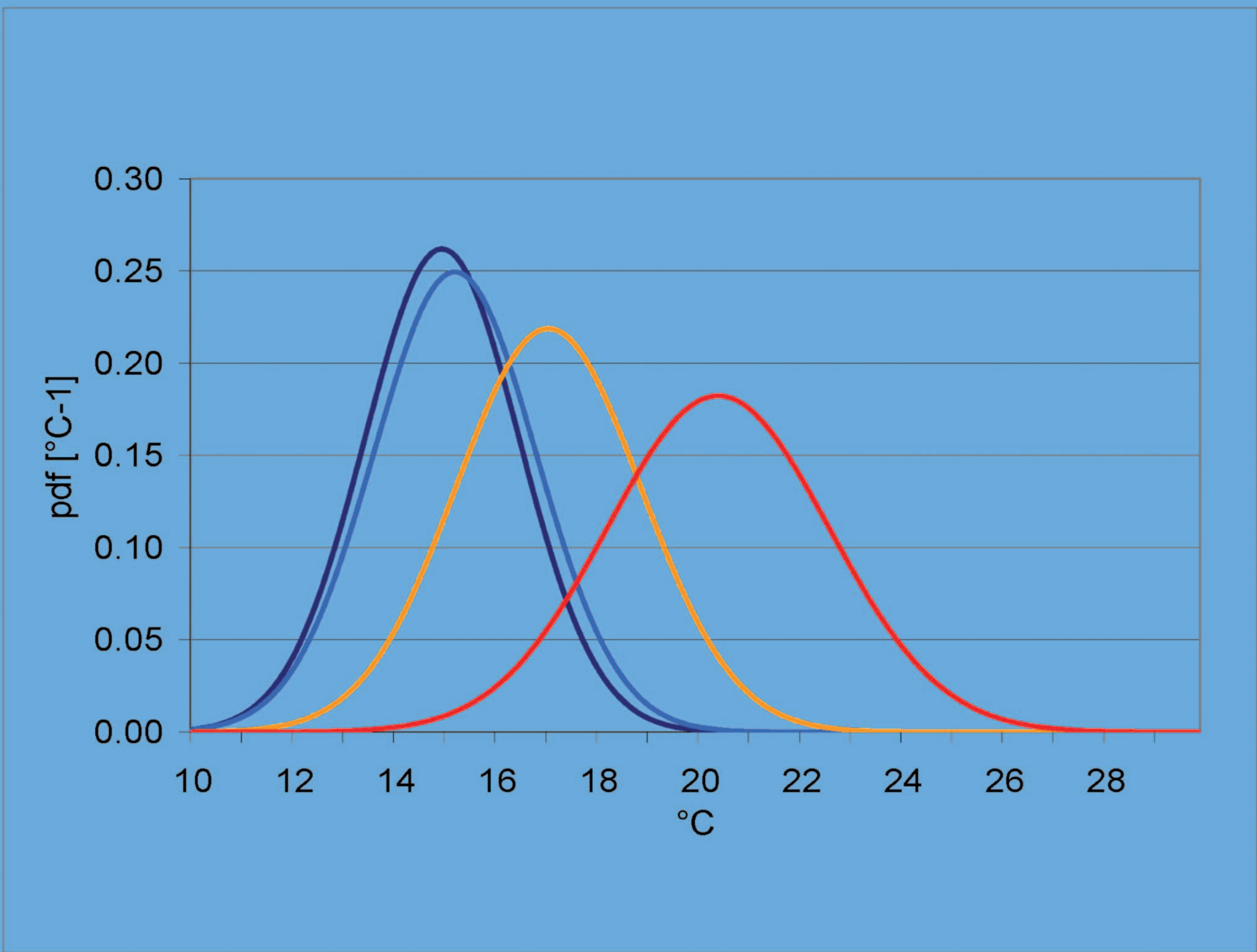
CLIMATE SERVICE CENTER

CSC Report 13

Statistical methods for the analysis of simulated and observed climate data

Applied in projects and institutions dealing with climate change impact and adaptation



CSC Climate Service Center Germany

An institution of Helmholtz-Zentrum Geesthacht

Citation:
Hennemuth, B., Bender, S., Bülow, K., Dreier, N., Keup-Thiel, E., Krüger, O., Mudersbach, C., Radermacher, C., Schoetter, R. (2013):
Statistical methods for the analysis of simulated and observed climate data, applied in projects and institutions dealing with climate change impact and adaptation.
CSC Report 13, Climate Service Center, Germany

Statistical methods for the analysis of simulated and observed climate data

Applied in projects and institutions dealing with climate change impact and adaptation

Collected, sorted and edited by
the working group statistics at the Climate Service Center (Hamburg)

Barbara Hennemuth (Helmholtz-Zentrum Geesthacht, Climate Service Center, Hamburg)
Steffen Bender (Helmholtz-Zentrum Geesthacht, Climate Service Center, Hamburg)
Katharina Bülow (Federal Maritime and Hydrographic Agency, Hamburg)
Norman Dreier (TU Hamburg-Harburg, Institute for Hydraulic Engineering)
Elke Keup-Thiel (Helmholtz-Zentrum Geesthacht, Climate Service Center, Hamburg)
Oliver Krüger (Helmholtz-Zentrum Geesthacht, Institute for Coastal Research)
Christoph Mudersbach (University Siegen, Research Institute for Water and Environment)
Christine Radermacher (Max-Planck-Institute for Meteorology, Hamburg)
Robert Schoetter (Meteorological Institute, University of Hamburg)

English Translation: Manfred Mudelsee, Climate Risk Analysis, Hannover

Version 2.0, August 2013
Contact: barbara.hennemuth@hzg.de

Contents

1 Introduction

Climate change concerns different sectors such as agriculture, forestry, urban and regional planning, nature conservation, water management, energy supply and tourism for example. Climate change impacts can already be observed at many places and they will inevitably be felt more in the future (see for example: DAS, 2008, Chmielewski et al. 2009, Henson, 2011, Jendritzky, 2007, Zebisch et al., 2005). It is necessary to develop adaptation measures and to stimulate their implementation by decision-makers in politics, administration, economy and society.

Global and regional climate projections have been calculated as part of the IPCC process but also for national and international projects. The calculated time period covers more than 140 years ranging from e.g. 1960 to 2100. The results are not only available for climate research, but also for studies dealing with climate change impact. This is the first time that experts from other disciplines than climate research can use climate model information as input for impact models.

The data records for simulations of present time (e.g. 1961 – 2000) and future (2001 – 2100) climate are very extensive. Statistical methods and evaluation procedures play a key role when dealing with large amounts of data. These methods can be different for questions related to groundwater and river management (Arbeitsgruppe KLIWA, 2011), heavy rain events (Aquaplan, 2010) or economic impacts (Morgan et al., 2009). Furthermore, quality characteristics of results can be determined only through statistical analysis, e.g. significance or robustness tests. Another important topic is the analysis of extreme values, since they have a strong impact on economy and society but are difficult to analyze (Field et al., 2012).

In December 2010 a workshop was held at the Climate Service Center (CSC) in cooperation with the research priority KLIMZUG (Managing climate change in regions for the future), www.klimzug.de. The workshop was initiated by CSC and focussed on "Statistical methods for the analysis of data from climate models and climate impact models". The presentations showed the variety of issues and methods associated with climate research and climate impact research. There was an agreement, that the structured, organized collection of statistical methods would be useful for both current projects as well as for future projects dealing with climate change adaptation. The collection of statistical methods is being realized in this brochure by the working group statistic at the Climate Service Center.

The brochure contains methods which can be applied to climate model and impact data as well as to observational data.

2 Aim of the brochure

Simulations using regional climate models typically extend over time periods of 140 years or more. Both the current climate as well as the projections of future climate, based on the greenhouse gas emission and landuse scenarios, developed by the International Panel on Climatic Change (IPCC) are calculated. Due to the variety of several climate models, scenarios and realisations huge amounts of data are obtained. They are stored in international data bases, e. g at the World Data Center for Climate (WDCC) at the German Climate Computing Centre (DKRZ) in Hamburg. Large amounts of climate data are used by scientists for a variety of applications and issues. For this purpose it is necessary to have an extensive knowledge of global and regional climate models as documented on CSC webpage:
http://www.hzg.de/science_and_industrie/klimaberatung/csc_web/011606/index_0011606.html.de
(status: June 2013)
or published in 'Leitlinien zur Interpretation regionaler Klimamodelldaten' (status: Mai 2010) of the informal working group ‚Interpretation of regional climate scenario results' of the German federal environment agencies: *http://klimawandel.hlug.de/?id=448.*

Many different statistical methods and procedures are used to analyse climate data. The statistics brochure has the intention to collect these statisitcal methods. This document contains the experience of scientists who work in current adaptation projects on various topics. The brochure shows clearly which methods and procedures are used in climate research and impact modelling. The statistical methods give a brief explanation of the scope of application, an evaluation of the method, and a short description of the requirements for the usage. The brochure is so to say a product 'from users for users'. Thus it serves as an addition to statistical literature and scientific publications.

The brochure is adressed to different users of from climate and impact model data as well as observational data who need help in finding suitable methods for their data evaluation. The brochure is not a textbook, which teaches the fundamental concepts of statistics. It rather complements the existing literature, e. g. von Storch and Zwiers, 1998, Schönwiese, 2006 as well as Mudelsee, 2010, and gives suggestions on how practical issues can be solved. The described methods additionally contain information about the authors of the respective method sheet, to give an opportunity for further inquiries. If the author cannot be contacted the CSC will provide help (csc-anfragen@hzg.de).

3 Structure of the statistics brochure

The concept of the brochure is 'from users for users' to establish a relation between the brochure and its readers. Thus it is possible to provide gained experience besides the actual methodology. Therefore it reflects the range of methods that are currently being used in research and adaptation projects. Statistical methods with different applications are listed multiple times in order to document the range of possibilities. The structuring of the methods is from easy to complex.

The structure of the statistic brochure is based on the experiences of the CSC-working group statistics. Expert advice was offered by Dr. Petra Friederichs (University of Bonn) and Dr. Manfred Mudelsee (Climate Risk Analysis, Hannover) to improve the compilation of the methods. The following categories have been established, which play an important role in adaptation projects:

- General statistic methods
- Frequency distributions
- Times-series analysis
- Bias-correction
- Significance tests
- Regionalisation
    - Downscaling
    - Interpolation
- Extreme value analysis
    - Selection method
    - Parameter estimation
    - Empirical methods
    - Extreme value analysis methods
- Indexes
    - Model evaluation measures
    - Statistical climate indexes
- Spatiotemporal methods
- Ensemble analysis

In the description of the statistical methods the requirements for their application, the assessment and application examples are specified.
The introduction to each categorie (chapter 5) has been written by Manfred Mudelsee.

The collection of statistical methods is continuously updated at irregular intervals. Therefore, there is the opportunity for all readers to submit missing methods or new application examples of already described methods. If necessary, new categories can be introduced.

4 Use of the methods

4.1 General information

The present document should be a help to facilitate decisions: which statistical methods can be applied for which question, which set of preconditions must be fulfilled and how is it assessed. The references cited in the statistical methods is given in bibliography. The compilation of the methods does not claim to be complete. The brochure relies on methods submitted by users.

When using any statistical method described here it is crucial to check in each case if all conditions for application are fulfilled. Sometimes methods are used when requirements are violeted. This may be justified in individual cases, when the method gives results that deviate only little from the results in case of fullfilled requirements. Such methods are called robust.

The brochure contains single methods. For certain methods it is often necessary to apply several single methods one after the other (see section 4.3).

4.2 Interpretation and assessment of results

The assessment of the statistical methods had a high priority at the query. This should help the users to estimate the quality of their results. However, for the evaluation and analysis of large amounts of data other aspects have to be considered, too. This concerns the recommended use of a model ensemble, for example. The gained results show a bandwidth that must be evaluated (see section 5.10 Ensemble analysis). It is also recommended that, if possible, several impact models and evaluations methods should be used (methodological diversity). Additional information is given in 'Leitlinien zur Interpretation regionaler Klimamodelldaten', *http://klimawandel.hlug.de/?id=448* and in Kreienkamp et al. (2012).

4.3 Combination of methods

The application of one single method in practice is rather the exception. Generally, problems are solved by using several methods. The objective of the brochure is not to create a recipe book "how to combine statistical methods". The following basically applies: Complex issues require statistical expertise!

Nevertheless, some possible and frequently used combinations of statistical methods will be presented, in order to make an easier access to the subject.
Example 1:
In practice one question more frequently asked is related to the exceedance probability or the average return period of certain extreme events. This problem can be tackled with an extreme value statistical analyses, for examples using the of general extreme value distribution of a time series (method No. xx). Such an analysis is, however, subject to certain conditions that must be checked in advance. The most important prerequisites for this are the stationarity, homogeneity

and independence of the events to be analyzed. This is usually achieved through an appropriate choice of the extreme value collective.

As a result we have the following combination of statistical methods:

1. Calculation of the linear trend of the time series (e. g. section No. 5.3.6) to test the stationarity
2. Review of the significance of the linear trend (e.g. method No. 5.5.1)
3. If necessary, correction of the time series with significant trends or jumps
4. Application of the general extreme value function on the (corrected) time series (method 5.7.4.2)

Example 2:
A further issue is the determination of the climate change signal either in climate models or impact models. This task is based on the changes of the frequency distribution of a model parameter and the testing for changes of the significance. A possible combination of statistical methods would be:

1. Determination of the relative frequency distribution of a parameter from a climate model or impact model related to a time period of the presence or future (section No. 5.2.2)
2. Calculation of the relative changes of frequency in the future related to that in presence
3. Test for significance of the difference between the relative frequencies (z-test) (section 5.5.6)

Example 3:
In the context of time series there are frequent investigations made to analyze short-or long-term fluctuations. This can be made for example with on low, high or band pass filter. However, for such applications it requires equidistant time series. But, sometimes time-series have gaps or measured values are non-equidistant. In such a case the following procedure is proposed.

1. Temporal interpolation of existing values with the aim to close gaps and generate equidistant time series using splines (section No. 5.6.2.4)
2. Application of various low, high or band pass filter (section No.5.3.5)

In general, it is preferable to directly analyse the unevenly spaced time series. Interpolation means ‘a step away’ from the original data, it may introduce bias. Note that filter methods exist that can treat unevenly spaced series (Ferraz-Mello, 1981).

Example 4:
Within extreme value analysis, sometimes the question arises which extreme value distribution (EVD) can represent the sample of selected extreme values best. In literatur these tests and methods are often called “goodness of fit” tests or tests of fit for the EVD. Here we give an example for the test of fit for the EVD which is based on distance values (D-values) between the empirical distribution function (EDF) and theoretical EVD. For doing this, the following methods can be combined:

1. Selection of extreme values (see section 5.7.1 Selection methods)
2. Fitting of statistical extreme value distributions to the sample (see section 5.7.2 Parameter Estimation)
3. Calculation of difference values between the EDF and the fitted EVDs (Lilliefors test: section 5.7.2.3)

5 Statistical methods

Summary. Climate is a paradigm of a complex system. It has many variables, which act nonlinearly on a wide range of space–time scales. Mathematical models simulate the climate and its impacts. Statistical methods use the model output data to infer properties of the climate system. Uncertainties of this inference are inevitable. They arise from (1) the variability of the climate itself, (2) the imperfectness of climate and impact models owing to limitations in our understanding and in computing power (nevertheless climate models belong to the most sophisticated computational endeavours) and (3) the non-availability of measurement data (necessary to calibrate climate models) at any space–time point. The statistical inference should therefore not only report the best guess (estimate) but also its uncertainty.

The presented statistical methods described in the following sections have been found useful by climate researchers to explore various properties of the climate system. General statistical methods (Section 5.1) treat fundamental concepts. Frequency distributions (Section 5.2) deal with probability and methods to infer the distribution of a climate variable. 5.7 Extreme value analysis (Section 5.7) requires selection of the extremes from the data. Bias correction (Section 5.4) and Regionalisation (Section 5.6) are tools specifically made for the improvement of climate model output data. The section Indexes (Section 5.8) describes measures for qualitative assessments of simulations as well as Indexes which are an elegant, modern way to distill the high-dimensional climate model output into a single number. More advanced fields of statistical analysis are spatiotemporal methods (Section 5.9), Significance tests (Section 5.5) and Time series analysis (Section 5.3). The section Ensemble analysis (Section 5.10) describes the handling of a large variety of climate models, greenhouse gas emissions and land-use scenarios, and realisations of the simulated climate.

Further reading. Books that cover most of the methods and are written by/for geoscientists include the classic Statistical Analysis in Climate Research (von Storch and Zwiers 1999) as well as Climate Time Series Analysis (Mudelsee 2010). An accessible and still thorough introduction to statistical inference has been written by statistician Wasserman (2004).

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht, 474 pp.

von Storch H, Zwiers FW (1999) Statistical Analysis in Climate Research. Cambridge University Press, Cambridge, 484 pp.

Wasserman L (2004) All of Statistics: A Concise Course in Statistical Inference. Springer, New York, 442 pp.

The methods sections are written by:
Arne Arns
Universität Siegen, Forschungsinstitut Wasser und Umwelt
arne.arns@uni-siegen.de

Jens Bender
Universität Siegen, Forschungsinstitut Wasser und Umwelt (fwu) und
Forschungskolleg Siegen (FoKoS)
jens.bender@uni-siegen.de

Steffen Bender
Helmholtz-Zentrum Geesthacht, Climate Service Center
steffen.bender@hzg.de

Katharina Bülow
Bundesamt für Seeschifffahrt und Hydrographie, Hamburg
katharina.buelow@bsh.de
KLIWAS

Norman Dreier
Hamburg Technical University, Institute of River and Coastal Engineering
norman.dreier@tuhh.de
KLIMZUG projekt RAdOst

Thomas Einfalt
hydro & meteo GmbH&Co.KG, Lübeck
thomas.einfalt@hydrometeo.de

Wolfgang Falk
Bayerische Landesanstalt für Wald und Forstwirtschaft, Freising
Wolfgang.Falk@lwf.bayern.de

Maria Foltyn (ehemals LfULG)
Technische Universität Bergakademie Freiberg
foltyn@mailserver.tu-freiberg.de
KLIMZUG project REGKLAM

Johannes Franke
Technische Universität Dresden
johannes.franke@tu-dresden.de
KLIMZUG project REGKLAM

Ulf Gräwe
Leibniz Institute for Baltic Sea Research Warnemuende
ulf.graewe@io-warnemuende.de
KLIMZUG project RAdOst

Stephanie Hänsel
Technische Universität Bergakademie Freiberg
stephanie.haensel@ioez.tu-freiberg.de
KLIMZUG project REGKLAM

Majana Heidenreich
Technische Universität Dresden
majana.heidenreich@tu-dresden.de
KLIMZUG project REGKLAM

Sandra Hellmers
Technische Universität Hamburg-Harburg
Institut für Wasserbau
s.hellmers@tuhh.de
KLIMZUG NORD

Nils Hempelmann
Helmholtz-Zentrum Geesthacht, Climate Service Center
Nils.hempelmann@hzg.de

Barbara Hennemuth
Helmholtz-Zentrum Geesthacht, Climate Service Center
Barbara.hennemuth@hzg.de

Frank Herrmann
Forschungszentrum Jülich GmbH
Institut für Bio- und Geowissenschaften
f.herrmann@fz-juelich.de
KLIMZUG Nord

Peter Hoffmann
Universität Hamburg, Meteorologisches Institut
peter.hoffmann@zmaw.de
KLIMZUG NORD

Andreas Hoy
Technische Universität, Bergakademie Freiberg
andreas.hoy@ioez.tu-freiberg.de
KLIMZUG project REGKLAM

Nina Hüffmeyer
Hamburger Stadtentwässerung AöR
nina.hueffmeyer@hamburgwasser.de
KLIMZUG NORD

Alrun Jasper-Tönnies
hydro & meteo GmbH&Co.KG, Lübeck
alrun.jasper-toennies@hydrometeo.de

Andreas Kochanowski
Andreas_kochanowski@gmx.de

Oliver Krüger
Helmholtz-Zentrum Geesthacht
Institut für Küstenforschung
Oliver.krueger@hzg.de

Daniel Leistner
Technische Universität Bergakademie Freiberg
Daniel.Leistner@ioez.tu-freiberg.de
KLIMZUG project REGKLAM

Christopher Moseley
MPI für Meteorologie
Christopher.moseley@zmaw.de
KLIMZUG NORD; KLIFF

Manfred Mudelsee
Climate Risk Analysis, Hannover, Germany;
Alfred Wegener Institute for Polar and Marine Research, Bremerhaven
mudelsee@climate-risk-analyis.com, www.climate-risk-analysis.com

Christoph Mudersbach
Forschungsinstitut Wasser und Umwelt
christoph.mudersbach@uni-siegen.de

Hannaleena Pöhler
UDATA Umweltschutz und Datenanalyse
Hydrologie, Klimafolgenforschung, Boden- und Grundwasserschutz
poehler@udata.de
KLIMZUG NORD

Susanne Pfeiffer
Helmholtz-Zentrum Geesthacht, Climate Service Center
Susanne.pfeiffer@hzg.de

Markus Qirmbach
dr. papadakis GmbH, Hattingen
M.Quirmbach@drpapadakis.de
KLIMZUG project DYNAKLIM, ExUS

Christine Radermacher
Max-Planck-Institut für Meteorologie, Hamburg, Germany
christine.radermacher@zmaw.de

Diana Rechid
MPI für Meteorologie
diana.rechid@zmaw.de
KLIMZUG NORD

Dörte Salecker
Institut für Wasserbau, Technische Universität Hamburg-Harburg
doerte.salecker@tuhh.de

Christian Schlamkow
Geotechnics and Coastal Engineering, University of Rostock
christian.schlamkow@uni-rostock.de
KLIMZUG project RAdOst

Robert Schoetter
Meteorologisches Institut, Universität Hamburg
robert.schoetter@zmaw.de
KLIMZUG NORD

Thomas Wahl
Universität Siegen, Forschungsinstitut Wasser und Umwelt (fwu)
und Forschungskolleg Siegen (FoKoS)
thomas.wahl@uni-siegen.de

Zhen-shan Xu,
College of Harbor, Coastal and Offshore Engineering,
Hohai University, Nanjing, P.R. China
xuzhenshanhhu@gmail.com

5.1 General statistical methods

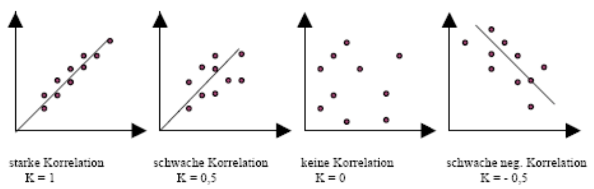
A fundamental concept for analysing bivariate data sets (two variables) is correlation analysis, that is, a quantitative measure of how strong both variables co-vary. The statistical methods present correlation methods of varying degree of robustness, from non-robust Pearson's correlation coefficient (Section 5.1.1), to more robust versions due to Spearman (Section 5.1.2) and Kendall (Section 5.1.3). Note that the usual price to be paid for enhanced robustness is reduced precision (e.g., wider error bars), but in climate sciences it often is advisable to buy robustness.

Further reading. The concept of robustness was introduced by Box (1953). Robust correlation methods are treated by Kendall and Gibbons (1990).

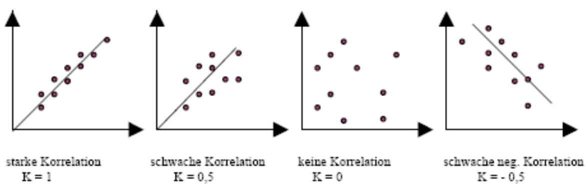
Box GEP (1953) Non-normality and tests on variances. Biometrika 40:318–335.

Kendall M, Gibbons JD (1990) Rank Correlation Methods. 5th edn., Edward Arnold, London, 260 pp.

5.1.1 Correlation measure: Pearson’s product moment correlation coefficient

Superordinate objective (category)	**General statistical methods**
Method	Correlation measure: Pearson’s product moment correlation coefficient
Description + literature	Dimensionsless measure for the degree of the linear relation between two variables: $r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2} \cdot \sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}},$ $\bar{x} = arithmetic\ mean\ of\ x(i)$ $\bar{y} = arithmetic\ mean\ of\ y(i)$ $n = sample\ size$ C.D Schönwiese (2006): Praktische Statistik für Meteorologen und Geowissenschaftler, pp.163ff.
Useful for (parameter, time resolution)	All variable pairs that are in a linearly increasing/decreasing relation
Requirements for application	Existence of linear relation, data on cardinal scale, independent data (no autocorrelation), absence of third variables influencing the relation, n ≥ 30
Result/interpretation	Pearson’s r is between –1 and +1, +1 = complete positive linear relation; 0 = no relation; –1 = complete negative linear relation. A statistical relation does not necessarily imply a causal relation, see the example of such a spurious relation between birth rate and stork population. The larger n, the more meaningful the result.
Assessment	Standard correlation measure, susceptible to outliers
Example/publication	 © BGW Software: Excel, R-Statistics
Contact/project	Andreas Kochanowski Andreas_kochanowski@gmx.de

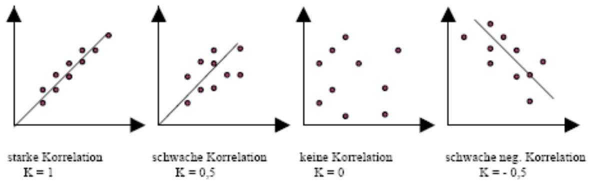
5.1.2 Correlation measure: Spearman’s rank correlation coefficient

Superordinate objective (category)	**General statistical methods**
Method	Correlation measure: Spearman’s rank correlation coefficient
Description + literature	Measures the relation between two variables; distribution-free method. Rank calculation: Data are brought into ascending order, original data values are replaced by their ranks, and the rank series are correlated with each other. Calculation of the rank correlation coefficient (ρ) can also be done as follows: $\rho = 1 - \frac{6 \cdot \sum_{i=1}^{n} (r_i - s_i)^2}{n^3 - n}$ $r_i = rank\ of\ x(i)$ $r_i = rank\ of\ y(i)$ $n = sample\ size$ C.D Schönwiese (2006): Praktische Statistik für Meteorologen und Geowissenschaftler, pp. 163ff.
Useful for (parameter, time resolution)	All variable pairs that are in a monotonically increasing/decreasing relation
Requirements for application	Data on ordinal scale, independent data (no autocorrelation); absence of third variables influencing the relation, n ≥ 30
Result/interpretation	Spearman’s ρ is between –1 and +1, +1 = complete positive monotonic relation; 0 = no relation; –1 = complete negative monotonic relation. A statistical relation does not necessarily imply a causal relation, see the example of such a spurious relation between birth rate and stork population. The larger n, the more meaningful the result.
Assessment	Robust against the presence of outliers; does not require normal distributional shape; does not require linearity of a relation (i.e., suited also for logarithmic or exponential relation).
Example/publication	 © BGW

	Software: R-Statistics
Contact/project	Andreas Kochanowski Andreas_kochanowski@gmx.de

5.1.3 Correlation measure: Kendall's tau

Superordinate objective (category)	**General statistical methods**
Method	Correlation measure: Kendall's tau
Description + literature	Measures the relation between two variables; distribution-free method. Rank calculation: Data are brought into ascending order, original data values are replaced by their ranks, and the rank series are correlated with each other. Calculation of tau: $\tau = \frac{C - D}{n(n-1)^2}$ $D - Number\,of\ discordant\,data\ pairs$ $C - Number\,of\ concordant\,data\ pairs$ $n - Sample\,size$ A data pair (x, y) is called concordant if the rank decreases/increases both in x and x (e.g., rank of x_1 > rank of x_4 and rank of y_1 > rank of y_4). If that is not the case, then the data pair is called discordant (e.g., rank of x_1 > rank of x_4 and rank of y_1 < rank of y_4). D.S. Wilks (2006): Statistical methods in atmospheric sciences, pp. 55–57 C.D Schönwiese (2006): Praktische Statistik für Meteorologen und Geowissenschaftler, pp. 163ff.
Useful for (parameter, time resolution)	All variable pairs that are in a monotonically increasing/decreasing relation; small sample sizes are possible.
Requirements for application	Data on ordinal scale, independent data (no autocorrelation); absence of third variables influencing the relation.
Result/interpretation	Kendall's tau is between –1 and +1, +1 = complete positive relation; 0 = no relation; –1 = complete negative relation. Kendall's tau usually takes somewhat smaller absolute values than Spearman's correlation measure. A statistical relation does not necessarily imply a causal relation, see the example of such a spurious relation between birth rate and stork population.
Assessment	Useful for small sample sizes and when scales of variables show different spacings; robust against the presence of outliers; does not require normal distributional shape; does not require linearity of a relation (i.e., suited also for logarithmic or exponential relation).

Example/publication	 © BGW Software: R-Statistics
Contact/project	Andreas Kochanowski Andreas_kochanowski@gmx.de

5.2 *Frequency distributions*

A fundamental conceptualization is that the uncertain or random components of climate (climate variability) are described by means of a distribution of the values a climate variable can assume. In statistical language (Wasserman 2004), the probability density function (PDF) of a continuous variable, X, determines the probability of finding X between some value, x, and another, x + dx, where dx goes against zero; that probability is given by the integral of the PDF over the interval [x; x + dx]. The presented statistical methods (Sections 5.2.1, 5.2.2 and 5.2.3) infer the PDF by means of histograms.

Many statistical inference methods make assumptions about the PDF of the random component, such as the normal or Gaussian assumption (bell curve). In practice the assumptions may be violated, and statistical methods are called robust if in the case of violation they still deliver results of acceptable accuracy.

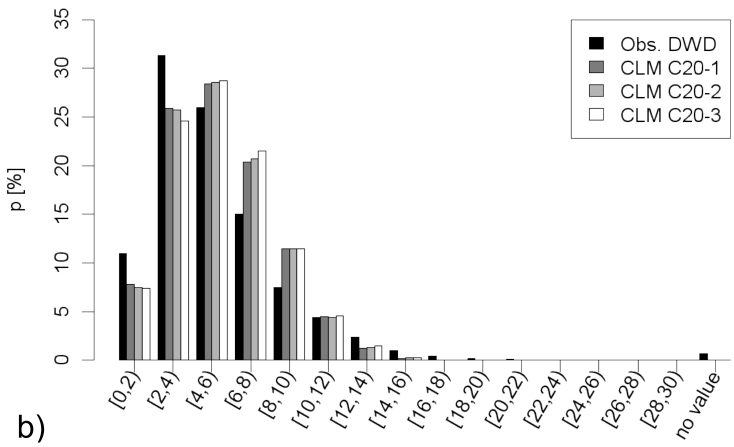
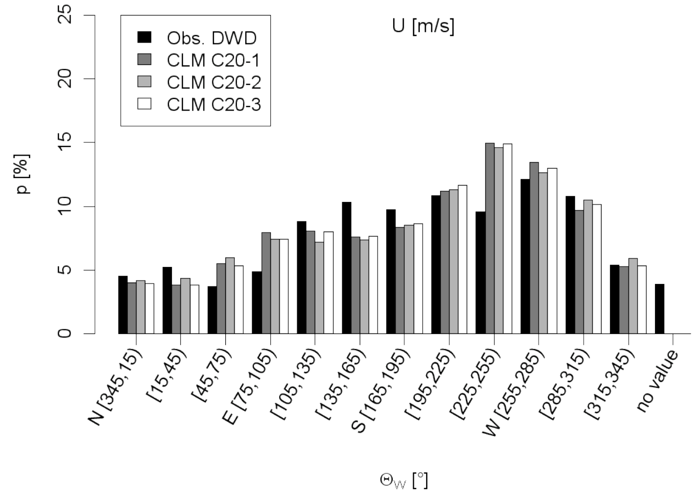
(What is "acceptable" should be set by the research communities. For climate modellers, we think it should be acceptable if, for example, a 95% confidence interval has a true coverage of just 91% due to a violation of the distributional assumption, but a true coverage of 78% should not be tolerated.)

Further reading. A short, relevant paper on the selection of the histogram bin width is by Scott (1979).

Scott DW (1979) On optimal and data-based histograms. Biometrika 66:605–610.

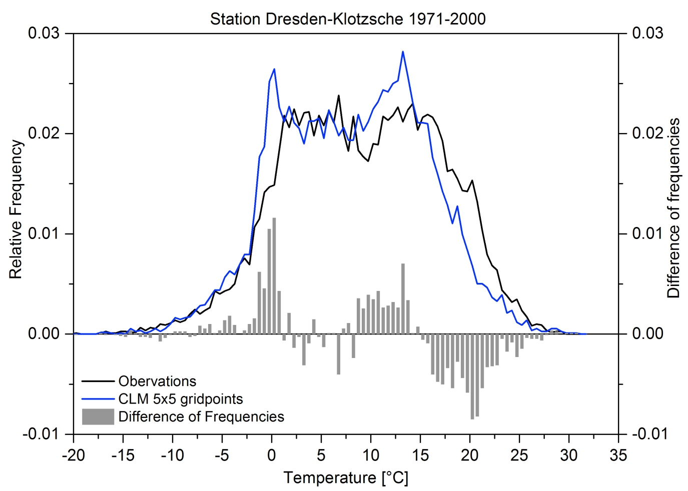
5.2.1 One-dimensional Frequency distributions

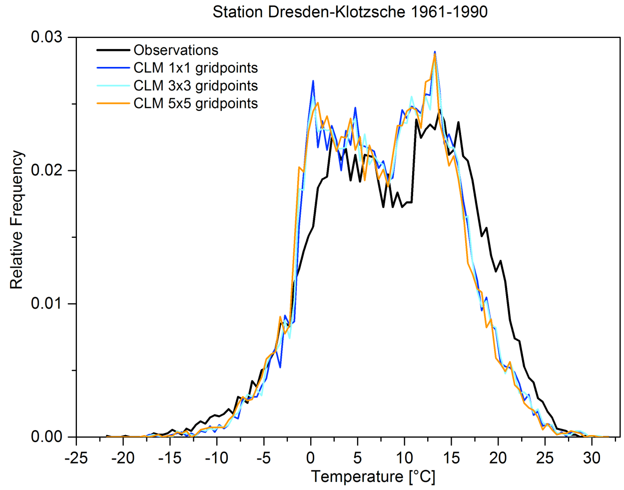
Superordinate objective (category)	**Frequency distributions** (histogram)
Method	One-dimensional frequency of occurrence (1D-histogram)
Description + literature	(1) Sorting of data of a sample according to size (2) Division into classes with a constant or varying class width (interval) and an upper (right) or lower (left) class boundary (3) Counting how many data points fall into a certain class (4) Plotting of frequency of occurrence with the help of a frequency table or bar plot (see example below). Step (2) needs to handle with care, because it changes the frequency plot and can lead to misinterpretation of the underlying empirical distribution function. Therefore, one has to pay attention to the following sub-steps: (a) Selection of the class width (interval) (b) Selection of the lower (left) class boundary For the calculation of a rough estimate for the class width (interval) of normally distributed data, the formula of SCOTT can be applied: $h = 3{,}49\ \sigma / \sqrt[3]{n}$ with h: class width (interval) σ: standard deviation n: number of elements For other distributions than Normal distribution, correction factors for skewness and kurtosis have been introduced: *Scott, D. W. On optimal and data-based histogram. In: Biometrika (1979) 66 (3): 605-610. doi: 10.1093/biomet/66.3.605* *To solve the problem of the selection of the lower (left) class boundary SCOTT recommends e.g. the average-shifted histogram:* *Scott, D. W. Multivariate Density Estimation: Theory, Practice, and Visualization. John Wiley, 1992. ISBN 978-0471547709.* References (Selection, in German only): *Sachs, L. Angewandte Statistik: Anwendung statistischer Methoden, 6. Aufl., Springer-Verlag Berlin, Heidelberg, New York, Tokio, 1984, ISBN 3-540-12800-X, S. 46-48.* *Von der Lippe, P. Deskriptive Statistik. Gustav Fischer Verlag, Stuttgart, Jena, 1993, ISBN 3-437-40268-4 http://www.von-der-lippe.org/dokumente/buch/buch03.pdf* *Plate E.-J.: Statistik und angewandte Wahrscheinlichkeitslehre für Bauingenieure, Ernst & Sohn Verlag für Architektur und technische Wissenschaften, Berlin, 1993, ISBN 3-433-01073-0, S.20-22.*
Useful for (parameter, time resolution)	Different parameter, e.g. hydrographical or meteorological data from observations or calculations

Requirements for application	metrical data which can be sorted according to their values
Result/interpretation	The table of the frequency of occurrence resp. the histogram is showing how many elements of the data, in absolute or relative numbers, fall into a certain class.
Assessment	Simple and intuitive method for statistical analysis of time series. If observed time series are analysed one needs to include a specific class for measurement errors (with no values) so that the sum of the frequency of occurrence is equal to one resp. one hundred per cent. With the help of this method the frequency of occurrence can be compared between different data sources (e.g. observed and modelled data, see example section) and the change of the frequency of occurrence can be calculated (see section 4.3 combination of methods, example 2).
Example/publication	Comparison of frequency of occurrence *p[%]* of mean wind speed with a class width of 2m/s (Fig. a) and mean wind direction with a class width of 30° (Fig. b) from model results (Cosmo-CLM) and observations (German Weather Service), near Warnemünde, reference period 1971–2000. a)  b)  Interpretation of Results: Compared to observations, the Cosmo-CLM model results show less events at low and high wind speeds, but more events for

	medium speeds (Fig. a). Regarding the wind direction of the model, there are more events from East resp. West and few events from South, than observed (Fig. b).
Contact/project	Norman Dreier, Hamburg Technical University, Institute of River and Coastal Engineering, norman.dreier@uni-rostock.de Christian Schlamkow, Geotechnics und Coastal Engineering, University of Rostock, christian.schlamkow@uni-rostock.de

5.2.2 Relative frequency distributions

Superordinate objective (category)	**Frequency distributions**
Method	Relative frequency distributions (descriptive statistics)
Description + literature	Sorting of data of a sample according to size, division into classes: counting how many data points fall into a class and normalizing (i.e., dividing by the total sample size). *Sachs L.: Angewandte Statistik: Anwendung statistischer Methoden, 6. Aufl., Springer-Verlag Berlin, Heidelberg, New York, Tokio, 1984, ISBN 3-540-12800-X, S. 46-48.* *Plate E.-J.: Statistik und angewandete Wahrscheinlichkeitslehre für Bauingenieure, Ernst & Sohn Verlag für Architektur und technische Wissenschaften, Berlin, 1993, ISBN 3-433-01073-0, S.20-22.*
Useful for (parameter, time resolution)	Applied to temperature and precipitation
Requirements for application	Time series with even spacing
Result/interpretation	Relative frequency (percentage) for a certain class (e.g., temperature, class width 0.5°C). The reported frequencies can be transformed into the relative sums (empirical distribution function).
Assessment	Simple and intuitive method for statistical analysis of time series. The choice of the class width influences the shape of the frequency plots (class number in dependence on sample size). If observational data are analysed you have to take care of measurement error (extra class) to ensure that relative frequencies add up to 1 or 100%.
Example/publication	Example 1: Comparison of observed and CLM-modelled frequencies of daily-mean temperature for station Dresden-Klotzsche à “cold” bias of CLM for temperatures >15°C  Example 2: Comparison of observed and CLM-modelled

	frequencies of daily-mean temperature – with/without spatial averaging à frequency distribution for Dresden-Klotzsche, independent of the number of analysed grid boxes 
Contact/project	Majana Heidenreich Technische Universität Dresden majana.heidenreich@tu-dresden.de KLIMZUG project: REGKLAM

5.2.3 Two-dimensional Frequency distributions

<table>
<tr><td>Superordinate objective (category)</td><td>Frequency distributions (histogram)</td></tr>
<tr><td>Method</td><td>Two-dimensional frequency of occurrence (2D-histogram)</td></tr>
<tr><td>Description + literature</td><td>
The two-dimensional frequency of occurrence specifies the entity of all combinations of two variables X (with values x_i, i=1,…,l) and Y (with values y_j, j=1,…,m). In coincidence with the one-dimensional frequency (see XXX), the occurrence of the combination of the values (x_i, y_j) can be given either in absolute numbers $n(x_i, y_j)$ and/or relative to the sample size $h(x_i,y_j)= n(x_i,y_j)/n_{total}$ on condition that:

$$\sum_{i=1}^{m}\sum_{j=1}^{n} n(x_i, y_i) = n_{ges} \qquad \sum_{i=1}^{m}\sum_{j=1}^{n} h(x_i, y_i) = 1$$

with n_{total}: sample size

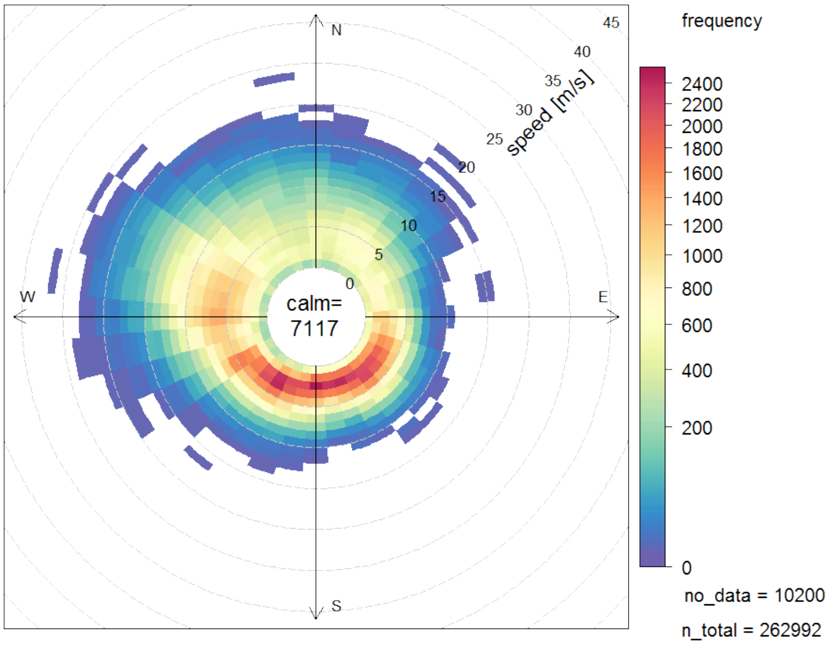
All combinations of the values (x_i, y_j) can be described with the help of a cross-classified table (sometime also called contingency table or cross-tabulation) or in form of a histogram (see example section). The cross-classified table of the relative frequency of occurrence can be written as:

<table>
<tr><th></th><th colspan="5">variable Y</th><th></th></tr>
<tr><th>variable X</th><th>y_1</th><th>…</th><th>y_j</th><th>…</th><th>y_m</th><th>one-dimensional frequency of occurrence of variable X</th></tr>
<tr><td>x_1</td><td>h_{11}</td><td>…</td><td>h_{1j}</td><td>…</td><td>h_{1m}</td><td>$h_{1.}$</td></tr>
<tr><td>…</td><td>…</td><td>…</td><td>…</td><td>…</td><td>…</td><td>…</td></tr>
<tr><td>x_i</td><td>h_{i1}</td><td>…</td><td>h_{ij}</td><td>…</td><td>h_{im}</td><td>$h_{i.}$</td></tr>
<tr><td>…</td><td>…</td><td>…</td><td>…</td><td>…</td><td>…</td><td>…</td></tr>
<tr><td>x_l</td><td>h_{l1}</td><td>…</td><td>h_{lj}</td><td>…</td><td>h_{lm}</td><td>$h_{l.}$</td></tr>
<tr><td>one-dimensional frequency of occurrence of variable Y</td><td>$h_{.1}$</td><td>…</td><td>$h_{.j}$</td><td>…</td><td>$h_{.m}$</td><td>$h_{..}=1$</td></tr>
</table>

Reference (in German only): http://mars.wiwi.hu-berlin.de/mediawiki/mmstat_de/index.php/Zweidimensionale_H%C3%A4ufigkeitsverteilung_-_STAT-Zweidimensionale_H%C3%A4ufigkeitstabellen

See also notes for the one-dimensional frequency of occurrence
</td></tr>
</table>

	(see XXX) regarding the selection of the class width and the lower (left) class boundary of the variable X resp. Y. References (Selection, in Germany only): *Sachs L.: Angewandte Statistik: Anwendung statistischer Methoden, 6. Aufl., Springer-Verlag Berlin, Heidelberg, New York, Tokio, 1984, ISBN 3-540-12800-X, S. 46-48.* *Von der Lippe, P. Deskriptive Statistik. Gustav Fischer Verlag, Stuttgart, Jena, 1993, ISBN 3-437-40268-4 http://www.von-der-lippe.org/dokumente/buch/buch07.pdf* *Plate E.-J.: Statistik und angewandte Wahrscheinlichkeitslehre für Bauingenieure, Ernst & Sohn Verlag für Architektur und technische Wissenschaften, Berlin, 1993, ISBN 3-433-01073-0, S.20-22.*
Useful for (parameter, time resolution)	Different combinations of parameters e.g. sea-state parameters (wave height and direction) or meteorological parameters (wind speed and direction).
Requirements for application	Metrical data or data with a nominal resp. ordinal scale.
Result/interpretation	The cross-classified table or the histogram informs about the absolute or relative number of combinations of the variable X and Y (e.g. wave height and direction). Moreover the one-dimensional frequency of occurrence of the variables X and Y can be described in the last row resp. column of the table (see example at description section).
Assessment	More complex method for statistical analysis of time series. If observed time series are analysed one needs to include a specific class for measurement errors (with no values) so that the sum of the frequency of occurrence is equal to one resp. one hundred per cent. With the help of this method the frequency of occurrence can be compared between different data sources (e.g. observed and modelled data) and the change of the frequency of occurrence can be calculated.
Example/publication	Histogram of the frequency of occurrence of observed wind speed and direction (German Weather Service) near Warnemünde and for the reference period 1971-2000. Please note that class width of the wind speed is 1m/s and of the direction 10°. The numbers of events are classified with colours from the colourbox to the right.

	 Interpretation of Results: It can be seen from the figure that there are only few strong wind events with wind speeds more than 20m/s (which corresponds to Beaufort class 9). For those events the main wind direction ranges from south-west to north-west. The majority of events with medium wind speeds (e.g. 5-20m/s) are coming from westerly directions too. Moreover it can be seen from the figure that the higher the wind speeds, the lower the number of events and the wind direction is turning towards north-west. In contrast events with low wind speeds (e.g. 0-5m/s), which occurred obviously most, are coming mainly from south-easterly to south-westerly directions.
Contact/project	Norman Dreier, Hamburg Technical University, Institute of River and Coastal Engineering, norman.dreier@uni-rostock.de Christian Schlamkow, Geotechnics und Coastal Engineering, University of Rostock, christian.schlamkow@uni-rostock.de

5.3 Time series analysis

"Climate change" refers to time, and the analysis of modelled or observed time series, such as global surface-air temperature over the past millennium, is an important field for climate analysis. One of the earliest papers in statistical time series analysis examined a "supposed 26 day period of meteorological phenomena" (Schuster 1898).

A possible view of climate change is a time-dependent random variable that is composed of trend, outliers / extremes and variability / noise (Mudelsee 2010); this structural approach is also the basis of a presented method (Section 5.3.1). The task of the analysis is to use the data for estimating the parameters describing the trend, variability and other components.

Trend estimation, that is, quantifying climate changes, is of high priority. This is reflected by the variety of presented methods: linear regression (Section 5.3.6), where a simple parametric trend model is employed; various applications of the running mean (Sections 5.3.1, 5.3.2 and 5.3.3), where no parametric trend form has to be assumed; and the running median (Section 5.3.4), which is a robust counterpart to the running mean; also flexible trend analysis (Section 5.3.8) is a nonparametric method. Nonparametric regression is also called smoothing. Its idea is to cancel out high-frequency variability (noise) by means of, for example, a running window. Other tools to extract low-frequency trends are numerical frequency filtering (Section 5.3.5) or the comparison of different time slices (Section 5.3.7). Besides trend, also the variability of a climate variable may be decomposed into different classes (Section 5.3.10).

Further reading. The book by Mudelsee (2010) is specifically on the analysis of climate time series in the univariate (one variable) and bivariate (two variables) settings. The book by von Storch and Zwiers (1999) contains sections on higher-dimensional time series as well. Both contain extensive lists of further literature.

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht, 474 pp.

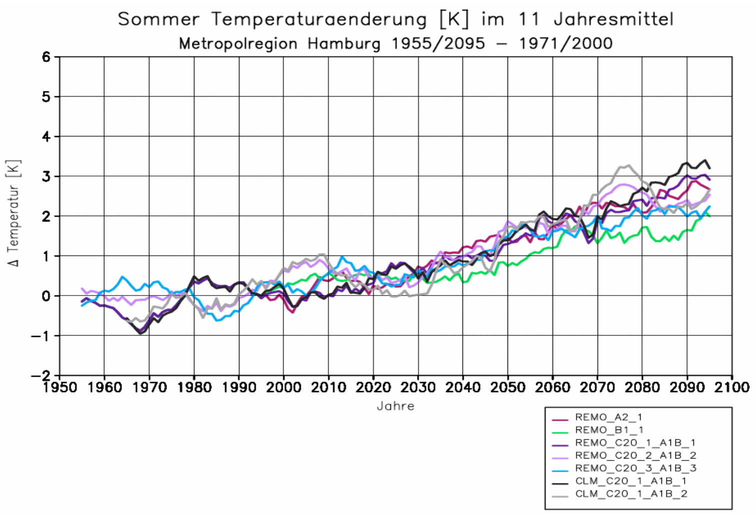
Schuster A (1898) On the investigation of hidden periodicities with application to a supposed 26 day period of meteorological phenomena. Terrestrial Magnetism 3:13–41.

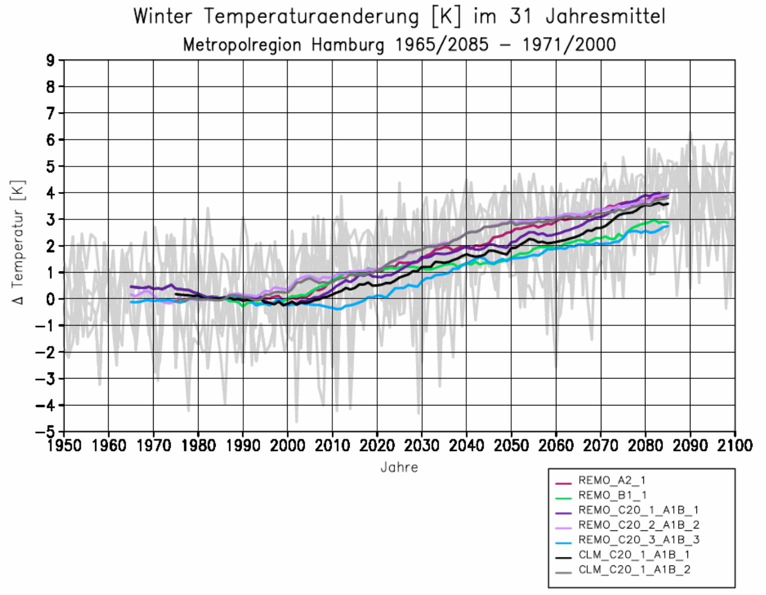
von Storch H, Zwiers FW (1999) Statistical Analysis in Climate Research. Cambridge University Press, Cambridge, 484 pp.

5.3.1 Running mean (1)

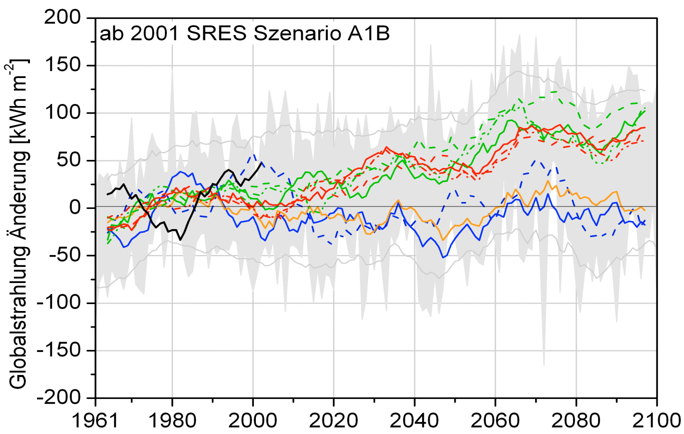
Superordinate objective (category)	**Time series analysis** Trend estimation
Method	Running mean
Description + literature	Calculation of arithmetic means of temporally successive data points
Useful for (parameter, time resolution)	For example, frequency of overflows, size of overflows; temporal resolution: any
Requirements for application	Gap-free time series
Result/interpretation	Reduces variability and allows analysis of trends
Assessment	Simple and fast analysis of time series
Example/publication	*Kuchenbecker et al., KA 2010*
Contact/project	Nina Hüffmeyer Hamburger Stadtentwässerung AöR nina.hueffmeyer@hamburgwasser.de KLIMZUG-NORD

5.3.2 *Running mean (2)*

Superordinate objective (category)	**Time series analysis** Trend estimation
Method	Running mean
Description + literature	Calculation of running 10- and 11-year averages as well as running 30- and 31-year averages, respectively, from transient time series of simulated climate parameters. (Note: If the central point of the chosen running time interval is considered, usage of 11- and 31-year averages is useful.)
Useful for (parameter, time resolution)	Arbitrary variables in monthly, seasonal and yearly resolution.
Requirements for application	Sufficiently long, gap-free time series
Result/interpretation	Rendering the time series as running 10- or 11-year means allows to visualize the decadal variability. Rendering the time series as running 30- or 31-year means allows to determined the bandwidth of the climate change.
Assessment	Simple, fast analysis and visualization
Example/publication	*Jacob D, Göttel H, Kotlarski S, Lorenz P, Sieck K (2008): Klimaauswirkungen und Anpassung in Deutschland: Erstellung regionaler Klimaszenarien für Deutschland mit dem Klimamodell REMO. Forschungsbericht 204 41 138 Teil 2, i.A. des UBA Dessau* *Jacob D, Bülow K, Kotova L, Moseley C, Petersen J, Rechid D: Regionale Klimasimulationen für Europa und Deutschland – in Vorbereitung* Example 1: Projected changes in winter temperature in the Hamburg metropolitan area as simulated with REMO and CLM, compared with the reference period 1971–2000; plotted as running 11-year means.  Example 2: Projected changes in winter temperature in the Hamburg metropolitan area as simulated with REMO and CLM, compared with the reference period 1971–2000; plotted as running 31-year means, also shown yearly values for various scenarios and runs (grey).

	
Contact/project	Diana Rechid MPI für Meteorologie diana.rechid@zmaw.de KLIMZUG NORD

5.3.3 Running mean (3)

Superordinate objective (category)	**Time series analysis** Trend estimation
Method	Running mean
Description + literature	Simple trend estimation using running means *J.-P. Kreiß & G. Neuhaus (2006):Einführung in die Zeitreihenanalyse, Springer-Verlag.*
Useful for (parameter, time resolution)	Temperature, precipitation, irradiance and other meteorological variables, runoff; monthly and yearly values
Requirements for application	Long, gap-free time series (here: > 100 years)
Result/interpretation	Reduced variability, visualized trends
Assessment	Simple, fast method
Example/publication	Central/symmetrical running 11-year means *Bernhofer et al. (2009, 2011)* 
Contact/project	Majana Heidenreich (TU Dresden), Daniel Leistner (TU BA Freiberg), Andreas Hoy (TU BA Freiberg) majana.heidenreich@tu-dresden.de daniel.leistner@ioez.tu-freiberg.de andreas.hoy@ioez.tu-freiberg.de KLIMZUG project: REGKLAM

Bernhofer C, Matschullat M, Bobeth A (Hrsg. 2011): Klimaprojektionen für die REGKLAM-Modellregion Dresden. Publikationsreihe des BMBF-geförderten Projektes REGKLAM – regionales Klimaanpassungsprogramm für die Modellregion Dresden, Heft 2, Rhombos-Verlag Dresden

Bernhofer C, Matschullat M, Bobeth A (Hrsg. 2009): Das Klima in der REGKLAM-Modellregion Dresden. Publikationsreihe des BMBF-geförderten Projektes REGKLAM – regionales Klimaanpassungsprogramm für die Modellregion Dresden, Heft 1, Rhombos-Verlag Dresden

5.3.4 *Running median*

Superordinate objective (category)	**Time series analysis** Trend estimation
Method	Running median
Description + literature	Robust nonparametric trend estimation. Robust means that the method is unaffected by the presence of extremes. You use the running median (calculated over the points inside a running window) for nonparametric background or trend estimation, and not the running mean. *Mudelsee M (2006) CLIM-X-DETECT: A Fortran 90 program for robust detection of extremes against a time-dependent background in climate records. Computers and Geosciences 32:141–144.*
Useful for (parameter, time resolution)	All parameters at any temporal resolution. Note that high time resolution may result in a strong autocorrelation, which has to be considered in the selection of the number of window points (i.e., more window points have to be used compared to an autocorrelation-free situation).
Requirements for application	Homogeneity and representativeness of the data. In the case of autocorrelated data, the cross-validation guideline may be less informative and other numbers of window points have to be tried.
Result/interpretation	Trend or time-dependent background estimate
Assessment	A robust standard method, there exist cross-validation guidelines (supplied by the software), but you should try also other values and study the sensitivity of the results.
Example/publication	See Section 5.7.1.3. The original paper (Mudelsee 2006) explains the method and describes the Fortran 90 software CLIM-X-DETECT.
Contact/project	Manfred Mudelsee Climate Risk Analysis, Hannover, Germany; mudelsee@climate-risk-analyis.com www.climate-risk-analysis.com

5.3.5 Numerical filtering: high-, low- and bandpass filters

Superordinate objective (category)	**Time series analysis**
Method	Numerical filtering: high-, low- and bandpass filters (filter weights from, e.g., standard normal distribution)
Description + literature	Representation of short- and long-term variations (of different periods) in time series Numerical filters are described in an accessible manner by: *C.-D. Schönwiese. Praktische Statistik für Meteorologen und Geowissenschaftler. Gebrüder Bornträger, Berlin, Stuttgart: 1985* An R function for calculating of the filtered time series is available upon request.
Useful for (parameter, time resolution)	Hydrological time series (precipitation, evaporation, runoff components, etc.); yearly, monthly, daily and hourly values
Requirements for application	Complete (gap-free), equidistant time series
Result/interpretation	Filtered time series, which shows the short-/long-term variations of the original time series.
Assessment	A lowpass filter shows better than a running mean the long-term variations.
Example/publication	*W. Roedel u. T. Wagner: Physik unserer Umwelt: Die Atmosphäre, 4th ed., Springer-Verlag Berlin Heidelberg 2011, auf S. 177*
Contact/project	Frank Herrmann Forschungszentrum Jülich GmbH Institut für Bio- und Geowissenschaften f.herrmann@fz-juelich.de KLIMZUG Nord

5.3.6 Linear Regression

Superordinate objective (category)	**Time series analysis** Trend estimation
Method	Linear regression
Description + literature	Describes a linear dependence of one variable, y, on another, independent variable, x, in the form y = c + a x. With least-squares estimation, the sum of the squares of the errors (i.e., difference between data value and the value of the regression function), also called the residual variance, is minimized. This means intuitively that a regression line fits best to the empirically determined (or measured) y-values. The sum of squares in the vertical (y) direction is smaller than the sums in any other direction. *von Storch and Zwiers, Statistical Analysis in Climate Research, Cambridge University Press, 1999* This method is extensively treated in introductory statistics textbooks.
Useful for (parameter, time resolution)	Variables that depend linearly on other, continuous variables.
Requirements for application	Linearity of the relation between dependent and independent variables. Independet and normally distributed residuals with constant variance. Violation of these assumptions may lead to erroneous results and conclusions.
Result/interpretation	Linear description of the relation, given by the determined parameters (a, c). In usual statistical software packages, also the estimation uncertainty of the parameters is quantified.
Example/publication	*"A simple empirical model for decadal climate prediction" (Krueger, O & J-S von Storch), Journal of Climate, 2011, doi: 10.1175/2010JCLI3726.1*
Contact/project	Oliver Krüger Helmholtz-Zentrum Geesthacht Institut für Küstenforschung Oliver.krueger@hzg.de

5.3.7 Comparison of different time slices with respect to mean, variability and/or distribution

Superordinate objective (category)	**Time series analysis** Trend estimation
Method	Difference between time slices à comparison of “future time slices” from the simulated projections (e.g., 2021–2050, 2071–2100) with the time slices from the reference period (e.g., 1961–1990); the latter period uses simulated or observed values or distributions.
Description + literature	Comparison of different time slices with respect to mean, variability and/or distribution
Useful for (parameter, time resolution)	Various climate variables, such as precipitation, temperature, wind speed, etc., as well as derived indexes, such as climatological threshold days. Principally suited for all temporal resolutions.
Requirements for application	Compared time slices should comprise the same span, and they should be long enough for a statistical climate description (preferably at least 30 years)
Result/interpretation	Detection of climate-change signals
Assessment	Since the relative change-signals are considered (related to modelled reference rather than to observed reference), trends resulting from different models with different systematic erros (bias), become comparable.
Example/publication	Bernhofer et al. (2009, 2011)
Contact/project	Majana Heidenreich (TU Dresden), Stephanie Hänsel (TU BA Freiberg) majana.heidenreich@tu-dresden, stephanie.haensel@ioez.tu-freiberg.de KLIMZUG project: REGKLAM

Bernhofer C, Matschullat M, Bobeth A (Hrsg. 2011): Klimaprojektionen für die REGKLAM-Modellregion Dresden. Publikationsreihe des BMBF-geförderten Projektes REGKLAM – regionales Klimaanpassungsprogramm für die Modellregion Dresden, Heft 2, Rhombos-Verlag Dresden

Bernhofer C, Matschullat M, Bobeth A (Hrsg. 2009): Das Klima in der REGKLAM-Modellregion Dresden. Publikationsreihe des BMBF-geförderten Projektes REGKLAM – regionales Klimaanpassungsprogramm für die Modellregion Dresden, Heft 1, Rhombos-Verlag Dresden

5.3.8 Flexible trend analysis

Superordinate objective (category)	**Time series analysis** Trend estimation
Method	Flexible trend analysis
Description + literature	Analysis of all trend combinations that can be utilized for a predefined time window Rapp J (2000) Konzeption, Problematik und Ergebnisse klimatologischer Trendanalysen für Europa und Deutschland . Berichte des DWD, 212, Offenbach, 145 S.
Useful for (parameter, time resolution)	Time series of frequencies (e.g., circulation types), climate parameters (e.g., Temperatur); temporal resolution: freely adjustable (e.g., in project: yearly resolution)
Requirements for application	Gap-free and preferably long and homogeneous time series
Result/interpretation	Maximum information at maximum compression; method avoids bias from subjectively predefined time windows for trend analysis
Example/publication	Allows to interpret climate change signals at maximum accuracy; high complexity makes interpretation harder
Contact/project	Rapp 2000; Hoy A, Sepp M, Matschullat J (in preparation): "Variability of atmospheric circulation in Europe and Russia (1901–2010)"
Method	Andreas Hoy (TU BA Freiberg) andreas.hoy@ioez.tu-freiberg.de KLIMZUG-Projekt: REGKLAM, TP 2.1

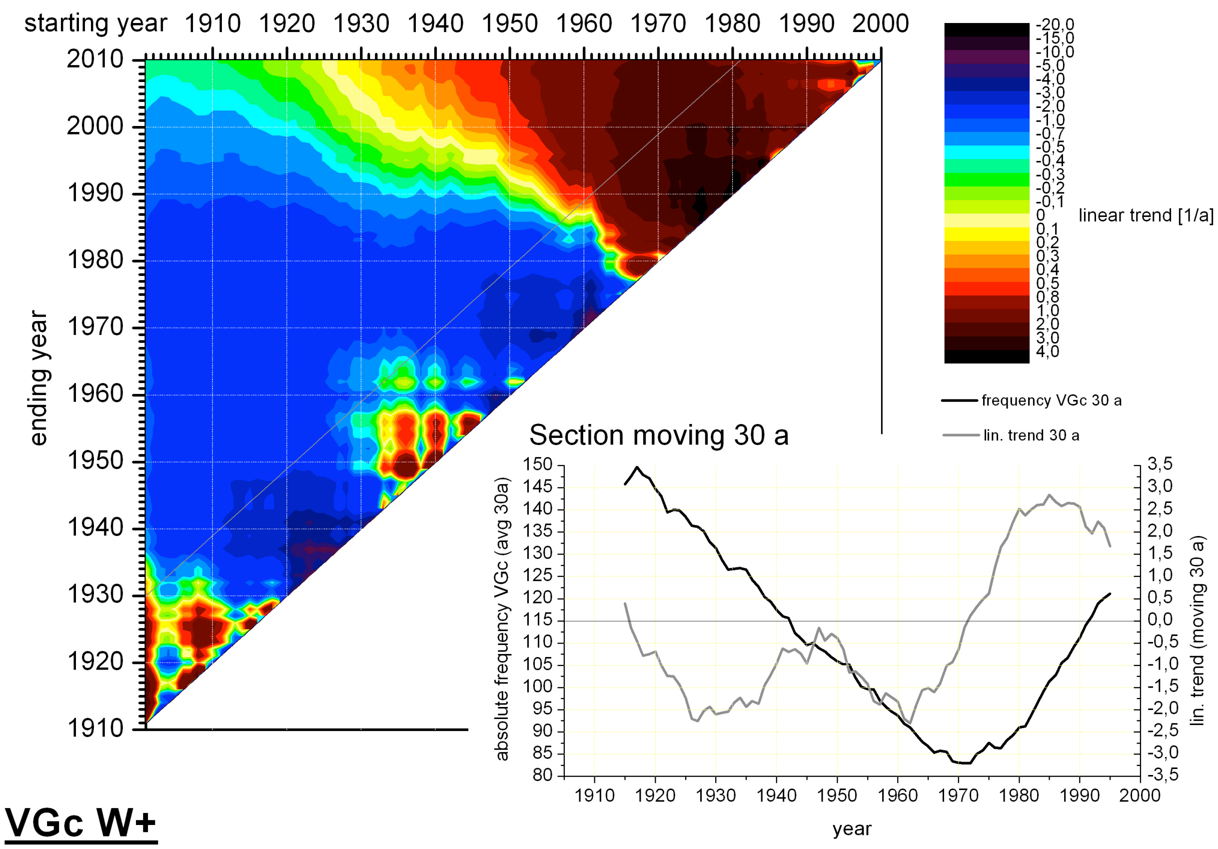


Figure 1: VGc W+ (1901-2010); a) variable trend analysis: depicted are all possible trend combinations for periods from 10 to 110 years (upper left); b) absolute frequency/ linear trend (30 year moving average) (lower right); the thin black line in the upper left picture depicts 30 year trends and is illustrated as linear trend line in the lower right picture

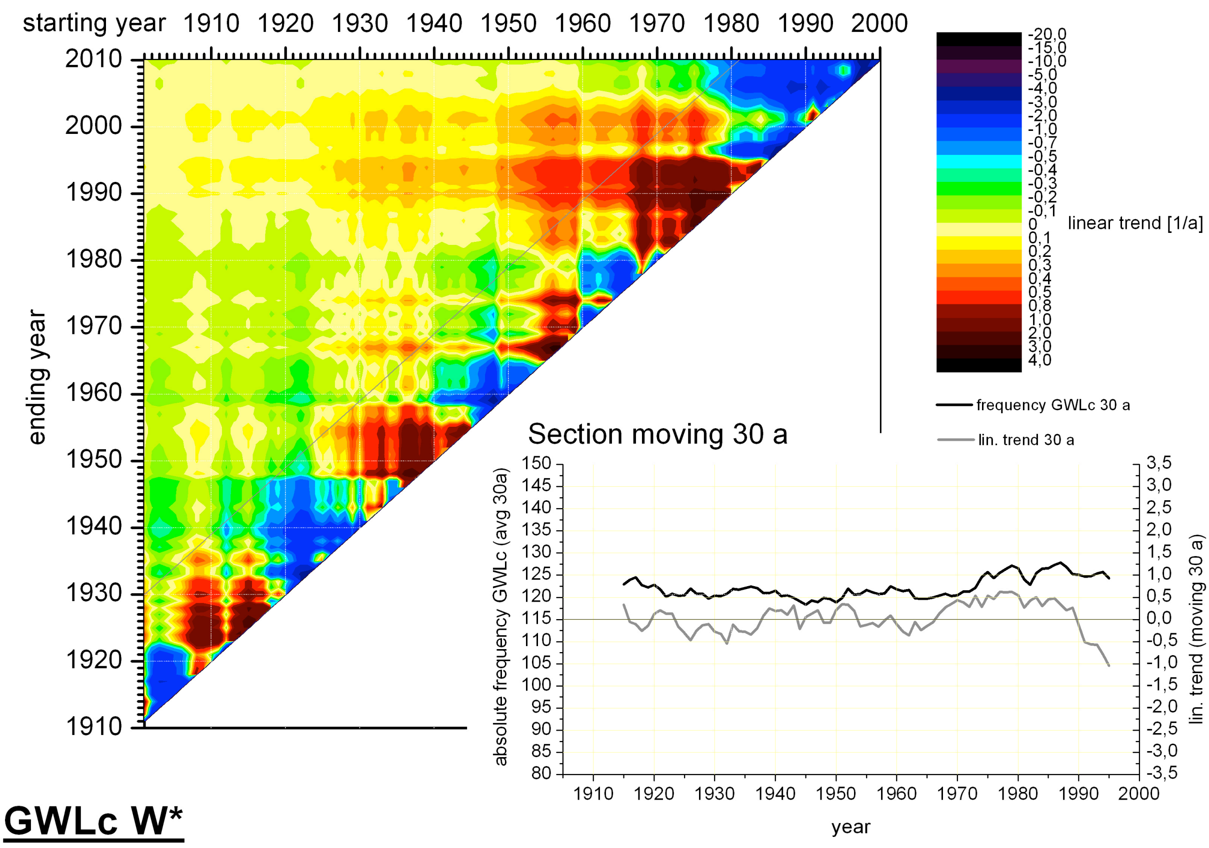


Figure 2: As in figure 5, but for GWLc W*

1) Applying a variable trend analysis (Rapp 2000) allows a thorough, yet manual (and subjective) investigation of trend behaviour. All possible combinations of linear trends during 1901-2010 are illustrated for periods lasting from 10 to 110 years in one matrix (figures 1 and 2; upper left). The trend matrixes illustrate complex pictures with high fluctuations of trend direction and magnitude in shorter time frames up to approximately 30 years, especially for W*. Here trends are generally weak, but more stable in longer periods. Relatively strong positive trends for W* are visible starting from the 1950s and ending in the 1990s. W+, on the other hand, shows very strong and unusually stable signals. Until the 1960s trends of most time scales were almost completely negative, while frequencies showed almost undisturbed, very strong increasing trends afterwards. It get´s visible that trends over 110 years do not easily get disturbed by short- and medium term fluctuations. Their temporal location, however, is always subjectively chosen and only allows robust conclusions for the chosen time frame, without the possibility of analysing fluctuations within that period. Given the time series of W+, it gets clear that long term linear trends do not yield much value given such pronounced opposing trend values within a time frame. On the other hand, a variable trend analysis depicts the trend behaviour with maximum completeness, but the involved complexity often impedes the observer from drawing clear conclusions of trend characteristics within an investigation period. The problem of complexity further multiplies when comparing a number of different circulation forms.

2) Analysing moving trend variables of a single length (e.g., 30 years) is therefore a method to reduce complexity, while still showing fluctuations in trend direction and magnitude over time (figures 1 and 2; lower right). Given the predominantly clear trend behaviour of W+ an interpretation of the trend line is relatively easy. This task gets more complicated, if the magnitude of fluctuations is smaller, but a higher number of changes in trend direction are visible over time, like for W*. Hence, while this method allows identifying periods of clear trend behaviour without varying temporal complexity, it still lacks an easy and clear way to detect and interpret frequency changes.

3) Finally, illustrating a smoothened time series of moving (e.g., 30 years) frequency values is a classical way of analysing fluctuations in time series (figures 1 and 2; lower right). Here a very clear and easily interpretable picture is given for W+, with a bisection of frequencies until the 1970s and a following strong increase. It also gets clear that no relevant trend is present for W*. Given the straightforward goal of interpreting changes in time series this common way of analysing time series is the clearest of the presented methods. It will be therefore used in the following section to investigate frequency changes in more detail compared to the inspection of linear trends. Shorter periods lasting 11 years (compared to 30 years in this chapter) are used to obtain a more detailed picture of frequency changes over time while still removing the noise of annual fluctuations.

5.3.9 Structural time series analysis, maximum likelihood method

Superordinate objective (category)	**Time series analysis**
Method	Structural time series analysis, maximum likelihood method
Description + literature	The Gaussian (normal), Gumbel and Weibull probability density functions are described by means of 2 time-dependent parameters (mean and standard deviation) *Trömel, S. (2004):* *Statistische Modellierung von Klimazeitreihen, Dissertation, J.W. Goethe Universität Frankfurt am Main, 2004.*
Useful for (parameter, time resolution)	Monthly mean temperature, monthly mean precipitation total
Requirements for application	Long, gap-free time series of at least 100 years length
Result/interpretation	Trends in mean and standard deviation
Assessment	Application of method requires the describability of the time series values by means of a probability density function (Kolmogorov–Smirnov test)
Example/publication	*Bülow, K. (2010): Zeitreihenanalyse von regionalen Temperatur- und Niederschlagssimulationen in Deutschland, Dissertation, Uni-Hamburg, Berichte zur Erdsystem Forschung 75, 2010.* *Trömel, S. and C.-D. Schönwiese (2007): Probability change of extreme precipitation observed from 1901 to 2000 in Germany, Theor. Appl. Climatol., 87, 29--39, doi:10.1007/s00704-005-0230-4.*
Contact/project	Katharina Bülow Bundesamt für Seeschifffahrt und Hydrographie katharina.buelow@bsh.de KLIWAS

5.3.10 Analysis of variance (ANOVA)

Superordinate objective (category)	**Time series analysis**
Method	Analysis of variance (ANOVA)
Description + literature	Decomposition of the variability of a variable in dependence on different classes. For that purpose, the investigated variable is divided into different classes (depending on selected factors). Insofar the factors influence the variability of the variable, you can see this in the averages of the classes that are associated with the factors; those averages differ from each other. You can also determine whether the variability is explained by known influences (the factors) or other, yet unknown influences. Several sub-branches of the analysis of variance exist. Common to all is that for each group of factors, a test statistic is calculated, which quantifies the ratio of explained to unexplained variance. The test statistic is F-distributed with two degrees of freedom. To decide among the selected null hypotheses (which usually state that no deviation exists between sub-groups of factors), you use the test statistic to compare it with that F distribution and obtains the probability, P, of finding a variance ratio that is at least as high as the observed ratio. If P is very small (less than the significance level), that null hypothesis is rejected. *von Storch and Zwiers, Statistical Analysis in Climate Research, Cambridge University Press, 1999* This method is extensively treated in introductory statistics textbooks.
Useful for (parameter, time resolution)	Variables that depend on other variables, which are factorized. The analysis of variance describes that dependence.
Requirements for application	Variables that can be grouped into factors. Each group of factors should have a similar size. Further assumptions: normal distributional shape of the investigated variable with constant variance as well as independence of realizations.
Result/interpretation	Determination whether significant deviations exist between single groups of a variable that can be factorized.
Example/publication	Krüger O, von Storch H (2011) Evaluation of an air pressure-based proxy for storm activity. *J. Climate* 24, 2612–2619. [*http://journals.ametsoc.org/doi/abs/10.1175/2011JCLI3913.1*] In this article, the “two-way analysis of variance” is used, which allows to assess interactions between two factors. The database comprises correlations between geostrophic winds (calculated from spatiotemporal air-pressure fields by means of triangulation) and near-surface winds, which had been transformed to approximate normal distributional shape. The authors studied the influence of the surface (land or ocean) and of the triangles’ size (large, medium or small) on the correlation between both wind variables, and they studied whether there exists an interaction between the factors surface and size. If those two factors are independent from each other, their respective influences on the analysed wind variable are also independent from each other.

	The data were sorted into 6 classes ("surface", 2; "size", 3) with equal class size. The employed method of analysis of variance uses three null hypotheses, from which two regard direct effects and one regards interactive effects. The first null hypothesis, H0, states that there is no difference in mean (of transformed correlations) that is related to the factor "surface". The related alternative hypothesis, H1, states that there is a difference. Analogously, H0 and H1 were constructed on basis of the factor "size". The null hypothesis, H0, regarding interactive effects states that effects of surface and size are independent from each other and influence each other. The alternative hypothesis, H1, states that there exists interaction and dependence. The ANOVA found for the test regarding ineractive factors a ratio between explained and unexplained variance of approximately 0.7. The F distribution (with 2 and 690 degrees of freedom) yields a P-value of approximately 0.45 for observing a variance ratio of 0.7 or higher. This large P-value (larger than typically used significance levels of, say 0.05 or 0.10) means that H0 ("no interaction") cannot be rejected. The factors "surface" and "size" turn out in this analysis to be independent from each other. The authors found further that both other tests lead to rejecting the null hypotheses: the factors "surface" and "size" do have a significant influence on the correlation of wind speeds.
Contact/project	Oliver Krüger Helmholtz-Zentrum Geesthacht Institut für Küstenforschung, Oliver.krueger@hzg.de

5.4 Bias correction

In the context of climate modelling, a bias means a systematic deviation of a climate model variable from its observed counterpart. Take for example precipitation during the time interval after 1950, for which there are indications from a range of regional climate models that for the region of central Europe–Scandinavia the bias is positive, that means, the climate models systematically overestimate precipitation (Goodess et al. 2009). The bias is usually thought to be due to inadequate model formulations, which root in our incomplete knowledge about climate processes and the limited power of our computers.

One remedy to this discomforting situation obviously is to construct better climate models; although this is done continuously by modelling groups, it is a process that requires development time. The other, "quick and dirty" remedy is to correct the climate model output such that the bias disappears. The success of climate model bias correction depends critically on (1) an appropriate stochastic description of the form of the bias (e.g., additive/multiplicative or constant/time-dependent) and (2) the availability of accurate and highly resolved (in space and time) observational data. Another critical point is the danger of inconsistencies between climate model variables that are bias-corrected and other variables that are not; consider for example the relation between air temperature and the type of precipitation (rain versus snow). The area of bias correction is rather new to climate modelling, and we should expect considerable new developments in the future.

The bias correction method of choice many climate modellers currently employ is quantile mapping (QM), where a relation between the distribution function of a modelled variable and the distribution function of an observed variable is established; the two presented QM methods (Sections 5.4.1 and 5.4.2) give more details. This may work well when mean climatic states are the objective of the analysis and the observational database is good, but QM may work less well when extreme climatic states are analysed in a nonstationary context (Kallache et al. 2011). A crucial assumption of QM is the stationarity of the bias form, which may be violated in the analysis of future climates.

Further reading. A short overview of climate model bias correction with several examples is given by Mudelsee et al. (2010). QM is described by Piani et al. (2010). Other corrections, including nonstationary methods, are briefly considered by Mudelsee (2010: Section 9.4.4 therein). Kallache et al. (2011) analyse nonstationary probabilistic downscaling of extreme precipitation.

Goodess CM, Jacob D, Déqué M, Guttiérrez JM, Huth R, Kendon E, Leckebusch GC, Lorenz P, Pavan V (2009) Downscaling methods, data and tools for input to impacts assessments. In: van der Linden P, Mitchell JFB (Eds.) ENSEMBLES: Climate change and its impacts at seasonal, decadal and centennial timescales. Met Office Hadley Centre, Exeter, 59–78.

Kallache M, Vrac M, Naveau P, Michelangeli P-A (2011) Nonstationary probabilistic downscaling of extreme precipitation. Journal of Geophysical Research 116:D05113 (doi:10.1029/2010JD014892).

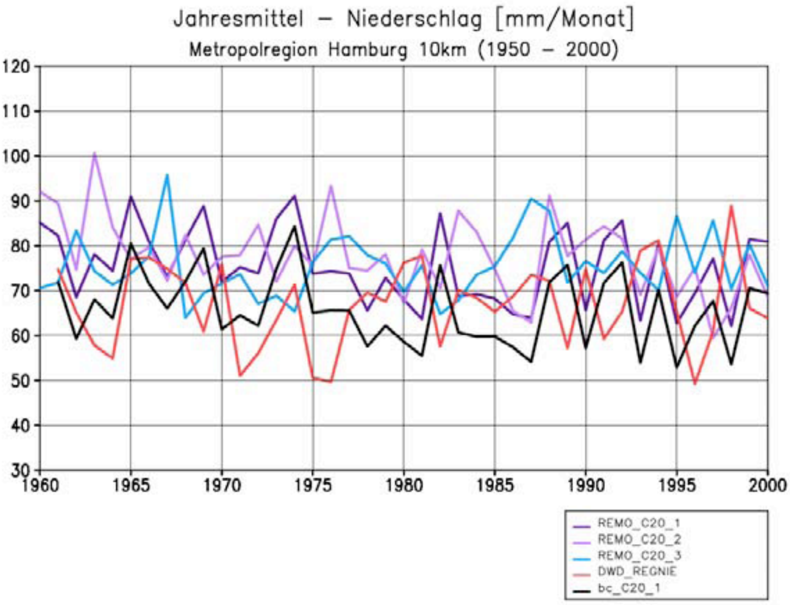
Mudelsee M, Chirila D, Deutschländer T, Döring C, Haerter J, Hagemann S, Hoffmann H, Jacob D, Krah, P, Lohmann G, Moseley C, Nilson E, Panferov O, Rath T, Tinz B (2010) Climate model bias correction und die Deutsche Anpassungsstrategie. Mitteilungen Deutsche Meteorologische Gesellschaft 3:2–7.

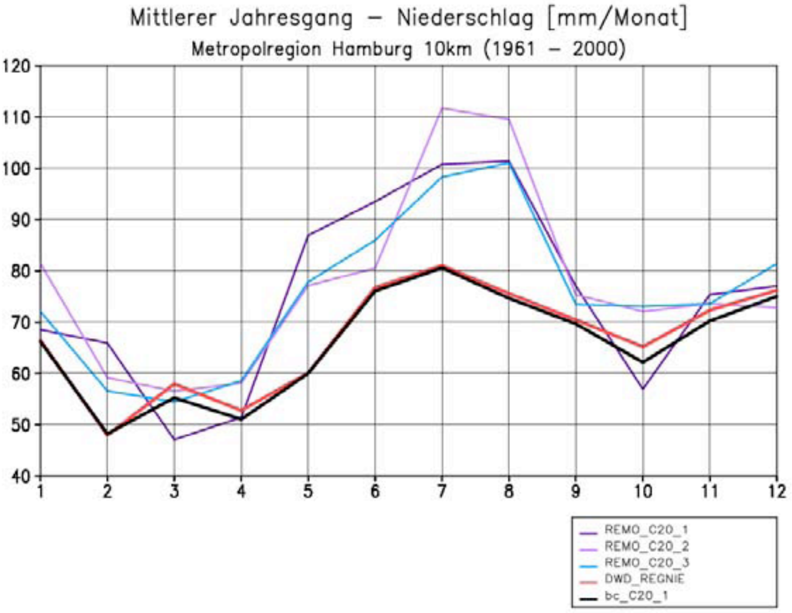
Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht, 474 pp.

Piani C, Haerter JO, Coppola E (2010) Statistical bias correction for daily precipitation in regional climate models over Europe. Theoretical and Applied Climatology 99:187–192.

5.4.1 Quantile mapping with transfer function

Superordinate objective (category)	**Bias correction**
Method	Quantile mapping with transfer function
Description + literature	Statistical correction of systematic deviations of climate model data from observed climate data in the past, used for application in process-based climate impact models *PIANI, C., G.P. WEEDON, M. BEST, S.M. GOMES, P. VITERBO, S. HAGEMANN, J.O. HAERTER, 2010: Statistical bias correction of global simulated daily precipitation and temperature for the application of hydrological models. Journal of Hydrology. 395, 199-215*
Useful for (parameter, time resolution)	For example, precipitation, surface air temperature, global irradiance
Requirements for application	Observational data of sufficient quality, in daily resolution and sufficiently high spatial resolution. Additionally, the observational series has to be long enough to secure that the apparent model bias is not a result of short-term variability.
Result/interpretation	Corrected daily climate parameters from REMO and CLM simulations. For making future projections of parameters you have to consider that the climate-change signal on the bias-corrected data can deviate from the signal on the uncorrected data; it is unclear which of the two climate-change signals is closer to reality.
Assessment	When applying bias-corrected climate data you have to consider: (1) the “model-internal” consistence among various climate variables may be lost due to the bias correction; (2) the climate-change signal may itself be subject to change due to the bias correction; (3) observational data and method itself are subject to uncertainty (and are currently being analysed in climate research).
Example/publication	Bias correction of temperature, precipitation, global irradiance, wind chill and runoff (projects KLIFF and KLIWAS) *Mudelsee, M., D. Chirila, T. Deutschländer, C. Döring, J.O. Haerter, S. Hagemann, H. Hoffmann, D. Jacob, P. Krahé, G. Lohmann, C. Moseley, E. Nilson, O. Panferov, T. Rath, B. Tinz, 2010: Climate Model Bias Correction und die Deutsche Anpassungsstrategie. Mitteilungen der Deutschen Meteorologischen Gesellschaft 03/2010.* Example of Hamburg metropolitan area: annual values (top panel) and seasonal cycle (bottom panel) of precipitation as simulated with REMO in 3 realizations of the climate control, 1961–2000, and bias-corrected precipitation of the 1st realization of the climate control (bc_C20_1) using the REGNIE observational data of the DWD:

<table>
<tr><td></td><td>


</td></tr>
<tr><td>Contact/project</td><td>Diana Rechid; Christopher Moseley
MPI für Meteorologie
diana.rechid@zmaw.de, christopher.moseley@zmaw.de
KLIMZUG NORD; KLIFF</td></tr>
</table>

5.4.2 Modified quantile mapping

Superordinate objective (category)	**Bias correction**
Method	Modified quantile mapping
Description + literature	*Piani C., Haerter J. O and Coppala E. (2010). Statistical bias correction for daily precipitation in regional climate models over Europe. Theor. Appl. Climatol. 99, 187–192 [quantile mapping as basis of method]* *Themeßl, M.J., Gobiet, A., Leuprecht, A. (2011): Empirical-statistical downscaling and error correction of daily precipitation from regional climate models. Int. J. Climatol., 31, 1530–1544.*
Useful for (parameter, time resolution)	Daily precipitation series; applications in water management and sanitary environmental engineering.
Requirements for application	Model data and observational data have to be available for a reference period.
Result/interpretation	On the daily values you make a fit for following parameters/indexes of relevance for water management: dry days and phases, monthly and annual precipitation totals, distribution of precipitation classes (daily values) and extreme-rainfall days. Daily rainfall totals below and above the 97% quantile are treated separately. Up to 97% quantile: perform quantile mapping in dependence on calendar month; above 97% quantile: perform linear regression separately for the hydrological half-years (May to October and November to April). Following procedure applies to the total data set: correction using a "dry value" to exclude very small daily totals; aggregation of neighboured grid boxes with similar properties; and combined analysis of both CLM realizations. The relationship functions (model–observational data) is transferred from the reference period to the future period.
Assessment	For the reference period all mentioned parameters/indexes are fitted realistically. Due to fitting to observational point data, also the CLM model data have to be interpreted as point data. This is meaningful regarding applications because also the water management models use point measurements. Interpretation of the spatial aspect assumes that the bias-corrected CLM data can occur at any point within the CLM grid box (DWD 2000). DWD (2000) KOSTRA-DWD-2000: Starkniederschlagshöhen für Deutschland (1951–2000), Grundlagenbericht. Offenbach am Main: Deutscher Wetterdienst, 32pp.
Example/publication	*Quirmbach, M., Freistühler, E., Papadakis, I. (2012): „Bias-Korrektur der Niederschlagsdaten aus dem Regionalen Klimamodell CLM in der Emscher-Lippe-Region", dynaklim-Publikation, No. 21, März 2012, http://www.dynaklim.de* *Quirmbach, M.; Freistühler, E.; Papadakis, I., Pfister, A. (2012): „Analyse und Korrektur des systematischen Fehlers (Bias) in den Niederschlagsdaten des Regionalen Klimamodells CLM in der Emscher-Lippe-Region", KW Korrespondenz Wasserwirtschaft, Jahrgang 5 (2012), Nr. 10, S. 544–555*
Contact/project	Markus Quirmbach dr. papadakis GmbH, Hattingen

	M.Quirmbach@drpapadakis.de KLIMZUG project DYNAKLIM, ExUS

5.5 Significance tests

Statistical inference is done in two ways: estimation and significance testing. The latter, also called hypothesis testing, investigates in the context of this brochure whether statements about the climate system are true.

Hypothesis testing utilizes a well-elaborated statistical procedure (Lehmann and Romano 2005). Following Mudelsee (2010): A null hypothesis (or short: null), H0, is formulated. H0 is tested against an alternative hypothesis, H1. The hypotheses H0 and H1 are mutually exclusive. Next, a test statistic, u, is calculated from the data. The quantity u is a realization of a random variable with a distribution function, F0(u), where the “0” indicates that u is computed “under H0”, that is, as if H0 were true. F0(u) is called the null distribution. The P-value is the probability that under H0 a value of the test statistic greater than or equal to the observed value, u, is observed (one-sided test). If P is small, then H0 is rejected and H1 accepted, otherwise H0 cannot be rejected against H1. In a two-sided test, you would study the absolute values for the observed u and its distribution under H0. The choice between one- and two-sided tests depends on the problem at hand. For example, a one-sided test of comparing two samples regarding their mean would correspond to H0 “equal means” and H1 “mean of first sample is larger than mean of second sample”, and a two-sided test would instead correspond to the same H0 but H1 “unequal means”.

The presented bootstrap approach to significance testing (Section 5.5.5) derives F0(u) by a computational resampling technique instead of making some assumptions (e.g., regarding the distributional shape), which may in the climatological practice be violated. The ratio between trend and noise (e.g., of a climate change signal) corresponds to an intuitive testing approach from physics (Section 5.5.1). The second presented method is a nonparametric test for trend after Mann and Kendall (Section 5.5.2), that is widely employed in climate sciences and elsewhere. Further tests are described in (Section 5.5.3, 5.5.4 und 5.5.6).

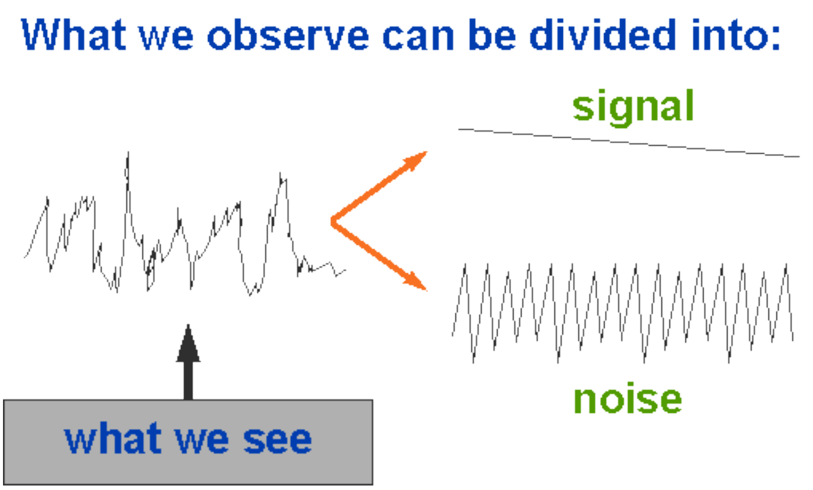
Further reading. A classic book in statistical science is by Lehmann and Romano (2005). If the level therein is found too high, then von Storch and Zwiers (1999) may be consulted. The book by Mudelsee (2010) contains a section on bootstrap hypothesis testing.

Lehmann EL, Romano JP (2005) Testing Statistical Hypotheses. 3 edn., Springer, New York, 784 pp.

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht, 474 pp.

von Storch H, Zwiers FW (1999) Statistical Analysis in Climate Research. Cambridge University Press, Cambridge, 484 pp.

5.5.1 *Trend/noise ratio*

Superordinate objective (category)	**Significance tests** linear trends
Method	Trend/noise ratio – T/N
Description + literature	Testing for significance by analysing the strength of the trend signal: trend/standard deviation (noise): T/N, trend > standard deviation (noise): T/N > 1. *Schönwiese (2006[4]): Praktische Methoden für Meteorologen und Geowissenschaftler, 232-234. Stuttgart*
Useful for (parameter, time resolution)	Time series data with a linear trend
Requirements for application	Approximate normally distributed data, linear trend, long time series *(http://www.kliwa.de/download/Verfahren.pdf)*
Result/interpretation	T/N > 1 means a significant trend with a P-value of at least 0.7 P-values (or significances are tabulated) *Schönwiese (2006[4]): Praktische Methoden für Meteorologen und Geowissenschaftler, 98. Stuttgart*
Assessment	Simple test for linear trends; weak power *(http://www.kliwa.de/download/Verfahren.pdf)*
Example/publication	 *http://www.socialresearchmethods.net/kb/Assets/images/expclas1.gif* *Schableger (1996): Statistische Analysen klimatologischer Zeitreihen. Historical Social Research, 21, 3, 4-33. http://hsr-trans.zhsf.uni-koeln.de/hsrretro/docs/artikel/hsr/hsr1996_395.pdf* *Kabas (2005): Das Klima in Südösterreich 1961-2004.*

	Wissenschaftlicher Bericht Nr.4-2005. http://www.uni-graz.at/igam7www_wcv-wissber-nr4-tkabas-okt2005.pdf
Contact/project	Andreas Kochanowski Helmholtz-Zentrum Geesthacht, Climate Service Center andreas.kochanowski@hzg.de

5.5.2 *Mann–Kendall test*

Superordinate objective (category)	**Significance tests**
Method	Mann–Kendall test
Description + literature	Distribution-free trend test, which considers the positive or negative course of successive values
Useful for (parameter, time resolution)	In principle, precipitation (at all durations), precipitation indexes and temperature
Requirements for application	Sample size at least 10
Result/interpretation	Statements about a change of a parameter with time possible, which are accompanied by a significance value.
Assessment	Changes can be assessed via the significance or, relatively, via comparing several results (e.g., several precipitation measurement stations). This test does not inform about the magnitude of change (e.g., mm per year).
Example/publication	ExUS – Studie des Landes NRW (LANUV NRW)
Contact/project	Markus Qirmbach dr. papadakis GmbH, Hattingen M.Quirmbach@drpapadakis.de KLIMZUG project DYNAKLIM, ExUS

5.5.3 Cox–Lewis test

Superordinate objective (category)	**Significance tests**
Method	Cox–Lewis test
Description + literature	The Cox–Lewis test belongs to the area of extreme value analysis (Section 0). It concerns the time-dependent occurrence rate λ(T), where T is time, for an inhomogeneous Poisson point process (Section 5.7.4.3). The null hypothesis tested is based on a logistic model for λ(T) and is given by H0: "λ(T) is constant." The statistic U to test this (Cox and Lewis 1966) is given by $$U = \frac{\sum_{j=1}^{m} T_{\mathrm{out}}(j)\,/m - [T(n) + T(1)]\,/2}{[T(n) - T(1)]\,(12m)^{-1/2}},$$ where j is an index, m is the number of extreme events, T_{out} is the date of an event, n is the total sample size, and [T(1); T(n)] is the observation interval. It can be shown that under H0, U becomes with increasing m rapidly standard normally distributed in shape, which allows a simple calculation of the P-value. Cox DR, Lewis PAW (1966) The Statistical Analysis of Series of Events. Methuen, London, 285 pp.
Useful for (parameter, time resolution)	Any parameter at any time resolution.
Requirements for application	Independent event dates.
Result/interpretation	Significance of a hypothesis test (which guides you whether or not to accept the null hypothesis).
Assessment	Simple test. Monte Carlo experiments (Mudelsee 2010) have shown the superiority (power) of the Cox–Lewis test over the Mann–Kendall test (Section 5.5.2) for studying nonstationarities in the occurrence of extremes.
Example/publication	The Cox–Lewis test was employed by Mudelsee et al. (2003) to confirm trends in occurrence of extreme river floods (see also Section 5.7.4.3). *Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht, 474 pp.* *Mudelsee M, Börngen M, Tetzlaff G, Grünewald U (2003) No upward trends in the occurrence of extreme floods in central Europe. Nature 425:166–169.*
Contact/project	Manfred Mudelsee Climate Risk Analysis, Hannover, Germany; mudelsee@climate-risk-analyis.com www.climate-risk-analysis.com

5.5.4 Kolmogorov–Smirnov test

Superordinate objective (category)	**Significance tests**
Method	Kolmogorov–Smirnov test
Description + literature	The Kolmogorov–Smirnov test is a hypothesis test that compares an empirical probability distribution function $S_n(x)$ with a specified theoretical probability distribution function P(x), the null hypothesis being that P(x) is the true, data-generating distribution. von Storch and Zwiers (1999): Statistical Analysis in Climate Research, Cambridge University Press.
Useful for (parameter, time resolution)	Any parameter at any time resolution (e.g., hydrographical or meteorological data).
Requirements for application	Data from independent and identically distributed random variables with a continuous distribution S(x).
Result/interpretation	The Kolmogorov–Smirnov test statistic, D, is given by the maximum absolute difference between the empirical and the specified distribution function, $D = \max\lvert S_n(x) - P(x)\rvert$, for all $-\infty < x < +\infty$. The null hypothesis, that P(x) is the correct distribution function, is rejected when D assumes a large value. For large enough samples sizes, n, it can be shown that $\text{prob}(D_n(X_1, \ldots, X_n) > 1.36/\sqrt{n}) \approx 0.05$. Under the null hypothesis, deviations larger than $1.36/\sqrt{n}$ occur with a probability of about 0.05.
Assessment	The Kolmogorov–Smirnov test is easy to use and implemented in many software packages.
Example/publication	An illustrative example (in German): Jürgen Lehn und Helmut Wegmann (2004): Einführung in die Statistik, 4. Auflage, Teubner, p. 98–105. In English with graphical illustration and Fortran code: Press, W. H., S.A. Teukolsky, W.T. Vettering und B.P. Flannery (1992): Numerical recipes in Fortran 77, Cambridge University Press, p. 617–622.
Contact/project	Katharina Bülow, KLIWAS, Bundesamt für Seeschifffahrt und Hydrographie, katharina.buelow@bsh.de
Software	The Fortran code implementing the Kolmogorov–Smirnov test is short and accessible; it has been transferred to and used in other computing environments (e.g., Matlab, R).

5.5.5 *Bootstrap hypothesis test*

Superordinate objective (category)	**Significance tests**
Method	Bootstrap hypothesis test
Description + literature	Bootstrapping is a resampling method. On basis of a single sample, the test is repeated on parametrically or nonparametrically obtained resamples, and a distribution of the test statistic determined (null distribution) Ususally the test statistic obtained on the sample is compared with the null distribution. This leads to the test significance by comparing the sample-statistic with quantiles of the null distribution. *Climate Time Series Analysis, Mudelsee, 2010, pp 91-94*
Useful for (parameter, time resolution)	You use bootstrap methods when the theoretical distribution of the statistic of interest is unknown or if no parametric method is available.
Requirements for application	Determination of the null distribution depends on the problem at hand. It is important that the determination of the null distribution has to preserve the original properties of the data generating process (e.g., autocorrelation). For that aim, bootstrap adaptations, such as block bootstrap resampling, can be employed.
Result/interpretation	Significance of a hypothesis test (which guides you whether or not to accept the null hypothesis).
Assessment	On the one hand, this method delivers results that are independent of strong assumptions (positive aspect), but the implementation and application may be difficult (negative). Depending on concept of the bootstrap method and the sample size, this method may be rather computing-intensive.
Example/publication	Signifikance test of correlations
Contact/project	Oliver Krüger Helmholtz-Zentrum Geesthacht Institut für Küstenforschung Oliver.krueger@hzg.de

5.5.6 Parametrical z- test

Superordinate objective (category)	**Significance tests**
Method	Parametrical significance test for large sample size (z-Test)
Description + literature	Parametrical tests (e.g. z-, t- and F-tests) are used for statistical hypothesis testing under the assumption that the variable of interest is e.g. normally distributed. Hypothesis tests can therefore be used for testing the significance of differences of e.g. averages, frequencies of occurrence, variances etc. from two samples. The z- and t-test are recommended for testing the significance of differences of averages and frequencies of occurrence, meanwhile the F-test is suitable for testing of variances. All parametrical significance tests are limited to a certain error level (or significance level). If the test statistic is equal or higher than a critical test value, the null hypothesis (stating that there is no significant difference between the two samples) is rejected and the alternative hypothesis is being accepted. The following general steps are recommended for a parametrical significance test: a) Set up the null (H_0) and alternative hypothesis (H_1) b) Selection of test statistic c) Definition of significance (error) level d) Calculation of test statistic and decision on the acceptance or rejection of the null hypothesis (H_0) References (Selection): *BUTLER,C. (1985): Statistics in Linguistics. Web-Edition, http://www.uwe.ac.uk/hlss/llas/statistics-in-linguistics/bkindex.shtml (zuletzt abgerufen am 27.06.2013), University of West England, Bristol.*
Useful for (parameter, time resolution)	Any parameter at any time resolution, e.g. sea-state parameters (wave heights) or meteorological parameters (wind velocities)
Requirements for application	The data tested (e.g. differences of frequencies of occurrence) have be normally distributed. Independent and large samples (number of elements n>30).
Result/interpretation	Decision of the hypothesis test (rejection or acceptance of the null hypothesis) and of the significance of differences between e.g. averages or frequencies of occurrence.
Assessment	Simple method for a classical significance test even if the assumptions are not fulfilled or tested. One disadvantage of the test is that it does not give any information about the strength of the significance of the difference. The significance of difference is easy to proof if the data has a small standard error (e.g. small standard deviation and/or large sample size) which is often the case when testing numerical climate model results.
Example/publication	Application of the z-Test for the testing of the significance of the difference between two frequencies of occurrence p_A and p_B: a) Set up the null (H_0) and alternative hypothesis (H_1) $H_0: p_A = p_B \quad H_1: p_A \neq p_B$ b) Calculation of the empirical z-value

<table>
<tr>
<td></td>
<td>

$$z_{calc} = \frac{p_A - p_B}{Stderr_{A,B}}$$

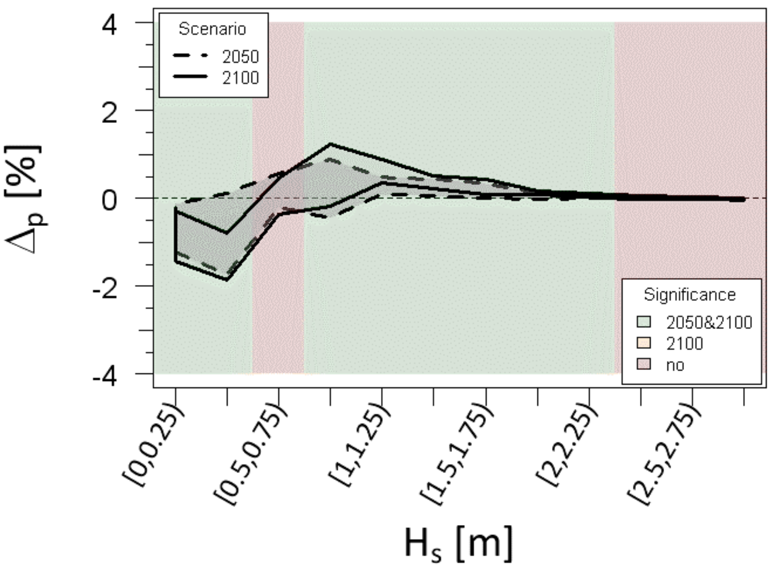
$$Stderr_{A,B} = \sqrt{\frac{p_A(1-p_A)}{N_A} + \frac{p_B(1-p_B)}{N_B}}$$

c) Definition of significance (error) level $\alpha = 0.05$

d) Calculation of critical z-value (see Table of the Normal distribution) and decision on the acceptance or rejection of the null hypothesis (H_0)

$$z_{crit} = q.norm(\alpha) \approx 1.65$$

Example:
Statistical assessment of the relative changes of the frequencies of occurrence (Δp[%] on the left axis) of calculated significant wave heights (H_s[m] on the bottom axis) near Warnemünde for two future scenarios 2050 (2001-2050) & 2100 (2071-2100) based on Cosmo-CLM model results for the IPCC emission scenarios A1B and B1 compared to actual conditions (C20, reference period 1971-2000).



Interpretation of Results:
Within the green highlighted background of the plot, the relative changes of the frequencies for H_s<0.5m and 0.75m≤H_s<2.25m are supposed to be statistical significant at an error level of 0.05 for both scenarios 2050 and 2100. For the wave heights marked with the red highlighted background no statistical significance was found.

</td>
</tr>
<tr>
<td>Contact/project</td>
<td>

Norman Dreier, Hamburg Technical University, Institute of River and Coastal Engineering, norman.dreier@uni-rostock.de

Christian Schlamkow, Geotechnics und Coastal Engineering, University of Rostock, christian.schlamkow@uni-rostock.de

</td>
</tr>
</table>

5.6 Regionalisation

Refining the spatial information of coarse-resolution global climate models output is called downscaling. Two downscaling approaches exist, via nested regional climate models and via statistical models between the global climate model output and high-resolution observations. The results of regional climate models often are needed in a higher resolution for impact models. In this chapter two methods of a statistical downscaling are presented (5.6.1.1 and 5.6.1.2). The presented method (Section 5.6.1.1) illustrates statistical downscaling with linear models.

Suppose that you have data values of a variable at some points in a space of a certain dimension, and you wish to know the values at the other points. The mathematical techniques to obtain these other values are called interpolation techniques; there may exist several techniques for a single problem.

The methods presented here deal with the two-dimensional geographical space (longitude–latitude), defining the field of geostatistics. These methods are of high relevance to the analysis of spatial climate model output.

The simplest method, also in the two-dimensional setting, is linear interpolation (Section 5.6.2). Interpolation can be seen as an estimation problem based on data, and you may adopt a weighting of the contribution of the data points to the estimation that is inversely proportional to the distance between the point of interest and a data point (Sections 5.6.2.2 and 5.6.2.3). The interpolated curve (e.g., in the two-dimensional plane) may be subjected to constraints regarding its differentiability, which leads to spline interpolation (Section 5.6.2.4). Finally, there exists the advanced technique of kriging, which takes spatial dependences into account (Section 5.6.2.5).

Further reading. The two reports from the IPCC (Christensen et al. 2007) and the ENSEMBLES project (van der Linden and Mitchell 2009) are comprehensive and accessible; they serve as good starting points. An easily accessible textbook on interpolation and geostatistics from a geological perspective is by Davis (1986). The more thorough (but still readable) statistical perspective is given by Diggle and Ribeiro (2007) and Cressie and Wikle (2011).

Christensen JH, Hewitson B, Busuioc A, Chen A, Gao X, Held I, Jones R, Kolli RK, Kwon W-T, Laprise R, Magaña Rueda V, Mearns L, Menéndez CG, Räisänen J, Rinke A, Sarr A, Whetton P (2007) Regional climate projections. In: Solomon S, Qin D, Manning M, Marquis M, Averyt K, Tignor MMB, Miller HLeR Jr, Chen Z (Eds.) Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, 847–940.

Cressie N, Wikle CK (2011) Statistics for Spatio-Temporal Data. Wiley, Hoboken, NJ, 588 pp.

Davis JC (1986) Statistics and Data Analysis in Geology. 2 edn., Wiley, New York., 646 pp.

Diggle PJ, Ribeiro Jr PJ (2007) Model-based Geostatistics. Springer, New York, 228 pp.

van der Linden P, Mitchell JFB (Eds.) ENSEMBLES: Climate change and its impacts at seasonal, decadal and centennial timescales. Met Office Hadley Centre, Exeter, 160 pp.

5.6.1 Downscaling

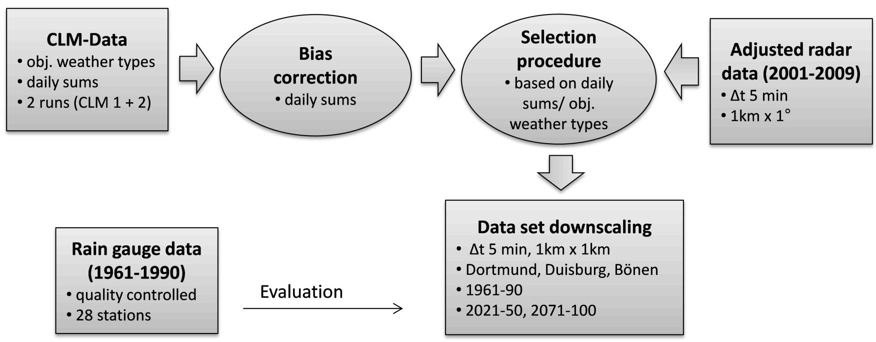
5.6.1.1 Statistical downscaling of climate projections by means of linear statistical models

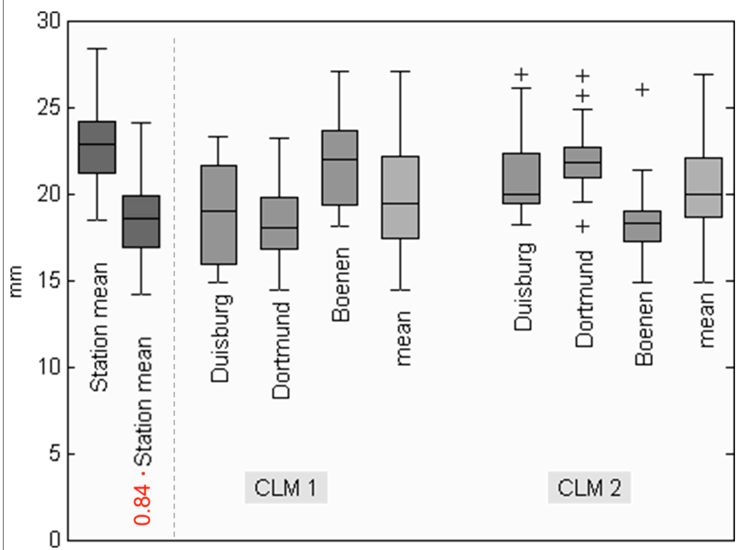
Superordinate objective (category)	**Regionalisation** (Downscaling)
Method	Statistical downscaling of climate projections by means of linear statistical models
Description + literature	A statistical model for some target variable is constructed. This is based on the statistical relationship between the target variable (response) and meteorological variables (predictors) that are independent of the target variable. The model parameters can be estimated by means of multivariate linear regression. For that purpose, several methods exist (e.g., generalized least squares). The database consists in the measured variables. For determining the future values of the target variable, the independent meteorological variables are determined by means of climate models. Subsequently, these meteorological values are plugged in into the statistical model to determine the future target variable and, for example, changes in that variable that are due to climate changes.
Useful for (parameter, time resolution)	Heat-island intensity, air quality, mortality
Requirements for application	Existence of a statistical relationship between target and independent variables; it is assumed that this relationship continues also in a future climate, which needs not be fulfilled. Model parameters must be estimated using observational data and should, if possible, also be tested.
Result/interpretation	Result is a statistical model for a target variable. Plugging in climate model data into the statistical-model equations, the change in the target variable due to climate changes can be determined. Since the statistical model can only partly describe the behaviour of the target variable, the climate-change signals should be assessed with caution.
Assessment	
Example/publication	Hoffmann et al. (2011) [urban heat island, Hamburg] Muthers et al. (2010) [mortality, Vienna] Wilby (2008) [urban heat island and mortality, London]
Contact/project	Peter Hoffmann Universität Hamburg, Meteorologisches Institut peter.hoffmann@zmaw.de KLIMZUG NORD

Hoffmann P., Krueger O., Schlünzen K.H. (2011): A statistical model for the urban heat island and its application to a climate change scenario. International Journal of Climatology (accepted)
Muthers, S.; Matzarakis, A.; Koch, E (2010). Climate Change and Mortality in Vienna—A Human Biometeorological Analysis Based on Regional Climate Modeling. Int. J. Environ. Res. Public Health, 7, 2965-2977

Wilby, R.L. (2008): Constructing climate change scenarios of urban heat island intensity and air quality. Environment and Planning B: Planning and Design, 35, 902-919.

5.6.1.2 Statistical downscaling of precipitation

Superordinate objective (category)	**Regionalisation** (Statistical downscaling of precipitation)
Method	Analogue method/ resampling of precipitation data from regional climate models using radar data
Description + literature	Empirical statistical downscaling method: Based on daily amounts of precipitation (spatial averages over RCM gridboxes) and objective weather classes (DWD), days with measurement data are chosen from an observation period wich behave ‘similar’ – concerning precipitation and objective weather class - to the RCM-data. The high-resolution observation data of the selected days are composed to synthetic time series. These time series are section-wise composed of observations which are consistent in space and time. However, transitions from one section to another are not consistent, therefore longer time events cannot be reproduced. In order to enlarge the database in the observation period, events are shifted within the selected region. Thus, small-scale orographic effects are neglected. Individual high model events without adequate similar events in the observation period may be replaced by lower events enhanced by a factor. 
Useful for (parameter, time resolution)	Precipitation data from regional climate models, spatial resolution e.g. 0.2°x0.2°, daily sums
Requirements for application	Observation data with high spatial and temporal resolution, e.g. corrected and adjusted radar data of at least 10 years (resolution 5 min, 1 km x 1 km).
Result / Interpretation	Time series of precipitation amounts or events with high spatial and temporal resolution. Aggregated to gridbox scale and one day, the values correspond to the RCM values.
Assessment	Empirical statistical downscaling for predefined event duration (here: < 1 d) produces precipitation data at appropriate scales. The data can directly be used as input for hydrological models. The example shows that realistic extreme values (return period: 5 y) as compared to observations are produced. Precipitation trends

	of the resulting data are mainly determined by trends in the RCM daily data. A previous bias correction of the daily RCM data is recommended (Piani et al., 2010, see method 5.4.2).
Example / publication	Jasper-Tönnies, A., Einfalt, T., Quirmbach, M., Jessen, M. (2012). Statistical downscaling of CLM precipitation using adjusted radar data and objective weather types. 9th International Workshop on Precipitation in Urban Areas. 2012, St. Moritz, Switzerland. Example: downscaling of precipitation data of CLM-model for three catchment areas in North Rhine-Westphalia (Germany).  Validation: extreme precipitation [mm] for duration 1h, return period 5 years in the reference period (1961-1990) from downscaling results (3 catchments, 2 CLM runs), 28 quality-controlled rain gauge stations and rain gauge results multiplied by 0.84 to account for the different characteristic between radar and rain gauge data.
Contact / project	Alrun Jasper-Tönnies (jasper-toennies@hydrometeo.de), Projekt dynaklim Thomas Einfalt (einfalt@hydrometeo.de), Projekt dynaklim
Software (if possible)	

5.6.2 Interpolation

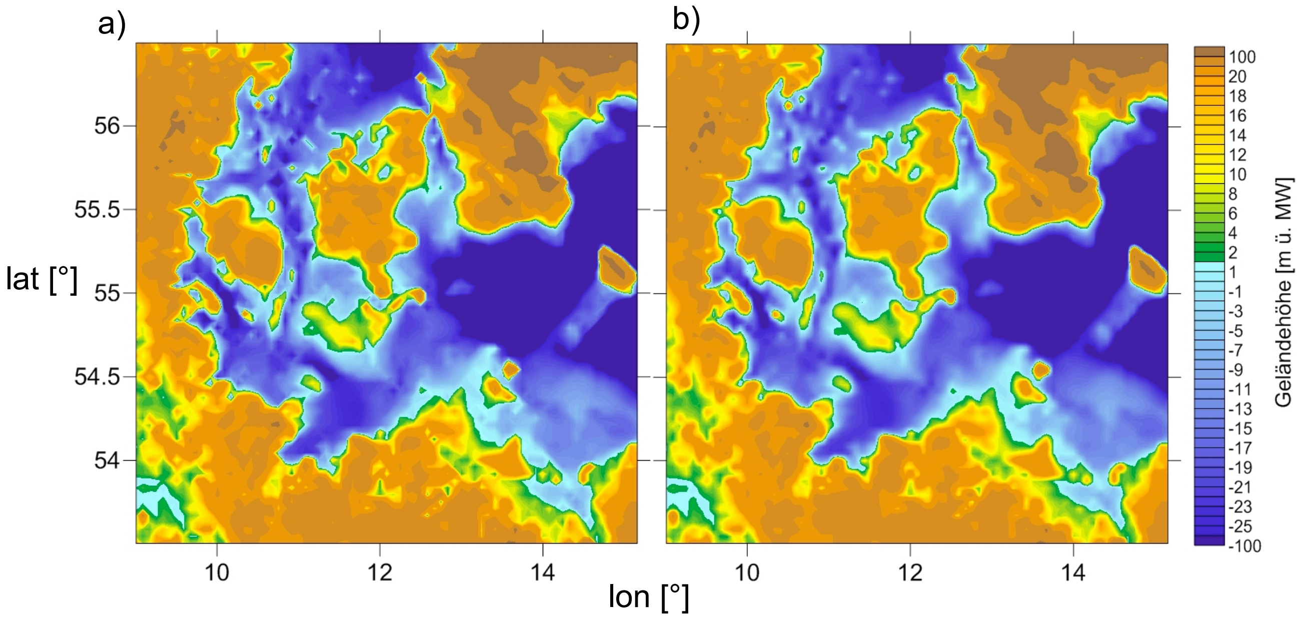
5.6.2.1 Two-dimensional linear interpolation in a grid model

Superordinate objective (category)	**Regionalisation** (Interpolation)
Method	Bilinear interpolation on a grid model
Description + literature	The two-dimensional bilinear interpolation (using 4 nodes) is a widely used interpolation method in digital image processing and analysis. Other well-known methods are e.g. the Nearest-Neighbor- (using one node) or the two-dimensional cubic interpolation (using 16 nodes). For the bilinear interpolation method two linear interpolations are carried out consecutively. The calculation effort of the method depends on the number of nodes used for interpolation. The number of nodes can be reduced e.g. by linear interpolation using triangles (3 nodes) on a regular grid. For more details see (in German only): *Rosiuta, A. A. (2003.) Minimierung der Stützstellen zur Interpolation in dreidimensionalen Texturen, Studienarbeit, Fakultät für Informatik, Institut für Visualisierung und Interaktive Systeme, Universität Stuttgart, http://elib.uni-stuttgart.de/opus/volltexte/2003/1451/* For the space between two nodes of a grid (column index j, row index i), the values are determined by means of linear interpolation and going into one direction (either j or i). Subsequently, the between-values are determined by the same means and going into the other direction (either i or j). Special case: Halving the grid size yields interpolated values that correspond to the arithmetic mean of neighbouring values. In the case of linear interpolation of multiple points within one mesh of the grid, the interpolation equations must be solved several times. For an time efficient bilinear interpolation of multiple points optimized algorithms exist. For more details see (in German only): *Behr, F. J. & Lutz, S. (1989): Ein schneller Algorithmus zur bilinearen Interpolation in Ankerpunktnetzen. Zeitschrift für Photogrammetrie und Fernerkundung, Bildmessung und Luftbildwesen, Heft 6, 57/1989, 222-229.* References (Selection): *Streit, U.: Vorlesungen zur Geoinformatik, Kap. 7.4.4 Zweidimensionale räumliche Interpolation im Rastermodell, Institut für Geoinformatik der Universität Münster, http://ifgivor.uni-muenster.de/vorlesungen/Geoinformatik/kap/kap7/k07_4.htm* *Umbaugh S. E. (2010). Digital Image Processing and Analysis: Human and Computer Vision Applications with Cviptools. 2nd edition, Crc Pr Inc, 2010. 977p.*
Useful for (parameter, time resolution)	All parameters like e.g. meteorological data (wind vector components, temperature etc.) or geographical data (marine

	bathymetry)
Requirements for application	Existence of two-dimensional regular grid, absence of strong (nonlinear) changes of the variable within the interpolated space (e.g. for bathymetry the absence of steep faces or ledges).
Result/interpretation	A spatially refined (alternatively: coarsened) grid of the investigated variable results. Due to the interpolation, the refined grid allows a better rendering, but it does not provide more information. Method is further used to project data on varying grid sizes for utilization in numerical simulations.
Assessment	Straightforward and fast computation (basic arithmetic's). At the grid boundary, only one interpolation direction exists; this is, however, no disadvantage.

Example/Publication:

Bathymetry of SW Baltic Sea (data source: IOW), two-dimensional interpolation from 75 columns x 73 rows to 150 columns x 146 rows

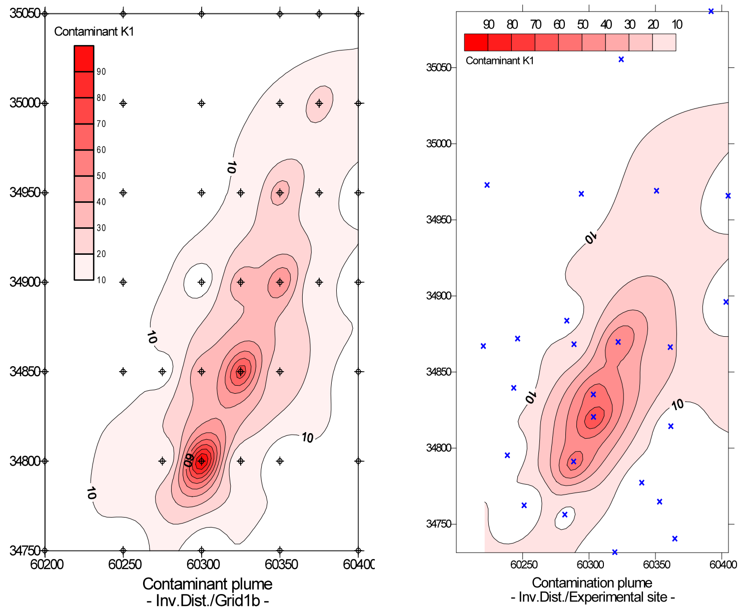


Interpretation of Results:
After the two-dimensional linear interpolation the bathymetry is optically smoothed (Fig. b), with less sharp contours (edges) compared to Fig. a.

Contact/project	Norman Dreier, Hamburg Technical University, Institute of River and Coastal Engineering, norman.dreier@uni-rostock.de Christian Schlamkow, Geotechnics und Coastal Engineering, University of Rostock, christian.schlamkow@uni-rostock.de

5.6.2.2 Inverse distance weighting

Superordinate objective (category)	**Regionalisation** (Interpolation)
Method	Inverse distance weighting (IDW)
Description + literature	Estimation of values at points that are between points with known (measured) values. Each measurement value is weighted according to its distance from the analysed point; the closer the point, the larger the weight. The interpolation can be done by adopting a search radius or employing a constant number of nearest neighbours. $$w_i = \frac{1}{d_i^2}$$ *w_i = Weight attached to point* *d_i = Distance from $z(x)$* $$z(x) = \frac{\sum_i w_i z_i}{\sum_i w_i}$$ *$z(x)$ = point in space to be interpolated* *z_i = known value (e.g., precipitation) at point $_i$* *w_i = Weight attached to point* Bonham-Carter, G. F. (1994): Geographic Information Systems for Geoscientists: Modeling with GIS. Pergamon/Elsevier Science Publications. 398 S. Bill, R. & D. Fritsch (1991): Grundlagen der Geo-Informationssysteme. Wichmann, Karlsruhe; Bd. 1: Hardware, Software und Daten. 429 S. Hartkamp et al. (1999): Interpolation Techniques for Climate Variables. Geographic Information Systems. Series 99-01.
Useful for (parameter, time resolution)	Geo-referenced point information; applicable to various physical–chemical parameters: temperature, pH, electrical conductivity, water components.
Requirements for application	Sufficient sample size (also outside of region of interest, for interpolating boundary regions). Since the method takes into account just the distance between measurement points, general properties (e.g., water-impermeable disturbances, water divides, aquifer variations) have to be taken into account prior to the analysis. The distances between measurement points should not vary too strongly to prevent occurrence of “bulls-eye” structures.
Result/interpretation	Interpolated areal distribution. This allows a simple presentation of measurement values without the need to take heterogenous influences into account. Extreme values are not smoothed away; hence, their spatial features can be inspected by eye.
Assessment	Simple and fast method that allows inference of heterogeneties (e.g., different water types, material inputs). A spatial assessment can be achieved even when the data situation dows not allow sophisticated interpolation methods. However, no

	directional weighting can be performed.
Example/publication	The figure below shows regional distributions of contaminants (so-called contaminant plumes) on basis of a measurement grid (left panel) and an “ordinary” irregular grid (right panel).  BENDER, S. (2007): Die Aussageunschärfe bei der Verwendung heterogener Datensätze im Rahmen wasserwirtschaftlicher Fragestellungen. – Bochumer Geowissenschaftliche Arbeiten, Heft 8, 99 S.
Contact/project	Steffen Bender Helmholtz-Zentrum Geesthacht, Climate Service Center Steffen.Bender@hzg.de Andreas Kochanowski andreas_kochanowski@gmx.de,
Software	Surfer (Golden Software, http://www.goldensoftware.com)

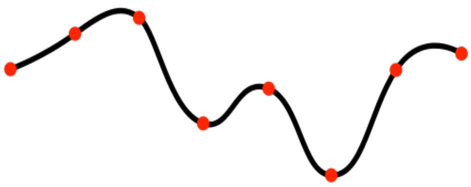
5.6.2.3 Linear regression with interpolation of residuals using inverse distance weighting

Superordinate objective (category)	**Regionalisation** (Interpolation)
Method	Linear regression with interpolation of residuals using IDW
Description + literature	Utilizing a digital elevation model, for each grid box the estimate (result field A) is calculated by means of a elevation-regression that is valid for the analysed time interval. The elevation-regression follows from the measurement values at stations and the associated elevation. To enhance the accuracy of the result (bias), the residuals (difference between measurement value and result field A per grid box) are interpolated by means of IDW (result field B). The resulting estimate is obtained by adding result fields A and B for corresponding grid boxes.
Useful for (parameter, time resolution)	Various climate elements (e.g., temperature, precipitation, irradiance)
Requirements for application	Dense network of stations and availability of digital elevation model
Result/interpretation	Grids at the same resolution as of the digital elevation model for the station-based climate elements
Assessment	An advantage is that spatial-distribution-relevant dependences of climate elements can be considered (e.g. dependence of temperature on elevation).
Example/publication	*Bernhofer et al. (2009, 2011)*
Contact/project	Johannes Franke Technische Universität Dresden johannes.franke@tu-dresden.de KLIMZUG project: REGKLAM

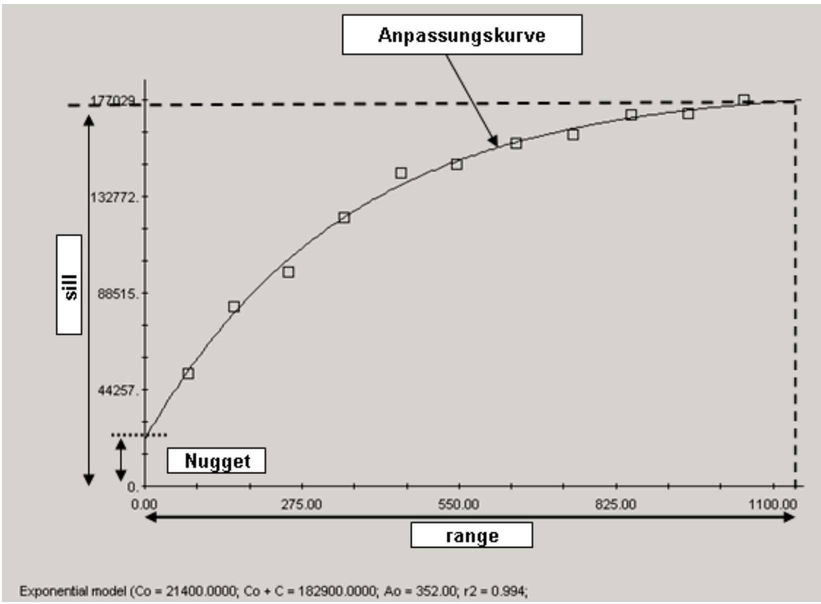
Bernhofer C, Matschullat M, Bobeth A (Hrsg. 2011): Klimaprojektionen für die REGKLAM-Modellregion Dresden. Publikationsreihe des BMBF-geförderten Projektes REGKLAM – regionales Klimaanpassungsprogramm für die Modellregion Dresden, Heft 2, Rhombos-Verlag Dresden

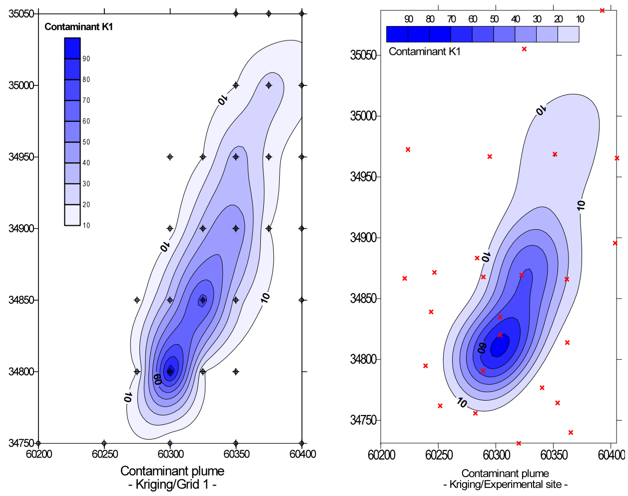
Bernhofer C, Matschullat M, Bobeth A (Hrsg. 2009): Das Klima in der REGKLAM-Modellregion Dresden. Publikationsreihe des BMBF-geförderten Projektes REGKLAM – regionales Klimaanpassungsprogramm für die Modellregion Dresden, Heft 1, Rhombos-Verlag Dresden

5.6.2.4 Splines

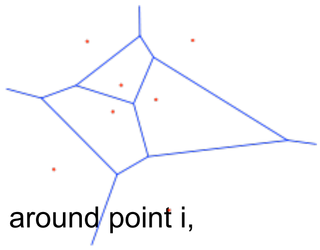
Superordinate objective (category)	**Regionalisation** (Interpolation)
Method	Splines
Description + literature	Construction of a surface with minimal curvature; interpolation by means of a series of different polynomials (often 3rd and higher order) for the space between data points *Burrough &. McDonnell* (2004): Principles of Geographical Information Systems. Oxford. *Schumacher (2007^{3}): Spline Functions: Basic Theory. New York.*
Useful for (parameter, time resolution)	Point data in space
Requirements for application	Sufficient sample size (also outside of region of interest, for interpolating boundary regions) W. Tobler „Erstes Gesetz der Geographie“ (see “Inverse distance weighting (IDW)”)
Result/interpretation	Change of a data value at one node has only local effects; small-scale properties are preserved owing to the segmented calculation (between nodes); problems may arise for sharp transitions (e.g., temperature inversion, rain-shadow effects); validation methods via “jackknife” or “cross validation”
Assessment	Difficult to make assessment of quality of interpolation
Example/publication	Splines with 8 nodes  Example calculation: *http://www.arndt-bruenner.de/mathe/scripts/kubspline.htm#rechner* gives several variations (e.g., “Thin Plate Spline”, cubic splines); is used for producing digital elevation models *Tait et al. (2006): Thin plate smoothing spline* interpolation of daily rainfall for New Zealand using a climatological rainfall surface. In: International Journal of Climatology, Vol. 26, 2097-2115. *Hong et al.* (2005): Spatial interpolation of monthly mean climate data for china. In: International Journal of Climatology, Vol. 25, 1369-1379.
Contact/project	Andreas Kochanowski Helmholtz-Zentrum Geesthacht, Climate Service Center andreas.kochanowski@hzg.de

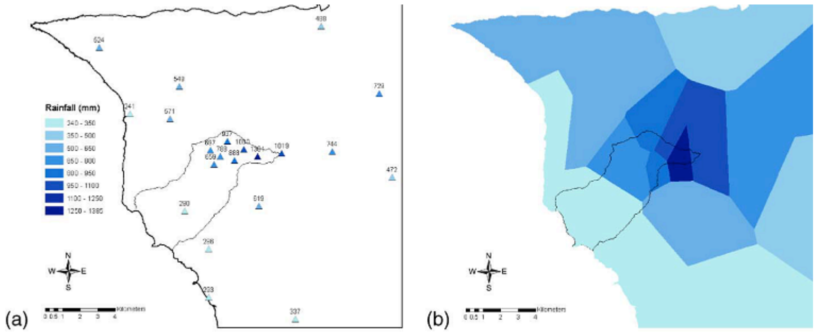
5.6.2.5 Kriging

Superordinate objective (category)	**Regionalisation** (Interpolation)
Method	Kriging
Description + literature	Geostatistical method on basis of spatial measurement data; least-squares estimation. The weighting is performed not only via distance, also the spatial distribution and anisotropies can be taken into account. Kriging delivers the semivariance, which quantifies the degree of spatial dependence between samples. If you determine the semivariances for different samples, you can plot this curve as the semivariogram: $\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \left(Z(x_i) - Z(x_i + h)\right)^2$ γ(h): semivariance between x_i and x_i+h h: distance between x_i and x_i+h N(h): number of data pairs with distance h Z(x_i): measurement value at point x_i Z(x_i+h): measurement value at point x_i+h  From: www.spatialanalysisonline.com Above figure shows the fitting of a theoretical variogram curve to the empirical variogram points. Descriptive properties are: (1) sill (variance of measurement values), (2) range (over which the interpolation can be meaningfully performed) and (3) nugget effect (small-scale variation from heterogeneities). M.-T. Schafmeister(1999): Geostatistik für die hydrogeologische Praxis, 172 S. Webster &. Oliver (2007²): Geostatistics for Environmental

	Scientists. Chichester. Stein (1999): Interpolation of Spatial Data: some theory for kriging. New York.
Useful for (parameter, time resolution)	Geo-referenced point information; applicable to various physical–chemical parameters: temperature, pH, electrical conductivity, water components.
Requirements for application	Sufficient sample size (also outside of region of interest, for interpolating boundary regions).
Result/interpretation	The semivariogram delivers information about the spatial relation of measurement points. By utilizing search ellipses in space you can perform an analysis of spatial directions (anisotropy).
Assessment	Prior knowledge about the form of the spatial distribution of a variable can be used in the method; this optimizes the estimation and yields minimal estimation variances. You can take into account spatial anisotropies.
Example/publication	The figure below shows regional distributions of contaminants (so-called contaminant plumes) on basis of a measurement grid (left panel) and an "ordinary" irregular grid (right panel).  BENDER, S. (2007): Die Aussageunschärfe bei der Verwendung heterogener Datensätze im Rahmen wasserwirtschaftlicher Fragestellungen. – Bochumer Geowissenschaftliche Arbeiten, Heft 8, 99 S.
Contact/project	Steffen Bender Helmholtz-Zentrum Geesthacht, Climate Service Center Steffen.Bender@hzg.de, Andreas Kochanowski Andreas_kochanowski@gmx.de
Software	Surfer (Golden Software, http://www.goldensoftware.com)

5.6.2.6 *Thiessen Polygons*

Superordinate objective (category)	**Regionalisation** (Interpolation)
Method	Thiessen polygons (also named after Voronoi or Dirichlet)
Description + literature	Simple interpolation method to plot geo-referenced measurement data. The basic assumption is that data values agree the stronger with each other the closer their measurement points are located. The full area is tesselated into polygon regions containing one measurement point by means of a construction via the perpendicular bisectors. All locations within a constructed polygon are closer to the corresponding measurement point than to any other measurement point. $P = 1 / A_T \cdot \sum A_i P_i$  A_i: area of a Thiessen polygon around point i, A_T: full area size. R. Klein (2005): *Algorithmische Geometrie*, Grundlagen, Methoden, Anwendungen, Springer, 426 S.
Useful for (parameter, time resolution)	Suitable method to present spatial distributions of discrete data and nominal (yes/no) data (e.g., assigning representative areas to precipitation gauges in plain areas).
Requirements for application	Spatial measurement data. Note that variables possibly influencing measurements are not taken into account (e.g., when assigning representative areas to precipitation gauges, topographic effects are ignored).
Result/interpretation	Weighted interpolation that takes into account irregularly distributed measurement stations.
Assessment	The method does not approximate observed measurement data well. Since at the polygon boundaries there may appear considerable jumps, it is not possible to describe continuous changes.
Example/publication	The figure below shows (a) locations and values of precipitation gauges and (b) the spatial distribution of precipitation estimated by means of Thiessen polygons (Mair and Fares 2011).

	 Mair, A. and Fares, A. (2011): Comparison of Rainfall Interpolation Methods in a Mountainous Region of a Tropical Island. – Journal of Hydrologic Engineering, 371–383.
Contact/project	Steffen Bender Helmholtz-Zentrum Geesthacht, Climate Service Center Steffen.Bender@hzg.de
Software	Surfer (Golden Software, http://www.goldensoftware.com)

5.7 *Extreme value analysis*

Consider that you are interested in the extremely large values of a climate time series simulated by a climate model. In principle, you may select these extremes in two ways. One is to take from a certain block of time the maximum and then analyse all block maxima (Section 5.7.1.1). The other way is to set a threshold and then analyse all peaks above that threshold. Section 5.7.1.2 explains the peaks over threshold (POT) approach for the case of a time-constant threshold, while Section 5.7.1.3 allows for a time-dependent threshold, a case that should also be considered in the analysis of nonstationary climate processes.

Block maxima follow, under some mathematical assumptions, a Generalized Extreme Value (GEV) distribution, while peaks-over-threshold (POT) data follow, under similar mathematical assumptions, a Generalized Pareto distribution.

Evidently, the same analytical machinery may also be applied to analysing extremely small values of a climate series, for example, when you are interested not in heavy rainfall events but in droughts.

The majority of papers on climate extremes tend to focus on block maxima and the GEV distribution, and also the presented methods (Sections 5.7.2 and 5.7.4) follow that tendency. However, there are also examples on the POT approach (Sections 5.7.3).

In the context of climate change, it is important to move from stationary to nonstationary (time-dependent) statistical models, since with climate changes also the risk of extremes may be associated. Nonstationary extreme value analysis with time-dependent parameters of the GEV distribution is illustrated in Section 5.7.4.2. A robust alternative to the nonstationary GEV model is the description via an inhomogeneous Poisson point process (Section 5.7.4.3).

A covariate, Y, bears information about the extremal part of the climate variable of interest, X. Simulating Y by means of a climate model can thus improve risk analysis on variable X (Section 5.7.4.6). Of high socioeconomical relevance are joint occurrences of extremes in two or more variables (e.g., high coastal water level and strong winds), which are mathematically–theoretically difficult to analyse: copulas (Section 5.7.4.4) may be one option to proceed here.

Further reading. A short and readable book (Coles 2001) treats the GEV and the Generalized Pareto distributions, their fitting to data and diagnostic plots; it also studies the nonstationary model variants. Theoretical concepts are described with mathematical rigour by Leadbetter et al. (1983) and Embrechts et al. (1997). Chapter 6 in the book by Mudelsee (2010) deals with stationary and nonstationary extreme value analysis; it covers also the Poisson point process estimation from a practical, analytical standpoint and gives examples.

Coles S (2001) An Introduction to Statistical Modeling of Extreme Values. Springer, London, 208 pp.

Embrechts P, Klüppelberg C, Mikosch T (1997) Modelling Extremal Events for Insurance and Finance. Springer, Berlin, 648 pp.

Leadbetter MR, Lindgren G, Rootzén H (1983) Extremes and Related Properties of Random Sequences and Processes. Springer, New York, 336 pp.

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht, 474 pp.

5.7.1 Selection method

5.7.1.1 Block maxima

Superordinate objective (category)	**Extreme value analysis**
Method	Block Maxima
Description + literature	Method for the selection of a sample for the extreme value analysis of time series. The method takes maximum values (e.g. years, months or weeks) from defined time intervals (blocks) and combines these values to a sample. To the sample different extreme value distributions can be fitted like e.g. the generalized extreme value distribution (GEV), Log-Normal-, Gumbel- or Weibull distribution function. The Approach can be extended when taking into account multiple (r-) maximum values within one interval (block). References (selection): *Embrechts, P., Klüppelberg, C. & Mikosch, T. (1997). Modelling Extremal Events. Vol. 33 of Applications in Mathematics. Springer-Verlag, New York.* *Coles, S. (2001). An Introduction to Statistical Modelling of Extreme Values. Springer Series in Statistics. Springer Verlag, London, 2001, 208p.* *Soukissian, T.H., Kalantzi, G. (2009). A new method for applying the r-largest maxima model for design sea-state prediction. International Journal of Offshore and Polar Engineering, Vol. 19, No. 3, September 2009, ISSN 1053-5381, 176–182.*
Useful for (parameter, time resolution)	All parameters with constant temporal resolution. Longer time series allow using longer time intervals (less blocks) for determining the maxima like e.g. annual maxima. For shorter time series, it is recommended to use shorter time intervals (more blocks) like e.g. monthly maxima.
Requirements for application	Homogeneity, independence and representativeness of the data
Result/interpretation	Sample for extreme value analysis
Assessment	The fitting of the extreme value distribution function to the sample depends on the size of the used time interval (block) and the number of maxima of each block (e.g. total maxima or r-largest maxima). One the one hand side, the uncertainty of the parameter estimation for the fitting is lower when using smaller time intervals (blocks) and a larger number of sample elements. But on the other hand side, the probability of specific extreme values can be over- or underestimated because some values of the sample might not be extreme values. Moreover one has to ensure that the elements of the sample are independent from each other, especially when using multiple (r-) maxima. Taking this into account, a minimum time period between to maxima can be defined within the selection procedure.
Example/publication	Annual maxima of water levels in the literature correspond per definition to block maxima, see e.g.

	Deutsches Gewässerkundliches Jahrbuch (DGJ), Küstengebiet der Nordsee, Landesamt für Natur und Umwelt Schleswig-Holstein, Flintbek, ISSN 0340-5184. (in German only) *Deutsches Gewässerkundliches Jahrbuch (DGJ), Küstengebiet der Ostsee, Landesamt für Umwelt, Naturschutz und Geologie Mecklenburg-Vorpommern, Güstrow, ISSN 1434-2448.* Further examples and analysis from financial economics can be found in: *Woeste B. (2010). Eine Anwendung der Block Maxima Methode im Risikomanagement. Diplomarbeit, Mathematisches Institut für Statistik, Fachbereich Mathematik und Informatik, Westfälische Wilhelms-Universität Münster. (in German only)*
Contact/project	Dörte Salecker & Norman Dreier, Hamburg Technical University, Institute of River and Coastal Engineering doerte.salecker@tuhh.de , norman.dreier@tuhh.de

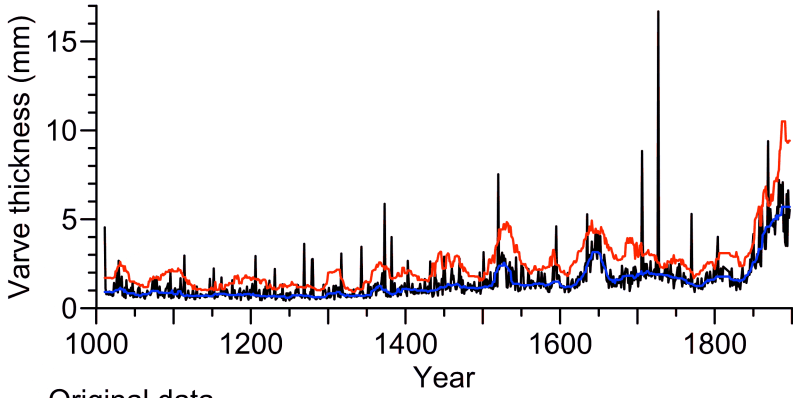
5.7.1.2 Peaks over threshold

Superordinate objective (category)	Extreme value analysis
Method	Peak over threshold (POT)
Description + literature	Method for the selection of a sample for extreme value analysis. The method takes maxima above a given threshold. The definition of the threshold depends on the problem analysed. Options to determine suitable thresholds are for example the mean excess plot or the Kolmogorov–Smirnov test (section 5.5.4). To the obtained sample, different extreme value distributions like e.g. the Generalized Pareto- (GPD), Log-Normal-, Gumber- or Weibull distribution can be fitted. References (Selection): *Embrechts, P., Klüppelberg, C. & Mikosch, T. (1997). Modelling Extremal Events. Vol. 33 of Applications in Mathematics. Springer-Verlag, New York.* *Coles, S. (2001.) An Introduction to Statistical Modelling of Extreme Values. Springer Series in Statistics. Springer Verlag, London, 2001, 208p*
Useful for (parameter, time resolution)	All parameters at constant temporal resolution
Requirements for application	Homogeneity, independence and representativeness of the data
Result/interpretation	Sample for extreme value analysis
Assessment	The challenge of the POT method consists in selecting the threshold. This corresponds to the challenge in selecting the time interval of the block-maxima method. Also for the POT method it is important to have an independent sample; for achieving this, you can additionally invoke a minimum time span between taken extreme events or a lower threshold.
Example/publication	An example for the utilization of the method for extreme value analysis of water levels can be found in section 5.7.4.5 Generalized Pareto Distribution (GPD). Defining POT events on sea-state data has been done by: *Kuratorium für Forschung im Küsteningenieurwesen (2002): Die Küste - EAK 2002: Empfehlungen für die Ausführung von Küstenschutzwerken, Bd. 65, Westholsteinische Verlagsanstalt Boyens und Co., Heide i. Holstein. S. 283.* *Van Vledder, G., Goda, Y., Hawkes, P. J., Mansard, E., Martin, M. J., Mathiesen, M., Peltier, E. and Thompson, E. 1993. A case study of extreme wave analysis: a comparative analysis. WAVES'93, pp. 978-992.* *Piscopia, R., Inghilesi, R., Panizzo, A., Corsini, S. and Franco, L. (2002): Analysis of 12-year wave measurements by the italian wave network. In: Smith, J. Mckee. COASTAL ENGINEERING 2002: Solving Coastal Conundrums. Proceedings of the 28th International Conference, Cardiff, Wales, July 2002, pp 121-133.*
Contact/project	Dörte Salecker & Norman Dreier, Hamburg Technical University,

	Institute of River and Coastal Engineering doerte.salecker@tuhh.de , norman.dreier@tuhh.de

5.7.1.3 Nonstationary peaks over threshold

Superordinate objective (category)	**Extreme value analysis**
Method	Nonstationary peaks over threshold
Description + literature	Selecting extremes in climatology may sometimes be done more realistically by allowing for a time-dependent "background," on which a time-dependent variability acts. This nonstationary situation leads then naturally to a time-dependent threshold, in contrast to a stationary situation with a constant threshold (Section 5.7.1.2). The method should perform the estimation of the time-dependent background in a robust manner, that is, unaffected by the presence of the assumed extremes. Therefore you use the running median (calculated over the points inside a running window) for nonparametric background or trend estimation, and not the running mean. Analogously, you use the running median of absolute distances to the median (MAD), and not the running standard deviation for variability estimation. Cross-validation techniques offer a guide for selecting the number of window points by optimizing the tradeoff between bias and variance. *Mudelsee M (2006) CLIM-X-DETECT: A Fortran 90 program for robust detection of extremes against a time-dependent background in climate records. Computers and Geosciences 32:141–144.*
Useful for (parameter, time resolution)	All parameters at any temporal resolution. Note that high time resolution may result in a strong autocorrelation, which has to be considered in the selection of the number of window points (i.e., more window points have to be used compared to an autocorrelation-free situation).
Requirements for application	Homogeneity and representativeness of the data. In the case of autocorrelated data, the cross-validation guideline may be less informative and other numbers of window points have to be tried.
Result/interpretation	Sample for extreme value analysis (Generalized Pareto distribution, inhomogeneous Poisson process)
Assessment	The challenge of the nonstationary POT method consists in selecting the threshold and the number of window points. Cross-validation guides may help, but it is mandatory to "play" with the data and study the sensitivity of the results in dependence of the selected analysis parameters (threshold, number of window points).

<table>
<tr>
<td>Example/publication</td>
<td>


— Original data
— Running median (17 window points)
— Running median + 5.2 x running MAD (17 window points)
[figure modified after Mudelsee (2010: Fig. 4.17);
see also Besonen et al. (2008)]

The original paper (Mudelsee 2006) explains the method and describes the Fortran 90 software CLIM-X-DETECT. This analysis type has been applied to a number of climate change analyses, for example, on observed and modelled wildfires 1769–2100 (Girardin and Mudelsee 2008) or hurricane proxy data 1000–1900 from a lake sediment core (Besonen et al. 2008).

Besonen MR, Bradley RS, Mudelsee M, Abbott MB, Francus P (2008) A 1,000-year, annually-resolved record of hurricane activity from Boston, Massachusetts. Geophysical Research Letters 35:L14705 (doi:10.1029/2008GL033950).

Girardin MP, Mudelsee M (2008) Past and future changes in Canadian boreal wildfire activity. Ecological Applications 18:391–406.

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht, 474 pp.
</td>
</tr>
<tr>
<td>Contact/project</td>
<td>Manfred Mudelsee
Climate Risk Analysis, Hannover, Germany;
mudelsee@climate-risk-analyis.com
www.climate-risk-analysis.com</td>
</tr>
</table>

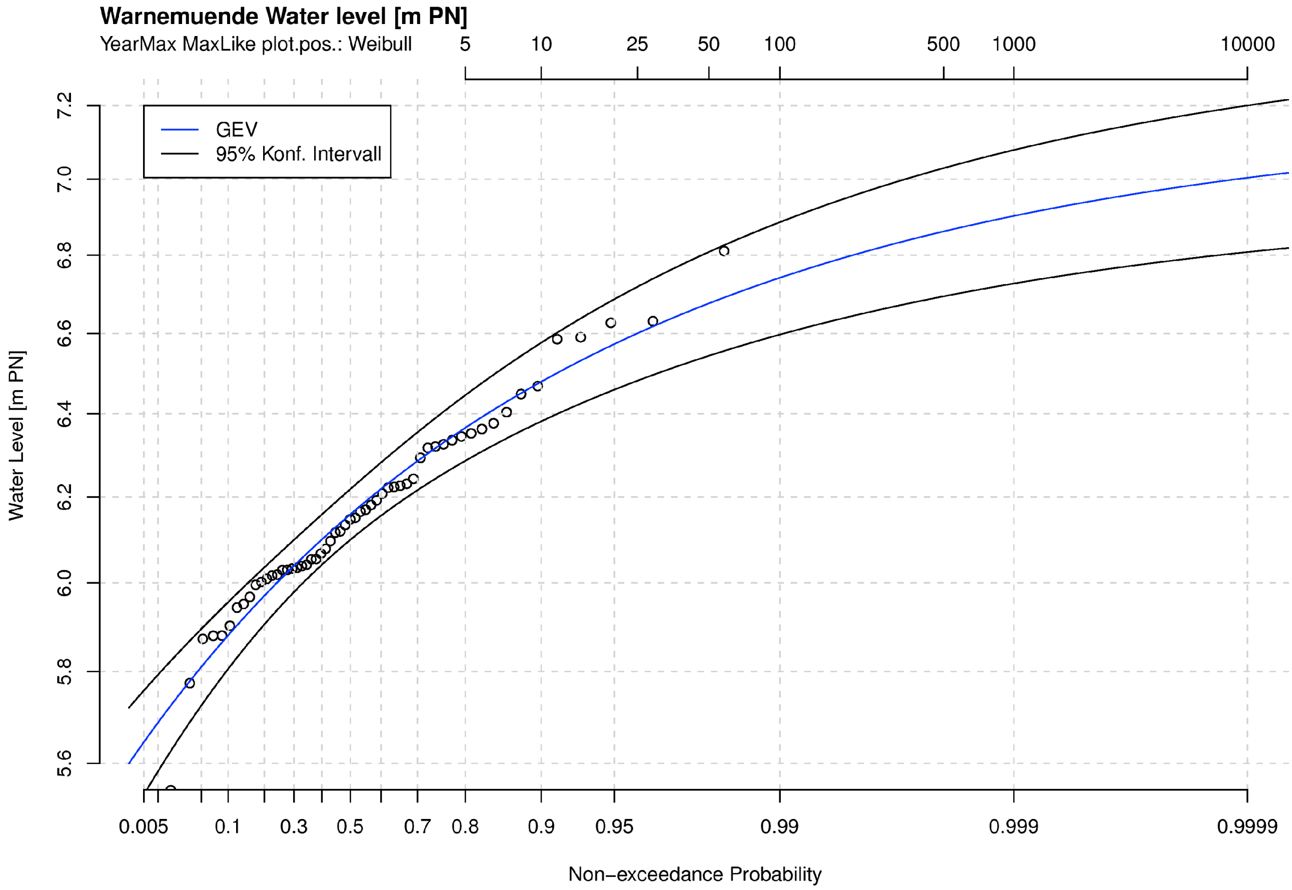
5.7.2 *Parameter estimation*

5.7.2.1 *Fitting statistical extreme value distributions by means of maximum likelihood or the method of moments*

Superordinate objective (category)	**Extreme value analysis**
Method	Fitting statistical extreme value distributions by means of maximum likelihood or the method of moments
Description + literature	Estimation of the distribution parameters of e.g. Generalized Extreme Value (GEV)-, Log-Normal-, Gumbel or Weibull distribution from a sample (see section 5.7.1.1 and 5.7.1.2 selection Methods). *Method of moments:* The moments of the sample are equalised to the moments of the distribution function of interest. After transformation of the equation the estimation parameters of the distribution can be calculated. *Maximum likelihood method:* After setting up the likelihood respectively the log-likelihood function of the distribution function of interest, the first derivative of the estimation parameter is calculated and set equal to zero so that the maxima of the likelihood function can be calculated (first derivative test). Other methods for the estimation of distribution parameters are e.g. the method of probability weighted moments (PWM) or L-moments (LM). References (Selection): *Kuratorium für Forschung im Küsteningenieurwesen (2002): Die Küste - EAK 2002: Empfehlungen für die Ausführung von Küstenschutzwerken, Bd. 65, Westholsteinische Verlagsanstalt Boyens und Co., Heide i. Holstein. S. 285-291.* *Coles, S. (2001). An Introduction to Statistical Modelling of Extreme Values. Springer Series in Statistics. Springer Verlag, London, 2001, 208p.* *Plate E.-J.: Statistik und angewandete Wahrscheinlichkeitslehre für Bauingenieure, Ernst & Sohn Verlag für Architektur und technische Wissenschaften, Berlin, 1993, ISBN 3-433-01073-0, S.20-22.* *Carter, D. J. T. & Challenor, P.G. Methods of Fitting the Fisher-Tippett Type 1 Extreme Value Distribution, Ocean Engineering (10), 1983, 191-199.*
Useful for (parameter, time resolution)	Sample of extreme values, which have previously been determined by means of a selection method (see section 5.7.1 Selection Methods).
Requirements for application	Homogeneity, independence and representativeness of the data
Result/interpretation	Estimated parameters of the distribution function of interest

<table>
<tr><td>Assessment</td><td>The method of moments yields reliable estimates for distribution parameters, but it may lead for small sample sizes and skewed distributions to large estimation errors (e.g. bias).
The maximum likelihood method yields small estimation errors of the distribution function. Often the calculation has to be performed numerically.</td></tr>
<tr><td colspan="2">Example/publication:

Fitting of the Generalized Extreme Value (GEV) distribution (plotted with blue solid line) to a sample of annual block maxima of water levels (reference level null, near Warnemünde) using the maximum likelihood method for parameter estimation of the GEV distribution. Moreover the upper and lower 0.95 confidence level are calculated (plotted with black solid lines).



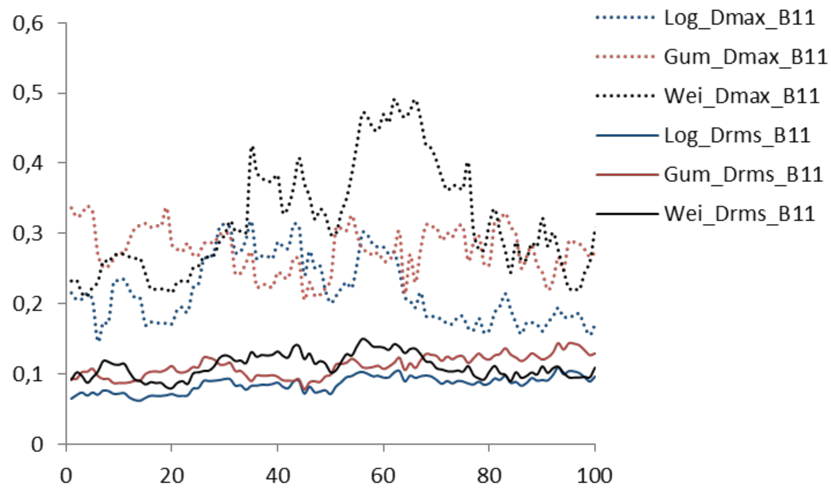
</td></tr>
<tr><td>Contact/project</td><td>Dörte Salecker & Norman Dreier, Hamburg Technical University, Institute of River and Coastal Engineering
doerte.salecker@tuhh.de , norman.dreier@tuhh.de</td></tr>
</table>

5.7.2.2 R-largest combined with a GEV

Superordinate objective (category)	**Extreme value analysis** analysis of storm-surge water levels
Method	R-largest combined with a Generalized Extreme Value (GEV) distribution
Description + literature	Application of GEV on R data points from a block
Useful for (parameter, time resolution)	No restrictions
Requirements for application	(1) Independence of events, (2) the number (R) of maxima per block has to be predefined.
Result/interpretation	
Assessment	Straightforward application, no threshold has to be predefined.
Example/publication	*Smith, Richard L.: Extreme value theory based on the r largest annual events, Journal of Hydrology 86(1-2), 27–43, 1986* *Katz, Richard W, Parlange, Marc B, and Naveau, Philippe: Statistics of extremes in hydrology, Advances in Water Resources 25(8-12), 1287–1304, 2002* *Soares, C. G., and Scotto, M. G.: Application of the r largest-order statistics for long-term predictions of significant wave height, Coastal Engineering 51(5-6), 387–394, 2004*
Contact/project	Ulf Gräwe Leibniz Institute for Baltic Sea Research Warnemuende ulf.graewe@io-warnemuende.de KLIMZUG project RADOST

5.7.2.3 Goodness of fit between the empirical and theoretical extreme value distribution (modified Kolmogorov-Smirnov-Lilliefors test)

Superordinate objective (category)	**Extreme value analysis**
Method	Lilliefors test (modified K-S test) for the assessment of the goodness of fit between the empirical and theoretical extreme value distribution
Description + literature	The concept of the Lilliefors test is based on a modified K-S test (see 5.5.4 Kolmogorov-Smirnov test). It can be used in hypothesis testing to answer the question if the sample can be represented trough a fitted extreme value distribution to a certain error level. For the comparison of the test statistic, a critical modified value (KS_{crit}, which depends on the significance level, error level, the number of elements and the shape parameter of the distribution) is used that can be obtained from Monte Carlo methods. For large difference values ($D>KS_{crit}$) the null hypothesis, that the empirical distribution function corresponds to the extreme value distribution function, is rejected and the data cannot be represented by the extreme value distribution. Here the Lilliefors test is used to assess of the goodness of fit between the empirical distribution function (EDF) and different theoretical extreme value distributions (EVDs). For this purpose, difference values (e.g. the largest difference D_{max} or the root mean square difference D_{rms}) are calculated between the EDF and the fitted EVDs (e.g. Log-Normal, Gumbel and Weibull distribution). The EVD with the smallest D value is assessed to be the best estimator for the sample. $D_{max} = \max_x \lvert F_n(x) - F(x) \rvert \quad D_{rms} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(F_n(x) - F(x)\right)^2}$ $F_n(x)$: empirical distribution function (EDF) $F_n\left(x_{(i)}\right) = i/n \qquad i = 1,2,\dots,n$ i: index of list of sorted elements from lowest value to highest value n: total number of elements F(x): theoretical, extreme value distribution function (EVD) References (Selection): *Chu, Pao-Shin, Jianxin Wang, 1998: Modeling Return Periods of Tropical Cyclone Intensities in the Vicinity of Hawaii*. J. Appl. Meteor., 37, 951–960. doi: http://dx.doi.org/10.1175/1520-0450(1998)037<0951:MRPOTC>2.0.CO;2* *Wilks, Daniel S. Statistical methods in the atmospheric sciences / 3rd ed. (International geophysics series; v. 100). Academic Press, Elsevier, 2011, 151-154*

	Lilliefors Test. In: Encyclopedia of Statistical Sciences. John Wiley & Sons, 2006, doi:10.1002/0471667196.ess1451.pub2
Useful for (parameter, time resolution)	Any parameter at any time resolution, e.g. sea-state parameters (wave heights) or meteorological parameters (wind velocities)
Requirements for application	Sample with independent extreme values (see Section 5.7.1 Selection Methods) and fitted EVD (see Section 5.7.2 Parameter Estimation)
Result/interpretation	Difference values D_{rms} or D_{max} for the assessment of the goodness of fit of different theoretical EVDs to the sample. The smallest difference value characterises the best fitting EVD.
Assessment	Simple and fast forward method for the assessment of the goodness of fit of different EVDs to the sample.
Example/publication	Assessment of goodness of fit from 40 years moving extreme value analysis of time series of calculated wave heights (for the first realisation of actual climate C20 and future IPCC emission scenario B1 based on the regional climate model Cosmo-CLM) consisting of 3 steps per each year from 2001 to 2100. (1) Selection of sample consisting of 40 elements from calculated annual maximum wave heights (the number of the sample/year is plotted on the bottom axis) (2) Fitting of different EVDs (Log-Normal, Gumbel, Weibull distribution) to the selected sample (3) Calculation of difference values D_{rms} resp. D_{max} (plotted on the left axis with solid resp. dotted lines)  Interpretation of Results: For the overall assessment the Log-Normal extreme value distribution (see blue line) has the smallest difference values D_{rms} resp. D_{max} in most of the comparisons within the time period of 100 years, thus the distribution it is best fitted to the EDF.
Contact/project	Norman Dreier, Hamburg Technical University, Institute of River and Coastal Engineering, norman.dreier@tuhh.de Zhen-shan Xu, College of Harbor, Coastal and Offshore Engineering, Hohai University, Nanjing, P.R. China, xuzhenshanhhu@gmail.com

5.7.3 Empirical Methods

5.7.3.1 Exceedance probability and return period

Superordinate objective (category)	**Extreme value analysis** single extreme events
Method	Determination of the exceedance probability and return period, respectively, of high and low flow in watercourses
Description + literature	Statistics of flood events: Ermittlung von Hochwasserwahrscheinlichkeiten (August 2012); DWA-M 552 (2012), Statistische Analyse von Hochwasserabflüssen; DVWK Merkblatt 251 (1999), Empfehlung zur Berechnung der Hochwasserwahrscheinlichkeit, DVWK-Regel 101 (1976), DVWK Regel 121/1992: Niedrigwasseranalyse Statistics of precipitation: ATV 121 1985: Starkniederschlagshöhen für Deutschland
Useful for (parameter, time resolution)	Extreme values of high and low runoff at preferably high temporal resolution, precipitation events at varying durations
Requirements for application	Independence of events (exceedances of a threshold); high temporal resolution (less than 1 hour) of precipitation series for peak-runoff simulations; sufficient amount of extreme events over a preferably long time span.
Result/interpretation	Comparison of exceedance probabilities and return periods, respectively, of high- and low-runoff events for the climate scenarios; determination of temporal trends in flood occurrence
Assessment	Established standard method for calculating flood probabilities; allows reference to other projects; simple method, well tested in practice.
Example/publication	*Wasserbauschrift Band 13: S. Hellmers: Hydrological Impacts of Climate Change on Flood Probability in Small Urban Catchments and Possibilities of Flood Risk Mitigation, 2010 (Ebook) ISBN 978-3-937693-13-2*
Contact/project	Sandra Hellmers, Hamburg Technical University, Institute of River and Coastal Engineering,s.hellmers@tuhh.de KLIMZUG NORD

5.7.3.2 Threshold statistics, empirical exceedance probabilities

Superordinate objective (category)	**Extreme value analysis**
Method	Threshold statistics, empirical exceedance probabilities
Description + literature	For predefined thresholds, you calculate for a time interval (e.g., 1961–1990, 2021–2050, 2071–2100) the relative frequency (empirical probability) that it is reached or exceeded. Subsequently you can compare different time intervals with respect to the exceedance probability.
Useful for (parameter, time resolution)	Various climate parameters such as precipitation, temperature and wind as well as derived indexes such as dry periods; used for daily data (in principal, other temporal resolutions can be sused, such as hour or minute)
Requirements for application	No special restrictions since distribution-free method
Result/interpretation	Visualization of changes in the data distribution and in the probability of extremes
Assessment	Simple empirical method (not computing-intensive), especially in view of the considerable uncertainty of the climate projections and their deficits in reflecting the observed frequency distributions
Example/publication	*Bernhofer et al. (2009, 2011)*
Contact/project	Johannes Franke (TU Dresden), Stephanie Hänsel (TU BA Freiberg) johannes.franke@tu-dresden stephanie.haensel@ioez.tu-freiberg.de KLIMZUG project: REGKLAM

Bernhofer C, Matschullat M, Bobeth A (Hrsg. 2011): Klimaprojektionen für die REGKLAM-Modellregion Dresden. Publikationsreihe des BMBF-geförderten Projektes REGKLAM – regionales Klimaanpassungsprogramm für die Modellregion Dresden, Heft 2, Rhombos-Verlag Dresden

Bernhofer C, Matschullat M, Bobeth A (Hrsg. 2009): Das Klima in der REGKLAM-Modellregion Dresden. Publikationsreihe des BMBF-geförderten Projektes REGKLAM – regionales Klimaanpassungsprogramm für die Modellregion Dresden, Heft 1, Rhombos-Verlag Dresden

5.7.4 Extreme value analysis methods

5.7.4.1 Extreme value analysis with a Generalized Extreme Value (GEV) distribution

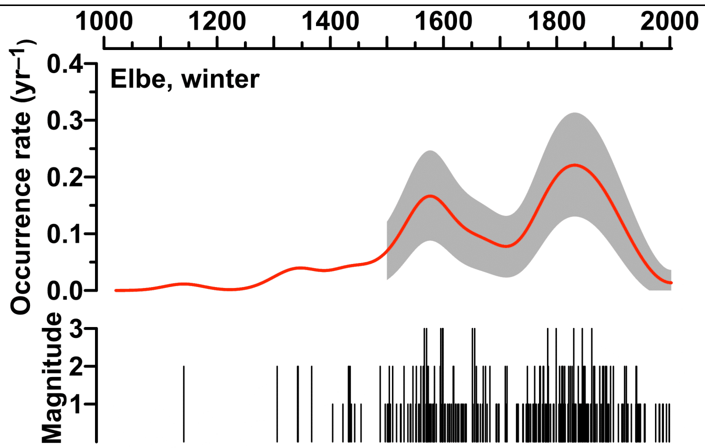
Superordinate objective (category)	**Extreme value analysis**
Method	Extreme value analysis with Generalized Extreme Value (GEV) distribution
Description + literature	Determination of exceedance probabilities of extreme values (univariate method)
Useful for (parameter, time resolution)	Monthly/annual maxima and minima, respectively; historical extreme events
Requirements for application	Stationary time series (possibly after correction for trend), independent data
Result/interpretation	Result is a univariate probability density function, which allows to determine the probability that an extreme event occurs.
Assessment	It is important that data (possibly after a transformation) stem from a stationary process In the presence of strong temporal trends the meaning of results is limited.
Example/publication	*Mudersbach, Ch. and Jensen, J. (2009): Extremwertstatistische Analyse von historischen, beobachteten und modellierten Wasserständen an der Deutschen Ostseeküste, Die Küste, Heft 75, Sonderheft MUSTOK, S. 131-162, Boyens Medien GmbH, Heide i. Holstein* *Mudersbach, Ch. and Jensen, J. (2010): Non-stationary extreme value analysis of annual maximum water levels for designing coastal structures on the German North Sea coastline, Journal of Flood Risk Management , Vol. 3., Issue 1, pp. 52-62, DOI:10.1111/j.1753-318X.2009.01054.x*
Contact/project	Christoph Mudersbach Universität Siegen Forschungsinstitut Wasser und Umwelt christoph.mudersbach@uni-siegen.de

5.7.4.2 Nonstationary extreme value analysis with a Generalized Extreme Value (GEV) distribution

Superordinate objective (category)	**Extreme value analysis**
Method	Nonstationary extreme value analysis with Generalized Extreme Value (GEV) distribution
Description + literature	Determination of temporal trends in exceedance probabilities of extreme values (univariate method)
Useful for (parameter, time resolution)	Maxima and minima, respectively, from observation periods (e.g., months or years) that exhibit a trend
Requirements for application	Independent data
Result/interpretation	Result is a time-dependent univariate probability density function, which allows to determine the probability that an extreme event occurs. Interpretation requires therefore to report the time dependence.
Assessment	Method yields for data with trends meaningful results on the time dependence of occurrence probabilities. The underlying trend model (e.g., linear, exponential) has to be tested for suitability.
Example/publication	*Mudersbach, Ch. and Jensen, J. (2010): Non-stationary extreme value analysis of annual maximum water levels for designing coastal structures on the German North Sea coastline, Journal of Flood Risk Management , Vol. 3., Issue 1, pp. 52-62, DOI:10.1111/j.1753-318X.2009.01054.x*
Contact/project	Christoph Mudersbach Universität Siegen Forschungsinstitut Wasser und Umwelt christoph.mudersbach@uni-siegen.de

5.7.4.3 Nonstationary extreme value analysis on basis of an inhomogeneous Poisson point process

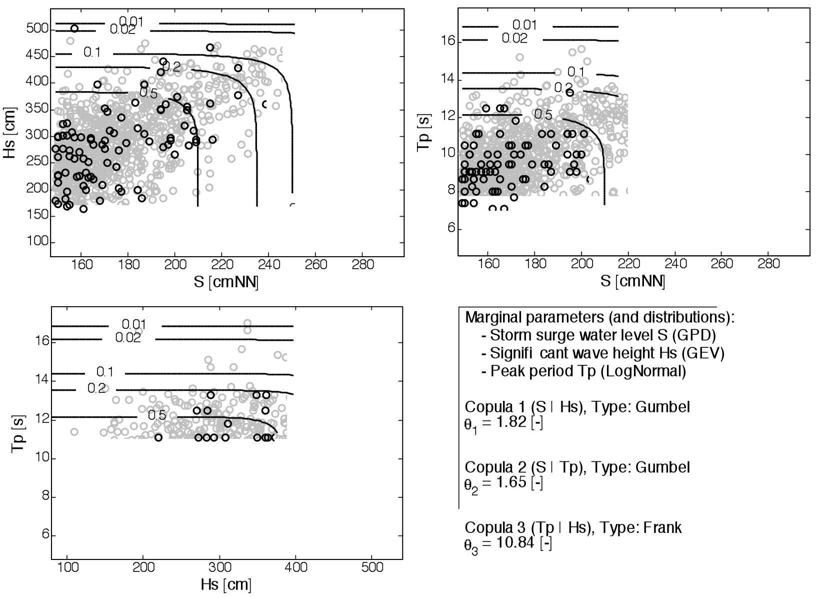
Superordinate objective (category)	**Extreme value analysis**
Method	Nonstationary extreme value analysis on basis of an inhomogeneous Poisson point process
Description + literature	The occurrence of an extreme event is described by a stochastic Poisson point process. The estimation target is the intensity or occurrence rate, which is given by the number of events per time unit. An inhomegeous Poisson process has a time-dependent occurrence rate. The estimation is performed using kernel estimation (smoothing), a cross-validation guideline exists for the selection of the kernel smoothing bandwidth. Boundary effects are reduced by means of generating pseudodata. Pointwise confidence bands are constructed by means of bootstrap resampling. Cowling A, Hall P, Phillips MJ (1996) Bootstrap confidence regions for the intensity of a Poisson point process. Journal of the American Statistical Association 91:1516–1524.
Useful for (parameter, time resolution)	Any parameter at any time resolution. You can analyse three data types: (1) time series on which a time-dependent threshold is applied to yield POT data, (2) existing POT data and (3) a set of the times when an event occurred. The latter option makes this method applicable also to historical documentary records, where often only the date of an event is recorded, but not its size.
Requirements for application	Independent event dates.
Result/interpretation	Result is the time-dependent occurrence rate of extremes with confidence band. This allows to assess the statistical significance of highs and lows in climate risk. The occurrence rate may be further compared with other records to assess, for example, the role of global warming for the occurrence of hurricanes or heavy floods.
Assessment	A robust, nonparametric method, for which no functional form of the time-dependence has to be prescribed.
Example/publication	The method has been introduced to flood risk analysis by Mudelsee et al. (2003, 2004). It has been subsequently applied to several types of extreme events, such as hurricanes (Besonen et al. 2008), soil erosion events (Fleitmann et al. 2007) and wildfires (Girardin and Mudelsee 2008).

	 Floods, river Elbe, winter; lower panel: event dates (3 magnitude classes); upper panel: occurrence rate (red line) of heavy floods (classes 2–3) with 90% confidence band (grey shading), constructed by means of a Gaussian kernel (35 year bandwidth) and 2000 bootstrap simulations. [modified after Mudelsee et al. (2003)] *Besonen MR, Bradley RS, Mudelsee M, Abbott MB, Francus P (2008) A 1,000-year, annually-resolved record of hurricane activity from Boston, Massachusetts. Geophysical Research Letters 35:L14705 (doi:10.1029/2008GL033950).* *Fleitmann D, Dunbar RB, McCulloch M, Mudelsee M, Vuille M, McClanahan TR, Cole JE, Eggins S (2007) East African soil erosion recorded in a 300 year old coral colony from Kenya. Geophysical Research Letters 34:L04401 (doi:10.1029/2006GL028525).* *Girardin MP, Mudelsee M (2008) Past and future changes in Canadian boreal wildfire activity. Ecological Applications 18:391–406.* Mudelsee M, Börngen M, Tetzlaff G, Grünewald U (2003) No upward trends in the occurrence of extreme floods in central Europe. Nature 425:166–169. Mudelsee M, Börngen M, Tetzlaff G, Grünewald U (2004) Extreme floods in central Europe over the past 500 years: Role of cyclone pathway “Zugstrasse Vb”. Journal of Geophysical Research 109:D23101 (doi:10.1029/2004JD005034).
Contact/project Software	Manfred Mudelsee Climate Risk Analysis, Hannover, Germany; mudelsee@climate-risk-analyis.com www.climate-risk-analysis.com Caliza (TM), Climate Risk Analysis, Hannover, Germany, www.climate-risk-analysis.com/software/caliza

5.7.4.4 Multivariate extreme value analysis with Archimedian copulas

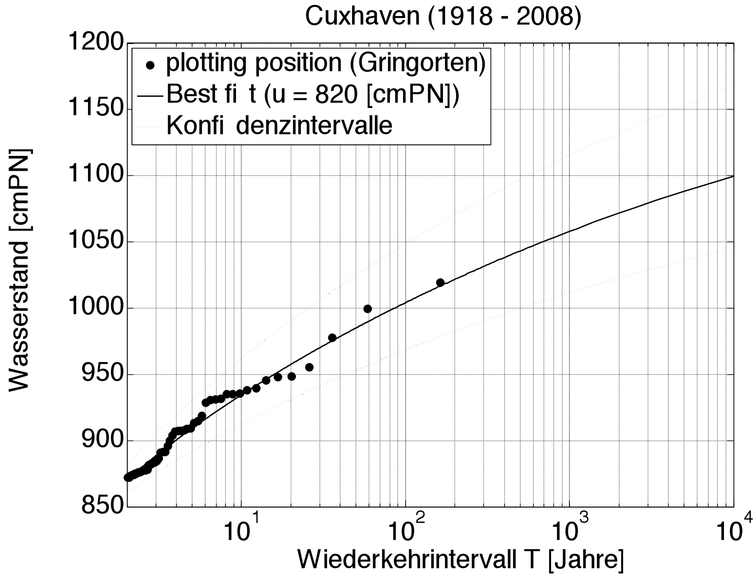
Superordinate objective (category)	**Extreme value analysis**
Method	Multivariate extreme value analysis with Archimedean copulas
Description + literature	The copula function (Sklar, 1959), denoted as C, describes the relation between a bivariate probability distribution, $F_{XY}(x,y)$, and the univariate marginal distributions, $F_X(x)$ and $F_Y(y)$, as follows: $$F_{X,Y}(x,y) = C[F_X(x), F_Y(y)].$$ Further information can be found in the work by Nelsen (1999), Genest and Favre (2007) and Wahl et al. (2012), and in the references cited therein. In analogy to the application of univariate statistical methods, there exist various copula families. In hydrology, and other research fields as well, you often employ Archimedean copulas, since these are rather flexible tools and relatively easy to construct. You can take into account asymmetries in the dependence structures of the examined variables. The copulas are constructed by means of the copula generator, φ(t), with the following relation between the generator, φ(t), and the parameter θ: $$C_\theta(u,v) = \varphi^{-1}[\varphi(u) + \varphi(v)].$$ *Genest, C. and Favre, A-C.: Everything you always wanted to know about copula modeling but were afraid to ask, J. Hydrol. Eng., 12(4), 347–368, 2007.* *Nelsen, R.B. (1999): An introduction to copulas. Lecture Notes in Statistics, 139, Springer, New York.* *Sklar, A. (1959): Fonctions de répartition à* n *dimensions et leurs marges. Publ. Inst. Statist. Univ. Paris, 8, 229–231 [cited after: Fisher, N.I. (1997) Copulas. In: Kotz, S., Read, C.B., and Banks, D.L. Encyclopedia of statistical sciences, U1, 159–163.]* *Wahl, T., Mudersbach, C., and Jensen, J.: Assessing the hydrodynamic boundary conditions for risk analyses in coastal areas: a multivariate statistical approach based on Copula functions, Nat. Hazards Earth Syst. Sci., 12, 495-510, 2012.*
Useful for (parameter, time resolution)	Any parameter at any time resolution.
Requirements for application	Sufficient data sizes to determine the univariate marginal distributions and the dependence structure (rank correlations).
Result/interpretation	Two- or higher-dimensional probability densities and associated measures (e.g., return periods).
Assessment	A useful and flexible tool for analysing multivariate data sets that comprise dependent variables with different marginal distributions.

<table>
<tr><td>Example/publication</td><td>The figure below shows the result of an analysis of storm-surge water levels, S, and the sea state variables wave height, Hs, and peak period, Tp, in the region of Westerland (Sylt, Germany). The observed data pairs are plotted as black circles, the resulting probability contours as black solid lines. Data pairs simulated by means of the copula functions (note their usefulness here) are shown as grey circles.

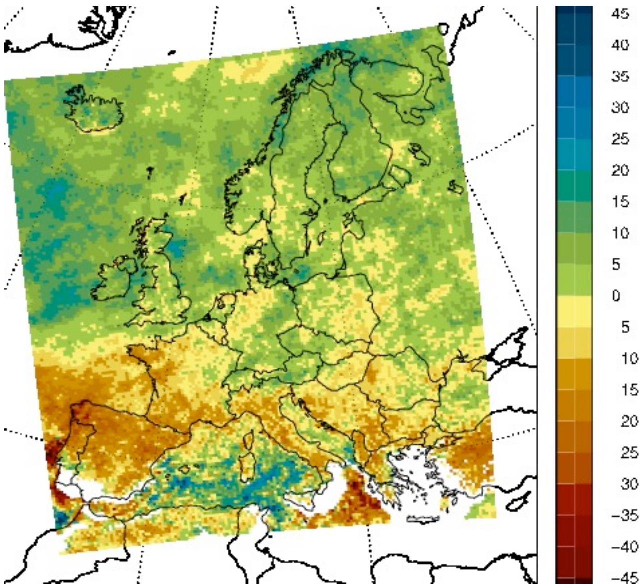

</td></tr>
<tr><td>Contact/project</td><td>Thomas Wahl & Jens Bender, Forschungsinstitut Wasser und Umwelt (fwu) und Forschungskolleg Siegen (FoKoS), Universität Siegen, thomas.wahl@uni-siegen.de, jens.bender@uni-siegen.de
BMBF- XtremRisK (www.xtremrisk.de)</td></tr>
</table>

5.7.4.5 Generalized Pareto distrubution (GPD)

Superordinate objective (category)	**Extreme value analysis**
Method	Generalized Pareto Distribution (GPD)
Description + literature	The POT method defines the data set to be further analysed via the exceedance of a threshold. The POT data set is assumed to be describable by means of the Generalized Pareto Distribution (GPD). The GPD is a distribution function with three parameters: μ (location), σ (scale) and ξ (shape); for the formula, see, for example, Coles (2001). The choice of threshold includes usually a subjective element. The paper by Arns et al. (in review) studies time series of water level along the German Bight and investigates various threshold selection strategies; the authors demonstrate that adopting as threshold the 99.7 percentile yields, in this case, the most reliable results. In addition, the analysis (Arns et al., in review) shows that consistent results can only be obtained when including into the data set the currently largest storm-surge height from 1976. Regarding other parameters and other locations, the threshold selection should, however, be further tested; for that purpose see, for example, Coles (2001) and Arns et al. (in review). Coles, S. (2001): An Introduction to Statistical Modeling of Extreme Values. Springer Verlag, London. Arns, A., Wahl, T., Haigh, I.D., Jensen, J., Pattiaratchi, C. (in review): Estimating extreme water level probabilities: a comparison of the direct methods and recommendations for best practise, sumitted to: Coastal Engineering.
Useful for (parameter, time resolution)	Any parameter (e.g., water level, wind speed or runoff).
Requirements for application	Sufficient amount of independent data, threshold selection.
Result/interpretation	GPD-derived probabilistic measures, such as return levels or return periods of the analysed variable.
Assessment	Next to the GEV-method the GPD method is a standard method for determining extreme water levels or return periods. The subjective threshold choice influences the results obtained.
Example/publication	The figure below shows the application of the POT–GPD method to a time series of water level from 1918 to 2008 at station Cuxhaven. The empirical probabilities are shown as black circles, the results from fitting a GPD are shown as black lines (best fit, solid; confidence interval bounds, dotted).

	
Contact/project	Arne Arns & Christoph Mudersbach, Forschungsinstitut Wasser und Umwelt (fwu), Universität Siegen, arne.arns@uni-siegen.de, christoph.mudersbach@uni-siegen.de

5.7.4.6 *Nonstationary extreme value analysis with covariates: peaks over threshold modelled with nonstationary Poisson process*

Superordinate objective (category)	**Extreme value analysis**
Method	Nonstationary extreme value analysis with covariates: peaks over threshold modelled with nonstationary Poisson process
Description + literature	Coles, S.: An Introduction to Statistical Modeling of Extreme Values, *Springer*, 2001, *208 pp.* Katz et al.: Statistics of extremes in hydrology, *Adv. Wat. Res.,* 2002, *25*, 1287–1304
Useful for (parameter, time resolution)	Point events that occur independently (e.g., heavy daily rainfall)
Requirements for application	Independence of events (no clustering); for analysing trends in the occurrence of extremes, the time series should be long enough (relative to the return period of the analysed events).
Result/interpretation	Temporal trends (high quantiles of, e.g., daily (high-)precipitation events)  Result: The figure shows the relative change [%] of the 99.9 % quantile of daily precipitation in a regional climate model simulation over Europe for the summer months (JJA) for 1961-2099, estimated with a non-stationary Poisson-Point-Process. While the quantiles slightly change to positive values over Northern Europe, the values over land masses in Southern Europe decrease up to 30 %.
Assessment	Following points should be considered.

	(1) Prior to the estimation, data should possibly be cleaned of “heavy-rainfall clusters” (e.g., by imposing a temporal span of one day for defining one event). This de-clustering is described by: Davison, A. C. & Smith, R. L.: Models for exceedances over high thresholds *J. R. Statist, Soc.*, 1990, *52*, 393–442 (2) At the trend analysis, the estimation uncertainty increases with the quantile level.
Example/publication	Radermacher, C. & Tomassini, L.: Thermodynamic causes for future trends in heavy precipitation over Europe based on an ensemble of regional climate model simulations, *Journal of Climate*, Early online release 2012
Contact/project	Christine Radermacher Max-Planck-Institut für Meteorologie, Hamburg, Germany christine.radermacher@zmaw.de

5.8 *Indexes*

Climate models render the elementary physical variables, such as temperature, pressure and precipitation, at certain space–time grid points. Yet the impacts of climate on the other system components (humans, agriculture, and so forth) typically depend on a subset of the grid point values, and with a degree of smoothing over space and time. Consider for example heatwaves, where the upper extremes of the temperature distribution are of interest with the additional temporal constraint of duration (Kürbis et al. 2009, Rahmstorf and Coumou, 2011).

A climate index is a way to distill the high-dimensional model output (and observations as well) into a single number. Owing to the rich variety of different impacts and the interests of climate researchers, there exists a variety of climate indexes employed in practice. We present the following: the difference in transpiration (Section 5.8.1.4), the frequency of frost days (Section 5.8.2.2) and the thermal vegetation period (Section 5.8.2.3).

Also the comparison of a climate model output and observations can be distilled into an index, which reflects the ponderance of the climate researcher's interest (i.e., which variable(s) at which space–time resolution). We show the following comparison indexes and approaches: the Nash–Sutcliffe model efficiency (Section 5.8.1), the percent bias (Section 5.8.1.5), the usage of a reference period (Section 5.8.1.2) and the skill score combined with the hit rate (Sections 5.8.1.3 and 5.8.1.4).

Further reading. An early report on climate indexes is by Easterling et al. (2003). The reports by Working Group II of the IPCC, the current (AR4) one edited by Parry et al. (2007), which deal with climate impacts, describe many indexes currently in use. Comparison indexes are presented in a book edited by Jolliffe and Stephenson (2003).

Easterling DR, Alexander LV, Mokssit A, Detemmerman V (2003) CCI/CLIVAR workshop to develop priority climate indices. Bulletin of the American Meteorological Society 84:1403–1407.

Jolliffe IT, Stephenson DB (2003) Forecast Verification: A Practitioner's Guide in Atmospheric Science. Wiley, Chichester, 240 pp.

Kürbis K, Mudelsee M, Tetzlaff G, Brázdil R (2009) Trends in extremes of temperature, dew point, and precipitation from long instrumental series from central Europe. Theoretical and Applied Climatology 98:187–195.

Parry M, Canziani O, Palutikof J, van der Linden P, Hanson C (2007) Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, 976 pp.

Rahmstorf S, Coumou D (2011) Increase of extreme events in a warming world. Proceedings of the National Academy of Sciences of the United States of America 108:17905–17909. [Correction: 109: 4708]

5.8.1 Model evaluation measures

5.8.1.1 Comparison of time series by means of the Nash–Sutcliffe model efficiency

Superordinate objective (category)	**Indexes**
Method	Comparison of simulated and measured (hydrological) time series by means of the Nash–Sutcliffe model efficiency (NSE)
Description + literature	The Nash–Sutcliffe model efficiency (Nash and Sutcliffe, 1970) is a normalized, dimensionless statistical index that informs how well an observed (hydrological) variable agrees with a variable simulated by means of a (hydrological) model. *Nash, J.E.; Sutcliffe, J.V.: River flow forecasting through conceptual models: Part I - A discussion of principles. In: Journal of Hydrology 10 (1970), Nr. 3, S. 282-290*
Useful for (parameter, time resolution)	Runoff, (hydrological) load; Yearly, monthly, daily and hourly values
Requirements for application	Complete (gap-free) equidistant time series
Result/interpretation	Index values less than 0 indicate that the mean of the observations describes the system better than the simulated variable, which can be viewed as an unacceptable model efficiency. A value of 1 means a perfect rendering of the reality by the model. Hydrological simulations should aim for values larger than 0.5.
Assessment	NSE ist rather susceptible against extreme model errors. NSE is considered as the best objective function to assess the fit to an observed time series.
Example/publication	*Moriasi, D. N.; Arnold, J. G.; Liew, M. W. V.; Bingner, R. L.; Harmel, R. D.; Veith, T. L.: Model Evaluation Guidelines for Systematic Quantification of Accuracy in Watershed Simulations. In: Transactions of the ASABE 50 (2007), Nr. 3, S. 885-900*
Contact/project	Frank Herrmann Forschungszentrum Jülich GmbH Institut für Bio- und Geowissenschaften f.herrmann@fz-juelich.de KLIMZUG Nord

5.8.1.2 Quantitative evaluation of climate model simulations for a reference period

Superordinate objective (category)	**Indexes**
Method	Quantitative evaluation of climate model simulations for a reference period: spatial pattern, variance of time series and climatologically averaged seasonal cycle of a meteorological variable
Description + literature	The indexes were developed for evaluating climate model simulations. The evaluation is based on comparing simulated and observed climatology, and not on comparing simulated and observed time series. *Keuler, K., A. Block, W. Ahrens, D. Jacob, D. Rechid, L. Kotova, S. Kotlarski, D. Heimann, M. Zemsch, R. Knoche, E. Dittmann, A. Walter, F. Berger, and M. Sommer, 2006: Quantification of uncertainties in regional climate and climate change simulations (QUIRCS).*
Useful for (parameter, time resolution)	Monthly values of temperature, precipitation, cloudiness, relative humidity and wind speed.
Requirements for application	Availability of observational data. Sufficient integration time period of the climate model under evaluation (e.g., 30 years climate period).
Result/interpretation	The indexes are partly with dimension (e.g., BIAS), partly without (e.g., pattern correlation). The various indexes can assume various ranges of value.
Assessment	The indexes allow to objectively quantify the skill of climate model simulations for a reference period. Not all indexes can be meaningfully applied to all meteorological variables. For example, the seasonal cycle in temperature at mid latitudes is clearly expressed. As a result, the indexes evaluating the climatologically averaged seasonal cycle may show good values, even when climate model simulations deviate considerably from the observations.
Example/publication	
Contact/project	Robert Schoetter Universität Hamburg, Meteorologisches Institut robert.schoetter@zmaw.de KLIMZUG NORD

5.8.1.3 *Evaluation of mesoscale meteorological models and mesoscale dispersion models*

Superordinate objective (category)	**Indexes**
Method	Evaluation of mesoscale meteorological models and mesoscale dispersion models
Description + literature	The model evaluation measures quantify the skill of simulations of mesoscale models. K.H. Schlünzen and R.S. Sokhi (editors), 2008: Overview of tools and methods for meteorological and air pollution mesoscale model evaluation and user training. Joint Report of COST Action 728 (Enhancing mesoscale meteorological modeling capabilities for air pollution and dispersion applications) and GURME (GAW Urban Research Meteorology and Environment Project). World Meteorological Organisation, 2008, 116 pp.
Useful for (parameter, time resolution)	Temperature, dew-point temperature, sea-level pressure, wind speed, wind direction, cloudiness, precipitation and concentrations. The evaluation employs hourly data since measurement data at higher temporal resolution are usually not available and results from Reynolds-averaged mesoscale models should not be interpreted at higher temporal resolution.
Requirements for application	Availability of quality-controlled and preferably representative measurement data. Some indexes (e.g., standard deviation) are meaningful only when the deviations between model and data are approximately normally distributed.
Result/interpretation	The model evaluation measures permit to objectively quantify the quality of the simulation results. You can compare different models as well as different versions of the same model.
Assessment	Not all model evaluation measures for all meteorological variables are meaningful at the same degree. For example, the correlation between hourly temperature data from model and measurement is high owing to the diurnal cycle. Some meteorological variables require specifically tailored evaluation measures (e.g., wind direction), which cannot be applied to other variables. Most of the evaluation measures are not suited for evaluating climate model results because no agreement of time series can be assumed.
Example/publication	K.H. Schlünzen and J.J. Katzfey, 2003: Relevance of sub-grid-scale land-use effects for mesoscale models. Tellus (2003), 55A, 232–246
Contact/project	Robert Schoetter Meteorologisches Institut, Universität Hamburg KLIMZUG-NORD

5.8.1.4 *Evaluation of the frequency distribution by means of skill score and hit rate of the percentiles*

Superordinate objective (category)	**Indexes**
Method	Evaluation of the frequency distribution by means of skill score (SSC) and hit rate of the percentiles (HRP)
Description + literature	The model evaluation measures SSC and HRP quantify how well simulated and observed frequency distributions agree. Both indexes are dimensionless and lie between 0 and 1. *Perkins et al. (2007), Schoetter et al. (2012)*
Useful for (parameter, time resolution)	Temperature, relative humidity, cloudiness, wind speed; daily values
Requirements for application	Reliable set of observational data for the area in which models are evaluated; or (for HRP) at least an estimate of the uncertainty of the observational data.
Result/interpretation	SSC measures the degree of overlap of the frequency distributions (0: distributions disjoint, 1: distributions agree perfectly). HRP measures the proportion of percentiles, which lies within the uncertainty interval of the observational data; HRP can therefore assume a value of 1 even when simulated and observed frequency distributions do not agree perfectly.
Assessment	SSC is a very robust measure; however, the theoretical range (between 0 and 1) is rarely found in practice. HRP is clearly less robust.
Example/publication	*Perkins, S.E., A.J. Pitman, N.J. Holbrook, and J. McAneney, 2007: Evaluation of the AR4 climate models' simulated daily maximum temperature, minimum temperature, and precipitation over Australia using probability density functions. J. Climate, 20, 4356-4376.* *Schoetter, R., P.Hoffmann, D.Rechid, and K.H. Schlünzen, 2012: Evaluation and bias correction of regional climate model results using model evaluation measures. J. Appl. Meteor. Climatol., 51, 1670–1684.*
Contact/project	Robert Schoetter Meteorologisches Institut, Universität Hamburg robert.schoetter@zmaw.de KLIMZUG NORD

5.8.1.5 *Comparison of time series by means of the percent bias*

Superordinate objective (category)	**Indexes**
Method	Comparison of time series by means of the percent bias (PBIAS)
Description + literature	Measures the average tendency of a simulated variable (time series) to be larger or smaller than the respective observed variable. Quantifies, thus, the tendency of a model to systematically over- or underestimate the observations. *Gupta, H. V.; Sorooshian, S.; Yapo, O. P.: Status of automatic calibration for hydrologic models: Comparison with multilevel expert calibration. In: Journal of Hydraulic Engineering 4 (1999), Nr. 2, S. 135-143*
Useful for (parameter, time resolution)	Runoff, (hydrological) load; Yearly, monthly, daily and hourly values
Requirements for application	Complete (gap-free) equidistant time series
Result/interpretation	The optimum value of PBIAS is 0. Positive values indicate overestimation, negative values indicate underestimation.
Assessment	Using PBIAS allows to clearly detect a bad model performance. PBIAS varies within different calibration periods (dry, wet) more or less strongly.
Example/publication	*Moriasi, D. N.; Arnold, J. G.; Liew, M. W. V.; Bingner, R. L.; Harmel, R. D.; Veith, T. L.: Model Evaluation Guidelines for Systematic Quantification of Accuracy in Watershed Simulations. In: Transactions of the ASABE 50 (2007), Nr. 3, S. 885-900*
Contact/project	Frank Herrmann Forschungszentrum Jülich GmbH Institut für Bio- und Geowissenschaften f.herrmann@fz-juelich.de KLIMZUG Nord

5.8.1.6 Aikaike Information Criterion

Superordinate objective (category)	**Indexes**
Method	Aikaike Information Criterion
Description + literature	The optimal model from a set of plausible models can be determined by the Aikaike Information Criterion (AIC, Aikaike (1973)), which is given by $AIC = -2 \log L + 2k$, where k is the number of parameters and L is the Likelihood. In contrast to the likelihood ratio test, the AIC can be used to compare models which are not nested. Aikaike, H., 1973: Information theory and an extension of the maximum likelihood principle. *nd International Symposium on Information Theory*, B. Petrov and F. Csaki, Eds., Budapest, Akademie Kiade, 267-281.
Useful for (parameter, time resolution)	Model selection (also non-nested models), e.g. to determine the best set of covariates for an extreme value model
Requirements for application	For finite (small) sample sizes, a corrected version of the AIC should be applied: AICc = AIC + 2k(k+1)/(n-k-1), where n is the sample size.
Result/interpretation	The model with the minimum AIC value is considered as best to fit the data.
Assessment	Note that the AIC is appropriate as a relative measure for model comparison. It does not assess the goodness of the fit.
Example/publication	*Maraun et al. (2009), Synoptic airflow in UK daily precipitation extremes - Development and validation of a vector generalised linear model, Extremes, 13, 133-153*
Contact/project	christine.radermacher@zmaw.de

5.8.1.7 Brier Skill Score

Superordinate objective (category)	**Indexes**
Method	Brier Skill Score
Description + literature	A model's ability to predict the exceedance of a threshold is assessed with the Brier Score (BS, Brier (1950)). The relative improvement of a model compared to a reference model is determined by the Brier Skill Score (BSS), which can be interpreted as a goodness-of-fit test for the statistical model. The reference model can for example be represented by the climatological probability for exceedance of the threshold. The values of the BSS range between -inf and 1, and describe the gain of predictive skill against the reference model. Brier, G. W., 1950: Verification of forecasts expressed in terms of probability. *Mon. Wea. Rev.*, 78, 1-3.
Useful for (parameter, time resolution)	Assessment of model performance, model selection
Requirements for application	-
Result/interpretation	The larger (closer to 1) the BSS, the better the predictive skill of the model.
Assessment	The Brier Skill Score is most appropriate for assessing the forecast skill of binary outcomes ("exceeding" or "not exceeding"). To assess the skill to predict actual values, other measures may be more suitable.
Example/publication	Friederichs et al. (2009), A probabilistic analysis of wind gusts using extreme value statistics, *Meteorologische Zeitschrift*, Vol. 18, No. 6, 615-629
Contact/project	christine.radermacher@zmaw.de

5.8.2 Statistical climate indexes

5.8.2.1 Difference in transpiration as measure of site suitability

Superordinate objective (category)	**Indexes**
Method	Difference between potential and actual transpiration as a measure of site suitability
Description + literature	Determination of the difference between potential and actual transpiration as a masure of the suitability of a location for different tree species. Spatial as well as temporal comparisons (e.g. climate scenarios) are possible. *Falk et al. (2008), Hammel and Kennel (2001), Schultze et al. (2005), Pöhler et al. (2010)*
Useful for (parameter, time resolution)	Potential and actual transpiration; temporal resolution: daily vegetation period: 1 year.
Requirements for application	Water balance model (1D - location or 2D - catchment model); daily meteorological input data: observations or climate model output (scenarios).
Result/interpretation	Essential indicator for the interaction of climate, soil, tree species and forest-stand density; overview of spatial variations; overview of possible future changes.
Assessment	Well suited index, no misleading results known.
Example/publication	*Pöhler et al. (2010)*
Contact/project	Hannaleena Pöhler & Jörg Scherzer UDATA – Umwelt und Bildung poehler@udata.de, scherzer@udata.de KLIMZUG NORD

Falk, W., Dietz, E., Grünert, S., Schultze, B., Kölling, C. (2008): Wo hat die Fichte genügend Wasser? - Neue überregional gültige Karten des Wasserhaushalts von Fichtenbeständen verbessern die Anbauentscheidung; LWF aktuell, 2008.

Hammel, K. U. Kennel, M. (2001): Charakterisierung und Analyse der Wasserverfügbarkeit und des Wasserhaushalts von Waldstandorten in Bayern mit dem Simulationsmodell BROOK90. Forstliche Forschungsberichte München, 185, 135 S.

Pöhler, H., Schultze, B., Scherzer, J. (2010): Auswirkungen des Klimawandels auf den Wasserhaushalt eines bewaldeten Kleineinzugsgebietes im Hochsauerland, Freiburger Forstliche Forschung, in Druck

Pöhler, H., Schultze, B., Wendel, S., Rust, S., Scherzer, J. (2012): Auswirkungen von Klimawandel und Waldbaustrategien auf das Grundwasserdargebot im Privatwald der Niedersächsischen Ostheide, Abschlussbericht KLIMZUG-NORD Teilprojekt 3.5

Schultze B., C. Kölling, C. Dittmar, T. Rötzer, W. Elling (2005): Konzept für ein neues quantitatives Verfahren zur Kennzeichnung des Wasserhaushalts von Waldböden in Bayern: Modellierung - Regression - Regionalisierung; Forstarchiv 76, 155-163

5.8.2.2 Frequency of frost days after vegetation start/time span between last frost day and vegetation start

Superordinate objective (category)	**Indexes**
Method	Determination of the frequency of frost days after vegetation start and the time span between last frost day and vegetation start
Description + literature	Agricultural vegetation start is defined as begin of flowering of *Salix caprea* (English pussy willow, German *Sal-Weide*) after Länderinitiative Klimaindikatoren (LIKI); in fruit growing, also the definition as begin of fruit flowering can be used; frost day = day with minimum temperature <0°C; determination of influencing time span after vegetation start is, following convention of fruit flowering, 10 days (*Chmielewski et al. 2009*) → determination of the freqeuncy of frost days. Possibly, classes of frost magnitude (e.g., < –2 °C) can be formed since not all plant types have the same frost susceptibility.
Useful for (parameter, time resolution)	Assessment of future frost risk in agriculture
Requirements for application	Information on start of flowering of *Salix caprea*, if unavailable, the vegetation start has to be otherwise defined (e.g., via temperature threshold)
Result/interpretation	Late-frost risk at a location increases with (1) the time span between last frost day and vegetation start and (2) the frequency of frost days within a defined time period after vegetation start.
Assessment	Yields a rough estimate at regional scale; microclimatological influences cannot be taken into account; making statements on the risk of individual plant species requires accurate knowledge of frost risk in the growth periods.
Example/publication	*Abschätzung der Spätfrostgefährdung in der Modellregion Dresden (Chapter Vegetationsperiode und Spätfrostgefährdung in Bernhofer et al. (2011))*
Contact/project	Maria Foltyn (former LfULG) Technische Universität Bergakademie Freiberg foltyn@mailserver.tu-freiberg.de KLIMZUG project: REGKLAM

Bernhofer C, Matschullat M, Bobeth A (Hrsg. 2011): Klimaprojektionen für die REGKLAM-Modellregion Dresden. Publikationsreihe des BMBF-geförderten Projektes REGKLAM – regionales Klimaanpassungsprogramm für die Modellregion Dresden, Heft 2, Rhombos-Verlag Dresden

5.8.2.3 *Counting method for determining the thermal vegetation period*

Superordinate objective (category)	**Indexes**
Method	Counting method for determining the thermal vegetation period (via temperature threshold)
Description + literature	Temperature threshold after Vogel is applied, as is implemented in, for example, the *Sächsische Klimadatenbank.* Begin: average daily temperature ≥ 5 °C for 7 successive days; End: average daily temperature < 10 °C for 7 successive days. Begin/end of the thermal vegetation period is then defined as the last of those successive days. Unusual warm periods in winter may lead to implausible, clearly too early vegetation start. To prevent this, you start with counting only when average temperatures of three successive months exceed 5 °C. The start of the month before this additional three-month criterion is the start day for counting.
Useful for (parameter, time resolution)	Water balances, agriculture, carbon balances
Requirements for application	Gap-free temperature series
Result/interpretation	Observational data over the past years as well as future projections show that vegetation begins earlier and ends later than in the past.
Assessment	Rather straightforward in application since only daily average temperature data are required; possibly large interannual variations of index
Example/publication	*Chapter Vegetationsperiode in Bernhofer et al. (2009, 2011)*
Contact/project	Majana Heidenreich (TU Dresden), Maria Foltyn (former LfULG, now TU BA Freiberg) majana.heidenreich@tu-dresden.de, foltyn@mailserver.tu-freiberg.de KLIMZUG project: REGKLAM, TP 2.1

Bernhofer C, Matschullat M, Bobeth A (Hrsg. 2011): Klimaprojektionen für die REGKLAM-Modellregion Dresden. Publikationsreihe des BMBF-geförderten Projektes REGKLAM – regionales Klimaanpassungsprogramm für die Modellregion Dresden, Heft 2, Rhombos-Verlag Dresden
Bernhofer C, Matschullat M, Bobeth A (Hrsg. 2009): Das Klima in der REGKLAM-Modellregion Dresden. Publikationsreihe des BMBF-geförderten Projektes REGKLAM – regionales Klimaanpassungsprogramm für die Modellregion Dresden, Heft 1, Rhombos-Verlag Dresden

5.9 Spatiotemporal methods

Spatiotemporal data are abundant in climate modelling as well as climate observing. Already the previous sections contain several methods to analyse this data type, such as multivariate extremes (Section 5.7.4), physical downscaling and two-dimensional interpolation (Section 5.6.1 und 5.6.2) and the construction of indexes (Section 5.8). The present section (5.9) explains some further methods.

Statistical models help to objectively classify general weather situations and decipher spatial patterns in high-dimensional spatiotemporal data (Section 5.9.1). temperature sums (Section 5.9.2) are used for projecting phenological dates; the relation of those sums to climate indexes is evident. Spatial maps showing the correlation between one climate time series and other series from a spatiotemporal field (Section 5.9.1) may also be used to explore spatial patterns; note the various correlation methods (Sections 5.1.1, 5.1.2 and 5.1.3) that principally could be applied.

Further reading. See the recommendations for further reading in the aforementioned sections.

5.9.1 Correlation between two variables (correlation maps)

Superordinate objective (category)	**Spatiotemporal methods** correlation maps
Method	Correlation between two variables (correlation maps)
Description + literature	Correlation of time series values from records of atmospheric circulation and atmospheric parameters *Sepp M & Jaagus J (2002) Frequency of circulation patterns and air temperature variations in Europe. Bor Env Res 7, 3: 273-279*
Useful for (parameter, time resolution)	Time series of the frequency of atmospheric circulation types and average values of climate parameters (air pressure, temperature, precipitation, etc.); temporal resolution: freely selectable (author’s experience: monthly, seasonally, half-yearly and yearly
Requirements for application	Gap-free and preferably long and homogeneous time series
Result/interpretation	Spatial maps of various correlations
Assessment	Allows interpretation of correlations in a spatial context; allows assessment of noise by comparing results from dividing the period into parts with average over whole period
Example/publication	*Sepp und Jaagus 2002* *Hoy A, Jaagus J Sepp M, Matschullat J (submitted to TAC): “Spatial response of two European atmospheric circulation classifications (data from 1901 to 2010)”*
Contact/project	Andreas Hoy Technische Universität, Bergakademie Freiberg andreas.hoy@ioez.tu-freiberg.de KLIMZUG project: REGKLAM

5.9.2 Temperature sums for projecting phenological entry dates

Superordinate objective (category)	**Spatiotemporal methods**
Method	Temperature sums for projecting phenological entry dates
Description + literature	Calculate the entry date (day in year), t_2, of a phenological phase by summing up average daily temperatures, T_i, from a start day, t_1 (here: 1 January), until the plant-dependent temperature sum, F*, is reached (Eq. 1). A simple calculation of the parameter R_f is after Eq. (2). Depending on the analysed area and the phenological phase, the nonlinear approach (Eq. 3) yields slight deviations from the observation. T_B is a basis temperature, from which a temperature stimulation becomes effective. [Eq. 1] $F(t) = \sum_{i=t_1}^{t} R_f(T_i) \quad where\ F(t_2) = F^*$ [Eq. 2] $R_f(T_i) = 0 \quad for\ T_i \leq T_B$ $R_f(T_i) = T_i - T_B \quad for\ T_i > T_B$ Eq. [3] $R_f(T_i) = 0 \quad for\ T_i \leq T_B$ $R_f(T_i) = \frac{28.4}{1 + e^{-0.185 \cdot (T_i - T_B - 18.4)}} \quad for\ T_i > T_B$ The parameters T_B, F* and, possibly, t_1, should be fitted in dependence of area and iteratively (root mean squared error as measure of error). Also a correction for elevation is required. *Pöhler et al. (2007), Chmielewski et al. (2009)*
Useful for (parameter, time resolution)	Spatial projection of point-value phenological entry dates on an area; possibly, filling of gaps in phenological time series; projections based on climate model output
Requirements for application	Preferably, gap-free, long series of input data at good spatial coverage to optimize parameter estimation and validation, availability of temperature data at daily resolution. If model parameters from the literature are used, the modelled area should be similar to that under analysis.
Result/interpretation	Estimation of future courses of vegetation is possible. Error margions are within the standard deviations of the observed data (i.e., acceptable).
Assessment	If using the Eqs. (1–3), only temperature data are required as input. However, a possible need of cold (to overcome dormancy) is not taken into account. This means that future entry dates very early in the year, may not be achievable from a plant-physiological view.
Example/publication	*Projektion phänologischer Phasen wildwachsender Pflanzen in Modellregion Dresden (Kapitel Phänologie in Bernhofer et al. (2011))*
Contact/project	Maria Foltyn (former LfULG) Technische Universität Bergakademie Freiberg

	foltyn@mailserver.tu-freiberg.de KLIMZUG project REGKLAM

Chmielewski, F.-M.; Blümel, K.; Henniges, Y.; Müller, A. (2009): Klimawandel und Obstbau in Deutschland. Endbericht des BMBF-Verbundprojekts KliO., Eigenverlag, Humboldt-Universität zu Berlin, 237 S

Bernhofer C, Matschullat M, Bobeth A (Hrsg. 2011): Klimaprojektionen für die REGKLAM-Modellregion Dresden. Publikationsreihe des BMBF-geförderten Projektes REGKLAM – regionales Klimaanpassungsprogramm für die Modellregion Dresden, Heft 2, Rhombos-Verlag Dresden

Pöhler H, Chmielewski F-M, Jasper, K, Henniges Y, Scherzer J (2007): KliWEP - Abschätzung der Auswirkungen der für Sachsen prognostizierten Klimaveränderungen auf den Wasser- und Stoffhaushalt im Einzugsgebiet der Parthe. Weiterentwicklung von WaSiM-ETH: Implikation dynamischer Vegetationszeiten und Durchführung von Testsimulationen für sächsische Klimaregionen. Abschlussbericht zum FuE-Vorhaben des Sächsischen Landesamtes für Umwelt und Geologie

5.9.3 Objective classification of weather situations with statistical methods

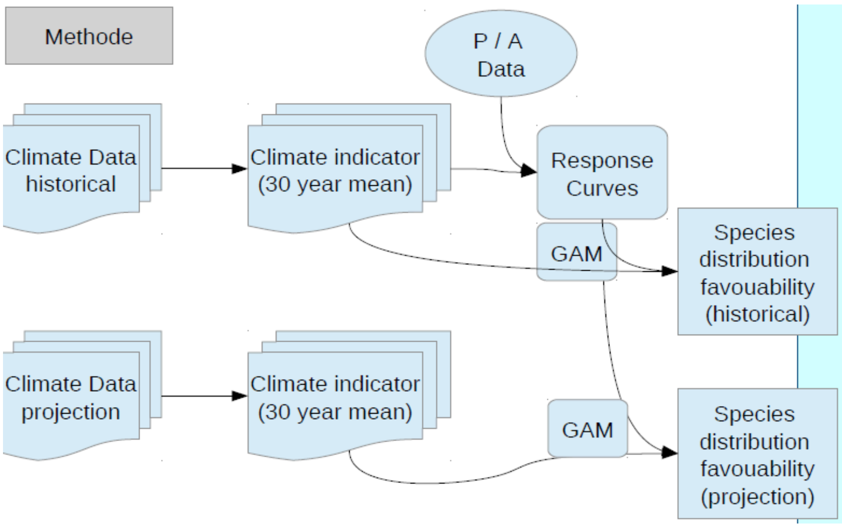
Superordinate objective (category)	**Spatiotemporal methods**

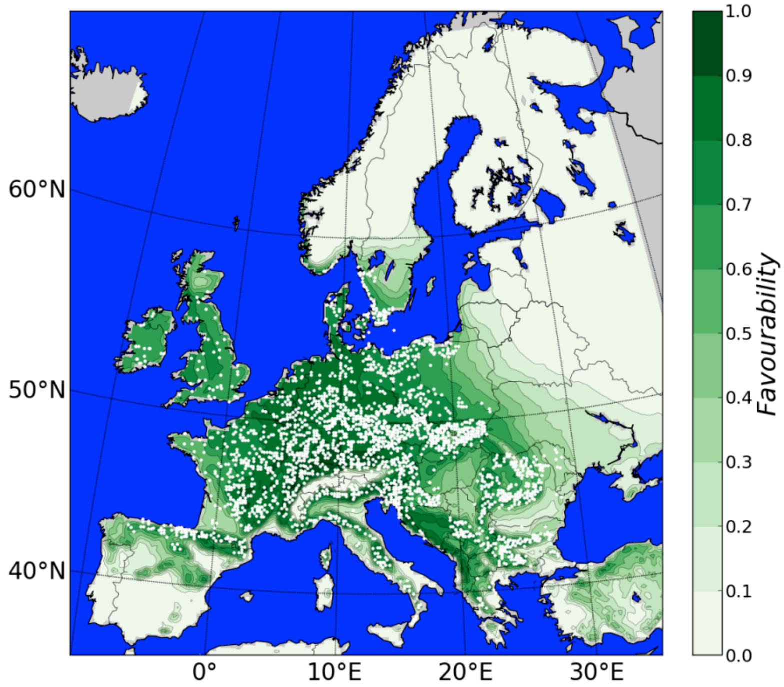
Method	Objective classification of weather situations with statistical methods
Description + literature	Data (atmospheric fields) can be grouped without prior knowledge about groups' properties (Huth et al. 2008)
Useful for (parameter, time resolution)	Sea-level pressure, geopotential height, relative humidity, temperature vorticity, layer thickness, etc.
Requirements for application	Meteorological field data should be on a grid (re-analysis, climate model output); analysed region should be large enough to resolve large-scale phenomena; time series of fields should be long enough (ideally more than 30 years at daily resolution)
Result/interpretation	You obtain spatial patterns (weather situations) and a time series, for which each time value (often: 1 day) corresponds to the weather situation on the following day.
Assessment	Well suited to reduce data amount because an analysis is only necessary for each single weather situation. Calculation is fast in most cases. But the suitable region and variables have to be determined. For methods based on k-means the optimal amount of weather situations has to be determined in addition.
Example/publication	COST733 software contains various methods for classifying weather situations *http://geo21.geo.uni-augsburg.de/cost733wiki/Cost733Software* *Huth et al. (2008); Philipp et al. (2010)*
Contact/project	Peter Hoffmann Universität Hamburg, Meteorologisches Institut peter.hoffmann@zmaw.de KLIMZUG NORD

Huth, R. and Beck, C. and Philipp, A. and Demuzere, M. and Ustrnul, Z. and Cahynova, M. and Kysely, J. and Tveito, O. E., (2008): Classifications of Atmospheric Circulation Patterns, Recent Advances and Applications, Trends and Directions in Climate Research: Ann. N.Y. Acad. Sci. 1146: 105-152

Philipp, A., J. Bartholy, C. Beck, M. Erpicum, P. Esteban, X. Fettweis, R. Huth, P. James, S. Jourdain, F. Kreienkamp, T. Krennert, S. Lykoudis, S. C. Michalides, K. Pianko-Kluczynska, P. Post, D. R. Álvarez, R. Schiemann, A. Spekat and F. S. Tymvios (2010): Cost733cat – A database of weather and circulation type classification. Physics and Chemistry of the Earth, 35, 360-373.

5.9.4 *Generalized Additive Model (GAM)*

Superordinate objective (category)	**Space-time-approach**
Method	Generalized additive Model (GAM)
Description + literature	GAMs are semi-parametric extensions of generalized linear models. They allow fitting of response curves with a nonparametric smoothing function instead of parametric terms. This improves the exploration of species responses to environmental gradients. GAMs can be used for the analysis of continuous metric as well as for binomial data (0 and 1). A GAM can be fitted to a climate data experiment of the present day time slice, based on presence-absense data of the species of interest. With the help of the models, visualized by response curves, a spatial probability of occurrence can be calculated. 
Useful for (parameter, time resolution)	probability of species distribution
Requirements for application	PresenceAbsence-data of appropriate species. Gridded data of climate indices to determine climate conditions.
Result / Interpretation	The output is a floating number between 0 (no) and 1 (maximum probality of occurence) and with the help of a transformation into favourabilites (Real et al. 2006) describes the environmental favourability of a site for a species.
Assessment	Methode to generate projections of future species favourabilites. Precondition is an existing presence-absence data base.
Example / publication	S. Wood, Generalized additive models: an introduction with R, Vol. 66, CRC Press, 2006. S. Wood, Mixed GAM Computation Vehicle with GCV/AIC/REML smoothness estimation (06 2012). E. A. Freeman, G. Moisen, PresenceAbsence: An R package for

	presence absence analysis, Journal of Statistical Software 23 (11) (2008) 1 -31. R. Real, A. M. Barbosa, J. M. Vargas, Obtaining environmental favourability functions from lo566 gistic regression, Environmental and Ecological Statistics 13 (2) (2006) 237{245.  Environmental favourability of Fagus sylvatica in Europe, based on mean climate data of the time period 1971-2000
Contact / project	Nils Hempelmann, Helmholtz-Zentrum Geesthacht, Climate Service Center, Hamburg nils.hempelmann@hzg.de Wolfgang Falk, Bayerische Landesanstalt für Wald und Forstwirtschaft, Freising Wolfgang.Falk@lwf.bayern.de
Software (if possible)	R package mgcv (Mixed GAM Computation) R package PresenceAbsence (plausibility tools)

5.10 Ensemble analysis

This category refers to ensembles of climate simulations. A transfer of the methods to another scope, particularly to an ensemble of measured series, was not tested.

An ensemble of model simulations may consist of different models but only one scenario (multi-model-ensemble), one model and different scenarios (multi-scenario-ensemble), one model and different parameterisation schemes (multi-parameterisation-ensemble), or one model, one parameterisation scheme and different realisations (multi-member-ensemble).

In adaptation projects, it is recommended to use a greatest possible model ensemble for evaluation and application of climate model results in order to achieve robust results. Only an ensemble analysis enables to make sensible use of the model-inherent uncertainties for assessing the results. Options for action and assistance for interpretation can e.g. be found in Haensler et al. (2013). They are partly based on recommendations of the International Panel on Climate Change (IPCC) to analyse ensembles which are described in Chapter 1.6 'The IPCC Assessments of Climate Change and Uncertainties' in Soloman et al. (2007). The main topics here are uncertainties which are the reason for the application of ensemble analysis.

The following statistical methods describe the percentile analysis (5.10.1), the likelihood scheme, based on the IPCC recommendations (5.10.2), and an example for aa test of robustness (5.10.3).

References

Haensler, A., F. Saeed, D. Jacob, 2013: Assessing the robustness of projected precipitation changes over central Africa on the basis of a multitude of global and regional climate projections. Climatic Change, DOI: 10.1007/s10584-013-0863-8

Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor and H.L. Miller (eds.), 2007: Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

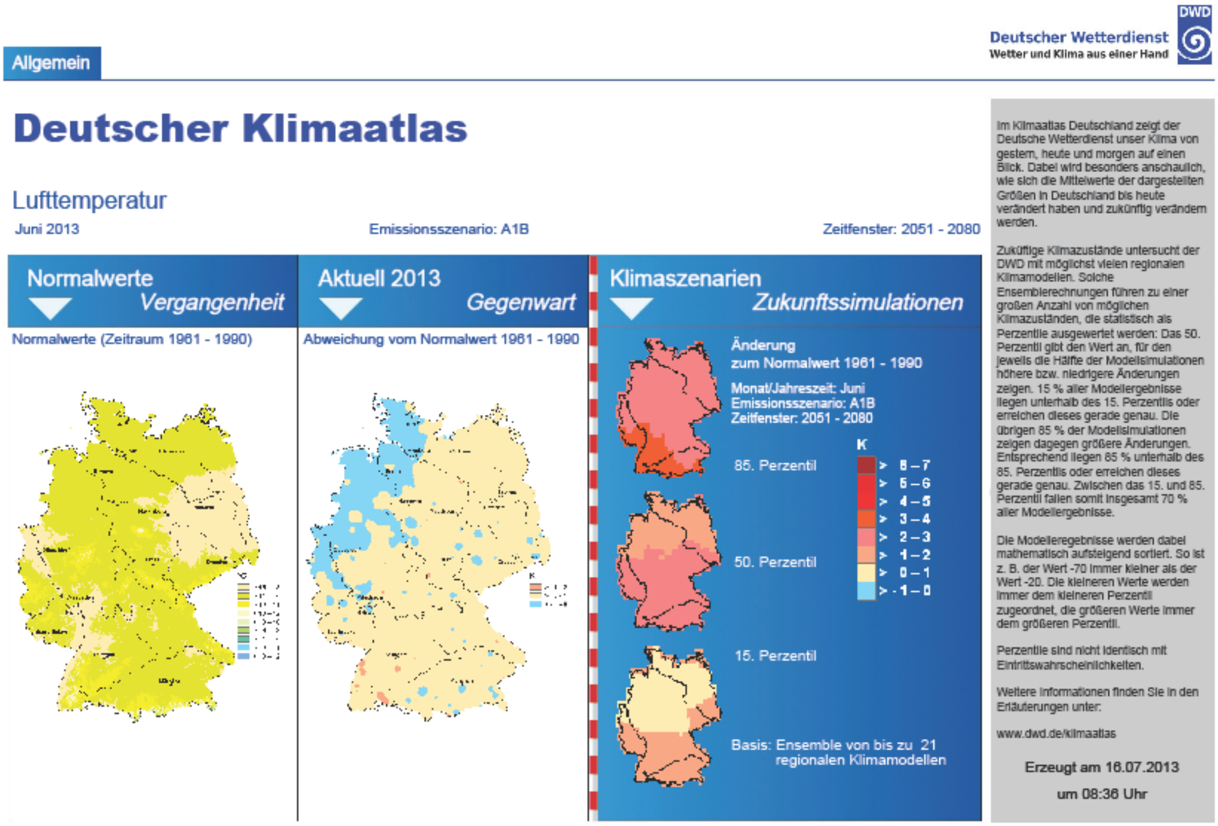
Further reading:

Knutti, R., G. Abramowitz, M. Collins,V. Eyring , P. J. Gleckler, B. Hewitson, L. Mearns, 2010: Good Practice Guidance Paper on Assessing and Combining Multi Model Climate Projections, IPCC Expert Meeting on Assessing and Combining Multi Model Climate Projections, National Center for Atmospheric Research, Boulder, Colorado, USA, 25-27 January 2010.

Knutti, R., R. Furrer, C. Tebaldi, J. Cermak, G. A. Meehl, 2010: Challenges in Combining Projections from Multiple Climate Models, J.Climate, 23, 2739-2758.

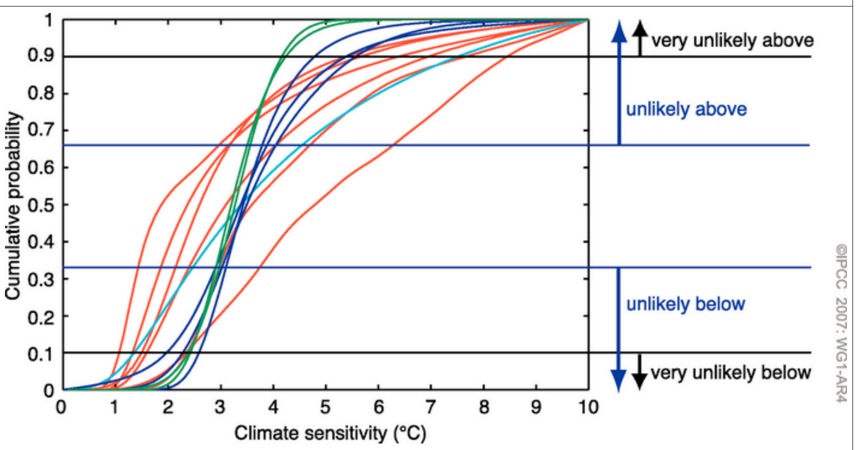
5.10.1 Percentile analysis

Superordinate objective (category)	**Ensemble analysis**
Method	Percentile analysis
Description + literature	An ensemble of climate simulations delivers a bandwidth of output variables for each time step and each gridbox. Reasonable statements can be derived by different tools. One possibility is offered by a percentile analysis. Percentiles are determined by sorting the variables of the ensemble outcome after their value for the chosen time interval. The x-th percentile is the value with a x % Unterschreitungsanteil. As an example: the 95th percentile is the value below with 95 % of all ensemble members are lying.
Useful for (parameter, time resolution)	Each ensemble with approximately 100 and more members. In case of less than 100 variables, the percentiles have to be determined by interpolation in between the values. The result is a set of percentile values for each timestep and grid box or station of the simulation..
Requirements for application	At least 20 ensemble members, better more than 100. mindestens 20 Ensemblemitglieder, besser mehr als 100.
Result / Interpretation	In most cases the 15th, 50th, and 85th percentile are evaluated, if not focussing on the edges of the distribution also the 25th, 50th and 75th percentile.
Assessment	The 50th percentile (median) is better suited to describe the average outcome of the ensemble simulation than the mean because single outliers do not influence this value. This is also true for low and high percentiles.
Examole / publication	German Climate Atlas of the German Meteorological Service (www.dwd.de -> Klima + Umwelt -> Klima in der Zukunft -> Deutscher Klimaatlas)
Contact / project	Barbara Hennemuth, HZG, Climate Service Center Barbara.hennemuth@hzg.de Diana Rechid, KLIMZUG-NORD, MPI für Meteorologie Diana.rechid@zmaw.de
Software (if possible)	



5.10.2 Likelihood of outcome

Superordinate objective (category)	**Ensemble analysis**
Method	Likelihood of outcome

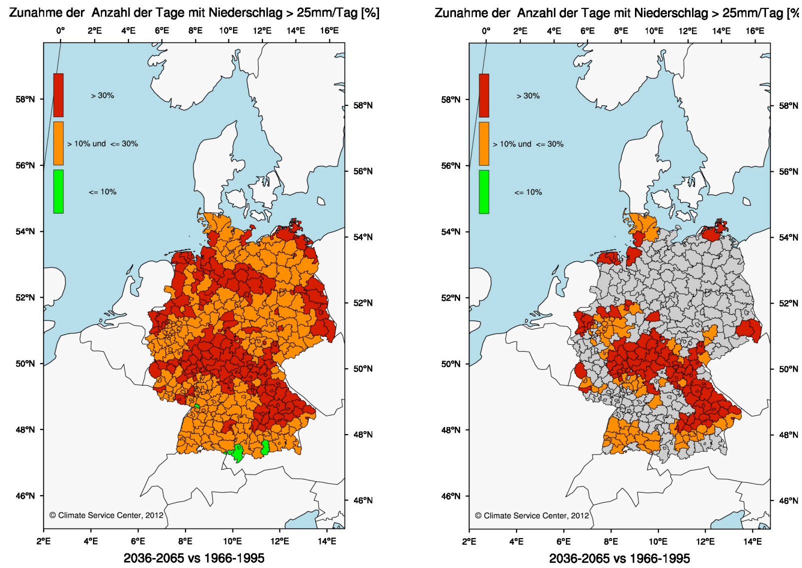
Description + literature	The degree of agreement is a simple measure for the standardised assessment of the results of an ensemble of climate simulations. After Solomon et al. (Eds., 2007), chapter.1.6 the following scale is defined: Likelihood Terminology Likelihood of the occurrence/ outcome Virtually certain > 99% probability Extremely likely > 95% probability Very likely > 90% probability Likely > 66% probability More likely than not > 50% probability About as likely as not 33 to 66% probability Unlikely < 33% probability Very unlikely < 10% probability Extremely unlikely < 5% probability Exceptionally unlikely < 1% probability
Useful for (parameter, time resolution)	Quantitative results (e.g. temperature) of a sufficiently large ensemble of climate simulations of different climate models which can be presented in frequency distribution.
Requirements for application	The data must be suitable for a probabilistic evaluation, e.g. be presented in a frequency distribution, and the value of a statement to be examined must be prescribed (e.g. the sign of anclimate change signal, the exceedence of a certain threshold by a modeled parameter). The statement must be quantifiable (see ‘description’).
Result / Interpretation	The interpretation depends on the kind of the result. Evaluating the sign of a trend, the likelihood can be assessed by the number of models with the same direction of trend. Evaluating the temperature increase, the likelihood of the exceedence of a threshold of e.g. 3 K can be assessed.
Assessment	Simple determination. In accordance with the definitions of IPCC.
Examole / publication	 Cumulative distributions of climate sensitivity derived from observed 20th-century warming (red), model climatology (blue), proxy evidence (cyan) and from climate sensitivities of AOGCMs

	(green). Horizontal lines and arrows mark the boundaries of the likelihood estimates defined in the IPCC Fourth Assessment Uncertainty Guidance Quelle: Solomon et al. (Eds, 2007)
Contact / project	Barbara Hennemuth, HZG, Climate Service Center barbara.hennemuth@hzg.de Diana Rechid, MPI für Meteorologie diana.rechid@zmaw.de
Software (if possible)	

Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor and H.L.Miller (eds.), 2007: Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, 2007, Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

5.10.3 Robustness of climate change signal

Superordinate objective (category)	**Ensemble analysis**
Method	Robustness of climate change signal
Description + literature	The robustness of the climate change result of an ensemble of climate simulations is defined in the IPCC Third Assessment Report - Climate Change 2001: Synthesis Report, Question 9: 'In this report, a robust finding for climate change is defined as one that holds under a variety of approaches, methods, models, and assumptions and one that is expected to be relatively unaffected by uncertainties.' The verification of robustness is based on different queries. Here, we describe the method which is applied in the 'Klimasignalkarten'. http://www.climate-service-center.de/031443/index_0031443.html.de 1. Agreement (see Method ‚Likelihood' 5.10.2) Following the IPCC, the direction of change is considered to be 'likely' when 66 % of all simulations agree in the direction. 2. Signifikance Test of a significant difference oft he future values compared tot he reference period. 66 % of the simulations must pass a suitable significance testing geeigneten (U-Test or Mann-Whitney-Wilcoxon Test). 3. No dependence on small time shifts Both the future time period and the reference period are shifted back and forth by 1 … 3 years. If the variance of the climate change signal of all such periods is less than 25 % of the originally calculated climate change signal independence is assumed. The methods are described in detail under: http://www.climate-service-center.de/031451/index_0031451.html.de
Useful for (parameter, time resolution)	Climate change signals – averaged over at least 30 years – of an ensemble of different climate simulations and corresponding uncertainty in the averaging time interval.
Requirements for application	The chosen significance test potentially needs a minimum number of data.
Result / Interpretation	Resilient statements on climate change signals which rely on an ensemble of climate simulations (different models, realisations, or projections).
Assessment	

	The robustness test does not provide quantitative results on the climate change signal
Examole / publication	Klimasignalkarten http://www.climate-service-center.de/031486/index_0031486.html.de  Increase of number of days with strong precipitation (> 25 mm/day) for the period 2036 – 2065 compared with the the number of the reference period 1966 – 1995 in percent. Shown is the median of an ensemble of 28 regional climate change simulations (left), and after applying the three-step robustness test (right). Shown are administrative districts. Regions with grey colour did not pass at least one test. The increase of days with strong precipitation is thus only robust for some regions in Germany.
Contact / project	Susanne Pfeifer, HZG, Climate Service Center susanne.pfeifer@hzg.de Diana Rechid, MPI für Meteorologie, diana.rechid@zmaw.de
Software (if possible)	-

IPCC, 2001: Climate Change 2001: Synthesis Report. A Contribution of Working Groups I, II, and III to the Third Assessment Report of the Integovernmental Panel on Climate Change [Watson, R.T. and the Core Writing Team (eds.)]. Cambridge University Press, Cambridge, United Kingdom, and New York, NY, USA, 398 pp.

Pfeifer, S., Hänsler, A., Ries, H., Weber, B., Jacob, D., Rechid, D., Teichmann, C., Gobiet, A., Mudelsee, M.,, 2013: Mapping the Robustness of Regional Climate Change Information, Submitted to: Journal of Applied Meteorology and Climatology.

5.10.4 Visualisation

In the following some figures are shown which offer opportunities how to visualise the complex outcome of an ensemble analysis in only one picture. They originate from the document *How to read a Climate-Fact-Sheet - Instructions for reading and interpretation of the Climate-Fact-Sheets. Climate-Fact-Sheets - Lese- und Interpretationsanleitung für die Climate-Fact-Sheets. Climate Service Center, Hamburg, Mai 2013 http://www.climate-service-center.de/036238/index_0036238.html.de*
The data base comprises global climate simulations of the ‚Coupled Model Intercomparison Project No.3' (CMIP3) and regional climate simulations of the EU-Project ENSEMBLES.

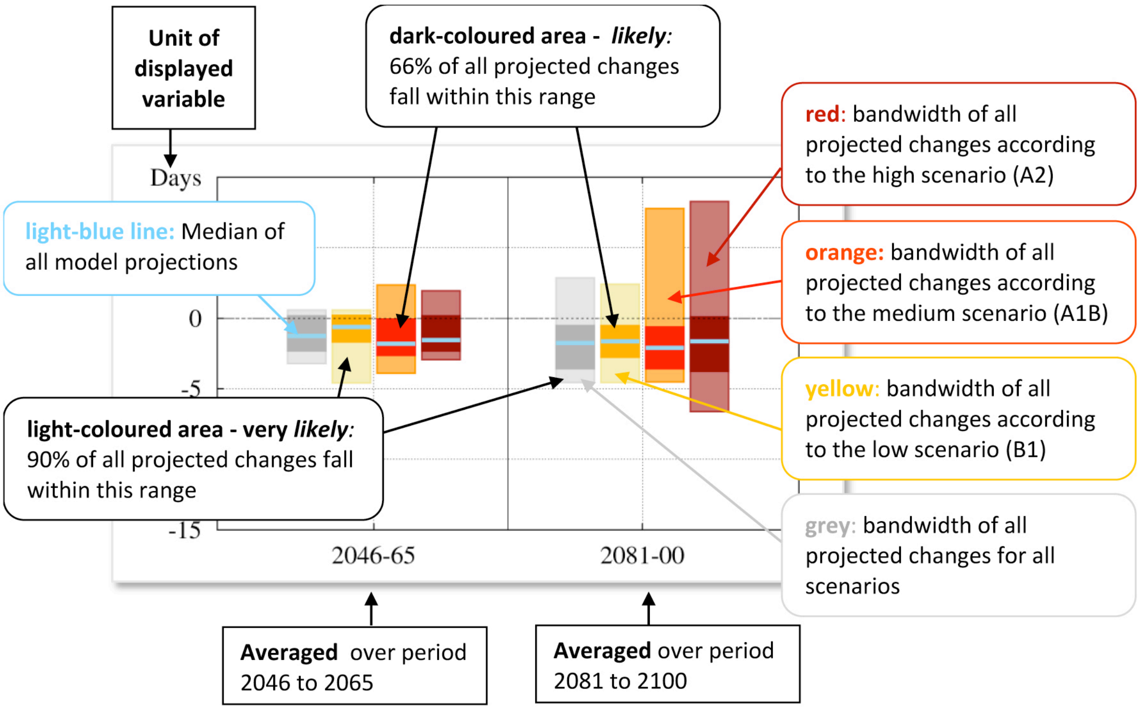


Figure 1: This figure shows the projected change in a parameter as averaged over two periods of twenty years 2046-2065 and 2081-2100 compared to the mean of the reference period 1961-1990. On the bars the median and the regions of likelihood 'likely' and 'very likely' are marked.

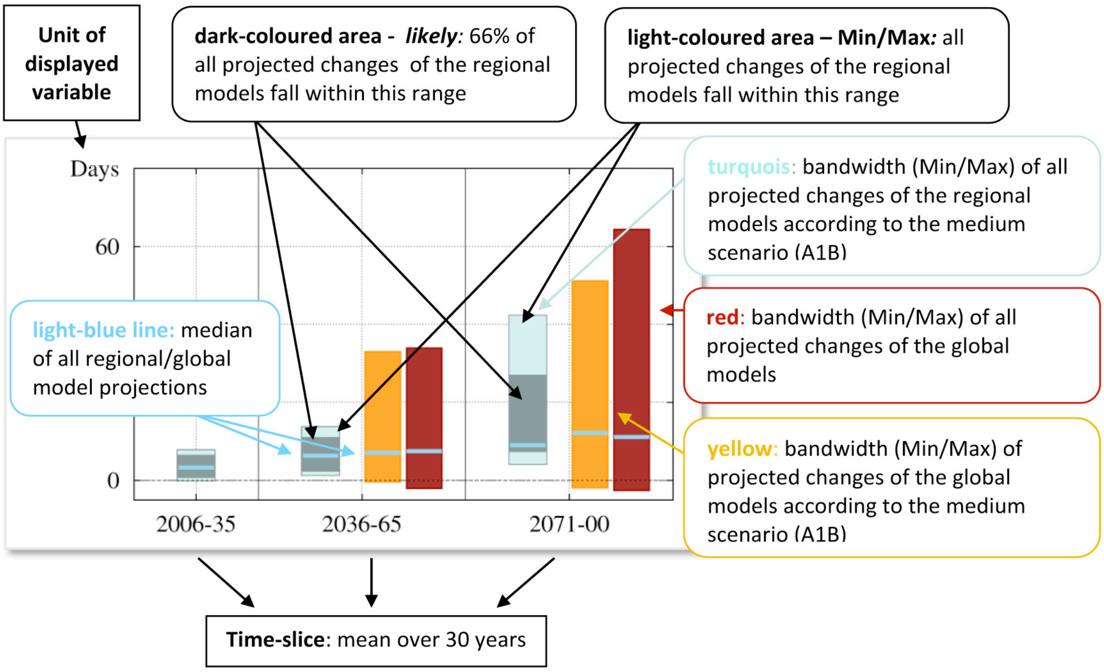


Figure 2: This figure shows the projected change in a parameter as averaged over three periods of 30 years 2006-2035, 2036-2065 and 2071-2100 compared to the mean of the reference period 1961-1990. On the bars the median and the regions of likelihood 'likely' and the complete bandwidth are marked.

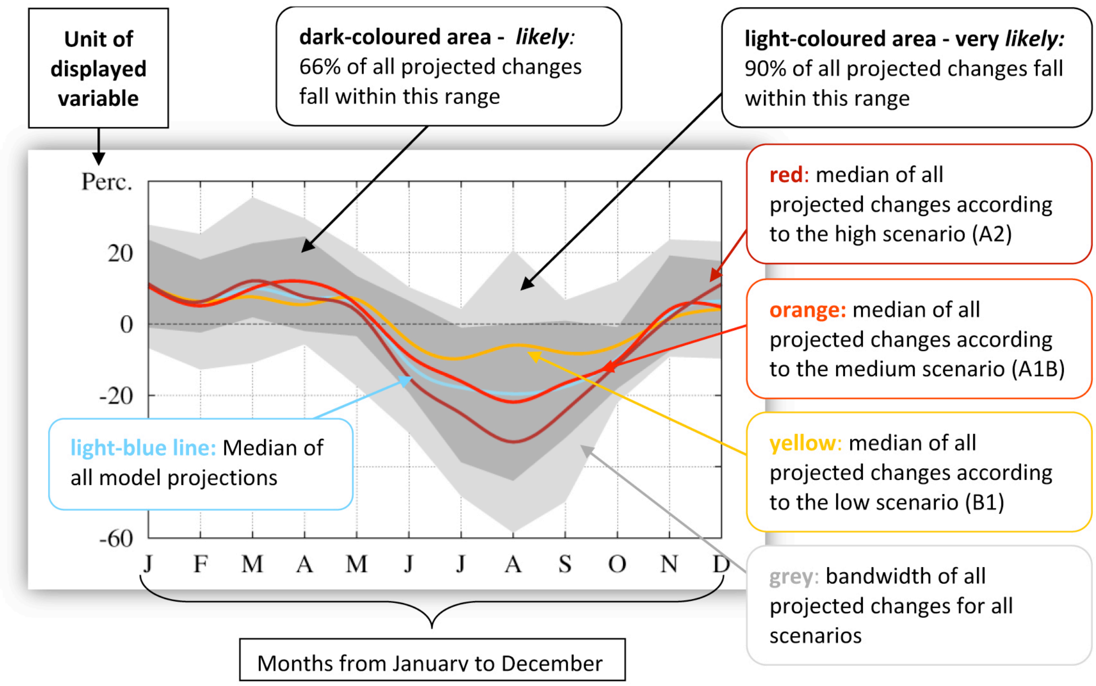


Figure 3: This figure shows the projected change of the annual cycle in a parameter in % as averaged over the period 2071-2100 compared to the mean of the reference period 1961-1990. Presented are lines of the medians of all scenarios and of each scenario, and the regions of likelihood ‘likely’ and ‘very likely’.

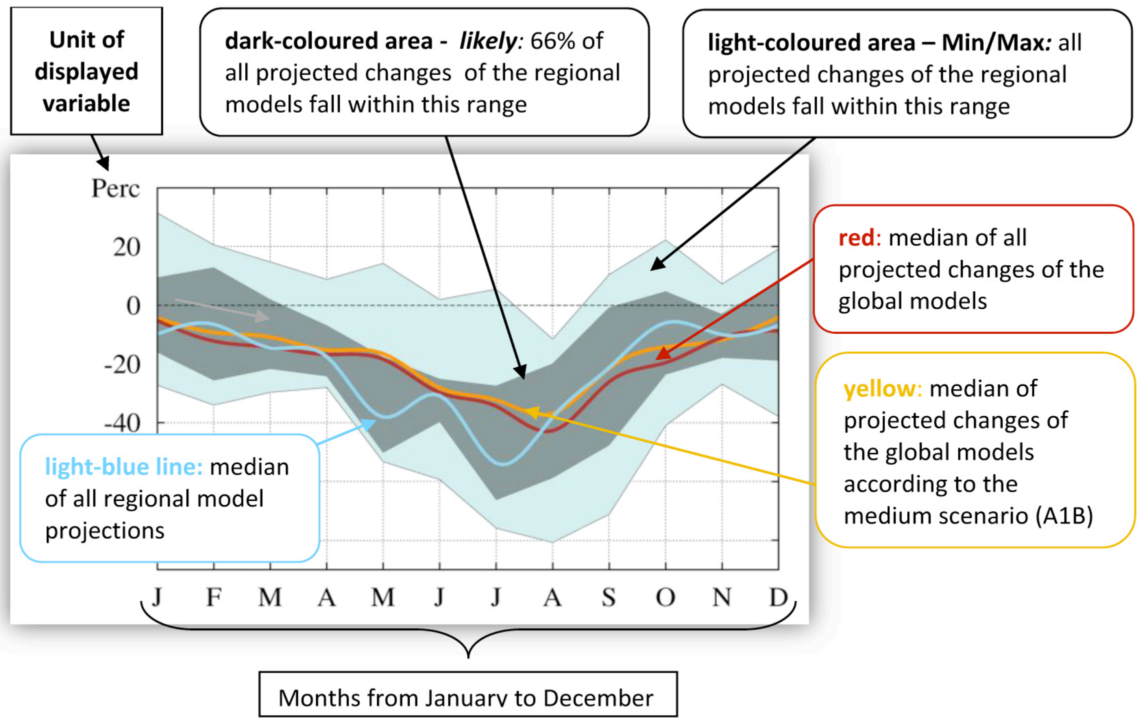


Figure 4: This figure shows the projected change of the annual cycle in a parameter in % as averaged over the period 2071-2100 compared to the mean of the reference period 1961-1990. Presented are lines of the medians of all global models of all global models of the scenario A1B, and of all regional models, and the regions of likelihood ‘likely’ and the complete bandwidth.

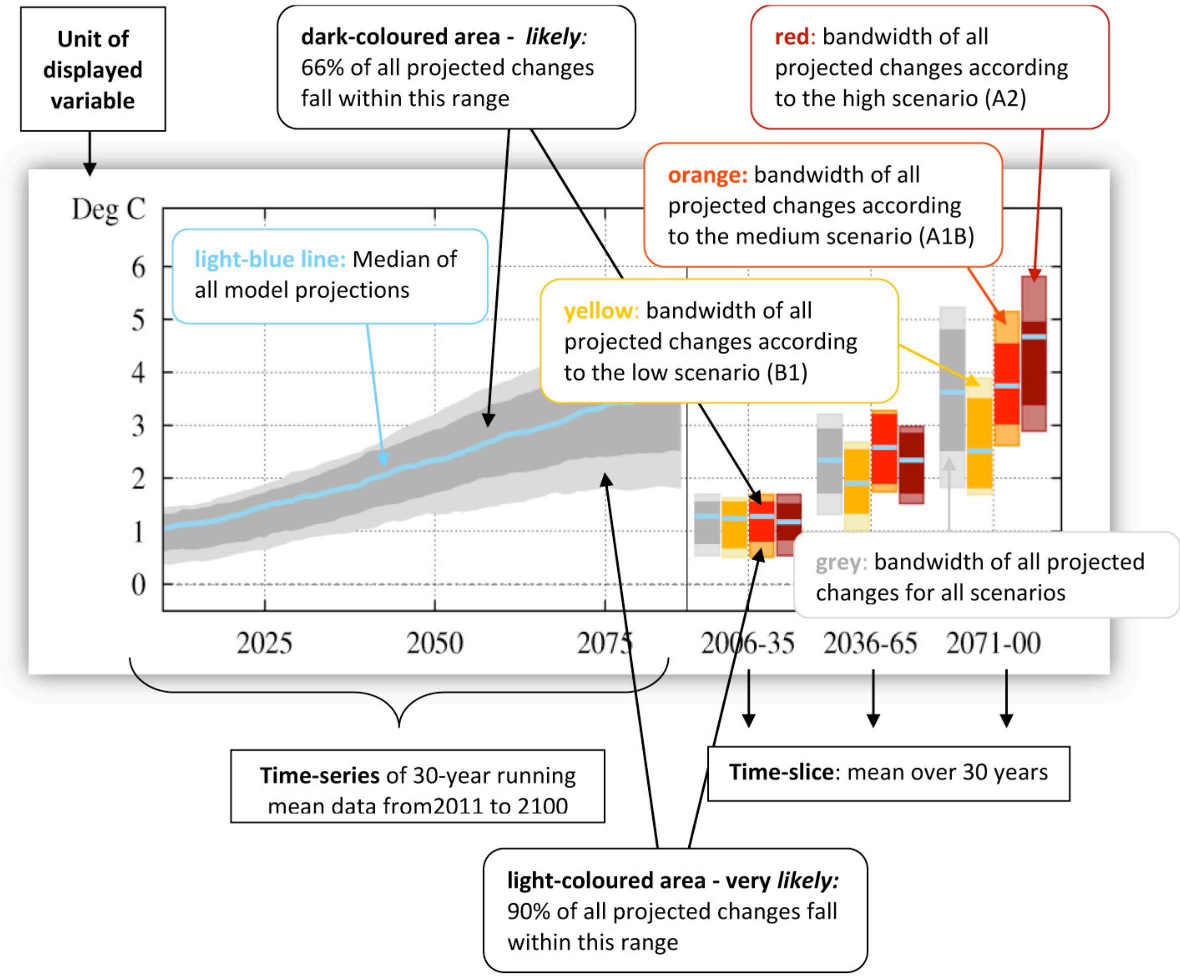


Figure 5: This figure shows in the left part the time series of the median of the projected temperature change as running mean over 30 years for the time period 2011-2100 and the regions of likelihood 'likely' and 'very likely'. In the right part the median and the regions of likelihood 'likely' and 'very likely' of three 30-year periods and three scenarios are shown.

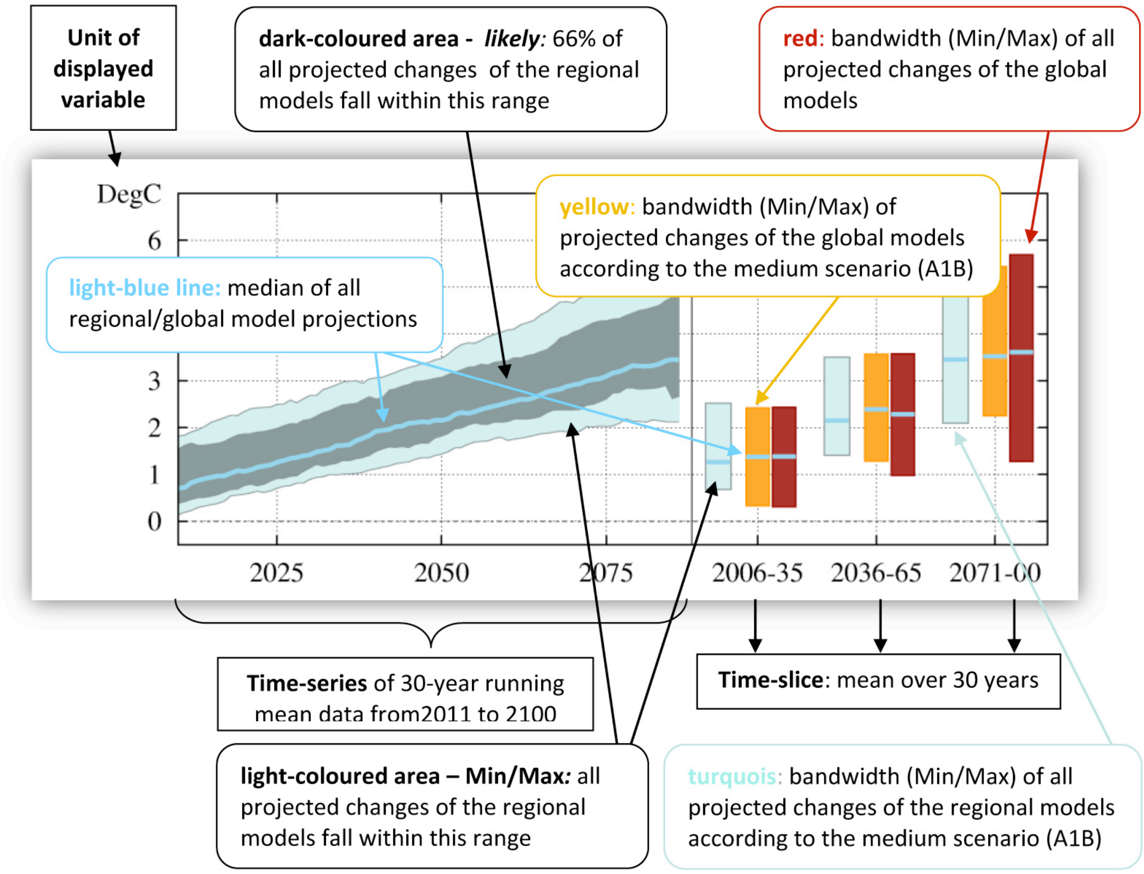


Figure 6: This figure shows in the left part the time series of the median of the projected temperature change as running mean over 30 years for the time period 2011-2100 and the regions of likelihood 'likely' and 'very likely'. In the right part the median and the complete bandwidth of three 30-year periods and two scenarios are shown.

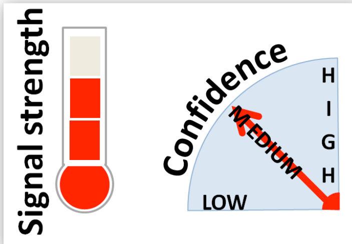


Figure 7: Graphic representation of confidence in the projected changes and the respective signal strength of the projected climate change signal using an example of medium confidence and moderate signal strength.

References

Arbeitsgemeinschaft aqua plan GmbH, hydro & meteo, dr. Papadakis GmbH, 2010: Extremwertstatistische Untersuchung von Starkniederschlägen in NRW (ExUS) Veränderung in Dauer, Intensität und Raum auf Basis beobachteter Ereignisse und Auswirkungen auf die Eintretenswahrscheinlichkeit. Abschlussbericht, erstellt für das Landesamt für Natur, Umwelt und Verbraucherschutz Nordrhein-Westfalen (LANUV NRW), Recklinghausen, 304 pp

Arbeitskreis KLIWA (Hrsg.), 2011: Langzeitverhalten von Grundwasserständen, Quellschüttungen und grundwasserbürtigen Abflüssen in Baden-Württemberg, Bayern und Rheinland-Pfalz. KLIWA-Berichte, Heft 16, Bezug über LUBW, Karlsruhe, BLU, Hof, LUWG, Mainz, 149 ff.

Behr, F. J. & Lutz, S. (1989): Ein schneller Algorithmus zur bilinearen Interpolation in Ankerpunktnetzen. Zeitschrift für Photogrammetrie und Fernerkundung, Bildmessung und Luftbildwesen, Heft 6, 57/1989, 222-229.

Bernhofer C, Matschullat M, Bobeth A (Hrsg. 2009): Das Klima in der REGKLAM-Modellregion Dresden. Publikationsreihe des BMBF-geförderten Projektes REGKLAM – regionales Klimaanpassungsprogramm für die Modellregion Dresden, Heft 1, Rhombos-Verlag Dresden

Bernhofer C, Matschullat M, Bobeth A (Hrsg. 2011): Klimaprojektionen für die REGKLAM-Modellregion Dresden. Publikationsreihe des BMBF-geförderten Projektes REGKLAM – regionales Klimaanpassungsprogramm für die Modellregion Dresden, Heft 2, Rhombos-Verlag Dresden

Bülow, K. (2010): Zeitreihenanalyse von regionalen Temperatur- und Niederschlagssimulationen in Deutschland, Dissertation, Uni-Hamburg, Berichte zur Erdsystem Forschung 75, 2010.

Burrough &. McDonnell (2004): Principles of Geographical Information Systems. Oxford.

Butler, C. (1985): Statistics in Linguistics. Web-Edition, http://www.uwe.ac.uk/hlss/llas/statistics-in-linguistics/bkindex.shtml (zuletzt abgerufen am 27.06.2013), University of West England, Bristol

Chmielewski, F.-M.; Blümel, K.; Henniges, Y. und Müller, A. (2009): Klimawandel und Obstbau in Deutschland. Endbericht des BMBF-Verbundprojekts KliO., Eigenverlag, Humboldt-Universität zu Berlin, 237 S.

Chu, Pao-Shin, Jianxin Wang, 1998: Modeling Return Periods of Tropical Cyclone Intensities in the Vicinity of Hawaii. J. Appl. Meteor., 37, 951–960.*
doi: http://dx.doi.org/10.1175/1520-0450(1998)037<0951:MRPOTC>2.0.CO;2

Clarke & Warwick (2001): Change in Marine Communities: An Approach to Statistical Analysis and Interpretation. PRIMER-E, Plymouth, UK, 172 pp.

Coles, S. (2001): An Introduction to Statistical Modeling of Extreme Values. Springer-Verlag, London.

DAS –Deutsche Anpassungsstrategie an den Klimawandel, 2008: http://www.bmu.de/klimaschutz/downloads/doc/42783.php

DVWK Merkblatt 251 (1999), Statistische Analyse von Hochwasserabflüssen. ATV-DVWK-Regelwerk, DVWK, Bonn.

DVWK-Regel 101 (1976) Empfehlung zur Berechnung der Hochwasserwahrscheinlichkeit, DVWK, Bonn.

DVWK Regel 121 (1992): Niedrigwasseranalyse Teil II: Statistische Untersuchung der Unterschreitungsdauer und des Abflussdefizits, DVWK, Bonn.

Embrechts, P., Klüppelberg, C. und Mikosch, T. (1997): Modelling Extremal Events. Vol. 33 of Applications in Mathematics. Springer-Verlag, New York, 648 pp.

Falk, W., Dietz, E., Grünert, S., Schultze, B. und Kölling, C. (2008): Wo hat die Fichte genügend Wasser? - Neue überregional gültige Karten des Wasserhaushalts von Fichtenbeständen verbessern die Anbauentscheidung; LWF aktuell, 2008.

Field, C.B. and Coauthors, Eds. (2012): Managing the risks of extreme events and disasters to advanced climate change adaptation. Spec.Report of Intergovernmental Panel on Climate Change, Cambridge University Press,19pp.

Ferraz-Mello, S. (1981): Estimation of periods from unequally spaced observations. The Astronomical Journal 86, 4, 619-624.

Freeman, E.A.,G. Moisen (2008): PresenceAbsence: An R package for presence absence analysis, Journal of Statistical Software 23, 111 -31.

Gupta, H. V.; Sorooshian, S. und Yapo, O. P. (1999): Status of automatic calibration for hydrologic models: Comparison with multilevel expert calibration. In: Journal of Hydraulic Engineering 4, Nr. 2, S. 135-143.

Hammel, K. und Kennel, M. (2001): Charakterisierung und Analyse der Wasserverfügbarkeit und des Wasserhaushalts von Waldstandorten in Bayern mit dem Simulationsmodell BROOK90. Forstliche Forschungsberichte München, 185, 135pp.

Hartkamp et al. (1999): Interpolation Techniques for Climate Variables. Geographic Information Systems. Series 99-01.

Hellmers, S. (2010): Hydrological Impacts of Climate Change on Flood Probability in Small Urban Catchments and Possibilities of Flood Risk Mitigation, ISBN 978-3-937693-13-2, Wasserbauschrift Band 13.

Henson, R. 2011, The rough guide to climate change, ISBN 13:978-1-84836-579-7, 401pp.

Hoffmann, P., Krüger, O., Schlünzen, K.H. (2011): A statistical model for the urban heat island and its application to a climate change scenario. Int. J. Climatol., 32:1238-1248, doi: 10.1002/joc.2348.

Hoffmann, P., Krüger, O., Schlünzen, K.H. (2011): A statistical model for the urban heat island and its application to a climate change scenario. International Journal of Climatology (accepted).

Hong et al. (2005): Spatial interpolation of monthly mean climate data for china. In: International Journal of Climatology, Vol. 25, 1369-1379.

Huth, R. and Beck, C. and Philipp, A. and Demuzere, M. and Ustrnul, Z. and Cahynova, M. and Kysely, J. and Tveito, O. E., (2008): Classifications of Atmospheric Circulation Patterns, Recent Advances and Applications, Trends and Directions in Climate Research: Ann. N.Y. Acad. Sci. 1146: 105-152.

Jacob D, Göttel H, Kotlarski S, Lorenz P, Sieck K (2008): Klimaauswirkungen und Anpassung in Deutschland: Erstellung regionaler Klimaszenarien für Deutschland mit dem Klimamodell REMO. Forschungsbericht 204 41 138 Teil 2, i.A. des UBA Dessau

Jacob D, Bülow K, Kotova L, Moseley C, Petersen J, Rechid D. (2011): Regionale Klimasimulationen für Europa und Deutschland – Ensemble-Simulationen für die Klimafolgenforschung. – in Vorbereitung

Jendritzky, M., T. Grothmann, D. Schröter, C. Hasse, U. Fritsch, W. Cramer (2007): Klimawandel in deutschland – Vulnerabilität und Anpassungssatrategien klimasensitiver Systeme. Umweltbundesamt, Forschungsbericht 201 41 253, UBA-FB 000844, ISSN 1611-8855

Kabas (2005): Das Klima in Südösterreich 1961-2004. Wissenschaftlicher Bericht Nr.4-2005. http://www.uni-graz.at/igam7www_wcv-wissber-nr4-tkabas-okt2005.pdf

Katz, Richard W, Parlange, Marc B, and Naveau, Philippe, 2002: Statistics of extremes in hydrology, Advances in Water Resources 25(8-12), 1287–1304.

Keuler, K., A. Block, W. Ahrens, D. Jacob, D. Rechid, L. Kotova, S. Kotlarski, D. Heimann, M. Zemsch, R. Knoche, E. Dittmann, A. Walter, F. Berger, and M. Sommer, 2006: Quantification of uncertainties in regional climate and climate change simulations (QUIRCS).

Kreienkamp, F. H. Huebener, C. Linke und A. Spekat, 2012: Good practice for the usage of climate model simulation results - a discussion paper. Environmental Systems Research 2012, http://www.environmentalsystemsresearch.com/content/1/1/9

Kreiß, J.-P., G. Neuhaus, 2006:Einführung in die Zeitreihenanalyse, Springer-Verlag.

Krüger, O & J-S von Storch, A simple empirical model for decadal climate prediction, Journal of Climate, 2011, doi: 10.1175/2010JCLI3726.1.

Kuratorium für Forschung im Küsteningenieurwesen (2002): Die Küste - EAK 2002: Empfehlungen für die Ausführung von Küstenschutzwerken, Bd. 65, Westholsteinische Verlagsanstalt Boyens und Co., Heide i. Holstein. S. 285-291.

Leander, R., T. Adri Buishand (2007): Resampling of regional climate model output for the simulation of extreme river flows; Journal of Hydrology 332, 487-496.

Leps & Smilauer, 2003: Multivariate Analysis of Ecological Data using CANOCO.

Lilliefors Test. In: Encyclopedia of Statistical Sciences. John Wiley & Sons, 2006, doi:10.1002/0471667196.ess1451.pub2

Longley et al. (2001): Geographic Information Systems and Science, Chichester.
Tobin et al. (2011): Improved interpolation of meteorological forcings for hydrologic applications in a Swiss Alpine region. In: Journal of Hydrology.

Ly et al. (2010): Spatial interpolation of daily rainfall at catchment scale: a case study of the Ourthe and Ambleve catchments, Belgium. In: Hydrology and Earth System Sciences Discussions, Vol. 7, pp 7383-7416, 27-9-2010.

Marques, J. C., Salas, F., Patricio, J., Teixeira, C. M., & Neto, J. M. (2009). Ecological indicators for Coastal and estuarine environmental assessment - a user guide. WIT Press.

McCune, B. and M. J. Mefford. 1999. PC-ORD. Multivariate Analysis of Ecological Data, Version 4.0. MjM Software Design, Gleneden Beach, Oregon. 237 pp.

Morgan G., H. Dowlatabadi, M. Henrion, D. Keith, R. Lempert, S. McBrid, M. Small, T. Wilbanks (eds.), 2009: SAP 5.2 CoverCCSP, 2009: Best practice approaches for characterizing, *communicating, and incorporating scientific uncertainty in decisionmaking. National Oceanic and Atmospheric Administration, Washington D.C., USA.*

Moriasi, D. N.; Arnold, J. G.; Liew, M. W. V.; Bingner, R. L.; Harmel, R. D.; Veith, T. L.: Model Evaluation Guidelines for Systematic Quantification of Accuracy in Watershed Simulations. In: Transactions of the ASABE 50 (2007), Nr. 3, 885-900.
Mudelsee, M., Climate Time Series, Analysis, 2010, pp 74-77.

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht Heidelberg London New York. 474 pp; Atmospheric and Oceanographic Sciences Library, Vol. 42]

MUDELSEE, M., D. CHIRILA, T. DEUTSCHLÄNDER, C. DÖRING, J.O. HAERTER, S. HAGEMANN, H. HOFFMANN, D. JACOB, P. KRAHÉ, G. LOHMANN, C. MOSELEY, E. NILSON, O. PANFEROV, T. RATH, B. TINZ, 2010: Climate Model Bias Correction und die Deutsche Anpassungsstrategie. Mitteilungen der Deutschen Meteorologischen Gesellschaft 03/2010.

Mudersbach, Ch. and Jensen, J. (2009): Extremwertstatistische Analyse von historischen, beobachteten und modellierten Wasserständen an der Deutschen Ostseeküste, Die Küste, Heft 75, Sonderheft MUSTOK, S. 131-162, Boyens Medien GmbH, Heide i. Holstein

Mudersbach, Ch. and Jensen, J. (2010): Non-stationary extreme value analysis of annual maximum water levels for designing coastal structures on the German North Sea coastline, Journal of Flood Risk Management , Vol. 3., Issue 1, pp. 52-62, DOI:10.1111/j.1753-318X.2009.01054.x

Muthers, S.; Matzarakis, A.; Koch, E (2010). Climate Change and Mortality in Vienna—A Human Biometeorological Analysis Based on Regional Climate Modeling. Int. J. Environ. Res. Public Health, 7, 2965-2977.

Nash, J.E.; Sutcliffe, J.V.: River flow forecasting through conceptual models: Part I - A discussion of principles. In: Journal of Hydrology 10 (1970), Nr. 3, 282- 290.

Pfeifer, S., Hänsler, A., Ries, H., Weber, B., Jacob, D., Rechid, D., Teichmann, C., Gobiet, A., Mudelsee, M.,, 2013: Mapping the Robustness of Regional Climate Change Information, Submitted to: Journal of Applied Meteorology and Climatology.

Philipp, A., J. Bartholy, C. Beck, M. Erpicum, P. Esteban, X. Fettweis, R. Huth, P. James, S. Jourdain, F. Kreienkamp, T. Krennert, S. Lykoudis, S. C. Michalides, K. Pianko-Kluczynska, P. Post, D. R. Álvarez, R. Schiemann, A. Spekat and F. S. Tymvios (2010): Cost733cat – A database of weather and circulation type classification. Physics and Chemistry of the Earth, 35, 360-373.

Piani, C., G.P. Weedon, M. Best, S.M. Gomes, P. Viterbo, S. Hagemann, J.O. Haerter, 2010: Statistical bias correction of global simulated daily precipitation and temperature for the application of hydrological models. Journal of Hydrology. 395, 199-215.

Piscopia, R., Inghilesi, R., Panizzo, A., Corsini, S. and Franco, L. (2002): Analysis of 12-year wave measurements by the italian wave network. In: Smith, J. Mckee. COASTAL ENGINEERING 2002: Solving Coastal Conundrums. Proceedings of the 28th International Conference, Cardiff, Wales, July 2002, pp 121-133.

Plate E.-J (1993).: Statistik und angewandete Wahrscheinlichkeitslehre für Bauingenieure, Ernst & Sohn Verlag für Architektur und technische Wissenschaften, Berlin, ISBN 3-433-01073-0, S.20-22.

Pöhler H, Chmielewski F-M, Jasper, K, Henniges Y, Scherzer J (2007): KliWEP - Abschätzung der Auswirkungen der für Sachsen prognostizierten Klimaveränderungen auf den Wasser- und Stoffhaushalt im Einzugsgebiet der Parthe. Weiterentwicklung von WaSiM-ETH: Implikation *dynamischer Vegetationszeiten und Durchführung von Testsimulationen für sächsische Klimaregionen. Abschlussbericht zum FuE-Vorhaben des Sächsischen Landesamtes für Umwelt und Geologie*

Pöhler, H., Schultze, B., Scherzer, J. (2010): Auswirkungen des Klimawandels auf den Wasserhaushalt eines bewaldeten Kleineinzugsgebietes im Hochsauerland, Freiburger Forstliche Forschung, in Druck.

Rapp 2000; Hoy A, Sepp M, Matschullat J (in Bearbeitung): Variability of atmospheric circulation in Europe and Russia, 1901-2010.

Real, R., A. M. Barbosa, J. M. Vargas (2006): Obtaining environmental favourability functions from logistic regression, Environmental and Ecological Statistics 13 (2), 237-245.

Roedel, W., T. Wagner: Physik unserer Umwelt: Die Atmosphäre, 4th ed., Springer-Verlag Berlin Heidelberg 2011, 177pp.

Rosiuta, A. A. (2003): Minimierung der Stützstellen zur Interpolation in dreidimensionalen Texturen, Studienarbeit, Fakultät für Informatik, Institut für Visualisierung und Interaktive Systeme, Universität Stuttgart, http://elib.uni-stuttgart.de/opus/volltexte/2003/1451/

Sachs L.: Angewandte Statistik: Anwendung statistischer Methoden, 6. Aufl., Springer-Verlag Berlin, Heidelberg, New York, Tokio, 1984, ISBN 3-540-12800-X, 46-48.

Schableger (1996): Statistische Analysen klimatologischer Zeitreihen. Historical Social Research, 21, 3, 4-33.
http://hsr-trans.zhsf.uni-koeln.de/hsrretro/docs/artikel/hsr/hsr1996_395.pdf

Scherzer, J., Schultze, B., Niederberger, J., Pöhler, H. (2010): WASKlim - Potenzielle Auswirkungen des Klimawandels auf den Wasserhaushalt am Beispiel der Wupper (NRW), der oberen Iller (Bayern) und der Salza (Sachsen-Anhalt). Forum für Hydrologie und Wasserbewirtschaftung, 29/10, 9-15.

Schönwiese, C.-D., 2006: Praktische Methoden für Meteorologen und Geowissenschaftler, 232-234. Stuttgart.

Schönwiese, C.-D.,1985: Praktische Statistik für Meteorologen und Geowissenschaftler. Gebrüder Bornträger, Berlin, Stuttgart: 1985

Schultze B., C. Kölling, C. Dittmar, T. Rötzer, W. Elling (2005): Konzept für ein neues quantitatives Verfahren zur Kennzeichnung des Wasserhaushalts von Waldböden in Bayern: Modellierung - Regression - Regionalisierung; Forstarchiv 76, 155-163.

Schumacher (2007): Spline Functions: Basic Theory. New York.

Scott, D. W. On optimal and data-based histogram. In: Biometrika (1979) 66 (3): 605-610. doi: 10.1093/biomet/66.3.605

Scott, D. W. Multivariate Density Estimation: Theory, Practice, and Visualization. John Wiley, 1992. ISBN 978-0471547709.

Sepp und Jaagus 2002; Hoy A, Jaagus J Sepp M, Matschullat J (eingereicht bei TAC): Spatial response of two European atmospheric circulation classifications (data from 1901 to 2010).

Serano et al., K. (2003): Comparative analysis of interpolation methods in the middle Ebro Valley (Spain): application to annual precipitation and temperature, Climate Research, 24, 160-180.

Soares, C. G., and Scotto, M. G.: Application of the r largest-order statistics for long-term predictions of significant wave height, Coastal Engineering 51(5-6), 387–394, 2004.

Soukissian, T.H., Kalantzi, G. (2009). A new method for applying the r-largest maxima model for design sea-state prediction. International Journal of Offshore and Polar Engineering, Vol. 19, No. 3, September 2009, ISSN 1053-5381, 176–182.

Smith, Richard L.: Extreme value theory based on the r largest annual events, Journal of Hydrology 86(1-2), 27–43, 1986.

Stein (1999): Interpolation of Spatial Data: some theory for kriging. New York.
Woeste B., Diplomarbeit (2010): Eine Anwendung der Block Maxima Methode im Risikomanagement. Mathematisches Institut für Statistik, Fachbereich Mathematik und Informatik, Westfälische Wilhelms-Universität Münster.

Streit, U.: Vorlesungen zur Geoinformatik, Kap. 7.4.4 Zweidimensionale räumliche Interpolation im Rastermodell, Institut für Geoinformatik der Universität Münster, http://ifgivor.uni-muenster.de/vorlesungen/Geoinformatik/kap/kap7/k07_4.htm

Tait et al. (2006): Thin plate smoothing spline interpolation of daily rainfall for New Zealand using a climatological rainfall surface. In: International Journal of Climatology, Vol. 26, 2097-2115.

Tobin et al. (2011): Improved interpolation of meteorological forcings for hydrologic applications in a Swiss Alpine region. In: Journal of Hydrology.

Tobler, W. (1970): „Erstes Gesetz der Geographie"
„The first law of geography is that everything is related to everything else, but near things are more related than distant things." in Abler et al. (1992): Geography's inner worlds, Pervasive Themes in Contemporary American Geography. New Jersey.

Trömel, S. (2004): Statistische Modellierung von Klimazeitreihen, Dissertation, J.W. Goethe Universität Frankfurt am Main.

Trömel, S. und C.-D. Schönwiese (2007): Probability change of extreme precipitation observed from 1901 to 2000 in Germany, Theor. Appl. Climatol., 87, 29--39, doi:10.1007/s00704-005-0230-4.

Umbaugh S. E. (2010). Digital Image Processing and Analysis: Human and Computer Vision Applications with Cviptools. 2nd edition, Crc Pr Inc, 2010. 977p.

Van Vledder, G., Goda, Y., Hawkes, P. J., Mansard, E., Martin, M. J., Mathiesen, M., Peltier, E. and Thompson, E. 1993. A case study of extreme wave analysis : a comparative analysis. WAVES'93, pp. 978-992.

Von der Lippe, P. Deskriptive Statistik. Gustav Fischer Verlag, Stuttgart, Jena, 1993, ISBN 3-437-40268-4
http://www.von-der-lippe.org/dokumente/buch/buch07.pdf

von Storch, H. and Zwiers, F.W.(1999), Statistical Analysis in Climate Research, Cambridge University Press, Cambridge, 484 pp.

Wahl, T., Jensen, J. and Mudersbach, Ch.: (2010), A multivariate statistical model for advanced storm surge analyses in the North Sea, International Conference on Coastal Engineering Shanghai.

Warwick, R. M., & Clarke, K. R. (2001). Practical measures of marine biodiversity based on relatedness of species. Oceanography And Marine Biology An Annual Review, 39, 207-231.

Webster &. Oliver (2007): Geostatistics for Environmental Scientists. Chichester.

Wilby, R.L. (2008): Constructing climate change scenarios of urban heat island intensity and air quality. Environment and Planning B: Planning and Design, 35, 902-919.

Wilks, Daniel S. Statistical methods in the atmospheric sciences / 3rd ed. (International geophysics series; v. 100). Academic Press, Elsevier, 2011, 151-154

Wood, S. (2006): Generalized additive models: an introduction with R, Vol. 66, CRC Press.

Wood, S. (2012): Mixed GAM Computation Vehicle with GCV/AIC/REML smoothness estimation (06 2012).

Zebisch, M., T. Grothmann, D. Schröter, Cl. Hasse, U. Fritsch, W. Cramer (2005): Vulnerabilität und Anpassungsstrategien klimasensitiver Systeme. Climate Change 08/05, Umweltbundesamt, ISSN 1611-8855, 203pp.

Acknowledgement

Many thanks to Andree Nather (Master student, Met.) and the colleagues of CSC for their kind help to complete the brochure.

Contact:
Climate Service Center
Fischertwiete 1
20095 Hamburg
Germany

Phone +49(0)40-226 338-424
Fax +49(0)40-226 338-163

www.climate-service-center.de

ISSN 2192-4058

SPONSORED BY THE

Federal Ministry
of Education
and Research