Assessing the capturing capacity of RegCM4 for the precipitation over Med-CORDEX using boundary data with higher resolution and improved accuracy

B. Sen[1], B.Sen[2], E. Sonuc[3] S. Topcu[4], S.O. Krichak[5], R. Kilic[3]

- [1] Turkish State Meteorology Service
- [2] Yildirim Beyazit University
- [3] Karabuk University
- [4] Cukurova University
- [5] Tel Aviv University

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ERA-Interim

The ERA-Interim project was initiated in 2006 to provide a bridge between ECMWF's previous reanalysis, ERA-40 (1957-2002), and the next-generation extended reanalysis envisaged at ECMWF. The main objectives of the project were to improve on certain key aspects of ERA-40, such as the representation of the hydrological cycle, the quality of the stratospheric circulation, and the handling of biases and changes in the observing system. These objectives have been largely achieved as a result of a combination of factors, including many model improvements, the use of 4-dimensional variational analysis, a revised humidity analysis, the use of variational bias correction for satellite data, and other improvements in data handling.

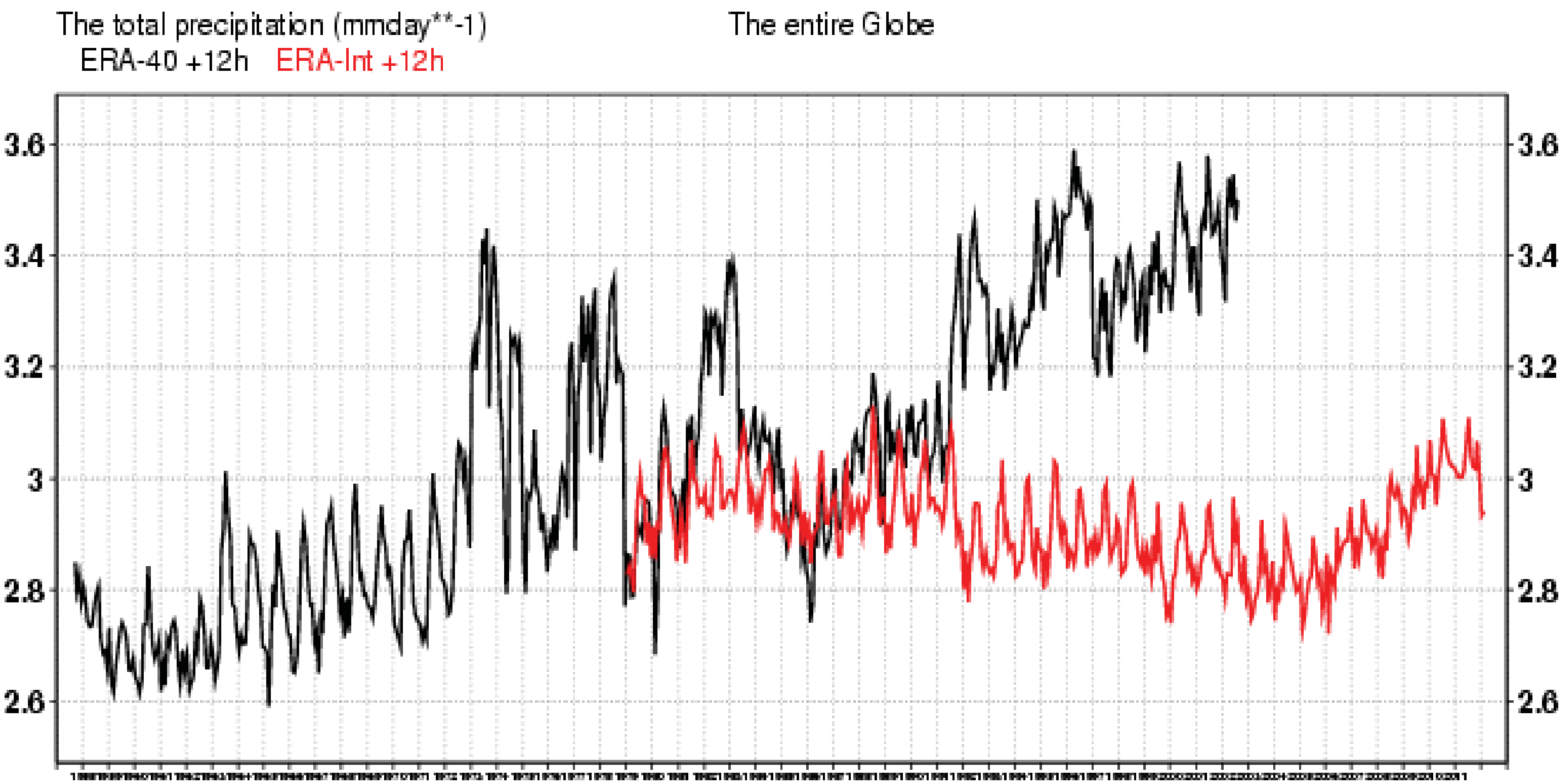
http://www.ecmwf.int/publications/library/ecpublications/_pdf/era/era_report_series/RS_1_v2.pdf

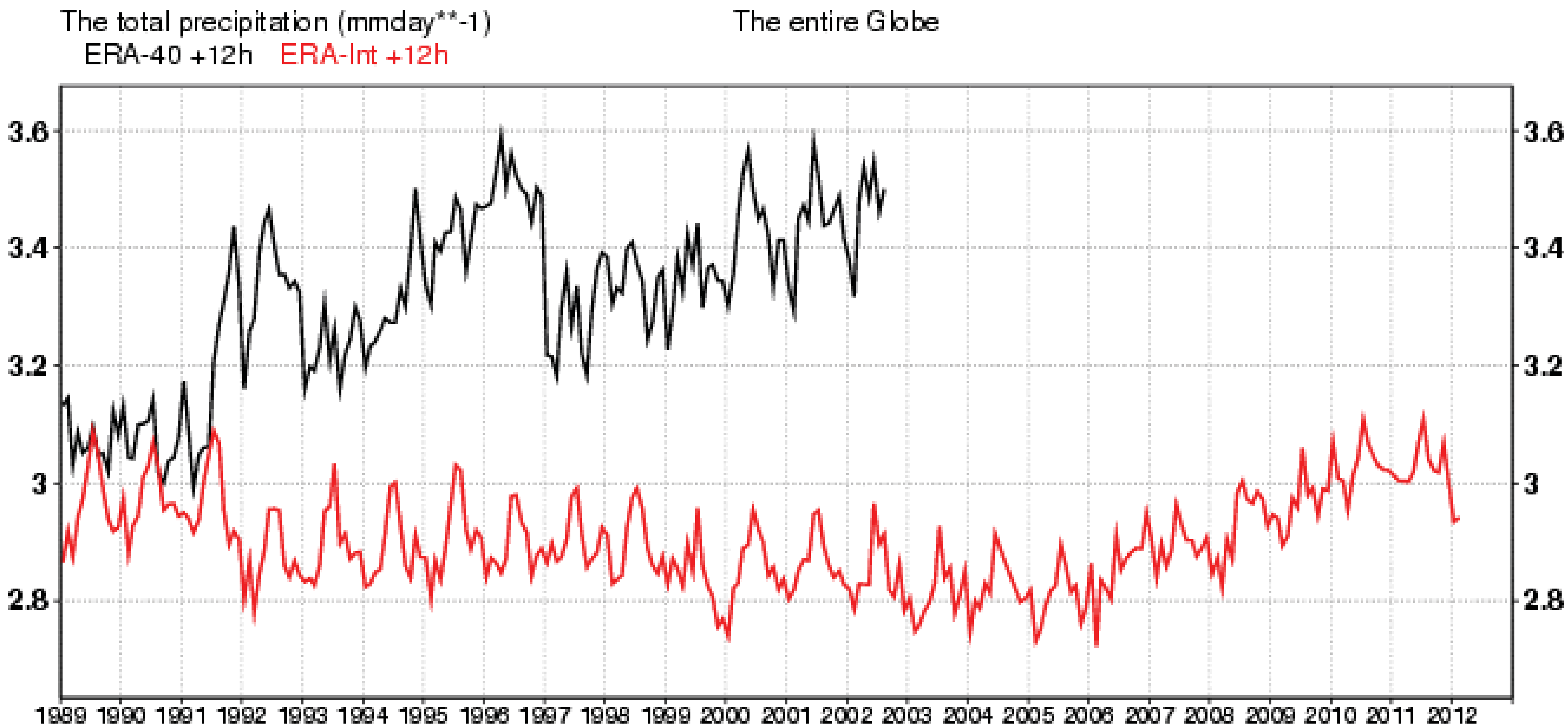
ERA-40 to ERA-Interim

The atmospheric model used for ERA-40 is known as IFS CY23r4.
ERA-40 had the following resolution:
• *60 levels in the vertical, (*23 pressure levels and 15 isentropic levels)*;*
• *T159 spherical-harmonic representation for basic dynamical fields;*
• *a reduced Gaussian grid with approximately uniform* ***125km*** *spacing for surface and other gridpoint* fields.
The atmospheric model was coupled to an ocean-wave model which resolved 25 wave frequencies and 12 wave directions at the nodes of its 1.5° grid.
Data available from **195709 to 200208**

The atmospheric model used ERA-Interim is known as IFS CY31r2. ERA-Interim had the following resolution:
• *60 levels in the vertical, (*37 pressure levels and 15/16 isentropic levels).
• *T255 spherical-harmonic representation for the basic dynamical fields;*
• *a reduced Gaussian grid with approximately uniform* ***79 km*** *spacing for surface and other grid-point fields.*
The atmospheric model is coupled to an ocean-wave model resolving 30 wave frequencies and 24 wave directions at the nodes of its reduced 1.0°x1.0° latitude/longitude grid.
Data available from **197901 to 201202**

http://www.ecmwf.int/publications/library/ecpublications/_pdf/era/era40/ERA40_PRS17_rev1.pdf
http://www.ecmwf.int/publications/library/ecpublications/_pdf/era/era_report_series/RS_1.pdf


The total precipitation (mmday**-1)
The entire Globe
ERA-40 +12h
ERA-Int +12h
3.6
3.4
3.2
3
2.8
2.6


The total precipitation (mmday**-1)
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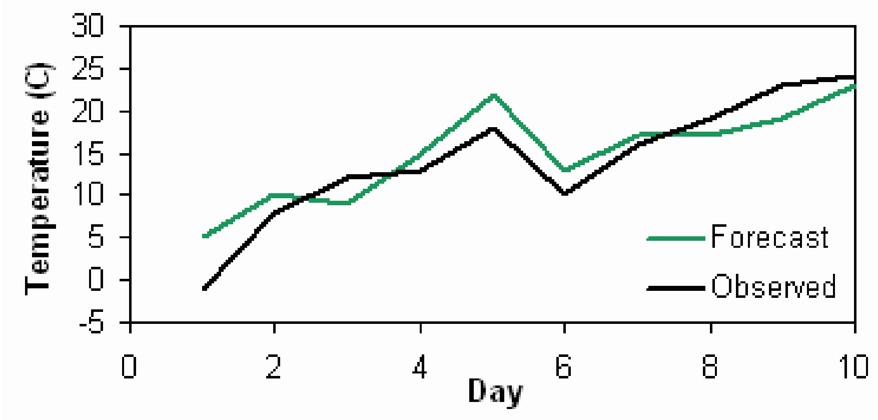
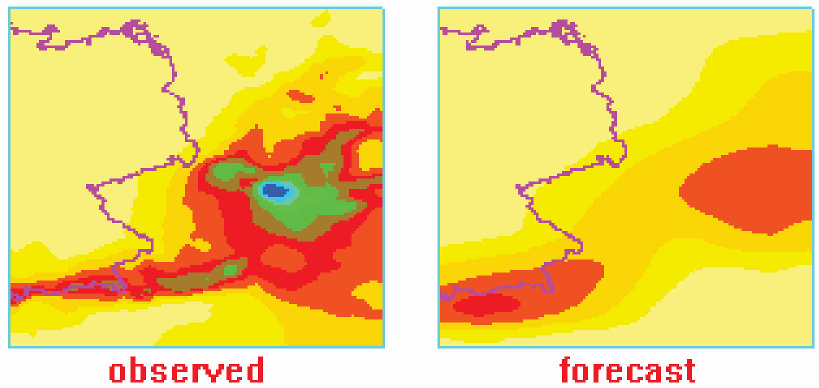
ERA-40 +12h
ERA-Int +12h
3.6
3.4
3.2
3
2.8
1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012

Standard verification methods

"Eyeball" verification ; One of the oldest and best verification methods is the good old fashioned visual, or "eyeball", method: look at the forecast and observations side by side and use human judgment to discern the forecast errors. Common ways to present data are as time series and maps.





The eyeball method is great if you only have a few forecasts, or you have lots of time, or you're not interested in quantitative verification statistics. Even when you do want statistics, it is a very good idea to look at the data from time to time!

However, the eyeball method is not quantitative, and it is very prone to individual, subjective biases of interpretation. Therefore it must be used with caution in any formal verification procedure.

The following sections give fairly brief descriptions of the standard verification methods and scores for dichotomous, multi-category, continuous, and probabilistic forecasts. For greater detail and discussion of the standard methods see Stanski et al. (1989) or one of the excellent books on forecast verification and statistics.

Methods for dichotomous (yes/no) forecasts

A dichotomous forecast says, "yes, an event will happen", or "no, the event will not happen". Rain and fog prediction are common examples of yes/no forecasts. For some applications a threshold may be specified to separate "yes" and "no", for example, winds greater than 50 knots.

To verify this type of forecast we start with a contingency table that shows the frequency of "yes" and "no" forecasts and occurrences. The four combinations of forecasts (yes or no) and observations (yes or no), called the *joint distribution*, are:

hit - event forecast to occur, and did occur

miss - event forecast not to occur, but did occur

false alarm - event forecast to occur, but did not occur

correct negative - event forecast not to occur, and did not occur

The total numbers of observed and forecast occurrences and non-occurences are given on the lower and right sides of the contingency table, and are called the *marginal distribution*.

Contingency Table				
		Observed		
		yes	no	Total
Forecast	yes	***hits***	***false alarms***	***forecast yes***
	no	***misses***	***correct negatives***	***forecast no***
Total		***observed yes***	***observed no***	***total***

The contingency table is a useful way to see what types of errors are being made. A perfect forecast system would produce only *hits* and *correct negatives*, and no *misses* or *false alarms*.

A large variety of *categorical statistics* are computed from the elements in the contingency table to describe particular aspects of forecast performance. We will illustrate these statistics using a (made-up) example. Suppose a year's worth of official daily rain forecasts and observations produced the following contingency table:

		Observed		
		yes	no	Total
Forecast	yes	**82**	**38**	**120**
	no	**23**	**222**	**245**
Total		**105**	**260**	**365**

Categorical statistics that can be computed from the yes/no contingency table are given below. Sometimes these scores are known by alternate names shown in parentheses.

Accuracy (fraction correct) $= \dfrac{hits + correct\ negatives}{total}$ **=PC**

Answers the question: *Overall, what fraction of the forecasts were correct?*
Range: 0 to 1. **Perfect score:** 1.
Characteristics: Simple, intuitive. Can be misleading since it is heavily influenced by the most common category, usually "no event" in the case of rare weather.
In the example above, *Accuracy* = (82+222) / 365 = 0.83, indicating that 83% of all forecasts were correct.

Bias score (frequency bias) $= \dfrac{hits + false\ alarms}{hits + misses}$ **= B**

Answers the question: *How did the forecast frequency of "yes" events compare to the observed frequency of "yes" events?*

Range: 0 to infinity. **Perfect score:** 1.

Characteristics: Measures the ratio of the frequency of forecast events to the frequency of observed events. Indicates whether the forecast system has a tendency to underforecast (*BIAS*<1) or overforecast (*BIAS*>1) events. Does not measure how well the forecast corresponds to the observations, only measures relative frequencies.

In the example above, *BIAS* = (82+38) / (82+23) = 1.14, indicating slight overforecasting of rain frequency.

Probability of detection (hit rate) $= \dfrac{hits}{hits + misses}$ **= POD**

Answers the question: *What fraction of the observed "yes" events were correctly forecast?*

Range: 0 to 1. **Perfect score:** 1.

Characteristics: Sensitive to hits, but ignores false alarms. Very sensitive to the climatological frequency of the event. Good for rare events.Can be artificially improved by issuing more "yes" forecasts to increase the number of hits. Should be used in conjunction with the false alarm ratio (below). *POD* is alsoan important component of the Relative Operating Characteristic (ROC) used widely for probabilistic forecasts.

In the example above, *POD* = 82 / (82+23) = 0.78, indicating that roughly 3/4 of the observed rain events were correctly predicted.

False alarm ratio (FAR) $= \dfrac{\textit{false alarms}}{\textit{hits} + \textit{false alarms}}$

Answers the question: *What fraction of the predicted "yes" events actually did not occur (i.e., were false alarms)?*

Range: 0 to 1. **Perfect score:** 0.

Characteristics: Sensitive to false alarms, but ignores misses. Very sensitive to the climatological frequency of the event. Should be used in conjunction with the probability of detection (above).

In the example above, *FAR* = 38 / (82+38) = 0.32, indicating that in roughly 1/3 of the forecast rain events, rain was not observed.

Probability of false detection (false alarm rate)
(POFD =F)

$$= \frac{\textit{false alarms}}{\textit{correct negatives} + \textit{false alarms}}$$

Answers the question: *What fraction of the observed "no" events were incorrectly forecast as "yes"?*

Range: 0 to 1. **Perfect score:** 0.

Characteristics: Sensitive to false alarms, but ignores misses. Can be artificially improved by issuing fewer "yes" forecasts to reduce the number of false alarms. Not often reported for deterministic forecasts, but is an important component of the Relative Operating Characteristic (ROC) used widely for probabilistic forecasts.

In the example above, *POFD* = 38 / (222+38) = 0.15, indicating that for 15% of the observed "no rain" events the forecasts were incorrect.

Threat score (critical success index)
TS=CSI

$$= \frac{hits}{hits + misses + false\ alarms}$$

Answers the question: *How well did the forecast "yes" events correspond to the observed "yes" events?*

Range: 0 to 1, 0 indicates no skill. **Perfect score:** 1.

Characteristics: Measures the fraction of observed and/or forecast events that were correctly predicted. It can be thought of as the *accuracy* when correct negatives have been removed from consideration, that is, *TS* is only concerned with forecasts that count. Sensitive to hits, penalizes both misses and false alarms. Does not distinguish source of forecast error. Depends on climatological frequency of events (poorer scores for rarer events) since some hits can occur purely due to random chance.

In the example above, *TS* = 82 / (82+23+38) = 0.57, meaning that slightly more than half of the "rain" events (observed and/or predicted) were correctly forecast.

***Equitable threat score* (*Gilbert skill score*)**

ETS

$$= \frac{hits - hits_{random}}{hits + misses + false\ alarms - hits_{random}}$$

where

$$hits_{random} = \frac{(hits + misses)(hits + false\ alarms)}{total}$$

Answers the question: *How well did the forecast "yes" events correspond to the observed "yes" events (accounting for hits due to chance)?*

Range: -1/3 to 1, 0 indicates no skill. **Perfect score:** 1.

Characteristics: Measures the fraction of observed and/or forecast events that were correctly predicted, adjusted for hits associated with random chance (for example, it is easier to correctly forecast rain occurrence in a wet climate than in a dry climate). The *ETS* is often used in the verification of rainfall in NWP models because its "equitability" allows scores to be compared more fairly across different regimes. Sensitive to hits. Because it penalises both misses and false alarms in the same way, it does not distinguish the source of forecast error.

In the example above, *ETS* = (82-34) / (82+23+38-34) = 0.44. *ETS* gives a lower score than *TS*.

Hanssen and Kuipers discriminant
(true skill statistic, Peirces's skill score)
=KSS

$$HK = \frac{hits}{hits + misses} - \frac{false\ alarms}{false\ alarms + correct\ \ negatives}$$

Answers the question: *How well did the forecast separate the "yes" events from the "no" events?*

Range: -1 to 1, 0 indicates no skill. **Perfect score:** 1

Characteristics: Uses all elements in contingency table. Does not depend on climatological event frequency. The expression is identical to *HK = POD - POFD*, but the Hanssen and Kuipers score can also be interpreted as *(accuracy for events) + (accuracy for non-events) - 1*. For rare events *HK* is unduly weighted toward the first term (same as *POD*), so this score may be more useful for more frequent events. Can be expressed in a form similar to the *ETS* except the *hitsrandom* term is unbiased. See Woodcock (1976) for a comparison of *HK* with other scores.

In the example above, *HK* = 82 / (82+23) - 38 / (38+222) = 0.63

Heidke skill score (Cohen's κ) HSS

$$= \frac{(hits + correct\ negatives) - (expected\ correct)_{random}}{N - (expected\ correct)_{random}}$$

where

$$(expected\ correct)_{random} = \frac{1}{N}\left[\begin{array}{l}(hits + misses)(hits + false\ alarms) \quad + \\ \quad (correct\ negatives + misses)(correct\ negatives + false\ alarms)\end{array}\right]$$

Answers the question: *What was the accuracy of the forecast relative to that of random chance?*

Range: minus infinity to 1, 0 indicates no skill. **Perfect score:** 1.

Characteristics: Measures the fraction of correct forecasts after eliminating those forecasts which would be correct due purely to random chance. This is a form of the generalized skill score, where the *score* in the numerator is the number of correct forecasts, and the reference forecast in this case is random chance. In meteorology, at least, random chance is usually not the best forecast to compare to - it may be better to use climatology (long-term average value) or persistence (forecast = most recent observation, i.e., no change) or some other standard.

In the example above, *HSS* = 0.61

Odds ratio **(OR)** $= \dfrac{\textit{hits} * \textit{correct negatives}}{\textit{misses} * \textit{false alarms}} = \dfrac{\left(\dfrac{POD}{1-POD}\right)}{\left(\dfrac{POFD}{1-POFD}\right)}$

Answers the question: *What is the ratio of the odds of a "yes" forecast being correct, to the odds of a "yes" forecast being wrong?*

Odds ratio - Range: 0 to infinity, 1 indicates no skill. **Perfect score:** infinity
Log odds ratio-Range: minus infinity to infinity, 0 indicates no skill.**Perfect score:** infinity

Characteristics: Measures the ratio of the odds of making a hit to the odds of making a false alarm. The logarithm of the odds ratio is often used instead of the original value. Takes prior probabilities into account. Gives better scores for rarer events. Less sensitive to hedging. Do not use if any of the cells in the contingency table are equal to 0. Used widely in medicine but not yet in meteorology -- see Stephenson (2000) for more information.

Note that the odds ratio is not the same as the ratio of the *probability* of making a hit (*hits / # forecasts*) to the *probability* of making a false alarm (*false alarms / # forecasts*), since both of those can depend on the climatological frequency (i.e., the prior probability) of the event.

In the example above, *OR* = (82 x 222) / (23 x 38) = 20.8, indicating that the odds of a "yes" prediction being correct are over 20 times greater than the odds of a "yes" forecast being incorrect.

Odds ratio skill score (Yule's Q)

$$ORSS = \frac{hits \times correct\ negatives - misses \times false\ alarms}{hits \times correct\ negatives + misses \times false\ alarms}$$

Answers the question: *What was the improvement of the forecast over random chance?*

Range: -1 to 1, 0 indicates no skill. **Perfect score:** 1

Characteristics: Independent of the marginal totals (i.e., of the threshold chosen to separate "yes" and "no"), so is difficult to hedge. See Stephenson (2000) for more information.

In the example above, *ORSS* = [(82 x 222)-(23 x 38)] / [(82 x 222)+(23 x 38)] = 0.91

Methods for multi-category forecasts

Methods for verifying multi-category forecasts also start with a contingency table showing the frequency of forecasts and observations in the various bins. It is analogous to a scatter plot for categories.

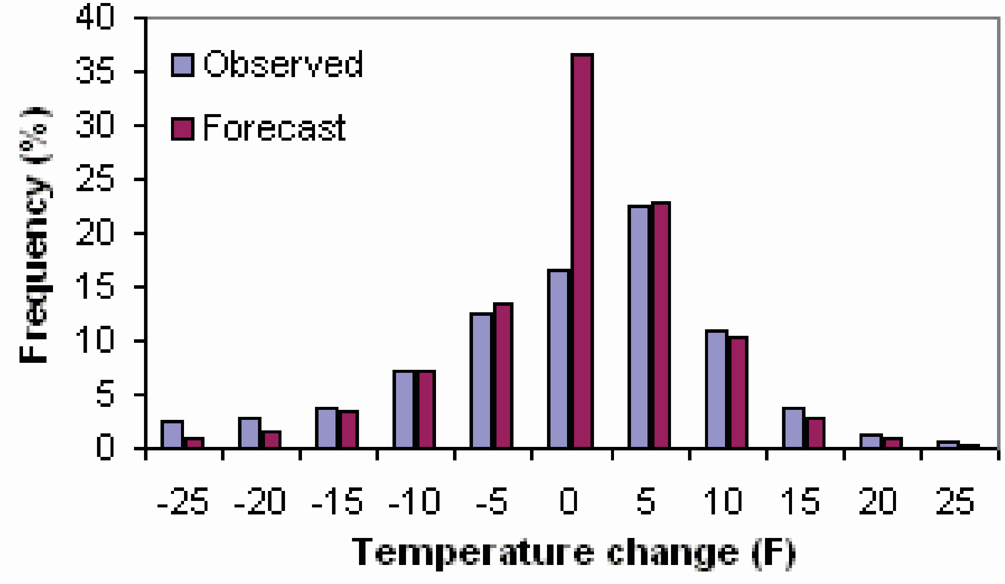
Multi-category Contingency Table						
		Observed Category				Total
	i,j	1	2	…	***K***	
Forecast Category	1	$n(F_1,O_1)$	$n(F_1,O_2)$	…	$n(F_1,O_K)$	$N(F_1)$
	2	$n(F_2,O_1)$	$n(F_2,O_2)$	…	$n(F_2,O_K)$	$N(F_2)$
	…	…	…	…	…	…
	K	$n(F_K,O_1)$	$n(F_K,O_2)$	…	$n(F_K,O_K)$	$N(F_K)$
Total		$N(O_1)$	$N(O_2)$	…	$N(O_K)$	N

In this table *n(Fi,Oj)* denotes the number of forecasts in category *i* that had observations in category *j*, *N(Fi)* denotes the total number of forecasts in category *i, N(Oj)* denotes the total number of observations in category *j*, and *N* is the total number of forecasts.

The *distributions approach* to forecast verification examines the relationship among the elements in the multi-category contingency table. A perfect forecast system would have values of non-zero elements only along the diagonal, and values of 0 for all entries off the diagonal. The off-diagonal elements give information about the specific nature of the forecast errors. The marginal distributions (*N*'s at right and bottom of table) show whether the forecast produces the correct distribution of categorical values when compared to the observations. Murphy and Winkler (1987), Murphy et al. (1989) and Brooks and Doswell (1996) develop this approach in detail.

The advantage of the distributions approach is that the nature of the forecast errors can more easily be diagnosed. The disadvantage is that it is more difficult to condense the results into a single number. There are fewer statistics that summarize the performance of multi-category forecasts. However, any multi-category forecast verification can be converted to a series of *K*-1 yes/no-type verifications by defining "yes" to be "in category *i*" or "in category *i* or higher", and "no" to be "not in category *i*" or "below category *i*".

Histogram - Plot the relative frequencies of forecast and observed categories



Answers the question: *How well did the distribution of forecast categories correspond to the distribution of observed categories?*

Characteristics: Shows similarity between location, spread, and skewness of forecast and observed distributions. Does not give information on the correspondence between the forecasts and observations. Histograms give information similar to box plots.

$$Accuracy = \frac{1}{N}\sum_{i=1}^{K} n(F_i, O_i)$$

Answers the question: *Overall, what fraction of the forecasts were in the correct category?*

Range: 0 to 1. **Perfect score:** 1.

Characteristics: Simple, intuitive. Can be misleading since it is heavily influenced by the most common category.

Heidke skill score

$$HSS = \frac{\frac{1}{N}\sum_{i=1}^{K} n(F_i,O_i) - \frac{1}{N^2}\sum_{i=1}^{K} N(F_i)N(O_i)}{1 - \frac{1}{N^2}\sum_{i=1}^{K} N(F_i)N(O_i)}$$

Answers the question: *What was the accuracy of the forecast in predicting the correct category, relative to that of random chance?*

Range: minus infinity to 1, 0 indicates no skill. **Perfect score:** 1.

Characteristics: Measures the fraction of correct forecasts after eliminating those forecasts which would be correct due purely to random chance. This is one form of a generalized skill score, where the *score* in the numerator is the number of correct forecasts, and the reference forecast in this case is random chance. Requires a large sample size to make sure that the elements of the contingency table are all adequately sampled. In meteorology, at least, random chance is usually not the best forecast to compare to - it may be better to use climatology (long-term average value) or persistence (forecast is most recent observation, i.e., no change) or some other standard.

Hanssen and Kuipers discriminant (true skill statistic, Peirces's skill score)

$$HK = \frac{\frac{1}{N}\sum_{i=1}^{K} n(F_i, O_i) - \frac{1}{N^2}\sum_{i=1}^{K} N(F_i)N(O_i)}{1 - \frac{1}{N^2}\sum_{i=1}^{K} (N(O_i))^2}$$

Answers the question: *What was the accuracy of the forecast in predicting the correct category, relative to that of random chance?*

Range: -1 to 1, 0 indicates no skill. **Perfect score:** 1

Characteristics: Similar to the Heidke skill score (above), except that in the denominator the fraction of correct forecasts due to random chance is for an unbiased forecast.

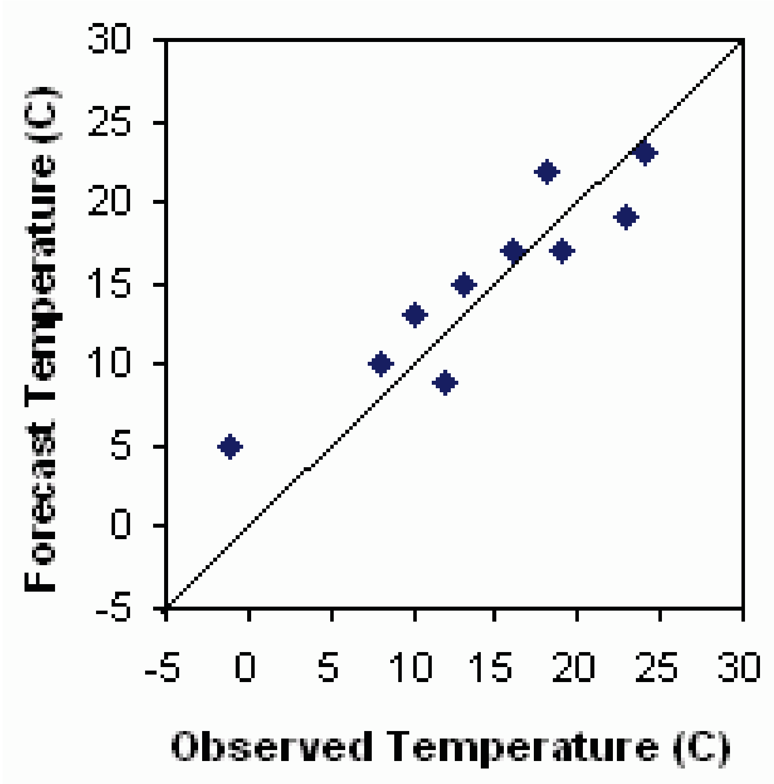
Methods for foreasts of continuous variables

Verifying forecasts of continuous variables measures how the *values* of the forecasts differ from the values of the observations. The continuous verification methods and statistics will be demonstrated on a sample data set of 10 temperature forecasts taken from Stanski et al. (1989):

Day	1	2	3	4	5	6	7	8	9	10
Forecast, F_i (C)	5	10	9	15	22	13	17	17	19	23
Observation, O_i (C)	-1	8	12	13	18	10	16	19	23	24

Verification of continous forecasts often includes some exploratory plots such as scatter plots and box plots, as well as various summary scores.

Scatter plot - Plots the forecast values against the observed values.



Answers the question: *How well did the forecast values correspond to the observed values?*

Characteristics: Good first look at correspondence between forecast and observations. An accurate forecast will have points on or near the diagonal.

WHAT HAVE WE DONE

OUR EFFORTS OVER MED-CORDEX
(Completed Runs “9”)

RUNS CORDEX RegCM3
*Domain (62X120), Regcm3, ERA40, 50 km, with BATS package,Grell AS74, GISST,1960010100-2002090100,
*Domain (62X120), Regcm3, ERAINT15, 50 km,with BATS package,Grell AS74, GISST,1989010100-2002090100;

************************* **2** **********************************
RUNS CORDEX RegCM4.0
*Domain (62X120), Regcm4, ERAINT75, 50 km, with BATS package, Grell FC80, OI_WK,1989010100-2005070100;
*Domain (62X120), Regcm4, ERAINT15, 50 km, sstERAI, with BATS package, Grell AS74, 1989010100-2007120100;
*Domain (62X120), Regcm4, ERAINT15, 50 km, sstERAI, with BATS package, Grell FC80, 1989010100-2007120100;
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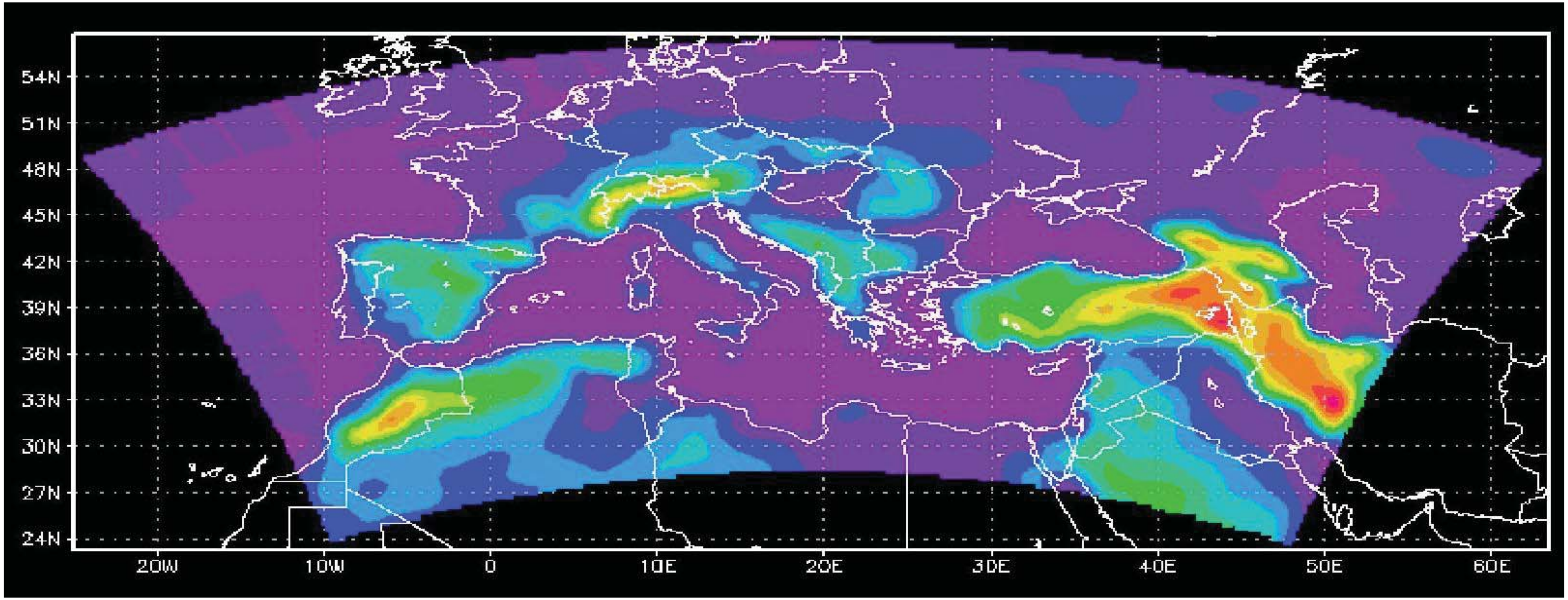
*Domain (62X120), Regcm4, ERAINT15, 50 km, sstERAI, with BATS package, Modified Kuo, 1989010100-2007120100;
*Domain (124X240), Regcm4, ERAINT15, 25 km, sstERAI, with BATS package, Grell AS74, 1989010100-2007120100;
*Domain (62X120), Regcm4, ERAINT15, 50 km, sstERAI, with BATS package, Grell AS74**, Zeng et a**l,1989010100-2007120100;

SPECIFICITIES of EVALUATED RUN

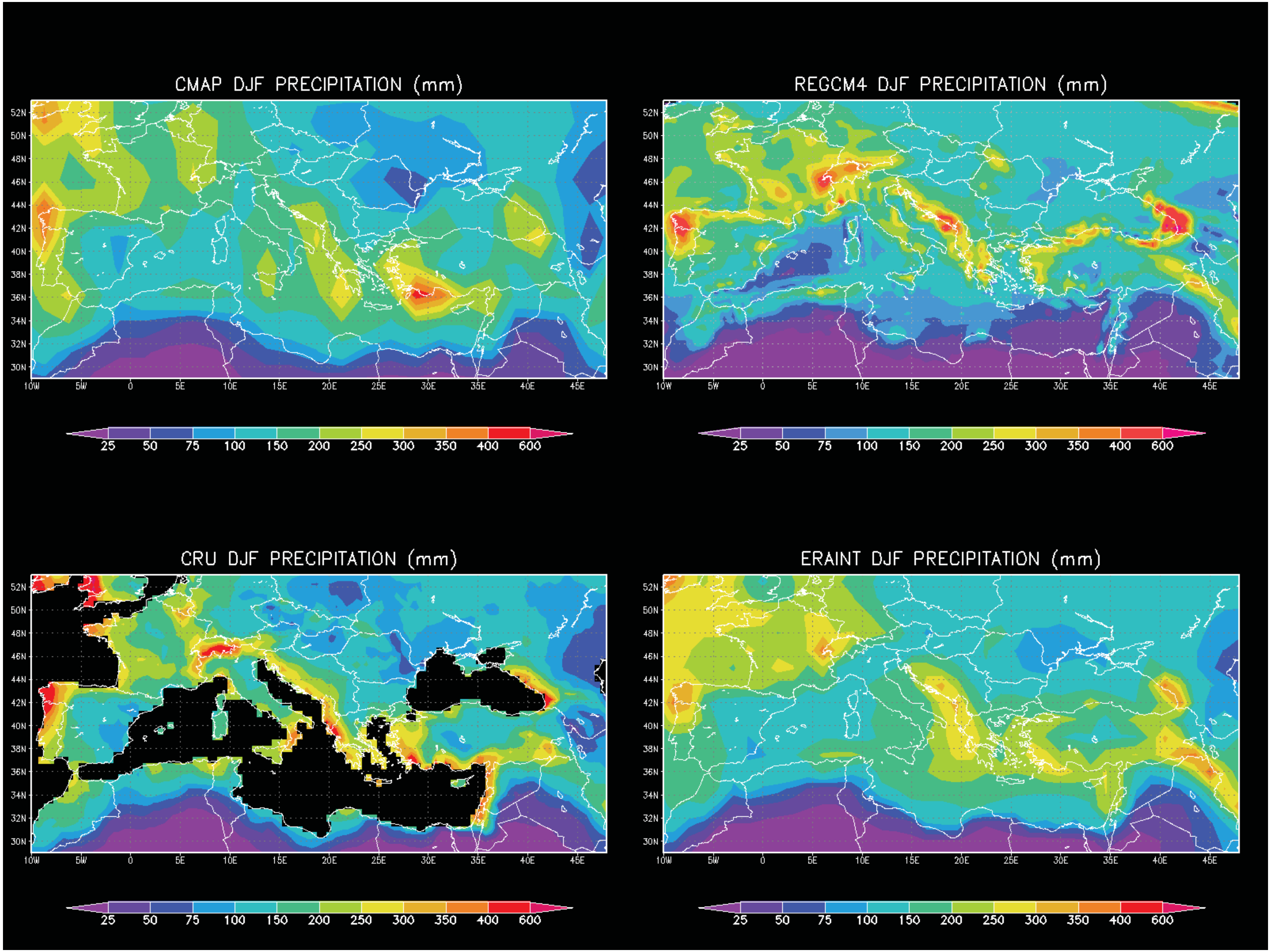


dattyp = ERAINT15	idate0=1989010100
ssttyp = sstERAI	idate2=2007120100
iy = 62	icup= Grell
ix= 120	igcc= AS74
ds= 50 km	İocnflx= BATS
Aertyp= AER00D0	kz = 18,
	iproj = LAMCON

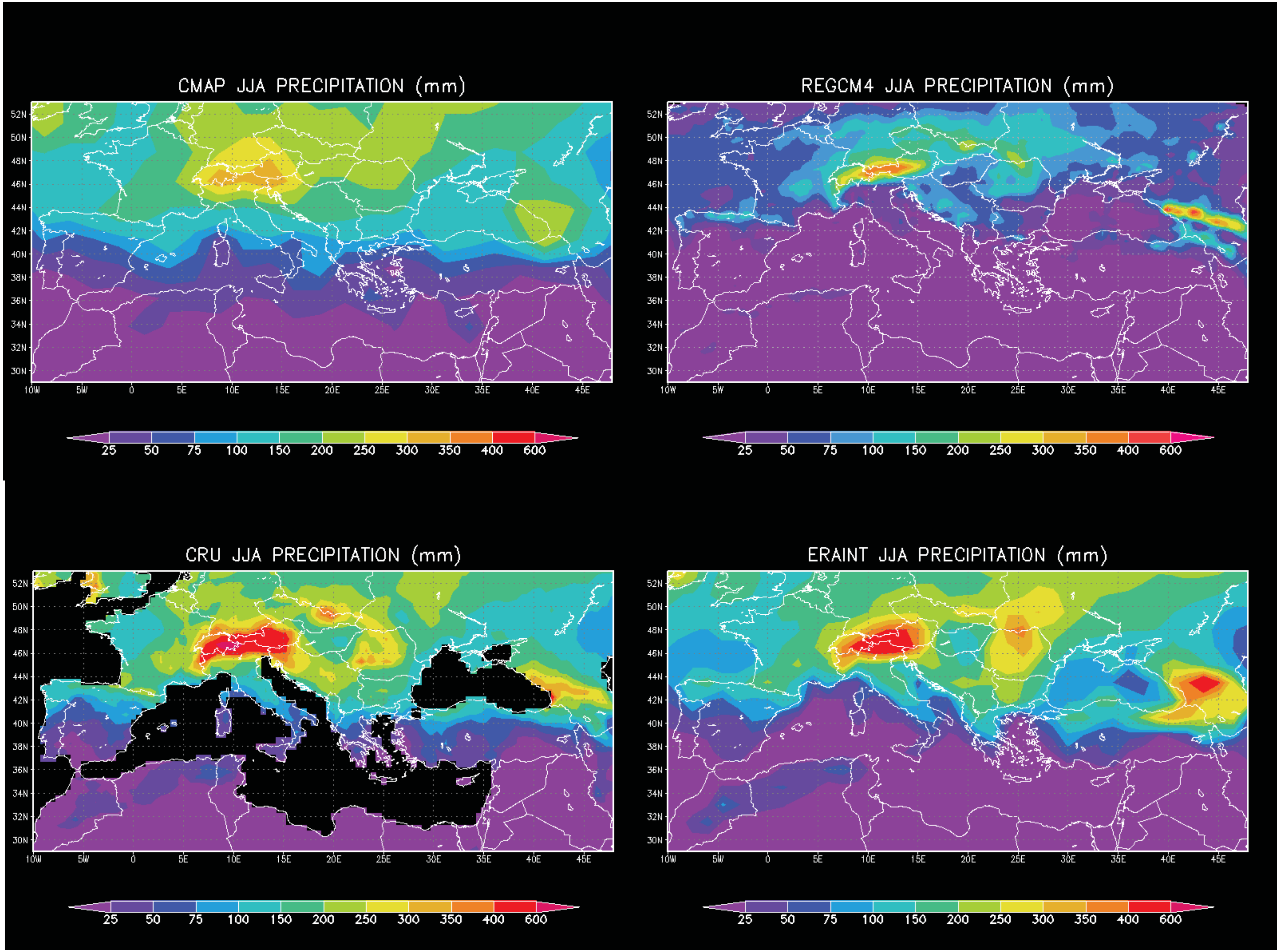
Verification of RegCM4 Precipitation

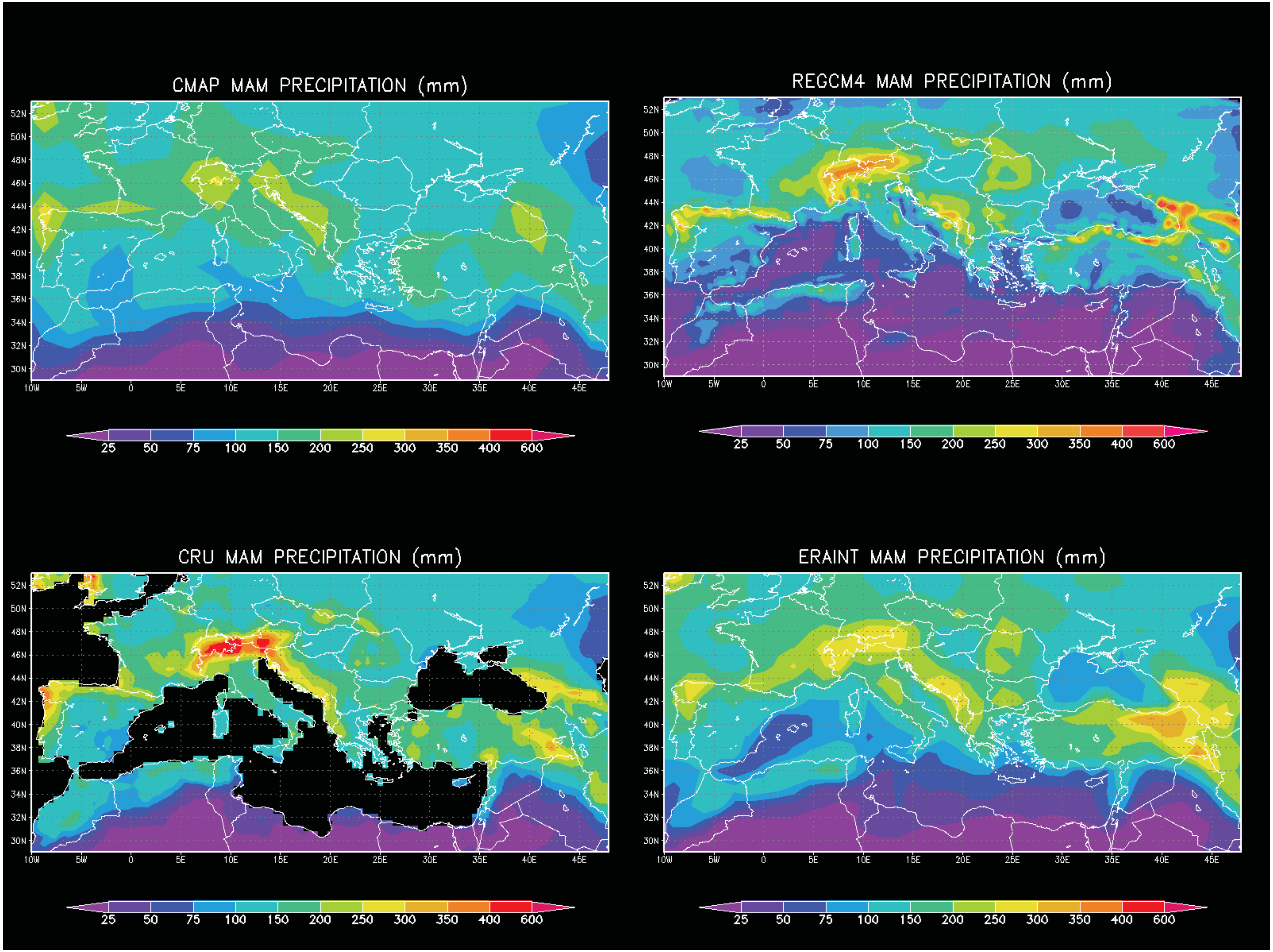
- **Annual , Seasenal over MedCORDEX**
  - CMAP
  - CRU
  - ERAINT
- **Extrem Precipitaiton over TURKEY**
  - 49 TSMS Station
  - B, PC, POD, FAR, F, TS, ETS, KSS, HSS, OR, ORSS
  - Muti category (Hit Rates; Correct, Small, Moderate, Signi., Large, Very Large Error Rate.
  - Histograms
  - Scatter Diyagrams

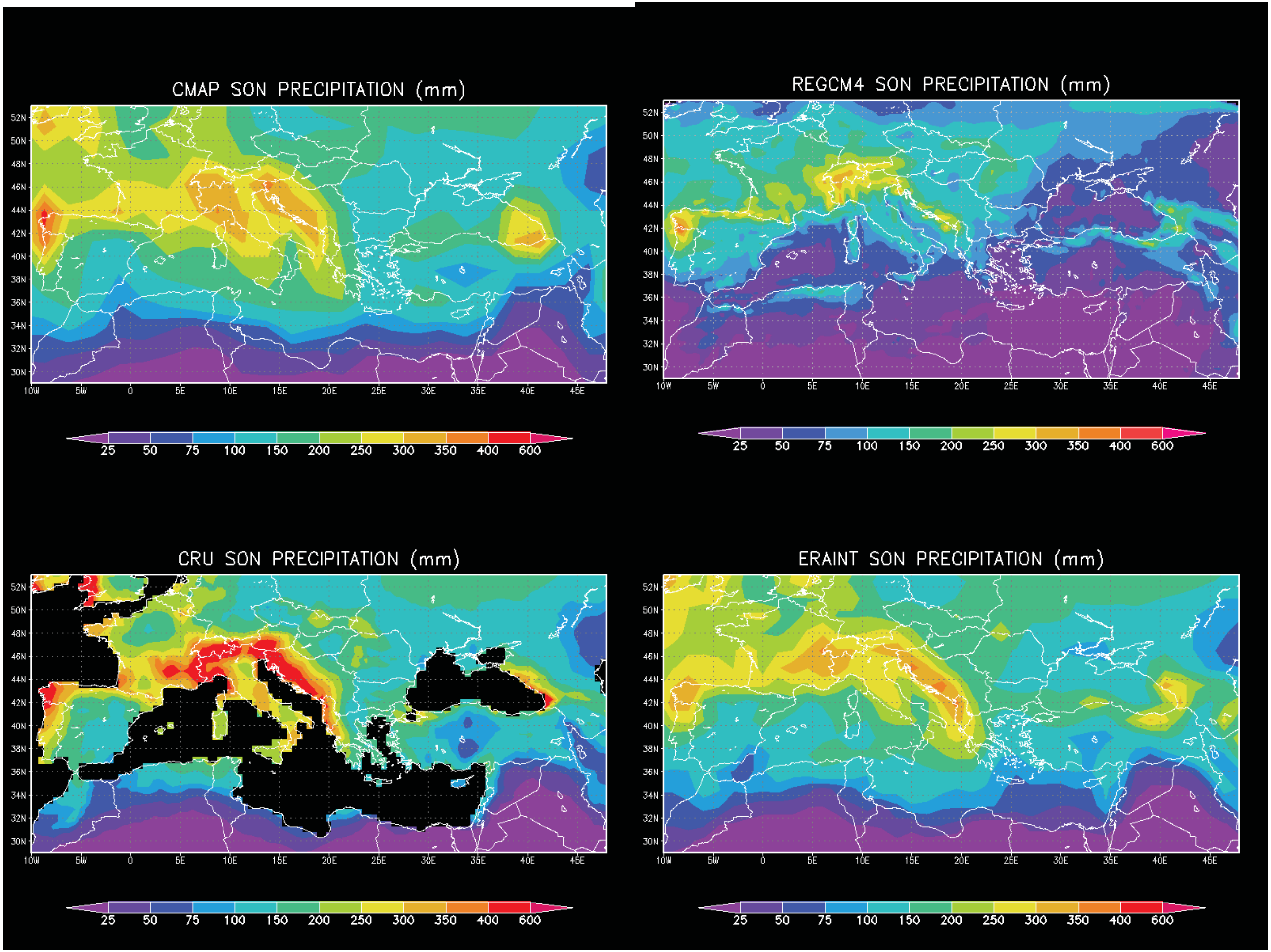
SUBJECTIVE VERIFICATION



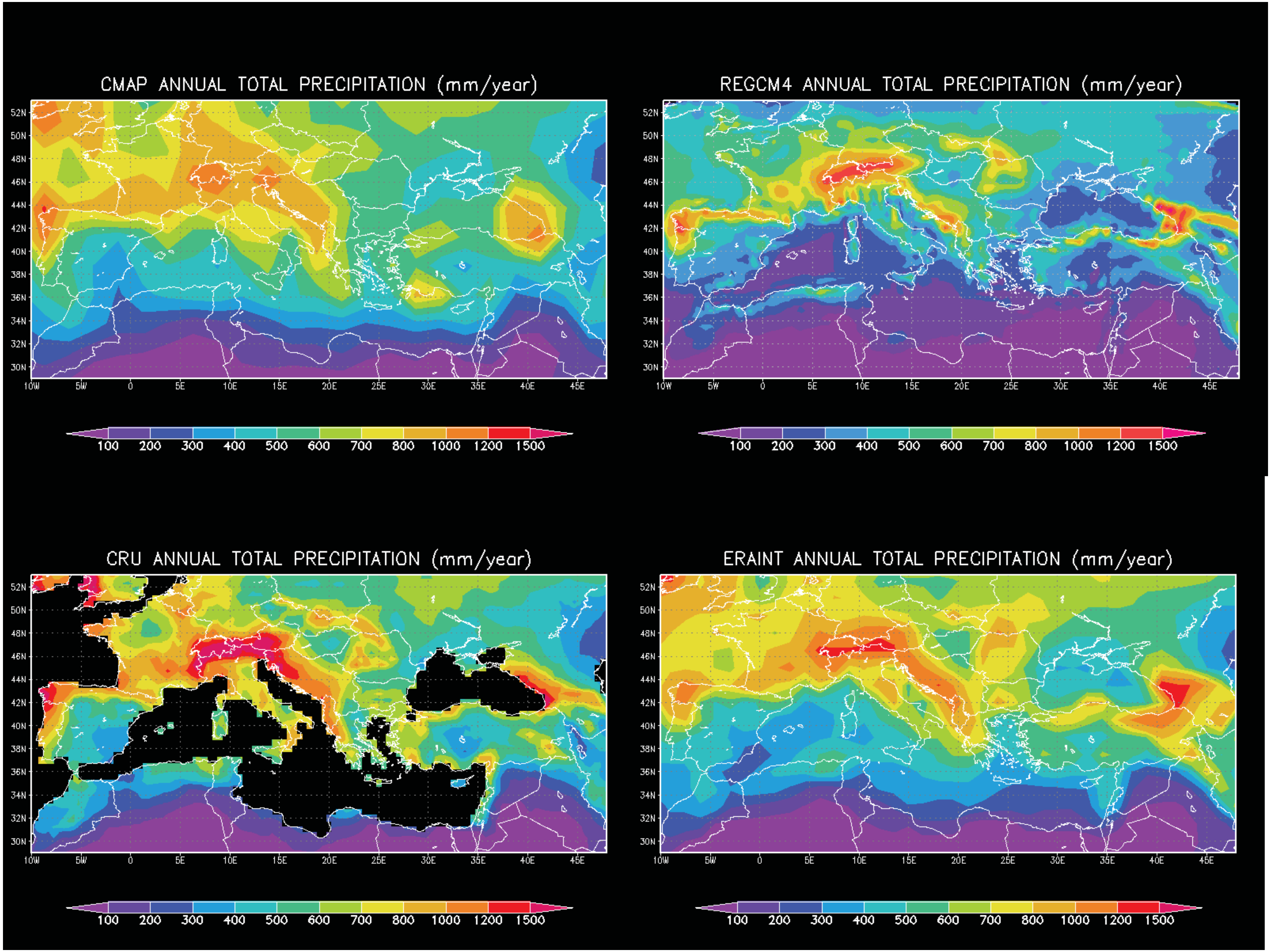
CMAP DJF PRECIPITATION (mm)
52N 50N 48N 46N 44N 42N 40N 38N 36N 34N 32N 30N
10W 5W 0 5E 10E 15E 20E 25E 30E 35E 40E 45E
25 50 75 100 150 200 250 300 350 400 600
REGCM4 DJF PRECIPITATION (mm)
52N 50N 48N 46N 44N 42N 40N 38N 36N 34N 32N 30N
10W 5W 0 5E 10E 15E 20E 25E 30E 35E 40E 45E
25 50 75 100 150 200 250 300 350 400 600
CRU DJF PRECIPITATION (mm)
52N 50N 48N 46N 44N 42N 40N 38N 36N 34N 32N 30N
10W 5W 0 5E 10E 15E 20E 25E 30E 35E 40E 45E
25 50 75 100 150 200 250 300 350 400 600
ERAINT DJF PRECIPITATION (mm)
52N 50N 48N 46N 44N 42N 40N 38N 36N 34N 32N 30N
10W 5W 0 5E 10E 15E 20E 25E 30E 35E 40E 45E
25 50 75 100 150 200 250 300 350 400 600


CMAP JJA PRECIPITATION (mm)
REGCM4 JJA PRECIPITATION (mm)
CRU JJA PRECIPITATION (mm)
ERAINT JJA PRECIPITATION (mm)
52N 50N 48N 46N 44N 42N 40N 38N 36N 34N 32N 30N
10W 5W 0 5E 10E 15E 20E 25E 30E 35E 40E 45E
25 50 75 100 150 200 250 300 350 400 600


CMAP MAM PRECIPITATION (mm)
REGCM4 MAM PRECIPITATION (mm)
CRU MAM PRECIPITATION (mm)
ERAINT MAM PRECIPITATION (mm)
52N 50N 48N 46N 44N 42N 40N 38N 36N 34N 32N 30N
10W 5W 0 5E 10E 15E 20E 25E 30E 35E 40E 45E
25 50 75 100 150 200 250 300 350 400 600

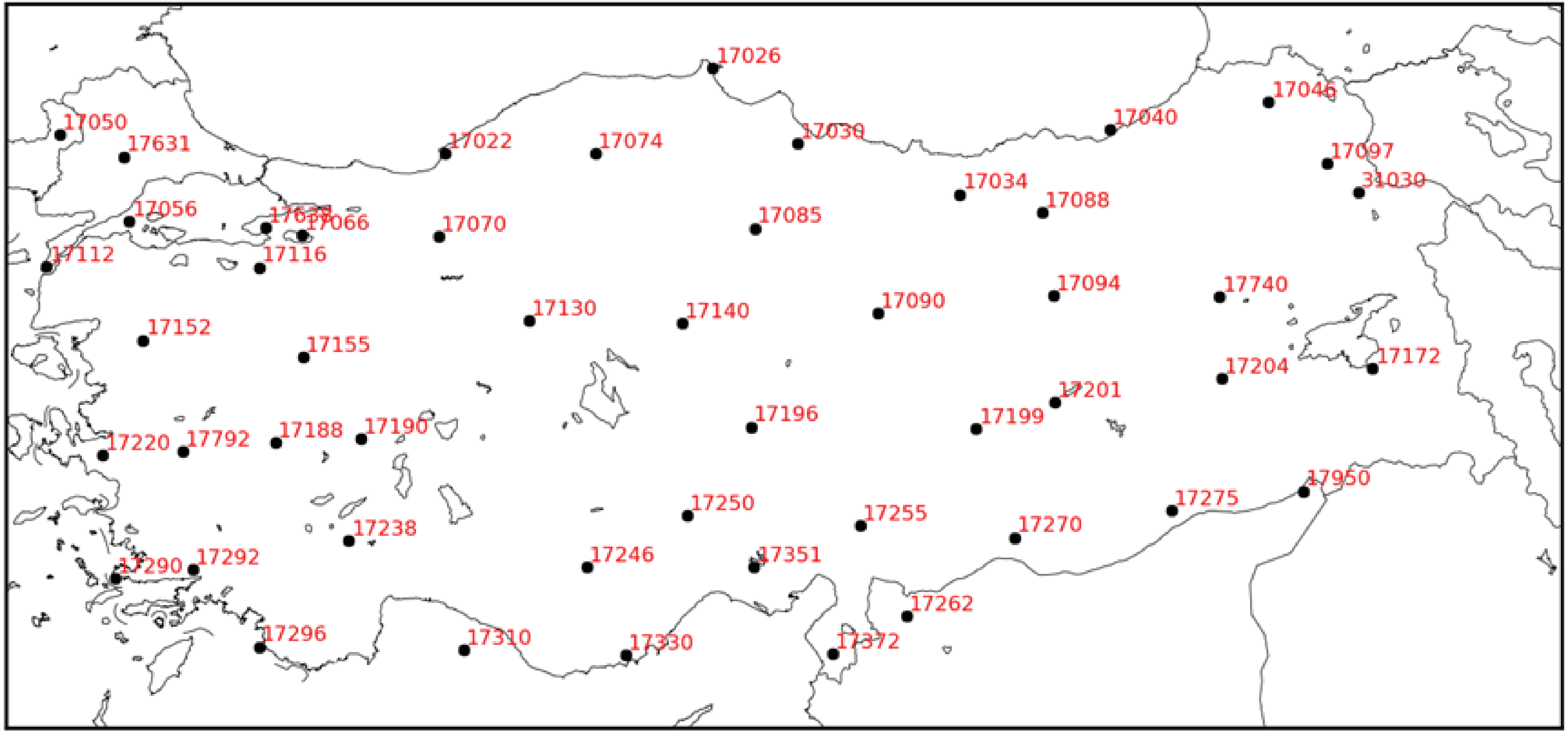


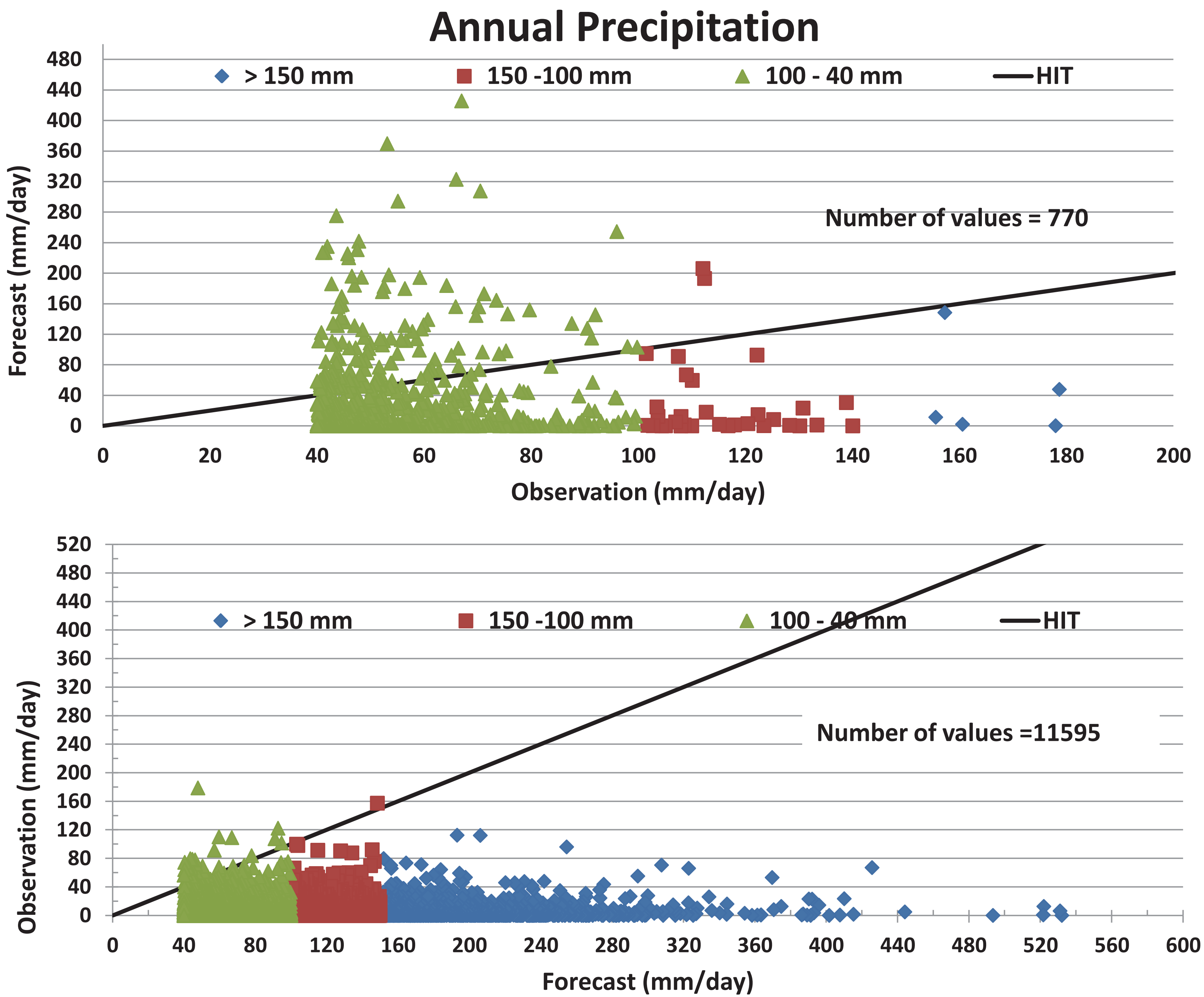
CMAP SON PRECIPITATION (mm)
52N 50N 48N 46N 44N 42N 40N 38N 36N 34N 32N 30N
10W 5W 0 5E 10E 15E 20E 25E 30E 35E 40E 45E
25 50 75 100 150 200 250 300 350 400 600
REGCM4 SON PRECIPITATION (mm)
52N 50N 48N 46N 44N 42N 40N 38N 36N 34N 32N 30N
10W 5W 0 5E 10E 15E 20E 25E 30E 35E 40E 45E
25 50 75 100 150 200 250 300 350 400 600
CRU SON PRECIPITATION (mm)
52N 50N 48N 46N 44N 42N 40N 38N 36N 34N 32N 30N
10W 5W 0 5E 10E 15E 20E 25E 30E 35E 40E 45E
25 50 75 100 150 200 250 300 350 400 600
ERAINT SON PRECIPITATION (mm)
52N 50N 48N 46N 44N 42N 40N 38N 36N 34N 32N 30N
10W 5W 0 5E 10E 15E 20E 25E 30E 35E 40E 45E
25 50 75 100 150 200 250 300 350 400 600


CMAP ANNUAL TOTAL PRECIPITATION (mm/year)
REGCM4 ANNUAL TOTAL PRECIPITATION (mm/year)
CRU ANNUAL TOTAL PRECIPITATION (mm/year)
ERAINT ANNUAL TOTAL PRECIPITATION (mm/year)
52N 50N 48N 46N 44N 42N 40N 38N 36N 34N 32N 30N
10W 5W 0 5E 10E 15E 20E 25E 30E 35E 40E 45E
100 200 300 400 500 600 700 800 1000 1200 1500

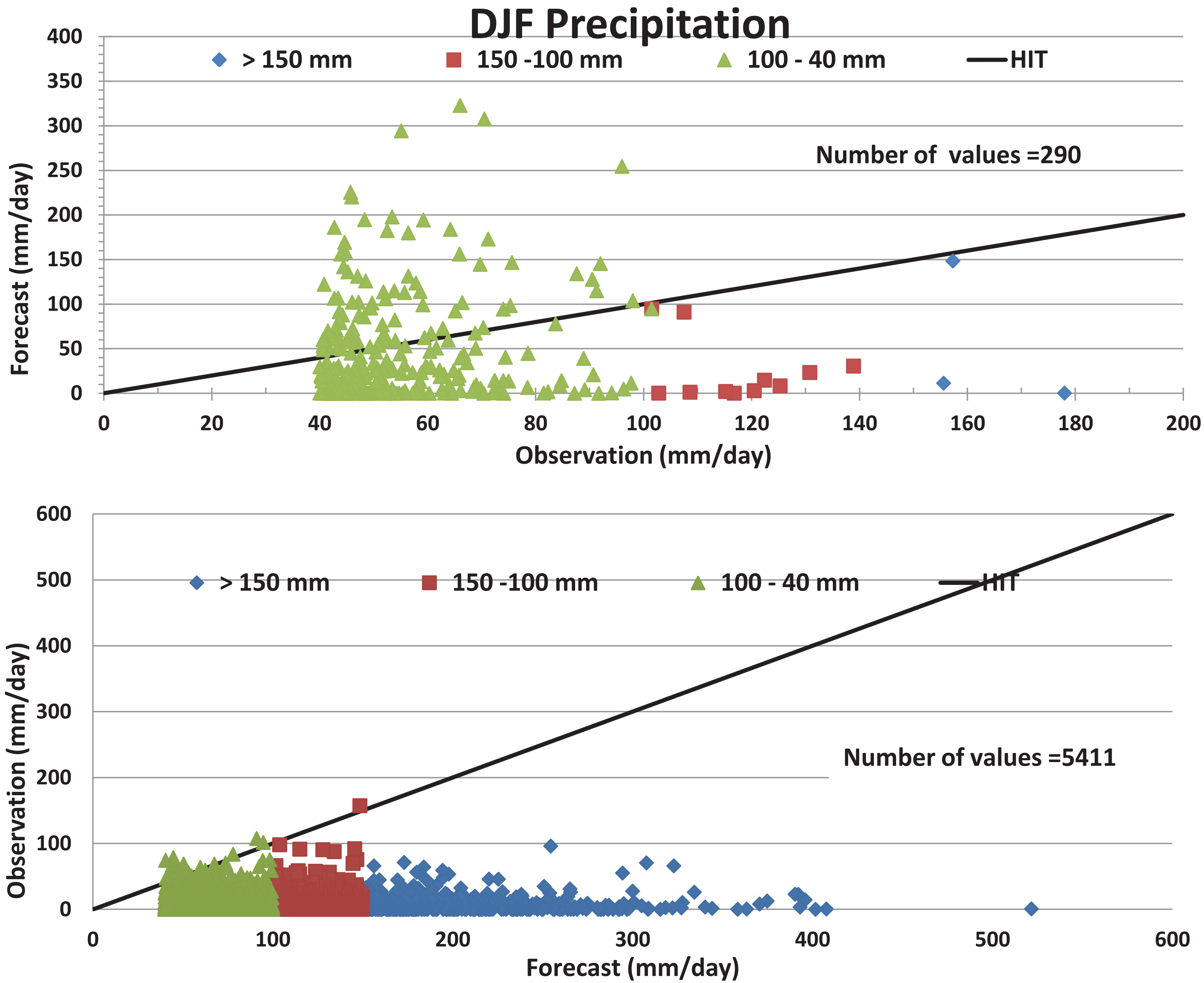
OBJECTIVE VERIFICATION

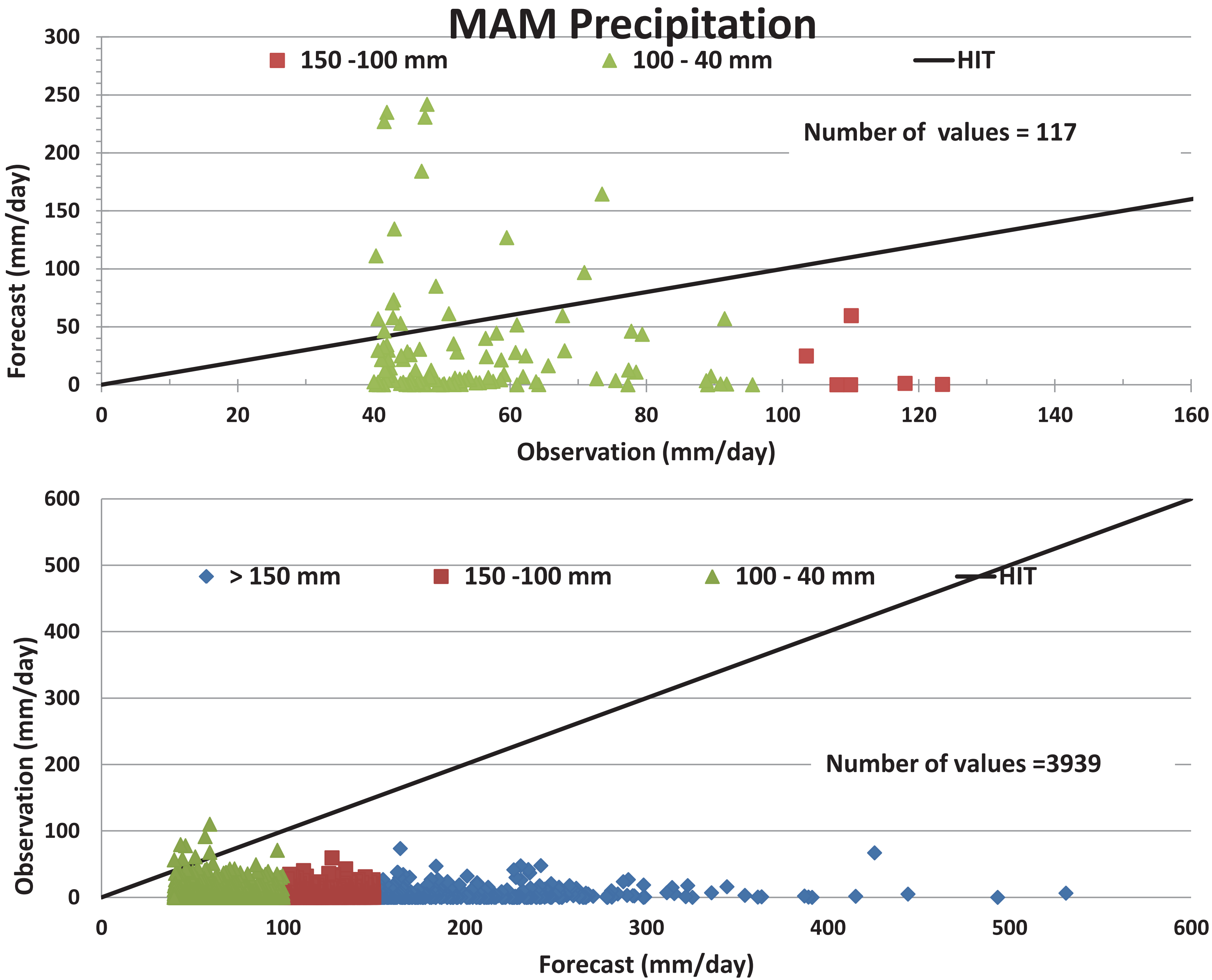
REGCM - STATIONS



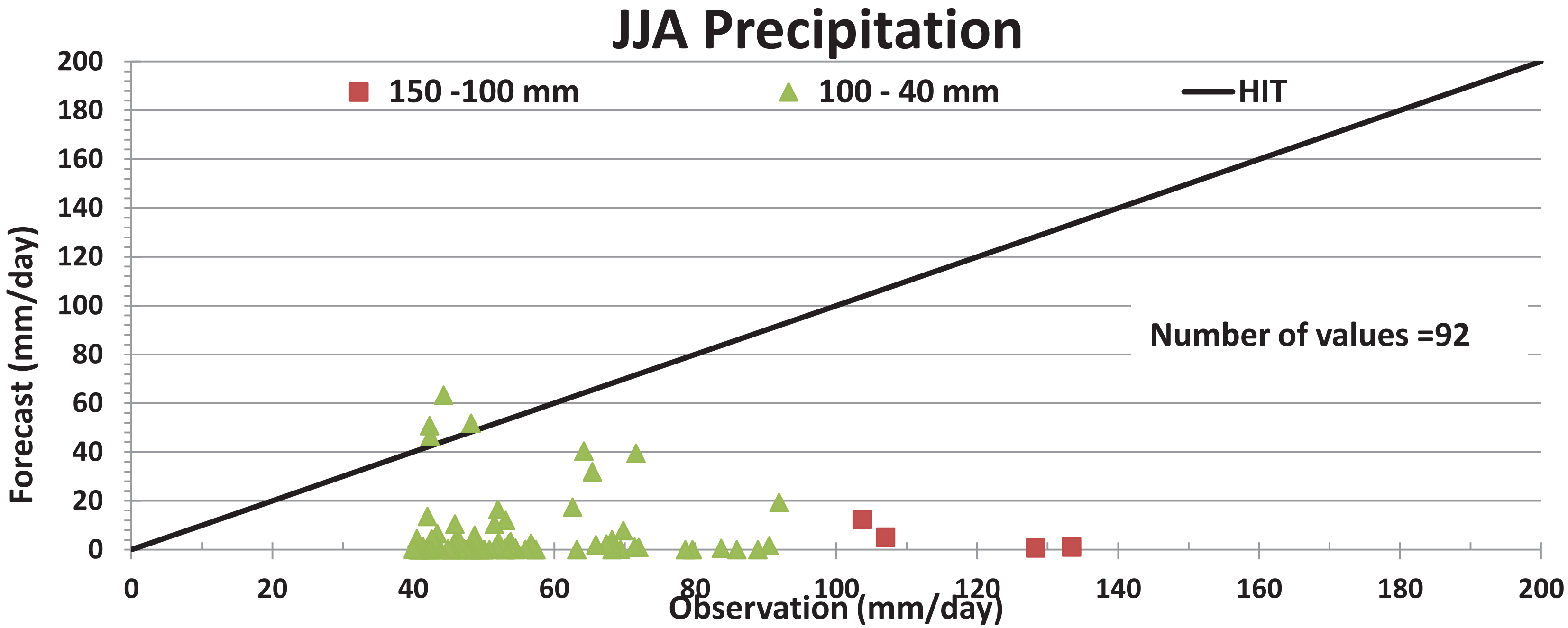


Annual Precipitation
> 150 mm
150 -100 mm
100 - 40 mm
HIT
Number of values = 770
Forecast (mm/day)
Observation (mm/day)
0
20
40
60
80
100
120
140
160
180
200
240
280
320
360
400
440
480
> 150 mm
150 -100 mm
100 - 40 mm
HIT
Number of values =11595
Observation (mm/day)
Forecast (mm/day)
520
560
600

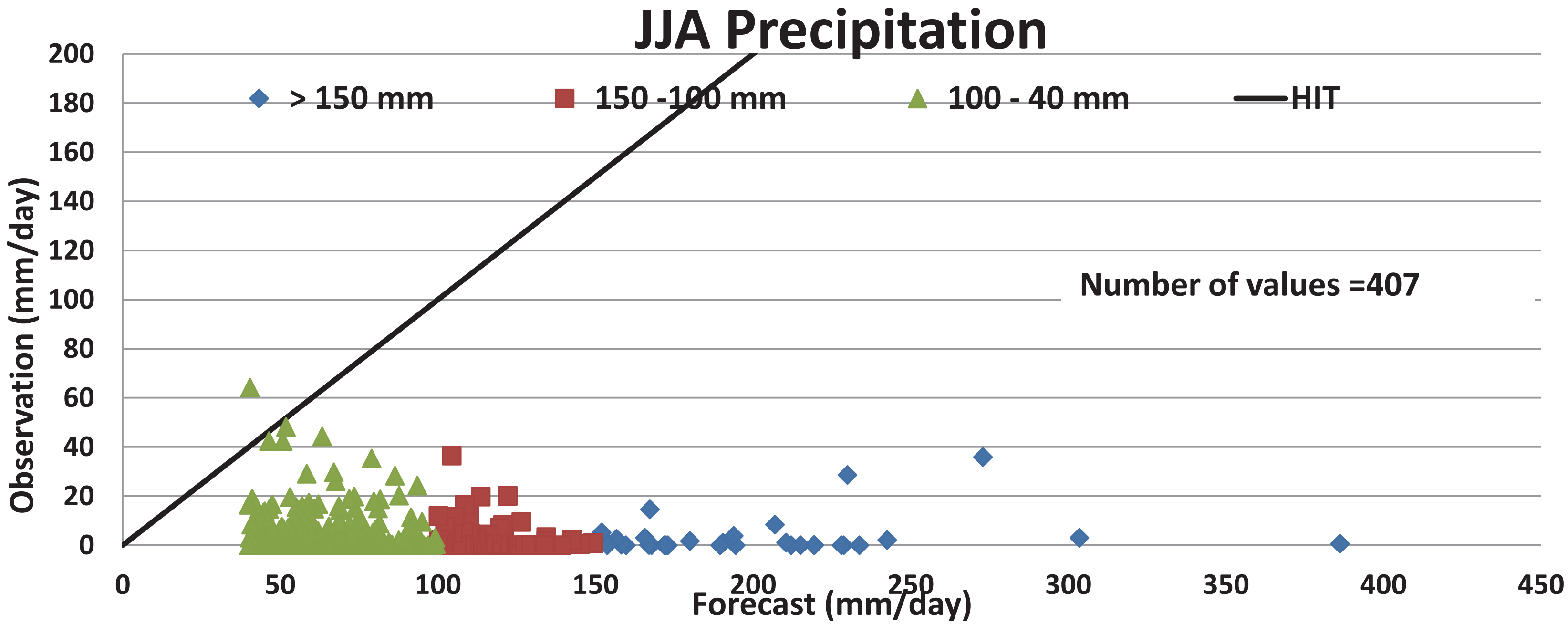

DJF Precipitation
> 150 mm
150 -100 mm
100 - 40 mm
HIT
Number of values =290
Forecast (mm/day)
Observation (mm/day)
> 150 mm
150 -100 mm
100 - 40 mm
HIT
Number of values =5411
Observation (mm/day)
Forecast (mm/day)



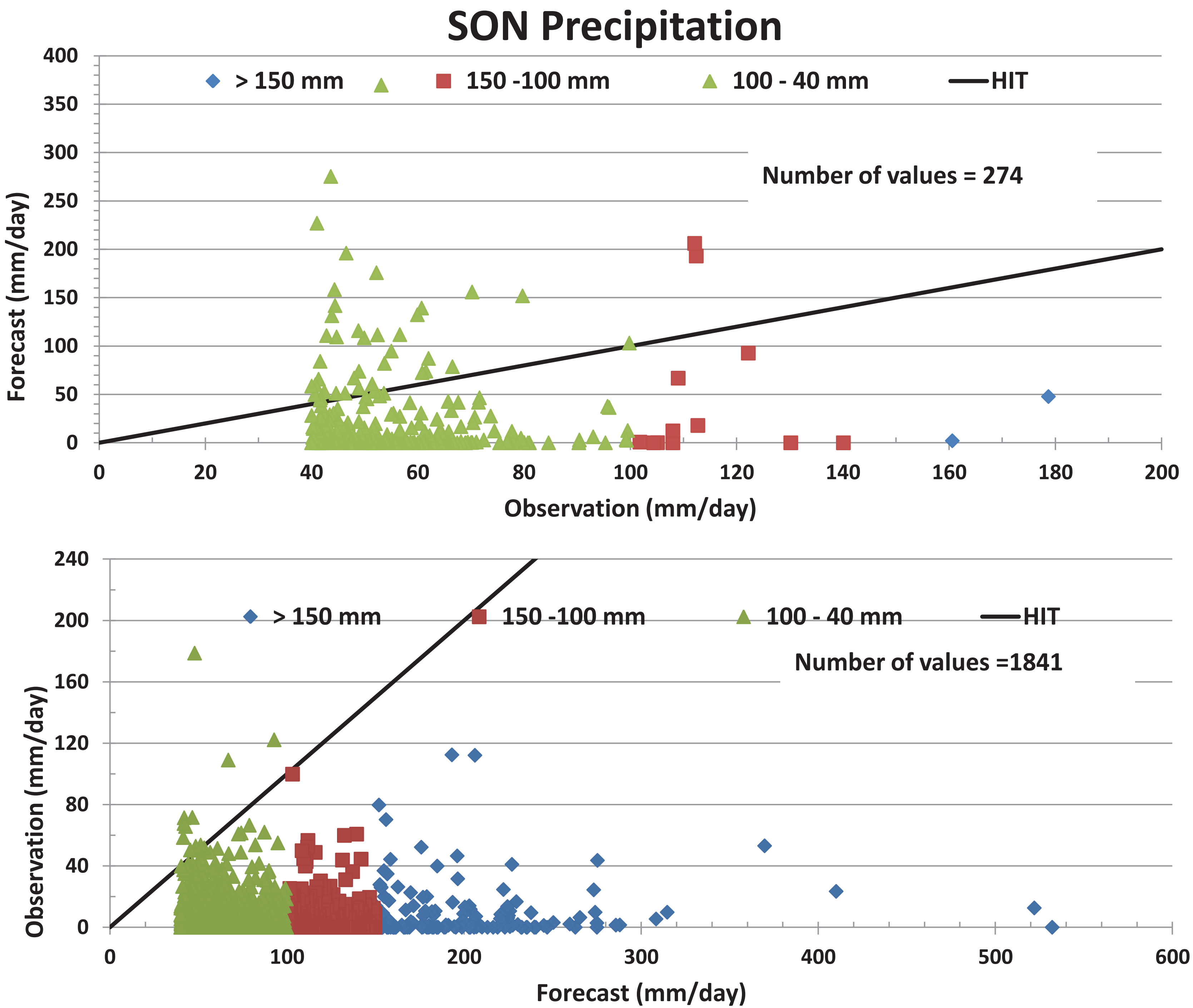
MAM Precipitation
150 -100 mm
100 - 40 mm
HIT
Number of values = 117
Forecast (mm/day)
Observation (mm/day)
0
50
100
150
200
250
300
0
20
40
60
80
100
120
140
160
> 150 mm
150 -100 mm
100 - 40 mm
HIT
Number of values =3939
Observation (mm/day)
Forecast (mm/day)
0
100
200
300
400
500
600



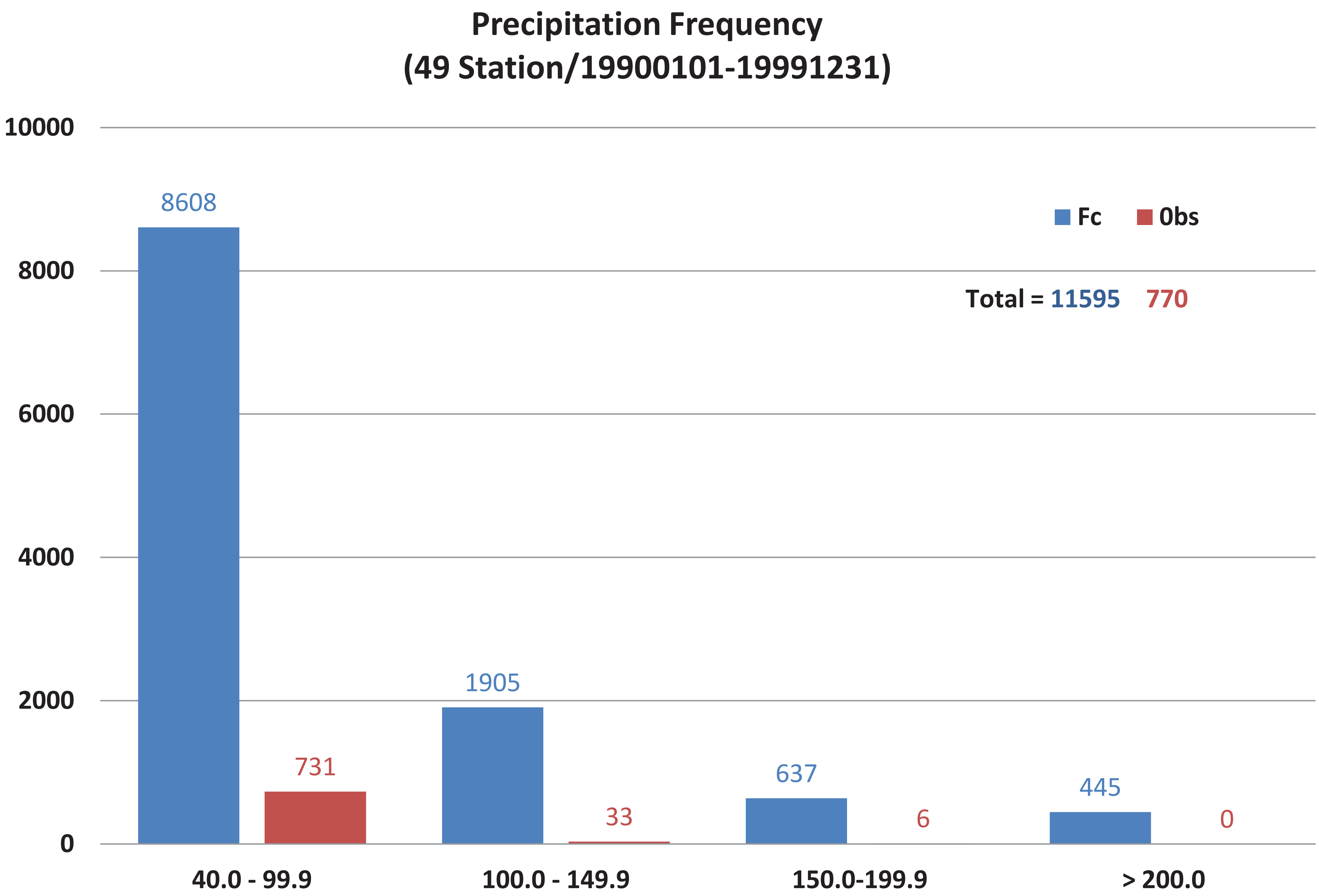
JJA Precipitation
150 -100 mm
100 - 40 mm
HIT
Number of values =92
Forecast (mm/day)
Observation (mm/day)
0
20
40
60
80
100
120
140
160
180
200

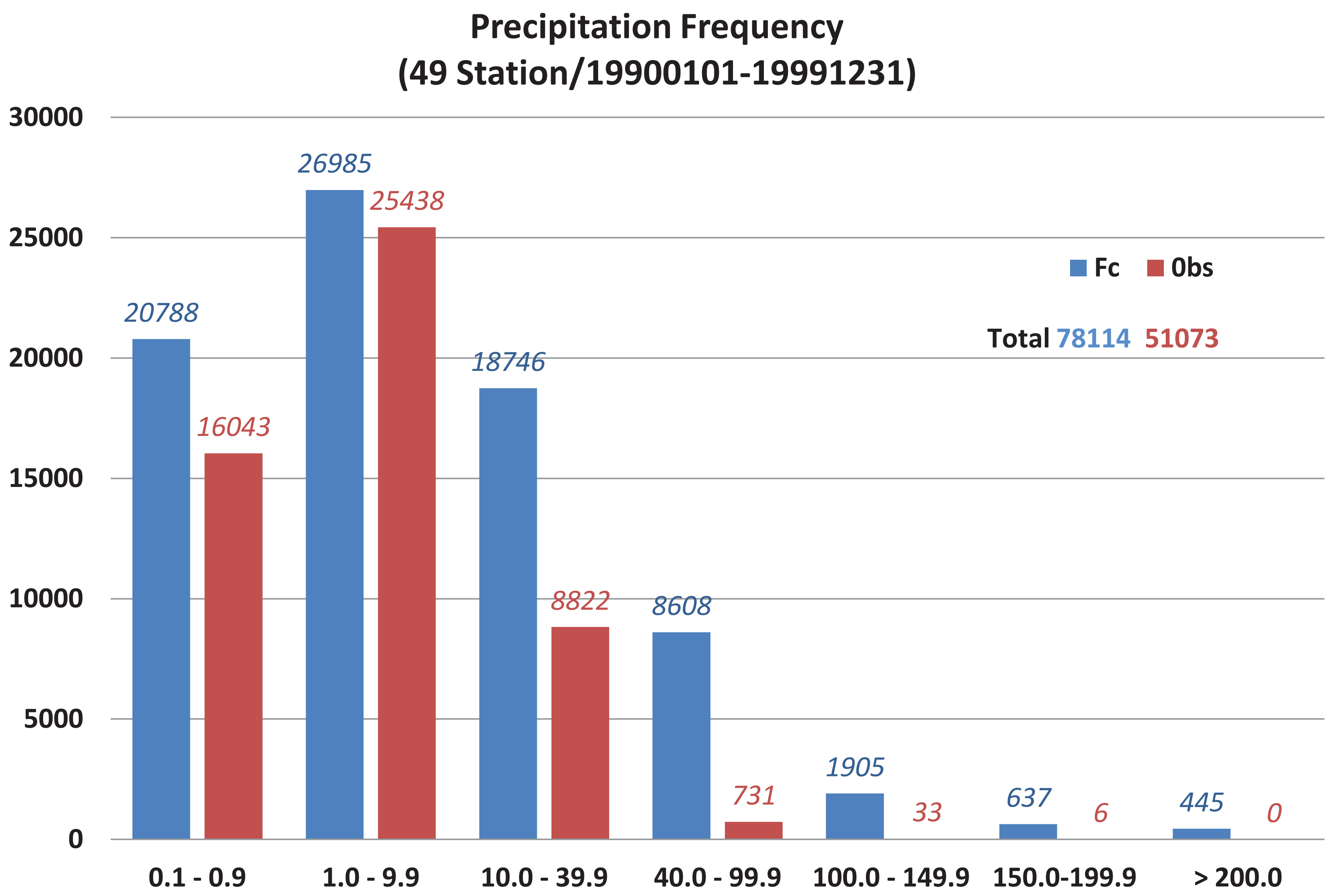


JJA Precipitation
> 150 mm
150 -100 mm
100 - 40 mm
HIT
Number of values =407
Observation (mm/day)
Forecast (mm/day)
0
50
100
150
200
250
300
350
400
450



SON Precipitation
> 150 mm
150 -100 mm
100 - 40 mm
HIT
Number of values = 274
Forecast (mm/day)
Observation (mm/day)
0
50
100
150
200
250
300
350
400
0
20
40
60
80
100
120
140
160
180
200
> 150 mm
150 -100 mm
100 - 40 mm
HIT
Number of values =1841
Observation (mm/day)
Forecast (mm/day)
0
40
80
120
160
200
240
0
100
200
300
400
500
600


Precipitation Frequency
(49 Station/19900101-19991231)
10000
8000
6000
4000
2000
0
8608
731
1905
33
637
6
445
0
40.0 - 99.9
100.0 - 149.9
150.0-199.9
> 200.0
Fc
Obs
Total = 11595 770


Precipitation Frequency
(49 Station/19900101-19991231)
30000
25000
20000
15000
10000
5000
0
26985
25438
20788
16043
18746
8822
8608
731
1905
33
637
6
445
0
Fc
Obs
Total 78114 51073
0.1 - 0.9
1.0 - 9.9
10.0 - 39.9
40.0 - 99.9
100.0 - 149.9
150.0-199.9
> 200.0

Contingency Table

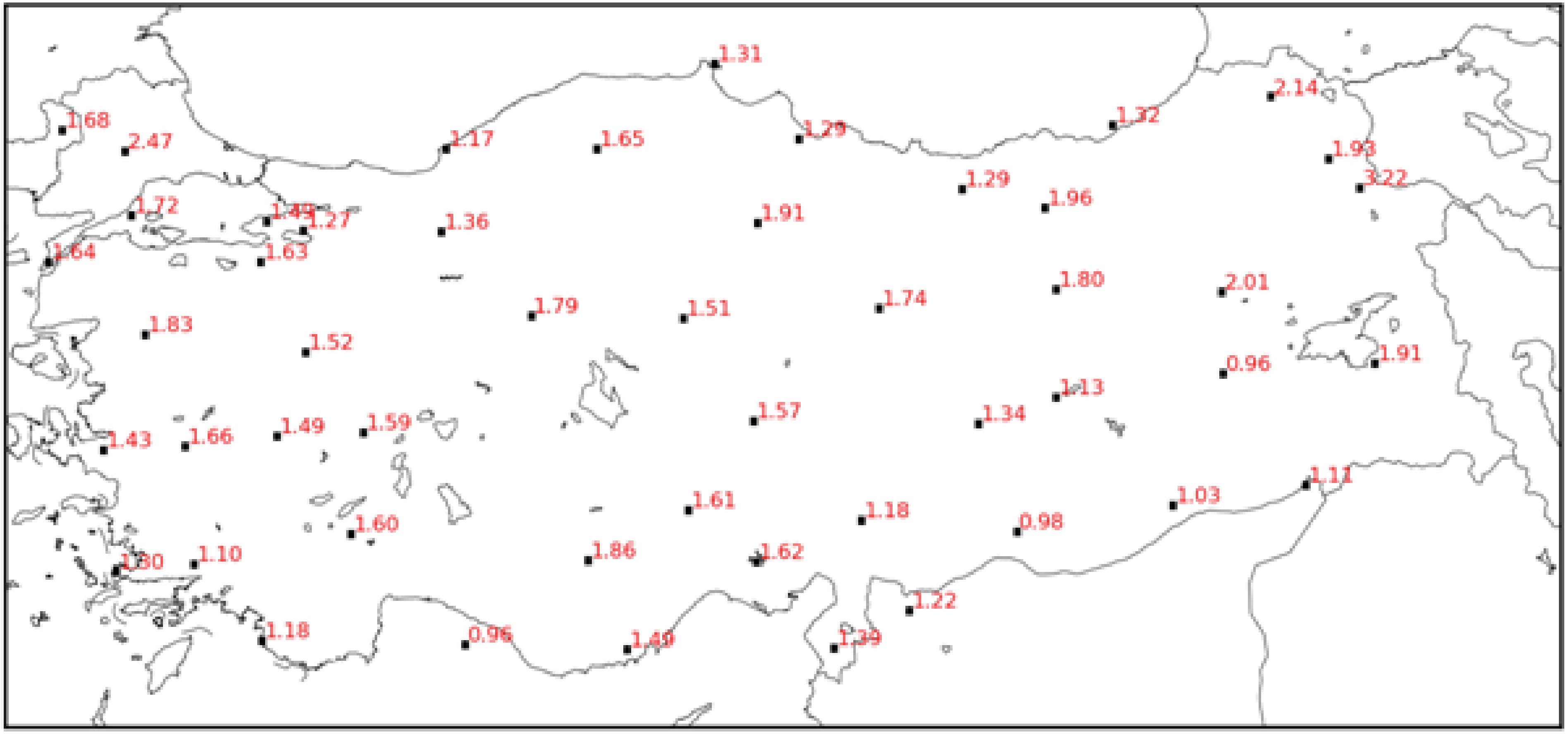
		Observed	
		yes	no
Forecast	yes	a	b
	no	c	d

FAR = b/(a+b)
Hit Rate = (a+d)/(a+b+c+d)
BIAS = (a+b)/(a+c)
POD = a/(a+c)
TS = a/(a+b+c)

TURKEY		Observed		
1990-1999		yes	no	Total
Forecast	yes	36906	41206	78112
	no	14166	89510	103676
Total		51072	130716	181788

False Alarm Ratio	**0,53**
Hit Rate	**0,70**
BIAS	**1,53**
Probabilty Of Dedection	**0,72**
Threat score	**0,40**

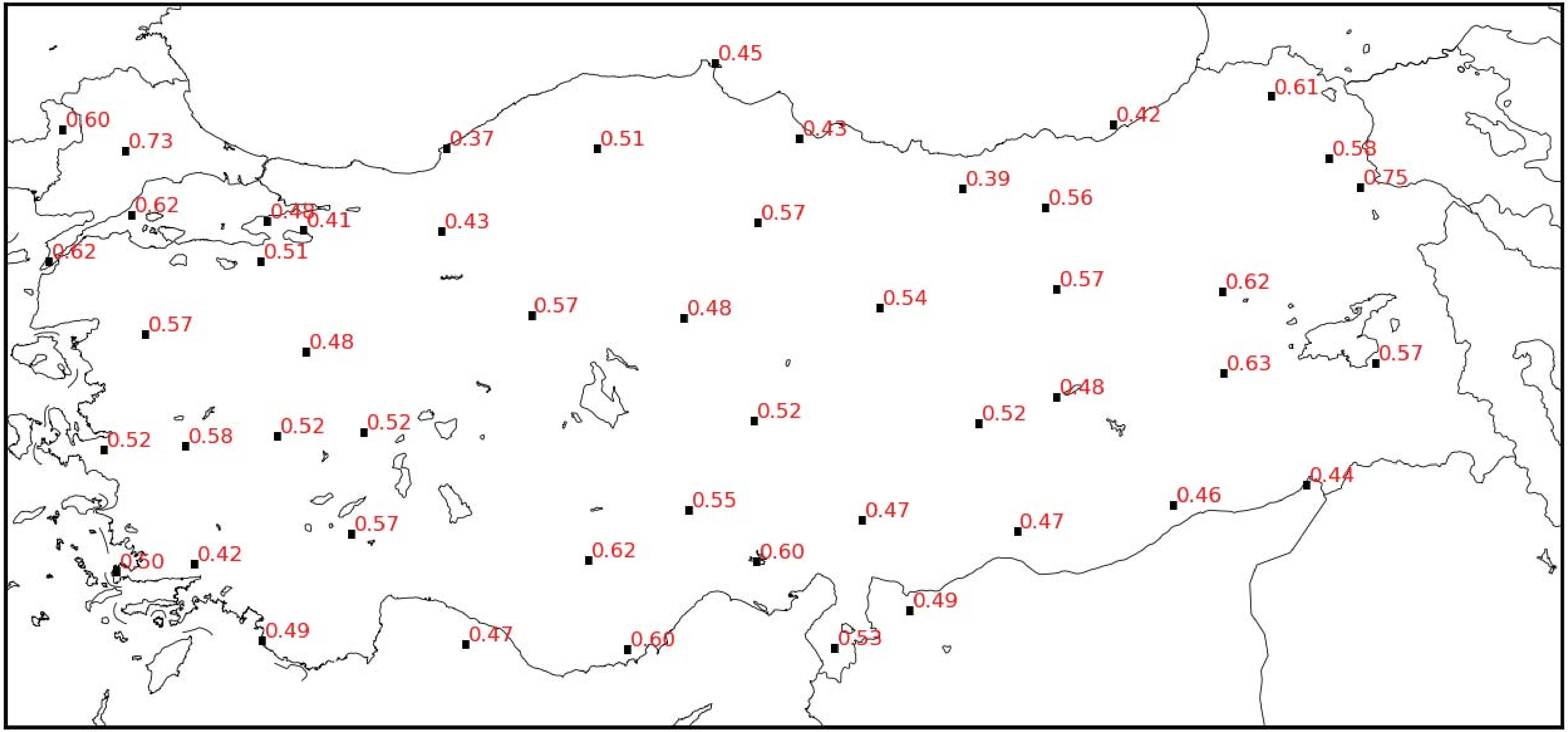
REGCM - BIAS



Bias score (frequency bias) $= \dfrac{hits + false\ alarms}{hits + misses}$

Range: 0 to infinity. **Perfect score:** 1.

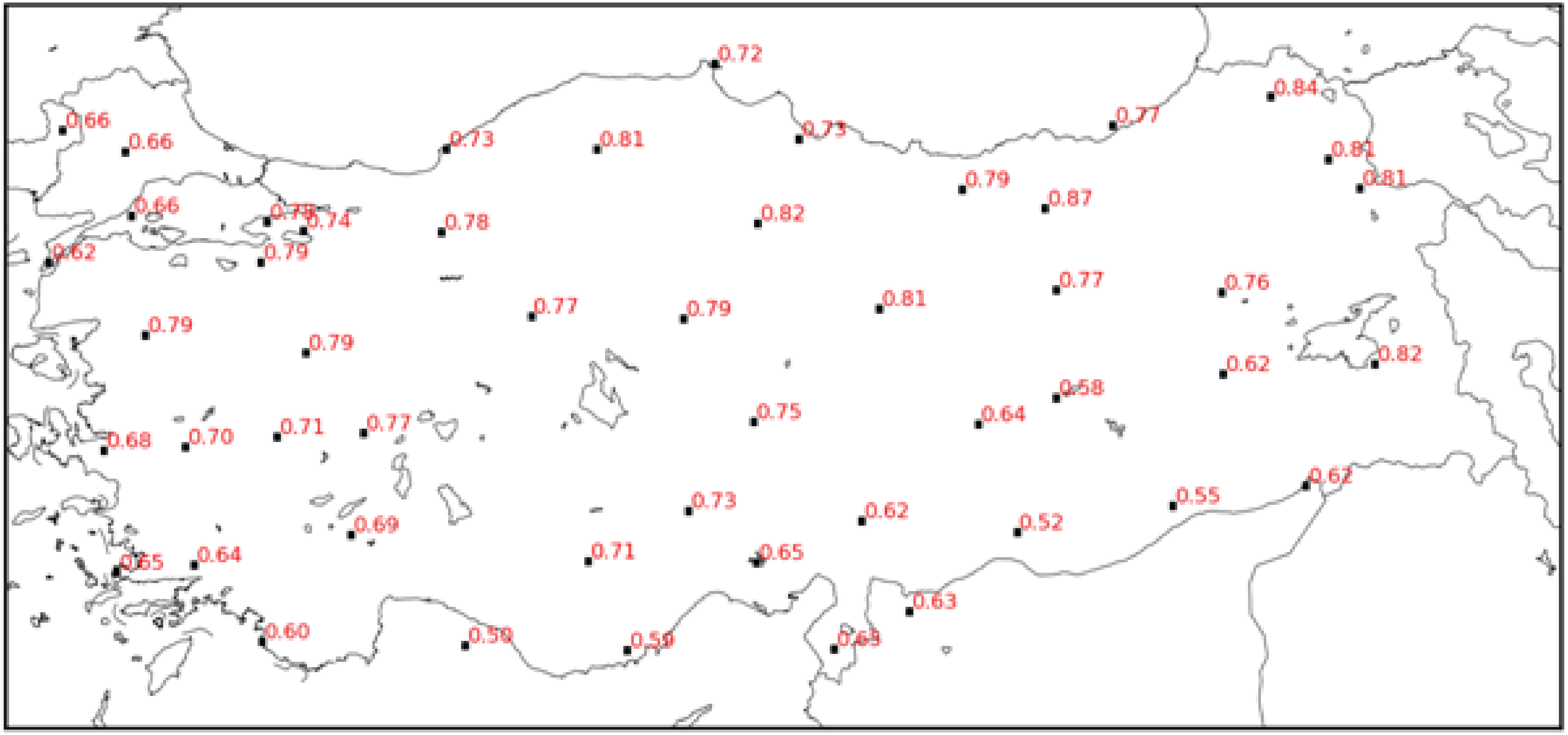
REGCM - FAR



False alarm ratio (FAR) $= \dfrac{false\ alarms}{hits + false\ alarms}$

Range: 0 to 1. **Perfect score:** 0.

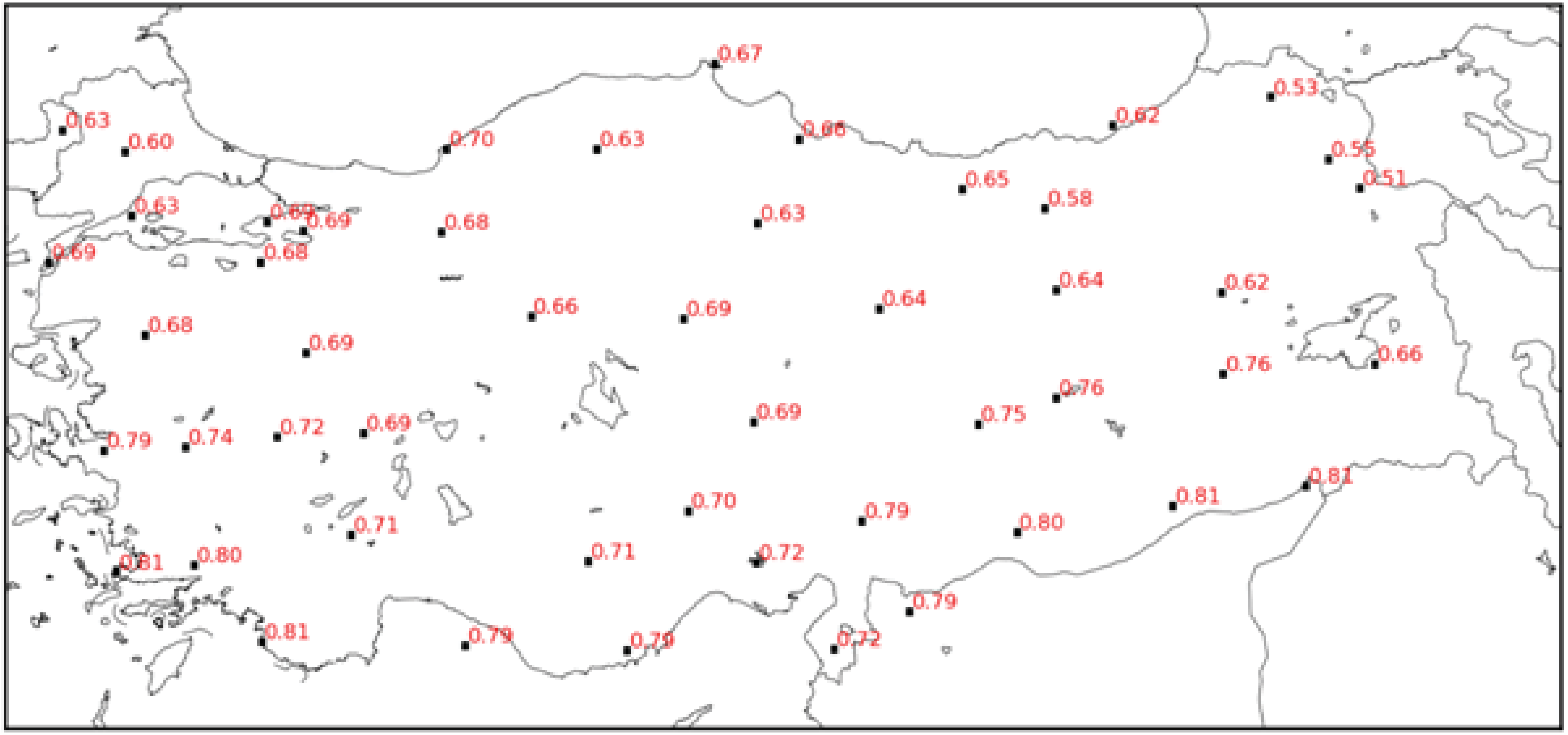
REGCM - POD



Probability of detection (hit rate) $= \dfrac{hits}{hits + misses}$

Range: 0 to 1. **Perfect score:** 1.

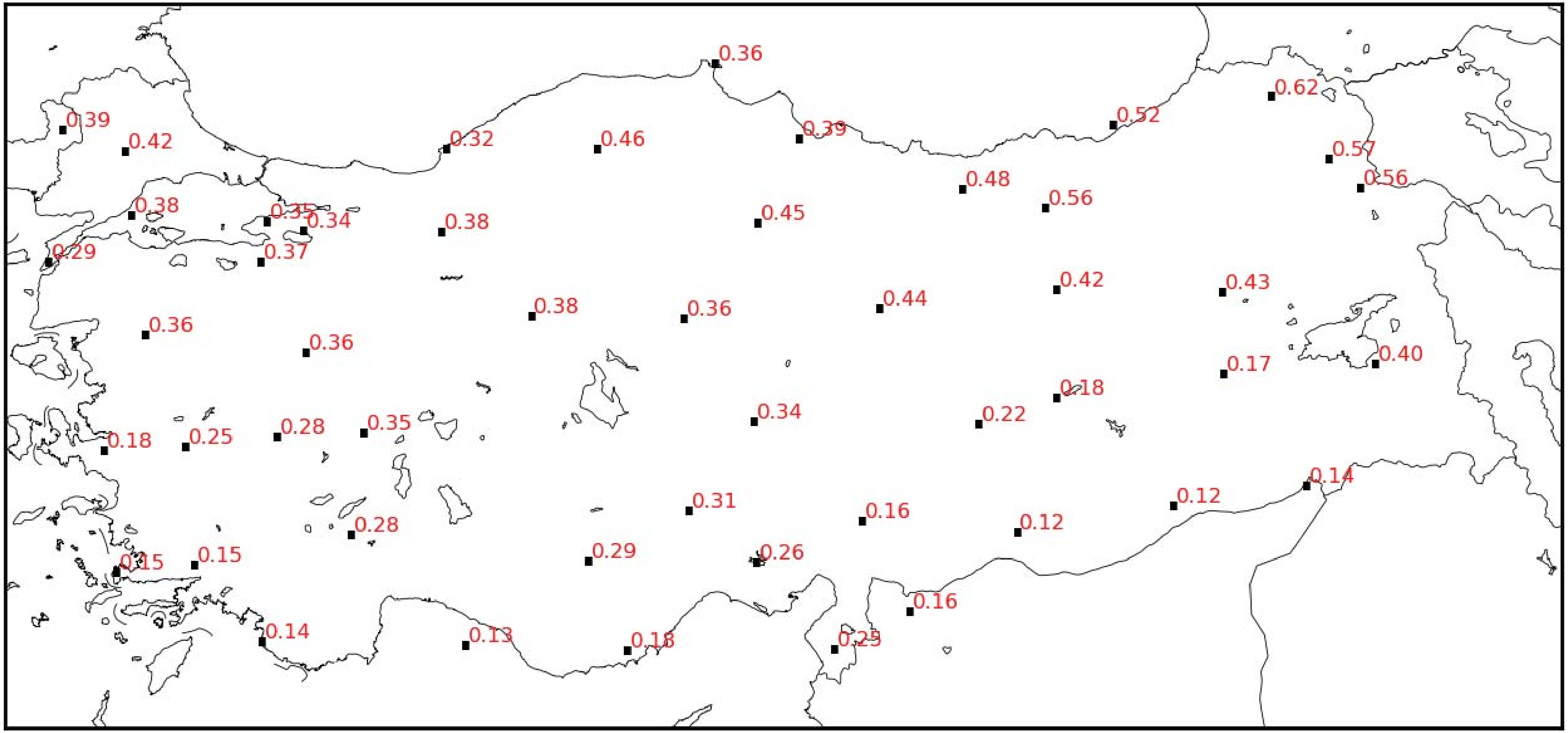
REGCM - PC



Proportion Correct $= \dfrac{hits + correct\ \ negatives}{total}$

Range: 0 to 1. **Perfect score:** 1.

REGCM - F

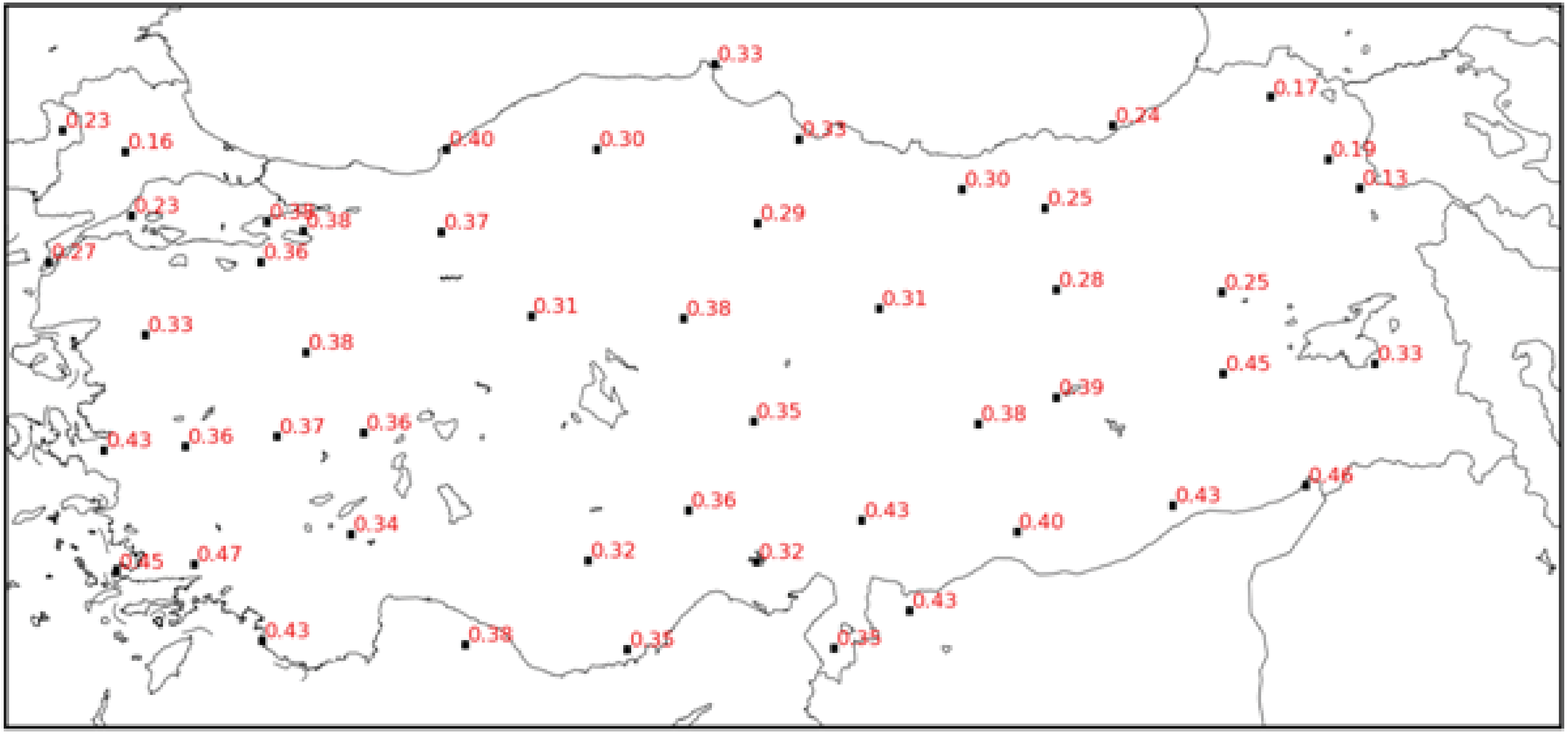


Probability of false detection (false alarm rate) (POFD =F)

$$= \frac{\textit{false alarms}}{\textit{correct negatives} + \textit{false alarms}}$$

Range: 0 to 1. **Perfect score:** 0.

REGCM - HSS



Heidke skill score (Cohen's κ) =HSS

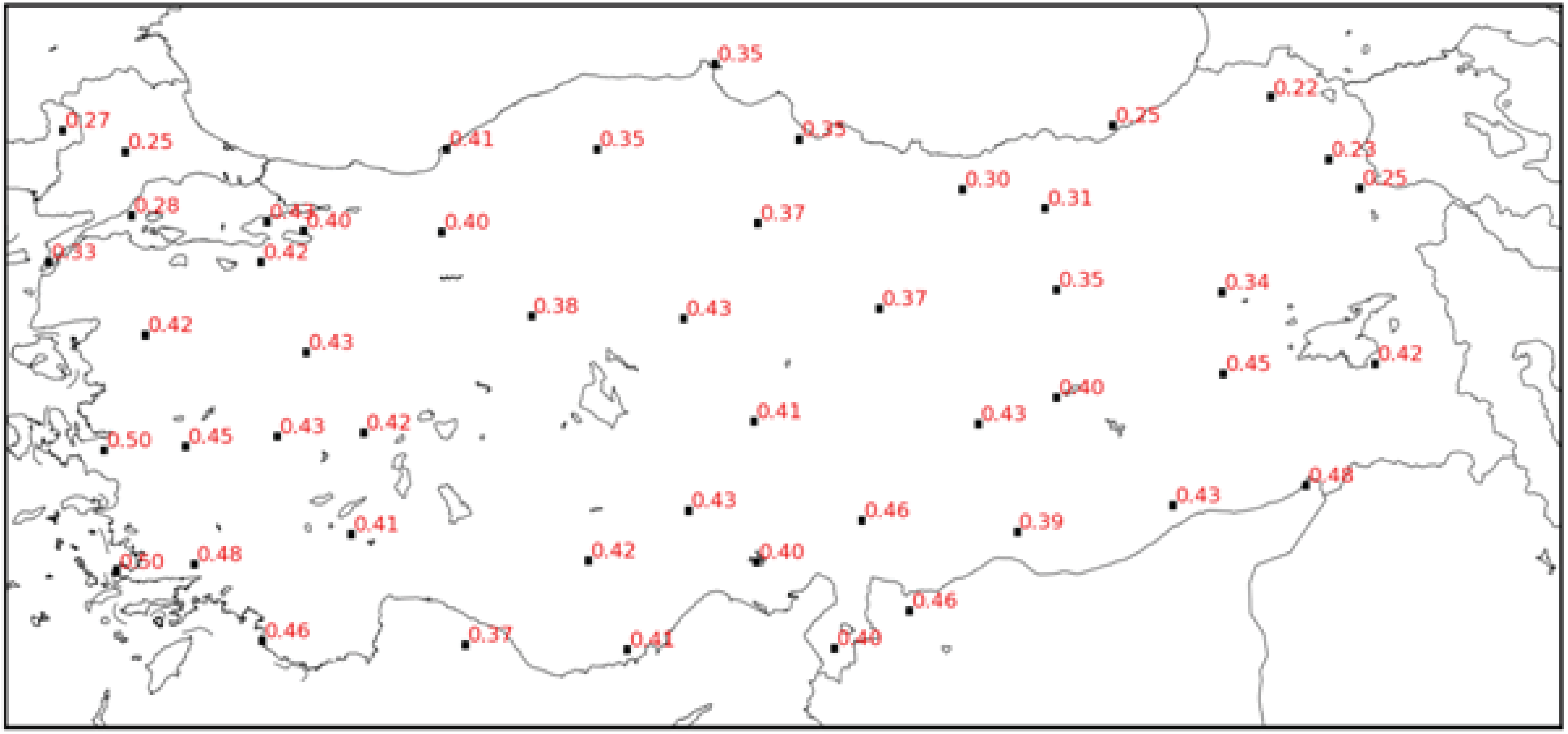
$$HSS = \frac{(hits + correct\ negatives) - (expected\ correct)_{random}}{N - (expected\ correct)_{random}}$$

where

$$(expected\ correct)_{random} = \frac{1}{N}\left[(hits + misses)(hits + false\ alarms) + (correct\ negatives + misses)(correct\ negatives + false\ alarms)\right]$$

Range: minus infinity to 1, 0 indicates no skill. **Perfect score:** 1.

REGCM - KSS

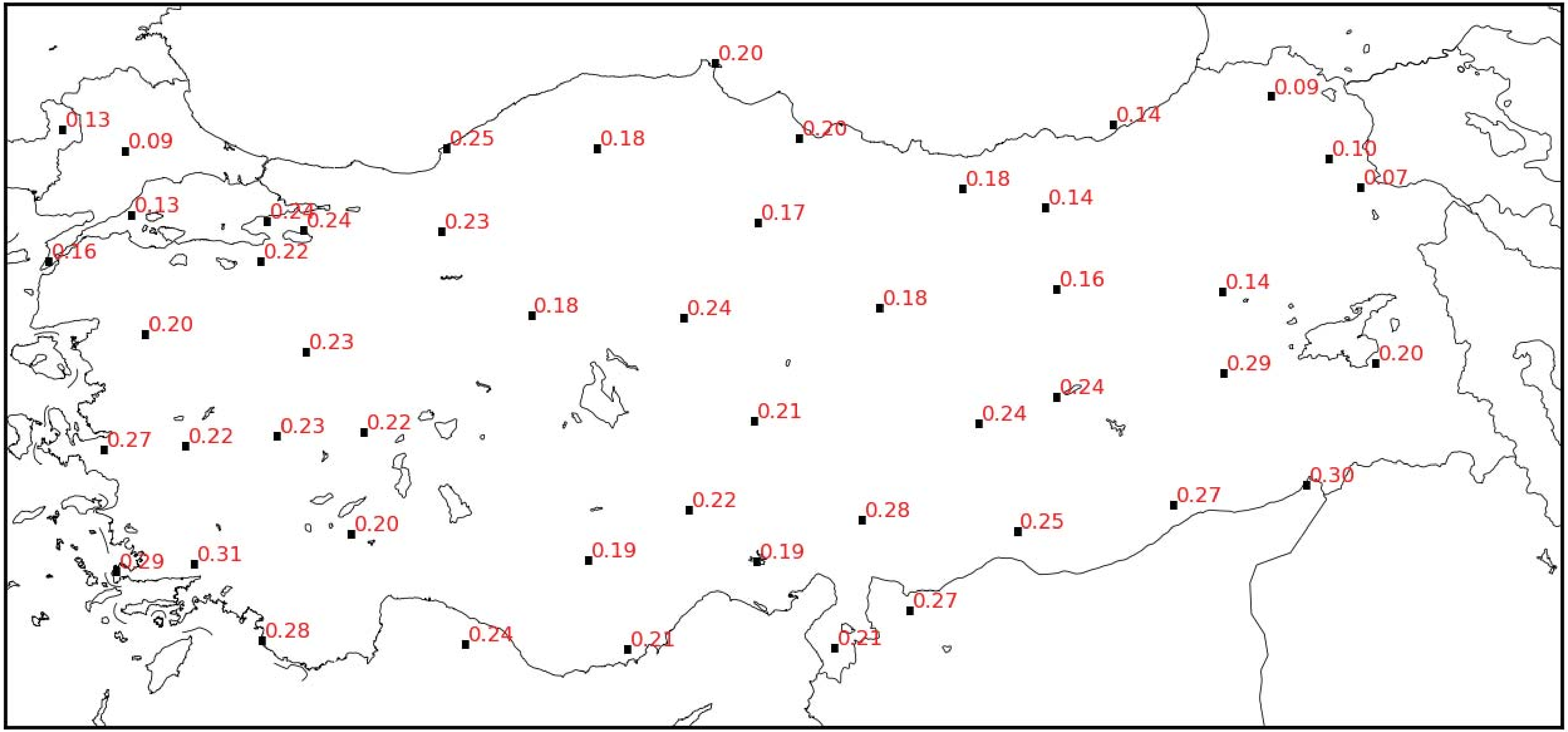


Hanssen and Kuipers discriminant
(true skill statistic, Peirces's skill score)
=KSS

$$HK = \frac{hits}{hits + misses} - \frac{false\ alarms}{false\ alarms + correct\ \ negatives}$$

Range: -1 to 1, 0 indicates no skill. **Perfect score:** 1

REGCM - ETS



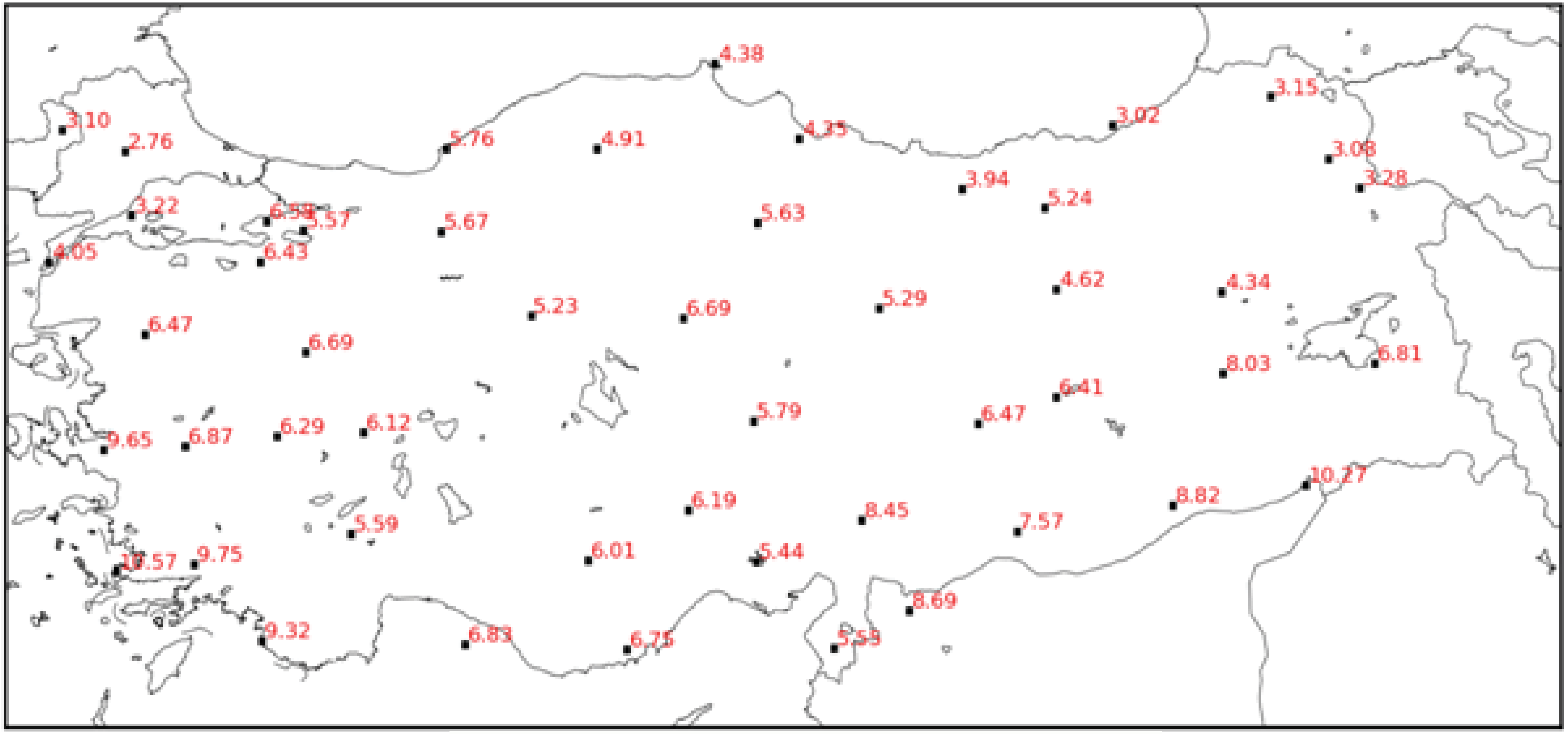
Equitable threat score (Gilbert skill score)
ETS

$$= \frac{hits - hits_{random}}{hits + misses + false\ alarms - hits_{random}}$$

$$hits_{random} = \frac{(hits + misses)(hits + false\ alarms)}{total}$$

Range: -1/3 to 1, 0 indicates no skill. **Perfect score:** 1.

REGCM - OR

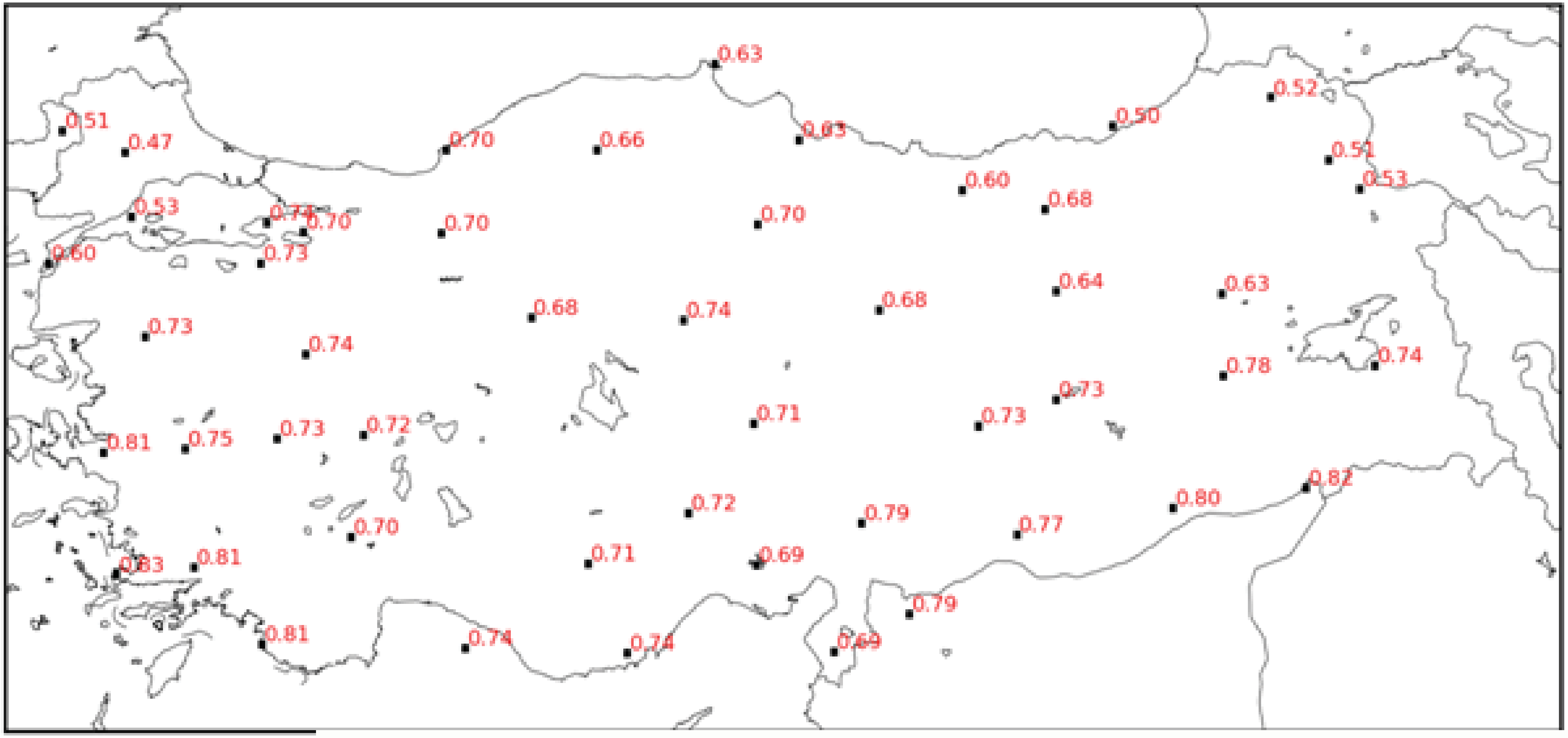


Odds ratio **(OR)** $= \dfrac{hits \times correct\ negatives}{misses \times false\ alarms} = \dfrac{\left(\dfrac{POD}{1-POD}\right)}{\left(\dfrac{POFD}{1-POFD}\right)}$

Odds ratio - Range: 0 to infinity, 1 indicates no skill. **Perfect score:** infinity

Log odds ratio-Range: minus infinity to infinity, 0 indicates no skill.**Perfect score:** infinity

REGCM - ORSS

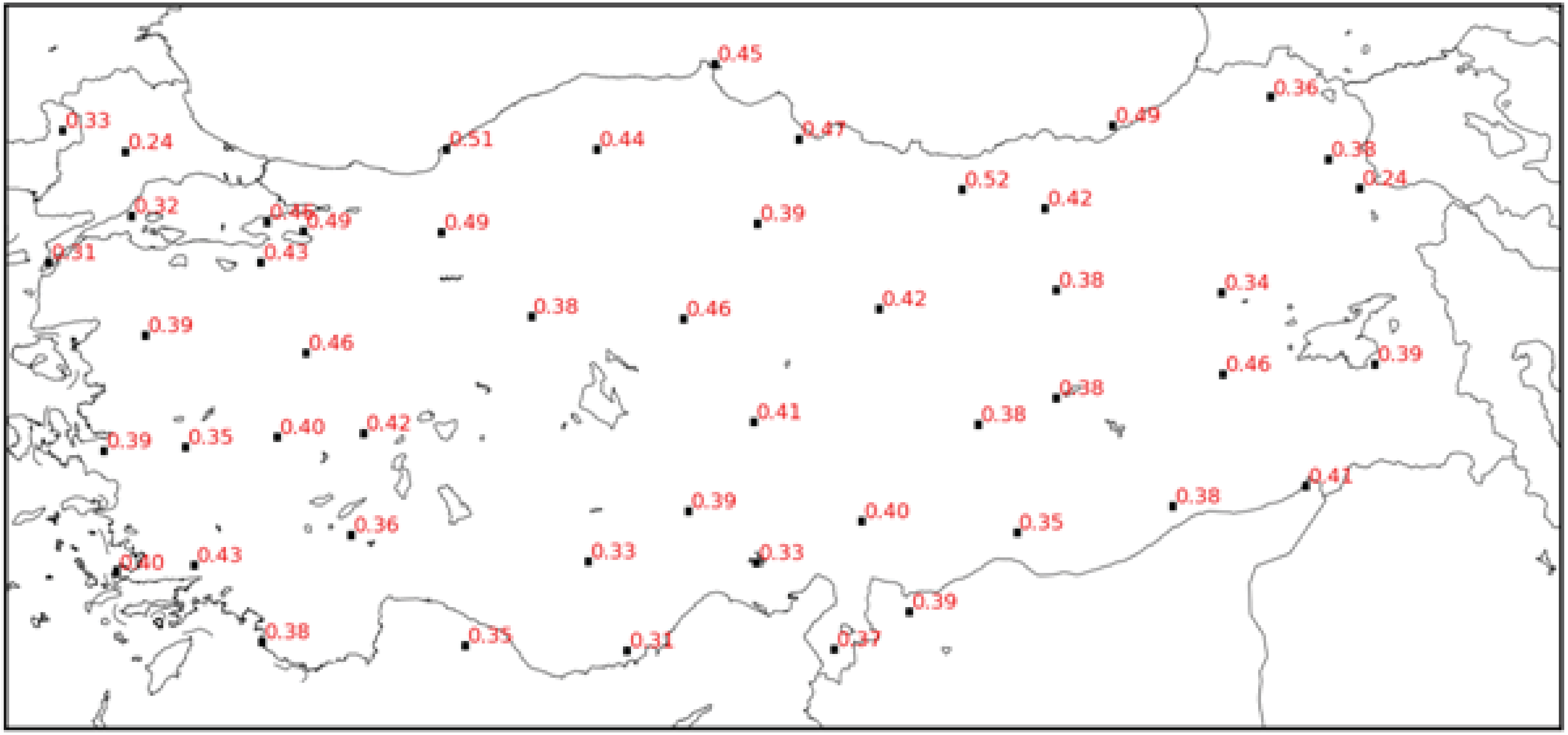


Odds ratio skill score (Yule's Q)

$$= \frac{hits \times correct\ negatives - misses \times false\ alarms}{hits \times correct\ negatives + misses \times false\ alarms}$$

Range: -1 to 1, 0 indicates no skill. **Perfect score:** 1

REGCM - TS



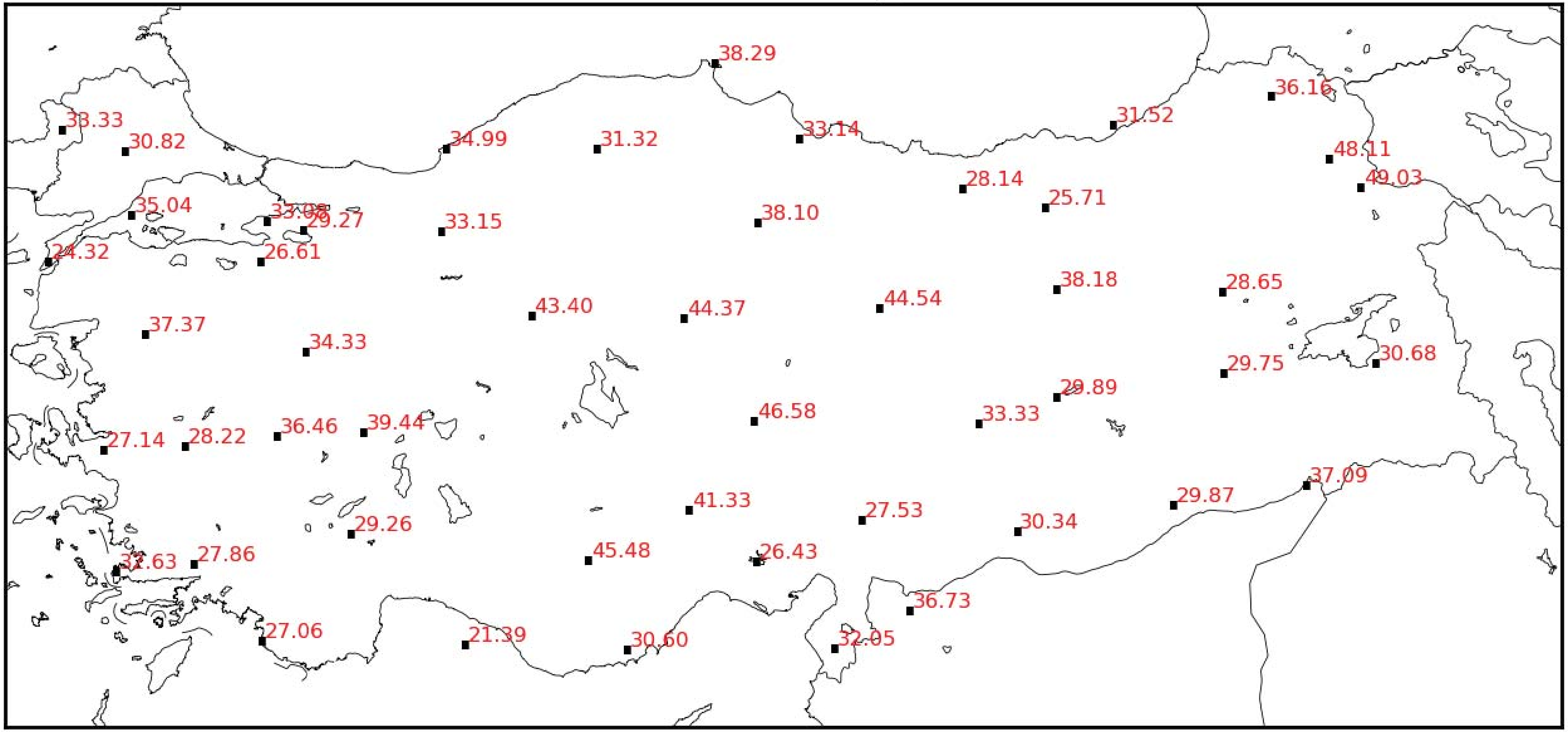
Threat score (critical success index)

TS=CSI

$$= \frac{hits}{hits + misses + false\ alarms}$$

Range: 0 to 1, 0 indicates no skill. **Perfect score:** 1.

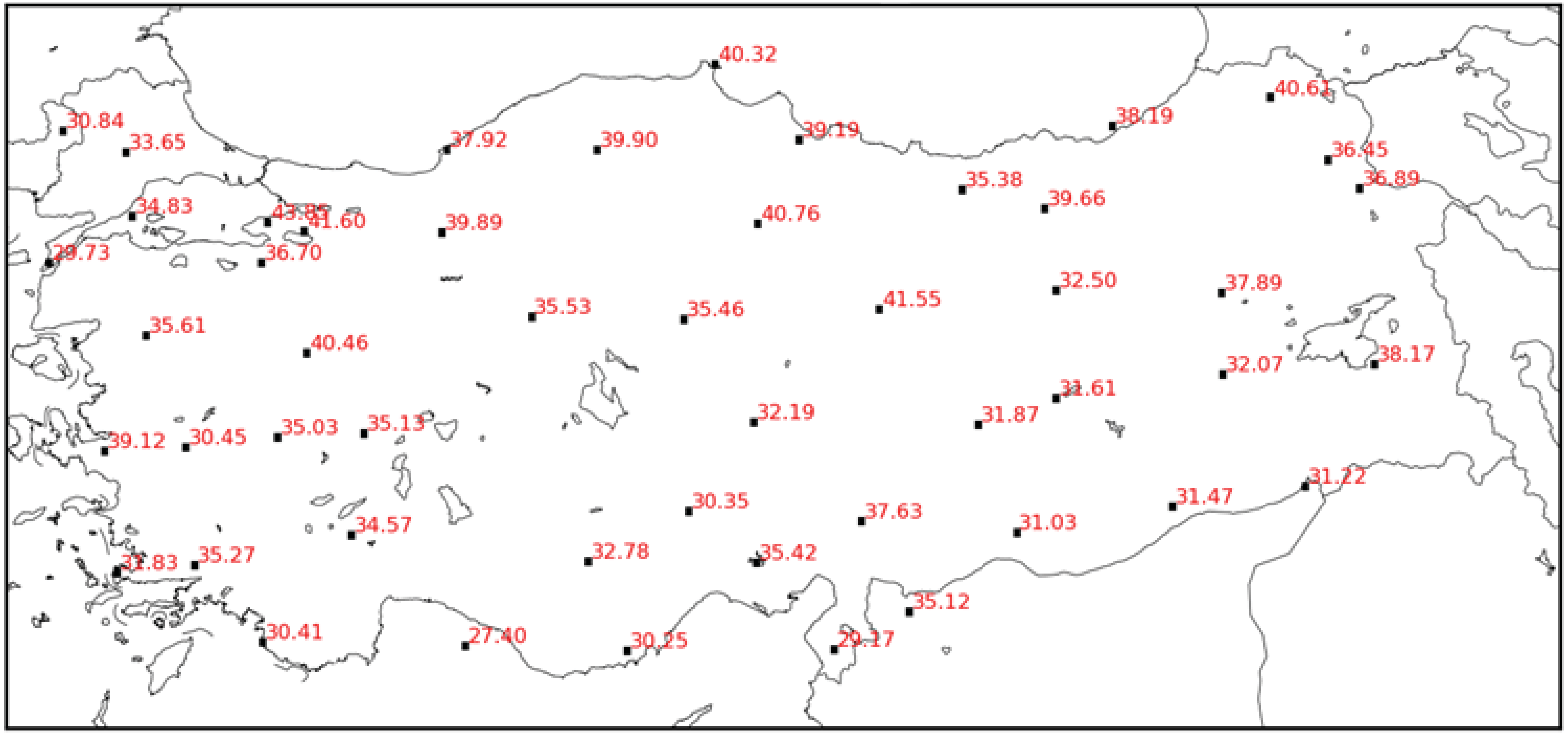
REGCM - HIT_RATES



$$Accuracy = \frac{1}{N}\sum_{i=1}^{K} n(F_i, O_i)$$

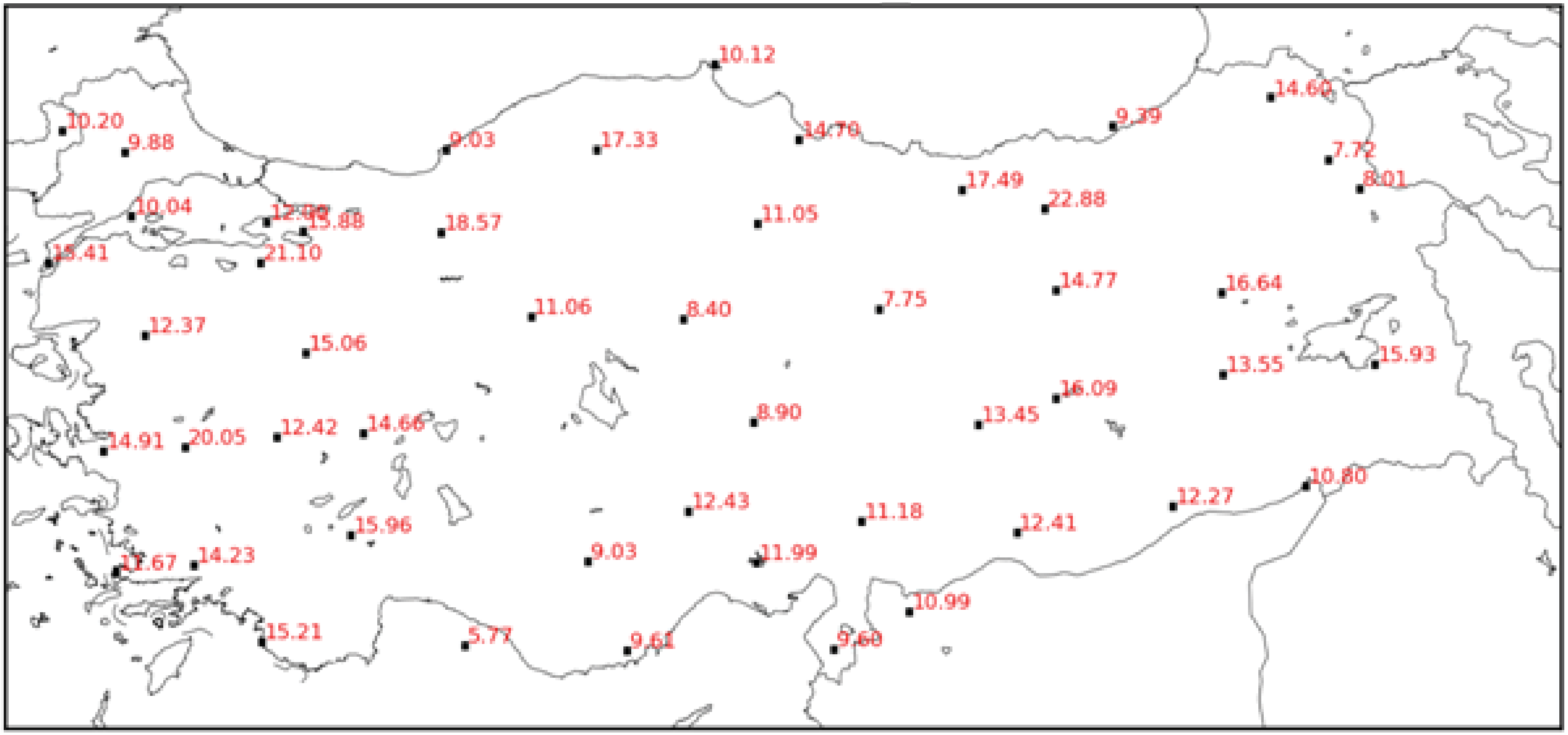
Range: 0 to 1. **Perfect score:** 1.

REGCM- Small Error Rate



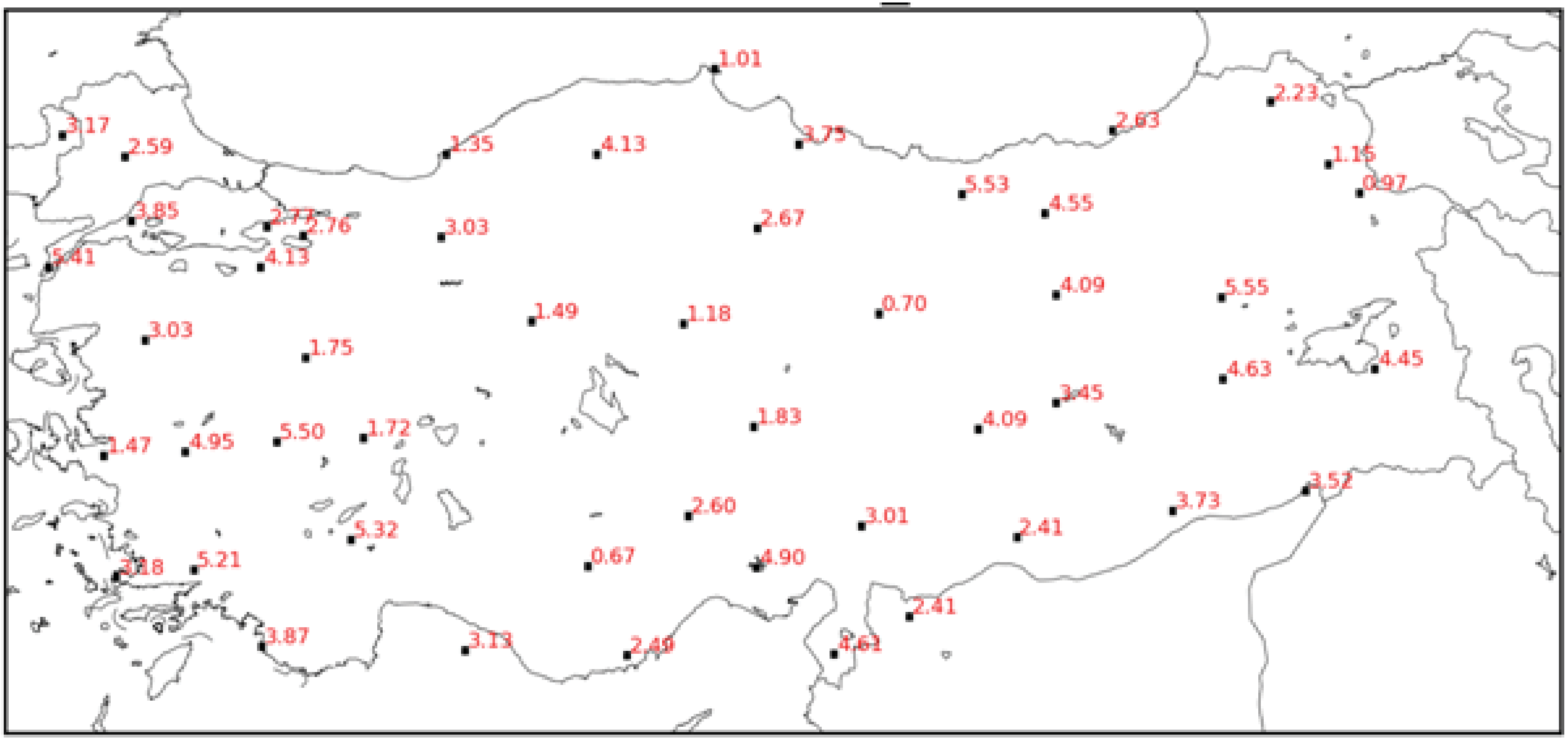
Range: 0 to 1. **Perfect score:** 1.

REGCM4- Moderate Error Rate



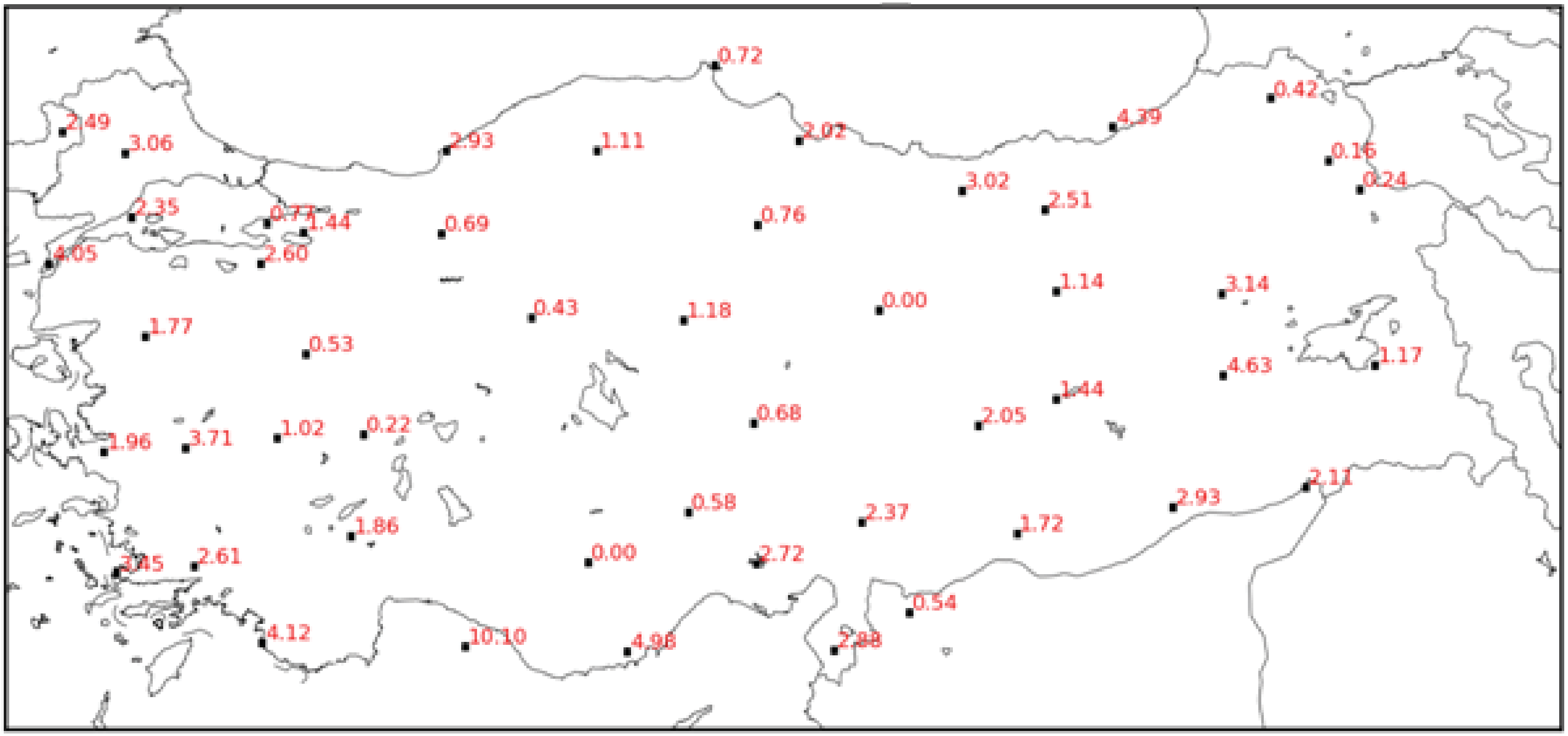
Range: 0 to 1. **Perfect score:** 1.

RegCM4- Significant Error Rate



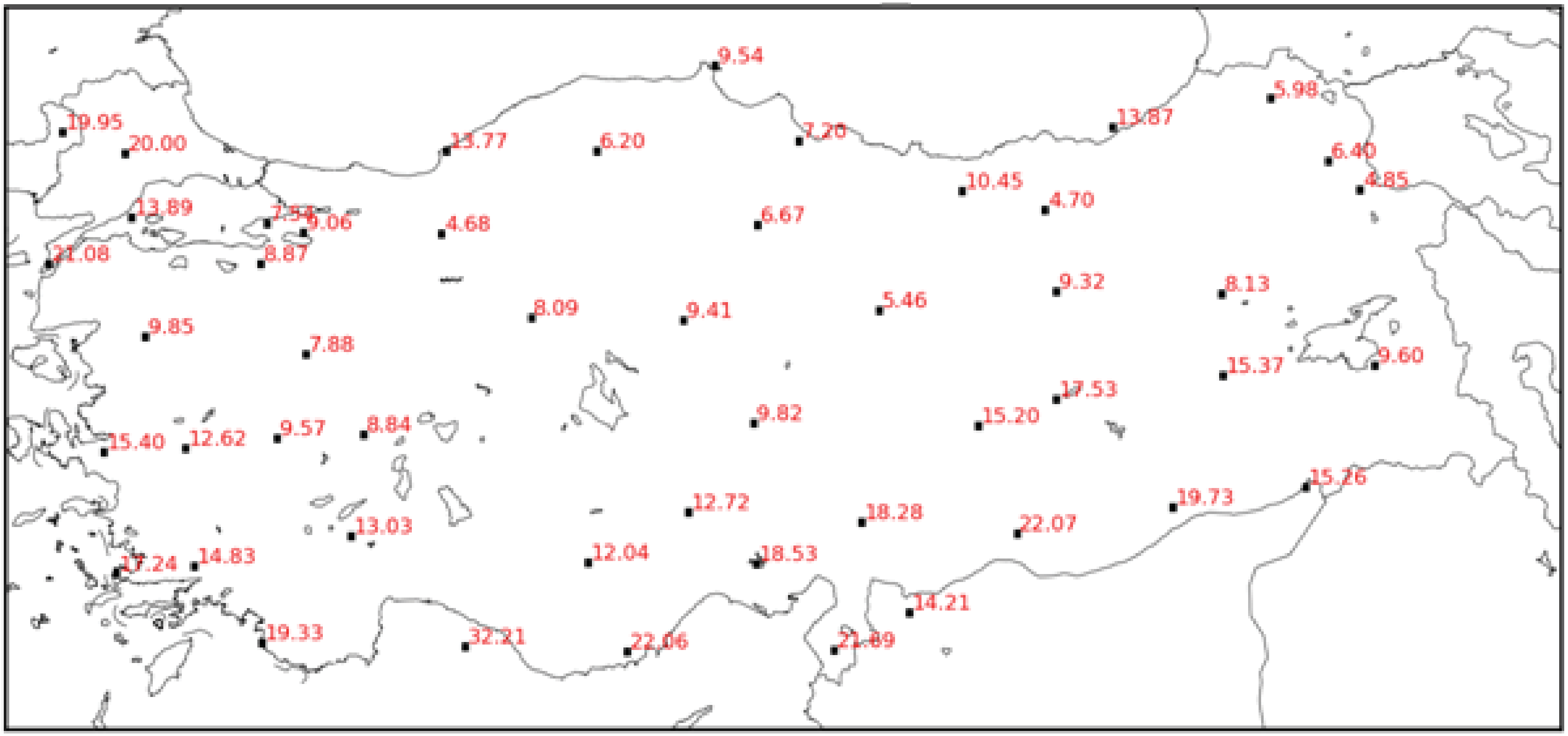
Range: 0 to 1. **Perfect score:** 1.

RegCM4- Large Error Rate



Range: 0 to 1. **Perfect score:** 1.

REGCM4- Very Large Error Rate



Range: 0 to 1. **Perfect score:** 1.

CONCLUSION

- All seasons and annual precipitation patern well representetive despite summer and autumm seasons show dry bias at some region.
- According to station , Obs2Fc better than Fc2Obs (because Model predic much more rain and rainly days.
- Model capturing capability of exterm rains lover than normals.

SUPPORTING FOUNDATIONS

The Scientific and Technological Research Council of Turkey

TURKISH ACADEMIC NETWORK and INFORMATION CENTER

TR-Grid | High Performance and Grid Computing Center

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(KBU-BAP-C-11-D005)