STATISTICAL EXTREME EVENTS ANALYSIS.

PRESENT ASSESSMENT FOR RELIABLE FUTURE SCENARIOS: STATISTICAL METHODS FOR EVALUATION OF CLIMATE-CHANGE IN TIME SERIES.

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STATISTICAL METHODS FOR EVIDENCE BASED EVALUATION OF EFFECTS OF CLIMATE-CHANGE IN METEOROLOGICAL TIME SERIES.

How to assess extreme events and climate variability in a changing climate scenario?

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Motivation:

- **The role of statistics (data analysis) is not so much to summarise what has already happened, but to infer the characteristics of randomness in the process that generated the data set regarding the sequence of its realisations.**

- One of the aims of this study is to verify whether extreme values related to weather attributes on a regional scale show structural change/break/intervention-points (**Chow & Pettitt** tests), which can reflects the pretended global "changing".

- **Extreme weather and climate events have received increased attention in the last few years**, due to the often large loss of human life and exponentially increasing costs associated with them. Variations and trends in extreme climate events have only recently received much attention.

- **Short-duration episodes of extreme heat or cold are often responsible for the major impacts on society**. It is likely that anthropogenic forcing will eventually cause global increases in extreme precipitation, primarily because of probable increases in atmospheric water vapour content and destabilization of the atmosphere.

What is a climatic extreme?

- A rare event?

  Approaches based on frequency of occurrence.

- An intense event?

  Approaches based on threshold exceedance.

- An extreme with respect to the impacts?

  Need to deal with the vulnerability and adaptability of system.

- An extreme impact is not always associated with a weather extreme! (extreme *versus* severe!)

Where do extremes come from?

- **The rapid growth due to instabilities caused by positive feedback: the rapid growth of storms due to convective and baroclinic instability;**

- **The displacement of weather systems into regions where extremes are uncommon into a : new spatial location (*e.g.*, heavy rain in the Australian desert during an ENSO event); different time period (*e.g.*, damaging frost in late spring);**

- **The simultaneous occurrence of several non-extreme conditions: soil moisture deficit + lack of vegetation + elevated temperatures leading to a heat wave;**

Where do extremes come from?

- The persistence or frequent recurrence of weather leading to chronic extremes: moderate but continuous precipitation leading to floods;

- The natural stochastic/chaotic variation resulting in more extreme values being recorded as the length of the record increases in time.

The perturbations leading to extremes!

- **Embedded** within the general atmospheric circulations;
- **Modulated** by decadal-scale climate variability (ENSO, NAO, AO, …);
- **Enhanced** by a warmer climate due to increased atmospheric greenhouse-gas concentrations.

Changes in mean and variance:

- It is often suggested that a warmer climate may be accompanied by a greater variability (IPCC, 2001).

  …, *i.e.*, warmer temperatures induce larger variance…

- However, an analysis of 20th century records in Switzerland shows that warmer temperatures have not experienced an increase in variance – rather the contrary!

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Studies of past climates show that some variables (e.g., temperature) are more closely linked to warming than others (e.g., precipitation or wind storms);

Because of the potential severity of the impacts related to extreme events, and the risk that extremes may increase in the future, current research is increasingly focusing on these aspects.

ILLUSTRATIVE EXAMPLES:

Changes in climate variability and persistence.

Beniston and Goyette, 2006: Global & Planetary Change.

Changes in Occurrences of Meteorological Extreme Events Over Continental Portugal.

Lucio, 2005: European Meteorological Society.

Geostatistical Assessment of HadCM3 Simulations via NCEP Reanalyses over Europe.

Lucio, 2004: Atmospheric Science Letters.

Assessing HadCM3 Simulations from NCEP Reanalyses over Europe: Diagnostics of block-seasonal extreme temperature's regimes.

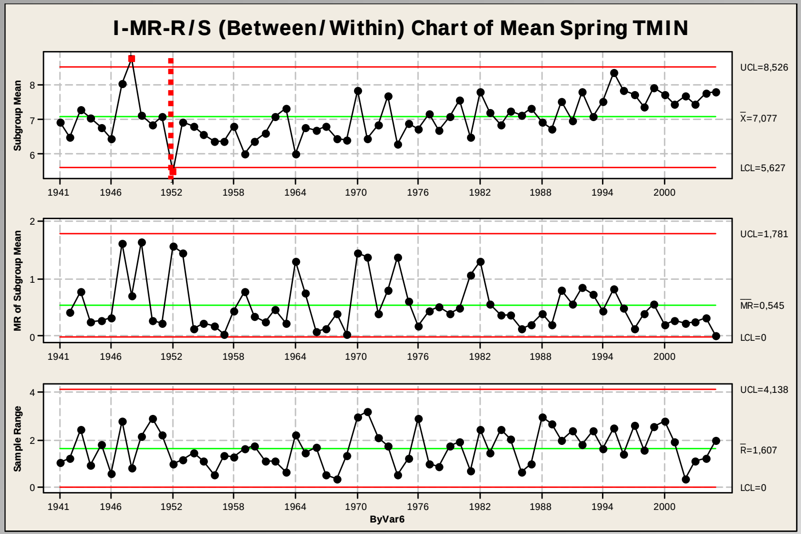
Lucio, 2004: Global & Planetary Change.

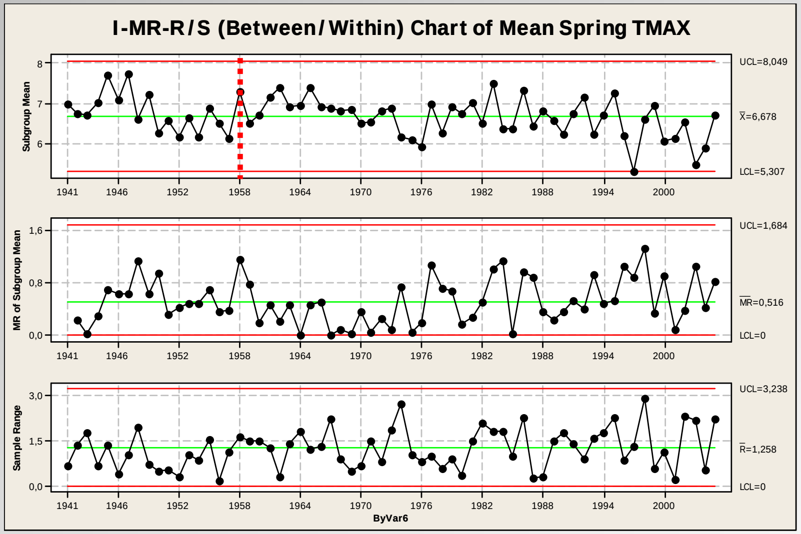
Spatial pattern recognition of extreme temperature climatology: Assessing HadCM3 simulations via NCEP reanalyses over Europe.

Lucio, Conde and Ramos, 2007: RBMET (SBMET).

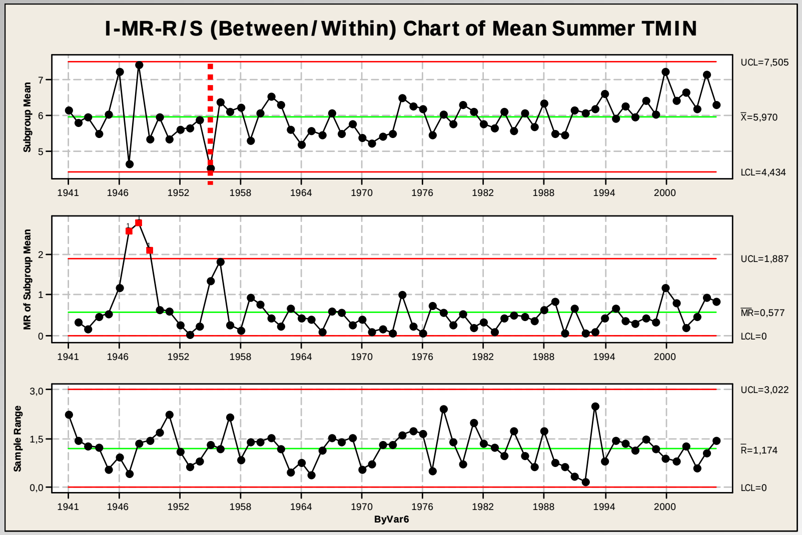
Seasonal Trends on Extreme Temperatures - Portugal

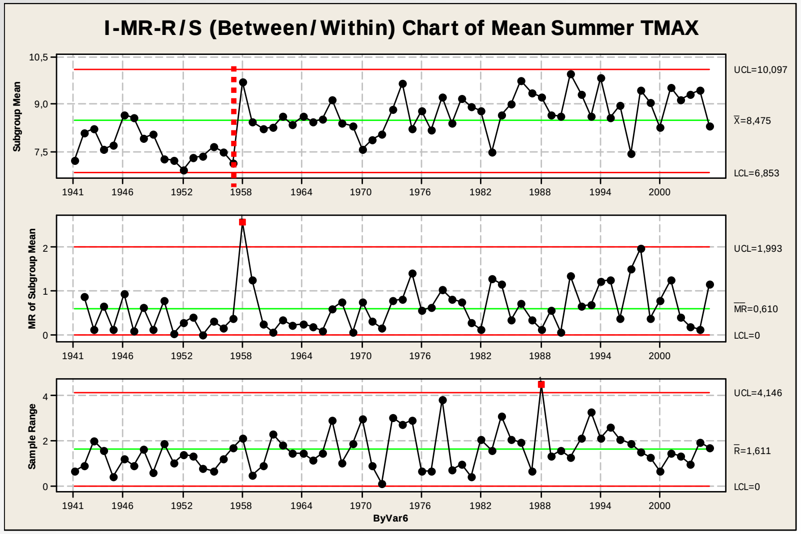
SPRING





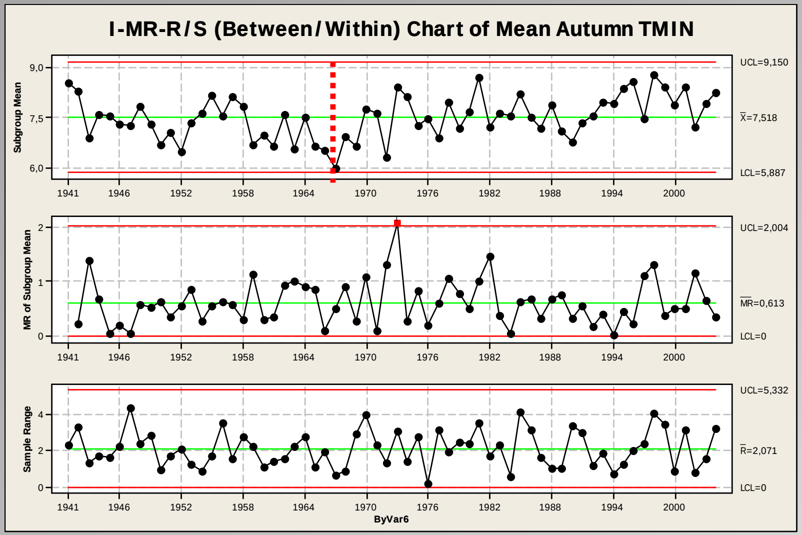
SUMMER

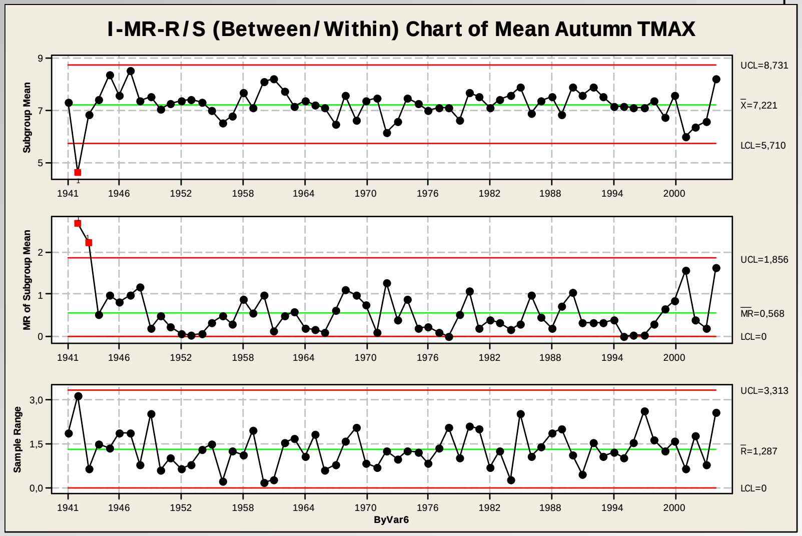




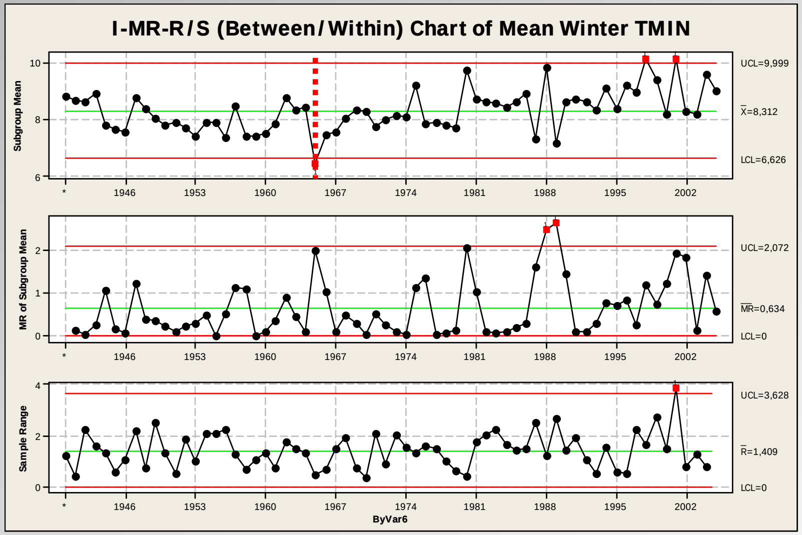
Seasonal Trends on Extreme Temperatures. Portugal

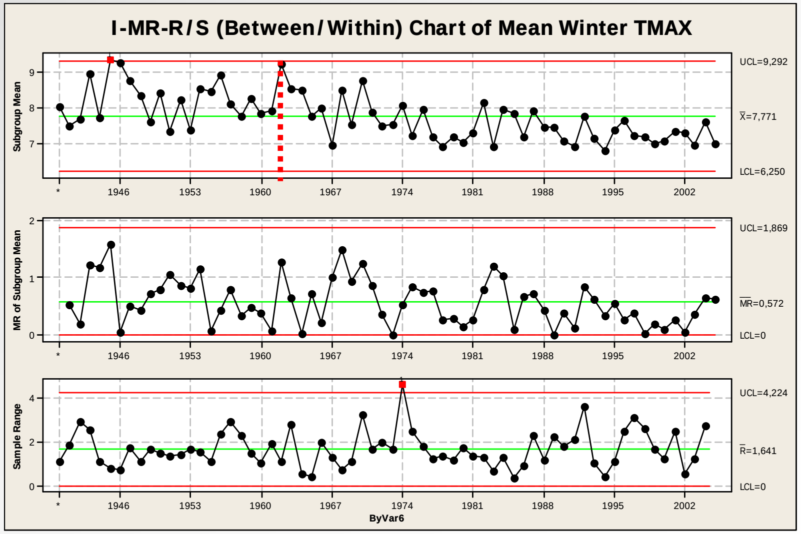
AUTUMN





WINTER





Seasonal Trends on Extreme Temperatures. Portugal - Summary (Trends & Drifts)

- **The analysis of extreme meteorological events indicates that there has been a sizable change in their frequency in Continental Portugal.** This suggests that natural variability of the climate system could be the cause of the recent changes, although anthropogenic forcing due to increasing greenhouse gas concentrations cannot be discounted as another cause.

- **The long-term trend detected for <u>TMIN</u> in Portugal indicates that the magnitude of the air temperature for "winter" max(TMIN) is increasing; whereas the long-term trend detected for <u>TMAX</u> indicates an increasing magnitude of the air temperature for "winter" min(TMAX).**

- **The long-term trend detected for <u>TMIN</u> and <u>TMAX</u> in Portugal indicates that the magnitude of the air temperature for "spring" and "summer" are increasing.**

Probably SUMMER is contaminating SPRING and SPRING is contaminating WINTER!

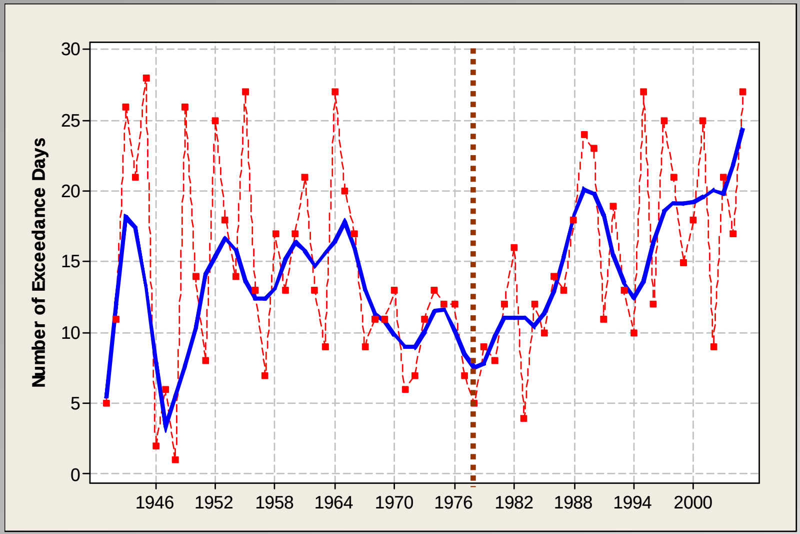
Peaks-over-Threshold – Portugal.

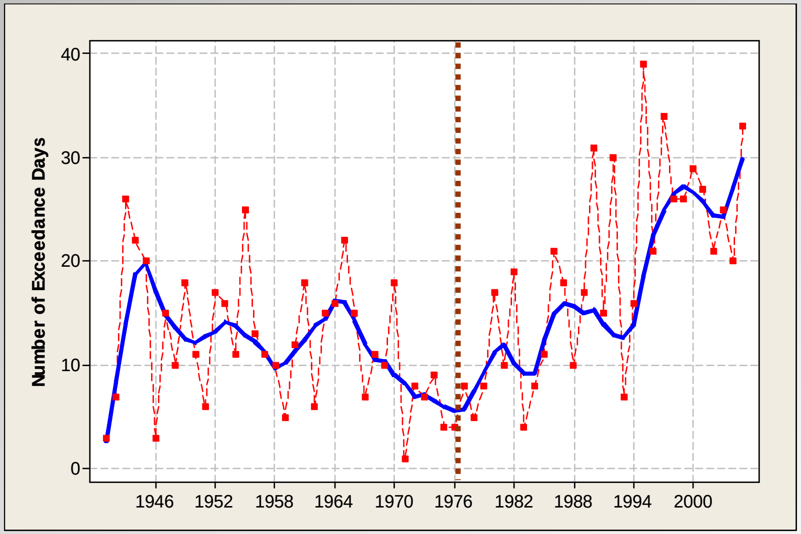
- **In the peaks-over-threshold (POT) methodology, inferences are based on exceedances over a low/high threshold. Under some general conditions, the distribution function of these exceedances (threshold excesses) is well approximated by the GPD (Generalised Pareto Distribution), defined by two basic parameters: scale (σ) and shape (ξ).**

- **The validity of the thresholds for TMIN and TMAX have been assessed checking the stability of the maximum likelihood estimates for the re-parameterised models:**
  - The threshold diagnostic (**min TMIN**) was made by taking into account 9, 16 and 13ºC for spring, summer and autumn, respectively.
  - The threshold diagnostic (**max TMIN**) was made by taking into account 15, 21 and 18ºC for spring, summer and autumn, respectively.
  - The threshold diagnostic (**min TMAX**) was made by taking into account 20, 27 and 23ºC for spring, summer and autumn, respectively.
  - The threshold diagnostic (**max TMAX**) was made by taking into account 27, 35 and 31ºC for spring, summer and autumn, respectively.

Exceedance Analyses for the Minimum Temperature Thresholds – Portugal.

SPRING





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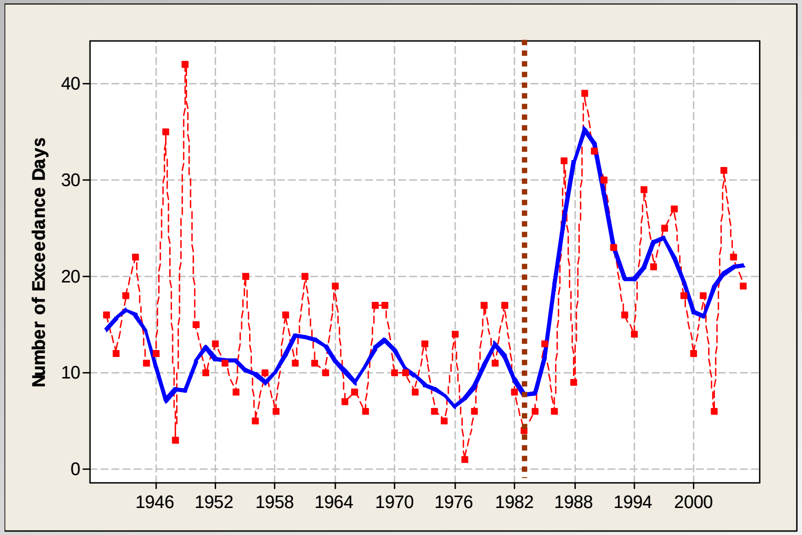
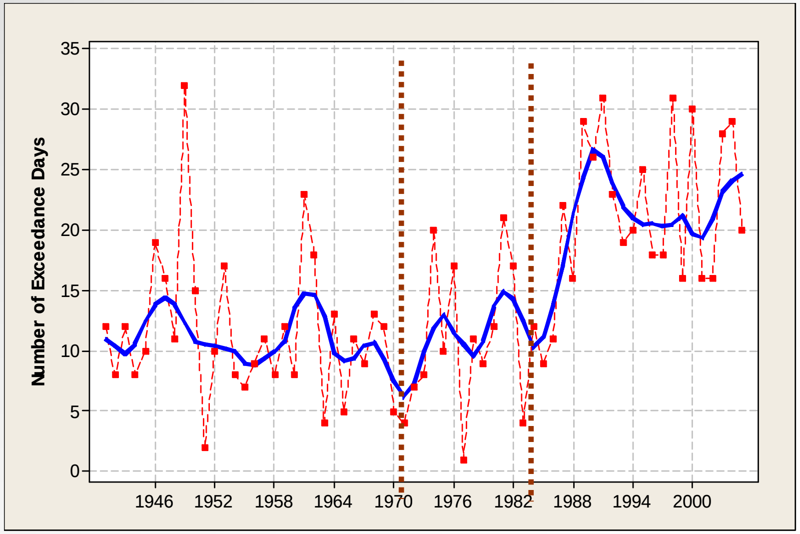
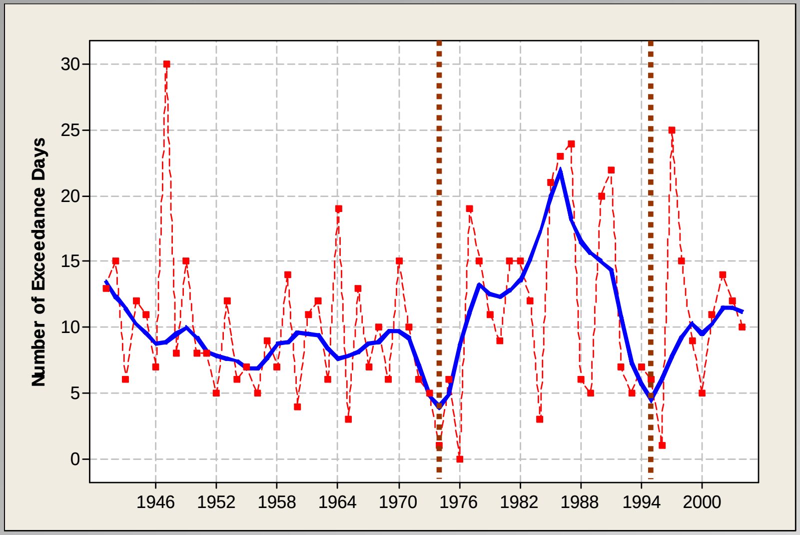
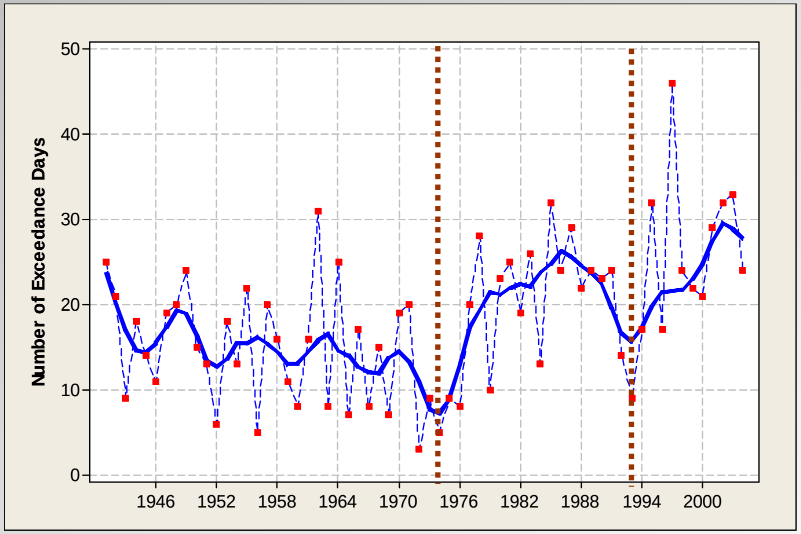




Exceedance Analyses for the Minimum Temperature Thresholds – Portugal.

AUTUMN





Exceedance Analyses for the Maximum Temperature Thresholds – Portugal.

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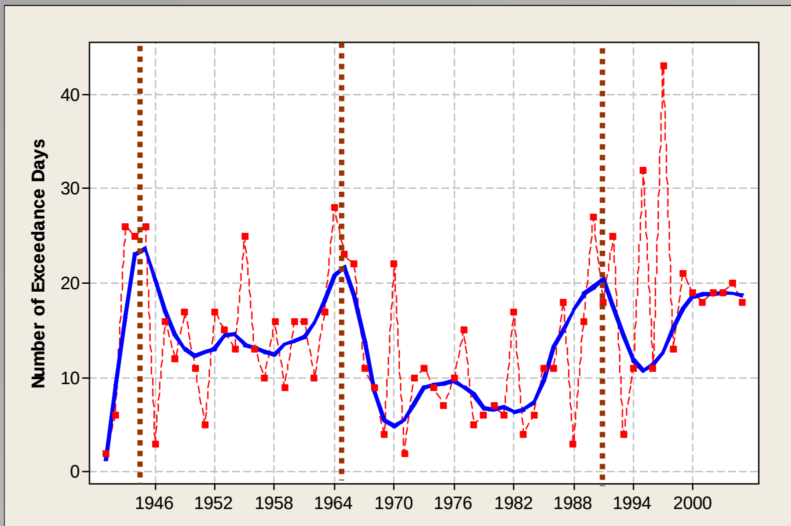
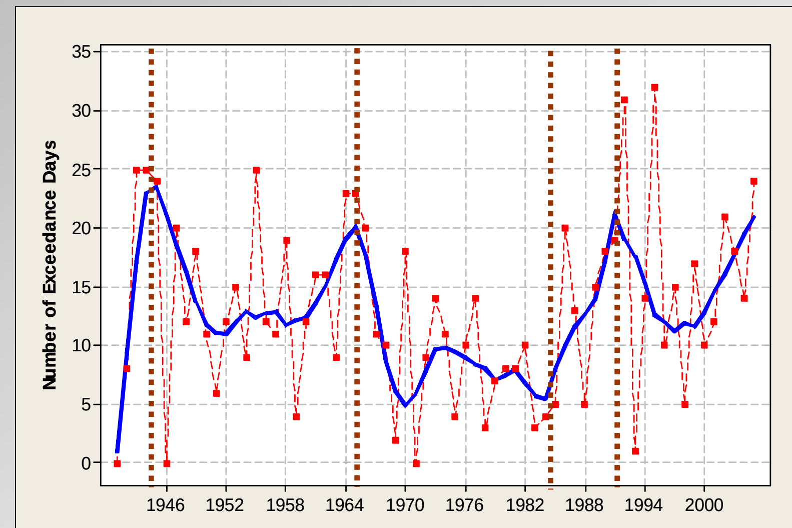
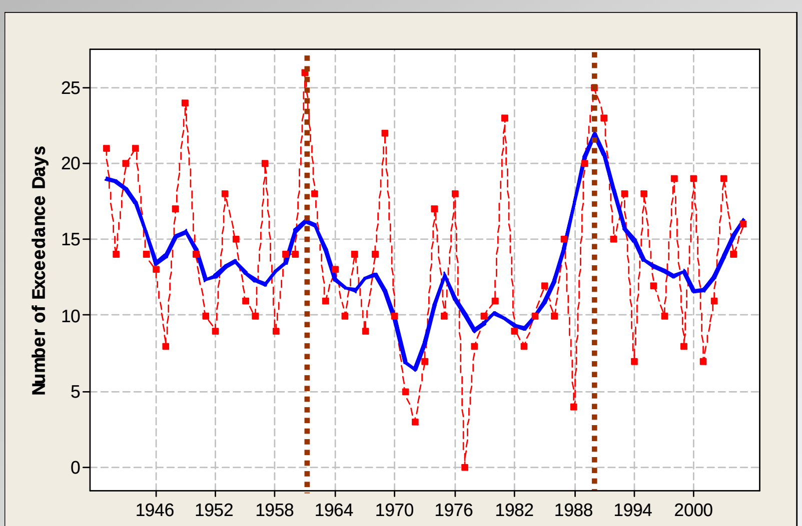
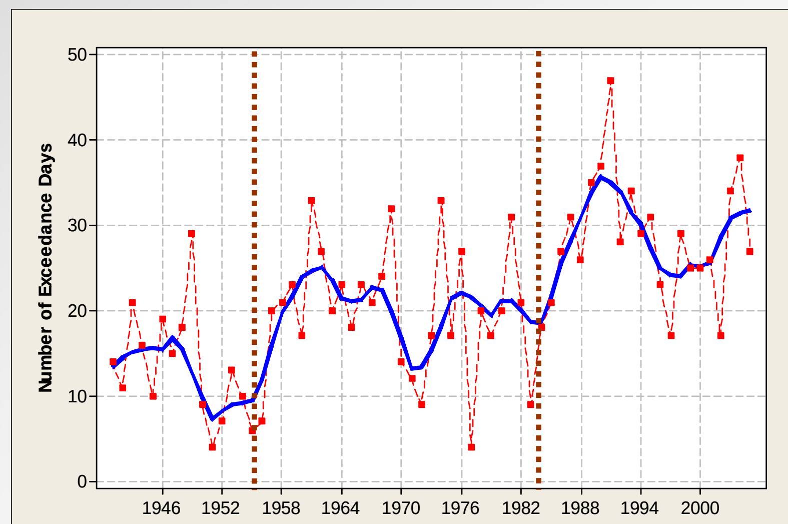




SUMMER





Exceedance Analyses for the Maximum Temperature Thresholds – Portugal.

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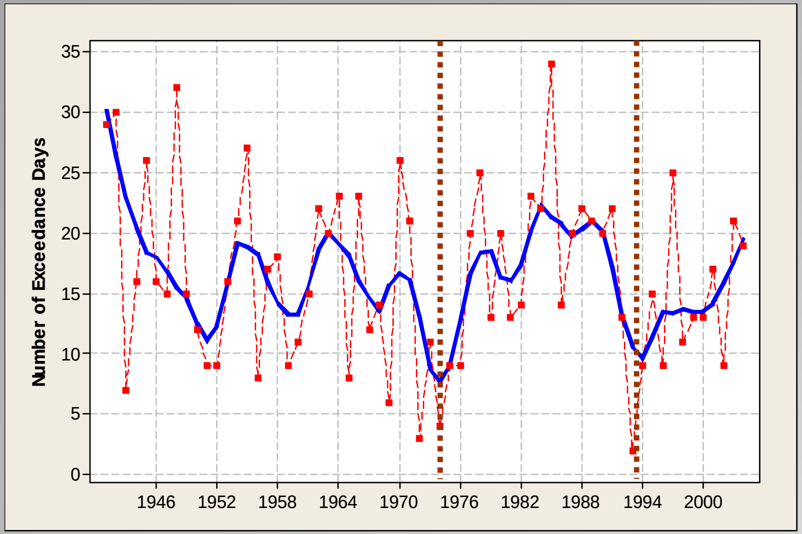
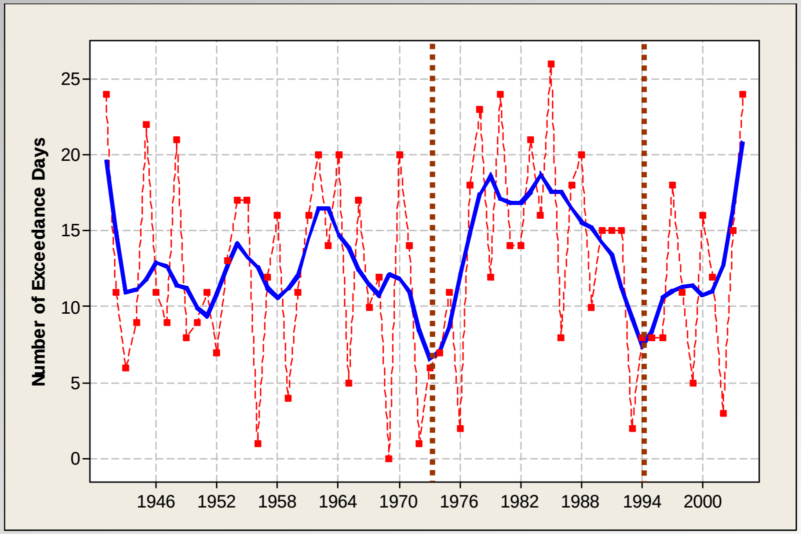




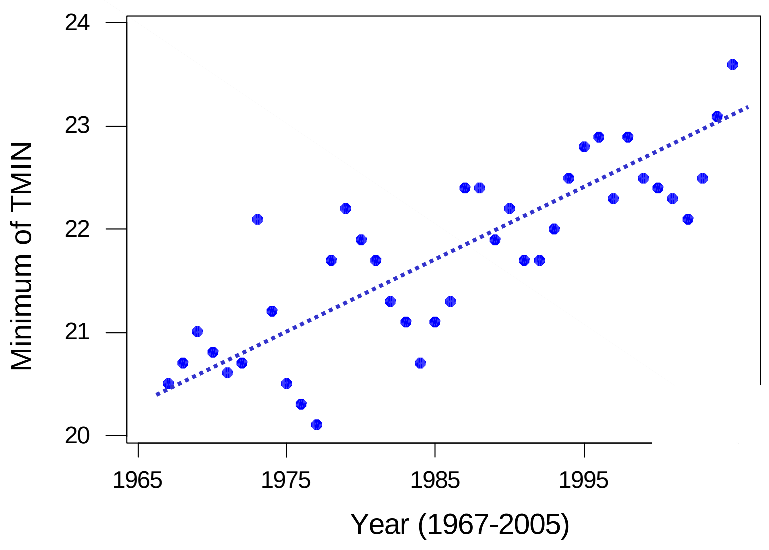
POT - Portugal - Summary

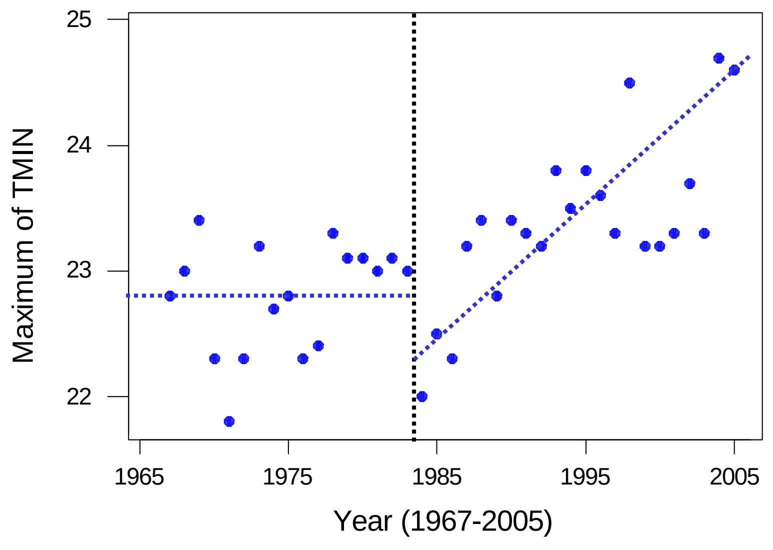
- **The number of warm nights is increasing on spring, summer and autumn!**

- **The number of warm days is increasing on summer!**

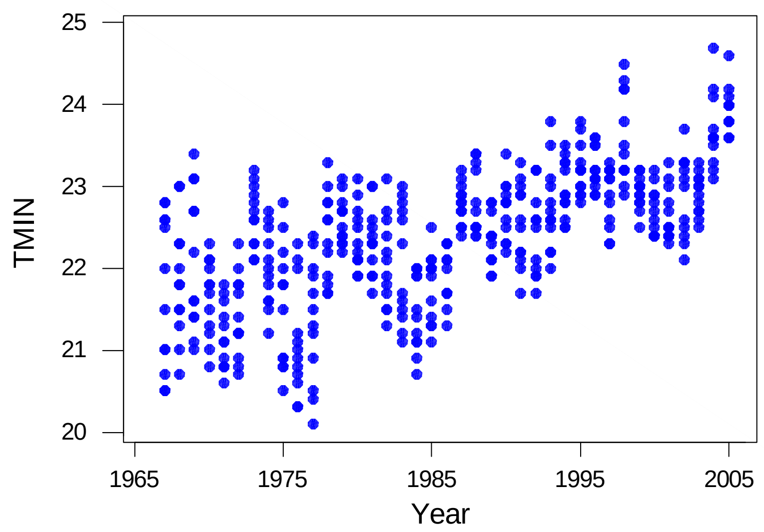
Probably SUMMER nights are contaminating SPRING nights and AUTUMN nights!

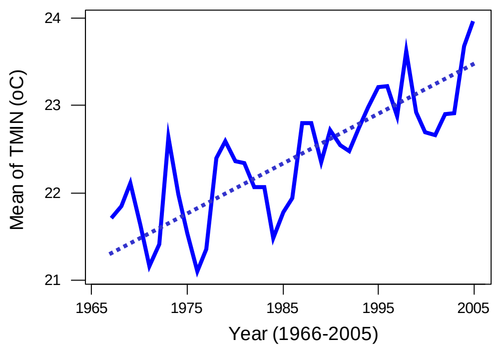
Changes in min/max of TMIN (PA-Brasil)

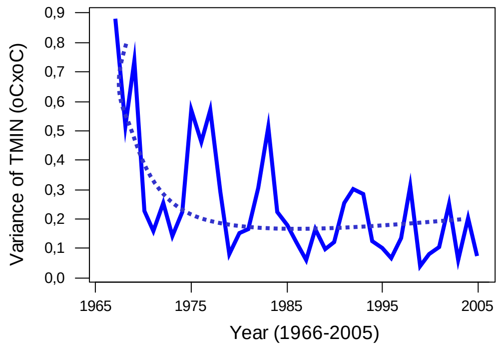




Changes in mean and variance: TMIN (PA-BR)







MeanTMIN = - 74,2 + <u>0,0487</u> YEAR

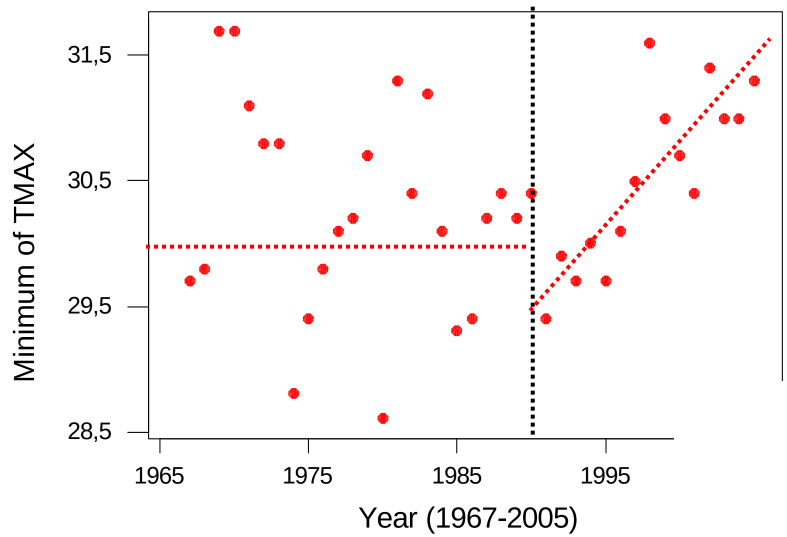
Predictor	Coef	SE Coef	T	P
Constant	-74,24	12,00	-6,19	0,000
Year	0,0487	0,006041	8,05	0,000

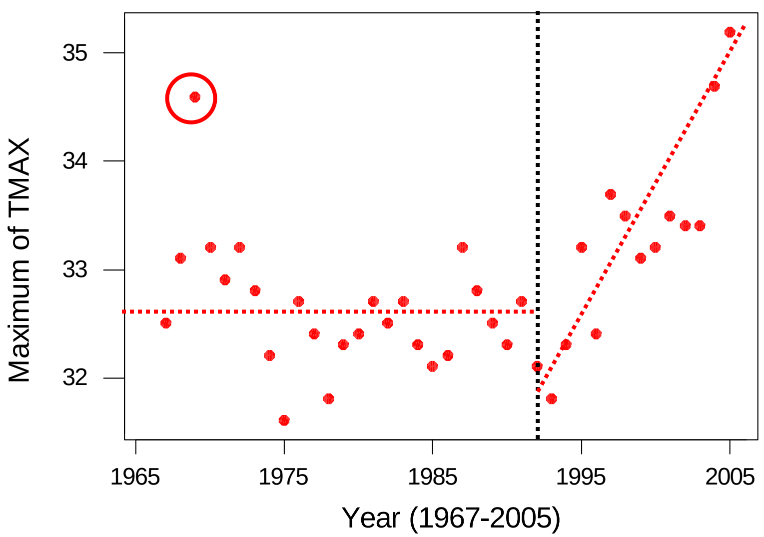
S = 0,4246   R-Sq = 63,7%   R-Sq(adj) = 62,7%

Analysis of Variance

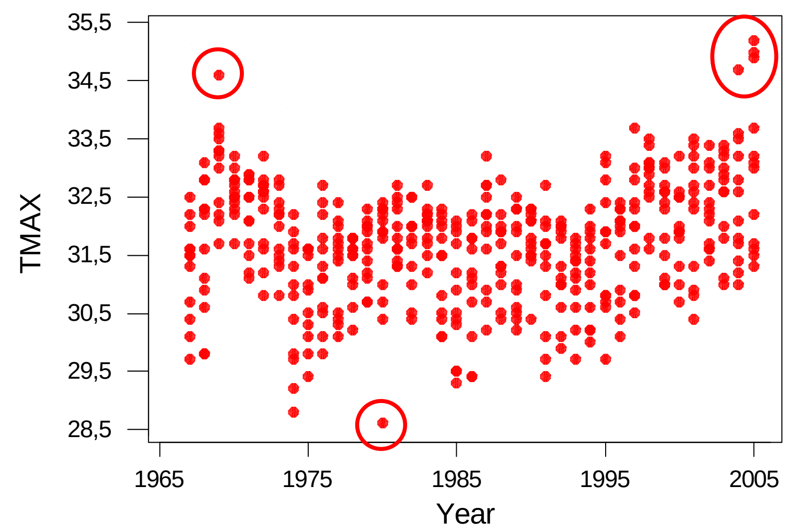
Source	DF	SS	MS	F	P
Regression	1	11,698	11,698	64,88	0,000
Residual Error	37	6,671	0,180		
Total	38	18,369			

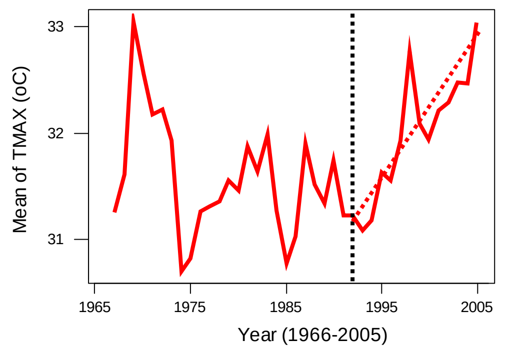
Changes in min/max of TMAX (PA -Brasil)

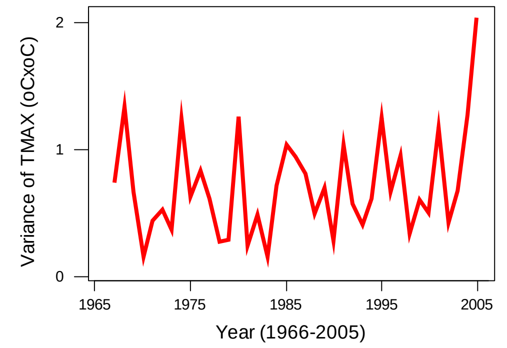




Changes in mean and variance: TMAX (PA-BR)







MeanTMAX = 4,7 + 0,0136 YEAR

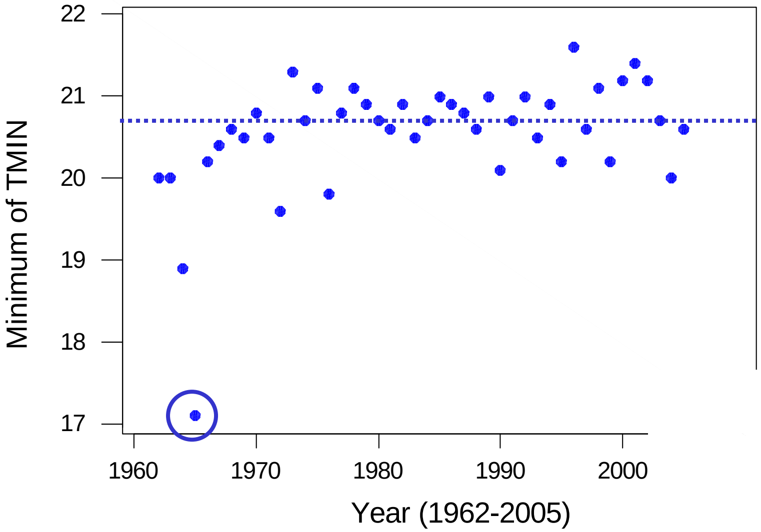
Predictor	Coef	SE Coef	T	P
Constant	4,71	16,45	0,29	0,776
Year	0,0136	0,008284	1,64	0,109

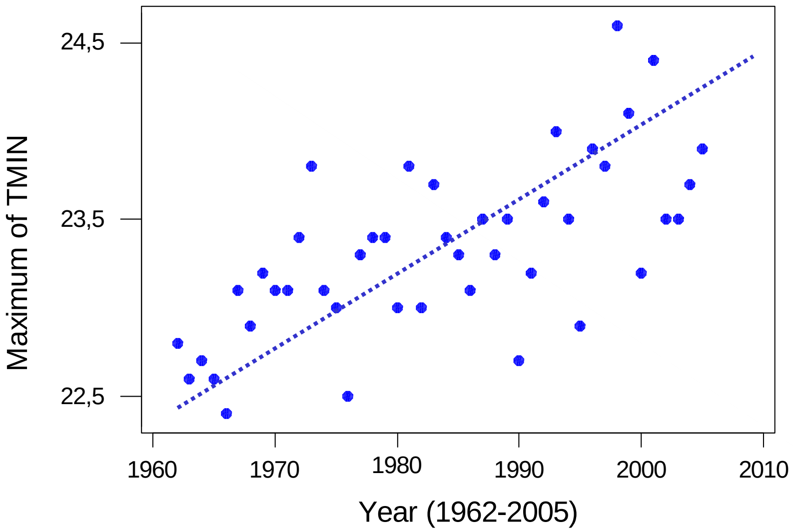
S = 0,5823   R-Sq = 6,8%   R-Sq(adj) = 4,3%

Analysis of Variance

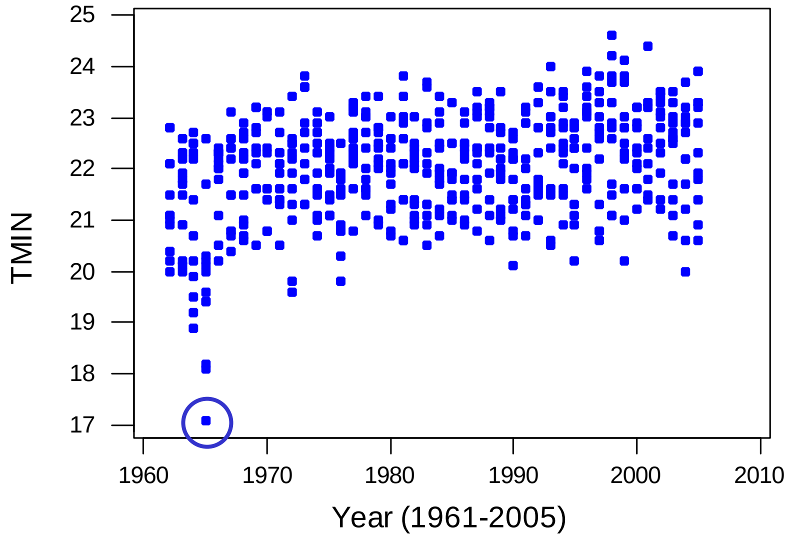
Source	DF	SS	MS	F	P
Regression	1	0,9148	0,9148	2,70	0,109
Residual Error	37	12,5439	0,3390		
Total	38	13,4587			

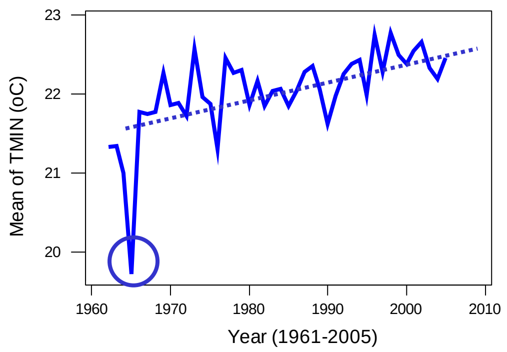
Changes in min/max of TMIN (PE - Brasil)

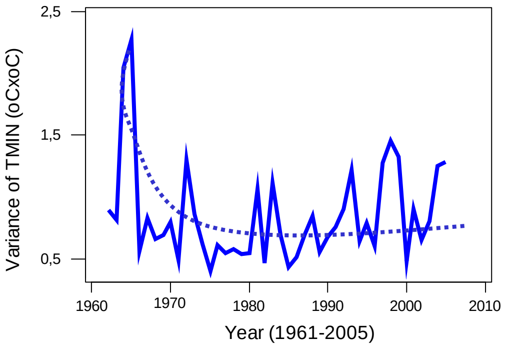




Changes in mean and variance: TMIN (PE-BR)







MeanTMIN = - 30,9 + <u>0,0267</u> YEAR

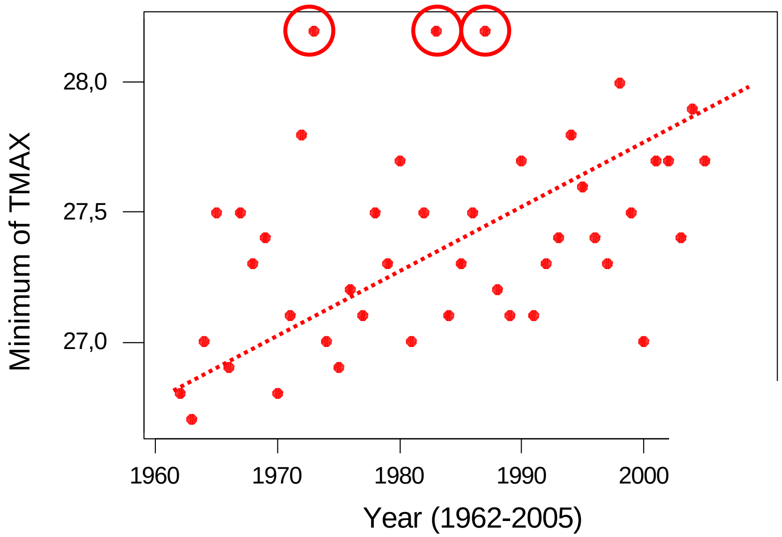
Predictor	Coef	SE Coef	T	P
Constant	-30,924	9,676	-3,20	0,003
Year	0,02667	0,004878	5,47	0,000

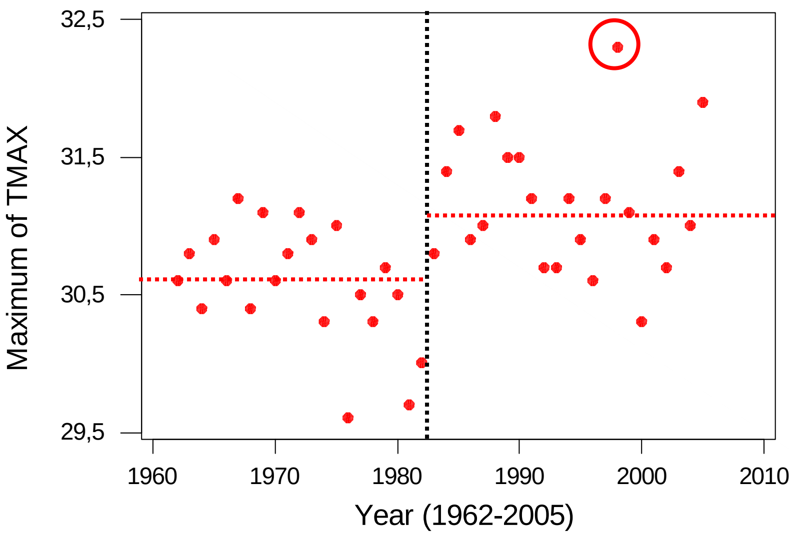
S = 0,4109 R-Sq = 41,6% R-Sq(adj) = 40,2%

Analysis of Variance

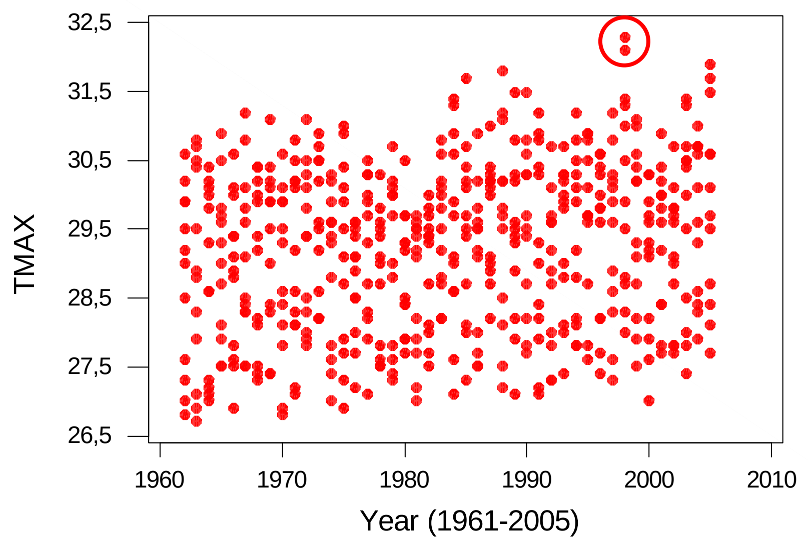
Source	DF	SS	MS	F	P
Regression	1	5,0565	5,0565	29,95	0,000
Residual Error	42	7,0913	0,1688		
Total	43	12,1478			

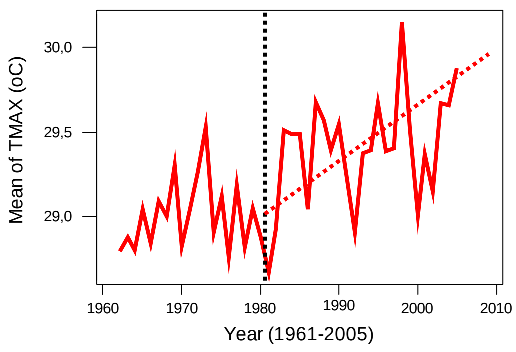
Changes in min/max of TMAX (PE - Brasil)

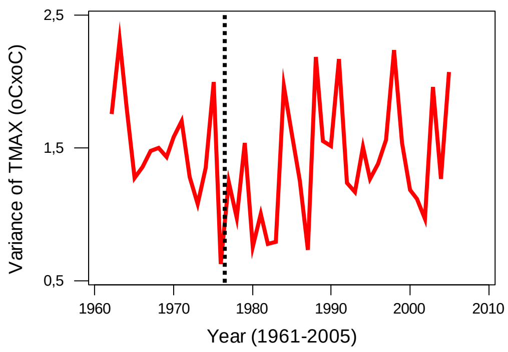




Changes in mean and variance: TMAX (PE-BR)







MeanTMAX = - 4,42 + <u>0,0170</u> YEAR

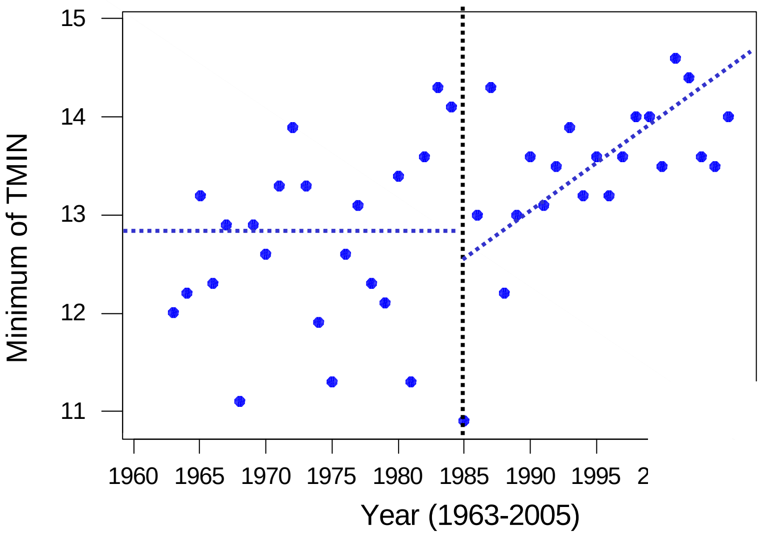
Predictor	Coef	SE Coef	T	P
Constant	-4,422	6,249	-0,71	0,483
Year	0,017	0,003150	5,39	0,000

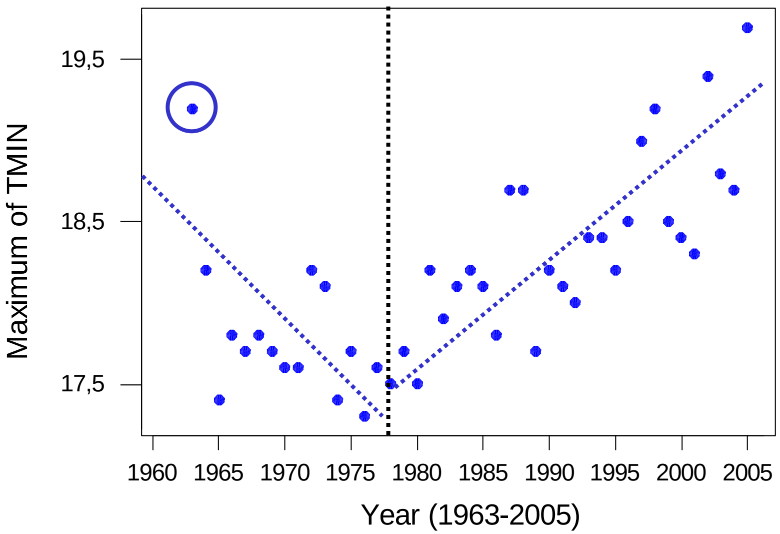
S = 0,2654 R-Sq = 40,8% R-Sq(adj) = 39,4%

Analysis of Variance

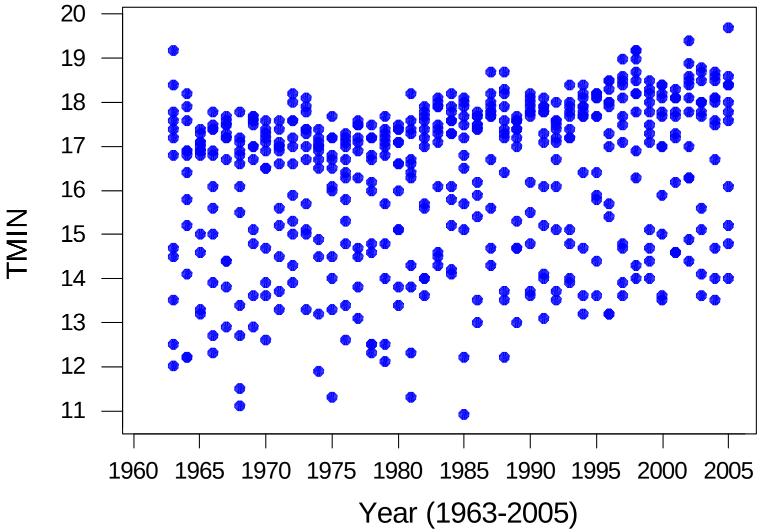
Source	DF	SS	MS	F	P
Regression	1	2,0423	2,0423	29,00	0,000
Residual Error	42	2,9577	0,0704		
Total	43	5,0000			

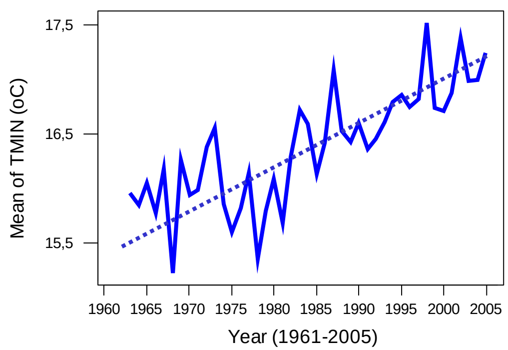
Changes in min/max of TMIN (DF - Brasil)

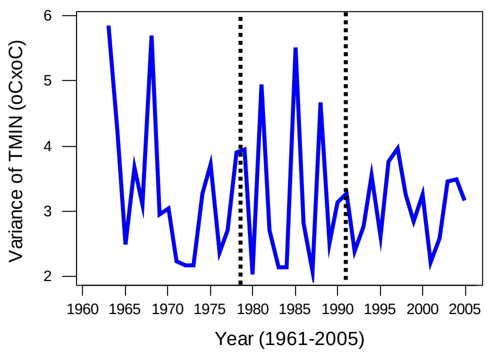




Changes in mean and variance: TMIN (DF-BR)







MeanTMIN = - 50,0 + <u>0,0335</u> YEAR

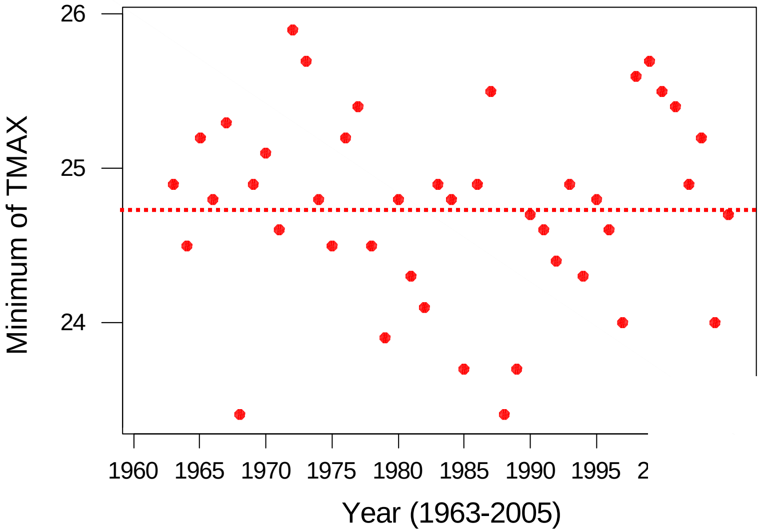
Predictor	Coef	SE Coef	T	P
Constant	-50,033	7,976	-6,27	0,000
Year	0,03345	0,004020	8,33	0,000

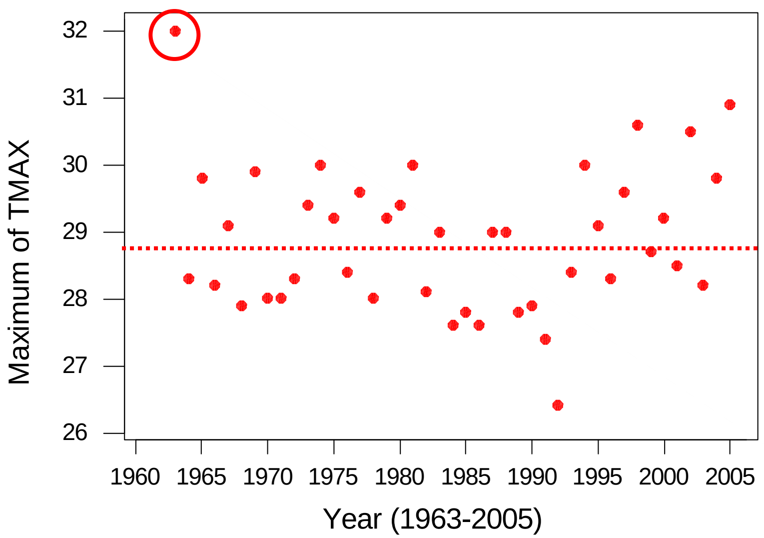
S = 0,3271 R-Sq = 62,8% R-Sq(adj) = 61,9%

Analysis of Variance

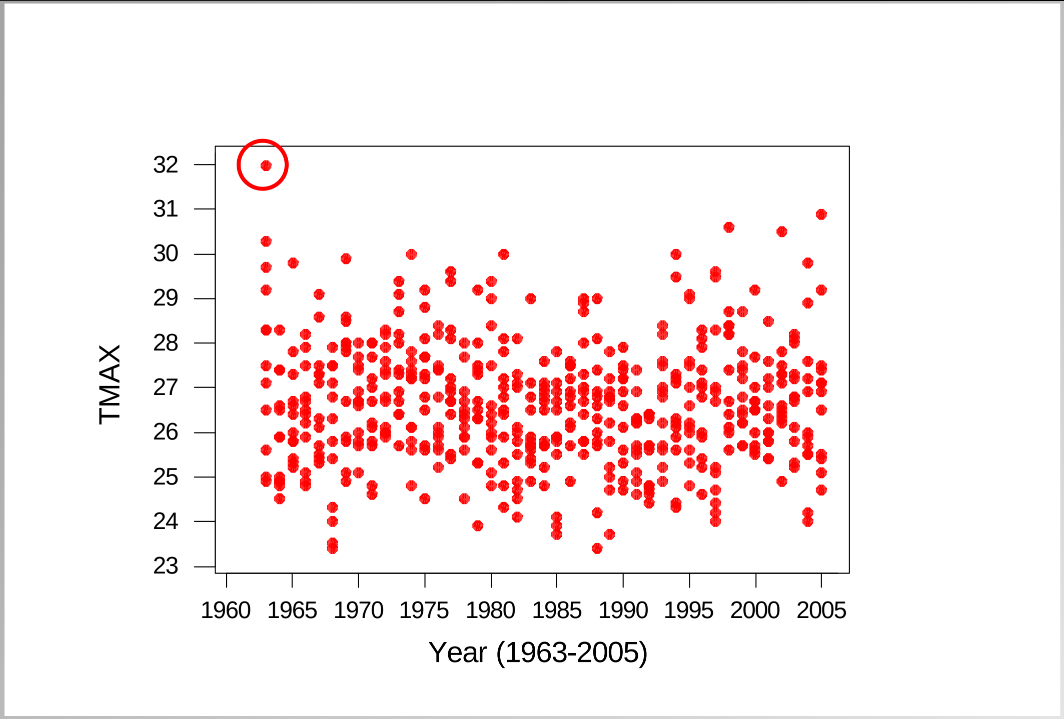
Source	DF	SS	MS	F	P
Regression	1	7,4212	7,4212	69,35	0,000
Residual Error	41	4,3876	0,1070		
Total	42	11,8088			

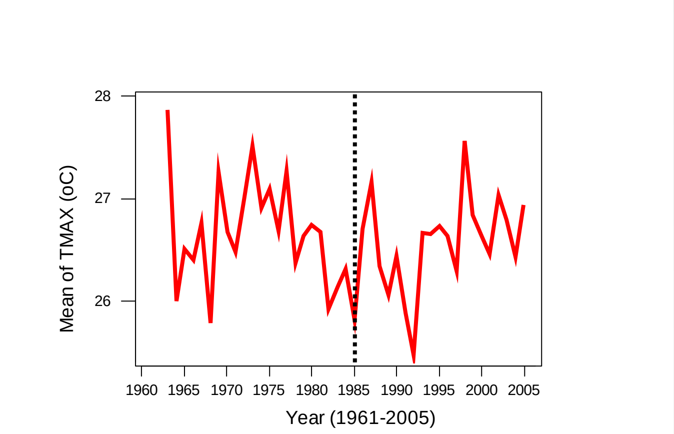
Changes in min/max of TMAX (DF - Brasil)

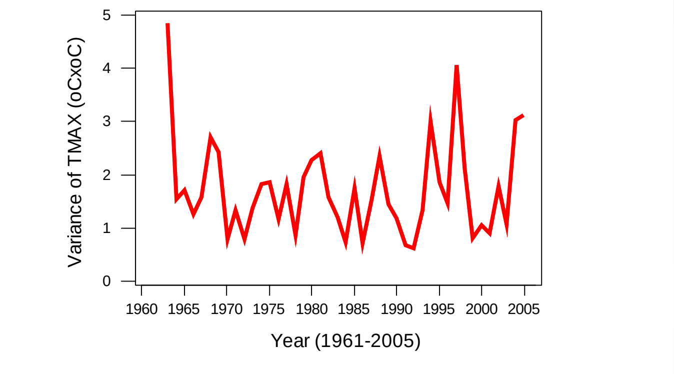




Changes in mean and variance: TMAX (DF-BR)







MeanTMAX = 33,3 - 0,00335 YEAR

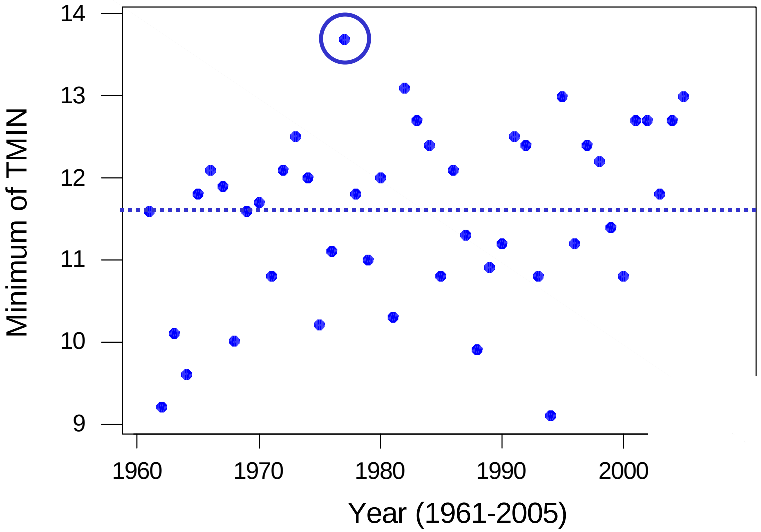
Predictor	Coef	SE Coef	T	P
Constant	33,27	12,17	2,73	0,009
Year	-0,00335	0,006134	-0,55	0,588

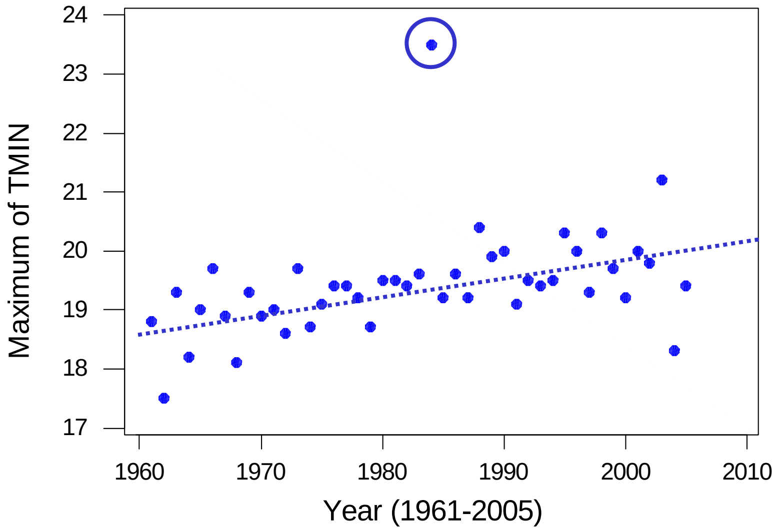
S = 0,4992 R-Sq = 0,7% R-Sq(adj) = 0,0%

Analysis of Variance

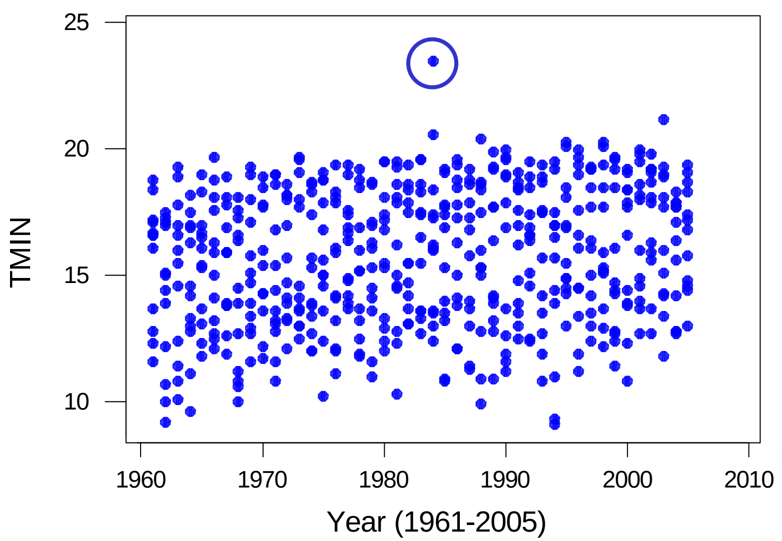
Source	DF	SS	MS	F	P
Regression	1	0,0743	0,0743	0,30	0,588
Residual Error	41	10,2160	0,2492		
Total	42	10,2903			

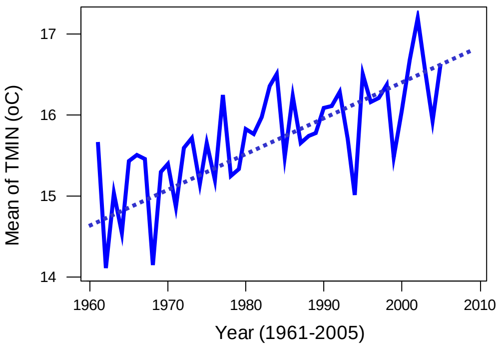
Changes in min/max of TMIN (SP - Brasil)

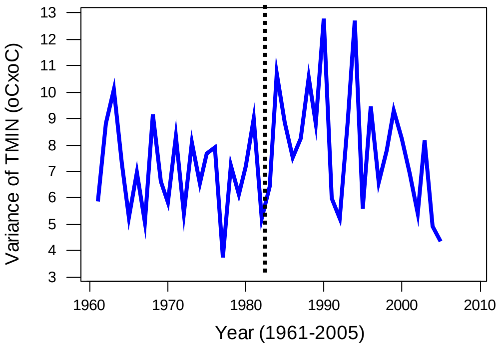




Changes in mean and variance: TMIN (SP-BR)







MeanTMIN= - 53,2 + 0,0348 YEAR

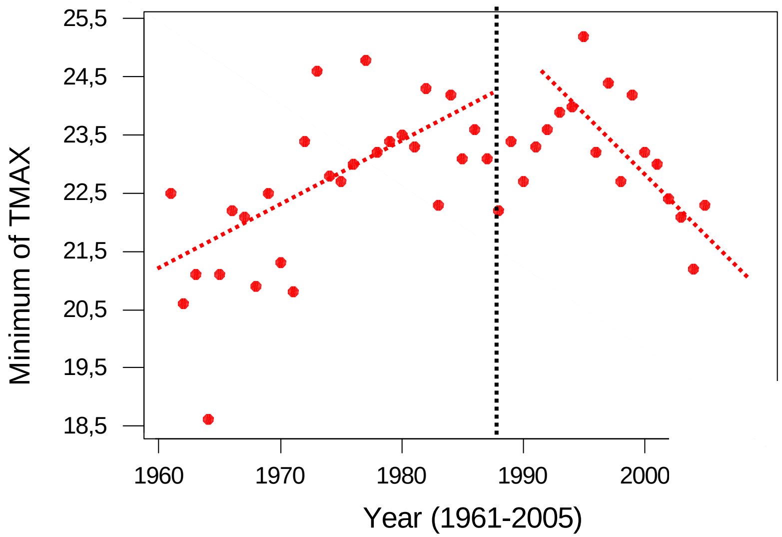
Predictor	Coef	SE Coef	T	P
Constant	-53,19	10,43	-5,10	0,000
Year	0,0348	0,005259	6,61	0,000

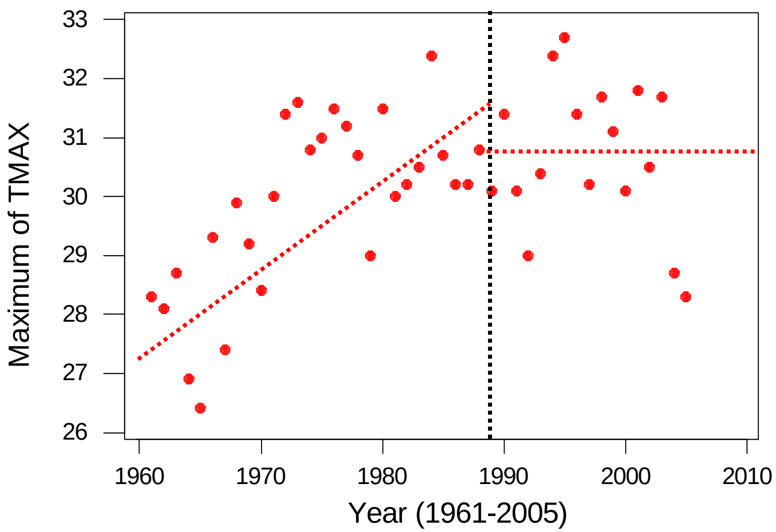
S = 0,4582 R-Sq = 50,4% R-Sq(adj) = 49,2%

Analysis of Variance

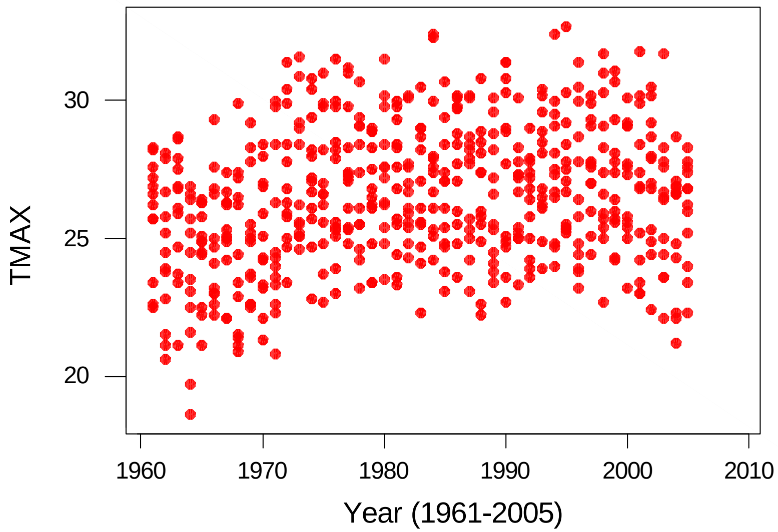
Source	DF	SS	MS	F	P
Regression	1	9,1675	9,1675	43,68	0,000
Residual Error	43	9,0258	0,2099		
Total	44	18,193			

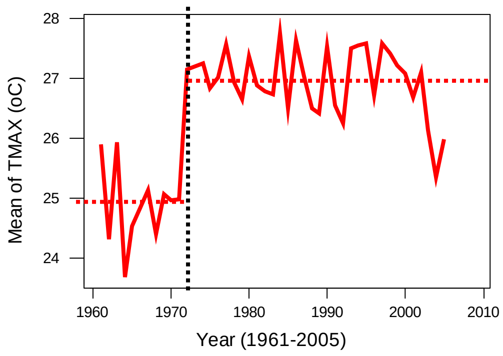
Changes in min/max of TMAX (SP - Brasil)

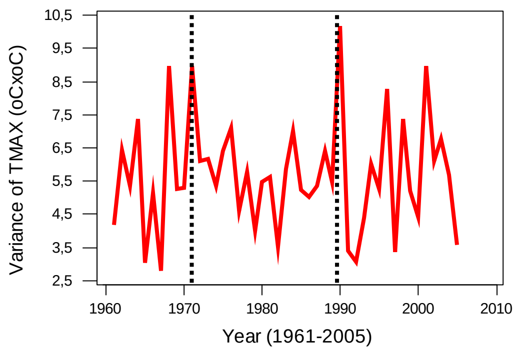




Changes in mean and variance: TMAX (SP-BR)







Mean8 = - 59,8 + 0,0435 YEAR

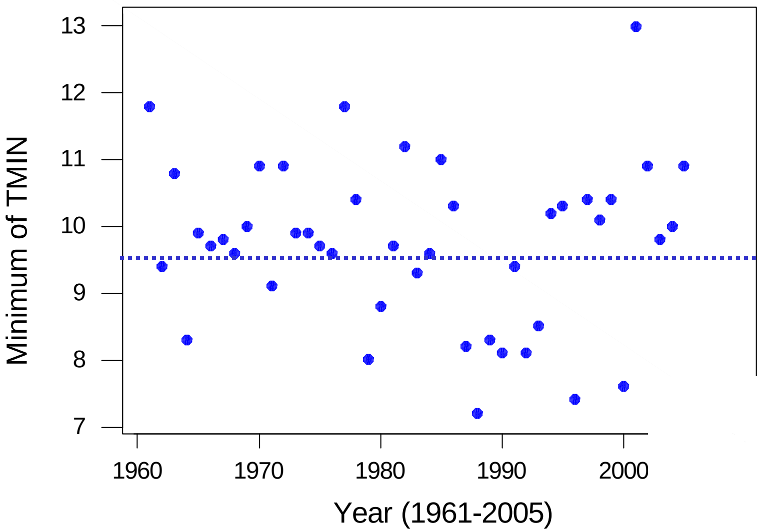
Predictor	Coef	SE Coef	T	P
Constant	-59,82	20,64	-2,90	0,006
Year	0,0435	0,01041	4,18	0,000

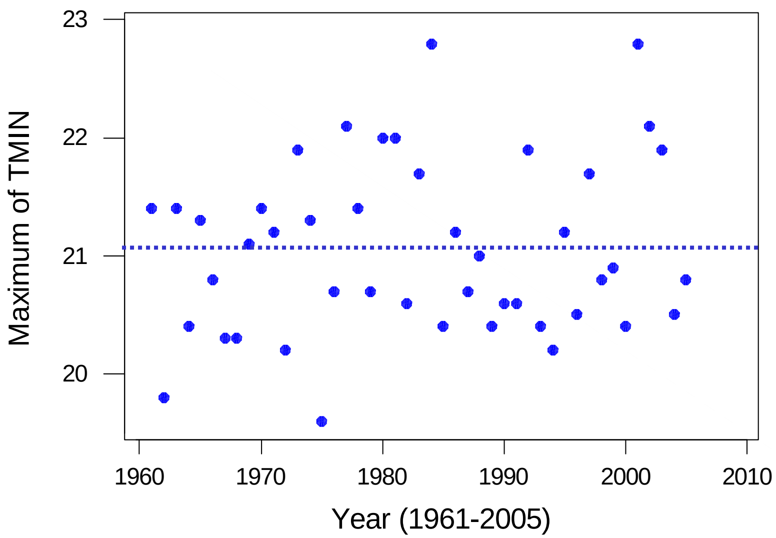
S = 0,9066 R-Sq = 28,9% R-Sq(adj) = 27,2%

Analysis of Variance

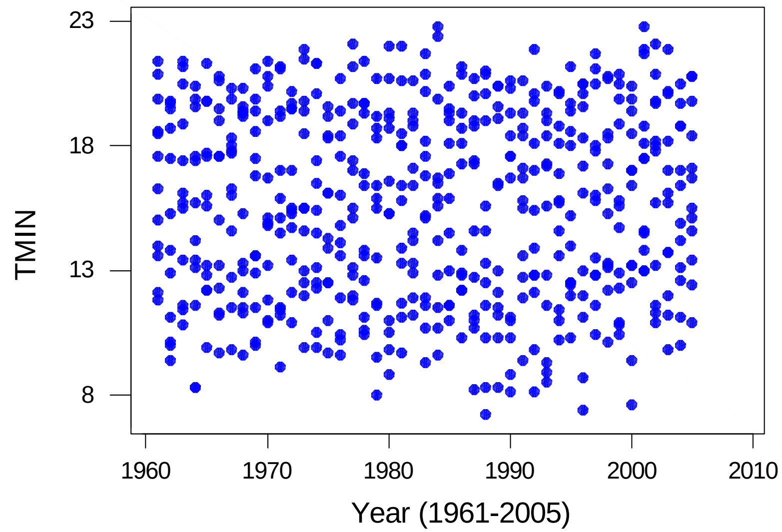
Source	DF	SS	MS	F	P
Regression	1	14,366	14,366	17,48	0,000
Residual Error	43	35,342	0,822		
Total	44	49,708			

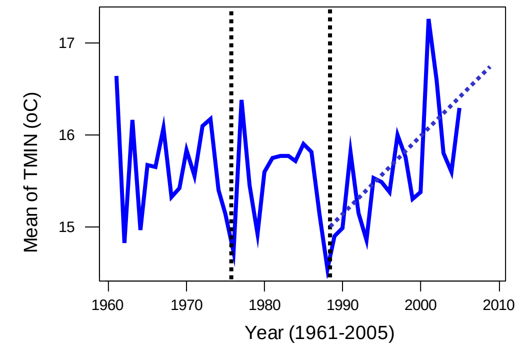
Changes in min/max of TMIN (RS - Brasil)

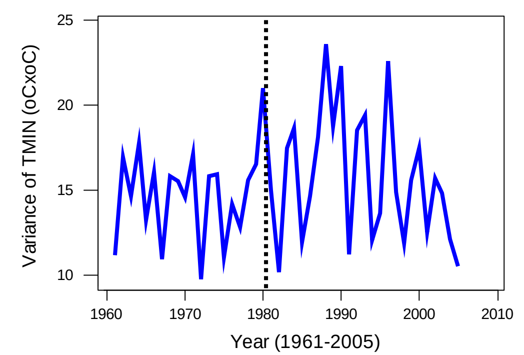




Changes in mean and variance: TMIN (RS-BR)







MeanTMIN = 8,8 + 0,00341 YEAR

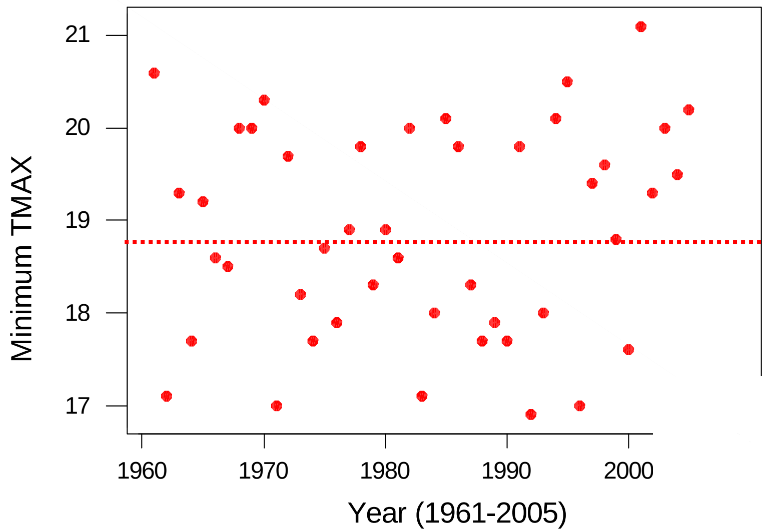
Predictor	Coef	SE Coef	T	P
Constant	8,85	12,69	0,70	0,490
Year	0,00341	0,006401	0,53	0,597

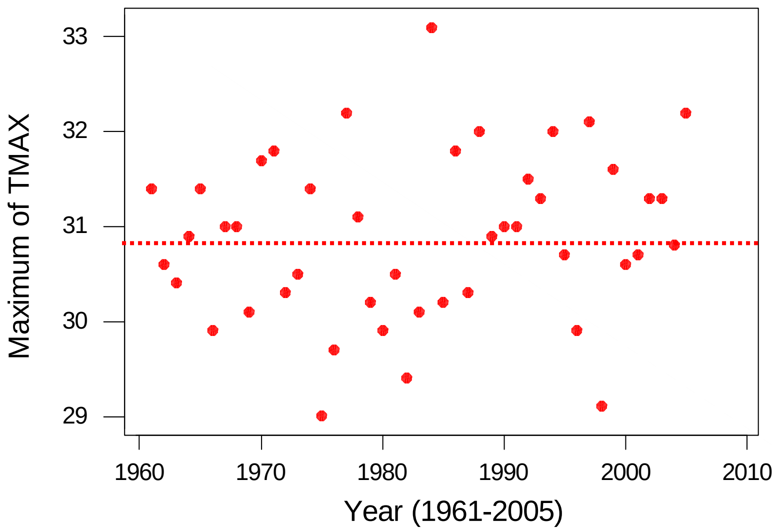
S = 0,5577 R-Sq = 0,7% R-Sq(adj) = 0,0%

Analysis of Variance

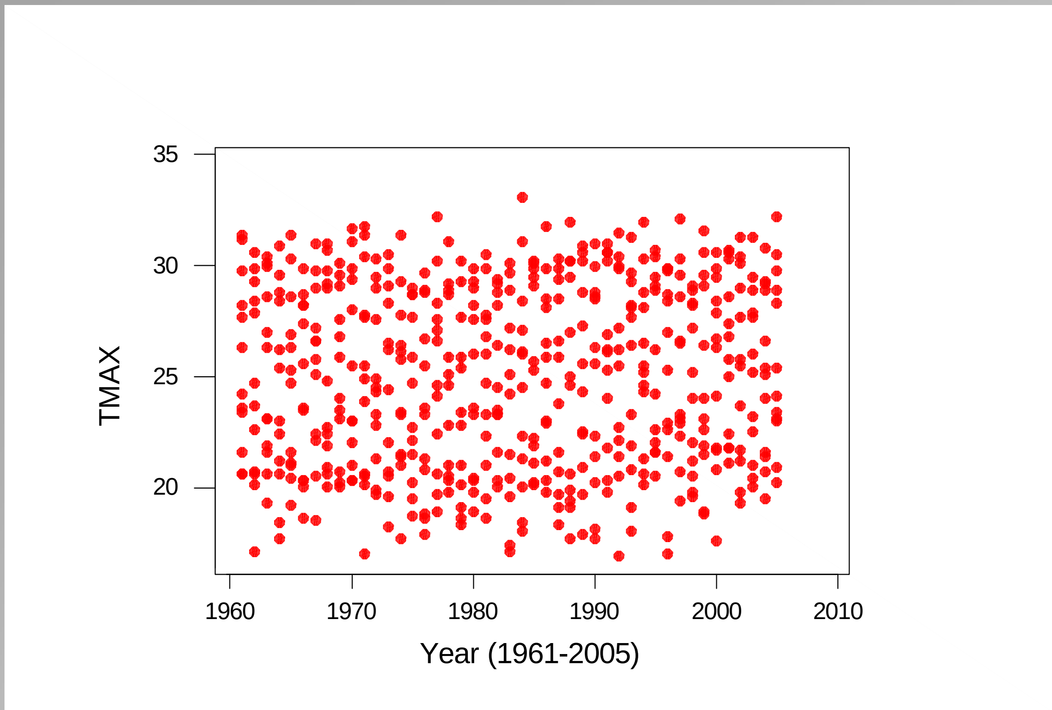
Source	DF	SS	MS	F	P
Regression	1	0,0883	0,0883	0,28	0,597
Residual Error	43	13,3719	0,3110		
Total	44	13,4601			

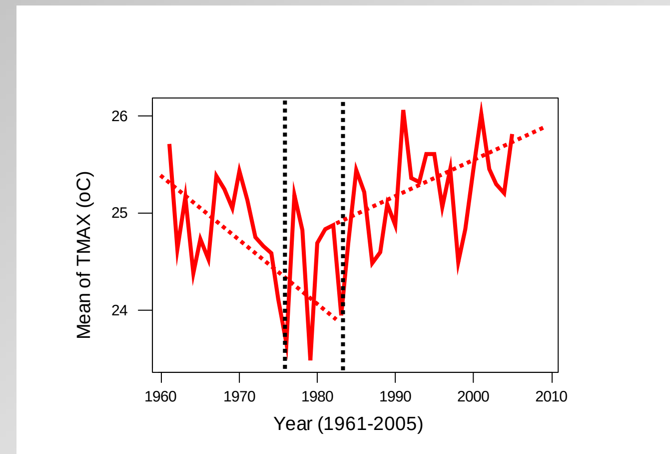
Changes in min/max of TMAX (RS - Brasil)

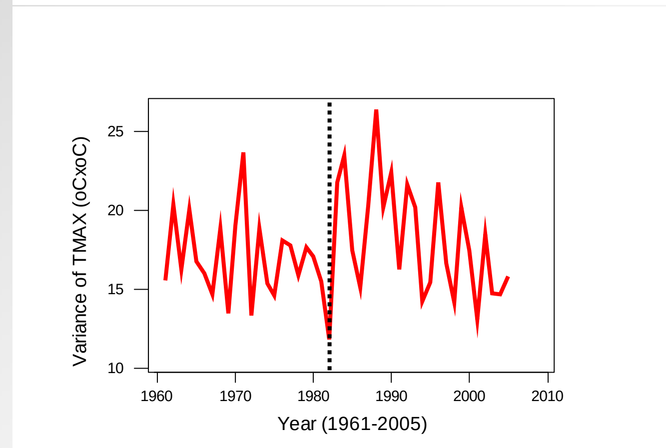




Changes in mean and variance: TMAX (RS-BR)







MeanTMAX = - 4,9 + 0,0151 YEAR

Predictor	Coef	SE Coef	T	P
Constant	-4,94	12,12	-0,41	0,686
Year	0,0151	0,006114	2,47	0,018

S = 0,5326 R-Sq = 12,4% R-Sq(adj) = 10,4%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	1	1,7286	1,7286	6,09	0,018
Residual Error	43	12,1988	0,2837		
Total	44	13,9274			

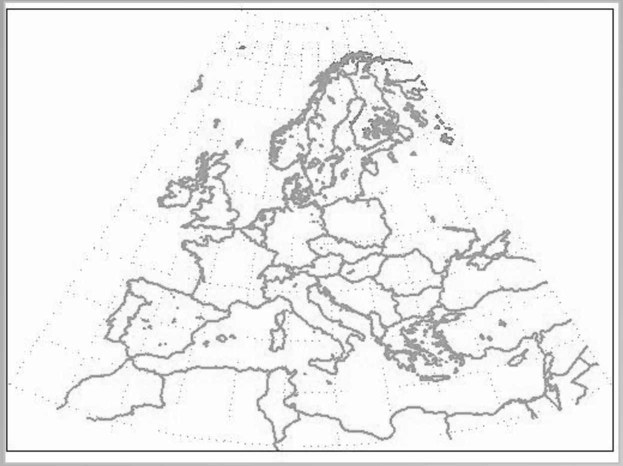
GEOSTATISTICAL ASSESSMENT OF HADCM3 SIMULATIONS VIA NCEP REANALYSES OVER EUROPE.

Case Study: Temperature Extremes.

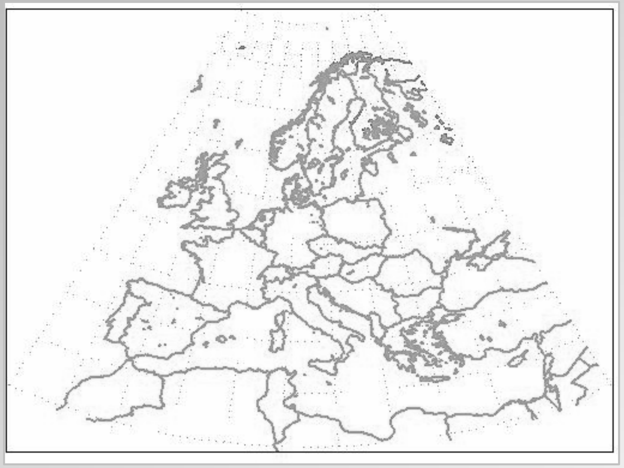
Paulo Sérgio Lucio

✉ pslucio@ccet.ufrn.br ✉ pslucio@uevora.pt

Experimental Design



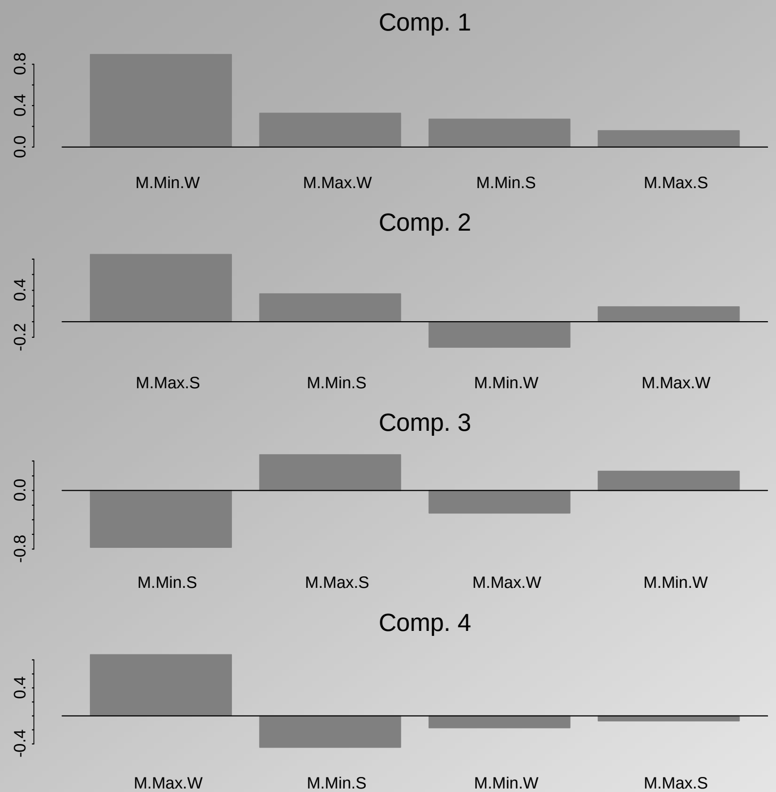
HadCM3 (CGM Model):
16 long x 19 lat = 304 pts
$15^{O}W - 41.25^{O}E$
$30^{O}N - 75^{O}N$

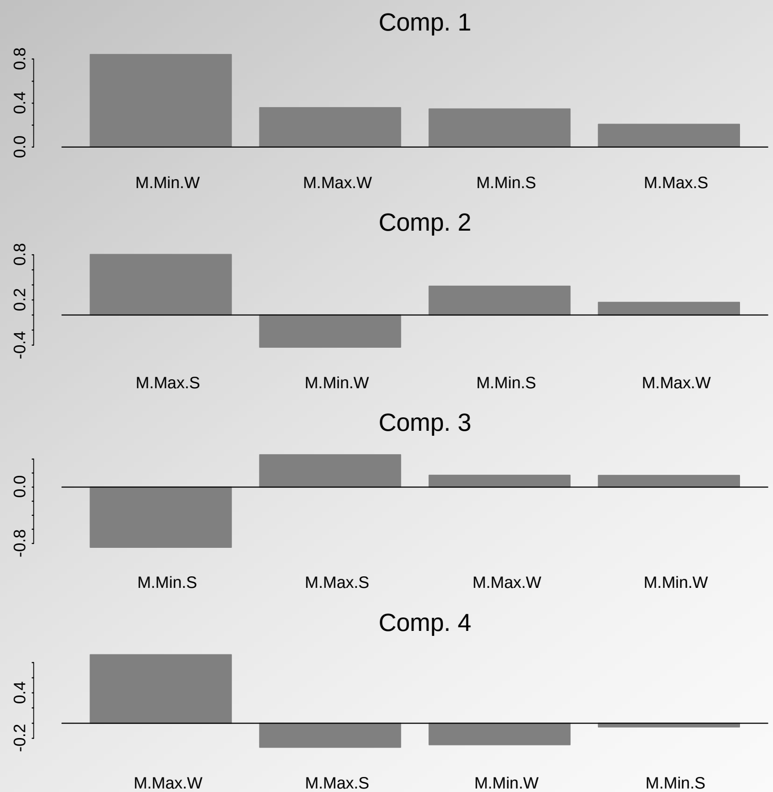


NCEP (Reanalysis):
31 long x 25 lat = 775 pts
$15^{O}W - 41.25^{O}E$
$29.52335^{O}N - 75.23505^{O}E$

The NCEP Reanalyses have different spatial resolution from the HadCM3 Simulations. So, it is not possible to compare the models directly. Rather, some regriding or rescaling (solution to the change of support problem) with an accurate bivariate interpolation for comparability defining a common grid (exploratory analyses). It requires a statistical procedure with "reasonable" precision.

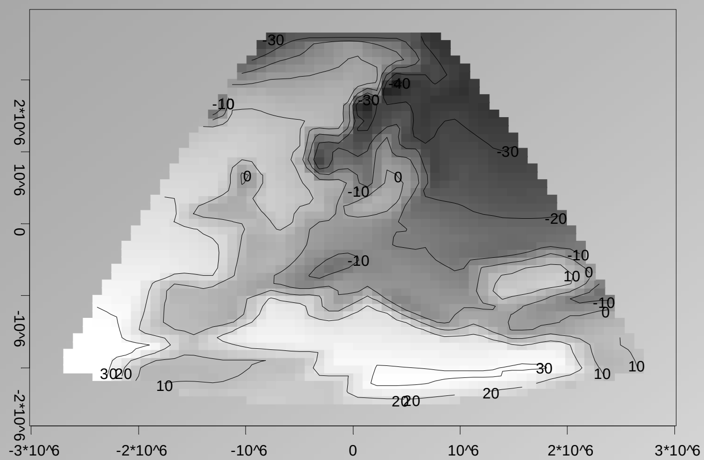
PC1 & PC2 – TMIN Climatology



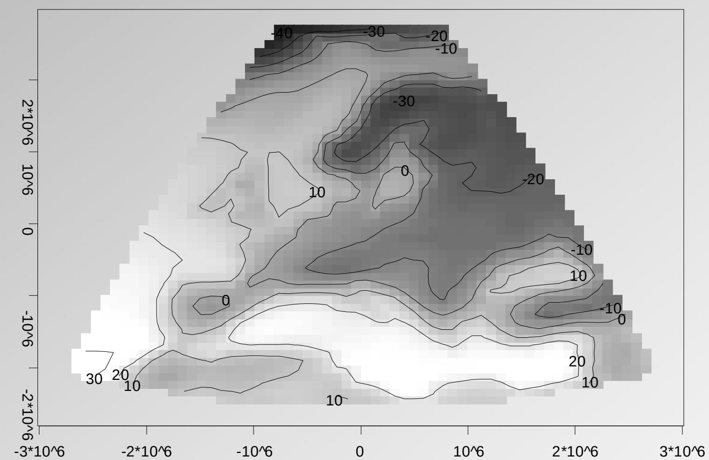


PC1 & PC2 – TMIN Climatology

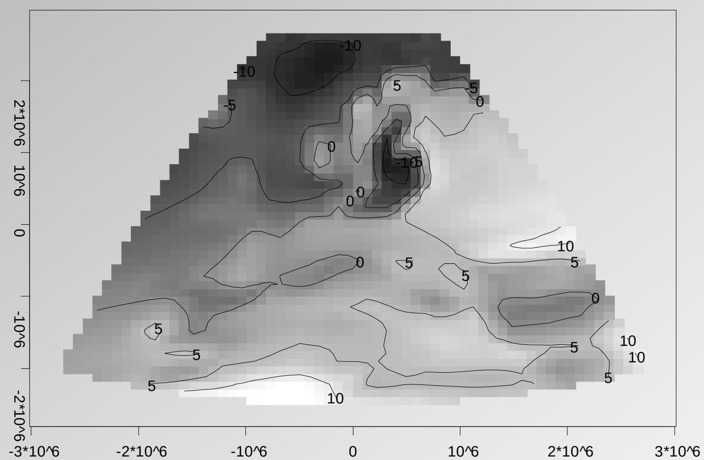
HadCM3 Simulations - Climatology 1st PCA



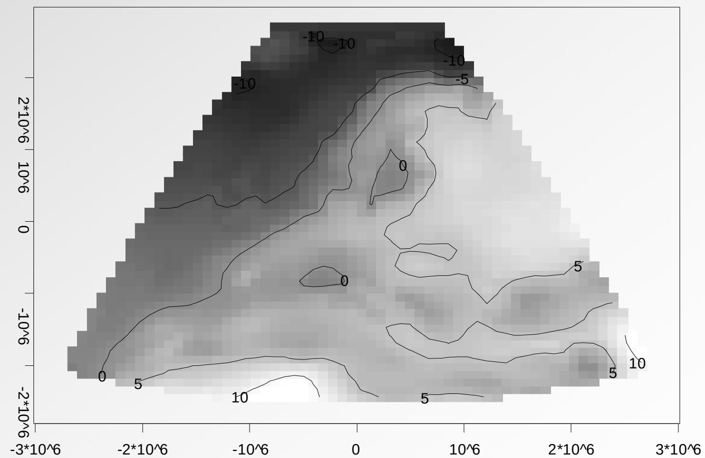
NCEP Reanalyses - Climatology 1st PCA



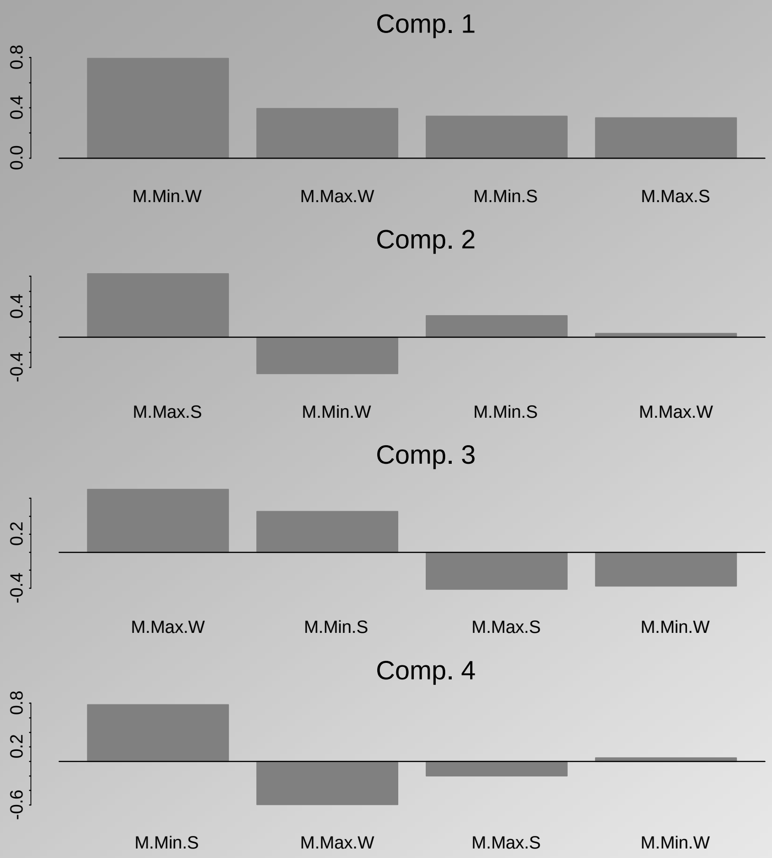
HadCM3 Simulations - Climatology 2nd PCA

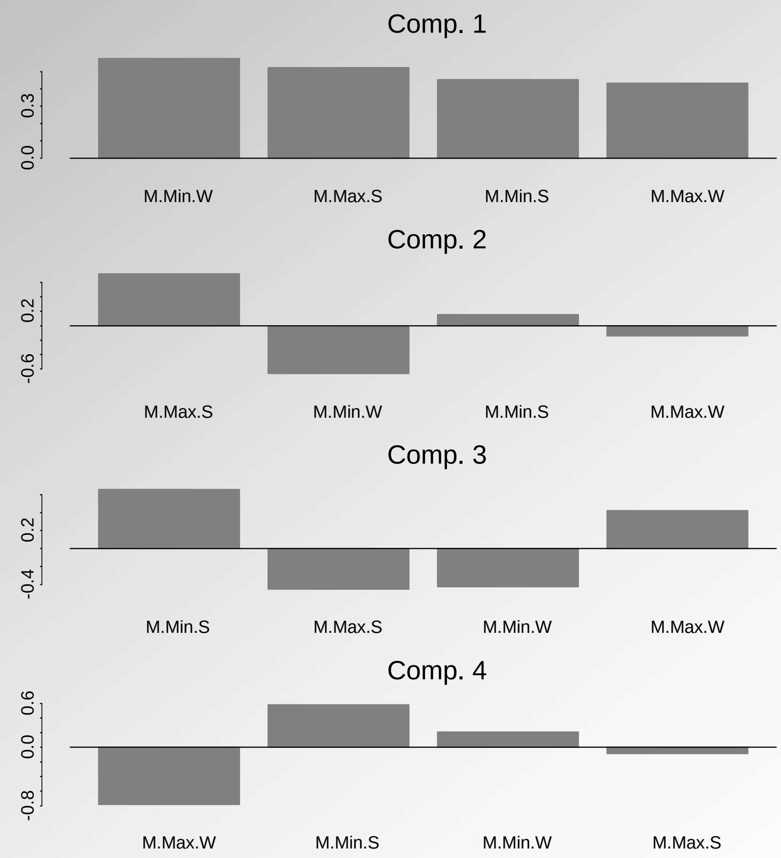


NCEP Reanalyses - Climatology 2nd PCA



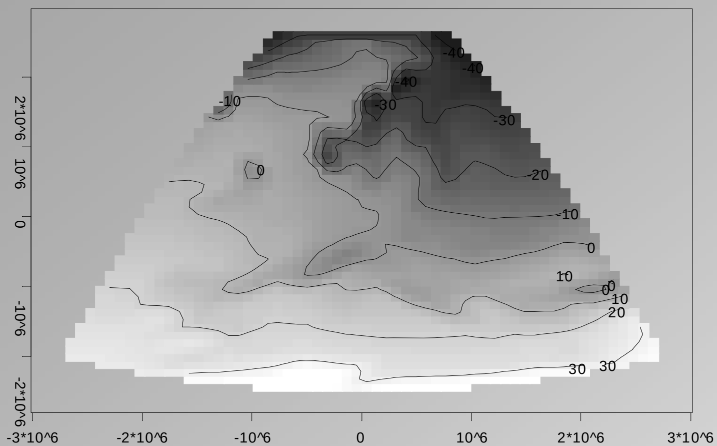
PC1 & PC2 – TMAX Climatology



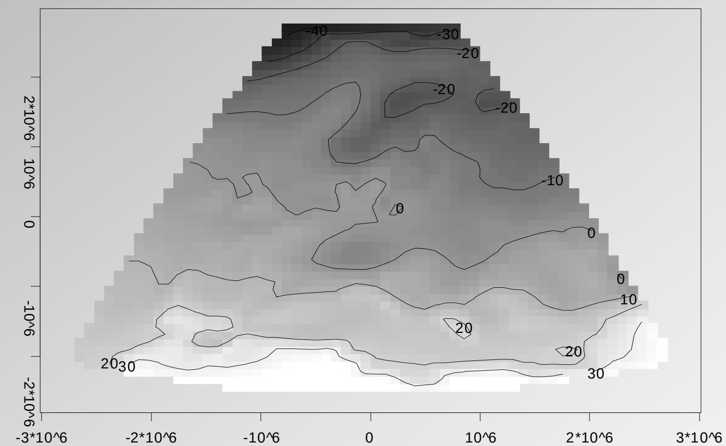


PC1 & PC2 – TMAX Climatology

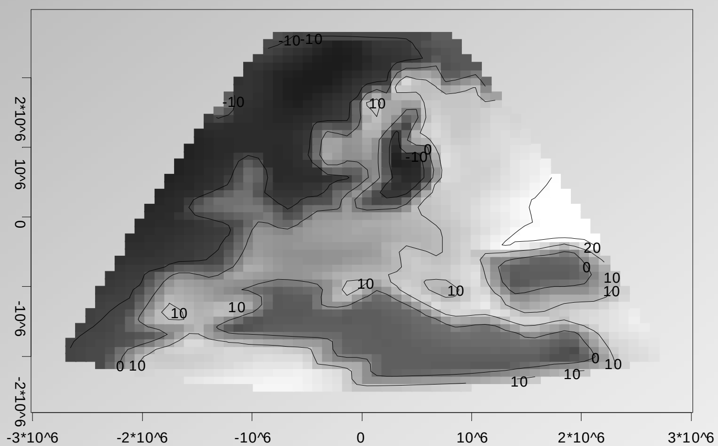
HadCM3 Simulations - Climatology 1st PCA



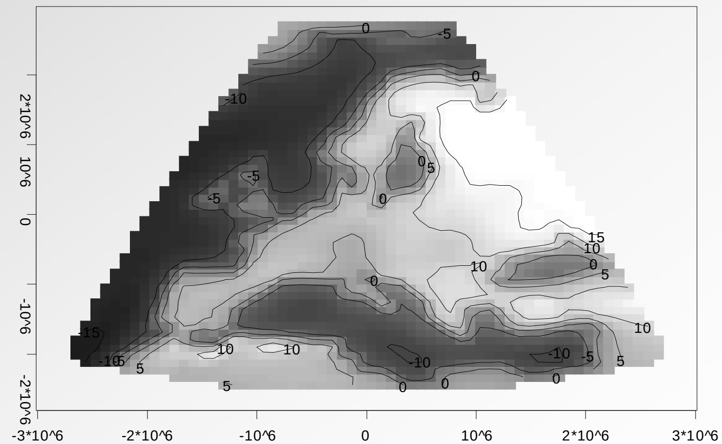
NCEP Reanalyses - Climatology 1st PCA



HadCM3 Simulations - Climatology 2nd PCA



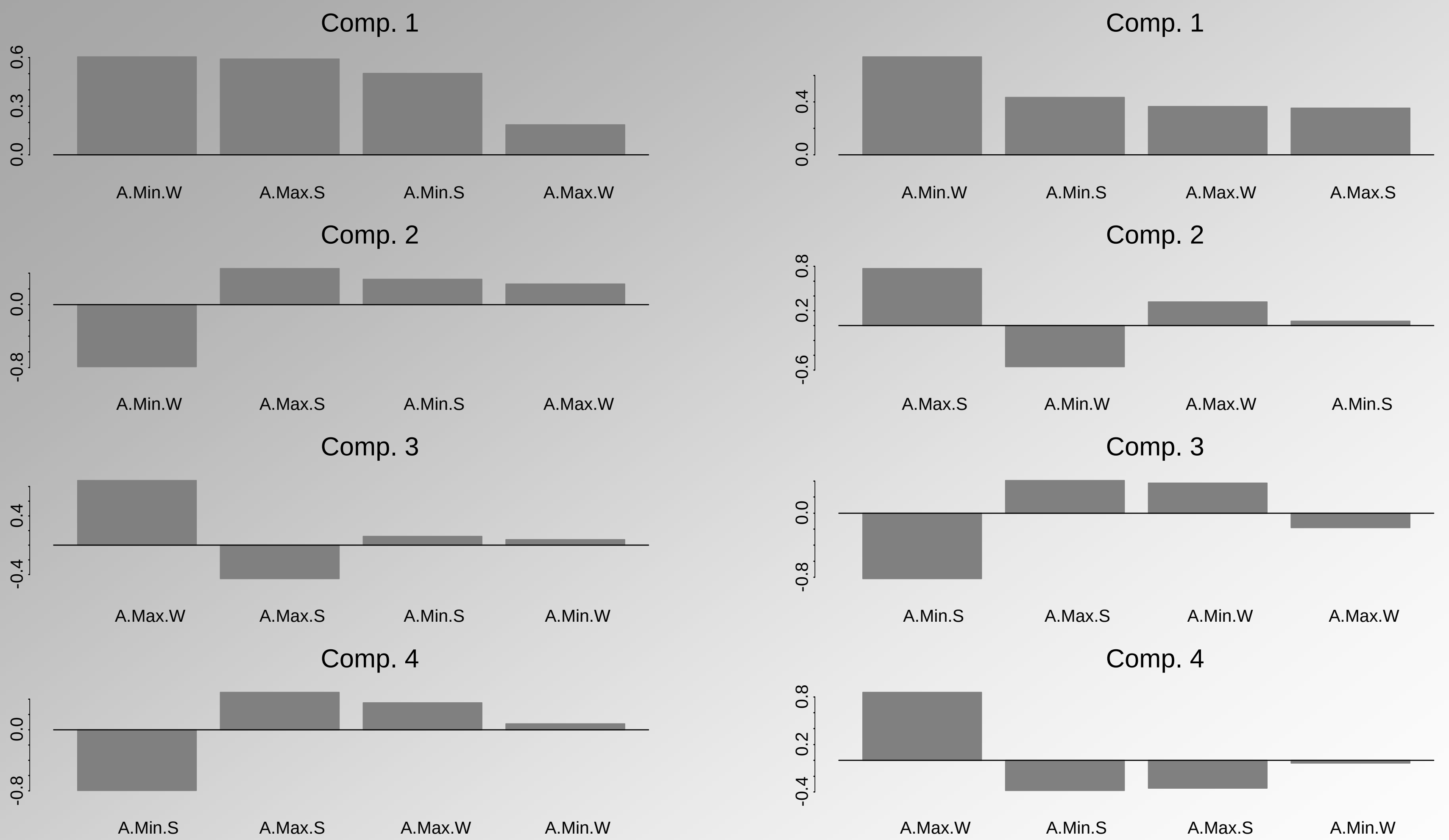
NCEP Reanalyses - Climatology 2nd PCA



Anomaly's Climatology

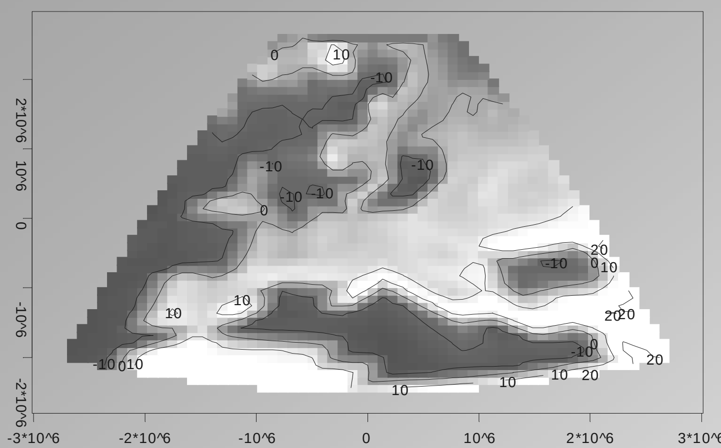
To get global comprehensible information, it is more useful to analyse the extremes considering their anomalies (δ): the grid-point deviation of the long term absolute extreme temperature from the long term average value. The reason for using anomalies is to attempt to remove the influence of latitude, longitude, and land/ocean differences.

PC1 & PC2 – TMIN Climatology Anomaly

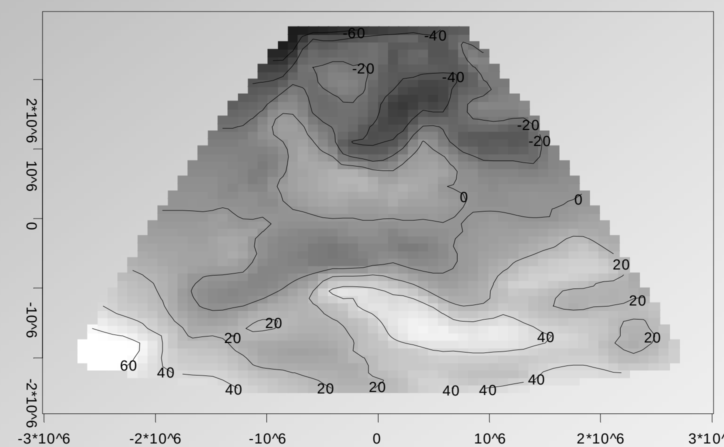


PC1 & PC2 – TMIN Climatology Anomaly

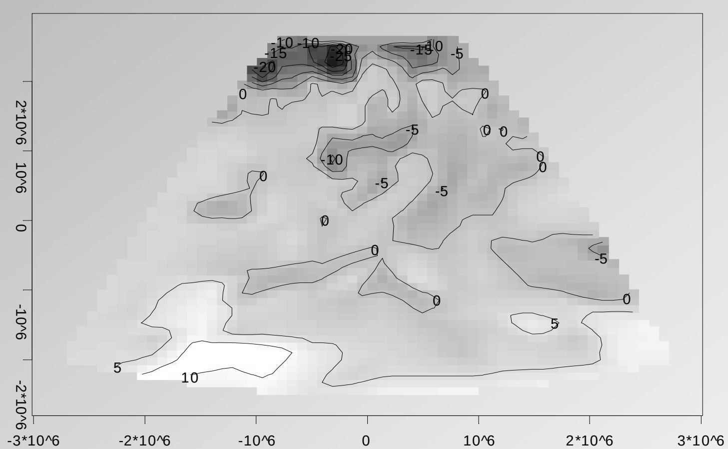
HadCM3 Simulations - Anomaly 1st PCA



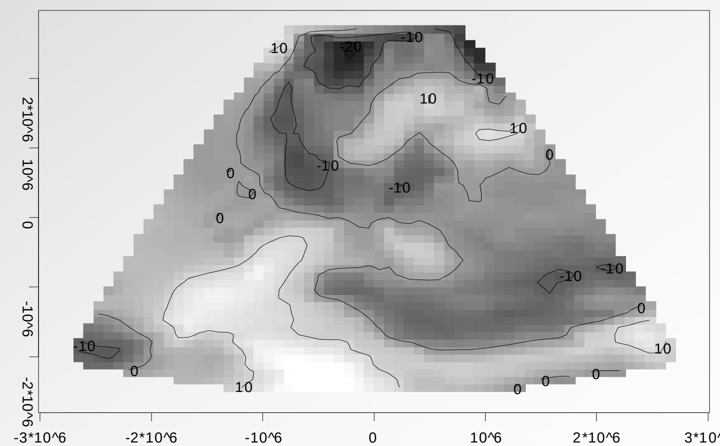
NCEP Reanalyses - Anomaly 1st PCA



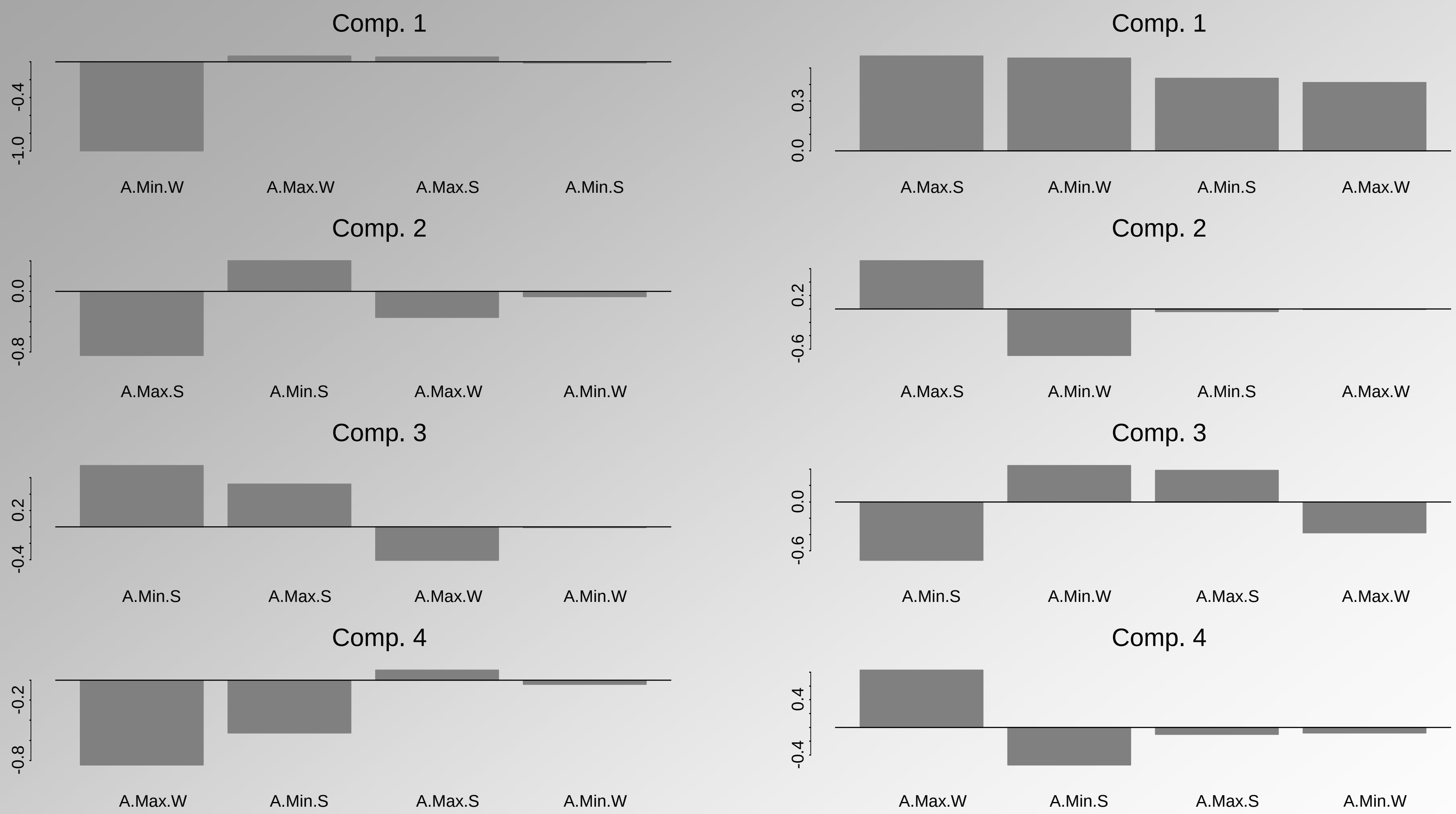
HadCM3 Simulations - Anomaly 2nd PCA



NCEP Reanalyses - Anomaly 2nd PCA

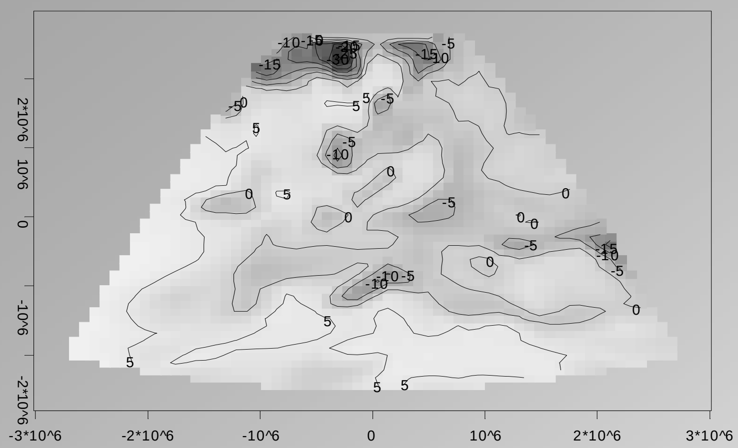


PC1 & PC2 – TMAX Climatology Anomaly

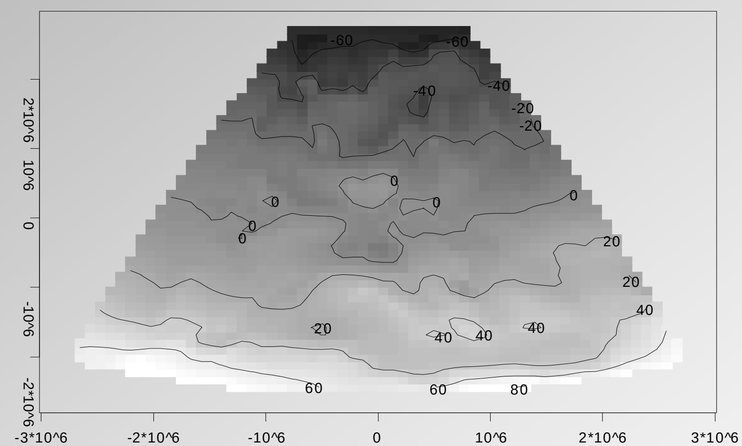


PC1 & PC2 – TMAX Climatology Anomaly

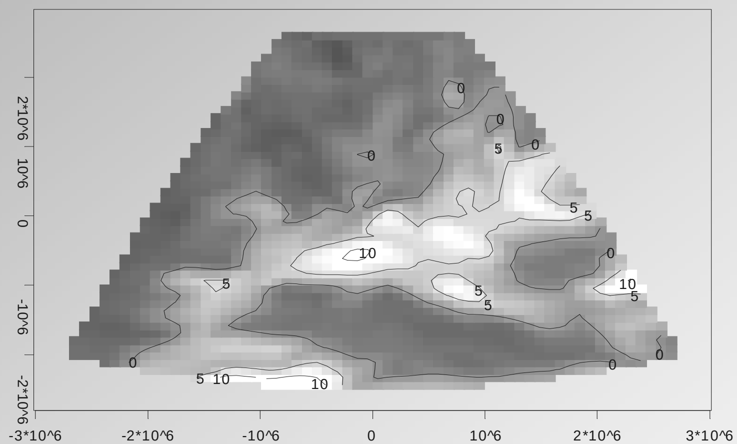
HadCM3 Simulations - Anomaly 1st PCA



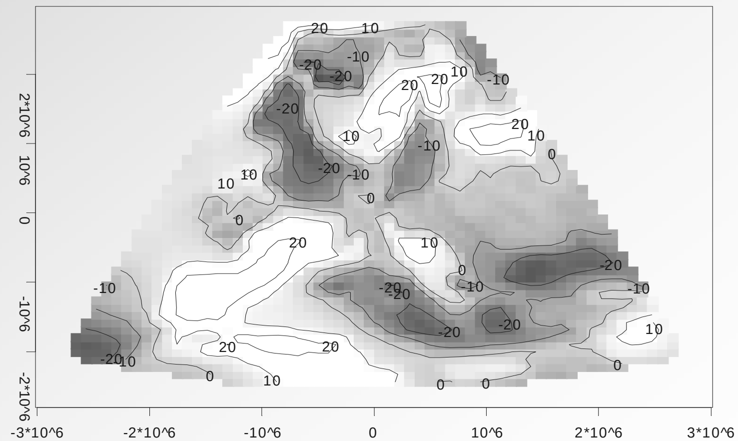
NCEP Reanalyses - Anomaly 1st PCA



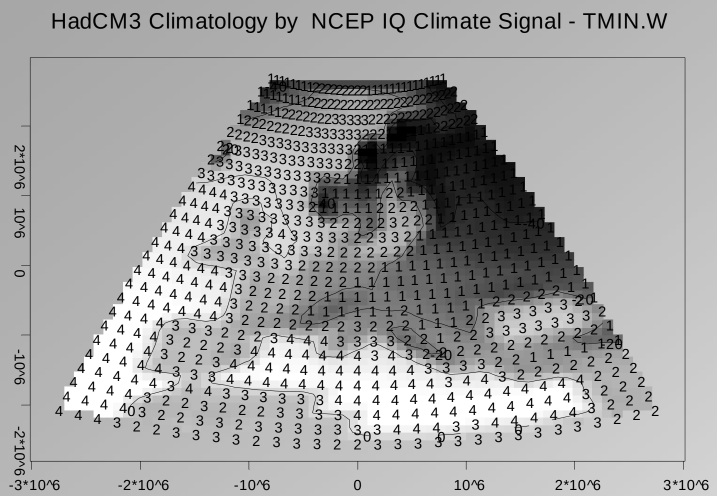
HadCM3 Simulations - Anomaly 2nd PCA

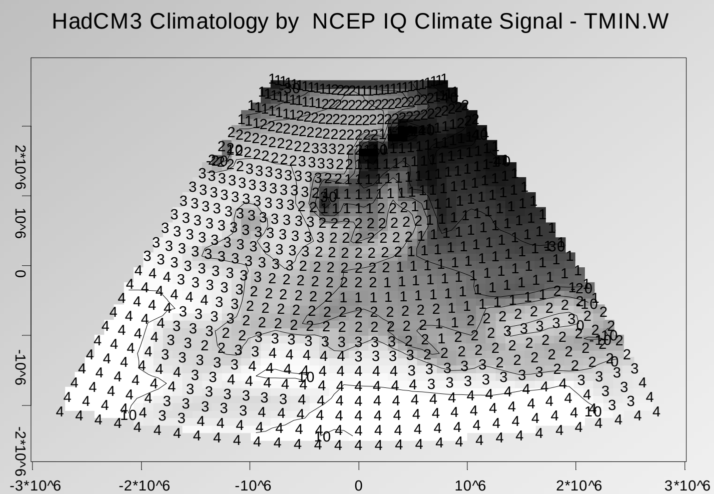


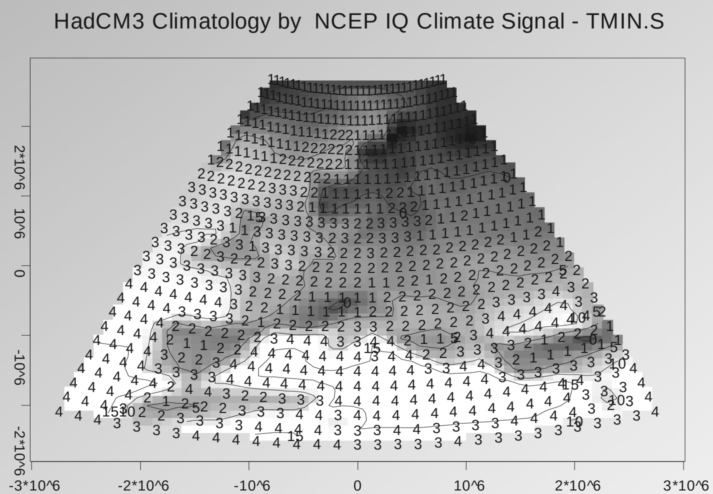
NCEP Reanalyses - Anomaly 2nd PCA

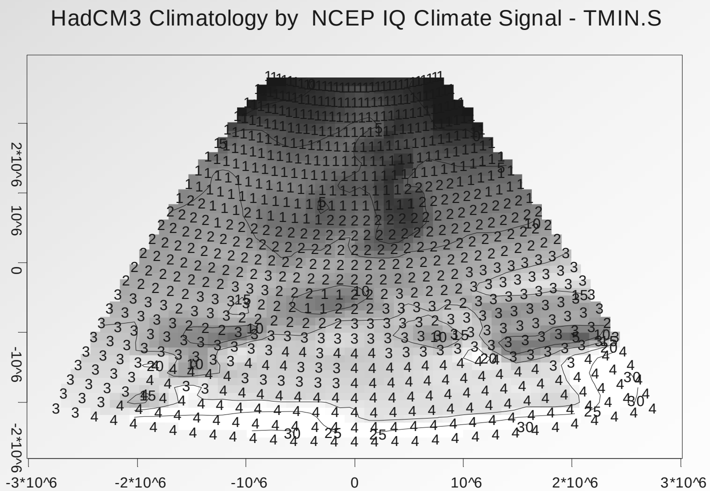


TMIN HadCM3 Climatology by NCEP Reanalyses Classification



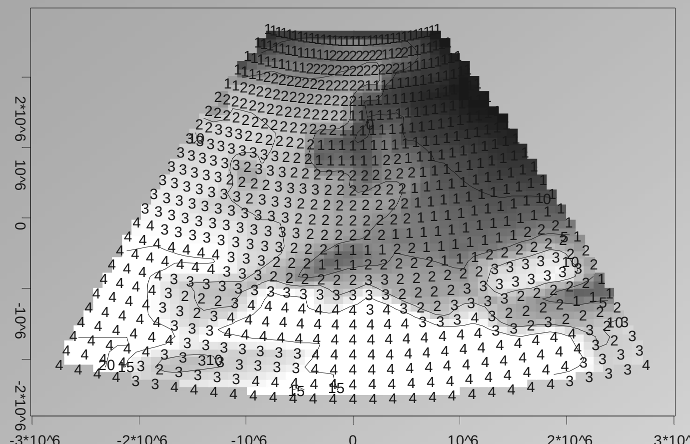




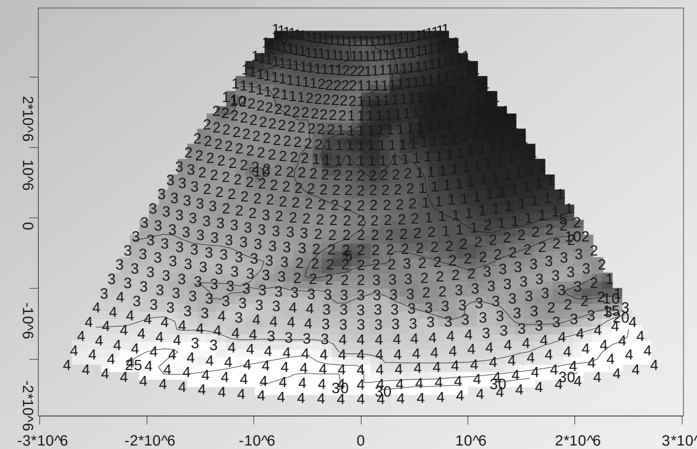


TMAX HadCM3 Climatology by NCEP Reanalyses Classification

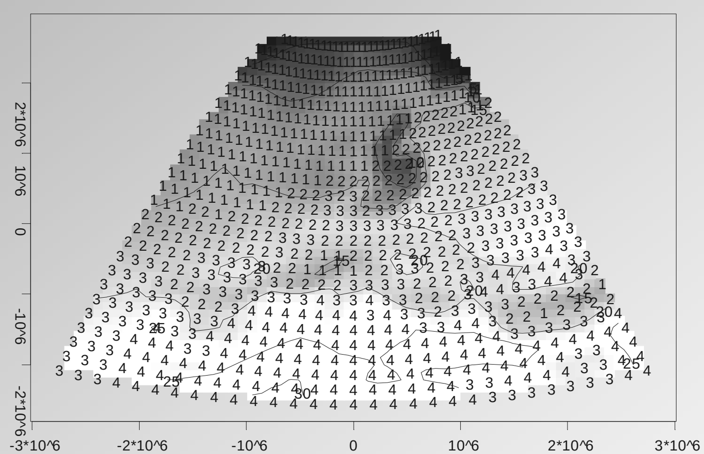
HadCM3 Climatology by NCEP IQ Climate Signal - TMAX.W



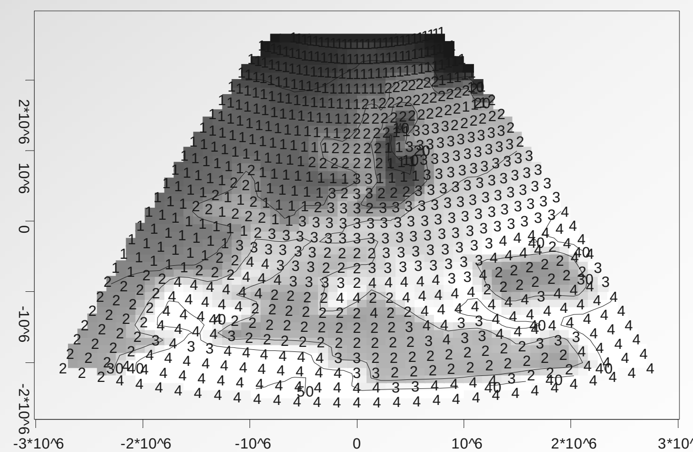
HadCM3 Climatology by NCEP IQ Climate Signal - TMAX.W



HadCM3 Climatology by NCEP IQ Climate Signal - TMAX.S

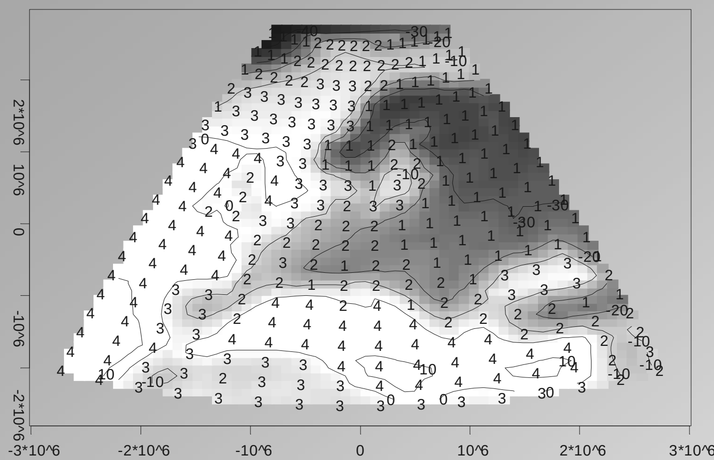


HadCM3 Climatology by NCEP IQ Climate Signal - TMAX.S

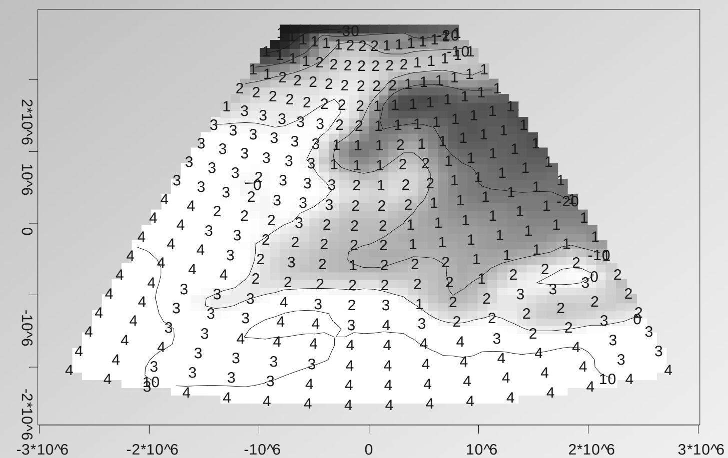


TMIN NCEP Reanalyses Climatology by HadCM3 Classification

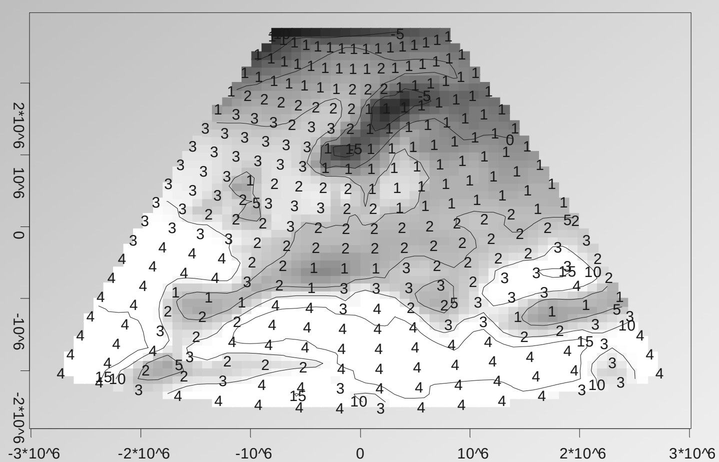
NCEP Climatology by HadCM3 IQ Climate Signal - TMIN.W



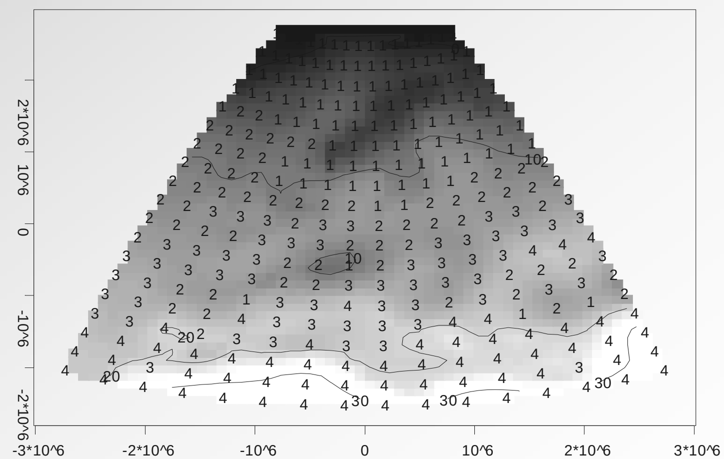
NCEP Climatology by HadCM3 IQ Climate Signal - TMIN.W



NCEP Climatology by HadCM3 IQ Climate Signal - TMIN.S

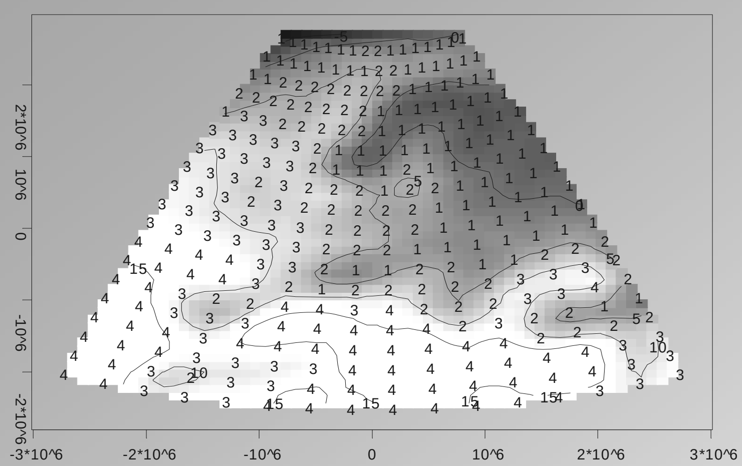


NCEP Climatology by HadCM3 IQ Climate Signal - TMIN.S

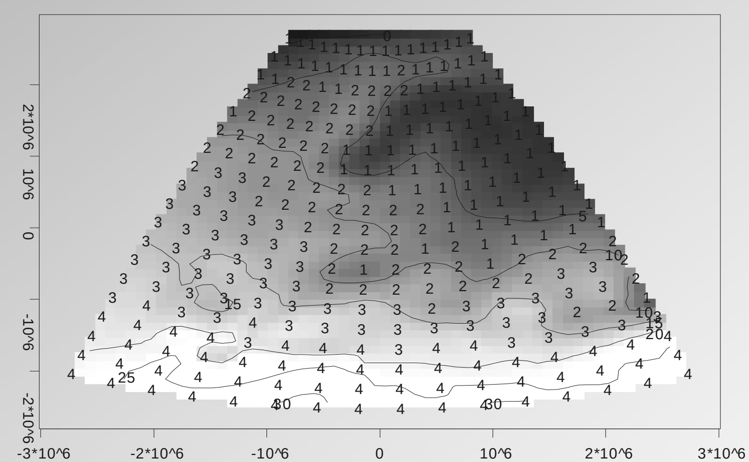


TMAX NCEP Reanalyses Climatology by HadCM3 Classification

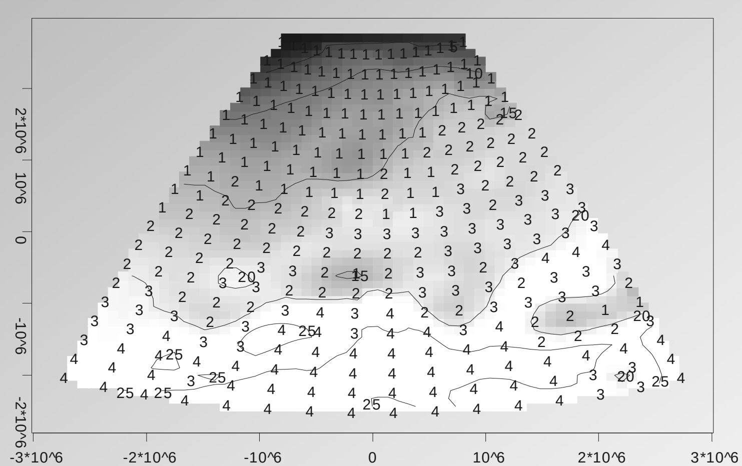
NCEP Climatology by HadCM3 IQ Climate Signal - TMAX.W



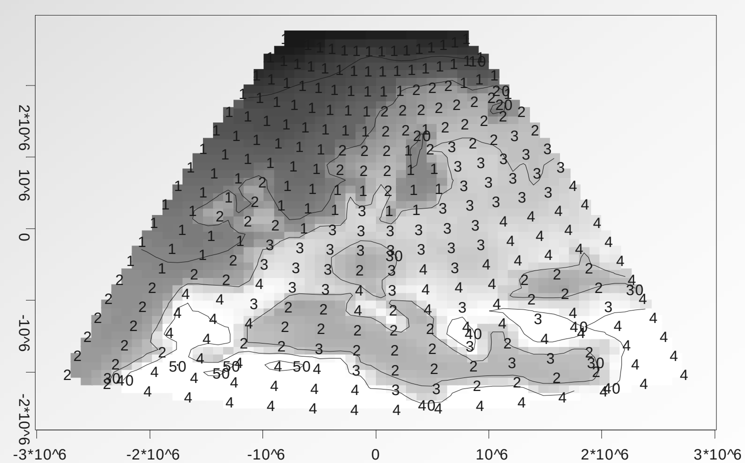
NCEP Climatology by HadCM3 IQ Climate Signal - TMAX.W



NCEP Climatology by HadCM3 IQ Climate Signal - TMAX.S

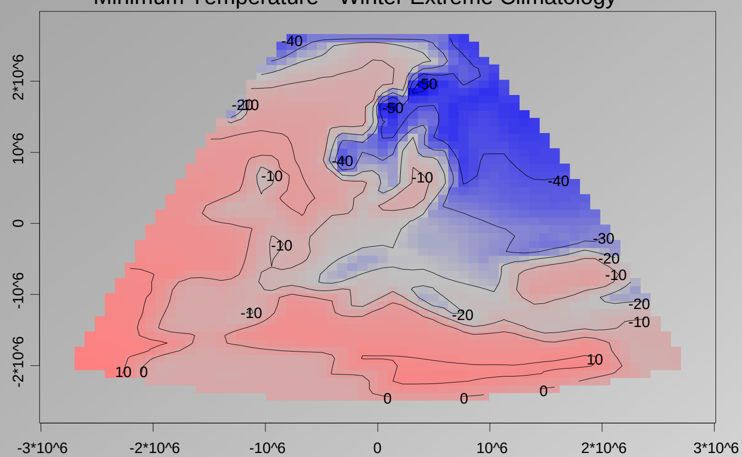


NCEP Climatology by HadCM3 IQ Climate Signal - TMAX.S

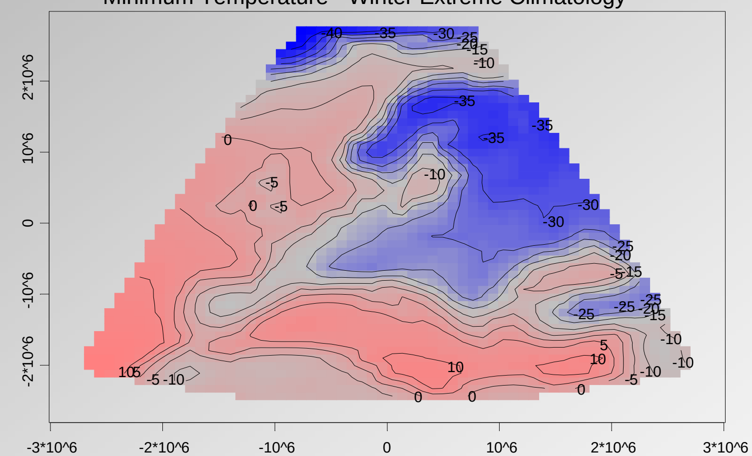


UK Interpolation

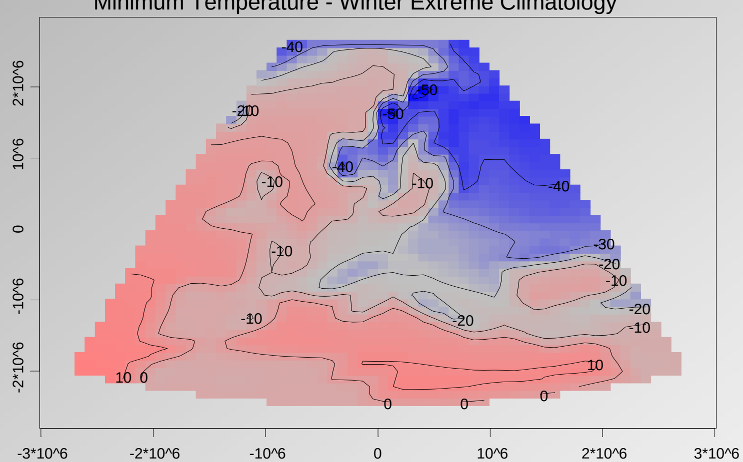
HadCM3 Simulations - Kriging Interpolation
Minimum Temperature - Winter Extreme Climatology



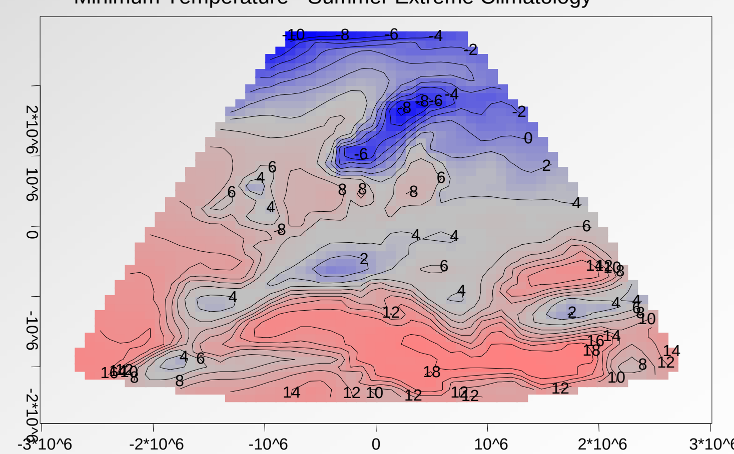
NCEP Reanalyses - Kriging Interpolation
Minimum Temperature - Winter Extreme Climatology



HadCM3 Simulations - Kriging Interpolation
Minimum Temperature - Winter Extreme Climatology

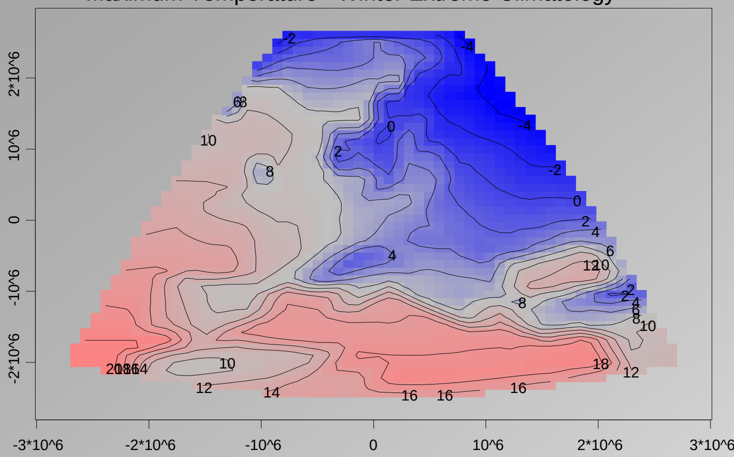


NCEP Reanalyses - Kriging Interpolation
Minimum Temperature - Summer Extreme Climatology

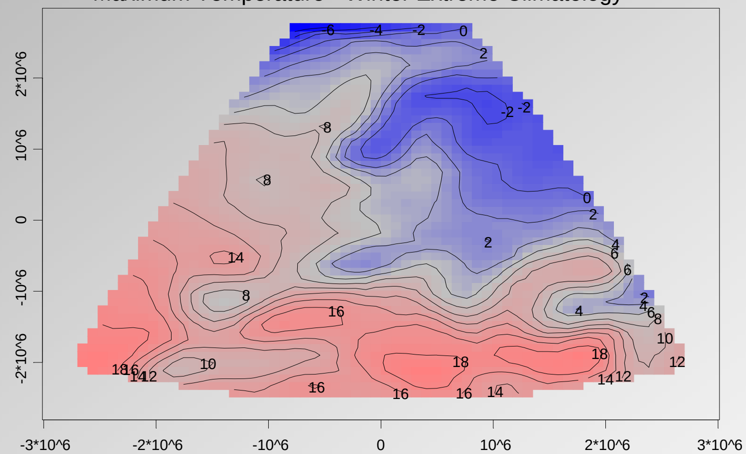


UK Interpolation

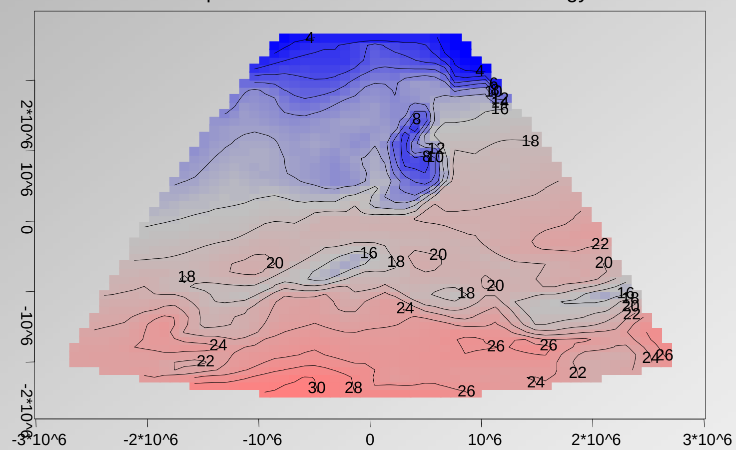
HadCM3 Simulations - Kriging Interpolation
Maximum Temperature - Winter Extreme Climatology



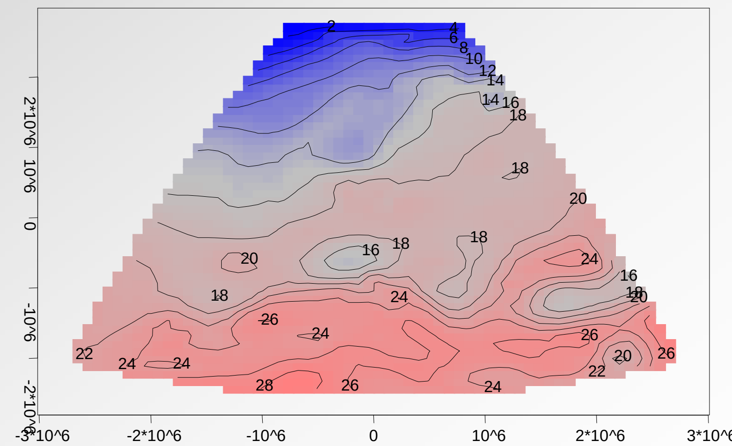
NCEP Reanalyses - Kriging Interpolation
Maximum Temperature - Winter Extreme Climatology



HadCM3 Simulations - Kriging Interpolation
Maximum Temperature - Summer Extreme Climatology

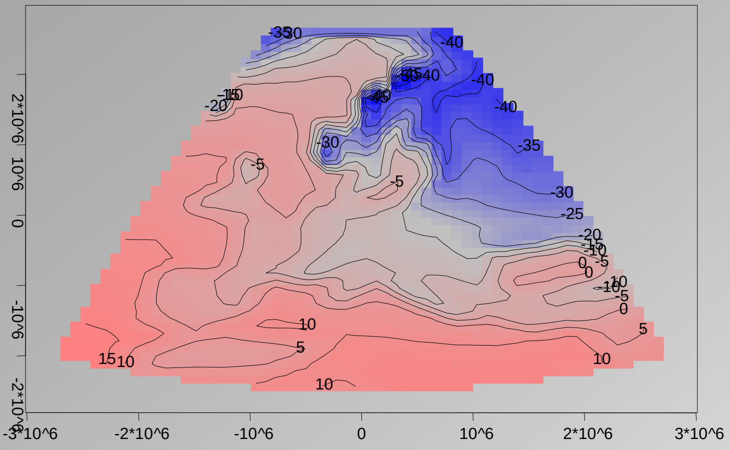


NCEP Reanalyses - Kriging Interpolation
Maximum Temperature - Summer Extreme Climatology

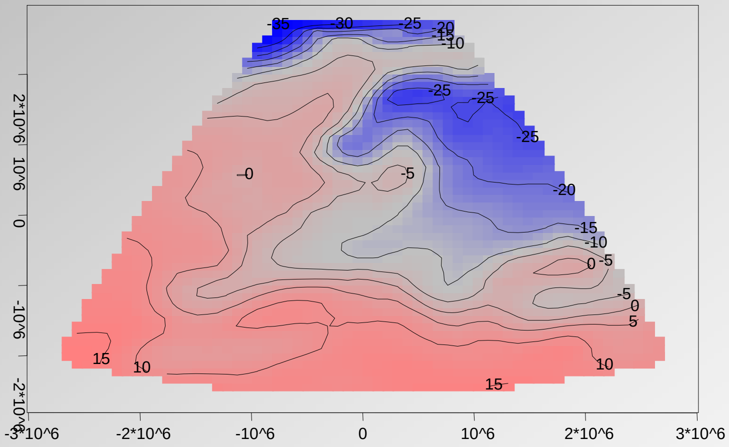


UK Interpolation

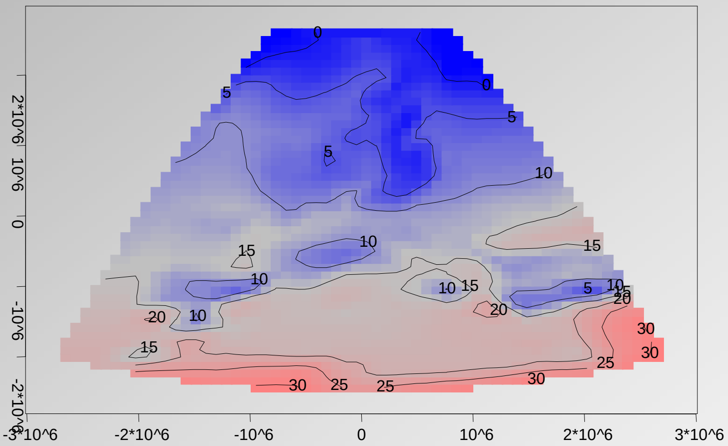
HadCM3 Simulations - Kriging Interpolation
Minimum Temperature - Winter Extreme Climatology



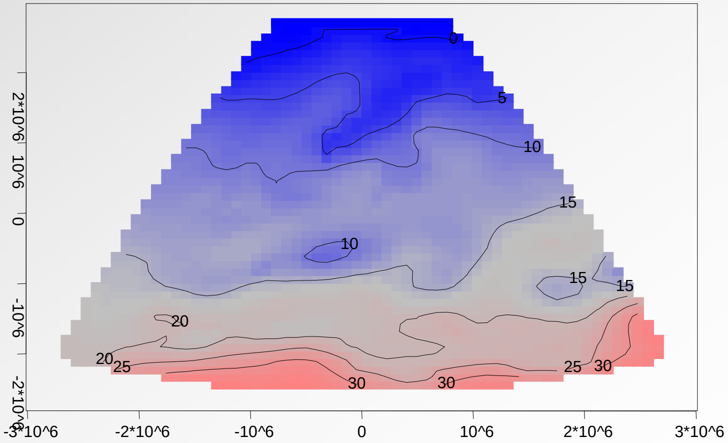
NCEP Reanalyses - Kriging Interpolation
Minimum Temperature - Winter Extreme Climatology



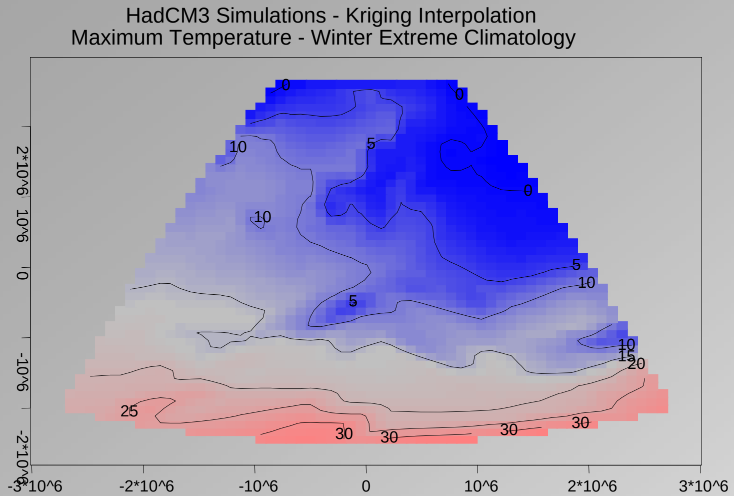
HadCM3 Simulations - Kriging Interpolation
Minimum Temperature - Summer Extreme Climatology

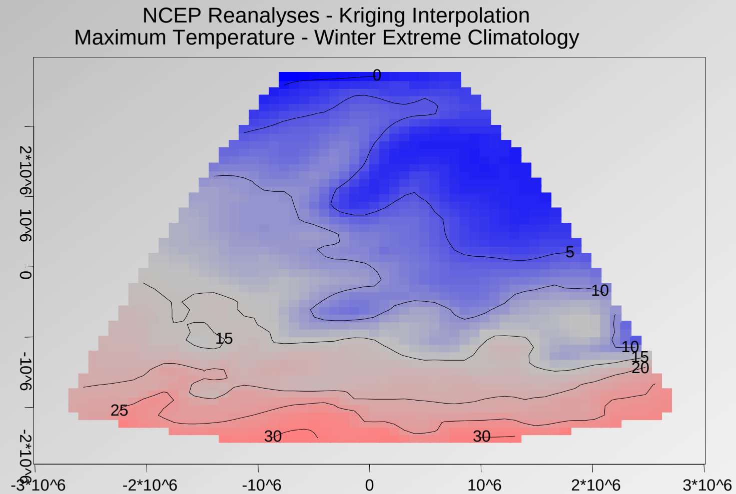


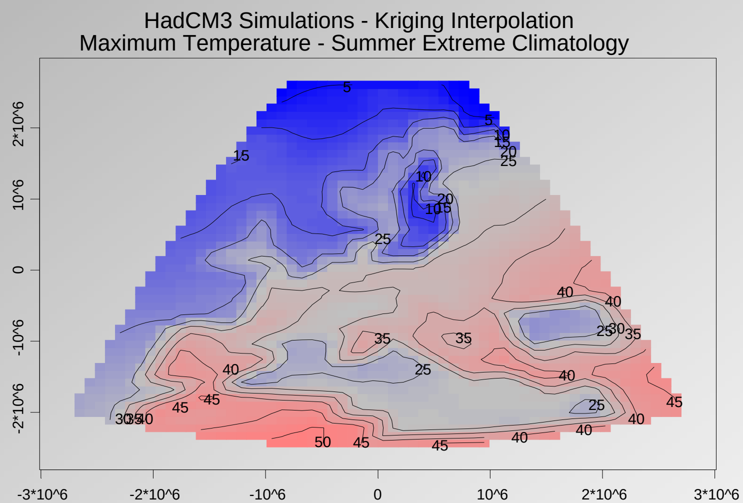
NCEP Reanalyses - Kriging Interpolation
Minimum Temperature - Summer Extreme Climatology

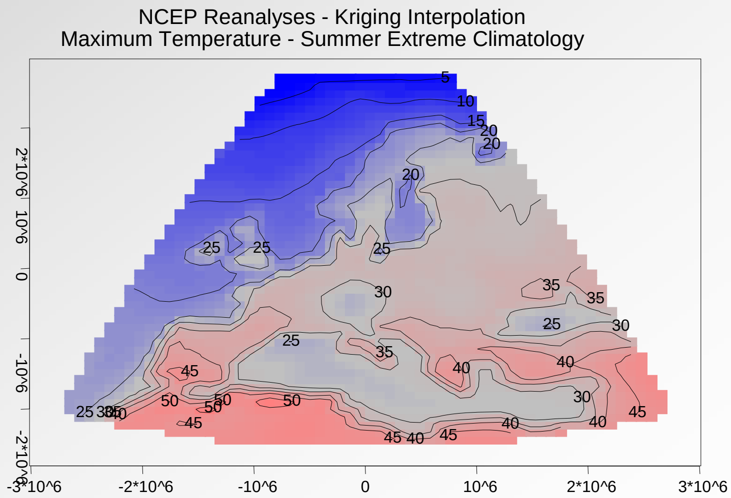


UK Interpolation









Summary

The objective of this basic analysis was just to present a way to validate spatially extremes of a particular GCM. The overall objective of this study was to understand HadCM3 limitations in simulating the current climate extremes in order to more appropriately interpret the simulations of the future climate. Based on this proposal, the spatial patterns of extreme anomalies in the NCEP Reanalyses are not recognised from the HadCM3 model. Such instability may persist in the future.

Though uncertainty is inherent in any statistical model, such uncertainties can be reduced by judicious choices of model and inference, and by the utilization of all sources of information.

Thinking about …

“A map is a poor model of reality if it does not depict characteristics of the real spatial distributions of those attributes that most affect how the phenomenon responds.“

Prof. André Journel

… FURTHERMORE …

”It is better to have a model of uncertainty than an illusion of reality.”

ASSESSMENT OF THE CPTEC/COLA AGCM PRECIPITATION EXTREMES VIA PEAKS-OVER-THRESHOLD ANALYSIS.

TARGET AREA: BRAZIL (1970-2001)

Paulo Sérgio Lucio

✉ pslucio@ccet.ufrn.br ✉ pslucio@uevora.pt

Introduction

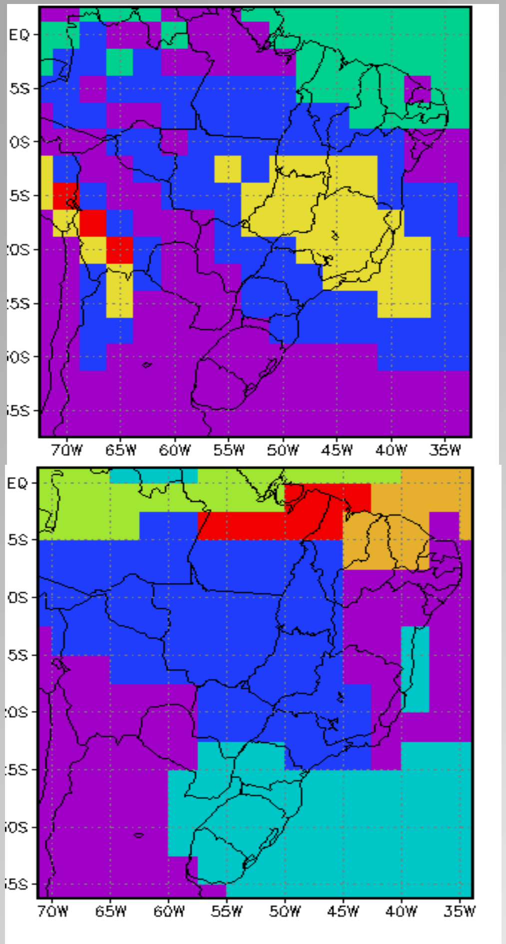
Since a good representation of the extreme distribution of probability can facilitate the development of "rectification and improvement" techniques seeking for a better numerical simulation of meteorological extremes events in climate models .

The purpose of this work is to apply the classical extreme value model, making use of the peaks-over-threshold (POT) methodology (inferences are supported on exceedances over a low/high threshold). Hence, daily precipitation totals measured at some Brazilian meteorological stations were used as an input dataset and the extreme value sub-series are declusterized considering the most intense event and excluding those which might be sprung by a common meteorological phenomenon.

Empirical Cluster Analysis for Meteorological Station Selection

In this work a hierarchical cluster analysis was performed over monthly precipitation over the Brazil for the simulated by model and observed data sets. We have used clustering of variables to identify groups whose variables share common characteristics – regional climatology and to classify the uncertainty associated to the grouping process. The results of the cluster analysis indicate differences in the spatial structure of the some regions with common characteristics for the model and observation. The number of clusters obtained is bigger in the model analysis, indicating a bigger spatial variability of the simulated precipitation than observed precipitation. The persistence feature of extreme precipitation attributes was analysed taking into account daily records of the long-term time period over 32 years (1970-2001).

Database: CPTEC/COLA AGCM



Modeled Data Clustering (top);
Observed Data Clustering (bottom).

In the present study, results of 50-year simulation, using the CPTEC/COLA AGCM for the period of 1952-2001 are analysed. The model is spectral and the resolution is T62L28, corresponding to 1.89º horizontal resolution. This model is derived from the Center for Ocean, Land and Atmosphere (COLA) interactions. Some preliminary results has shown relative high skill in north-eastern and northern South America, assessed using anomaly correlation and ranked probability skill score.

Extremes by POT modelled with GPD

Extreme events occur naturally in physical systems. The same physical processes that are responsible for generating non-extreme events can contribute to the occurrence of extremes. When the distribution of extreme events is considered in the phase space of a system, the extremes are found, by definition, near the edges of the distribution, at least in the directions/variables in which extremes are defined.

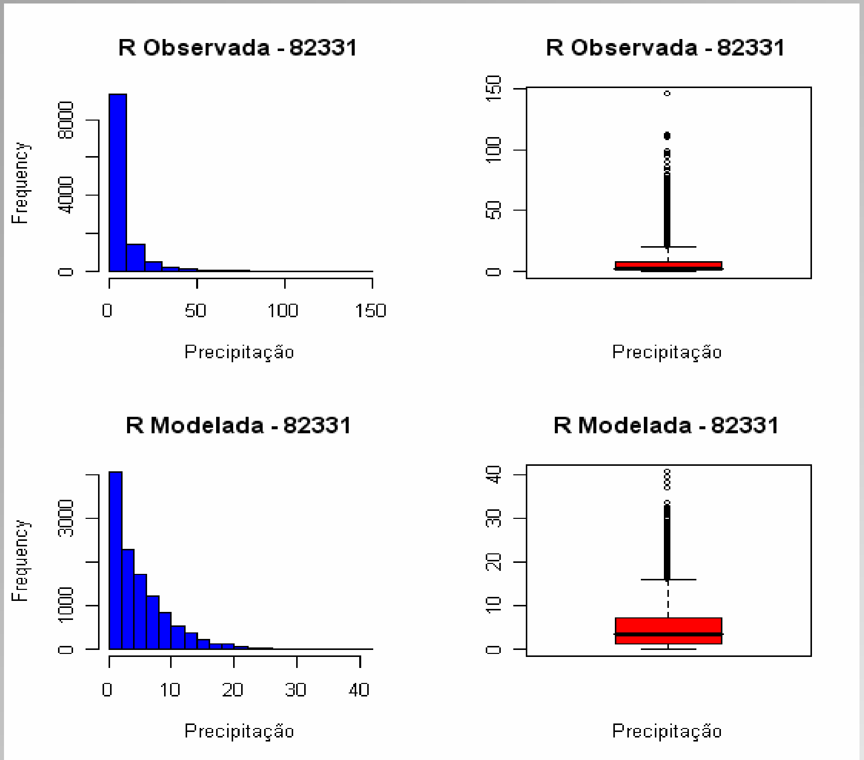
The analysis of the tail behavior of asset returns is important from the point of view of climate risk management. The most commonly used definition of extreme weather is based on an event's climatologically on exceedances over threshold distribution, the peaks-over-threshold (POT) methodology. The Generalized Pareto Distribution (GPD) is widely used for modeling exceedances of a random variable over a high threshold and it has been shown to be one of the best ways to apply extreme value theory in practice.

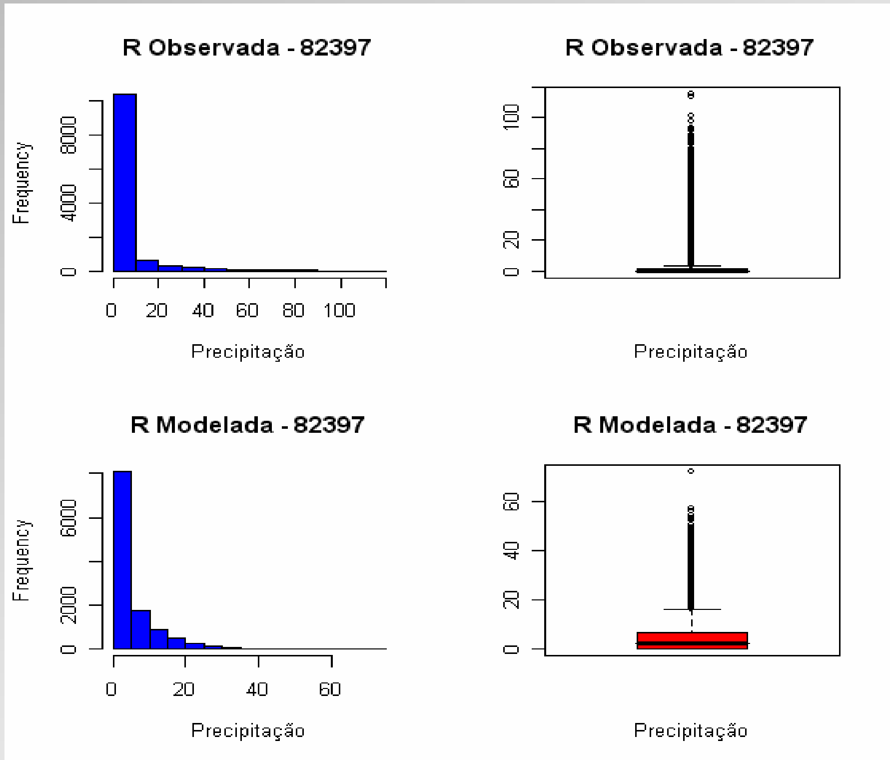
Extremes by POT modelled with GPD

The POT model is based on "*Pickands-Balkema-de Haan Theorem*" that postulates that the distribution of the observations in excess of certain high threshold can be approximated by a GPD. In the POT model, first a threshold is identified to define the start of the tail region. Then the distribution of the *excesses* over the threshold point is estimated with the help of a GPD approximation. Hence, for the POT methodology, inferences are based on exceedances over a low/high threshold.

Under some general conditions, the distribution function of the exceedances (threshold excesses) is well approximated by the GPD, defined by two basic parameters: scale (σ) and shape (ξ). The validity of the thresholds for precipitation has been assessed checking the stability of the maximum likelihood estimates.

Illustration – Exploratory Analysis - BR



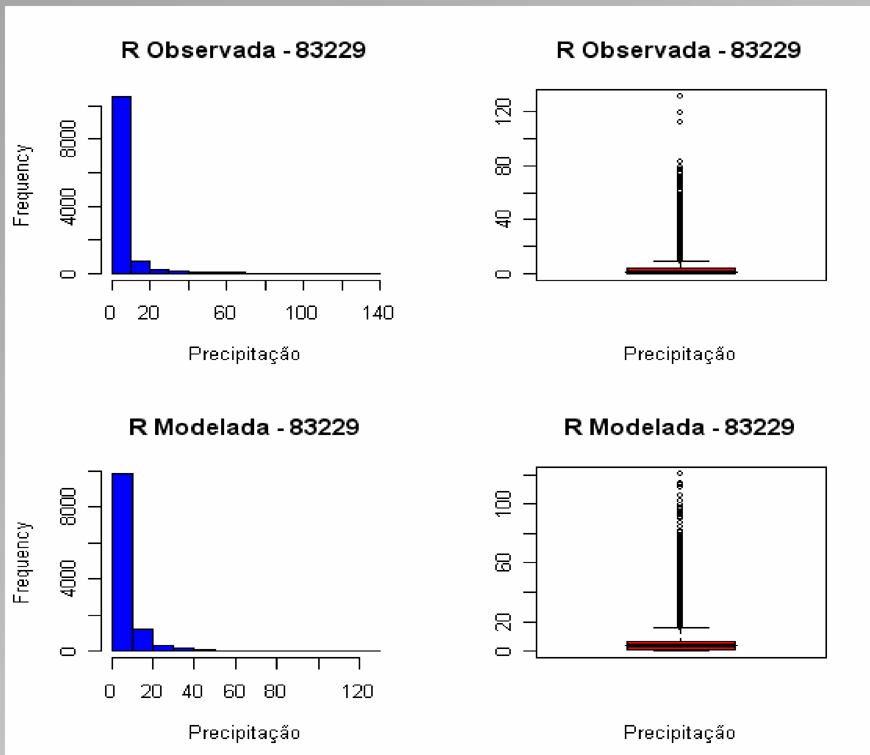


Manaus (High Predictability)

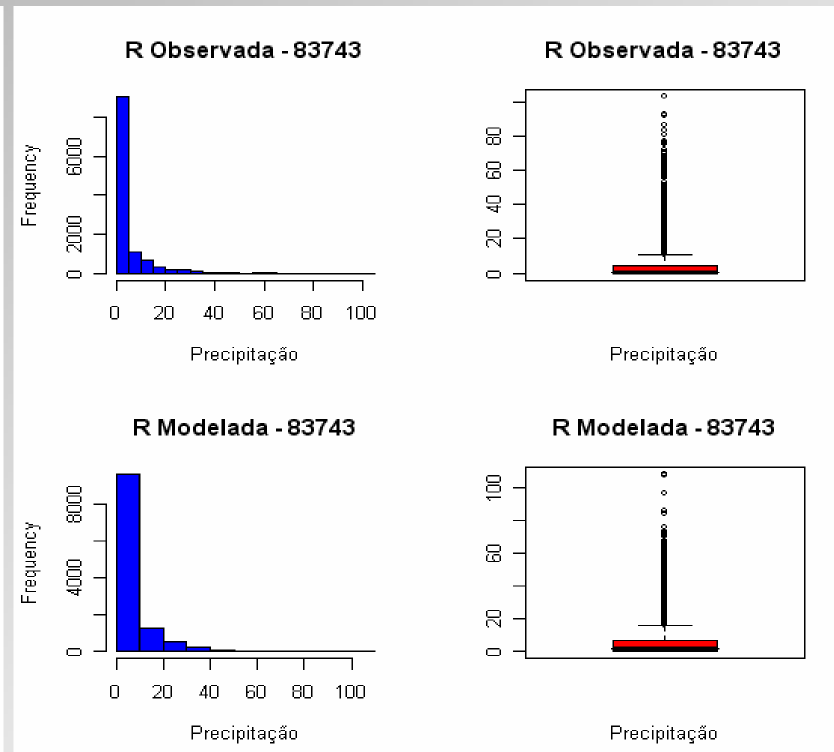
Fortaleza (High Predictability)

Histograms and Box-Whiskers Plot of daily precipitation, observed and generated by the CPTEC/COLA AGCM (1971-2001).

Illustration - Exploratory Analysis - BR



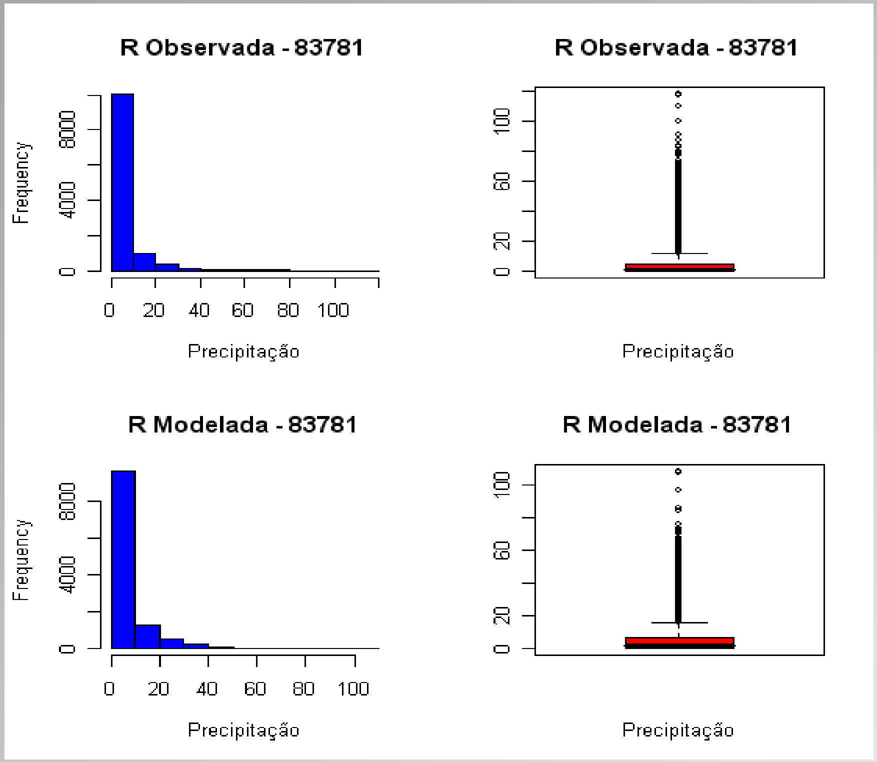
Salvador (Low Predictability)

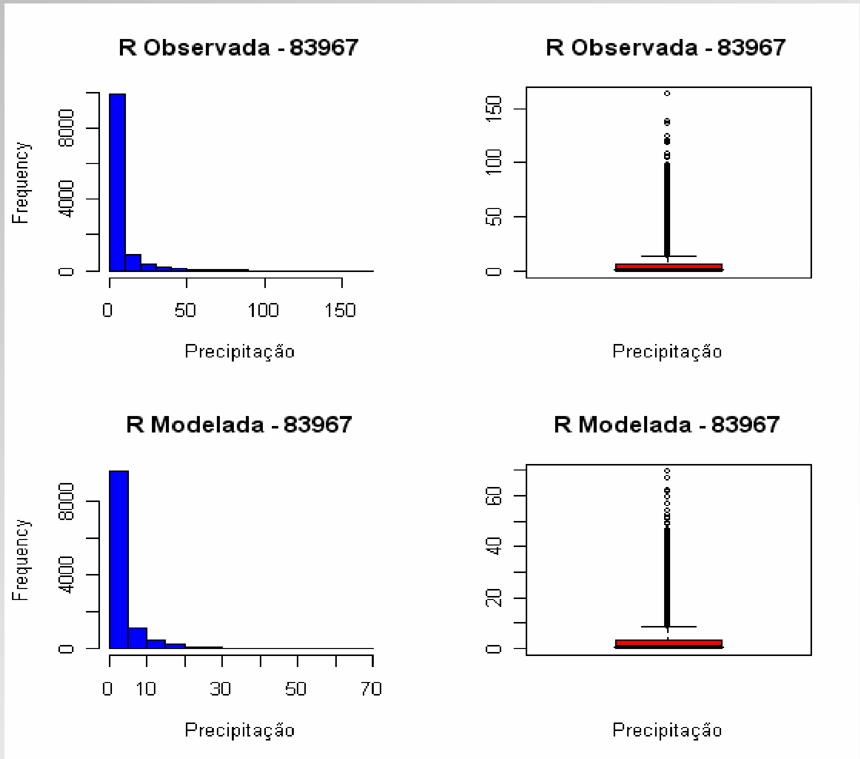


Rio de Janeiro (Low Predictability)

Histograms and Box-Whiskers Plot of daily precipitation, observed and generated by the CPTEC/COLA AGCM (1971-2001).

Illustration - Exploratory Analysis - BR





São Paulo (High Predictability)

Porto Alegre (High Predictability)

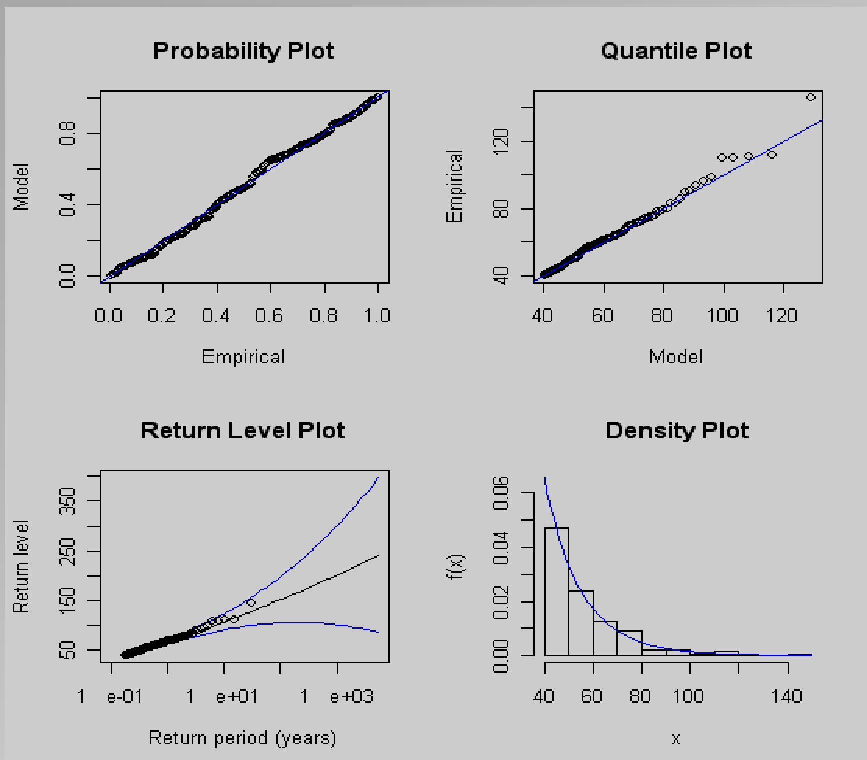
Histograms and Box-Whiskers Plot of daily precipitation, observed and generated by the CPTEC/COLA AGCM (1971-2001).

Illustration – GPD diagnosis - BR

GPD OBS – Manaus (82331)

Threshold: **40mm** ; Rate of Exceedances: **1.5%**

MLE: 15.27 0.046; SE (MLE): 1.716 0.0836

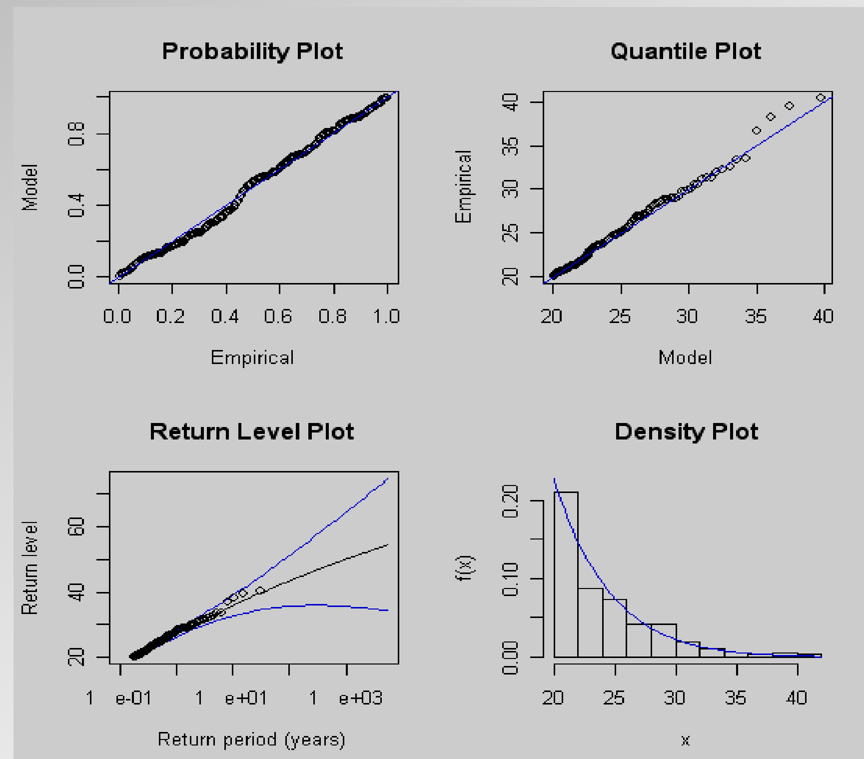


Manaus (High Predictability)

GPD MOD – Manaus (82331)

Threshold: **20mm** ; Rate of Exceedance s: **1.5%**

MLE: 4.418 -0.057; SE (MLE): 0.49 0.081

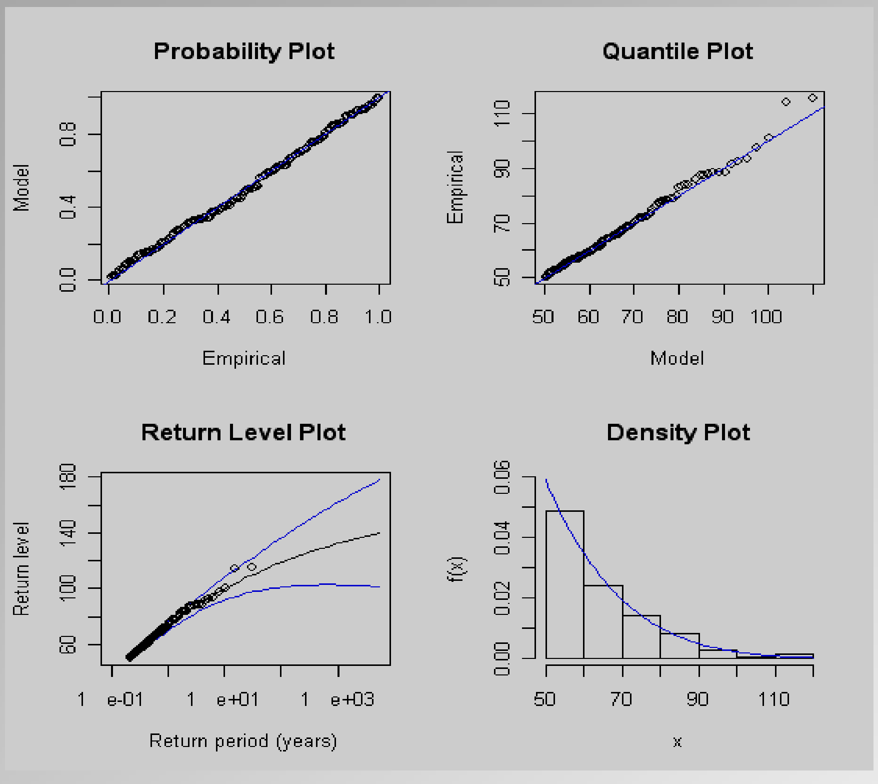


Manaus (High Predictability)

Diagnostic plots for threshold exceedance analysis. MLE are the maximum likelihood estimate for both GPD parameters and SE (MLE) is the associated standard error.

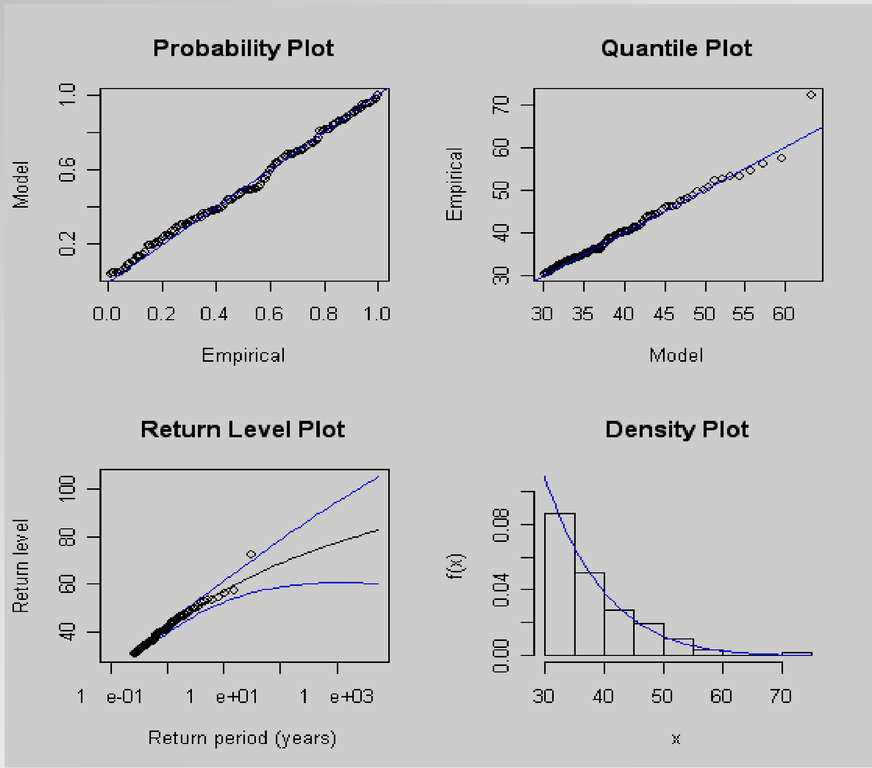
Illustration - GPD diagnostic - BR

GPD OBS – Fortaleza (82397)
Threshold: **50 mm** ; Rate of Exceedances: **1.2%**
MLE: 16.94 -0.145; SE (MLE): 1.88 0.075



Fortaleza (High Predictability)

GPD MOD – Fortaleza (82397)
Threshold: **30mm** ; Rate of Exceedances: **1.0%**
MLE: 9.18 -0.124 ; SE (MLE): 1.06 0.072



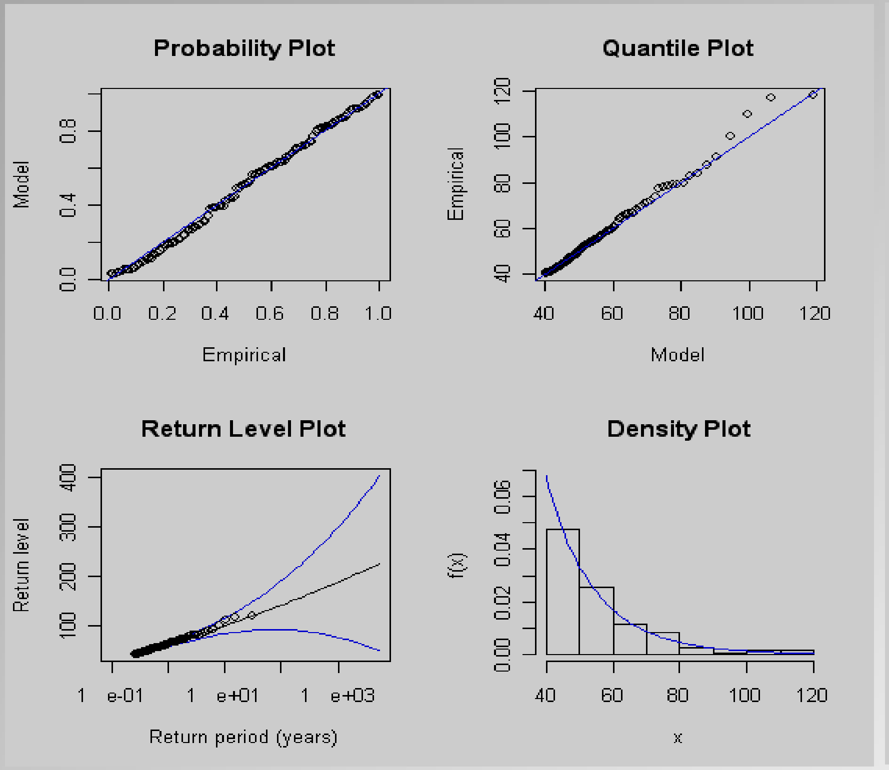
Fortaleza (High Predictability)

Diagnostic plots for threshold exceedance analysis. MLE are the maximum likelihood estimate for both GPD parameters and SE (MLE) is the associated standard error.

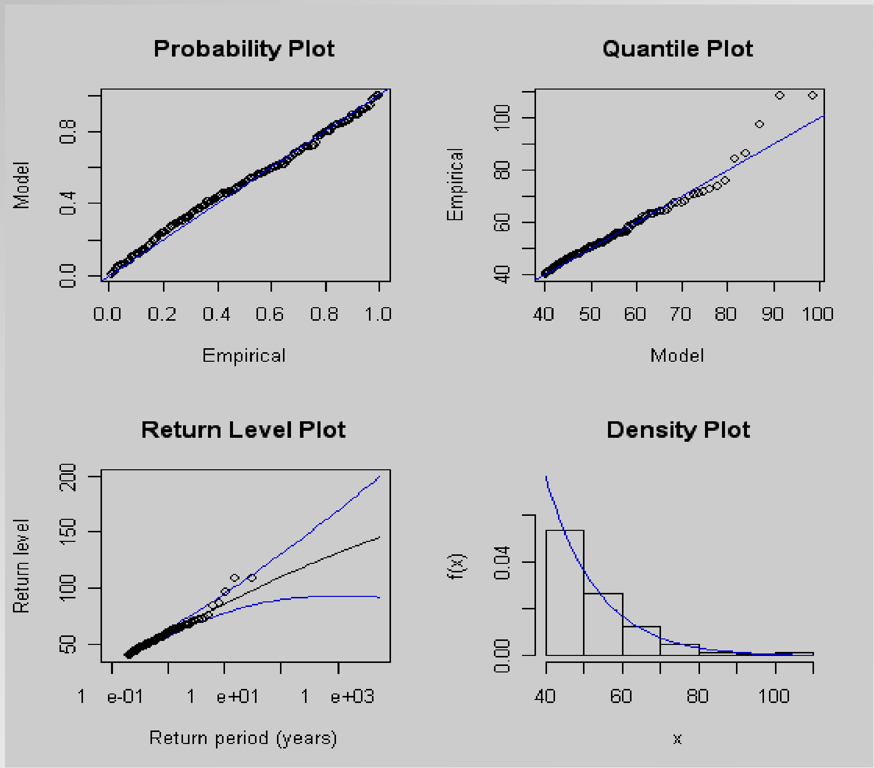
Illustration - GPD diagnostic - BR

GPD OBS – São Paulo (83781)
Threshold: **40mm** ; Rate of Exceedances: **1.0%**
MLE: 14.78 0.045; SE (MLE): 2 .11 0.110

GPD MOD – São Paulo (83781)
Threshold: **35 mm** ; Rate of Exceedances: **1.3%**
MLE: 13.13 -0.048; SE (MLE): 1.39 0.068



São Paulo (High Predictability)



São Paulo (High Predictability)

Diagnostic plots for threshold exceedance analysis. MLE are the maximum likelihood estimate for both GPD parameters and SE (MLE) is the associated standard error.

Illustration - GPD diagnostic - BR

GPD OBS – Porto Alegre (83967)

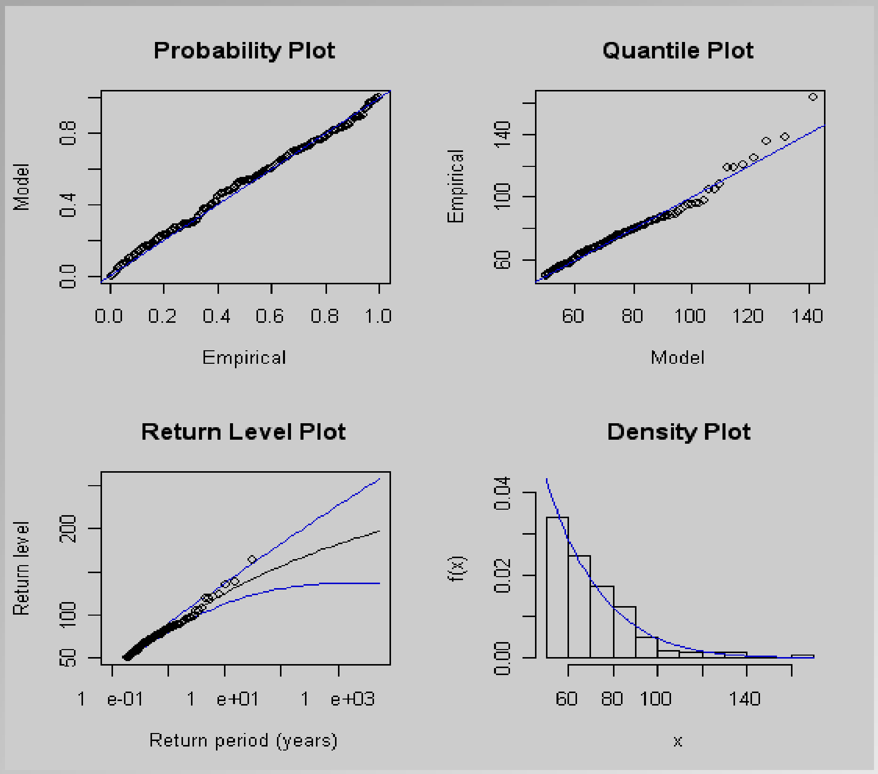
Threshold: **50mm** ; Rate of Exceedances: **1.4%**

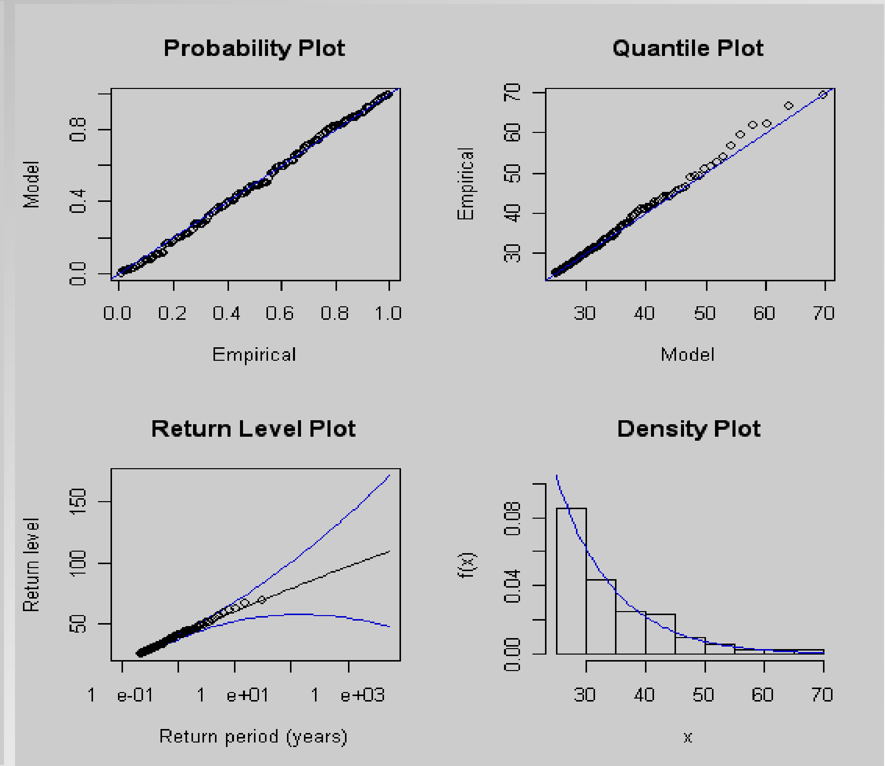
MLE: 23.061 -0.101; SE (MLE): 2.32 0.063

GPD MOD – Porto Alegre (83967)

Threshold: **25mm** ; Rate of Exceedances: **1.3%**

MLE: 9.60 -0.028;SE (MLE): 1.218 0.095





Porto Alegre (High Predictability)

Porto Alegre (High Predictability)

Diagnostic plots for threshold exceedance analysis. MLE are the maximum likelihood estimate for both GPD parameters and SE (MLE) is the associated standard error.

Summary

There are realistic misfits between the empirical and simulated probability distribution of precipitation for some Brazilian cities. The goodness-of-fit in the quantiles plot seems convincing and the confidence intervals on the return level plot suggest acceptable uncertainties that become bigger once the model is extrapolated to higher level of complexity. The results are very interesting, since they put in evidence the main differences of the distributions of extremes between model and observation. The diagnostics suggest that there is reasonable evidence that the CPTEC/COLA AGCM simulations are insufficient for reproducing precipitation extremes. In general, the model overestimates precipitation over Brazil - the return levels as well the frequency of extremes are underestimated.

Acknowledgements

- Departamento de Estatística da UFRN – Brazil.
- Centro de Geofísica de Évora – Portugal.
- Instituto Nacional de Meteorologia – INMET – Brazil.

Thank you for your attention!

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