value at grid point n
$\bar{f}$ = area mean of the forecasted values
$\bar{o}$ = area mean of the observed values
F = area where event is forecasted
O = area where event is observed
H = hit area, or overlap of areas F and O

N_f = number of grid points where event is forecasted
N_o = number of grid points where event is observed.