Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

Manfred Mudelsee

Climate Time Series Analysis

Classical Statistical and Bootstrap Methods

Springer

Dr. Manfred Mudelsee
Climate Risk Analysis
Schneiderberg 26
30167 Hannover
Germany

Alfred Wegener Institute for Polar and Marine Research
Bussestrasse 24
27570 Bremerhaven
Germany
mudelsee@mudelsee.com

ISSN 1383-8601
ISBN 978-90-481-9481-0 e-ISBN 978-90-481-9482-7
DOI 10.1007/978-90-481-9482-7
Springer Dordrecht Heidelberg London New York

Library of Congress Control Number: 2010930656

Cover design: Integra Software Services Pvt. Ltd.

Printed on acid-free paper

Springer is part of Springer Science+Business Media (www.springer.com)

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

To my parents,

Anna-Luise Mudelsee,
née Widmann

and

Richard Mudelsee

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

Preface

Climate is a paradigm of a complex system. Analysing climate data is an exciting challenge. Analysis connects the two other fields where climate scientists work, measurements and models. Climate time series analysis uses statistical methods to learn about the time evolution of climate. The most important word in this book is "estimation." We wish to know the truth about the climate evolution but have only a limited amount of data (a time series) influenced by various sources of error (noise). We cannot expect our guess (estimate), based on data, to equal the truth. However, we can determine the typical size of that deviation (error bar). Related concepts are confidence intervals or bias. Error bars help to critically assess estimation results, they prevent us from making overstatements, they guide us on our way to enhance the knowledge about the climate. Estimates without error bars are useless.

The complexity of the climate system and the nature of the measurement or modelling act may introduce (1) non-normal distributional shape, (2) serial dependence, (3) uneven spacing and (4) timescale uncertainties. These difficulties prohibit in many cases the classical statistical approach to derive error bars by means of calculating the theoretical distribution of the estimates. Therefore we turn to the bootstrap approach, which generates artificial resamples of the time series in the computer, repeats for each resample the estimation (yielding the replication) and calculates the error bars from the distribution of the replications. The typical number of replications is 2000. This computing-intensive approach yields likely more realistic error bars.

Still, there is theoretical work to be done: how to best preserve the shape and serial dependence in the bootstrap resamples, how to estimate with smallest error bars. Uneven spacing in time series analysis has not been the preferred study object of statisticians. Timescale uncertainties and their effect on error bars (widening, but how much?) is almost completely unexplored. This book adapts existing and introduces new bootstrap algorithms for handling such problems.

We test our methods by means of Monte Carlo experiments. When the true parameter values are known, it is possible to generate random samples and calculate bootstrap error bars and confidence intervals and check whether, for example, a 95% confidence interval for the estimated parameter does indeed contain in 95% of the Monte Carlo runs the known parameter. The number of Monte Carlo runs is typically 47,500. The computational burden increases to $2000 \times 47{,}500$. To create of this book required relatively powerful computers. In Chapter 9, we look on what may become possible when quantum computers exist.

Chapter 1 introduces you to climate time series and their statistical properties. Chapter 2 gives stochastic models of serial dependence or persistence, which are needed in Chapter 3, where bootstrap resampling, the determination of error bars and the construction of confidence intervals is explained. This concludes Part I on fundamental concepts. Chapters 4, 5 and 6 employ the concepts in the univariate setting (Part II), where the sample consists of only one time series. Chapters 7 and 8 deal with the bivariate setting (Part III).

Each of the chapters has a section "Background material," which contains supplementary material from statistics and climatology. You find also reported "stories"—comments, discussions and replies on certain papers in a scientific journal. Such exchanges, as also the "discussion" parts in read statistical papers, provide insight into the production of science—often more intimate than what polished journal articles reveal. The chapters have also a section entitled "Technical issues," where you find, besides information about numerical algorithms, listed software with internet links.

Intuition and creativity is needed for developing statistical estimation techniques for complex problems. Therefore I praise occasionally the artistic scientist, not at least in response to papers that make derogative remarks on that capacity. On the other hand, the artist in us must not forget to look for previous work on the same subject done in other disciplines and to scrutinize the own development by means of objective methods, such as Monte Carlo tests.

Regarding the notation, I have tried to find a route between convention on the one hand and consistency on the other. However, the most important symbols, including t for sampled time, x for a sampled climate variable, n for data size and $\{t(i), x(i)\}_{i=1}^{n}$ for a time series sample, possess their role throughout the book. I take this opportunity to introduce the counterpart of the time series sample, the stochastic process, $\{T(i), X(i)\}_{i=1}^{n}$. I hope that not only statisticians find that traditional

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

distinction (Fisher 1922) between sample (i.e., numbers) and process (i.e., random variables) useful. Regarding the reference list, this notes only the first of the places of a publisher and it gives, in square brackets, additional information. This is not done consistently (e.g., the doi is given mostly to identify more recent papers published by the American Geophysical Union). The author list may be more aptly denoted as "first-author list."

The URL for this book is `http://www.manfredmudelsee.com/book`. It has the links to the sites of the software (including own products) and the data. It has also, inevitably, an errata section. As the person responsible for the content, I offer my apologies in advance of the discovered errors, and I thank you for informing me. My email address is `mudelsee@mudelsee.com`.

Sincere thanks go to my academic teachers, Augusto Mangini and Karl Stattegger, and the hosts of my subsequent stays, Howell Tong and Qiwei Yao, Gerd Tetzlaff, Maureen Raymo and Gerrit Lohmann. They and the colleagues at the respective institutions (Institute of Environmental Physics at the University of Heidelberg, Germany; today's Institute of Geosciences at the University of Kiel, Germany; today's School of Mathematics, Statistics and Actuarial Science at the University of Kent, Canterbury, UK; Institute of Meteorology at the University of Leipzig, Germany; Department of Earth Sciences at Boston University, USA; Alfred Wegener Institute for Polar and Marine Research, Bremerhaven, Germany) helped me to shape my thinking and flourish in the field of climate time series analysis.

The above and following had an influence, gratefully acknowledged, on this book via discussing with me or supplying data, knowledge or literature: Mersku Alkio, Susana Barbosa, Rasmus Benestad, André Berger, Wolfgang Berger (whom I owe the term "ramp"), Mark Besonen, Matthias Bigler, Michael Börngen, Armin Bunde, Steven Burns, Dragos Chirila (who went through the whole manuscript), Ann Cowling, Michel Cruzifix, Anthony Davison (who went through Chapters 1, 2, 3, 4, 5 and 6 of the manuscript), Cees Diks, Reik Donner, Heinz Engel, Dominik Fleitmann, Imola Fodor, Eigil Friis-Christensen, Martin Girardin, the late Clive Granger, Uwe Grünewald, Peter Hall, Gerald Haug, Jonathan Hosking, Daniela Jacob, Malaak Kallache (who went through Chapter 6), Vit Klemeš, Demetris Koutsoyiannis, Thomas Laepple, Peter Laut, Martin Losch (who went through Chapter 9), Werner Metz, Alberto Montanari, Eric Moulines, Alfred Musekiwa, Germán Prieto, Stefan Rahmstorf, Regine Röthlisberger, Henning Rust, Michael Sarnthein, Denis Scholz, Michael Schulz, Walter Schwarzacher, Martin Trauth, Dietmar Wagenbach, Heinz Wanner, Eric Wolff, Peili Wu and Carl Wunsch.

The computing centres from following institutions provided computing time: Alfred Wegener Institute and University of Leipzig. Following institutions gave data: British Antarctic Survey, Cambridge, UK; Global Runoff Data Centre, Koblenz, Germany; National Oceanic and Atmospheric Administration, Washington, DC, USA. Libraries from following research institutes and universities helped with literature: Alfred Wegener Institute, Boston University, University of Massachusetts Boston, Cambridge, Halle, Hannover, Harvard, Heidelberg, Kassel, Leipzig, Massachusetts Institute of Technology, Michigan State University and Yale. Following institutions funded own research that contributed to this book: British Antarctic Survey, Deutsche Forschungsgemeinschaft, European Commission, Niedersächsisches Ministerium für Wissenschaft und Kultur and Risk Prediction Initiative.

Rajiv Monsurate helped adapting the Latex style file.

Last, but not least, I thank the editors at Springer as well as former Kluwer for their patience over the past six years: Chris Bendall, Robert Doe, Gert-Jan Geraeds, Kevin Hamilton, Lawrence Mysak and Christian Witschel.

Hannover, Germany
December 2009

Manfred Mudelsee

Acknowledgements

Copyright permissions are gratefully acknowledged for reproducing Figs. 1.14 and 2.8 (American Geophysical Union, Washington, DC) and the photograph of the author (Silke Storjohann, Hamburg).

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

Contents

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

List of Algorithms

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

List of Figures

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

List of Tables

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

Part I

Fundamental Concepts

Chapter 1

Introduction

Superiority of quantitative methods over qualitative

—Popper

"Weather is important but hard to predict"—lay people and scientists alike will agree. The complexity of that system limits the knowledge about it and therefore its predictability even over a few days. It is complex because many variables within the Earth's atmosphere, such as temperature, barometric pressure, wind velocity, humidity, clouds and precipitation, are interacting, and they do so nonlinearly. Extending the view to longer timescales, that is, the climate system in its original sense (the World Meteorological Organization defines a timescale boundary between weather and climate of 30 years), and also to larger spatial and further processual scales considered to influence climate (Earth's surface, cryosphere, Sun, etc.), does not reduce complexity. This book loosely adopts the term "climate" to refer to this extended view, which shall also include "paleoclimate" as the climate within the geologic past.

Man observes nature and climate to learn, or extract information, and to predict. Since the climate system is complex and not all variables can be observed at arbitrary spatial and temporal range and resolution, our knowledge is, and shall be, restricted and uncertainty is introduced. In such a situation, we need the statistical language to acquire quantitative information. For that, we take the axiomatic approach by assuming that to an uncertain event ("it rains tomorrow" or "before 20,000 years the tropics were more than 5°C colder than at present") a probability (real number between 0 and 1) can be assigned (Kolmogoroff 1933). Statistics then deciphers/infers events and probabilities from data. This is an

M. Mudelsee, *Climate Time Series Analysis*, Atmospheric and Oceanographic Sciences Library 42, DOI 10.1007/978-90-481-9482-7_1,

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

assumption like others in the business: three-dimensional space, time arrow and causality, mathematical axioms (Kant 1781; Polanyi 1958; Kandel 2006). The book also follows the optimistic path of Popper (1935): small and accurately known ranges of uncertainty about the climate system enable more precise climate hypotheses to be tested, leading to enhanced knowledge and scientific progress. Also if one shares Kuhn's (1970) view, paradigm shifts in climatology have better success chances if they are substantiated by more accurate knowledge. It is the aim of this book to provide methods for obtaining accurate information from complex time series data.

Climate evolves in time, and a stochastic process (a time-dependent random variable representing a climate variable with not exactly known value) and time series (the observed or sampled process) are central to statistical climate analysis. We shall use a wide definition of trend and decompose a stochastic process, X, as follows:

$$X(T) = X_{\text{trend}}(T) + X_{\text{out}}(T) + S(T) \cdot X_{\text{noise}}(T), \tag{1.1}$$

where T is continuous time, $X_{\text{trend}}(T)$ is the trend process, $X_{\text{out}}(T)$ is the outlier process, $S(T)$ is a variability function scaling $X_{\text{noise}}(T)$, the noise process. The trend is seen to include all systematic or deterministic, long-term processes such as a linear increase, a step change or a seasonal signal. The trend is described by parameters, for example, the rate of an increase. Outliers are events with an extremely large absolute value and are usually rare. The noise process is assumed to be weakly stationary with zero mean and autocorrelation. Giving $X_{\text{noise}}(T)$ standard deviation unity enables introduction of $S(T)$ to honour climate's definition as not only the mean but also the variability of the state of the atmosphere and other compartments (Brückner 1890; Hann 1901; Köppen 1923). A version of Eq. (1.1) is written for discrete time, $T(i)$, as

$$X(i) = X_{\text{trend}}(i) + X_{\text{out}}(i) + S(i) \cdot X_{\text{noise}}(i), \tag{1.2}$$

using the abbreviation $X(i) \equiv X(T(i))$, etc. However, for unevenly spaced $T(i)$ this is a problematic step because of a possibly non-unique relation between $X_{\text{noise}}(T)$ and $X_{\text{noise}}(i)$, see Section 2.1.2.1. The observed, discrete time series from process $X(i)$ is the set of size n of paired values $t(i)$ and $x(i)$, compactly written as $\{t(i), x(i)\}_{i=1}^{n}$. To restate, the aim of this book is to provide methods for obtaining quantitative estimates of parameters of $X_{\text{trend}}(T)$, $X_{\text{out}}(T)$, $S(T)$ and $X_{\text{noise}}(T)$ using the observed time series data $\{t(i), x(i)\}_{i=1}^{n}$.

A problem in climate analysis is that the observation process superimposes on the climatic process. $X_{\text{noise}}(T)$ may show not only climatic

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

but also measurement noise. Outliers can be produced by power loss in the recording instrument. Non-climatic trends result, for example, from changing the recording situation. An example is temperature measurements made in a town that are influenced by urbanization (meaning an increased heat-storage capacity). However, measurement noise can in principle be reduced by using better instruments, and outliers and trends owing to the observation system can be removed from the data—climatologists denote such observation trend free data as homogeneous.

A further problem in real-world climatology is that also the time values have to be estimated, by dating (Section 1.1). Dating errors are expected to add to the noise and make the result more uncertain.

Consider a second climate variable, $Y(T)$, composed as $X(T)$ in Eq. (1.1) of trend, outliers, variability and noise. The interesting new point is the dependence between $X(T)$ and $Y(T)$. Take as example the relation between concentration of CO_2 in the atmosphere and the global surface temperature. In analogy to univariate X, we write $\{X(T), Y(T)\}$, $\{T(i), X(i), Y(i)\}$ and $\{t(i), x(i), y(i)\}_{i=1}^{n}$ for such bivariate processes and time series. This book describes methods only for uni- and bivariate time series. Possible extensions to higher dimensions are mentioned in Chapter 9.

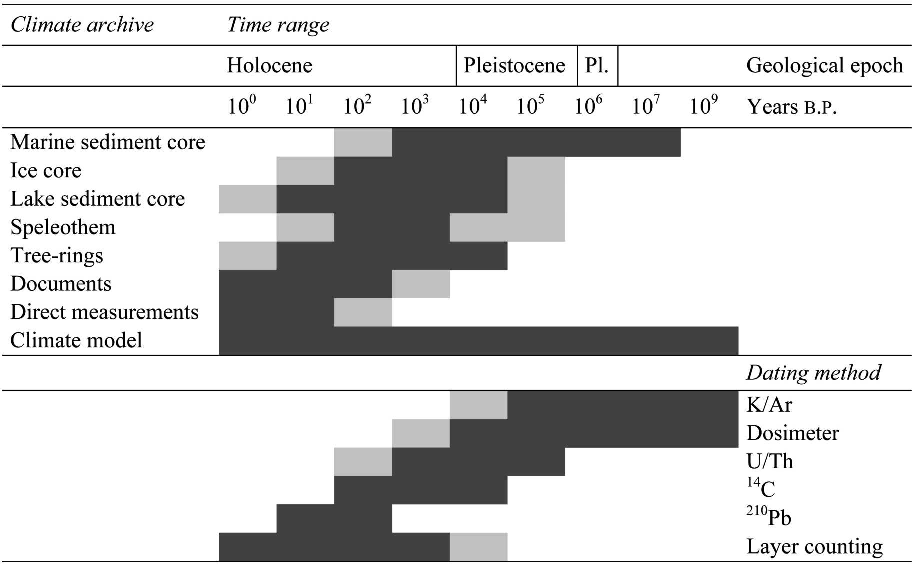
$\{t(i), x(i), y(i)\}_{i=1}^{n}$ need not result from the natural climate system but may also be the output from a mathematical climate model. Such models attempt to rebuild the climate system by connecting climate variables with governing mathematical–physical equations. Owing to the limited performance of computers and the uncertain knowledge about climatic processes, climate models are necessarily limited in spatial, processual and temporal resolution (McAvaney et al. 2001; Randall et al. 2007). On the other hand, climate models offer the possibility to perform and repeat climate experiments (say, studying the influence of doubled concentrations of CO_2 in the atmosphere on precipitation in dependence on different model implementations of the role of clouds).

1.1 Climate archives, variables and dating

Climate archives "contain" the time series. The measured variables $(x(i), y(i))$ either are of direct interest, as in case of precipitation and temperature, or they bear indirect information (indicator or proxy variables). The estimated times $(t(i))$, in geosciences often called timescale, are obtained either by direct, absolute dating methods or indirectly by comparison with another, dated time series. Table 1.1 gives an overview about climate archives and absolute dating methods. Table 1.2 informs about climate variables and their proxies studied in this book. More details are provided in Figs. 1.1, 1.2, 1.3, 1.4, 1.5, 1.6, 1.7, 1.8, 1.9 and

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

Table 1.1. Main types of climate archives, covered time ranges and absolute dating methods.



Dark shading means "frequently used," *light shading* means "occasionally used." Pl., Pliocene; B.P., "before the present." Background material (Section 1.6) gives details and references on geological epochs (also before Pliocene), archives and dating.

1.10, where some of the time series analysed in this book are presented, and in the background material (Section 1.6).

1.2 Noise and statistical distribution

The noise, $X_{\text{noise}}(T)$, has been written in Eq. (1.1) as a zero-mean and unit-standard deviation process, leaving freedom as regards its other second and higher-order statistical moments, which define its distributional shape and also its spectral and persistence properties (next section). The probability density function (PDF), $f(x)$, defines

$$\text{prob}\left(a \le X_{\text{noise}}(T) \le a+\delta\right)\big|_{\delta\to 0} = \int_a^{a+\delta} f(x)dx, \tag{1.3}$$

putting our incomplete knowledge in quantitative form.

For analysing, by means of explorative tools, the shape of $f(x)$ using time series data $\{t(i), x(i)\}_{i=1}^{n}$, it is important to estimate and remove the trend from the data. An unremoved trend would deliver a false, broadened picture of $f(x)$. Trend removal has been done for constructing Fig. 1.11, which shows histograms as estimates of the distributions of $X_{\text{noise}}(T)$ for various climate time series. The estimation of trends is

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

Table 1.2. Climate archives and variables studied in this book (selection).

Climate archive	*Location*	*Time range* (a)	*Proxy variable*	*Resolution* (a)	*Climate variable*
Marine sediment core	Eastern equatorial Pacific	10^6	$\delta^{18}O$, benthic foraminifera	10^3	Ice volume, bottom water temperature
Ice core	Antarctica	10^5	CO_2, air bubbles	10^3	CO_2, atmosphere
			δD, ice	10^2	Air temperature
	Greenland	10^5	SO_4 content, ice	10^0	Volcanic activity
			Ca content, ice	10^0	Aeolian dust, wind
			Dust content, ice	10^0	Aeolian dust, wind
			Conductivity,[a] ice	10^0	Soluble material, wind
			Na content, ice	10^0	Seasalt, wind
Tree-rings	Worldwide	10^4	$\Delta^{14}C$, wood	10^0	Solar irradiance, ocean circulation
Lake sediment core	Boston area	10^3	Varve thickness	10^0	Wind[b]
Speleothem	Southern Oman	10^4	$\delta^{18}O$, carbonate	10^1	Monsoon rainfall
Documents	Weikinn source texts	10^3		10^0	Floods, river Elbe
Climate model	Hadley Centre, HadCM3	10^2		10^0	River runoff
Direct measurements	Siberia, North Atlantic	10^2		10^{-1}	Surface temperature

Time range refers to the length of a record, resolution to the order of the average time spacing (see Section 1.4). "Proxy variable" denotes what was actually measured on which material. "Climate variable" refers to the climatic variations recorded by the variations in the proxy variable. The ability of a proxy variable to indicate a climate variable depends on the characteristic timescales (between resolution and time range). For example, $\delta^{18}O$ variations in benthic foraminifera over timescales of only a few decades do not record ice-volume variations (which are slower). The Weikinn source texts are given by Weikinn (1958, 1960, 1961, 1963, 2000, 2002).
[a] Electrical conductivity of the melted water.
[b] Extremely thick varves (graded beds) indicate extremely high wind speed (hurricane).

one of the primary tasks in climate time series analysis and described in Chapter 4. In Fig. 1.11, outliers, sitting at the tail of the distribution, are tentatively marked. The variability, $S(T)$, has only been normalized in those panels in Fig. 1.11 where it is not time-constant.

As the histogram estimates of the PDFs reveal, some distributions (Fig. 1.11b, i, j) exhibit a fairly symmetrical shape, resembling a Gaussian

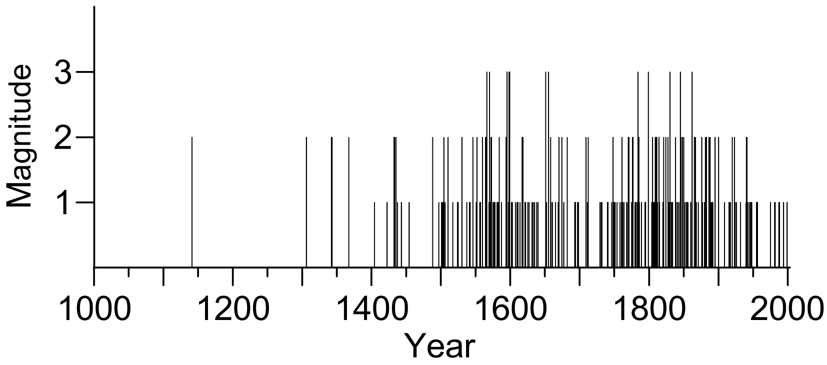


Figure 1.1. Documentary data: floods of the river Elbe during winter over the past 1000 years. x, the flood magnitude, is in three classes (1, minor; 2, strong; 3, exceptionally strong). Hydrological winter is from November to April. Data for $t \leq 1850$ were extracted from Curt Weikinn's compilation (Weikinn 1958, 1960, 1961, 1963, 2000, 2002) of source texts on hydrography in Europe; accuracy of flood dates is ~ 1 month. Data for $t > 1850$ were inferred from daily measurements of water stage and runoff (volume per time interval) at Elbe station Dresden (Global Runoff Data Centre, Koblenz, Germany) via a calibration of magnitude versus water stage/runoff (Mudelsee et al. 2003). Because floods can last up to several weeks, only the peaks in stage/runoff were used to ensure independence of the data. Total number of points is 211. Data sparseness for $t \lessapprox 1500$ is likely caused by document loss (inhomogeneity). One climatological question associated with the data is whether floods occur at a constant rate or there is instead a trend. (Data from Mudelsee et al. 2003.)

(Fig. 3.1). Other PDFs (Fig. 1.11c–h, k), however, have more or less strongly right-skewed shape. Possibly Fig. 1.11d (Vostok δD) reflects a bimodal distribution.

Table 1.3 informs about the size of the variability, $S(T)$, in relation to the uncertainty associated with the pure measurement for the time series analysed here. $S(T)$ reflects the variability of the climate around its trend (Eq. 1.1), the limited proxy quality when no directly measured variables are available and, finally, measurement error. As is evident from the data shown, the measurement error is often comparably small in climatology. It is in many studies that use proxy variables one of the major tasks to quantify the proxy error. For example, if δ^{18}O in shells of benthic foraminifera from deep-sea sediment cores is used as proxy for global ice volume, bottom-water temperature fluctuations make up nearly 1/3 of $S(T)$, see Table 1.3.

A relation proxy variable–climate variable established under laboratory conditions is not perfect but shows errors, quantifiable through regression (Chapter 8). Assuming that such a relation holds true also in

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

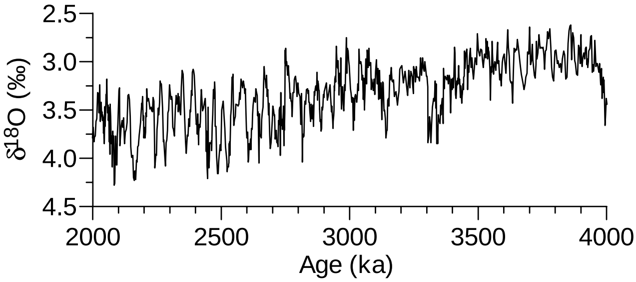


Figure 1.2. Marine sediment core data: δ^{18}O record from Ocean Drilling Program (ODP) site 846 (eastern equatorial Pacific) within 2–4 Ma. The core was drilled from a ship through $\sim$ 3300 m water into the ocean floor, it has a length of $\sim$ 460 m and a diameter of $\sim$ 35 cm. The oxygen isotope record (Shackleton et al. 1995b) was measured on the calcareous shells of benthic foraminifera, mainly *C. wuellerstorfi* and *Uvigerina* spp., using a mass spectrometer. Values are given in delta notation: $\delta^{18}\mathrm{O} = \left[({}^{18}\mathrm{O}/{}^{16}\mathrm{O})_{\mathrm{sample}}/({}^{18}\mathrm{O}/{}^{16}\mathrm{O})_{\mathrm{PDB}} - 1\right] \cdot 1000‰$, where $({}^{18}\mathrm{O}/{}^{16}\mathrm{O})$ is the number ratio of oxygen isotopes ^{18}O and ^{16}O and PDB is "Pee Dee Belemnite" standard. A value of 0.64‰ was added to all δ^{18}O values from *C. wuellerstorfi* to correct for a species-dependent offset (Shackleton and Hall 1984). The depth scale was transformed into a timescale in several steps (Shackleton et al. 1995a). First, biostratigraphic positions, that is, core depths documenting first or last appearances of marine organisms, provided a rough time frame. (Unlike many other marine sediment cores, site ODP 846 lacks a magnetostratigraphy, that is, recorded events of reversals of the Earth's magnetic field, which might had improved the temporal accuracy at this step.) Second, a proxy record of sediment density was measured using a gamma-ray attenuation porosity evaluation (GRAPE) tool. Third, the ODP 846 GRAPE record was tuned (Section 1.6) to the combined GRAPE record from ODP sites 849, 850 and 851. This stacked GRAPE record had in turn been previously tuned to the time series of solar insolation at 65°N (Berger and Loutre 1991), calculated using standard procedures from astronomy. The reason behind this cross-tuning procedure is the observation (Hays et al. 1976) that Earth's climatic variations in the order of tens of thousands to several hundreds of thousands of years are influenced by solar insolation variations. Since the sedimentation rate in the geographic region of site ODP 846 varies with climate (Shackleton et al. 1995a), one cannot assume a constant accumulation of the marine archive. Hence, the dates of sediment samples between the biostratigraphic fixpoints cannot be obtained by interpolation and the GRAPE density records had to be used to obtain an absolute timescale by tuning. Note that time runs "in paleoclimatic manner" from the right to the left. In the same fashion, the δ^{18}O scale is inverted such that glacial conditions (large ice volume, low bottom water temperature or large δ^{18}O values) are indicated by the bottom part and interglacial conditions by the top part of the plot. The number of data points, n, within the shown interval is 821, the average spacing is $\sim$ 2.4 a. A comparison between absolutely dated and tuned magnetostratigraphic timescales for the Pliocene to early Pleistocene (Mudelsee 2005) suggests an average age deviation of $\sim$ 25 ka; this value can also serve to indicate the magnitude of the absolute error of the ODP 846 timescale. The record indicates variations in global ice volume and regional bottom water temperature. One task is to quantify the long-term δ^{18}O increase, which reflects the glaciation of the northern hemisphere in the Pliocene.

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

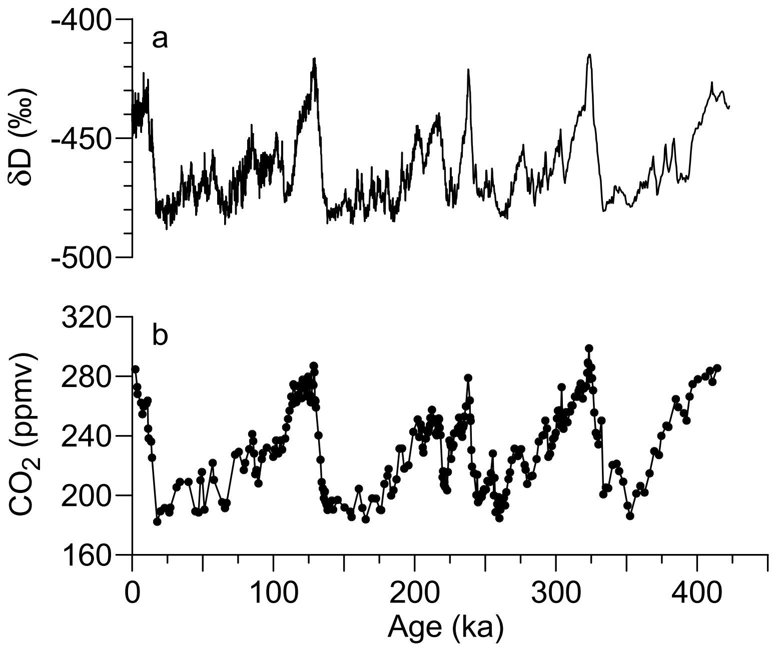


Figure 1.3. Ice core data: deuterium and CO_2 records from the Vostok station (Antarctica) over the past 420,000 years. The core was drilled into the ice (diameter: 12 cm, length: 3623 m) and recovered in segments. The deuterium record (**a**) was measured on ice material using a mass spectrometer. Values are given in delta notation: $\delta\mathrm{D} = [(\mathrm{D/H})_{\mathrm{sample}}/(\mathrm{D/H})_{\mathrm{SMOW}} - 1] \cdot 1000‰$, where (D/H) is the number of D particles over the number of H particles and SMOW is "Standard Mean Ocean Water" standard. Total number of points, n, is 3311. The CO_2 record (**b**) was measured on air bubbles enclosed in the ice. Values are given as "parts per million by volume," n is 283. In **b,** values (*dots*) are connected by lines; in **a,** only lines are shown. The present-day CO_2 concentration ($\sim$ 389 ppmv) is not recorded in **b.** The construction of the timescale (named GT4) was achieved using a model of the ice accumulation and flow. Besides glaciological constraints, it further assumed that the points at 110 and 390 ka correspond to dated stages in the marine isotope record. Construction of the CO_2 timescale required additional modelling because in the ice core, air bubbles are younger in age than ice at the same depth. One climatological question associated with the data is whether variations in CO_2 (the values in air bubbles presenting the atmospheric value accurately) lead over or lag behind those of deuterium (which indicate temperature variations, low δD meaning low temperature). (Data from Petit et al. 1999.)

the geologic past increases the proxy error. Spatially extending the range for which a variable is thought to be representative is a further source of error. This is the case, for example, when variations in air temperature in the inversion height above Antarctic station Vostok are used to repre-

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

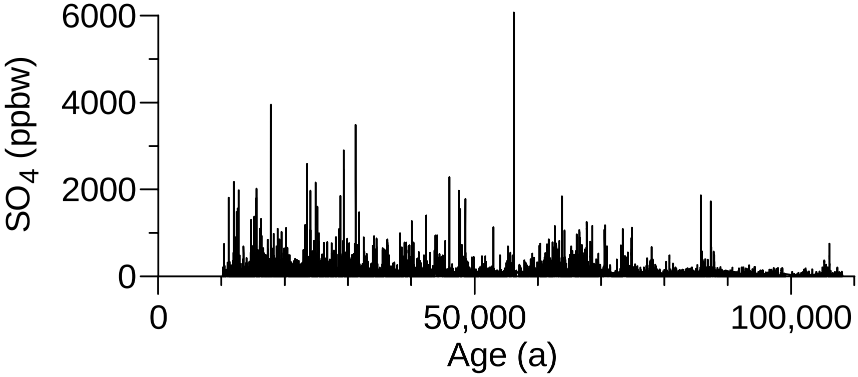


Figure 1.4. Ice core data: sulfate record from the NGRIP core (Greenland) over the interval from $\sim$ 10 to $\sim$ 110 ka. The sulfate content was determined by continuously melting the ice core along its axis and measuring SO_4 of the melt water by means of a photometer (continuous flow analysis, CFA; see Röthlisberger et al. (2000) and Bigler et al. (2002)); ppbw, parts per billion by weight. Meltspeed and signal dispersion limit the length resolution to $\sim$ 1 cm over the measured record length (1530 m). In the young part of the record ($t \leq 105$ ka), the NGRIP timescale was obtained by tuning to the ss09sea timescale of the Greenland GRIP ice core (Johnsen et al. 2001) using the records of ice isotopes (North Greenland Ice Core Project members 2004), electrical conductivity and dielectric properties. In the old part, the NGRIP timescale was obtained by tuning to the GT4 timescale of the Vostok ice core (Fig. 1.3) using the records of $\delta^{18}O$ and methane concentration. (An absolutely dated alternative to the GRIP ss09sea timescale was published by Shackleton et al. (2004).) The sulfate record was finally averaged to 1-year resolution. Using the Ca and Na records, proxies for mineral dust and seasalt content, respectively, it is possible to remove peaks in the sulfate record from dust and salt input—the remaining peaks in the "excess" SO_4 record, shown here, likely reflect the input from volcanic eruptions via the atmosphere. The record therefore bears the possibility to reconstruct volcanic activity throughout the last glacial period. (Data from Bigler M 2004, personal communication.)

sent those of the total southern hemisphere. However, such uncertainties are often unavoidable when general statements about the climate system are sought. All individual noise influences on a climate variable (natural variability, proxy and measurement noise) seem to produce a process $X_{\mathrm{noise}}(T)$ with a PDF that is better described by a product than a sum of individual PDFs and that likely has a right-skewed shape, such as the lognormal distribution (Aitchison and Brown 1957).

1.3 Persistence

The other property of $X_{\mathrm{noise}}(T)$ besides distributional shape regards serial dependence. The autocovariance, $E\left[X_{\mathrm{noise}}(T_1) \cdot X_{\mathrm{noise}}(T_2)\right]$ for

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

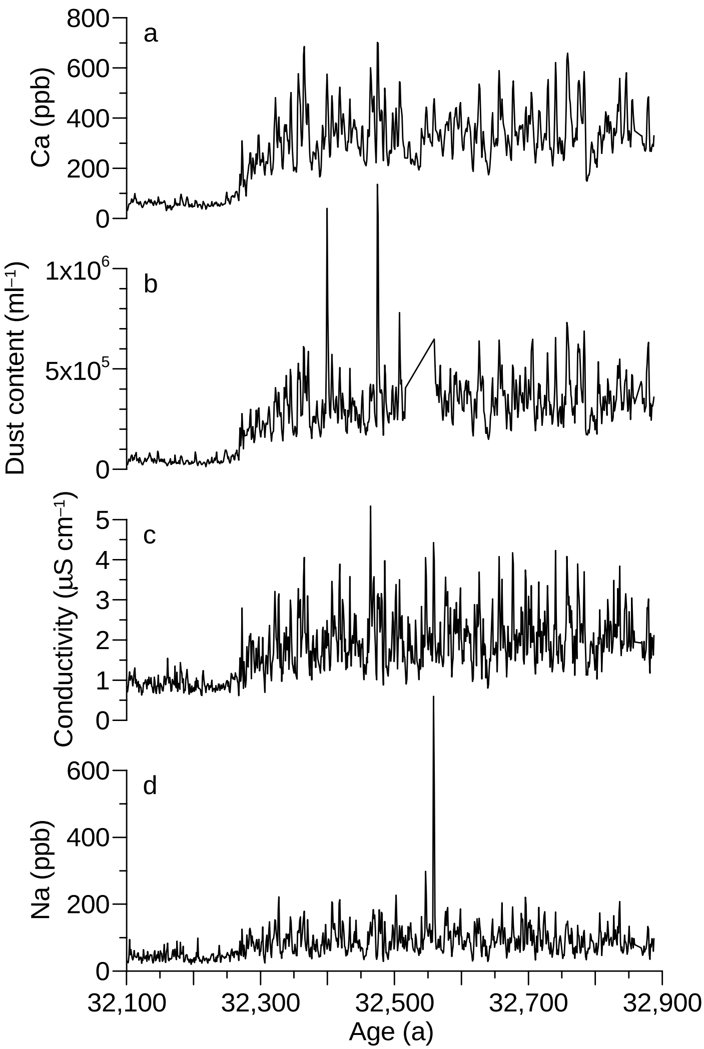


Figure 1.5. Ice core data: Ca concentration (**a**), dust content (**b**), electrical conductivity (**c**) and Na concentration (**d**) from the NGRIP core (Greenland) during the onset of Dansgaard–Oeschger (D–O) event 5. The four variables were measured using CFA on the melted water (Fig. 1.4). ppb, parts per billion; ml^{-1}, number of particles per ml; S m^{-1}, SI unit for electrical conductivity. A data gap (hiatus) exists at around 32,550 a in the dust-content record. Records were "downsampled" to annual resolution. The Ca record indicates variations of mineral dust transported to the atmosphere over Greenland, the dust content indicates atmospheric dust load, electrical conductivity is a proxy for input of soluble material (integrating various environmental signals) and Na is a proxy for seasalt. One climatological question is whether the changes in all four variables happened simultaneously at the onset of D–O event 5. D–O events are short-term warmings during the last glacial period. (Data from Röthlisberger R 2004, personal communication.)

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

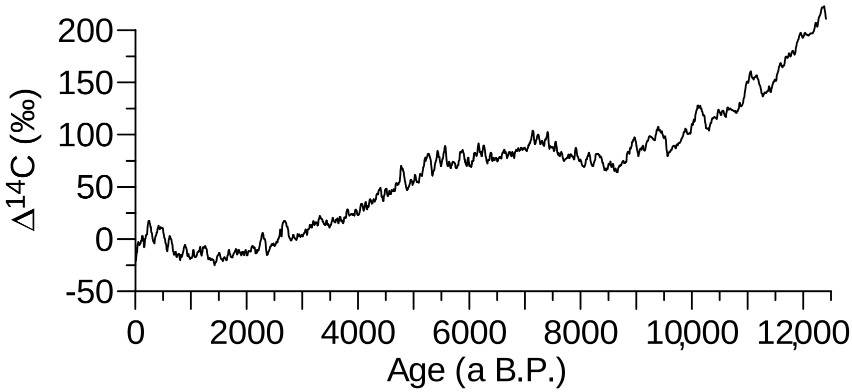


Figure 1.6. Tree-ring data: record of atmospheric radiocarbon content over the past 12,410 years. The tree-ring radiocarbon equilibrates with atmospheric radiocarbon via the photosynthetic cycle. The ^{14}C radioactivity was measured by counting the β particles on CO_2 produced by combusting the wood material. Original sampling resolution was yearly (individual tree-rings) and lower; data shown are 5-year averages ($n = 2483$). The values are presented in delta notation (Fig. 1.3) with the oxalic acid standard of the National Bureau of Standards, for conventional reasons "Δ" is used instead of "δ." The timescale (given as years before present (B.P.) where "present" is, as in "radiocarbon terminology," the year 1950) is based on a counted tree-ring chronology, established by matching radiocarbon patterns from individual trees. Since the age spans of the trees overlap, it is possible to go back in time as far as shown (and beyond). Since the radiocarbon data act as a proxy for solar activity (high Δ^{14}C means low solar irradiance), it is possible to analyse Sun–climate connections by studying correlations between Δ^{14}C and climate proxy records. (Data from Reimer et al. 2004.)

$T_1 \neq T_2$, is here of interest; higher-order moments are neglected. Lag-1 scatterplots ($x(i-1)$ versus $x(i)$) of the climate time series, using detrended $\{t(i), x(i)\}_{i=1}^{n}$ as realizations of the noise process, explore the autocovariance structure (Fig. 1.12). It is evident that all examples exhibit a more or less pronounced orientation of the points along the 1:1 line. This indicates positive serial dependence, or "memory," also called persistence in the atmospheric sciences. The reason for that memory effect is twofold. First, it is characteristic for many types of climatic fluctuations (Wilks 1995). Second, it can be induced by the sampling of the data. A record sampled at high resolution has often stronger persistence than when sampled at low resolution (see next section).

The lag-1 scatterplots (Fig. 1.12) reflect also the right-skewed shape of many of the distributions (more spreading towards right-up) and let some outliers appear.

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

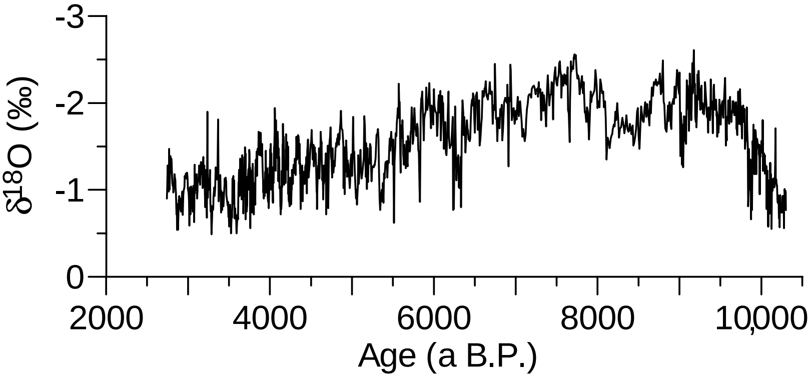


Figure 1.7. Speleothem data: oxygen isotope record from stalagmite Q5 from southern Oman over the past 10,300 years. Along the growth axis of the nearly 1 m long stalagmite, every ~ 0.7 mm about 5 mg material ($CaCO_3$) was drilled, yielding $n = 1345$ samples. The carbonate powder was analysed with an automatic preparation system linked to a mass spectrometer to determine the δ^{18}O values. (The (^{18}O/^{16}O) ratio is given relative to the Vienna Pee Dee Belemnite (VPDB) standard analogously to the description in Fig. 1.3.) The timescale (years before 1950) is based on 18 U/Th mass-spectrometric ages, obtained on separated and purified material. Dates for samples between absolutely dated positions were obtained by linear interpolation. Time runs from right to left. The δ^{18}O scale is inverted "in paleoclimatic manner" so that the transition from the last glacial to the present Holocene interglacial at around 10 ka is "upwards." Note that growth of stalagmite Q5 ceased at ~ 2740 a B.P. Climatological questions associated with the data are whether the transition to the Holocene occurred synchronously with climatic transitions in other locations and whether there exist solar influences on the variations in monsoon rainfall (indicated by δ^{18}O variations, low δ^{18}O reflecting strong monsoon). (Data from Fleitmann et al. 2003.)

1.4 Spacing

Archives other than documentary collections or climate models require measurements on the archive material. Material-size requirements lead in many cases to a constant length interval, $L(i)$, from which material for one measurement is taken, and also the length spacing, $l(i)$, between the measurement mid-points on the length axis is often constant (Fig. 1.13). Dating transfers from length into the time domain with the "sample duration," $D(i)$, and the temporal spacing, $d(i) = t(i) - t(i-1)$, here in this book briefly denoted as "spacing." The spacing is frequently nonconstant: archives normally accumulate not at a constant rate. They might also be subject to postdepositional length distortions such as compressing in the case of ice cores. Archives that allow pre-sampling (visual)

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

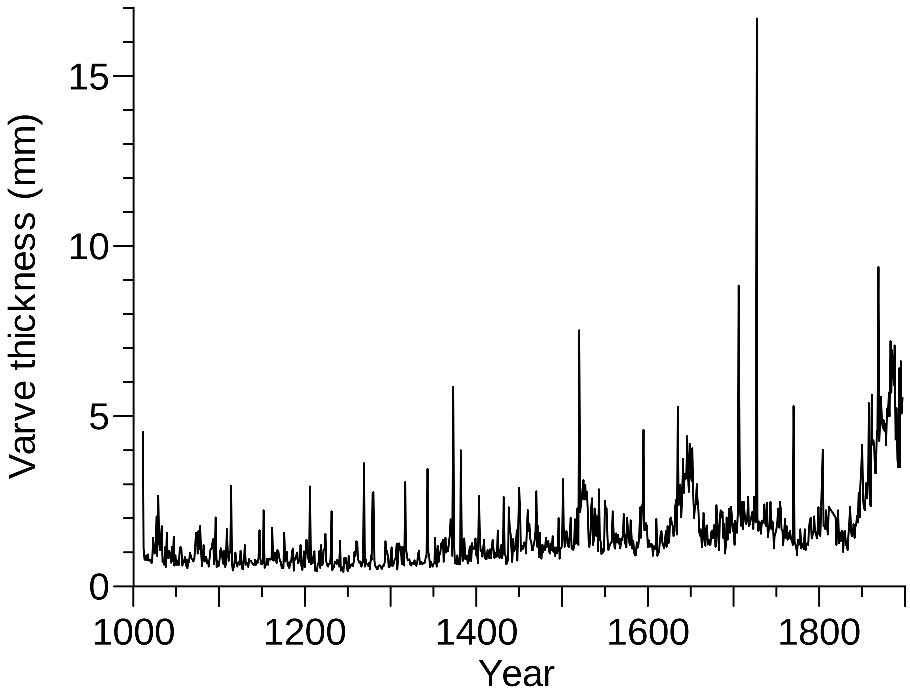


Figure 1.8. Lake sediment core data: varve thickness record from Lower Mystic Lake (Boston area) over the past 1000 years. Multiple overlapping cores were retrieved from the lake, split and photographed in the laboratory. The sediments consist of varves of alternating siliciclastic (bright) and biogenic (dark) layers. The total combined length of the records is about 2 m. Sediment blocks extracted from cores were embedded in epoxy resin to produce petrographic thin sections and X-ray densitometry slabs. A master, composite sequence of stratigraphy was constructed from high-resolution imagery of observations made via petrographic microscopy, back scattered electron microscopy and X-ray densitometry (Besonen 2006). Age control from varve counting was confirmed by means of radiocarbon dating on terrestrial macrofossils. In addition to varve thickness, Besonen (2006) determined the dates of graded beds based on visual examination of the petrographic thin sections and X-ray imagery. A thick varve and a graded bed can be jointly used as a proxy for hurricane activity in the area of the lake. Hurricane-strength precipitation saturates the watershed, results in erosive overland flow that entrains sediment and carries it into the lake where it is deposited as a graded bed. This is enhanced by hurricane-strength winds that disturb vegetation and uproot trees, exposing loose sediment (Besonen 2006). The proxy information was verified by means of pollen data and documentary information (available from about 1630 to the present). The time series ($n = 877$) covers the interval from A.D. 1011 to 1897, minor hiatuses are present (1720–1721, 1803, 1812–1818), also a major above the depth corresponding to 1897. The record bears information on hurricane activity in the Boston area over the past 1000 years. (Data from Besonen et al. 2008.)

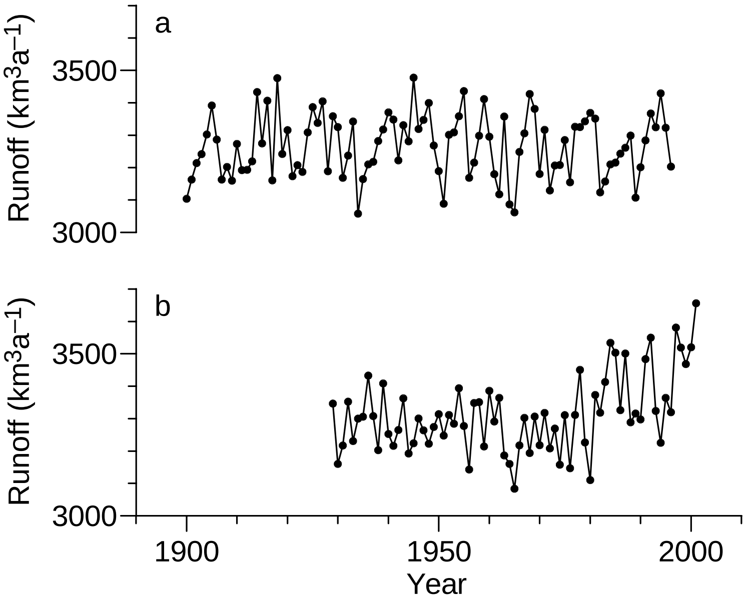


Figure 1.9. Climate model data: runoff from Arctic rivers. **a** Natural forcing only; **b** combined anthropogenic and natural forcing. In a climate model, the physical equations for energy, momentum and mass conservation are numerically solved in time steps over a spatial grid. HadCM3 (Gordon et al. 2000) is a coupled Atmosphere–Ocean General Circulation Model (AOGCM) for the global domain, run by the Hadley Centre for Climate Prediction and Research, Bracknell, United Kingdom. The atmospheric component has a horizontal grid spacing of 2.5° in latitude by 3.75° in longitude and 19 vertical levels. The oceanic component has 20 vertical levels on a 1.25° by 1.25° grid. The time step used for integrating the differential equations representing the atmospheric component was 30 min, for the oceanic component one hour. The total interval simulated ($\sim$ 140 years) was longer than the data shown (**a** 1900–1996; **b** 1929–2001). Plotted are annual-mean ensemble averages, for which the model year starts on 1 December. The averages were constructed from four ensemble runs, that is, runs with identical forcings but different initial conditions. The initial conditions used were taken from states separated by 100 years in a HadCM3 run, in which external forcings where set to have no year-to-year variations ("control run"). Unlike previous models, HadCM3 does not require flux adjustments of heat and water at the air–sea interface to maintain a stable climate without drift behaviour (Johns et al. 1997; Stott et al. 2000). This makes the results obtained with HadCM3 more reliable than previous results. The natural forcing included changes in the amount of stratospheric aerosols stemming from volcanic eruptions and variations in solar irradiation. The anthropogenic forcing included changes in atmospheric concentrations of CO_2, methane, sulfate aerosols and ozone. The river runoff records were generated (Wu et al. 2005) by summing the precipitation contributions from affected grid cells north of 65°N. Model simulations can be used to analyse past and forecast future climate changes. Questions associated with the data are those after the size and the timing of changes in runoff as a result of an intensified hydrological cycle caused by anthropogenically induced warming. (Data from Wu et al. 2005.)

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

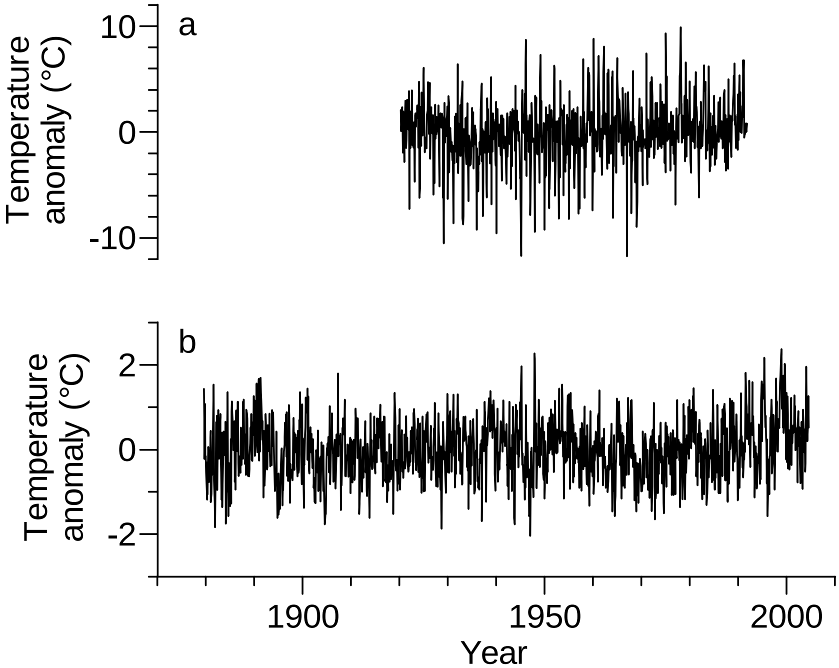


Figure 1.10. Measured data: surface air temperature records from Siberia (**a**) and North Atlantic (**b**). Data are monthly temperature anomalies with respect to the 1961–1990 means from a gridded, global set. Siberia is presented by the grid cell 50–55°N, 90–95°E, effectively reflecting station Krasnojarsk; the North Atlantic by 35–40°N, 25–30°W. Shown are the gap-free time intervals (**a** May 1920 to November 1991, $n = 859$; **b** July 1879 to July 2004, $n = 1501$). The annual cycles were removed by subtracting the monthly averages. (Raw data from Jones and Moberg 2003.)

detection of time-equidistant sampling points, such as tree-rings, varves (that is, annually laminated sediments) or speleothems (Fig. 1.14), appear to be the exception rather than the rule. That mixture of deterministic and stochastic influences on the spacing, is pictured in Fig. 1.15. The Elbe floods (Fig. 1.1) are an example where $d(i)$ (or equivalently $t(i)$) is the major research object, not $x(i)$, see Chapter 6.

The nonzero sample duration, $D(i)$, imposed by material requirements, can be subject to extension to $D'(i)$ by diffusion-like processes in the archive (Fig. 1.13). Besides physical diffusion of material, for example in ice cores, bioturbation in sedimentary archives (mixing by activities of worms and other animals in the upper (young) layer) can play a role. The other data archives studied here (Table 1.1) likely have no diffusion effects.

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

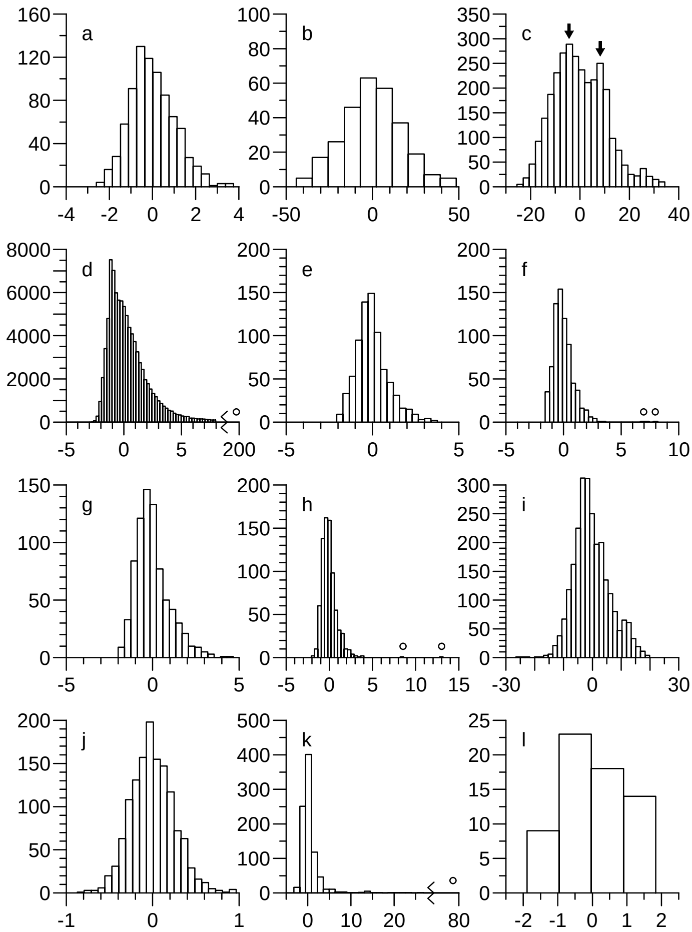


Figure 1.11. Statistical noise distributions of selected climate time series. **a** ODP 846 δ^{18}O; **b** Vostok CO_2; **c** Vostok δD; **d** NGRIP SO_4; **e** NGRIP Ca; **f** NGRIP dust content; **g** NGRIP electrical conductivity; **h** NGRIP Na; **i** tree-ring Δ^{14}C; **j** Q5 δ^{18}O; **k** Lower Mystic Lake varve thickness; **l** HadCM3 runoff. The distributions are estimated with histograms. Data and units are given in Figs. 1.2, 1.3, 1.4, 1.5, 1.6, 1.7, 1.8 and 1.9. In **a** and **e–h,** the trend component was estimated (and removed prior to histogram calculation) using a ramp regression model (Figs. 4.6 and 4.7); in **b** and **c** using a harmonic filter (Section 5.2.4.3); in **d** and **k** using the running median (Figs. 4.16 and 4.17); in **i** using nonparametric regression (Fig. 4.14); in **j** using a combination of a ramp model in the early and a sinusoidal in the late part (Fig. 4.18); and in **l** using the break regression model (Fig. 4.12). Outliers are tentatively marked with *open circles* (note broken axes in **d, k**). In **c,** the modes of the suspected bimodal distribution are marked with *arrows*. In **a, e–h** and **j,** time-dependent variability, $S(T)$, was estimated using a ramp regression model (Chapter 4); in **d** and **k** using the running MAD (Figs. 4.16 and 4.17); and in **l** using a linear model. Normalizing (dividing by $S(T)$) for those time series was carried out prior to histogram calculation. The other time series assume constant $S(T)$, values are given in Table 1.3.

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

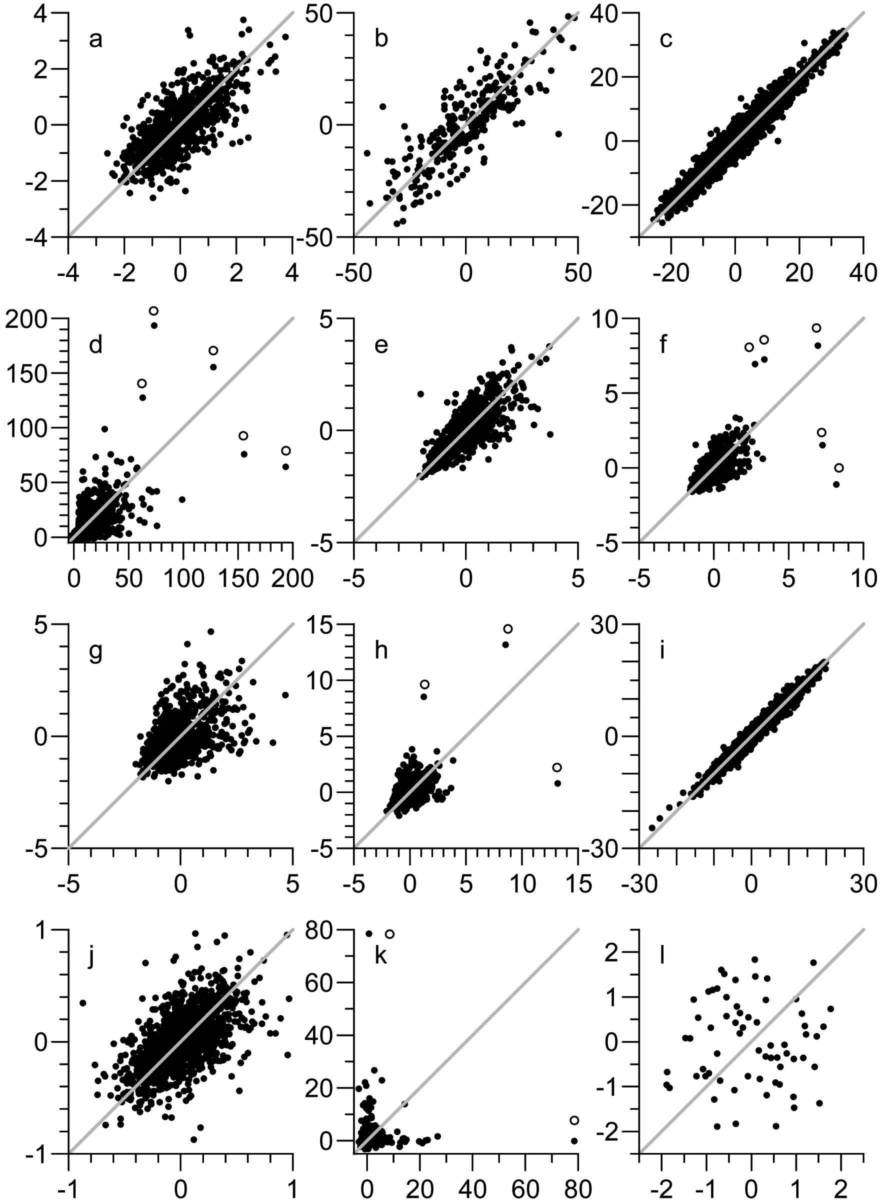


Figure 1.12. Persistence of noise in selected climate time series. **a** ODP 846 δ^{18}O; **b** Vostok CO_2; **c** Vostok δD; **d** NGRIP SO_4; **e** NGRIP Ca; **f** NGRIP dust content; **g** NGRIP electrical conductivity; **h** NGRIP Na; **i** tree-ring Δ^{14}C; **j** Q5 δ^{18}O; **k** Lower Mystic Lake varve thickness; **l** HadCM3 runoff. Noise data are shown as lag-1 scatterplots (in each panel, $x(i-1)$ is plotted on the ordinate against $x(i)$ on the abscissa as *points*), together with 1:1 lines (*grey*). Data and units are given in Figs. 1.2, 1.3, 1.4, 1.5, 1.6, 1.7, 1.8 and 1.9. Detrending and $S(T)$ normalization prior to analysis was carried out as in Fig. 1.11. Note that in **d,** all points are shown (unlike as in Fig. 1.11d). Outliers are tentatively marked with *open circles*.

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

Table 1.3. Measurement and proxy errors in selected climate time series (Table 1.2).

Archive	*Variable*	*Error range*		
		Total, $S(T)$	*Measurement*	*Proxy*
Marine core	δ^{18}O	0.2–0.3‰ [a]	0.06‰ [b]	∼ 1/3 [c]
Ice core	CO_2 content	17.5 ppmv [a]	2–3 ppmv [d]	Small [e]
	δD	10.5‰ [a]	≤ 1‰ [d]	7‰ [f]
	SO_4 content	40.5 ppbw [g]	10% [h]	Unknown [i]
	Ca content	43 ppb [j]	10% [h]	Unknown [i]
	Dust content	$0.56 \cdot 10^5$ ml^{-1} [j]	10% [h]	Unknown [i]
	Conductivity	0.37 µS cm^{-1} [j]	10% [h]	Unknown [i]
	Na	28 ppb [j]	10% [h]	Unknown [i]
Tree-rings	Δ^{14}C	6.2‰ [a]	∼ 2‰ [k]	Small [l]
Speleothem	δ^{18}O	0.25‰ [a]	0.08‰ [m]	Unknown [n]
Lake core	Varve thickness	0.33 mm [g]	0.1 mm [o]	NA [p]
Climate model	River runoff	93 km^{3}a^{-1} [q]	0	NA
Direct measure-	Temperature	0.69°C [r]	0.03°C [s]	0
ment		2.97°C [t]	0.03°C [s]	0

Measurement errors were usually determined using repeated measurements. Proxy errors refer to the climate variables in Table 1.2 unless otherwise noted. NA, not applicable.

[a] Standard deviation of detrended $\{t(i), x(i)\}_{i=1}^{n}$ (Fig. 1.11).

[b] Shackleton et al. (1995b).

[c] As ice-volume indicator, relative error. This error comes from other variations than of ice volume: mainly of bottom water temperature and to a lesser degree of salinity (Mudelsee and Raymo 2005).

[d] Petit et al. (1999).

[e] Raynaud et al. (1993).

[f] As air-temperature indicator; own determination of $MS_E^{1/2}$ (Eq. 4.8) after Jouzel et al. (2007: Fig. S4 therein).

[g] Average MAD value (Figs. 4.16 and 4.17), divided by 0.6745 (a standard normal distribution has an MAD of ∼ 0.6745).

[h] Relative error (Röthlisberger et al. 2000).

[i] Trace substances are part of a complex system, involving variations at the source, during transport (wind) and at deposition; they represent a more local or regional climate signal.

[j] Time-average of $\widehat{S}(i)$ (Fig. 4.7).

[k] Reimer et al. (2004).

[l] Δ^{14}C in tree-rings on yearly to decadal resolution has a (small) proxy error as atmospheric Δ^{14}C indicator because the wood formation is not constant (the major portion is formed in spring and early summer) and because tree-ring thickness varies (Stuiver et al. 1998). Δ^{14}C variations are a good proxy of solar activity variations because other influences (variations in ocean circulation, changes in the intensity of the Earth's magnetic field) are weak on Holocene timescales (Solanki et al. 2004).

[m] Fleitmann et al. (2003).

[n] Unknown on longer timescales (Table 1.2) because observed monsoon rainfall time series (Parthasarathy et al. 1994) are too short (150 a) to permit comparison.

[o] Time-average; depends on varve distinctiveness and human component (Besonen MR 2010, personal communication).

[p] Only information about hurricane existence sought, not about hurricane strength.

[q] Time-average of $\widehat{S}(i)$ (Fig. 4.12).

[r] North Atlantic, time-average.

[s] Upper limit (Tetzlaff G 2006, personal communication).

[t] Siberia, time-average.

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

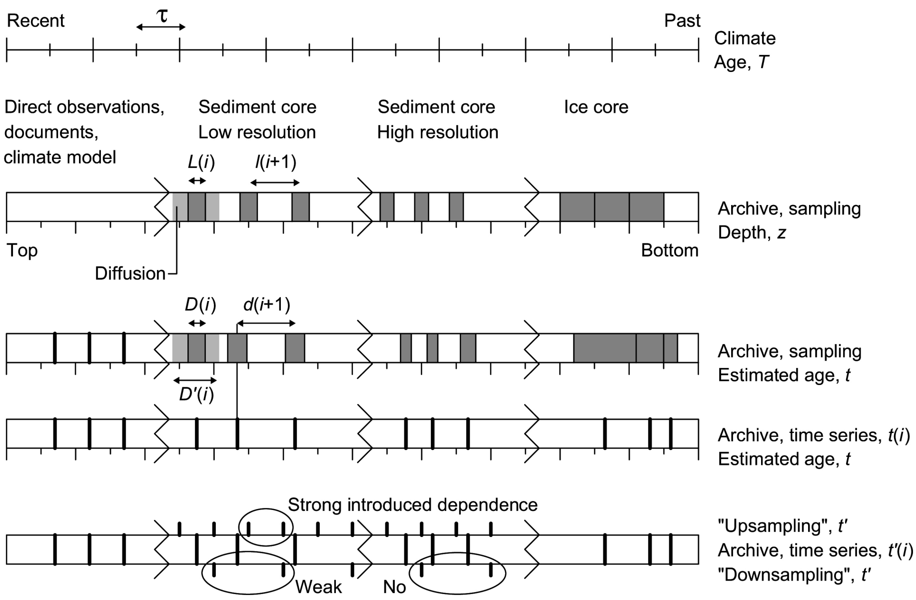


Figure 1.13. Sampling of time series from climate archives. The archive, documenting climate over a time span, is sampled (depth domain), dated (time domain) and possibly interpolated to an evenly spaced time grid. τ denotes a typical timescale of climatic fluctuations, $X_{\text{noise}}(T)$. $L(i)$, length over which material is sampled (*dark shading*); $l(i)$, length spacing between mid-points of $L(i)$; $D(i)$, time-domain analogue of $L(i)$; $d(i)$, time-domain analogue of $l(i)$, denoted as "spacing." *Light shading* indicates effects of a diffusion-like process, that is, extension of $D(i)$ to $D'(i)$. Diffusion need not act symmetrically. *Thick vertical lines* indicate $t(i)$. Terms "sediment core", "ice core", etc. denote here the sampling type rather than a specific archive (for example, a speleothem is often sampled like a "sediment core"). In case of ice cores, $t(i)$ often is not the average time but the time at the upper end of the sample. Real ice cores contain two sub-archives, ice material and enclosed air bubbles, with different age–depth relations (Chapter 8). Interpolation to a fine grid ("upsampling") introduces a strong additional dependence in addition to climatic dependence; "downsampling" introduces weak or no additional dependence. High-resolution time series ($d(i)$ small) have the advantage that this effect is weaker than for low-resolution records. (Note that our usage of "grid" is not restricted to two dimensions.)

The sampled time series $\{t(i), x(i)\}_{i=1}^{n}$ carries information about observed climatic variations up to an upper bound equal to the record length and down to a lower bound of

$$\max\left(\tau, D'(i), \bar{d}\,\right), \tag{1.4}$$

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

where $\bar{d}$ is the average of $d(i)$. Whereas the upper bound is obvious, the lower bound is explained as follows. The "persistence time," τ, of the climatic noise measures the decay of the autocorrelation function ("memory loss") of $X_{\text{noise}}(T)$, see Chapter 2. Deterministic influences acting on shorter timescales are by definition (Eq. 1.1) not part of the description. Information within interval $D'(i)$ is lost by the sampling process and eventual diffusion. Information theory shows that for evenly spaced time series ($d(i) = d =$ const.) the lower limit is $2\,d$ (or one over Nyquist frequency). The factor 2 is omitted in Eq. (1.4) because for uneven spacing the bound may be lower than for even spacing (Chapter 5).

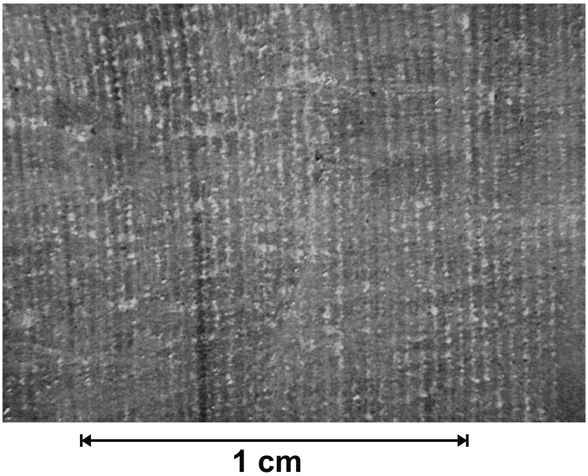


Figure 1.14. Plain-light photomicrograph from a polished section of stalagmite S3 from southern Oman. U/Th dating of samples and the seasonally varying monsoon precipitation pattern in the geographic region suggest that the laminae are annual. Dark (bright) layers reflect a higher (lower) density of pores and fluid inclusions (Fleitmann 2001). The stalagmite covers the period from approximately A.D. 1215 to 1996. Annual layer thickness and oxygen isotopic (δ^{18}O) composition, measured on the stalagmite, record variations in the intensity of Indian monsoonal rainfall. (From Burns et al. (2002), with permission from the publisher).

Interpolation of the unevenly spaced time series $\{t(i), x(i)\}_{i=1}^{n}$ is in climatology usually done to obtain an evenly spaced series $\{t'(i), x'(i)\}_{i=1}^{n'}$. This series can then be analysed with sophisticated statistical methods for which currently only implementations exist that require even spacing. This advantage, however, is accompanied by following disadvantages. First, additional serial dependence can be introduced, depending mainly on n'. If $n' > n$ ("upsampling"), that effect is strong (Fig. 1.13).

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

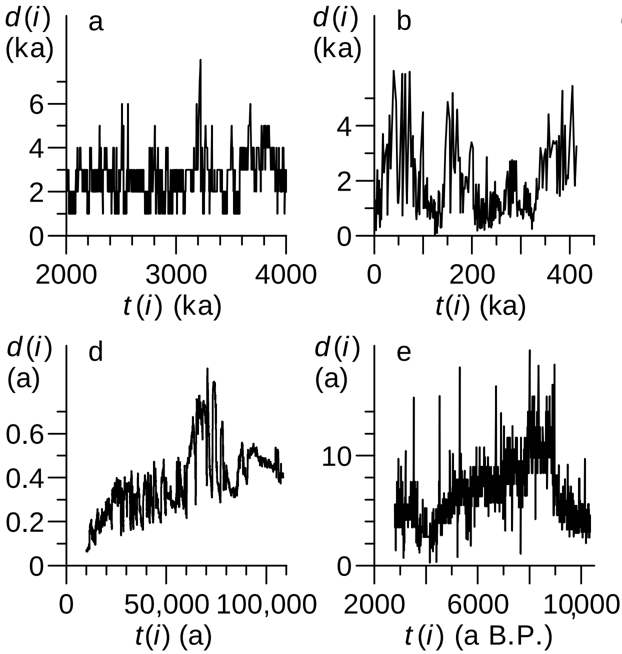


Figure 1.15. Spacing of selected climate time series. **a** ODP 846 $\delta^{18}O$; **b** Vostok CO_2; **c** Vostok δD; **d** NGRIP SO_4; **e** Q5 $\delta^{18}O$. Data are given in Figs. 1.2, 1.3, 1.4 and 1.7. In **d,** $d(i)$ is shown for the $D(i) = 0.5$ cm data; the time series with $t(i) = 1$ a (Fig. 1.4) is obtained from the 0.5-cm data using "downsampling." The ice core data (**b–d**) reflect to some degree the effects of ice compaction, that means, $d(i)$ increases with $t(i)$. The Q5 speleothem spacing time series (**e**) suggests visually a strong negative correlation with the speleothem $\delta^{18}O$ series (Fig. 1.7). This is explained as follows. Low (high) $\delta^{18}O$ means strong (weak) Indian monsoonal rainfall, this in turn faster (slower) movement of the rainwater through the soil, weaker (stronger) uptake of soil-CO_2, lower (higher) pH of the water, reduced (enhanced) solution of soil-carbonate, less (more) material for calcite precipitation, small (large) annual stalagmite layers and, finally, a higher (lower) temporal spacing because the depth spacing is nearly constant (Fig. 1.7). Note that at places with other soil properties, the relation $\delta^{18}O$–spacing may be different (Burns et al. 2002). The values of the average spacing, $\bar{d}$, and the coefficient of variation of spacing, CV_d, which is defined as the standard deviation of the spacing divided by $\bar{d}$, are as follows. **a** $\bar{d} = 2.40$ a, $CV_d = 0.41$; **b** $\bar{d} = 1.46$ a, $CV_d = 0.82$; **c** $\bar{d} = 0.13$ a, $CV_d = 0.85$; **d** $\bar{d} = 0.32$ a, $CV_d = 0.47$; **e** $\bar{d} = 5.62$ a, $CV_d = 0.49$.

If $n' \approx n$ it is weaker, and only for $n' < n$ ("downsampling") it may be absent. That means, interpolation does not allow to go in resolution below the limit set by Eq. (1.4). Second, depending on the type of interpolation method (linear, cubic spline, etc.), $x'(i)$ may show serious deviations from $x(i)$ in terms of variability or noise properties. That is, interpolation takes us a step further away from the observed process.

Achieving insight into shorter-term climatic processes through sampling an archive is best done by increasing the resolution. Reducing $d(i)$ might require reducing $D(i)$ by employing a measurement method that consumes less material. However, the restriction imposed by diffusion processes and climatic persistence still applies (Eq. 1.4). "Overlapped sampling," $d(i) < D(i)$, is no means to obtain higher resolved information than with $d(i) \geq D(i)$.

1.5 Aim and structure of this book

We have certain hypotheses about time-dependent climate processes, about $X_{\text{trend}}(T)$, $X_{\text{out}}(T)$, $S(T)$ and $X_{\text{noise}}(T)$, which we would like to test. Alternatively, we wish to estimate parameters of climate processes. For that purpose, we use certain methods that take uncertainty into account, that means, statistical methods. Smaller error bars or narrower confidence intervals for the results obtained with the methods, guarantee better testability or more accurate knowledge. To construct confidence intervals, in principle, two approaches exist: classical and bootstrap. The classical approach makes substantial assumptions, such as normally distributed data, no serial dependence, and, often, even time spacing, whereas the bootstrap approach does not make such. Since the preceding sections showed that the assumptions made by the classical approach may be violated when applied to climate time series analysis, the bootstrap may yield more reliable results.

That does not imply that all results obtained on climate time series using classical methods are invalid. However, caution as regards their statistical accuracy is appropriate. The reasons why the classical approach was used are obvious. First, the bootstrap was invented late (Efron 1979), but it soon became accepted in the statistical community and recognized/accepted in the natural sciences (Casella 2003). Bootstrap methods for time series (serially dependence) lag one decade behind in their development. Second, there has been an increase in computing power, which made bootstrap calculations feasible.

This book presents the bootstrap approach adapted to a number of statistical analysis methods that have been found useful for analysing climate time series at least by the author. Linear and nonlinear regression (Chapter 4), spectral analysis (Chapter 5) and extreme value time series analysis (Chapter 6) are explained in case of univariate climate time series analysis (Part II). Correlation (Chapter 7) as well as lagged and other variants of regression (Chapter 8) come from the field of bivariate time series (Part III). Application of each method is illustrated with one or more climate time series, several of which already presented. A section ("Background material") reports alternative techniques and provides a look at the literature that is intended to serve climatologists who wish to learn about the statistical basics of the method, as well as statisticians who wish to learn about the relevant climatology encountered. While both lists cannot be exhaustive, this is more the aim for the also given literature where the bootstrap approach to a statistical method has been used in climatology and related fields as, for example, ecology. A further section ("Technical issues") informs about details such as numerical accuracy and software implementations, it gives also internet references where the computer programs implementing the method can be obtained.

Some topics are not covered in this book. Extension to tri- and higher dimensional multivariate time series seems to be straightforward. Methods from dynamical systems theory, attempting to describe climate as a low-dimensional chaotic system, are likely too demanding in terms of data size (Section 1.6). Also other methods that require even spacing are not dealt with but briefly reviewed in Section 1.6.

However, before starting with adaptions of the bootstrap approach to statistical methods in climatology we need to review bootstrap methodology for time series in some detail, which is done in Chapter 3. Necessary statistical concepts such as confidence intervals or standard errors are also explained. One bootstrap variant ("parametric bootstrap") employed in this book assumes a statistical model of the climatological persistence (Chapter 2). These chapters complete Part I.

Sceptics among the readers may ask whether or not the bootstrap approach brings indeed more reliable results than the classical approach. Therefore you will find throughout the book comparisons between both approaches. These are based on Monte Carlo simulations, that means, artificial time series with pre-defined attributes, for which the true result is known a priori. In the same way, different bootstrap variants are also compared with each other. Finally, the (adverse) effects of interpolation are also explored by means of Monte Carlo simulations.

The final part (IV) of the book is an outlook on future directions in climate time series analysis with the bootstrap. Chapter 9 outlines climate archive modelling to take into account timescale uncertainties and includes "normal" extensions to novel estimation problems and higher dimensions. We also look on paradigm changes that may result from a strong increase in computing power in the future and influence the way how we model the climate and analyse climate time series.

1.6 Background material

The **prologue** is a translation from Popper (1935: p. 78 therein). Other relevant books on quantification and philosophy of science are predominantly written by physicists: Einstein (1949), Heisenberg (1969), Lakatos and Musgrave (1970), von Weizsäcker (1985) and Sokal and Bricmont (1998).

As **statistics texts,** accessible to non-statisticians, describing the various roads to probability and estimation, may serve Priestley (1981: Chapters 1–3 therein), Fine (1983), Davison (2003) and Wasserman (2004). The Bayesian road (Lindley 1965; Spall 1988; Bernardo and Smith 1994; Bernardo et al. 2003) seems not to be so well followed in geosciences, but this may change in future. Davis (1986) is a text book written by a geologist; Wilks (2006) and von Storch and Zwiers (1999) were written by climatologists. The latter three contain parts on time series analysis. As text books on time series analysis, accessible to non-statisticians, the following can be used: Priestley (1981), Diggle (1990), Brockwell and Davis (1996) and Shumway and Stoffer (2006); the latter work includes software examples in the R computing environment. A further book on time series analysis is by Anderson (1971). The only book devoted to time series analysis of unevenly spaced data seems to be Parzen (1984); an early review is by Marquardt and Acuff (1982); there is a thesis (Martin 1998) from the field of signal processing. We finally mention the Encyclopedia of statistical sciences (Kotz et al. 1982a,b, 1983a,b, 1985a,b, 1986, 1988a,b, 1989, 1997, 1998, 1999).

Climatology text books: The reports by Working Group I of the Intergovernmental Panel on Climate Change (IPCC–WG I) (Houghton et al. 2001; Solomon et al. 2007) are useful on weather (that is, meteorology) and short-term climate. Paleoclimate, covering longer-term processes in, say, the Holocene (last $\sim$ 10,000 years) and before, is described by Crowley and North (1991), Bradley (1999) and Cronin (2010). We finally mention the Encyclopedia of Atmospheric Sciences (Holton et al. 2003), the Encyclopedia of Earth System Science (Nierenberg 1992), the Encyclopedia of Geology (Selley et al. 2005), the Glossary of Geology (Neuendorf et al. 2005), the Handbook of Hydrology (Maidment 1993) and the Encyclopedia of Ocean Sciences (Steele et al. 2001).

The form of **decomposition** in Eq. (1.1) of a process into trend, outliers, variability and noise is non-standard. Outliers are often considered as gross errors in the data that only have to be removed. However, in climatology, outliers may bear information on extreme events and can also be the object of analysis (Chapter 6). The notion of systematic behaviour of a trend leaves space for interpretation of what can be included. Certainly worth so are nonlinear trends to account for climatic changes (Chapter 4). Also incorporated are harmonic signals like the daily or annual cycle, which can be recorded in climate archives. Since the focus here in this book is on longer-term processes, we omit to write an own seasonal signal into Eq. (1.1); such an approach is common in econometrics (Box et al. 1994). Other, longer-term cyclic influences on climate are also astronomical in origin, such as variations in solar activity or Milankovitch variations in Earth orbital parameters. However, since their imprint in the climate system as regards amplitude, phase and frequency, is not precisely known (and also sometimes debated), these signals are investigated in this book by analysing the spectral properties of the noise process (Chapter 5).

Detailed accounts of **climate archives** give the following. Usage of marine sediment cores is a standard method (has been applied over decades), see Kennett (1982), Seibold and Berger (1993) and the series of reports on and results of scientific drilling into the ocean floor (Deep Sea Drilling Project 1969–1986; Ocean Drilling Program 1986–2004, 1988–2007). Ice cores (Oeschger and Langway 1989; Hammer et al. 1997) and lake sediment cores (Negendank and Zolitschka 1993; Zolitschka 1999) are likewise regularly employed. Usefulness of speleothems (Baker et al. 1993; Gillieson 1996; Daoxian and Cheng 2002; Fairchild et al. 2007) is recognized since the 1990s. Dendroclimatology has a long tradition (Douglass 1919, 1928, 1936; Schweingruber 1988). Analysis of documentary climate data is described by Pfister (1999), Brázdil et al. (2005) and Glaser (2001). Construction and use of climate models is a growing field, see McGuffie and Henderson-Sellers (1997) or Randall et al. (2007). From this book's data analysis view, climate modelling is similar to probing and measuring a natural climate archive.

An upper limit to the **time range** over which climate can be studied is set by the age of Earth ($\sim$ 4.6 Ga). The course of the evolution of Earth, including its climate, division and subdivision into different geological epochs, is described by Stanley (1989). A geological timescale refers to a chronology of events (first or last appearance of species, reversals of Earth's magnetic field, climatic, etc.) which is updated as new data and new datings become available. Currently used are: Gradstein et al. (2004) covering the whole time range, Cande and Kent (1992, 1995) going back before the Cenozoic (last $\sim$ 65 Ma) into the late Cretaceous, Berggren et al. (1995b) for the Cenozoic and Berggren et al. (1995a) for the last 6 Ma. (Note the various meanings of "timescale" in geosciences.)

Absolute dating methods almost entirely use one of the many clocks provided by natural radioactive elements. A comprehensive treatise is Geyh and Schleicher (1990), see also Walker (2005). K/Ar dating (Dalrymple and Lanphere 1969) utilizes the decay of ^{40}K. The potas-

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

sium isotope has a half-life, $T_{1/2}$, of 1.266 Ga (Section 8.7), it decays into ^{40}Ar with a chance of $\sim 11\%$ and ^{40}Ca ($\sim 89\%$). One measures ^{40}K and also the amount of ^{40}Ar that accumulated in a sample since argon was removed by a process whose age is to be determined. Such a zeroing process can be a volcanic eruption, which produced the rock sample. The natural decay chains in uranium and thorium provide a wealth of clocks, running on a wide range of timescales (Ivanovich and Harmon 1992). U/Th dating utilizes the decays of ^{234}U to ^{230}Th ($T_{1/2} \approx 245$ ka) and ^{230}Th to ^{226}Ra ($T_{1/2} \approx 76$ ka). Since speleothems contain essentially no thorium at the time of formation, dating means measuring the amount of accumulated thorium since that time. ^{210}Pb dating (Appleby and Oldfield 1992) takes the decay chain of ^{210}Pb ($T_{1/2} \approx 22.3$ a) to ^{206}Pb. Radiocarbon dating (Taylor 1987) employs the decay of ^{14}C to ^{14}N ($T_{1/2} \approx 5730$ a). $T_{1/2}$ determines the limits for a reliable age determination. For ages below, say, $\sim 0.1 \cdot T_{1/2}$ and above $\sim 10 \cdot T_{1/2}$, the uncertainties introduced at the determination of the amounts of parent or daughter products become likely too large. Using modern mass spectrometers, this range can be somewhat widened. Besides measurement uncertainties and those owing to imperfectly known half-lifes, another error source is bias that occurs when assumptions, such as complete zeroing or absent sample contamination, are violated. In fact, eliminating measurement bias is often the major task in absolute dating. Using an archive as a dosimeter for dating (Table 1.1) means to measure the dose (effect) a sample has received over time exposed to a dose-rate (effect per time interval). One example is electron-spin-resonance dating, where the effect consists in the number of trapped electrons (for example in carbonate material in a sediment core) and the dose-rate is from natural radioactivity (Grün 1989); the other is cosmic-ray-exposure dating, where one of the effects used regards the number of ^{10}Be atoms transported to an archive from the atmosphere, where cosmic rays had produced them (Gosse and Phillips 2001). Another absolute dating method is counting of yearly layers, either of tree-rings or growth layers in a stalagmite (Fig. 1.14). The assumption that layers present a constant time interval is crucial. Documentary data contain together with the variable usually also the date (which is susceptible to reporting errors).

Relative dating methods rely on an assumed relation between the measured series in the depth domain, $\{z(i), x(i)\}_{i=1}^{n_X}$, and another, dated time series, $\{t_Y(j), y(j)\}_{j=1}^{n_Y}$. If the relation between X and Y is simple (linear, no lag), $t_Y(j)$ can be projected onto $t_X(i)$ rather easily. If it is more complex, a mathematical model may have to be used. Climatologists denote that procedure as correlation or "tuning." As illustration we note that besides the GT4 timescale for the Vostok ice core (Fig. 1.3), two tuned timescales exist. One uses as $x(i)$ Vostok δ^{18}O in air bubbles and as $y(i)$ the precession of Earth's orbit (Shackleton 2000); the other uses as $x(i)$ Vostok methane content in air and as $y(i)$ mid-July insolation at 30°N (Ruddiman and Raymo 2003). One critical point with relative dating is how well the assumed relation holds. Bayesian approaches to timescale construction were developed by Agrinier et al. (1999) for a geomagnetic polarity record from the Cretaceous–Cenozoic and by Blaauw and Christen (2005) for a Holocene archive in form of a peat-bog core. Section 4.4 gives more details and references on the approaches.

Most before mentioned textbooks on climate and climate archives contain also information on **proxy variables** and how well those indicate climate. Other sources are Broecker and Peng (1982) and Henderson (2002). δ^{18}O in shells of marine living foraminifera (Fig. 1.2) was in the beginning seen as a "paleothermometer" (Emiliani 1955) until Shackleton (1967) showed that the major recorded climate variable is global ice volume, although he partly withdraw later from this position (Shackleton 2000). The main idea is that polar ice is isotopically light (low δ^{18}O) and that during an interglacial (warm) more of that is as water in the ocean, where foraminifera build their calcareous, δ^{18}O-light shells. Stacks of ice volume records, such as that from the "Spectral Analysis, Mapping, and Prediction" (SPECMAP) project (Imbrie et al. 1984), going back nearly 800 ka, and that of Shackleton et al. (1995b), extending into the Miocene (before $\sim$ 5.2 Ma), were produced and a nomenclature (Prell et al. 1986) of marine isotope stages (MISs) erected. A recently constructed Plio- to Pleistocene δ^{18}O stack is by Lisiecki and Raymo (2005). Atmospheric CO_2 is rather accurately reflected by CO_2 in air bubbles from Antarctic ice cores (Fig. 1.3), mainly because CO_2 mixes well in the atmosphere (Raynaud et al. 1993). The currently longest record comes from the European Project for Ice Coring in Antarctica (EPICA), Dome C site, the core covering the past $\sim$ 800 ka (Section 8.6.1). For earlier times, other proxies for atmospheric CO_2 have to be used, such as the size and spatial density of stomata in fossil leaves (Kürschner et al. 1996), resulting in significantly larger proxy errors. δD variations in polar ice (Fig. 1.3) reflect variations in air temperature as this variable determines how enriched the precipitation becomes during its net transport from the mid-latitudes to the poles (Rayleigh destillation) (Dansgaard and Oeschger 1989). As regards the various proxy variables from the NGRIP ice core (Figs. 1.4 and 1.5), see the captions and references given therein. Radiocarbon (Fig. 1.6) is produced in the upper atmosphere via reactions with cosmogenic neutrons; the cosmic-ray flux is

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

modulated by the Sun's activity through the solar wind. Another influence that can be seen using Δ^{14}C is variations in the exchange between the oceanic carbon storage and the atmosphere, see Beer et al. (1994) and Cini Castagnoli and Provenzale (1997). Pollen records and their proxy quality are explained by Moore et al. (1991) and Traverse (2007). The proxy quality of δ^{18}O in speleothems from the Arabian peninsula as indicator of monsoon rainfall is largely based on Rayleigh destillation processes (Fleitmann et al. 2004, 2007a).

Ergodicity. Detrended and normalized $x(i)$ were used for analysing the distributional shape for the process $X_{\mathrm{noise}}(T)$ (Fig. 1.11). That is, instead of an ensemble of different realizations at a particular time, one realization was taken at different times. A process for which this replacement gives same results is called ergodic. Since in climatological practice no repeated experiment can be carried out, except with climate models, ergodicity has to be added to the set of made assumptions in this book.

Density estimation. The histograms in Fig. 1.11 were constructed using a bin width equal to $3.49\, s_{n-1}\, n^{-1/3}$ (Scott 1979), where s_{n-1} is the sample standard deviation. More elaborated approaches to density estimations use kernel functions (Silverman 1986; Simonoff 1996; Wasserman 2006). Applications of density estimation to climatology have been made occasional. They include analyses of the Pleistocene ice age (Matteucci 1990; Mudelsee and Stattegger 1997) and of the recent planetary-scale atmospheric circulation (Hansen and Sutera 1986). Standard references on statistical properties of distributions are Johnson et al. (1994, 1995) on continuous univariate and Kotz et al. (2000) on continuous multivariate distributions. Random variables that are composed of products or ratios of other random variables have since long successfully defied analytical derivation of their PDF. Only very simple forms, like $Z = X^2 + Y^2$ with Gaussian X and Y, which has a chi-squared density (right-skewed), can be solved. See Haldane (1942) or Lomnicki (1967) for other cases.

Bioturbation in deep-sea sediments acts as a low-pass filter (Eq. 1.4) (Goreau 1980; Dalfes et al. 1984; Pestiaux and Berger 1984). However, since the accumulated sediment passes the bioturbation zone (the upper few tens of cm of sediment) unidirectionally, signal processing techniques, termed "deconvolution," have been successfully developed to use that information to improve the construction of the timescale (Schiffelbein 1984, 1985; Trauth 1998). An example demonstrating what effects have to anticipated when sampling natural climate archives such as sediment cores is given by Thomson et al. (1995), who found offsets of ~ 1.1 ka between ages of large ($> 150\,\mu$m diameter) foraminifera and fine bulk carbonate at same depth in a core. The most likely explanation is a size-dependent bioturbation that preferentially transports fine material downwards because that is cheaper in terms of energy.

Inhomogeneities in time series owing to systematic changes in the observation system (i.e., the archive) may arise in manifold ways. It is evidently of importance to detect and correct for these effects. A simple case is a sudden change, such as when the time at which daily temperature is recorded, is shifted. This type can be detected using methods (Basseville and Nikiforov 1993) that search for an abrupt change in the mean, $X_{\text{trend}}(T)$. Inhomogeneities in the form of gradual changes in mean, or variability, may be analysed using regression techniques (Chapter 4). Quality assessment of climate data deals predominantly with types and sizes of inhomogeneities (Peterson et al. 1998a,b). Inhomogeneities in the form of periodic changes of the observation system can influence the estimated spectral properties (Chapter 5).

Physics' **nonlinear dynamical systems theory** has developed time series analysis techniques (Abarbanel et al. 1993; Kantz and Schreiber 1997; Diks 1999; Chan and Tong 2001; Tsonis and Elsner 2007; Donner and Barbosa 2008) that can be applied to study, for example, the question whether the climatic variability sampled by $\{t(i), x(i)\}_{i=1}^{n}$ is the product of low-dimensional chaos. A positive answer would have serious consequences for the construction of climate models because only a handful of independent climate variables had to be incorporated; and also the degree of climate predictability would be precisely known (Lyapunov exponents). Although it was meteorology that boosted development of dynamical systems theory by constructing a simplified atmosphere model (Lorenz 1963), we will not pursue related time series analysis methods for two reasons. First, for most applications in climatology the data sizes are not sufficient to allow reasonably accurate conclusions. For example, Nicolis and Nicolis (1984) analysed one late Pleistocene (last ~ 900 ka) δ^{18}O time series (cf. Fig. 1.2) and found a "climatic attractor" with dimensionality ~ 3.1, meaning that four variables could explain the ice age. Grassberger (1986), and later Ruelle (1990), convincingly refuted that claim, which was based on a data size of a few hundred instead of several thousand necessary (Eckmann and Ruelle 1992). Later, Mudelsee and Stattegger (1994) analysed the longest Plio-/Pleistocene δ^{18}O records then available. They found no low-dimensional attractor and could only conclude that at least five variables are acting. Since one assumption for such analyses is that the proxy quality of the measured variable (δ^{18}O, indicating ice volume) holds over all timescales sampled, the limits owing to the sampling process (Eq. 1.4) and the proxy quality (Table 1.2) effectively prohibit exploration of low-dimensional climatic chaos—not to mention the amount of measurements required. Lorenz (1991) considered that decoupled climatic subsystems with low dimensionality could be found. Second, nonlinear dynamical systems methods reconstruct the physical phase space by the method of delay-time coordinates (Packard et al. 1980). Instead of using multivariate time series $\{t(i), x(i), y(i), z(i), \ldots\}_{i=1}^{n}$ (forming the data matrix), this method takes $\{t(i), x(i), x(i+L), x(i+2L), \ldots\}_{i=1}^{n'}$, with $n' < n$ and L (integer) appropriately selected. The delay-time method requires equidistance. For many climate time series encountered in practice, this would mean interpolation, which this book does not advocate (Section 1.4).

Even time spacing is also required for current implementations of two other analysis techniques. The first, Singular Spectrum Analysis or SSA (Broomhead and King 1986), also uses delay-time coordinates explained in the preceding paragraph to reconstruct the data matrix from one univariate time series. The eigenvectors associated with the largest eigenvalues yield the SSA decomposition of the time series into trend and other more variable portions. There exists a successful approach based on computer simulations to assess the significance of eigenvalues in the presence of persistence, which has been applied to observed equidistant temperature time series (Allen and Smith 1994). Again, because for many real-world paleoclimatic time series interpolation would have to be performed, we do not include SSA here. Note that similar to SSA is Principal Component Analysis (PCA), also termed Empirical Orthogonal Function (EOF) analysis, which does the same as SSA on multivariate time series. PCA is a standard method to search for patterns in high-dimensional meteorological time series such as pressure and temperature fields (Preisendorfer 1988; von Storch and Zwiers 1999). The second time series analysis method that requires even spacing and is often applied in climatology, is wavelet analysis, which composes a time series using "wave packets," localized in time and frequency. Percival and Walden (2000) is a textbook accessible to non-statisticians. Applications to climatology include Fligge et al. (1999), who analyse sunspot time series (Fig. 2.12), and Torrence and Compo (1998), who analyse time series of the El Niño–Southern Oscillation (ENSO) climatic mode. (El Niño is defined by sea-surface temperature anomalies in the eastern tropical Pacific, while the Southern Oscillation Index is a measure of the atmospheric circulation response in the Pacific–Indian Ocean region.) It might well be possible to develop adaptions of phase-space reconstruction and nonlinear dynamical systems analysis, SSA, PCA and wavelet analysis to explore unevenly spaced time series directly, circumventing adverse effects of interpolation—at the moment, such adaptions seem not to be available (but see Section 5.3 as regards wavelets).

Chapter 2

Persistence Models

Climatic noise often exhibits persistence (Section 1.3). Chapter 3 presents bootstrap methods as resampling techniques aimed at providing realistic confidence intervals or error bars for the various estimation problems treated in the subsequent chapters. The bootstrap works with artificially produced (by means of a random number generator) resamples of the noise process. Accurate bootstrap results need therefore the resamples to preserve the persistence of $X_{\text{noise}}(i)$. To achieve this requires a model of the noise process or a quantification of the size of the dependence. Model fits to the noise data inform about the "memory" of the climate fluctuations, the span of the persistence. The fitted models and their estimated parameters can then be directly used for the bootstrap resampling procedure.

It turns out that for climate time series with discrete times and uneven spacing, the class of persistence models with a unique correspondence to continuous-time models is rather limited. This "embedding" is necessary because it guarantees that our persistence description has a foundation on physics. The first-order autoregressive or AR(1) process has this desirable property.

2.1 First-order autoregressive model

The AR(1) process is a simple persistence model, where a realization of the noise process, $X_{\text{noise}}(i)$, depends on just the value at one time step earlier, $X_{\text{noise}}(i-1)$. We analyse even and uneven spacing separately.

M. Mudelsee, *Climate Time Series Analysis*, Atmospheric and Oceanographic Sciences Library 42, DOI 10.1007/978-90-481-9482-7_2,

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

2.1.1 Even spacing

In Eq. (1.2) we let the time increase with constant spacing $d(i) = d > 0$ and write the discrete-time Gaussian AR(1) noise model,

$$\begin{aligned} X_{\text{noise}}(1) &= \mathcal{E}_{\mathrm{N}(0,\,1)}(1), \\ X_{\text{noise}}(i) &= a \cdot X_{\text{noise}}(i-1) + \mathcal{E}_{\mathrm{N}(0,\,1-a^2)}(i), \qquad i = 2, \ldots, n. \end{aligned} \tag{2.1}$$

Herein, $-1 < a < 1$ is a constant and $\mathcal{E}_{\mathrm{N}(\mu,\,\sigma^2)}(\cdot)$ is a Gaussian random process with mean μ, variance σ^2 and no serial dependence, that means, $E\left[\mathcal{E}_{\mathrm{N}(\mu,\,\sigma^2)}(i) \cdot \mathcal{E}_{\mathrm{N}(\mu,\,\sigma^2)}(j)\right] = 0$ for $i \neq j$. It readily follows that $X_{\text{noise}}(i)$ has zero mean and unity variance, as assumed in our decomposition (Eq. 1.2). Figure 2.1 shows a realization of an AR(1) process.

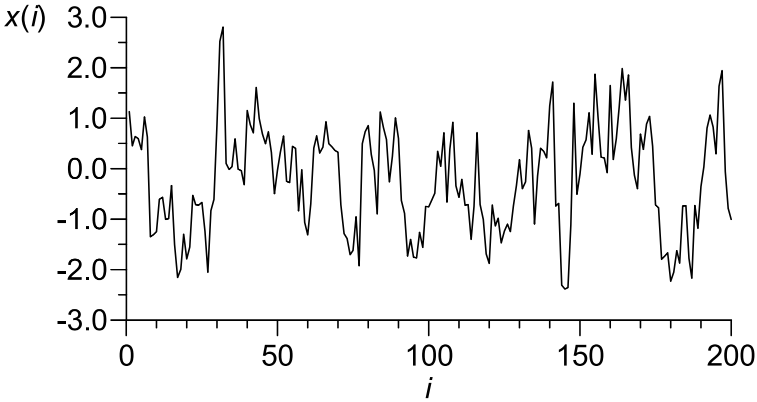


Figure 2.1. Realization of an AR(1) process (Eq. 2.1); $n = 200$ and $a = 0.7$.

The autocorrelation function,

$$\begin{aligned} \rho(h) &= \frac{E\Big[\big\{X_{\text{noise}}(i+h) - E\big[X_{\text{noise}}(i+h)\big]\big\} \cdot \big\{X_{\text{noise}}(i) - E\big[X_{\text{noise}}(i)\big]\big\}\Big]}{\Big\{VAR\big[X_{\text{noise}}(i+h)\big] \cdot VAR\big[X_{\text{noise}}(i)\big]\Big\}^{1/2}} \\ &= E\Big[X_{\text{noise}}(i+h) \cdot X_{\text{noise}}(i)\Big], \end{aligned} \tag{2.2}$$

where h is the time lag, E is the expectation operator and VAR is the variance operator, is given by (Priestley 1981: Section 3.5 therein)

$$\rho(h) = a^{|h|}, \qquad h = 0, \pm 1, \pm 2, \ldots. \tag{2.3}$$

For $a > 0$, this behaviour may be referred to as “exponentially decreasing memory” (Fig. 2.2).

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

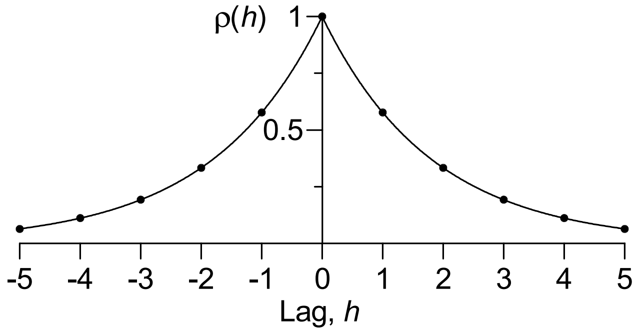


Figure 2.2. Autocorrelation function of the AR(1) process, $a > 0$. In the case of even spacing (Section 2.1.1) $\rho(h)$ is given by $a^{|h|} = \exp\left[-|h| \cdot d/\tau\right]$, in the case of uneven spacing (Section 2.1.2) by $\exp\left[-|T(i+h) - T(i)|/\tau\right]$. In both cases, the decrease is exponential with decay constant τ.

Note that the assumptions in Eq. (1.2), namely $E\left[X_{\text{noise}}(i)\right] = 0$ and $VAR\left[X_{\text{noise}}(i)\right] = 1$, required the formulation of the AR(1) model as in Eq. (2.1), which is non-standard. See Section 2.6 for the standard formulation.

Persistence estimation for the AR(1) model means estimation of the autocorrelation parameter, a. To illustrate autocorrelation estimation, assume that from the time series data, $\{x(i)\}_{i=1}^{n}$, the outliers have been removed and the trend and variability properties (Eq. 1.2) determined and used (as in Fig. 1.11) to extract $\{x_{\text{noise}}(i)\}_{i=1}^{n}$, realizations of the noise process. An estimator of the autocorrelation parameter, that means, a recipe how to calculate a from $\{x_{\text{noise}}(i)\}_{i=1}^{n}$, is given by

$$\widehat{a} = \sum_{i=2}^{n} x_{\text{noise}}(i) \cdot x_{\text{noise}}(i-1) \Bigg/ \sum_{i=2}^{n} x_{\text{noise}}(i)^2. \qquad (2.4)$$

(Chapter 3 introduces estimators and the "hat notation.") Note that estimator $\widehat{a}$ is biased, that means, if $\{X_{\text{noise}}(i)\}$ is an AR(1) process with parameter a, then $E\left(\widehat{a}\right) \neq a$. Only approximation formulas exist for the bias in general autocorrelation estimation. Such formulas can be used for bias correction. Similarly, also the estimation variance, $VAR\left(\widehat{a}\right)$, is only approximately known. In general, bias and variance decrease with n. The background material (Section 2.6) gives various bias and variance formulas, informs about bias correction and lists other autocorrelation estimators.

Chapter 3

Bootstrap Confidence Intervals

In statistical analysis of climate time series, our aim (Chapter 1) is to estimate parameters of $X_{\text{trend}}(T)$, $X_{\text{out}}(T)$, $S(T)$ and $X_{\text{noise}}(T)$. Denote in general such a parameter as θ. An estimator, $\widehat{\theta}$, is a recipe how to calculate θ from a set of data. The data, discretely sampled time series $\{t(i), x(i)\}_{i=1}^{n}$, are influenced by measurement and proxy errors of $x(i)$, outliers, dating errors of $t(i)$ and climatic noise. Therefore, $\widehat{\theta}$ cannot be expected to equal θ. The accuracy of $\widehat{\theta}$, how close it comes to θ, is described by statistical terms such as standard error, bias, mean squared error and confidence interval (CI). These are introduced in Section 3.1.

With the exploration of new archives or innovations in proxy, measurement and dating techniques, new $\widehat{\theta}$ values, denoted as estimates, become available and eventually join or replace previous estimates. A telling example from geochronology is where θ is the time before present when the Earth's magnetic field changed from reversed polarity during the Matuyama epoch to normal polarity during the Brunhes epoch, at the beginning of the late Pleistocene. Estimates published over the past decades include 690 ka (Cox 1969) and 730 ka (Mankinen and Dalrymple 1979), both based on K/Ar dating; and 790 ka (Johnson 1982) and 780 ka (Shackleton et al. 1990), both based on astronomical tuning. The currently accepted value is 779 ka with a standard error of 2 ka (Singer and Pringle 1996), written as 779 ± 2 ka, based on $^{40}\text{Ar}/^{39}\text{Ar}$ dating (a high-precision variant of K/Ar dating). An example with a much greater uncertainty regards the case where θ is the radiative forcing (change in net vertical irradiance at the tropopause) of changes in atmospheric concentrations of mineral dust, where even the sign of θ is uncertain (Penner et al. 2001; Forster et al. 2007). It is evident that the

M. Mudelsee, *Climate Time Series Analysis*, Atmospheric and Oceanographic Sciences Library 42, DOI 10.1007/978-90-481-9482-7_3,

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

growth of climatological knowledge depends critically on estimates of θ that are accompanied by error bars or other measures of their accuracy.

Bootstrap resampling (Sections 3.2 and 3.3) is an approach to construct error bars and CIs. The idea is to draw random resamples from the data and calculate error bars and CIs from repeated estimations on the resamples. For climate time series, the bootstrap is potentially superior to the classical approach, which relies partly on unrealistic assumptions regarding distributional shape, persistence and spacing (Chapter 1). However, the bootstrap, developed originally for data without serial dependence, has to be adapted before applying it to time series. Two classes of adaptions exist for taking persistence into account. First, nonparametric bootstrap methods resample sequences, or blocks, of the data. They preserve the dependence structure over the length of a block. Second, the parametric bootstrap adopts a dependence model. As such, the AR(1) model (Chapter 2) is our favorite.

It turns out that both bootstrap resampling types have the potential to yield acceptably accurate CIs for estimated climate parameters. A problem for the block bootstrap arises from uneven time spacing. Another difficult point is to find optimal block lengths. This could make the parametric bootstrap superior within the context of this book, especially for small data sizes (less than, say, 50). The block bootstrap, however, is important when the deviations from AR(1) persistence seem to be strong. Various CI types are investigated. We prefer a version (so-called BCa interval) that automatically corrects for estimation bias and scale effects. Computing-intensive calibration techniques can further increase the accuracy.

3.1 Error bars and confidence intervals

Let θ be the parameter of interest of the climatic process $\{X(T)\}$ and $\widehat{\theta}$ be the estimator. Extension to a set of parameters is straightforward. Any meaningful construction lets the estimator be a function of the process, $\widehat{\theta} = g(\{X(T)\})$. That means, $\widehat{\theta}$ is a random variable with statistical properties. The standard deviation of $\widehat{\theta}$, denoted as standard error, is

$$\mathrm{se}_{\widehat{\theta}} = \left[VAR\left(\widehat{\theta}\right)\right]^{1/2}. \tag{3.1}$$

The bias of $\widehat{\theta}$ is

$$\mathrm{bias}_{\widehat{\theta}} = E\left(\widehat{\theta}\right) - \theta. \tag{3.2}$$

$\mathrm{bias}_{\widehat{\theta}} > 0$ ($\mathrm{bias}_{\widehat{\theta}} < 0$) means a systematic overestimation (underestimation). $\mathrm{se}_{\widehat{\theta}}$ and $\mathrm{bias}_{\widehat{\theta}}$ are illustrated in Fig. 3.1. Desirable estimators have small $\mathrm{se}_{\widehat{\theta}}$ and small $\mathrm{bias}_{\widehat{\theta}}$. In many estimations, a trade-off problem

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

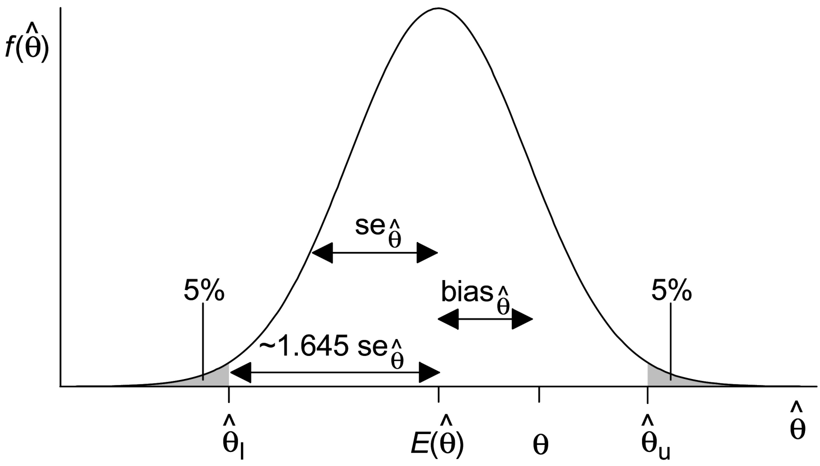


Figure 3.1. Standard error ($\mathrm{se}_{\widehat{\theta}}$), bias ($\mathrm{bias}_{\widehat{\theta}}$) and equi-tailed confidence interval ($\mathrm{CI}_{\widehat{\theta},1-2\alpha} = [\widehat{\theta}_\mathrm{l}; \widehat{\theta}_\mathrm{u}]$) for a Gaussian distributed estimator, $\widehat{\theta}$. The true parameter value is θ; the confidence level is $1-2\alpha = 90\%$.

between $\mathrm{se}_{\widehat{\theta}}$ and $\mathrm{bias}_{\widehat{\theta}}$ occurs. A convenient measure is the root mean squared error,

$$\begin{aligned}\mathrm{RMSE}_{\widehat{\theta}} &= \left\{ E\left[\left(\widehat{\theta} - \theta \right)^2 \right] \right\}^{1/2} \\ &= \left(\mathrm{se}_{\widehat{\theta}}^{\;2} + \mathrm{bias}_{\widehat{\theta}}^{\;2} \right)^{1/2} .\end{aligned} \tag{3.3}$$

The coefficient of variation is

$$\mathrm{CV}_{\widehat{\theta}} = \mathrm{se}_{\widehat{\theta}} \Big/ \left| E\left(\widehat{\theta} \right) \right| . \tag{3.4}$$

While $\widehat{\theta}$ is a best guess of θ or a point estimate, a CI is an interval estimate that informs how good a guess is (Fig. 3.1). The CI for θ is

$$\mathrm{CI}_{\widehat{\theta},1-2\alpha} = \left[\widehat{\theta}_\mathrm{l}; \widehat{\theta}_\mathrm{u} \right] , \tag{3.5}$$

where $0 \leq 1 - 2\alpha \leq 1$ is a prescribed value, denoted as confidence level. The practical examples in his book consider 90% ($\alpha = 0.05$) or 95% ($\alpha = 0.025$) CIs, which are reasonable choices for climatological problems. $\widehat{\theta}_\mathrm{l}$ is the lower, $\widehat{\theta}_\mathrm{u}$ the upper endpoint of the CI. $\widehat{\theta}_\mathrm{l}$ and $\widehat{\theta}_\mathrm{u}$ are random variables and have statistical properties such as standard error

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

or bias. The properties of interest for CIs are the coverages,

$$\gamma_{\mathrm{l}} = \mathrm{prob}\left(\theta \le \widehat{\theta}_{\mathrm{l}}\right), \tag{3.6}$$

$$\gamma_{\mathrm{u}} = \mathrm{prob}\left(\theta \ge \widehat{\theta}_{\mathrm{u}}\right) \tag{3.7}$$

and

$$\gamma = \mathrm{prob}\left(\widehat{\theta}_{\mathrm{l}} < \theta < \widehat{\theta}_{\mathrm{u}}\right) = 1 - \gamma_{\mathrm{l}} - \gamma_{\mathrm{u}}. \tag{3.8}$$

Exact CIs have coverages, γ, equal to the nominal value $1 - 2\alpha$. Construction of exact CIs requires knowledge of the distribution of $\widehat{\theta}$, which can be achieved only for simple problems. In more complex situations, only approximate CIs can be constructed (Section 3.1.3). As regards the division of the nominal coverage between the CI endpoints, this book adopts a practical approach and considers only equi-tailed CIs, where nominally $\gamma_{\mathrm{l}} = \gamma_{\mathrm{u}} = \alpha$. As a second CI property besides coverage, we consider interval length, $\widehat{\theta}_{\mathrm{u}} - \widehat{\theta}_{\mathrm{l}}$, which is ideally small.

Preceding paragraphs considered estimators on the process level. In practice, on the sample level, we plug in the data $\{t(i), x(i)\}_{i=1}^{n}$ for $\{T(i), X(i)\}_{i=1}^{n}$. Following the usual convention, we denote also the estimator on the sample level as $\widehat{\theta}$. An example is the autocorrelation estimator (Eq. 2.4).

3.1.1 Theoretical example: mean estimation of Gaussian white noise

Let the process $\{X(i)\}_{i=1}^{n}$ be given by

$$X(i) = \mathcal{E}_{\mathrm{N}(\mu,\, \sigma^2)}(i), \qquad i = 1, \ldots, n, \tag{3.9}$$

which is called a Gaussian purely random process or Gaussian white noise. There is no serial dependence, and the times $T(i)$ are not of interest. Consider as estimator $\widehat{\theta}$ of the mean, μ, the sample mean, written on process level as

$$\widehat{\mu} = \bar{X} = \sum_{i=1}^{n} X(i)/n. \tag{3.10}$$

Let also σ be unknown and estimated by the sample standard deviation, $\widehat{\sigma} = S_{n-1}$, given in the next example (Eq. 3.19). The properties of $\bar{X}$ readily follow as

$$\mathrm{se}_{\bar{X}} = \sigma \cdot n^{-1/2}, \tag{3.11}$$

$$\mathrm{bias}_{\bar{X}} = 0, \tag{3.12}$$

$$\mathrm{RMSE}_{\bar{X}} = \mathrm{se}_{\bar{X}} \tag{3.13}$$

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

and

$$\mathrm{CV}_{\bar{X}} = \sigma \cdot n^{-1/2} \cdot \mu^{-1}. \tag{3.14}$$

An exact CI of level $1-2\alpha$ can be constructed by means of the Student's t distribution of $\bar{X}$ (von Storch and Zwiers 1999):

$$\mathrm{CI}_{\bar{X},1-2\alpha} = \left[\bar{X} + t_{n-1}(\alpha) \cdot S_{n-1} \cdot n^{-1/2}; \bar{X} + t_{n-1}(1-\alpha) \cdot S_{n-1} \cdot n^{-1/2}\right]. \tag{3.15}$$

$t_\nu(\beta)$ is the percentage point at β of the t distribution function with ν degrees of freedom (Section 3.9).

On the sample level, we write the estimated sample mean,

$$\widehat{\mu} = \bar{x} = \sum_{i=1}^{n} x(i)/n, \tag{3.16}$$

the estimated standard error,

$$\widehat{\mathrm{se}}_{\bar{x}} = \left\{\sum_{i=1}^{n} \left[x(i) - \bar{x}\right]^2 / n^2\right\}^{1/2}, \tag{3.17}$$

and the confidence interval,

$$\mathrm{CI}_{\bar{x},1-2\alpha} = \left[\bar{x} + t_{n-1}(\alpha) \cdot s_{n-1} \cdot n^{-1/2}; \bar{x} + t_{n-1}(1-\alpha) \cdot s_{n-1} \cdot n^{-1/2}\right], \tag{3.18}$$

where s_{n-1} is given by Eq. (3.25).

The performance of the CI in Eq. (3.18) for Gaussian white noise is analysed by means of a Monte Carlo simulation experiment. The CI performs excellent in coverage (Table 3.1), as expected from its exactness. The second CI property, length, decreases with data size. It can be further compared with CI lengths for other location measures.

3.1.2 Theoretical example: standard deviation estimation of Gaussian white noise

Consider the Gaussian white-noise process (Eq. 3.9) with unknown mean, and as estimator of σ the sample standard deviation, written on process level as

$$\widehat{\sigma} = S_{n-1} = \left\{\sum_{i=1}^{n} \left[X(i) - \bar{X}\right]^2 / (n-1)\right\}^{1/2}. \tag{3.19}$$

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

Part II

Univariate Time Series

Chapter 4

Regression I

Regression is a method to estimate the trend in the climate equation (Eq. 1.1). Assume that outlier data do not exist or have already been removed by the assistance of an extreme value analysis (Chapter 6). Then the climate equation is a regression equation,

$$X(T) = X_{\mathrm{trend}}(T) + S(T) \cdot X_{\mathrm{noise}}(T). \tag{4.1}$$

One choice is to write $X_{\mathrm{trend}}(T)$ as a function with parameters to be estimated. A simple example is the linear function (Section 4.1), which has two parameters, intercept and slope. A second example is the nonlinear regression model (Section 4.2). The other choice is to estimate $X_{\mathrm{trend}}(T)$ nonparametrically, without reference to a specific model. Nonparametric regression (Section 4.3) is also called smoothing.

Trend is a property of genuine interest in climatology, it describes the mean state. This chapter deals also with quantifying $S(T)$, the variability around the trend, as second property of climate. Regression methods can be used to measure climate changes: their size and timing. For that aim, the ramp regression (Section 4.2.1) constitutes a useful parametric model of climate changes.

We compare the bootstrap with the classical approach to determine error bars and CIs for estimated regression parameters. The difficulties imposed by the data are non-Gaussian distributions, persistence and uneven spacing. We meet another difficulty, uncertain timescales. This leads to adaptions of the bootstrap (Section 4.1.7), where the resampling procedure is extended to include also the time values, $t(i)$.

The present chapter studies regression as a tool for quantifying the time-dependence of $X_{\mathrm{trend}}(T)$, the relation between trend and time in univariate time series. A later chapter (Regression II) uses regression to

M. Mudelsee, *Climate Time Series Analysis*, Atmospheric and Oceanographic Sciences Library 42, DOI 10.1007/978-90-481-9482-7_4,

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

analyse the relation in bivariate time series, between one time-dependent climate variable, $X(T)$, and another, $Y(T)$.

4.1 Linear regression

The linear regression uses a straight-line model,

$$X_{\mathrm{trend}}(T) = \beta_0 + \beta_1 T. \tag{4.2}$$

The climate equation without outlier component is then written in discrete time as a linear regression equation,

$$X(i) = \beta_0 + \beta_1 T(i) + S(i) \cdot X_{\mathrm{noise}}(i). \tag{4.3}$$

T is called the predictor or regressor variable, X the response variable, β_0 and β_1 the regression parameters.

4.1.1 Weighted least-squares and ordinary least-squares estimation

In a simple, theoretical setting, where the variability $S(i)$ is known and $X_{\mathrm{noise}}(i)$ has no serial dependence, the linear regression model can be fitted to data $\{t(i), x(i)\}_{i=1}^{n}$ by minimizing the weighted sum of squares,

$$SSQW(\beta_0, \beta_1) = \sum_{i=1}^{n} \left[x(i) - \beta_0 - \beta_1 t(i)\right]^2 / S(i)^2 \,, \tag{4.4}$$

yielding the weighted least-squares (WLS) estimators

$$\widehat{\beta}_0 = \left[\sum_{i=1}^{n} x(i)/S(i)^2 - \widehat{\beta}_1 \sum_{i=1}^{n} t(i)/S(i)^2\right] \Big/ W, \tag{4.5}$$

$$\begin{aligned}\widehat{\beta}_1 = &\left\{\left[\sum_{i=1}^{n} t(i)/S(i)^2\right]\left[\sum_{i=1}^{n} x(i)/S(i)^2\right] \Big/ W - \sum_{i=1}^{n} t(i)\, x(i)/S(i)^2\right\} \\ &\times \left\{\left[\sum_{i=1}^{n} t(i)/S(i)^2\right]^2 \Big/ W - \sum_{i=1}^{n} t(i)^2/S(i)^2\right\}^{-1}, \end{aligned} \tag{4.6}$$

where

$$W = \sum_{i=1}^{n} 1/S(i)^2. \tag{4.7}$$

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

In a practical setting, $S(i)$ is often not known and has to be replaced by $\widehat{S}(i)$. If prior knowledge indicates that $S(i)$ is constant, then one may take as estimator the square root of the residual mean square MS_E (Montgomery and Peck 1992),

$$\widehat{S}(i) = \widehat{S} = \left\{ \sum_{i=1}^{n} \left[x(i) - \widehat{\beta}_0 - \widehat{\beta}_1 t(i) \right]^2 \Big/ (n-2) \right\}^{1/2} = MS_E^{1/2}. \quad (4.8)$$

If $S(i)$ is unknown and possibly time-dependent, the following iterative estimation algorithm can be applied (Algorithm 4.1). As long as $S(i)$ is required only for weighting, this produces the correct estimators also if only the relative changes of $S(i)$, instead of the absolute values, are estimated. Analogously, if $S(i)$ is required only for weighting and known to be constant, then Eqs. (4.5) and (4.6) can be used with $S(i) = 1$, $i = 1, \ldots, n$ and $W = n$. This estimation without weighting is called ordinary least squares (OLS). For the construction of classical CIs (Section 4.1.4), however, an estimate of $S(i)$ has to be available.

Step 1	Make an initial guess, $\widehat{S}^{(0)}(i)$, of the variability.
Step 2	Estimate the regression parameters, $\widehat{\beta}_0^{(0)}$ and $\widehat{\beta}_1^{(0)}$, with the guessed variability used instead of $S(i)$ in Eqs. (4.5), (4.6) and (4.7).
Step 3	Calculate $e(i) = x(i) - \widehat{\beta}_0 - \widehat{\beta}_1 t(i), i = 1, \ldots, n$. The $e(i)$ are called the unweighted regression residuals.
Step 4	Obtain a new variability estimate, $\widehat{S}^{(1)}(i)$ from the residuals. This can be done either nonparametrically by smoothing (e.g., running standard deviation of $e(i)$) or fitting a parametric model of $S(i)$ to $e(i)$.
Step 5	Go to Step 2 with the new, improved variability estimate until regression estimates converge.

Algorithm 4.1. Linear weighted least-squares regression, unknown variability.

4.1.1.1 Example: Arctic river runoff

The climate model run with natural forcing only (Fig. 4.1a) does not exhibit a slope significantly different from zero. (See Section 4.1.4 for the determination of regression standard errors.) The run with combined anthropogenic and natural forcing (Fig. 4.1b) displays significant upwards trends in runoff. Wu et al. (2005) conjecture that there might be a change-point at around 1965, when the slope changed.

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

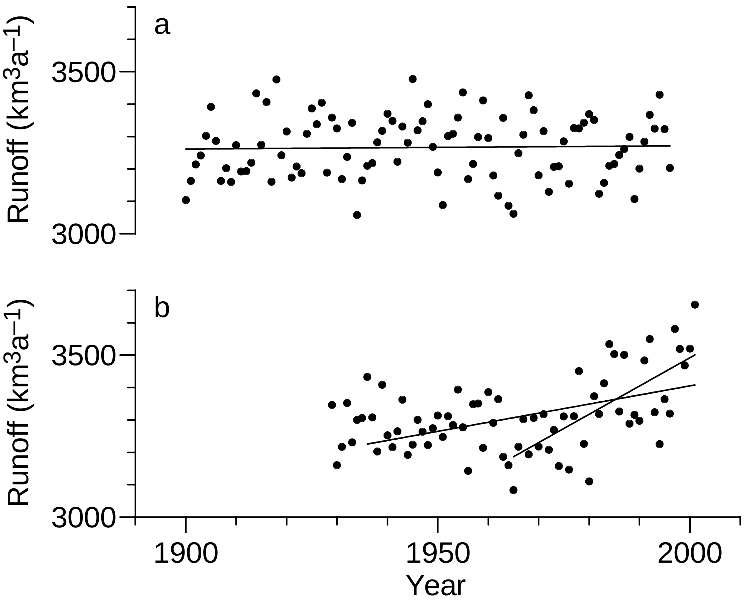


Figure 4.1. Linear regression models fitted to modelled Arctic river runoff (Fig. 1.9). **a** Natural forcing only; **b** combined anthropogenic and natural forcing. Following Wu et al. (2005), the fits (*solid lines*) were obtained by OLS regression using the data from (**a**) the whole interval 1900–1996 and (**b**) from two intervals, 1936–2001 and 1965–2001. The estimated regression parameters (Eqs. 4.5 and 4.6) and their standard errors (Eqs. 4.24 and 4.25) are as follows. **a** $\widehat{\beta}_0 = 3068 \pm 694$ km^{3}a^{-1}, $\widehat{\beta}_1 = 0.102 \pm 0.356$ km^{3}a^{-2}; **b** 1936–2001, $\widehat{\beta}_0 = -2210 \pm 1375$ km^{3}a^{-1}, $\widehat{\beta}_1 = 2.807 \pm 0.698$ km^{3}a^{-2}; **b** 1965–2001, $\widehat{\beta}_0 = -13{,}977 \pm 3226$ km^{3}a^{-1}, $\widehat{\beta}_1 = 8.734 \pm 1.627$ km^{3}a^{-2}.

4.1.2 Generalized least-squares estimation

In a practical climatological setting, $X_{\text{noise}}(i)$ often exhibits persistence. This means more structure or information content than a purely random process has. This knowledge can be used to apply the generalized least-squares (GLS) estimation, where the following sum of squares is minimized:

$$SSQG(\boldsymbol{\beta}) = (\mathbf{x} - \mathbf{T}\boldsymbol{\beta})' \, \mathbf{V}^{-1} \, (\mathbf{x} - \mathbf{T}\boldsymbol{\beta}) \,. \tag{4.9}$$

Herein,

$$\boldsymbol{\beta} = \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} \text{ (parameter vector)}, \tag{4.10}$$

$$\mathbf{x} = \begin{bmatrix} x(1) \\ \vdots \\ x(n) \end{bmatrix} \text{ (data vector)}, \tag{4.11}$$

$$\mathbf{T} = \begin{bmatrix} 1 & t(1) \\ \vdots & \vdots \\ 1 & t(n) \end{bmatrix} \text{ (time matrix)} \tag{4.12}$$

and $\mathbf{V}$ is an $n \times n$ matrix, the covariance matrix. The solution is the GLS estimator,

$$\widehat{\boldsymbol{\beta}} = \left(\mathbf{T}'\mathbf{V}^{-1}\mathbf{T}\right)^{-1} \mathbf{T}'\mathbf{V}^{-1}\mathbf{x}. \tag{4.13}$$

GLS has the advantage of providing smaller standard errors of regression estimators than WLS in the presence of persistence. Analogously, in the case of time-dependent $S(i)$, the WLS estimation is preferable (Sen and Srivastava 1990) to OLS estimation. The covariance matrix has the elements

$$V(i_1, i_2) = S(i_1) \cdot S(i_2) \cdot E\left[X_{\text{noise}}(i_1) \cdot X_{\text{noise}}(i_2)\right], \tag{4.14}$$

$i_1, i_2 = 1, \ldots, n$. Climatological practice normally requires to estimate besides the variability also the persistence (Chapter 2) to obtain the $\mathbf{V}$ matrix. In the case of the AR(1) persistence model for uneven spacing (Eq. 2.9), the only unknown besides $S(i)$ required for calculating $\mathbf{V}$ is the persistence time, τ. The estimated $\mathbf{V}$ matrix has then the elements

$$\widehat{V}(i_1, i_2) = \widehat{S}(i_1) \cdot \widehat{S}(i_2) \cdot \exp\left[-|t(i_1) - t(i_2)|/\widehat{\tau}'\right], \tag{4.15}$$

$i_1, i_2 = 1, \ldots, n$, where $\widehat{\tau}'$ is the estimated, bias-corrected persistence time (Section 2.6). For even spacing, replace the exponential expression by $(\widehat{a}')^{|i_1 - i_2|}$. (In the case of persistence models more complex than AR(1), $\mathbf{V}$ is calculable and, hence, GLS applicable only for evenly spaced time series.) The autocorrelation or persistence time estimation formulas (Eqs. 2.4 and 2.11) are applied to the weighted WLS regression residuals,

$$r(i) = \left[x(i) - \widehat{\beta}_0 - \widehat{\beta}_1 t(i)\right] \Big/ \widehat{S}(i), \tag{4.16}$$

$i = 1, \ldots, n$. Detrending by a linear regression is not the same as mean subtraction, and the bias of those autocorrelation and persistence time estimators need not follow the approximations given for mean subtraction (Section 2.6), but are unknown. However, the deviations are likely negligible compared with the other uncertainties. Also in the case of unknown persistence, an iterative procedure similar to that for WLS can be applied, which is called estimated generalized least squares (EGLS) (Sen and Srivastava 1990: Section 7.3 therein). Section 4.1.4.1 gives an EGLS procedure for the case of AR(1) persistence.

4.1.3 Other estimation types

Least squares (OLS, WLS, GLS) is one type of fit criterion. Another is maximum likelihood (Section 2.6, p. 58). Further criteria result from further preferences in the regression procedure. A notable choice is robustness against the influence of outlier data, $X_{\mathrm{out}}(i)$. This can be achieved by minimizing instead of the sum of squares (Eq. 4.4), the median of squares,

$$\widehat{m} \left\{ \left[x(i) - \beta_0 - \beta_1 t(i) \right]^2 / S(i)^2 \right\}_{i=1}^{n} . \tag{4.17}$$

Preferably (background material) is to minimize the trimmed sum of squares,

$$SSQT(\beta_0, \beta_1) = \sum_{i=j+1}^{n-j} \left[x'(i) - \beta_0 - \beta_1 t'(i) \right] / S'(i)^2 , \tag{4.18}$$

where $j = INT(\delta n)$, $INT(\cdot)$ is the integer function, $0 < \delta < 0.5$, $x'(i)$ is size-sorted $x(i)$, and $t'(i)$ and $S'(i)$ are the "slaves," correspondingly rearranged. Trimming excludes the $2j$ most extreme terms from contributing to the estimation. Also by the minimization of the sum of absolute deviations,

$$SSQA(\beta_0, \beta_1) = \sum_{i=1}^{n} \left| x(i) - \beta_0 - \beta_1 t(i) \right| / S(i) , \tag{4.19}$$

outlier values (if not already excluded by means of a prior analysis) can be given less influence on regression estimates than in least-squares minimization. Such criteria could also be preferable (in terms of, say, standard errors of estimates) to least squares when instead of $X_{\mathrm{out}}(i)$ we considered heavy-tailed or skewed $X_{\mathrm{noise}}(i)$ distributions.

The various criteria introduced so far and the related minimization techniques represent the computational aspect of the regression estimation problem. The second and perhaps more relevant aspect is suitability of the linear regression model. In climatology this means whether a linear increase or decrease is not too simple for describing $X_{\mathrm{trend}}(T)$. Model suitability can be evaluated graphically via various types of plots of the regression residuals (Eq. 4.16). These realizations of the noise process should nominally not exhibit more structure than the assumed persistence model.

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

Chapter 5

Spectral Analysis

Spectral analysis investigates the noise component in the climate equation (Eq. 1.2). A Fourier transformation into the frequency domain makes it possible to separate short-term from long-term variations and to distinguish between cyclical forcing mechanisms of the climate system and broad-band resonances. Spectral analysis allows to learn about the climate physics.

The task is to estimate the spectral density function, and to test for harmonic (cyclical) signals. This poses more difficulties than, for example, linear regression because now we estimate a function and not just two parameters. Spectral smoothing becomes therefore necessary, and this brings a trade-off between estimation variance and frequency resolution.

The multitaper smoothing method achieves the optimal trade-off for evenly spaced time series. The method of choice for unevenly spaced records is Lomb–Scargle, which estimates in the time domain and avoids distortions caused by interpolation.

Bootstrap resampling enhances multitaper and Lomb–Scargle methods by providing a bias correction and CIs. It supplies also a detection test for a spectral peak against realistic noise alternatives in form of an AR(1) process ("red noise"). Section 5.2.8 introduces bootstrap adaptions to take into account the effects of timescale uncertainties on detectability and frequency resolution.

5.1 Spectrum

Let us assume in this chapter that the climate process in continuous time, $X(T)$, has no trend and no outlier components and a constant

M. Mudelsee, *Climate Time Series Analysis*, Atmospheric and Oceanographic Sciences Library 42, DOI 10.1007/978-90-481-9482-7_5,

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

variability, S,

$$\begin{aligned} X(T) &= X_{\text{trend}}(T) + X_{\text{out}}(T) + S(T) \cdot X_{\text{noise}}(T) \\ &= S \cdot X_{\text{noise}}(T). \end{aligned} \tag{5.1}$$

Such a process could be derived from a "real" climate process, that is, with trend and so forth, by subtracting the trend and outlier components and normalizing (standard deviation). Techniques for quantifying trend and variability and detecting outliers are presented in Chapter 4.

It is then straightforward (Priestley 1981) to define a truncated process,

$$X_{T'}(T) = \begin{cases} X(T) & \text{for } -T' \leq T \leq T', \\ 0 & \text{elsewhere,} \end{cases} \tag{5.2}$$

and express it as a Fourier integral,

$$X_{T'}(T) = (2\pi)^{1/2} \int_{-\infty}^{\infty} G_{T'}(f) e^{2\pi i f T} df, \tag{5.3}$$

where

$$\begin{aligned} G_{T'}(f) &= (2\pi)^{-1/2} \int_{-\infty}^{\infty} X_{T'}(T) e^{-2\pi i f T} dT \\ &= (2\pi)^{-1/2} \int_{-T'}^{T'} X(T) e^{-2\pi i f T} dT. \end{aligned} \tag{5.4}$$

This introduces the frequency, f. (The symbol i in the exponent denotes $\sqrt{-1}$.) This is a useful quantity for describing phenomena that exhibit a periodic behaviour in time. The period (time units) is given by $T_{\text{period}} = 1/f$. If one associates $X(T)$ with movement and kinetic energy, then $2\pi |G_{T'}(f)^2| df$ can be seen as the energy contribution of components with frequencies within the (arbitrarily small) interval $[f; f + df]$. Regarding the truncation, because with $T' \rightarrow \infty$ also the energy goes to infinity, one defines the power, $\pi |G_{T'}(f)^2| / T'$. Because the previous formulas in this section apply to a time series rather than a stochastic process, one uses the expectation operator to define

$$h(f) = \lim_{T' \rightarrow \infty} \left\{ E \left[2\pi \left| G_{T'}(f)^2 \right| / T' \right] \right\}. \tag{5.5}$$

The function $h(f)$ is called one-sided non-normalized power spectral density function of the process $X(T)$, often denoted just as (non-normalized) spectrum. It is the average (over all realizations) of the contribution to the total power from components in $X(T)$ with frequencies within the interval $[f; f + df]$. $h(f)$ is defined for $f \geq 0$ and integrates to S^2. A closely related function is

$$g(f) = h(f) \,/S^2, \tag{5.6}$$

the one-sided normalized power spectral density function, which integrates to unity. A two-sided version of the spectrum, symmetric about $f = 0$, is also used (Bendat and Piersol 1986).

The functions $h(f)$ and $g(f)$ are the Fourier transforms of the autocovariance and autocorrelation functions, $R(\tau)$ and $\rho(\tau)$, respectively, provided they exist (Priestley 1981: Section 4.8 therein):

$$h(f) = \pi^{-1} \int_{-\infty}^{\infty} R(\tau) e^{-2\pi i f \tau} d\tau, \tag{5.7}$$

$$g(f) = \pi^{-1} \int_{-\infty}^{\infty} \rho(\tau) e^{-2\pi i f \tau} d\tau. \tag{5.8}$$

Herein,

$$R(\tau) = E\left[X(T) \cdot X(T + \tau)\right], \tag{5.9}$$

$$\rho(\tau) = R(\tau) \,/R(0) \tag{5.10}$$

and the symbol τ is used to denote a lag in continuous time. The caveat refers to the fact that not all processes $X(T)$ have a spectral representation; however, the existence of the Fourier transform of the autocovariance function $R(\tau)$ of $X(T)$ is a sufficient condition.

Turning to the discrete-time version of the climate process, $X(i)$, we assume also here absent trend, absent outliers and constant variability and find

$$X(i) = S \cdot X_{\text{noise}}(i). \tag{5.11}$$

The spectral theory is in this case similar to the continuous-time case (Priestley 1981: Section 4.8.3 therein), except that the frequency range is now restricted in both directions and the discrete Fourier transform is invoked to calculate the power spectral density functions. For example, with even time spacing, $d(i) = d > 0$,

$$g(f) = (d/\pi) \sum_{l=-\infty}^{\infty} \rho(l) e^{-2\pi i f l} dl, \qquad 0 \leq f \leq 1/(2d). \tag{5.12}$$

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

Herein, l denotes a lag in discrete time. The frequency $f_{\mathrm{Ny}} = (2d)^{-1}$ is denoted as Nyquist frequency; it sets the upper frequency bound.

5.1.1 Example: AR(1) process, discrete time

Consider the discrete-time AR(1) process (Section 2.1.1) with an autocorrelation parameter a on an evenly spaced timescale, $d(i) = d > 0$, with $n = \infty$ points. Then (Priestley 1981: Section 4.10 therein),

$$g(f) = 2d(1 - a^2) \,/\left[1 - 2a\cos(2\pi f d) + a^2\right], \qquad 0 \le f \le 1/(2d). \tag{5.13}$$

Plots of the AR(1) spectrum (Fig. 5.1) show higher power at lower frequencies for $a > 0$; such a spectrum is, hence, called "red."

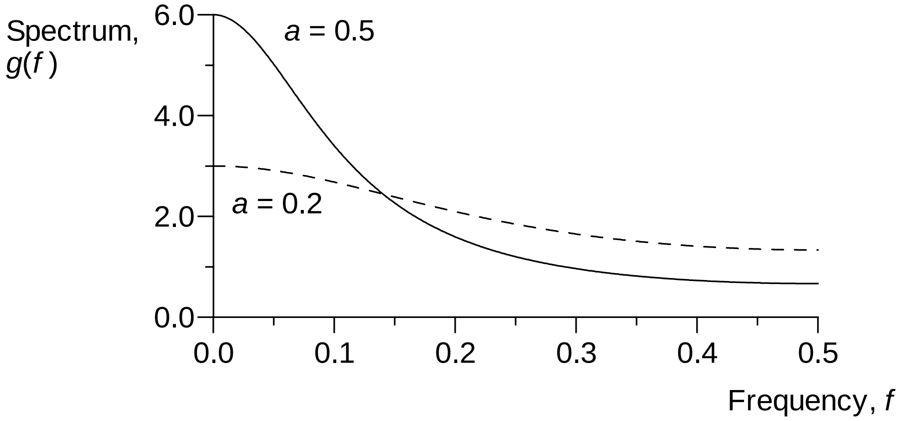


Figure 5.1. Spectrum of the AR(1) process (Eq. 5.13). Two parameter settings are shown; $d = 1$ and $f_{\mathrm{Ny}} = 0.5$.

5.1.2 Example: AR(2) process, discrete time

Consider the discrete-time AR(2) process (Section 2.2) with parameters a_1 and a_2 on an evenly spaced timescale with $d > 0$ and $n = \infty$. Then (Priestley 1981: Section 4.10 therein),

$$\begin{aligned} g(f) &= 2d(1 + a_2)(1 - a_2)^{-1}\left[(1 - a_2)^2 - a_1^2\right]\left[(1 + a_2)^2\right. \\ &\quad \left. + a_1^2 - 2a_1(1 - a_2)\cos(2\pi f d) - 4a_2\cos(2\pi f d)^2\right]^{-1}, \end{aligned} \tag{5.14}$$

with $0 \le f \le 1/(2d)$. Plots of the AR(2) spectrum (Fig. 5.2) reveal that besides redness such spectra may exhibit quasi-cyclical behaviour (Eq. 2.15).

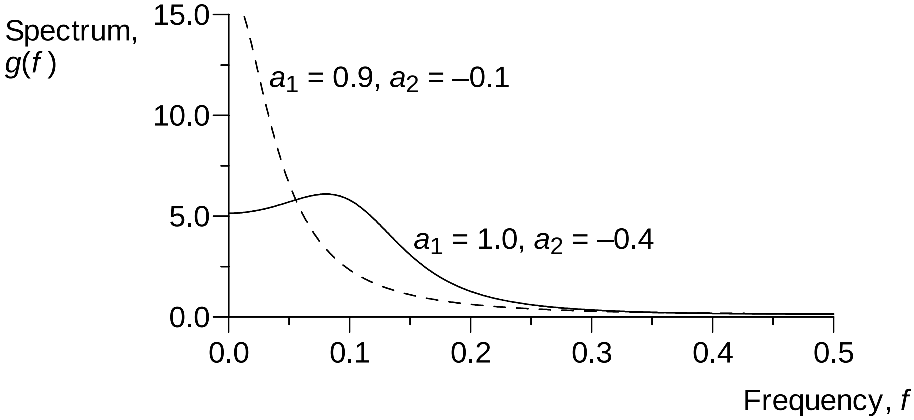


Figure 5.2. Spectrum of the AR(2) process (Eq. 5.14). Two parameter settings are shown; $d = 1$ and $f_{\mathrm{Ny}} = 0.5$.

5.1.3 Physical meaning

The importance of the power spectral density functions $h(f)$ and $g(f)$ lies in the possibility of decomposing a process into contributions from different frequency intervals. That allows to separate short-term from long-term variations and also to distinguish between cyclical forcing mechanisms of the climate system and broad-band resonances. This means that spectral analysis permits to learn about the physics of the sampled climate system. As always when having instead of a perfect knowledge only a handful of data contaminated with measurement and, perhaps, proxy errors, the task is to *estimate,* namely the spectrum. The following sections explain methods to infer $h(f)$ or $g(f)$ from $\{t(i), x(i)\}_{i=1}^{n}$.

We expect the climate spectrum either as continuous (Fig. 5.3b), reflecting a random process, or as a mixture of continuous and line components (Fig. 5.3c), the latter representing a deterministic, periodic influence. Note that estimating a spectrum is estimating a function from a finite data set. This means we can expect more difficulties and a higher susceptibility to the validness of made assumptions than for easier tasks, where only few parameters have to estimated, such as in linear regression.

A word on the notation: The literature has developed a rich variety of different notations (factors 2π, frequency versus angular velocity, etc.),

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

Chapter 6

Extreme Value Time Series

Extreme value time series refer to the outlier component in the climate equation (Eq. 1.2). Quantifying the tail probability of the PDF of a climate variable—the risk of climate extremes—is of high socioeconomical relevance. In the context of climate change, it is important to move from stationary to nonstationary (time-dependent) models: with climate changes also risk changes may be associated.

Traditionally, extreme value data are evaluated in two forms: first, block extremes such as annual maxima, and second, exceedances of a high threshold. A stationary model of great flexibility for the first and the second form is the Generalized Extreme Value distribution and the generalized Pareto distribution, respectively. Classical estimation techniques based on maximum likelihood exist for both distributions.

Nonstationary models can be constructed parametrically, by writing the extreme value models with time-dependent parameters. Maximum likelihood estimation may impose numerical difficulties here. The inhomogeneous Poisson process constitutes an interesting nonparametric model of the time-dependence of the occurrence of an extreme. Here, bootstrap confidence bands can be constructed and hypothesis tests performed to assess the significance of trends in climate risk. A recent development is a hybrid, which estimates the time-dependence nonparametrically and, conditional on the occurrence of an extreme, models the extreme value parametrically.

6.1 Data types

We distinguish among several types of extreme value data. One guide for doing so is the accuracy of $X_{\mathrm{out}}(i)$, the outlier or extreme component in the climate equation (Eq. 1.2). Even data with a very low accuracy

M. Mudelsee, *Climate Time Series Analysis*, Atmospheric and Oceanographic Sciences Library 42, DOI 10.1007/978-90-481-9482-7_6,

can be analysed, for example, cases where only the time an extreme occurred is known. A related guide comes from considering how the extreme data were obtained. An example is outlier detection by imposing a threshold (Section 4.3.3).

6.1.1 Event times

In the low-accuracy case it is just known about an event that it did occur, that means, $X_{\text{out}}(i) \neq 0$. The time points of the events recorded by a time series are

$$\left\{T_{\text{out}}(j)\right\}_{j=1}^{m} = \left\{T(i) \middle| X_{\text{out}}(i) \neq 0\right\}_{i=1}^{n}. \tag{6.1}$$

On the sample level, the set of time points inferred from analysing $\{t(i), x(i)\}_{i=1}^{n}$ is written as $\{t_{\text{out}}(j)\}_{j=1}^{m}$. The number of extreme events is m; it is $m \leq n$.

A second constraint imposed on $X_{\text{out}}(i)$, besides being unequal to zero, is independence. The observed extreme should have occurred because a climate process generated it and not because there had previously been another, interfering event.

6.1.1.1 Example: Elbe winter floods

The winter floods of the river Elbe (Fig. 1.1) were recorded with a slightly higher accuracy ($x'_{\text{out}}(j)$ = 1, 2 or 3). For the documentary period (up to 1850), independence of events was achieved by studying the historical sources (Mudelsee et al. 2003). Consider the ice flood in 1784, for which Weikinn (2000) gives 32 source texts that report about the breaking ice cover in the last week of February, the rising water levels, the considerable damages this and the moving ice floes caused and, finally, the decreasing water levels in the first week of March 1784. Mudelsee et al. (2003) considered this as one single event ($t_{\text{out}}(j) = 1784.167$) and not two (February, March).

The question after the flood risk, whether winter floods occur at a constant rate or there exist instead changes, is analysed by means of occurrence rate estimation (Section 6.3.2).

6.1.2 Peaks over threshold

If $X(i)$ is known with higher accuracy, a threshold criterion may be applied to detect extremes.

$$\left\{T_{\text{out}}(j), X'_{\text{out}}(j)\right\}_{j=1}^{m} = \left\{T(i), X(i) \middle| X(i) > u\right\}_{i=1}^{n} \tag{6.2}$$

is a rule for detecting maxima with a constant threshold, u. The extension to detecting minima is straightforward.

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

The peaks-over-threshold (POT) data can be analysed in two ways. Occurrence rate estimation (Section 6.3.2) uses the sample $\{t_{\mathrm{out}}(j)\}_{j=1}^{m}$ to infer trends in the occurrence of extremes. Fitting a generalized Pareto distribution (Section 6.2.2) to $\{x'_{\mathrm{out}}(j)\}_{j=1}^{m}$ is helpful for studying the risk of an event of pre-defined size, $\mathrm{prob}(X(i) > u + v)$ with $v > 0$.

In climatology it is also useful to consider a time-dependent threshold to take into account effects of trends in mean, $X_{\mathrm{trend}}(T)$, and variability, $S(T)$. To fulfill the assumption of mutual independence of the POT data, imposing further criteria than passing the threshold may be necessary.

6.1.2.1 Example: volcanic peaks in the NGRIP sulfate record (continued)

Outlier/extremes detection in the NGRIP sulfate record (Fig. 4.16) employed a time-dependent threshold, $X_{\mathrm{trend}}(i) + z \cdot S(i)$, and robust estimates of trend ("background") and variability, to take into account variable oceanic input. A second criterion was the absence of contemporaneous Ca and Na peaks to extract the extremes caused by volcanic eruptions (Fig. 1.4). To satisfy the independence assumption, further threshold exceedances closely neighboured in time were discarded (third criterion). In general, the size of such a neighbourhood can be estimated using persistence models (Chapter 2). Instead of taking $\{X'_{\mathrm{out}}(j)\}_{j=1}^{m}$ from $\{X(i)\}_{i=1}^{n}$, one may also collect scaled extremes $\{X'_{\mathrm{out}}(j)\}_{j=1}^{m}$ from $\{[X(i) - X_{\mathrm{trend}}(i)]/S(i)\}_{i=1}^{n}$. Scaling is one form of taking nonstationarity into account (Section 6.3).

6.1.3 Block extremes

It may sometimes be that climate or weather data are in the form of extremes over a certain time period. An example of such a block extreme is the annual maximum,

$$X'_{\mathrm{out}}(j) = \max\Big(\{X(i)\}_{T(i)\ \text{within}\ j\text{th year of time series}}\Big), \tag{6.3}$$

$$T_{\mathrm{out}}(j) = j\text{th year of time series}. \tag{6.4}$$

The block extremes $X'_{\mathrm{out}}(j)$ are the input for fitting a Generalized Extreme Value distribution (Section 6.2.1). The estimation result sheds light on the risk at which an extreme of a pre-defined size and at a pre-defined block length occurs.

Risk estimation (Section 6.2.1) assumes that an extreme is taken from a block with a large number k (at least, say, 100) of independent observations. This can be done explicitly, by segmenting or "blocking" an original series $\{X(i)\}_{i=1}^{n}$. Alternatively, the blocking may have already been done implicitly. An example is documentary data in form of max-

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

imum annual water stage in a river, where original daily observations have not been preserved or have simply not been made. Another possibility, theoretically also conceivable, are proxy measurements with a machine that records not the mean value (e.g., of a concentration) but the extreme value. In any case, the independence assumption should be approximately fulfilled if the block length (time units) is large compared with $\max(\tau, D'(i))$ (Fig. 1.13). For practical applications, τ and $D(i)$ have to be estimated.

6.1.4 Remarks on data selection

The rules for selecting $\{X'_{\text{out}}(j)\}_{j=1}^{m}$ from $\{X(i)\}_{i=1}^{n}$ are not uniquely determined. This allows the analyst to explore various climate system properties regarding extremes.

One area is threshold selection in the POT approach. Besides allowing time-dependence, the size can be adjusted. A high (low) threshold size for maxima detection leads evidently to fewer (more) cases and, hence, to more conservative (liberal) results but likely also to wider (narrower) CIs. Furthermore, a too low threshold may lead to violations of the conditions of convergence to an extreme value distribution. Data in form of event times have implicitly also undergone a threshold selection. The documentary data about Elbe floods, for example, were critically screened (Mudelsee et al. 2003) whether there is enough evidence that merits inclusion into the flood record or there had instead been just an elevated water level noticed by a hypercritical observer.

For block extremes, the adjustable parameter is the block length. In the case of original data $X(i)$ with even spacing, this corresponds to a fixed number, k, of $X(i)$ values per block. In the case of uneven spacing, besides leaving the block length constant, one may also fix k. The connection to nonparametric regression and the smoothing problem (Section 4.3) is evident.

Henceforth we omit for convenience the prime and write $\{X_{\text{out}}(j)\}_{j=1}^{m}$ on the process and $\{x_{\text{out}}(j)\}_{j=1}^{m}$ on the sample level.

6.2 Stationary models

In stationary models, the distribution parameters and related quantities, such as risk, do not change over time.

6.2.1 Generalized Extreme Value distribution

The Generalized Extreme Value (GEV) distribution is suitable for analysing block extremes. Our treatment follows closely that of Coles (2001b: Chapter 3 therein).

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

6.2.1.1 Model

The GEV distribution function is given by

$$F_{\mathrm{GEV}}(x_{\mathrm{out}}) = \begin{cases} \exp\Big\{-\big[1+\xi\,(x_{\mathrm{out}}-\mu)\,/\sigma\big]^{-1/\xi}\Big\} & (\xi \neq 0), \\ \exp\Big\{-\exp\big[-(x_{\mathrm{out}}-\mu)\,/\sigma\big]\Big\} & (\xi = 0), \end{cases} \tag{6.5}$$

where $1+\xi\,(x_{\mathrm{out}}-\mu)\,/\sigma > 0$, $-\infty < \mu < \infty$, $\sigma > 0$ and $-\infty < \xi < \infty$. The parameters μ and σ identify location and scale, respectively, while the shape parameter, ξ, determines the tail behaviour of $F_{\mathrm{GEV}}(x_{\mathrm{out}})$.

The importance of the GEV distribution lies in the fact that it is the limiting distribution of the block maximum (for k large). Under mild conditions, nearly irrespective of what the common, but generally unknown distributional shape of the individual variables $X(i)$ is, the distribution of $X_{\mathrm{out}}(j)$ approaches the GEV (Fig. 6.1). This is in essence the extreme value analogue of the central limit theorem (Coles 2001b).

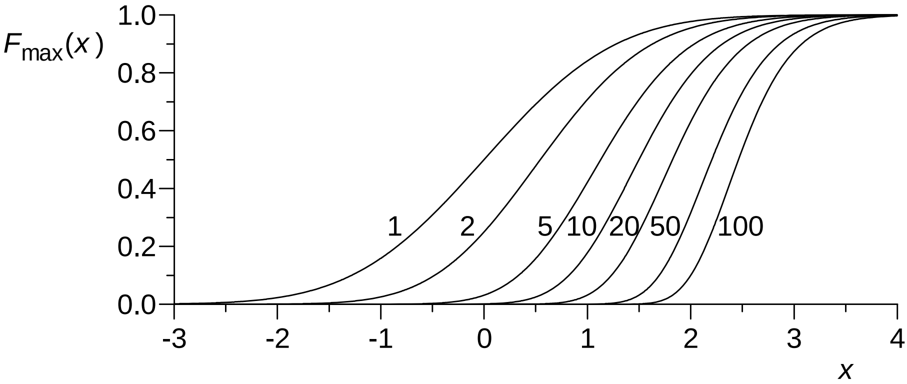


Figure 6.1. Distribution of the maximum of k independent standard normal variates. The plotted distribution functions, $F_{\max}(x)$, are labelled with k. For $k = 1$, the symmetric form of the standard normal distribution, $F_{\mathrm{N}}(x)$ (Eq. 3.49), appears. In general, $F_{\max}(x) = [F_{\mathrm{N}}(x)]^k$. Letting k increase has three effects: the location (average) is shifted to the right, the scale (standard deviation) is decreased and the right-skewness (shape parameter) is increased. With increasing k, $F_{\max}(x)$ approaches $F_{\mathrm{GEV}}(x)$. This is a theoretical example, with prescribed $F_{\mathrm{N}}(x)$ and exactly determined $F_{\max}(x)$. In a practical setting, with distribution and parameters of the independent variables unknown, $F_{\max}(x)$ can still be approximated by $F_{\mathrm{GEV}}(x)$.

6.2.1.2 Maximum likelihood estimation

Assume that the approximation is perfect and the block maxima $\{x_{\mathrm{out}}(j)\}_{j=1}^{m}$ do come from a GEV distribution (Eq. 6.5). Assume further that $\xi \neq 0$. Adopting the maximum likelihood principle (Section 2.6,

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

Part III

Bivariate Time Series

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

Chapter 7

Correlation

The correlation measures how strong a coupling is between the noise components of two processes, $X_{\text{noise}}(i)$ and $Y_{\text{noise}}(i)$. Using a bivariate time series sample, $\{t(i), x(i), y(i)\}_{i=1}^{n}$, this measure allows to study the relationship between two climate variables, each described by its own climate equation (Eq. 1.2).

Pearson's correlation coefficient (Section 7.1) estimates the degree of the *linear* relationship. It is one of the most widely used statistical quantities in all branches of the natural sciences. Spearman's correlation coefficient (Section 7.2) estimates the degree of the *monotonic* relationship. Although clearly less often used, it offers robustness against violations of the Gaussian assumption, as also the Monte Carlo experiments (Section 7.3) show.

Explorative climate data analyses should strongly benefit from correlation estimates that are supported by a CI and not only a P-value of a test of the null hypothesis of no correlation. It is then possible to take several pairs of variables and rank the associations. One finding may be, for example, that global temperature changes are stronger associated to variations of CO_2 than to those of solar activity (background material). The challenge of providing accurate CIs is met by pairwise bootstrap resampling (MBB or ARB), which takes into account the serial dependence structures of both climate processes.

A second, rarely mentioned challenge appears when the processes differ in their sampling times (Section 7.5). This book introduces two novel estimators, denoted as binned and synchrony correlation, respectively. These are able (and outperform interpolation) to recover correlation information under the conditions of (1) persistence in the system, which is realistic for climate, and (2) not too large spacings of the time series.

M. Mudelsee, *Climate Time Series Analysis*, Atmospheric and Oceanographic Sciences Library 42, DOI 10.1007/978-90-481-9482-7_7,

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

7.1 Pearson's correlation coefficient

Let us assume in this chapter, for simplicity of exposition, that the climate process, $X(i)$, has a constant trend function at level μ_X, a constant variability, S_X, and no outlier component. In discrete time,

$$\begin{aligned} X(i) &= X_{\text{trend}}(i) + X_{\text{out}}(i) + S(i) \cdot X_{\text{noise}}(i) \\ &= \mu_X + S_X \cdot X_{\text{noise}}(i). \end{aligned} \tag{7.1}$$

Assume analogously for the second climate process, $Y(i)$, which is on the same time points, $T(i)$, as the first climate process,

$$Y(i) = \mu_Y + S_Y \cdot Y_{\text{noise}}(i). \tag{7.2}$$

The correlation coefficient is then defined as

$$\rho_{XY} = \frac{E\left[\{X(i) - \mu_X\} \cdot \{Y(i) - \mu_Y\}\right]}{S_X \cdot S_Y}. \tag{7.3}$$

The correlation measures the degree of the linear relationship between the variables X and Y; ρ_{XY} is between -1 ("anti-correlation") and 1.

For convenience of presentation we introduce here the correlation operator,

$$CORR\left[X(i), Y(i)\right] = \frac{COV\left[X(i), Y(i)\right]}{\{VAR\left[X(i)\right] \cdot VAR\left[Y(i)\right]\}^{1/2}}. \tag{7.4}$$

The definition of the correlation coefficient is thus based on the assumption of time-constancy of $CORR\left[X(i), Y(i)\right] = \rho_{XY}$.

Let $\{X(i), Y(i)\}_{i=1}^{n}$ be a bivariate sample (process level). Pearson's (1896) estimator of ρ_{XY} is

$$r_{XY} = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{X(i) - \bar{X}}{S_{n,X}}\right) \cdot \left(\frac{Y(i) - \bar{Y}}{S_{n,Y}}\right), \tag{7.5}$$

where

$$\bar{X} = \sum_{i=1}^{n} X(i) \,/\, n \tag{7.6}$$

and

$$\bar{Y} = \sum_{i=1}^{n} Y(i) \,/\, n \tag{7.7}$$

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

are the sample means and

$$S_{n,X} = \left\{ \sum_{i=1}^{n} \left[X(i) - \bar{X} \right]^2 / \, n \right\}^{1/2} \tag{7.8}$$

and

$$S_{n,Y} = \left\{ \sum_{i=1}^{n} \left[Y(i) - \bar{Y} \right]^2 / \, n \right\}^{1/2} \tag{7.9}$$

are the sample standard deviations calculated with the denominator n (instead of $n - 1$). On the sample level, given a bivariate sample $\{x(i), y(i)\}_{i=1}^{n}$, plug in those values for $X(i)$ and $Y(i)$ in Eqs. (7.5), (7.6), (7.7), (7.8) and (7.9). The estimator r_{XY} is called Pearson's correlation coefficient. Also r_{XY} is between -1 and 1.

7.1.1 Remark: alternative correlation measures

It is of course possible to employ other estimators. For example, S_{n-1} (Eq. 3.19) may replace S_n for estimating S_X or S_Y, leading to an (unfortunate) correlation estimator that can have values < -1 or > 1. Another option may be to subtract the sample medians (Galton 1888) and not the sample means (Eqs. 7.6 and 7.7). More complex examples arise when time-dependent trend functions are subtracted or time-dependent variability functions used for normalization. Such cases may be relevant for climate time series analysis. All those examples lead to other correlation measures than ρ_{XY} and other correlation estimators than r_{XY}. Their properties and CI performance can in principle be studied in the same manner with Monte Carlo methods. Here we focus on r_{XY}, stationary trends and variabilities. Another measure (Spearman's) is analysed in Section 7.2.

7.1.2 Classical confidence intervals, non-persistent processes

Let $X(i)$ and $Y(i)$ both be a stochastic process without persistence or "memory." Let further $X(i)$ and $Y(i)$ both have a Gaussian distributional shape; their joint distribution is then denoted as bivariate normal or binormal distribution (Section 7.1.3.1). The PDF of Pearson's corre-

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

lation coefficient is then (Fisher 1915):

$$\begin{aligned} f(r_{XY}) &= \frac{\left(1-\rho_{XY}^2\right)^{(n-1)/2}\,\left(1-r_{XY}^2\right)^{(n-4)/2}}{\sqrt{\pi}\,\Gamma[(n-1)/2]\,\Gamma[(n-2)/2]} \\ &\quad \times \sum_{j=0}^{\infty} \frac{\{\Gamma[(n-1+j)/2]\}^2}{j!}\,(2\,\rho_{XY}\,r_{XY})^j\,. \end{aligned} \tag{7.10}$$

Numerous discussions on, and much work in the implementation of, this celebrated formula exist in statistical science. Hotelling (1953) gave approximations for the moments of r_{XY}. In particular,

$$\begin{aligned} \mathrm{bias}_{r_{XY}} = \left(1-\rho_{XY}^2\right)\Bigg[&-\frac{\rho_{XY}}{2n}+\frac{\rho_{XY}-9\rho_{XY}^3}{8n^2} \\ &+\frac{\rho_{XY}+42\rho_{XY}^3-75\rho_{XY}^5}{16n^3}+\mathcal{O}\left(n^{-4}\right)\Bigg] \end{aligned} \tag{7.11}$$

and

$$\begin{aligned} \mathrm{se}_{r_{XY}} = \left(1-\rho_{XY}^2\right)\Bigg[&\frac{1}{n^{1/2}}+\frac{11\rho_{XY}^2}{4n^{3/2}} \\ &-\frac{192\rho_{XY}^2-479\rho_{XY}^4}{32n^{5/2}}+\mathcal{O}\left(n^{-7/2}\right)\Bigg]. \end{aligned} \tag{7.12}$$

Regarding the focus of this chapter, CI construction, it is common practice to employ Fisher's (1921) transformation. The quantity

$$z = \tanh^{-1}(r_{XY}) \tag{7.13}$$

approaches with increasing n a normal distributional shape considerably faster than r_{XY}, particularly when $\rho_{XY} \neq 0$. Fisher's z has for large n the following properties (Rodriguez 1982):

$$E[z] \approx \tanh^{-1}(\rho_{XY}) \tag{7.14}$$

and

$$\mathrm{se}_z \approx (n-3)^{-1/2}\,. \tag{7.15}$$

This leads to the approximate classical CI for r_{XY},

$$\mathrm{CI}_{r_{XY},1-2\alpha} = \Big[\tanh\left[z+z(\alpha)\cdot \mathrm{se}_z\right];\tanh\left[z-z(\alpha)\cdot \mathrm{se}_z\right]\Big], \tag{7.16}$$

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

where $z(\alpha)$ is the percentage point of the normal distribution (Section 3.9).

If we keep the assumption of absence of persistence for processes $X(i)$ and $Y(i)$, but drop the Gaussian assumption, less is known, and no exact formula for the distribution of r_{XY} has been found. One recipe is then to work with higher-moment properties of the distributions and approximate solutions (Section 7.6). The alternative recipe is to use still the formulas for the Gaussian case (Eqs. 7.13, 7.14, 7.15 and 7.16) and assume robustness of this method. Johnson et al. (1995: Chapter 32 therein) give an account of the bewildering diversity of opinions in the research literature on the suitability of this approach.

7.1.3 Bivariate time series models

A bivariate model describes not only the distributional and persistence properties of two processes, $X(i)$ and $Y(i)$, but also the correlation between them. The bivariate white-noise model characterizes persistence-free processes and serves to build bivariate autoregressive and higher-order processes.

7.1.3.1 Bivariate white noise

The bivariate Gaussian white noise model is given by

$$\begin{aligned} X(i) &= \mathcal{E}^{X}_{\mathrm{N}(0,\,1)}(i), \qquad i = 1, \ldots, n, \\ Y(i) &= \mathcal{E}^{Y}_{\mathrm{N}(0,\,1)}(i), \qquad i = 1, \ldots, n. \end{aligned} \tag{7.17}$$

The Gaussian random processes $\mathcal{E}^{X}_{\mathrm{N}(0,\,1)}(\cdot)$ and $\mathcal{E}^{Y}_{\mathrm{N}(0,\,1)}(\cdot)$ are indexed. The correlation coefficient between them is denoted as $\rho_{\mathcal{E}}$.

The moments of this special case of the bivariate Gaussian white noise model are by definition

$$E\left[X(i)\right] = E\left[Y(i)\right] = 0, \tag{7.18}$$

$$VAR\left[X(i)\right] = VAR\left[Y(i)\right] = 1 \tag{7.19}$$

and

$$CORR\left[X(i), Y(i)\right] = \rho_{XY} = \rho_{\mathcal{E}}. \tag{7.20}$$

In the general case, $X(i)$ has mean μ_X and variance S_X^2, and $Y(i)$ has mean μ_Y and variance S_Y^2. The binormal PDF of $X(i)$ and $Y(i)$ (Section 7.6) is uniquely determined by the means, variances and correlation.

Chapter 8

Regression II

Regression serves in this chapter to relate two climate variables, $X(i)$ and $Y(i)$. This is a standard tool for formulating a quantitative "climate theory" based on equations. Owing to the complexity of the climate system, such a theory can never be derived alone from the pure laws of physics—it requires to establish empirical relations between observed climate processes.

Since not only $Y(i)$ but also $X(i)$ are observed with error, the relation has to be formulated as an errors-in-variables model, and the estimation has to be carried out using adaptions of the OLS technique. This chapter focuses on the linear model and studies three estimation techniques (denoted as OLSBC, WLSXY and Wald–Bartlett procedure). It presents a novel bivariate resampling approach (pairwise-MBBres), which enhances the coverage performance of bootstrap CIs for the estimated regression parameters.

Monte Carlo simulations allow to assess the role of various aspects of the estimation. First, prior knowledge about the size of the measurement errors is indispensable to yield a consistent estimation. If this knowledge is not exact, which is typical for a situation in the climatological practice, it contributes to the estimation error of the slope (RMSE and CI length). This contribution persists even when the data size goes to infinity; the RMSE does then not approach zero. Second, autocorrelation has to be taken into account to prevent estimation errors unrealistically small and CIs too narrow.

This chapter studies two extensions of high relevance for climatological applications: linear prediction and lagged regression.

Regression as a method to estimate the trend in the climate equation (Eq. 1.2) is presented in Chapter 4.

M. Mudelsee, *Climate Time Series Analysis*, Atmospheric and Oceanographic Sciences Library 42, DOI 10.1007/978-90-481-9482-7_8,

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

8.1 Linear regression

To make a regression of the predictor variable, X, on the response variable, Y, we re-apply the errors-in-variables model (Section 4.1.7),

$$Y(i) = \beta_0 + \beta_1 \left[X(i) - S_X(i) \cdot X_{\text{noise}}(i)\right] + S_Y(i) \cdot Y_{\text{noise}}(i), \qquad (8.1)$$

$i = 1, \ldots, n$. The variability of process $X(i)$ and $Y(i)$ is denoted as $S_X(i)$ and $S_Y(i)$, respectively; the noise component, $X_{\text{noise}}(i)$ and $Y_{\text{noise}}(i)$, is of assumed AR(1) type with persistence time τ_X and τ_Y, respectively. One task is to estimate the regression parameters, β_0 and β_1, given a bivariate sample, $\{t(i), x(i), y(i)\}_{i=1}^{n}$. Another, related task is to make a prediction of an unknown Y for a given value of X.

The errors-in-variables model (Eq. 8.1) differs from the simple model (Eq. 4.3) in its nonzero noise component of the predictor. Several estimators for the errors-in-variables model have been developed to deal with this more complex situation.

8.1.1 Ordinary least-squares estimation

The simple OLS estimation minimizes the unweighted sum of squares,

$$SSQ(\beta_0, \beta_1) = \sum_{i=1}^{n} \left[y(i) - \beta_0 - \beta_1 x(i)\right]^2 . \qquad (8.2)$$

This yields the estimators

$$\widehat{\beta}_0 = \left[\sum_{i=1}^{n} y(i) - \widehat{\beta}_1 \sum_{i=1}^{n} x(i)\right] \Big/ n \qquad (8.3)$$

and

$$\widehat{\beta}_1 = \left\{\left[\sum_{i=1}^{n} x(i)\right]\left[\sum_{i=1}^{n} y(i)\right] \Big/ n - \sum_{i=1}^{n} x(i)\, y(i)\right\} \times \left\{\left[\sum_{i=1}^{n} x(i)\right]^2 \Big/ n - \sum_{i=1}^{n} x(i)^2\right\}^{-1} . \qquad (8.4)$$

Using OLS means ignoring heteroscedasticity, persistence and errors in the predictor variable, X. However, heteroscedasticity and persistence can successfully be taken into account by employing WLS and GLS estimation, respectively. The success of ignoring errors in X depends on how large these are relative to the spread of the "true" X values (Eq.

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

4.34), which are given by $X_{\text{true}}(i) = X(i) - S_X(i) \cdot X_{\text{noise}}(i)$. If $S_X(i) = S_X$ is constant and $S_X^2 \ll VAR[X_{\text{true}}(i)]$, the estimation bias should be negligible. If $S_X(i)$ is not constant, one may expect a similar condition to the average of $S_X(i)$. The decisive quantity is $VAR[X_{\text{true}}(i)]$, which may be difficult to control for an experimenter prior to sampling the process.

If $X_{\text{noise}}(i)$ and $Y_{\text{noise}}(i)$ are independent, the estimator $\widehat{\beta}_1$ is biased downwards (Section 4.1.7) as $E\left(\widehat{\beta}_1\right) = \kappa \cdot \beta_1$, where $\kappa \le 1$ is the attenuation factor or reliability ratio,

$$\kappa = \left(1 + S_X^2 \,/VAR\left[X_{\text{true}}(i)\right]\right)^{-1}. \tag{8.5}$$

The intuitive reason of the bias downwards is that "smearing" the "true" predictor variable, $X_{\text{true}}(i)$, leads to a situation where the "cheapest fit solution" in terms of SSQ is a line that is horizontally tilted (Fig. 8.1).

8.1.1.1 Bias correction

Eq. (8.5) points to a bias-corrected slope estimation. Let $S_X(i) = S_X$ be constant and known, and let the variance of the "true" predictor values be given by $VAR[X_{\text{true}}(i)] = VAR[X(i)] - S_X^2$. This leads to

$$\widehat{\beta}_1 = \widehat{\beta}_{1,\text{OLS}} \,/\left\{1 - S_X^2 \,/VAR\left[X(i)\right]\right\}, \tag{8.6}$$

where $\widehat{\beta}_{1,\text{OLS}}$ is the simple OLS slope estimator (Eq. 8.4). We denote this estimation method (Eq. 8.6) as ordinary least squares with bias correction (OLSBC). The OLSBC intercept estimator equals the OLS intercept estimator (Eq. 8.3). In practice (sample level), plug in $x(i)$ for $X(i)$.

8.1.1.2 Prior knowledge about standard deviations

Assume homoscedastic noise components, $S_Y(i) = S_Y$ and $S_X(i) = S_X$, and denote their squared ratio as

$$\lambda = S_Y^2 \,/S_X^2. \tag{8.7}$$

Knowledge prior to the estimation about S_X, S_Y or λ can increase the estimation accuracy.

If S_X is known, then OLSBC can be readily performed (Eq. 8.6). Such prior knowledge may be acquired, for example, by repeating measurements. Or there may exist theoretical information about the measuring device and, hence, S_X.

If S_X is only known within bounds, OLSBC estimation can still be applied. CI construction has then to take into account the limited prior

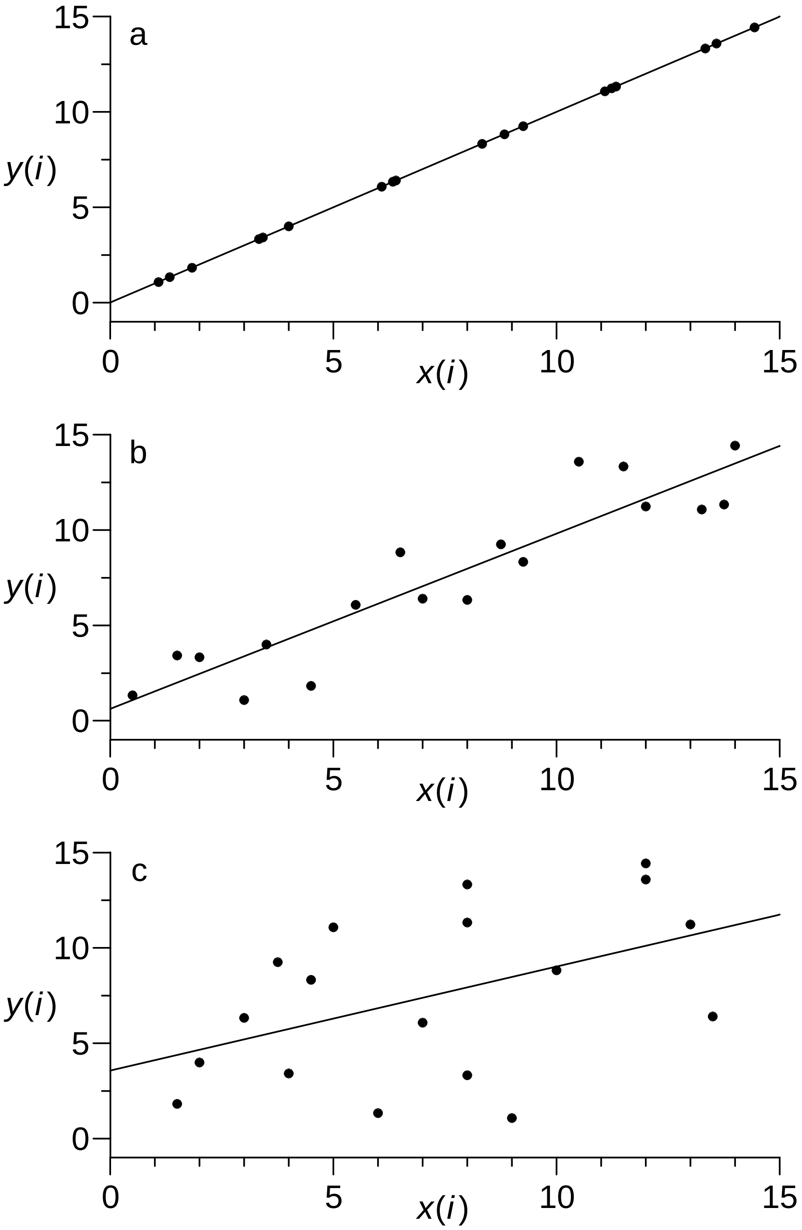


Figure 8.1. Linear errors-in-variables regression model, OLS estimation. The $\{y(i)\}_{i=1}^{n}$ are identical in panels **a–c;** the data size is $n = 18$; and the $\{x(i)\}_{i=1}^{n}$ are realizations of a predictor variable, $X(i)$, with constant zero (**a**), small (**b**) and large (**c**) noise components, $S_X(i) \cdot X_{\mathrm{noise}}(i)$. The true slope is $\beta_1 = 1.0$ (**a**). The OLS fits (*solid lines*) exhibit slope estimates that are unbiased (**a** $\widehat{\beta}_1 = 1.0$) or biased (**b** $\widehat{\beta}_1 = 0.92$; **c** $\widehat{\beta}_1 = 0.55$).

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

Part IV

Outlook

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

Chapter 9

Future Directions

What changes may bring the future to climate time series analysis? First we outline (Sections 9.1, 9.2 and 9.3) more short-term objectives of "normal science" (Kuhn 1970), extensions of previous material (Chapters 1, 2, 3, 4, 5, 6, 7 and 8). Then we take a chance (Sections 9.4 and 9.5) and look on paradigm changes in climate data analysis that may be effected by virtue of strongly increased computing power (and storage capacity). Whether this technological achievement comes in the form of grid computing (Allen 1999; Allen et al. 2000; Stainforth et al. 2007) or quantum computing (Nielsen and Chuang 2000; DiCarlo et al. 2009; Lanyon et al. 2009)—the assumption here is the availability of machines that are faster by a factor of ten to the power of, say, twelve, by a mid-term period of, say, less than a few decades.

9.1 Timescale modelling

Climate time series consist not only of measured values of a climate variable, but also of observed time values. Often the latter are not evenly spaced and also influenced by dating uncertainties. Conventional time series analysis largely ignored uneven and uncertain timescales, climate time series analysis has to take them into account.

The process that generated the times, $\{t_X(i)\}$ for univariate and also $\{t_Y(j)\}$ for bivariate series, depends on the climate archive. We have studied linear and piecewise linear processes for speleothem or sedimentary archives (Section 4.1.7) and nonparametric models for ice cores (Section 8.6.1). Such types of models are the basis for including uncertain timescales in the error determination by means of bootstrap resampling ($\{t^*_X(i)\}$ and also $\{t^*_Y(j)\}$). In bivariate and higher dimensional estimation problems, also the joint distributions of the timescale processes are

M. Mudelsee, *Climate Time Series Analysis*, Atmospheric and Oceanographic Sciences Library 42, DOI 10.1007/978-90-481-9482-7_9,

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

important. See the example of the Vostok ice core (Section 8.6.1) with the coupled timescales for the ice and the gas.

Climate archive modelling should be enhanced in the future to provide accurate descriptions of uncertain timescales. Archive models should evidently include the physics of the accumulation of the archive. One may even think of physiological models describing the performance of humans in layer counting of regular sequences such as varves (Table 1.3). A second ingredient of climate archive modelling are statistical constraints, for example, a strictly monotonically increasing age–depth curve in a speleothem archive or an absolutely dated fixpoint in a marine sediment core. An exemplary paper (Parrenin et al. 2007) of climate archive modelling studies the accumulation and flow in an ice sheet, into which a core is drilled. The Bayesian approach may be suitable for combining the inputs from physics and statistical constraints (Buck and Millard 2004).

9.2 Novel estimation problems

Chapters 2, 3, 4, 5 and 6 presented stochastic processes and estimation algorithms for inferring the fundamental properties of univariate climate processes in the climate equation (Eq. 1.2): trend, variability, persistence, spectrum and extremes. Chapters 7 and 8 studied bivariate processes: correlation and the regression relation between two univariate processes. We believe to have covered with these chapters the vast majority of application fields for the climate sciences.

However, in science there is always room for asking more questions, that means in a quantitative approach, for attempting to estimate different climate parameters in the uni- or bivariate setting.

An obvious example of such a novel estimation problem is SSA, mentioned in the background material of Chapter 1. This decomposition method has been formulated so far only for evenly spaced, discrete time series. Interpolation to equidistance is obsolete because it biases the objectives of the decomposition (estimates of trend, variability, etc.). SSA formulations applicable to unevenly spaced records should therefore be developed.

Other novel estimation approaches are expected to come from the array of nonlinear dynamical systems theory (Section 1.6). This field has a focus more on application data from controlled measurements or computer experiments and less on unevenly spaced, short paleoclimatic time series. A breakthrough, also with respect to SSA, may come from techniques of reconstructing the phase space at irregular points.

9.3 Higher dimensions

Climate is a complex, high-dimensional system, comprising many variables. Therefore it makes sense to study not only univariate processes (Part II), X, or bivariate processes (Part III), X and Y, but also trivariate processes, X and Y and Z, and so forth. A simple estimation problem for such high-dimensional processes is the multivariate regression, mentioned occasionally in previous chapters (Sections 4.2 and 8.7),

$$Y(i) = \theta_0 + \theta_1 X(i) + \theta_2 Z(i) + \cdots + S_Y(i) \cdot Y_{\text{noise}}(i). \tag{9.1}$$

The higher number of dimensions may also result from describing the climate evolution in the spatial domain (e.g., X is temperature in the northern, Y in the southern hemisphere). There is a variety of high-dimensional, spatial estimation problems: multivariate regression, PCA and many more (von Storch and Zwiers 1999: Part V therein).

As regards the bootstrap method, there is no principle obstacle to perform resampling in higher dimensions. An important point is that resampling the marginal distributions, of X and Y and Z separately, is not sufficient; the joint distribution of (X, Y, Z), including dependences among variables, has to be resampled to preserve the original covariance structure. This requires adaptions of the block bootstrap (MBB) approach. A further point, which may considerably exacerbate the estimation as well as the bootstrap implementation, is unequal observation times. The sets

$$\{t_X(i)\}_{i=1}^{n_X}, \ \{t_Y(j)\}_{j=1}^{n_Y}, \ \{t_Z(k)\}_{k=1}^{n_Z} \tag{9.2}$$

need not be identical. Depending on the estimation problem and the properties of the joint climate data generating process (e.g., persistence times), the algorithm for determining $\theta_0, \theta_1, \theta_2$, and so forth, has to be adapted. This is a step into new territory. An example from the bivariate setting is the "synchrony correlation coefficient" (Section 7.5.2). A final point of complication from the move into higher dimensions is dependence among the timescale variables. Since this type of complication can occur already in two-dimensional problems (Section 8.6.1), we expect it in higher dimensions as well. This challenge must be met by means of timescale modelling (Section 9.1).

9.4 Climate models

Computer models render the climate system in the form of mathematical equations. The currently most sophisticated types, AOGCMs (Fig. 1.9), require the most powerful computers. Nevertheless, the rendered spatial and temporal scales are bounded by finite resolutions and finite domain sizes. Also the number of simulated climate processes is limited.

References

Abarbanel HDI, Brown R, Sidorowich JJ, Tsimring LS (1993) The analysis of observed chaotic data in physical systems. *Reviews of Modern Physics* 65(4): 1331–1392.

Abraham B, Wei WWS (1984) Inferences about the parameters of a time series model with changing variance. *Metrika* 31(3–4): 183–194.

Abram NJ, Gagan MK, Cole JE, Hantoro WS, Mudelsee M (2008) Recent intensification of tropical climate variability in the Indian Ocean. *Nature Geoscience* 1(12): 849–853.

Abram NJ, Mulvaney R, Wolff EW, Mudelsee M (2007) Ice core records as sea ice proxies: An evaluation from the Weddell Sea region of Antarctica. *Journal of Geophysical Research* 112(D15): D15101. [doi:10.1029/2006JD008139]

Abramowitz M, Stegun IA (Eds) (1965) *Handbook of Mathematical Functions.* Dover, New York, 1046 pp.

Adams JB, Mann ME, Ammann CM (2003) Proxy evidence for an El Niño-like response to volcanic forcing. *Nature* 426(6964): 274–278.

Adcock RJ (1877) Note on the method of least squares. *Analyst* 4(6): 183–184.

Adcock RJ (1878) A problem in least squares. *Analyst* 5(2): 53–54.

Agrinier P, Gallet Y, Lewin E (1999) On the age calibration of the geomagnetic polarity timescale. *Geophysical Journal International* 137(1): 81–90.

Ahrens JH, Dieter U (1974) Computer methods for sampling from gamma, beta, Poisson and binomial distributions. *Computing* 12(3): 223–246.

Aitchison J, Brown JAC (1957) *The Lognormal Distribution.* Cambridge University Press, Cambridge, 176 pp.

Akaike H (1960) Effect of timing-error on the power spectrum of sampled-data. *Annals of the Institute of Statistical Mathematics* 11: 145–165.

Akaike H (1973) Information theory and an extension of the maximum likelihood principle. In: Petrov BN, Csáki F (Eds) *Second International Symposium on Information Theory.* Akadémiai Kiadó, Budapest, pp 267–281.

Alexander LV, Zhang X, Peterson TC, Caesar J, Gleason B, Klein Tank AMG, Haylock M, Collins D, Trewin B, Rahimzadeh F, Tagipour A, Rupa Kumar K, Revadekar J, Griffiths G, Vincent L, Stephenson DB, Burn J, Aguilar E, Brunet M, Taylor M, New M, Zhai P, Rusticucci M, Vazquez-Aguirre JL (2006) Global observed changes in daily climate extremes of temperature and precipitation. *Journal of Geophysical Research* 111(D5): D05109. [doi:10.1029/2005JD006290]

M. Mudelsee, *Climate Time Series Analysis*, Atmospheric and Oceanographic Sciences Library 42, DOI 10.1007/978-90-481-9482-7,

Allamano P, Claps P, Laio F (2009) Global warming increases flood risk in mountainous areas. *Geophysical Research Letters* 36(24): L24404. [doi:10.1029/2009GL041395]

Allen M (1999) Do-it-yourself climate prediction. *Nature* 401(6754): 642.

Allen MR, Smith LA (1994) Investigating the origins and significance of low-frequency modes of climate variability. *Geophysical Research Letters* 21(10): 883–886.

Allen MR, Stott PA (2003) Estimating signal amplitudes in optimal fingerprinting, Part I: Theory. *Climate Dynamics* 21(5–6): 477–491.

Allen MR, Stott PA, Mitchell JFB, Schnur R, Delworth TL (2000) Quantifying the uncertainty in forecasts of anthropogenic climate change. *Nature* 407(6804): 617–620.

Ammann CM, Genton MG, Li B (2009) Technical note: Correcting for signal attenuation from noise: Sharpening the focus on past climate. *Climate of the Past Discussions* 5(3): 1645–1657.

Ammann CM, Naveau P (2003) Statistical analysis of tropical explosive volcanism occurrences over the last 6 centuries. *Geophysical Research Letters* 30(5): 1210. [doi:10.1029/2002GL016388]

Anderson E, Bai Z, Bischof C, Blackford S, Demmel J, Dongarra J, Du Croz J, Greenbaum A, Hammarling S, McKenney A, Sorensen D (1999) *LAPACK Users' Guide*. Third edition. SIAM, Philadelphia, PA.

Anderson TW (1971) *The Statistical Analysis of Time Series*. Wiley, New York, 704 pp.

Andrews DWK, Buchinsky M (2000) A three-step method for choosing the number of bootstrap repetitions. *Econometrica* 68(1): 23–51.

Andrews DWK, Buchinsky M (2002) On the number of bootstrap repetitions for BC_a confidence intervals. *Econometric Theory* 18(4): 962–984.

Andrews DWK, Lieberman O (2002) *Higher-order Improvements of the Parametric Bootstrap for Long-memory Gaussian Processes*. Cowles Foundation for Research in Economics, Yale University, New Haven, CT, 40 pp. [Discussion Paper No. 1378]

Angelini C, Cava D, Katul G, Vidakovic B (2005) Resampling hierarchical processes in the wavelet domain: A case study using atmospheric turbulence. *Physica D* 207(1–2): 24–40.

Angus JE (1993) Asymptotic theory for bootstrapping the extremes. *Communications in Statistics—Theory and Methods* 22(1): 15–30.

Antle CE (1985) Lognormal distribution. In: Kotz S, Johnson NL, Read CB (Eds) *Encyclopedia of statistical sciences*, volume 5. Wiley, New York, pp 134–136.

Appleby PG, Oldfield F (1992) Application of lead-210 to sedimentation studies. In: Ivanovich M, Harmon RS (Eds) *Uranium-series Disequilibrium: Applications to Earth, Marine, and Environmental Sciences*, second edition. Clarendon Press, Oxford, pp 731–778.

Arnold L (2001) Hasselmann's program revisited: The analysis of stochasticity in deterministic climate models. In: Imkeller P, von Storch J-S (Eds) *Stochastic Climate Models*. Birkhäuser, Basel, pp 141–158.

Atkinson AC, Cox DR (1988) Transformations. In: Kotz S, Johnson NL, Read CB (Eds) *Encyclopedia of statistical sciences*, volume 9. Wiley, New York, pp 312–318.

Bai J, Perron P (1998) Estimating and testing linear models with multiple structural changes. *Econometrica* 66(1): 47–78.

Baker A, Smart PL, Edwards RL, Richards DA (1993) Annual growth banding in a cave stalagmite. *Nature* 364(6437): 518–520.

Bard E, Frank M (2006) Climate change and solar variability: What's new under the sun? *Earth and Planetary Science Letters* 248(1–2): 1–14.

Barnard GA (1959) Control charts and stochastic processes (with discussion). *Journal of the Royal Statistical Society, Series B* 21(2): 239–271.

Barnard GA (1982) Causation. In: Kotz S, Johnson NL, Read CB (Eds) *Encyclopedia of statistical sciences*, volume 1. Wiley, New York, pp 387–389.

Barnett T, Zwiers F, Hegerl G, Allen M, Crowley T, Gillett N, Hasselmann K, Jones P, Santer B, Schnur R, Stott P, Taylor K, Tett S (2005) Detecting and attributing external influences on the climate system: A review of recent advances. *Journal of Climate* 18(9): 1291–1314.

Barnola JM, Raynaud D, Korotkevich YS, Lorius C (1987) Vostok ice core provides 160,000-year record of atmospheric CO_2. *Nature* 329(6138): 408–414.

Bartlett MS (1946) On the theoretical specification and sampling properties of autocorrelated time-series. *Journal of the Royal Statistical Society, Supplement* 8(1): 27–41. [Corrigendum: 1948 Vol. 10(1)]

Bartlett MS (1949) Fitting a straight line when both variables are subject to error. *Biometrics* 5(3): 207–212.

Bartlett MS (1950) Periodogram analysis and continuous spectra. *Biometrika* 37(1–2): 1–16.

Bartlett MS (1955) *An introduction to stochastic processes with special reference to methods and applications.* Cambridge University Press, Cambridge, 312 pp.

Basseville M, Nikiforov IV (1993) *Detection of Abrupt Changes: Theory and Application.* Prentice-Hall, Englewood Cliffs, NJ, 447 pp.

Bayley GV, Hammersley JM (1946) The "effective" number of independent observations in an autocorrelated time series. *Journal of the Royal Statistical Society, Supplement* 8(2): 184–197.

Beasley WH, DeShea L, Toothaker LE, Mendoza JL, Bard DE, Rodgers JL (2007) Bootstrapping to test for nonzero population correlation coefficients using univariate sampling. *Psychological Methods* 12(4): 414–433.

Becker A, Grünewald U (2003) Flood risk in central Europe. *Science* 300(5622): 1099.

Beer J, Baumgartner S, Dittrich-Hannen B, Hauenstein J, Kubik P, Lukasczyk C, Mende W, Stellmacher R, Suter M (1994) Solar variability traced by cosmogenic isotopes. In: Pap JM, Fröhlich C, Hudson HS, Solanki SK (Eds) *The Sun as a Variable Star: Solar and Stellar Irradiance Variations.* Cambridge University Press, Cambridge, pp 291–300.

Beer J, Tobias S, Weiss N (1998) An active sun throughout the Maunder Minimum. *Solar Physics* 181(1): 237–249.

Beersma JJ, Buishand TA (1999) A simple test for equality of variances in monthly climate data. *Journal of Climate* 12(6): 1770–1779.

Beirlant J, Goegebeur Y, Teugels J, Segers J (2004) *Statistics of Extremes: Theory and Applications.* Wiley, Chichester, 490 pp.

Beirlant J, Teugels JL, Vynckier P (1996) *Practical Analysis of Extreme Values.* Leuven University Press, Leuven, 137 pp.

Belaire-Franch J, Contreras-Bayarri D (2002) Improving cross-correlation tests through re-sampling techniques. *Journal of Applied Statistics* 29(5): 711–720.

Belcher J, Hampton JS, Tunnicliffe Wilson G (1994) Parameterization of continuous time autoregressive models for irregularly sampled time series data. *Journal of the Royal Statistical Society, Series B* 56(1): 141–155.

Bell B, Percival DB, Walden AT (1993) Calculating Thomson's spectral multitapers by inverse iteration. *Journal of Computational and Graphical Statistics* 2(1): 119–130.

Bendat JS, Piersol AG (1986) *Random Data: Analysis and Measurement Procedures.* Second edition. Wiley, New York, 566 pp.

Bengtsson L, Botzet M, Esch M (1996) Will greenhouse gas-induced warming over the next 50 years lead to higher frequency and greater intensity of hurricanes? *Tellus, Series A* 48(1): 57–73.

Beniston M (2004) The 2003 heat wave in Europe: A shape of things to come? An analysis based on Swiss climatological data and model simulations. *Geophysical Research Letters* 31(2): L02202. [doi:10.1029/2003GL018857]

Bennett KD (1994) Confidence intervals for age estimates and deposition times in late-Quaternary sediment sequences. *The Holocene* 4(4): 337–348.

Bennett KD, Fuller JL (2002) Determining the age of the mid-Holocene *Tsuga canadensis* (hemlock) decline, eastern North America. *The Holocene* 12(4): 421–429.

Beran J (1994) *Statistics for Long-Memory Processes.* Chapman and Hall, Boca Raton, FL, 315 pp.

Beran J (1997) Long-range dependence. In: Kotz S, Read CB, Banks DL (Eds) *Encyclopedia of statistical sciences*, volume U1. Wiley, New York, pp 385–390.

Beran J (1998) Fractional ARIMA models. In: Kotz S, Read CB, Banks DL (Eds) *Encyclopedia of statistical sciences*, volume U2. Wiley, New York, pp 269–271.

Beran R (1987) Prepivoting to reduce level error of confidence sets. *Biometrika* 74(3): 457–468.

Beran R (1988) Prepivoting test statistics: A bootstrap view of asymptotic refinements. *Journal of the American Statistical Association* 83(403): 687–697.

Berger A, Loutre MF (1991) Insolation values for the climate of the last 10 million years. *Quaternary Science Reviews* 10(4): 297–317.

Berger A, Loutre MF (2002) An exceptionally long interglacial ahead? *Science* 297(5585): 1287–1288.

Berger A, Loutre MF, Mélice JL (1998) Instability of the astronomical periods from 1.5 Myr BP to 0.5 Myr AP. *Paleoclimates* 2(4): 239–280.

Berggren WA, Hilgen FJ, Langereis CG, Kent DV, Obradovich JD, Raffi I, Raymo ME, Shackleton NJ (1995a) Late Neogene chronology: New perspectives in high-resolution stratigraphy. *Geological Society of America Bulletin* 107(11): 1272–1287.

Berggren WA, Kent DV, Swisher III CC, Aubry M-P (1995b) A revised Cenozoic geochronology and chronostratigraphy. In: Berggren WA, Kent DV, Aubry M-P, Hardenbol J (Eds) *Geochronology, Time Scales and Global Stratigraphic Correlation.* Society for Sedimentary Geology, Tulsa, OK, pp 129–212. [SEPM Special Publication No. 54]

Berkowitz J, Kilian L (2000) Recent developments in bootstrapping time series. *Econometric Reviews* 19(1): 1–48.

Berman SM (1964) Limit theorems for the maximum term in stationary sequences. *Annals of Mathematical Statistics* 35(2): 502–516.

Bernardo JM, Bayarri MJ, Berger JO, Dawid AP, Heckerman D, Smith AFM, West M (Eds) (2003) *Bayesian Statistics 7: Proceedings of the Seventh Valencia International Meeting.* Clarendon Press, Oxford, 750 pp.

Bernardo JM, Smith AFM (1994) *Bayesian theory.* Wiley, Chichester, 586 pp.

Besonen MR (2006) *A 1,000 year high-resolution hurricane history for the Boston area based on the varved sedimentary record from the Lower Mystic Lake (Medford/Arlington, MA).* Ph.D. Dissertation. University of Massachusetts at Amherst, Amherst, MA, 297 pp.

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(14): L14705. [doi:10.1029/2008GL033950]

Beutler FJ (1970) Alias-free randomly timed sampling of stochastic processes. *IEEE Transactions on Information Theory* 16(2): 147–152.

Bickel P (1988) Robust estimation. In: Kotz S, Johnson NL, Read CB (Eds) *Encyclopedia of statistical sciences*, volume 8. Wiley, New York, pp 157–163.

Bickel PJ, Freedman DA (1981) Some asymptotic theory for the bootstrap. *The Annals of Statistics* 9(6): 1196–1217.

Bigler M, Wagenbach D, Fischer H, Kipfstuhl J, Miller H, Sommer S, Stauffer B (2002) Sulphate record from a northeast Greenland ice core over the last 1200 years based on continuous flow analysis. *Annals of Glaciology* 35(1): 250–256.

Blaauw M, Christen JA (2005) Radiocarbon peat chronologies and environmental change. *Applied Statistics* 54(4): 805–816.

Bloomfield P, Royle JA, Steinberg LJ, Yang Q (1996) Accounting for meteorological effects in measuring urban ozone levels and trends. *Atmospheric Environment* 30(17): 3067–3077.

Bloomfield P, Steiger WL (1983) *Least Absolute Deviations: Theory, Applications, and Algorithms.* Birkhäuser, Boston, 349 pp.

Blunier T, Chappellaz J, Schwander J, Dällenbach A, Stauffer B, Stocker TF, Raynaud D, Jouzel J, Clausen HB, Hammer CU, Johnsen SJ (1998) Asynchrony of Antarctic and Greenland climate change during the last glacial period. *Nature* 394(6695): 739–743.

Boessenkool KP, Hall IR, Elderfield H, Yashayaev I (2007) North Atlantic climate and deep-ocean flow speed changes during the last 230 years. *Geophysical Research Letters* 34(13): L13614. [doi:10.1029/2007GL030285]

Bolch BW (1968) More on unbiased estimation of the standard deviation. *The American Statistician* 22(3): 27.

Bond G, Kromer B, Beer J, Muscheler R, Evans MN, Showers W, Hoffmann S, Lotti-Bond R, Hajdas I, Bonani G (2001) Persistent solar influence on North Atlantic climate during the Holocene. *Science* 294(5549): 2130–2136.

Bond G, Showers W, Cheseby M, Lotti R, Almasi P, deMenocal P, Priore P, Cullen H, Hajdas I, Bonani G (1997) A pervasive millennial-scale cycle in North Atlantic Holocene and glacial climates. *Science* 278(5341): 1257–1266.

Booth JG, Hall P (1993) Bootstrap confidence regions for functional relationships in errors-in-variables models. *The Annals of Statistics* 21(4): 1780–1791.

Booth JG, Hall P (1994) Monte Carlo approximation and the iterated bootstrap. *Biometrika* 81(2): 331–340.

Booth NB, Smith AFM (1982) A Bayesian approach to retrospective identification of change-points. *Journal of Econometrics* 19(1): 7–22.

Bose A (1988) Edgeworth correction by bootstrap in autoregressions. *The Annals of Statistics* 16(4): 1709–1722.

Box GEP (1953) Non-normality and tests on variances. *Biometrika* 40(3–4): 318–335.

Box GEP (1966) Use and abuse of regression. *Technometrics* 8(4): 625–629.

Box GEP, Jenkins GM, Reinsel GC (1994) *Time Series Analysis: Forecasting and Control.* Third edition. Prentice-Hall, Englewood Cliffs, NJ, 598 pp.

Box GEP, Muller ME (1958) A note on the generation of random normal deviates. *Annals of Mathematical Statistics* 29(2): 610–611.

Bradley RS (1999) *Paleoclimatology: Reconstructing Climates of the Quaternary.* Second edition. Academic Press, San Diego, 610 pp.

Brázdil R, Glaser R, Pfister C, Dobrovolný P, Antoine J-M, Barriendos M, Camuffo D, Deutsch M, Enzi S, Guidoboni E, Kotyza O, Rodrigo FS (1999) Flood events of selected European rivers in the sixteenth century. *Climatic Change* 43(1): 239–285.

Brázdil R, Pfister C, Wanner H, von Storch H, Luterbacher J (2005) Historical climatology in Europe—the state of the art. *Climatic Change* 70(3): 363–430.

Breiman L (1996) Bagging predictors. *Machine Learning* 24(2): 123–140.

Brent RP (1973) *Algorithms for minimization without derivatives.* Prentice-Hall, Englewood Cliffs, NJ, 195 pp.

Brillinger DR (1975) *Time Series: Data Analysis and Theory.* Holt, Rinehart and Winston, New York, 500 pp.

Brillinger DR (2002) John W. Tukey's work on time series and spectrum analysis. *The Annals of Statistics* 30(6): 1595–1618.

Brockmann M, Gasser T, Herrmann E (1993) Locally adaptive bandwidth choice for kernel regression estimators. *Journal of the American Statistical Association* 88(424): 1302–1309.

Brockwell PJ, Davis RA (1991) *Time Series: Theory and Methods.* Second edition. Springer, New York, 577 pp.

Brockwell PJ, Davis RA (1996) *Introduction to Time Series and Forecasting.* Springer, New York, 420 pp.

Broecker WS, Henderson GM (1998) The sequence of events surrounding Termination II and their implications for the cause of glacial–interglacial CO_2 changes. *Paleoceanography* 13(4): 352–364.

Broecker WS, Peng T-H (1982) *Tracers in the Sea.* Eldigio Press, New York, 690 pp.

Brohan P, Kennedy JJ, Harris I, Tett SFB, Jones PD (2006) Uncertainty estimates in regional and global observed temperature changes: A new data set from 1850. *Journal of Geophysical Research* 111(D12): D12106. [doi:10.1029/2005JD006548]

Bronez TP (1988) Spectral estimation of irregularly sampled multidimensional processes by generalized prolate spheroidal sequences. *IEEE Transactions on Acoustics, Speech, and Signal Processing* 36(12): 1862–1873.

Brooks MM, Marron JS (1991) Asymptotic optimality of the least-squares cross-validation bandwidth for kernel estimates of intensity functions. *Stochastic Processes and their Applications* 38(1): 157–165.

Broomhead DS, King GP (1986) Extracting qualitative dynamics from experimental data. *Physica D* 20(2–3): 217–236.

Brown RL, Durbin J, Evans JM (1975) Techniques for testing the constancy of regression relationships over time (with discussion). *Journal of the Royal Statistical Society, Series B* 37(2): 149–192.

Brückner E (1890) Klimaschwankungen seit 1700 nebst Bemerkungen über die Klimaschwankungen der Diluvialzeit. *Geographische Abhandlungen* 4(2): 153–484.

Brüggemann W (1992) A minimal cost function method for optimizing the age–depth relation of deep-sea sediment cores. *Paleoceanography* 7(4): 467–487.

Brumback BA, Ryan LM, Schwartz JD, Neas LM, Stark PC, Burge HA (2000) Transitional regression models, with application to environmental time series. *Journal of the American Statistical Association* 95(449): 16–27.

Buck CE, Millard AR (Eds) (2004) *Tools for Constructing Chronologies: Crossing Disciplinary Boundaries.* Springer, London, 257 pp.

Bühlmann P (1994) Blockwise bootstrapped empirical process for stationary sequences. *The Annals of Statistics* 22(2): 995–1012.

Bühlmann P (1997) Sieve bootstrap for time series. *Bernoulli* 3(2): 123–148.

Bühlmann P (1998) Sieve bootstrap for smoothing in nonstationary time series. *The Annals of Statistics* 26(1): 48–83.

Bühlmann P (2002) Bootstraps for time series. *Statistical Science* 17(1): 52–72.

Bühlmann P, Künsch HR (1999) Block length selection in the bootstrap for time series. *Computational Statistics and Data Analysis* 31(3): 295–310.

Buishand TA (1989) Statistics of extremes in climatology. *Statistica Neerlandica* 43(1): 1–30.

Buja A, Hastie T, Tibshirani R (1989) Linear smoothers and additive models. *The Annals of Statistics* 17(2): 453–510.

Bunde A, Eichner JF, Havlin S, Koscielny-Bunde E, Schellnhuber HJ, Vyushin D (2004) Comment on "Scaling of atmosphere and ocean temperature correlations in observations and climate models." *Physical Review Letters* 92(3): 039801. [doi:10.1103/PhysRevLett.92.039801]

Bunde A, Eichner JF, Kantelhardt JW, Havlin S (2005) Long-term memory: A natural mechanism for the clustering of extreme events and anomalous residual times in climate records. *Physical Review Letters* 94(4): 048701. [doi:10.1103/PhysRevLett.94.048701]

Burns SJ, Fleitmann D, Mudelsee M, Neff U, Matter A, Mangini A (2002) A 780-year annually resolved record of Indian Ocean monsoon precipitation from a speleothem from south Oman. *Journal of Geophysical Research* 107(D20): 4434. [doi:10.1029/2001JD001281]

Butler A, Heffernan JE, Tawn JA, Flather RA (2007) Trend estimation in extremes of synthetic North Sea surges. *Applied Statistics* 56(4): 395–414.

Caers J, Beirlant J, Maes MA (1999a) Statistics for modeling heavy tailed distributions in geology: Part I. Methodology. *Mathematical Geology* 31(4): 391–410.

Caers J, Beirlant J, Maes MA (1999b) Statistics for modeling heavy tailed distributions in geology: Part II. Application. *Mathematical Geology* 31(4): 411–434.

Caillon N, Severinghaus JP, Jouzel J, Barnola J-M, Kang J, Lipenkov VY (2003) Timing of atmospheric CO_2 and Antarctic temperature changes across Termination III. *Science* 299(5613): 1728–1731.

Cande SC, Kent DV (1992) A new geomagnetic polarity time scale for the late Cretaceous and Cenozoic. *Journal of Geophysical Research* 97(B10): 13917–13951.

Cande SC, Kent DV (1995) Revised calibration of the geomagnetic polarity timescale for the late Cretaceous and Cenozoic. *Journal of Geophysical Research* 100(B4): 6093–6095.

Candolo C, Davison AC, Demétrio CGB (2003) A note on model uncertainty in linear regression. *The Statistician* 52(2): 165–177.

Carlstein E (1986) The use of subseries values for estimating the variance of a general statistic from a stationary sequence. *The Annals of Statistics* 14(3): 1171–1179.

Carlstein E, Do K-A, Hall P, Hesterberg T, Künsch HR (1998) Matched-block bootstrap for dependent data. *Bernoulli* 4(3): 305–328.

Carpenter J, Bithell J (2000) Bootstrap confidence intervals: When, which, what? A practical guide for medical statisticians. *Statistics in Medicine* 19(9): 1141–1164.

Carroll RJ, Ruppert D, Stefanski LA, Crainiceanu CM (2006) *Measurement Error in Nonlinear Models: A Modern Perspective.* Second edition. Chapman and Hall, Boca Raton, FL, 455 pp.

Casella G (Ed) (2003) *Silver Anniversary of the Bootstrap*, volume 18(2) of *Statistical Science*. [Special issue]

Castillo E, Hadi AS (1997) Fitting the generalized Pareto distribution to data. *Journal of the American Statistical Association* 92(440): 1609–1620.

Caussinus H, Mestre O (2004) Detection and correction of artificial shifts in climate series. *Applied Statistics* 53(3): 405–425.

Chan K-S, Tong H (2001) *Chaos: A Statistical Perspective*. Springer, New York, 300 pp.

Chan KS, Tong H (1987) A note on embedding a discrete parameter ARMA model in a continuous parameter ARMA model. *Journal of Time Series Analysis* 8(3): 277–281.

Chan W, Chan DW-L (2004) Bootstrap standard error and confidence intervals for the correlation corrected for range restriction: A simulation study. *Psychological Methods* 9(3): 369–385.

Chang EKM, Guo Y (2007) Is the number of North Atlantic tropical cyclones significantly underestimated prior to the availability of satellite observations? *Geophysical Research Letters* 34(14): L14801. [doi:10.1029/2007GL030169]

Chatfield C (1995) Model uncertainty, data mining and statistical inference (with discussion). *Journal of the Royal Statistical Society, Series A* 158(3): 419–466.

Chatfield C (2004) *The Analysis of Time Series: An Introduction*. Sixth edition. Chapman and Hall, Boca Raton, FL, 333 pp.

Chaudhuri P, Marron JS (1999) SiZer for exploration of structures in curves. *Journal of the American Statistical Association* 94(447): 807–823.

Chave AD, Luther DS, Filloux JH (1997) Observations of the boundary current system at 25.5°N in the subtropical North Atlantic Ocean. *Journal of Physical Oceanography* 27(9): 1827–1848.

Chavez-Demoulin V, Davison AC (2005) Generalized additive modelling of sample extremes. *Applied Statistics* 54(1): 207–222.

Chen J, Gupta AK (2000) *Parametric Statistical Change Point Analysis*. Birkhäuser, Boston, 184 pp.

Choi E, Hall P (2000) Bootstrap confidence regions computed from autoregressions of arbitrary order. *Journal of the Royal Statistical Society, Series B* 62(3): 461–477.

Chree C (1913) Some phenomena of sunspots and of terrestrial magnetism at Kew observatory. *Philosophical Transactions of the Royal Society of London, Series A* 212: 75–116.

Chree C (1914) Some phenomena of sunspots and of terrestrial magnetism—Part II. *Philosophical Transactions of the Royal Society of London, Series A* 213: 245–277.

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 Jr HL, 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, pp 847–940.

Chu CK (1994) Estimation of change-points in a nonparametric regression function through kernel density estimation. *Communications in Statistics—Theory and Methods* 23(11): 3037–3062.

Chu JT (1955) On the distribution of the sample median. *Annals of Mathematical Statistics* 26(1): 112–116.

Chylek P, Lohmann U, Dubey M, Mishchenko M, Kahn R, Ohmura A (2007) Limits on climate sensitivity derived from recent satellite and surface observations. *Journal of Geophysical Research* 112(D24): D24S04. [doi:10.1029/2007JD008740]

Cini Castagnoli G, Provenzale A (Eds) (1997) *Past and Present Variability of the Solar–Terrestrial System: Measurement, Data Analysis and Theoretical Models.* Società Italiana di Fisica, Bologna, 491 pp.

Clarke RT (1994) *Statistical Modelling in Hydrology.* Wiley, Chichester, 412 pp.

Clement BM (2004) Dependence of the duration of geomagnetic polarity reversals on site latitude. *Nature* 428(6983): 637–640.

Cobb GW (1978) The problem of the Nile: Conditional solution to a changepoint problem. *Biometrika* 65(2): 243–251.

Cochrane D, Orcutt GH (1949) Application of least squares regression to relationships containing autocorrelated error terms. *Journal of the American Statistical Association* 44(245): 32–61.

Coles S (2001a) Improving the analysis of extreme wind speeds with information-sharing models. *Institut Pierre Simon Laplace des Sciences de l'Environnement Global, Notes des Activitês Instrumentales* 11: 23–34.

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

Coles S (2004) The use and misuse of extreme value models in practice. In: Finkenstädt B, Rootzén H (Eds) *Extreme Values in Finance, Telecommunications, and the Environment.* Chapman and Hall, Boca Raton, FL, pp 79–100.

Coles S, Pericchi L (2003) Anticipating catastrophes through extreme value modelling. *Applied Statistics* 52(4): 405–416.

Comte F, Renault E (1996) Long memory continuous time models. *Journal of Econometrics* 73(1): 101–149.

Cook RD, Weisberg S (1982) *Residuals and Influence in Regression.* Chapman and Hall, New York, 230 pp.

Cooley D, Nychka D, Naveau P (2007) Bayesian spatial modeling of extreme precipitation return levels. *Journal of the American Statistical Association* 102(479): 824–840.

Cooley JW, Tukey JW (1965) An algorithm for the machine calculation of complex Fourier series. *Mathematics of Computation* 19(90): 297–301.

Cowling A, Hall P (1996) On pseudodata methods for removing boundary effects in kernel density estimation. *Journal of the Royal Statistical Society, Series B* 58(3): 551–563.

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(436): 1516–1524.

Cowling AM (1995) *Some problems in kernel curve estimation.* Ph.D. Dissertation. Australian National University, Canberra, 130 pp.

Cox A (1969) Geomagnetic reversals. *Science* 163(3864): 237–245.

Cox DR, Isham V (1980) *Point Processes.* Chapman and Hall, London, 188 pp.

Cox DR, Isham VS, Northrop PJ (2002) Floods: Some probabilistic and statistical approaches. *Philosophical Transactions of the Royal Society of London, Series A* 360(1796): 1389–1408.

Cox DR, Lewis PAW (1966) *The Statistical Analysis of Series of Events.* Methuen, London, 285 pp.

Cramér H (1946) *Mathematical Methods of Statistics.* Princeton University Press, Princeton, 575 pp.

Cronin TM (2010) *Paleoclimates: Understanding Climate Change Past and Present.* Columbia University Press, New York, 441 pp.

Crow EL, Shimizu K (Eds) (1988) *Lognormal Distributions: Theory and Applications.* Marcel Dekker, New York, 387 pp.

Crowley TJ, North GR (1991) *Paleoclimatology.* Oxford University Press, New York, 339 pp.

Crutzen PJ (2002) Geology of mankind. *Nature* 415(6867): 23.

Crutzen PJ, Steffen W (2003) How long have we been in the Anthropocene era? *Climatic Change* 61(3): 251–257.

Cuffey KM, Vimeux F (2001) Covariation of carbon dioxide and temperature from the Vostok ice core after deuterium-excess correction. *Nature* 412(6846): 523–527.

Cureton EE (1968a) Priority correction to "Unbiased estimation of the standard deviation." *The American Statistician* 22(3): 27.

Cureton EE (1968b) Unbiased estimation of the standard deviation. *The American Statistician* 22(1): 22.

Cutter SL, Emrich C (2005) Are natural hazards and disaster losses in the U.S. increasing? *Eos, Transactions of the American Geophysical Union* 86(41): 381, 389.

Dahlquist G, Björck Å (2008) *Numerical Methods in Scientific Computing*, volume 1. SIAM, Philadelphia, PA, 717 pp.

Dahlquist G, Björck Å (in press) *Numerical Methods in Scientific Computing*, volume 2. SIAM, Philadelphia, PA.

Dalfes HN, Schneider SH, Thompson SL (1984) Effects of bioturbation on climatic spectra inferred from deep sea cores. In: Berger A, Imbrie J, Hays J, Kukla G, Saltzman B (Eds) *Milankovitch and Climate*, volume 1. D. Reidel, Dordrecht, pp 481–492.

Dalrymple GB, Lanphere MA (1969) *Potassium–Argon Dating.* Freeman, San Francisco, 258 pp.

Damon PE, Laut P (2004) Pattern of strange errors plagues solar activity and terrestrial climate data. *Eos, Transactions of the American Geophysical Union* 85(39): 370, 374.

Dansgaard W, Oeschger H (1989) Past environmental long-term records from the Arctic. In: Oeschger H, Langway Jr CC (Eds) *The Environmental Record in Glaciers and Ice Sheets.* Wiley, Chichester, pp 287–317.

Daoxian Y, Cheng Z (Eds) (2002) *Karst Processes and the Carbon Cycle.* Geological Publishing House, Beijing, 220 pp.

Dargahi-Noubary GR (1989) On tail estimation: An improved method. *Mathematical Geology* 21(8): 829–842.

Daubechies I, Guskov I, Schröder P, Sweldens W (1999) Wavelets on irregular point sets. *Philosophical Transactions of the Royal Society of London, Series A* 357(1760): 2397–2413.

David FN, Mallows CL (1961) The variance of Spearman's rho in normal samples. *Biometrika* 48(1–2): 19–28.

Davis JC (1986) *Statistics and Data Analysis in Geology.* Second edition. Wiley, New York, 646 pp.

Davison AC (2003) *Statistical models.* Cambridge University Press, Cambridge, 726 pp.

Davison AC, Hinkley DV (1997) *Bootstrap methods and their application.* Cambridge University Press, Cambridge, 582 pp.

Davison AC, Hinkley DV, Schechtman E (1986) Efficient bootstrap simulation. *Biometrika* 73(3): 555–566.

Davison AC, Hinkley DV, Young GA (2003) Recent developments in bootstrap methodology. *Statistical Science* 18(2): 141–157.

Davison AC, Ramesh NI (2000) Local likelihood smoothing of sample extremes. *Journal of the Royal Statistical Society, Series B* 62(1): 191–208.

Davison AC, Smith RL (1990) Models for exceedances over high thresholds (with discussion). *Journal of the Royal Statistical Society, Series B* 52(3): 393–442.

DeBlonde G, Peltier WR (1991) A one-dimensional model of continental ice volume fluctuations through the Pleistocene: Implications for the origin of the mid-Pleistocene climate transition. *Journal of Climate* 4(3): 318–344.

Deep Sea Drilling Project (Ed) (1969–1986) *Initial Reports of the Deep Sea Drilling Project*, volume 1–96. U.S. Govt. Printing Office, Washington, DC.

Della-Marta PM, Haylock MR, Luterbacher J, Wanner H (2007) Doubled length of western European summer heat waves since 1880. *Journal of Geophysical Research* 112(D15): D15103. [doi:10.1029/2007JD008510]

Deming WE (1943) *Statistical Adjustment of Data.* Wiley, New York, 261 pp.

Dempster AP, Laird NM, Rubin DB (1977) Maximum likelihood from incomplete data via the *EM* algorithm (with discussion). *Journal of the Royal Statistical Society, Series B* 39(1): 1–38.

De Pol-Holz R, Ulloa O, Lamy F, Dezileau L, Sabatier P, Hebbeln D (2007) Late Quaternary variability of sedimentary nitrogen isotopes in the eastern South Pacific Ocean. *Paleoceanography* 22(2): PA2207. [doi:10.1029/2006PA001308]

De Ridder F, de Brauwere A, Pintelon R, Schoukens J, Dehairs F (2006) Identification of the accretion rate for annually resolved archives. *Biogeosciences Discussions* 3(2): 321–344.

de Vries H (1958) Variation in concentration of radiocarbon with time and location on Earth. *Proceedings of the Koninklijke Nederlandse Akademie van Wetenschappen, Series B* 61(2): 94–102.

Dhrymes PJ (1981) *Distributed Lags: Problems of Estimation and Formulation.* Second edition. North-Holland, Amsterdam, 470 pp.

Diaz HF, Pulwarty RS (1994) An analysis of the time scales of variability in centuries-long ENSO-sensitive records in the last 1000 years. *Climatic Change* 26(2–3): 317–342.

DiCarlo L, Chow JM, Gambetta JM, Bishop LS, Johnson BR, Schuster DI, Majer J, Blais A, Frunzio L, Girvin SM, Schoelkopf RJ (2009) Demonstration of two-qubit algorithms with a superconducting quantum processor. *Nature* 460(7252): 240–244.

DiCiccio T, Efron B (1992) More accurate confidence intervals in exponential families. *Biometrika* 79(2): 231–245.

DiCiccio TJ, Efron B (1996) Bootstrap confidence intervals (with discussion). *Statistical Science* 11(3): 189–228.

Diebold FX, Inoue A (2001) Long memory and regime switching. *Journal of Econometrics* 105(1): 131–159.

Diggle P (1985) A kernel method for smoothing point process data. *Applied Statistics* 34(2): 138–147.

Diggle P, Marron JS (1988) Equivalence of smoothing parameter selectors in density and intensity estimation. *Journal of the American Statistical Association* 83(403): 793–800.

Diggle PJ (1990) *Time Series: A Biostatistical Introduction.* Clarendon Press, Oxford, 257 pp.

Diggle PJ, Hutchinson MF (1989) On spline smoothing with autocorrelated errors. *Australian Journal of Statistics* 31(1): 166–182.

Diks C (1999) *Nonlinear Time Series Analysis: Methods and Applications.* World Scientific, Singapore, 209 pp.

Diks C, DeGoede J (2001) A general nonparametric bootstrap test for Granger causality. In: Broer HW, Krauskopf B, Vegter G (Eds) *Global Analysis of Dynamical Systems.* Institute of Physics Publishing, Bristol, pp 391–403.

Diks C, Mudelsee M (2000) Redundancies in the Earth's climatological time series. *Physics Letters A* 275(5–6): 407–414.

Divine DV, Polzehl J, Godtliebsen F (2008) A propagation-separation approach to estimate the autocorrelation in a time-series. *Nonlinear Processes in Geophysics* 15(4): 591–599.

Donner RV, Barbosa SM (Eds) (2008) *Nonlinear Time Series Analysis in the Geosciences: Applications in Climatology, Geodynamics and Solar–Terrestrial Physics.* Springer, Berlin, 390 pp.

Doornik JA, Ooms M (2001) *A Package for Estimating, Forecasting and Simulating Arfima Models: Arfima package 1.01 for Ox.* Nuffield College, University of Oxford, Oxford, 32 pp.

Doornik JA, Ooms M (2003) Computational aspects of maximum likelihood estimation of autoregressive fractionally integrated moving average models. *Computational Statistics and Data Analysis* 42(3): 333–348.

Doran HE (1983) Lag models, distributed. In: Kotz S, Johnson NL, Read CB (Eds) *Encyclopedia of statistical sciences*, volume 4. Wiley, New York, pp 440–448.

Douglass AE (1919) *Climatic Cycles and Tree-Growth: A Study of the Annual Rings of Trees in Relation to Climate and Solar Activity*, volume 1. Carnegie Institution of Washington, Washington, DC, 127 pp.

Douglass AE (1928) *Climatic Cycles and Tree-Growth: A Study of the Annual Rings of Trees in Relation to Climate and Solar Activity*, volume 2. Carnegie Institution of Washington, Washington, DC, 166 pp.

Douglass AE (1936) *Climatic Cycles and Tree Growth: A Study of Cycles*, volume 3. Carnegie Institution of Washington, Washington, DC, 171 pp.

Doukhan P, Oppenheim G, Taqqu MS (Eds) (2003) *Theory and Applications of Long-Range Dependence.* Birkhäuser, Boston, 719 pp.

Draper D (1995) Assessment and propagation of model uncertainty (with discussion). *Journal of the Royal Statistical Society, Series B* 57(1): 45–97.

Draper NR, Smith H (1981) *Applied Regression Analysis.* Second edition. Wiley, New York, 709 pp.

Draschba S, Pätzold J, Wefer G (2000) North Atlantic climate variability since AD 1350 recorded in δ^{18}O and skeletal density of Bermuda corals. *International Journal of Earth Sciences* 88(4): 733–741.

Drysdale RN, Zanchetta G, Hellstrom JC, Fallick AE, Zhao J, Isola I, Bruschi G (2004) Palaeoclimatic implications of the growth history and stable isotope (δ^{18}O and δ^{13}C) geochemistry of a middle to late Pleistocene stalagmite from central-western Italy. *Earth and Planetary Science Letters* 227(3–4): 215–229.

Durbin J, Watson GS (1950) Testing for serial correlation in least squares regression I. *Biometrika* 37(3–4): 409–428.

Durbin J, Watson GS (1951) Testing for serial correlation in least squares regression II. *Biometrika* 38(1–2): 159–178.

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

Durbin J, Watson GS (1971) Testing for serial correlation in least squares regression III. *Biometrika* 58(1): 1–19.

Easterling DR, Meehl GA, Parmesan C, Changnon SA, Karl TR, Mearns LO (2000) Climate extremes: Observations, modeling, and impacts. *Science* 289(5487): 2068–2074.

Eastoe EF, Tawn JA (2009) Modelling non-stationary extremes with application to surface level ozone. *Applied Statistics* 58(1): 25–45.

Ebisuzaki W (1997) A method to estimate the statistical significance of a correlation when the data are serially correlated. *Journal of Climate* 10(9): 2147–2153.

Eckmann J-P, Ruelle D (1992) Fundamental limitations for estimating dimensions and Lyapunov exponents in dynamical systems. *Physica D* 56(2–3): 185–187.

Edgington ES (1986) Randomization tests. In: Kotz S, Johnson NL, Read CB (Eds) *Encyclopedia of statistical sciences*, volume 7. Wiley, New York, pp 530–538.

Edwards M, Richardson AJ (2004) Impact of climate change on marine pelagic phenology and trophic mismatch. *Nature* 430(7002): 881–884.

Efron B (1979) Bootstrap methods: Another look at the jackknife. *The Annals of Statistics* 7(1): 1–26.

Efron B (1982) *The Jackknife, the Bootstrap and Other Resampling Plans.* SIAM, Philadelphia, PA, 92 pp.

Efron B (1987) Better bootstrap confidence intervals. *Journal of the American Statistical Association* 82(397): 171–185.

Efron B (1994) Missing data, imputation, and the bootstrap (with discussion). *Journal of the American Statistical Association* 89(426): 463–479.

Efron B, Hinkley DV (1978) Assessing the accuracy of the maximum likelihood estimator: Observed versus expected Fisher information (with discussion). *Biometrika* 65(3): 457–487.

Efron B, Tibshirani R (1986) Bootstrap methods for standard errors, confidence intervals, and other measures of statistical accuracy (with discussion). *Statistical Science* 1(1): 54–77.

Efron B, Tibshirani RJ (1993) *An Introduction to the Bootstrap.* Chapman and Hall, London, 436 pp.

Einsele G, Ricken W, Seilacher A (Eds) (1991) *Cycles and Events in Stratigraphy.* Springer, Berlin, 955 pp.

Einstein A (1949) Autobiographisches—Autobiographical notes. In: Schilpp PA (Ed) *Albert Einstein: Philosopher–Scientist.* Library of Living Philosophers, Evanston, IL, pp 1–95.

El-Aroui M-A, Diebolt J (2002) On the use of the peaks over thresholds method for estimating out-of-sample quantiles. *Computational Statistics and Data Analysis* 39(4): 453–475.

Ellis TMR, Philips IR, Lahey TM (1994) *Fortran 90 Programming.* Addison-Wesley, Harlow, 825 pp.

Elsner JB (2006) Evidence in support of the climate change–Atlantic hurricane hypothesis. *Geophysical Research Letters* 33(16): L16705. [doi:10.1029/2006GL026869]

Elsner JB, Kara AB (1999) *Hurricanes of the North Atlantic: Climate and Society.* Oxford University Press, New York, 488 pp.

Elsner JB, Kara AB, Owens MA (1999) Fluctuations in North Atlantic hurricane frequency. *Journal of Climate* 12(2): 427–437.

Elsner JB, Kossin JP, Jagger TH (2008) The increasing intensity of the strongest tropical cyclones. *Nature* 455(7208): 92–95.

Emanuel K (2005) Increasing destructiveness of tropical cyclones over the past 30 years. *Nature* 436(7051): 686–688.

Emanuel KA (1987) The dependence of hurricane intensity on climate. *Nature* 326(6112): 483–485.

Emanuel KA (1999) Thermodynamic control of hurricane intensity. *Nature* 401(6754): 665–669.

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

Emiliani C (1955) Pleistocene temperatures. *Journal of Geology* 63(6): 538–578.

Engel H, Krahé P, Nicodemus U, Heininger P, Pelzer J, Disse M, Wilke K (2002) *Das Augusthochwasser 2002 im Elbegebiet*. Bundesanstalt für Gewässerkunde, Koblenz, 48 pp.

EPICA community members (2004) Eight glacial cycles from an Antarctic ice core. *Nature* 429(6992): 623–628.

Esterby SR, El-Shaarawi AH (1981) Inference about the point of change in a regression model. *Applied Statistics* 30(3): 277–285.

Fairchild IJ, Frisia S, Borsato A, Tooth AF (2007) Speleothems. In: Nash DJ, McLaren SJ (Eds) *Geochemical Sediments and Landscapes*. Blackwell, Malden, MA, pp 200–245.

Fan J, Yao Q (2003) *Nonlinear Time Series: Nonparametric and Parametric Methods*. Springer, New York, 551 pp.

Fawcett L, Walshaw D (2006) A hierarchical model for extreme wind speeds. *Applied Statistics* 55(5): 631–646.

Fawcett L, Walshaw D (2007) Improved estimation for temporally clustered extremes. *Environmetrics* 18(1–2): 173–188.

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

Ferreira A, de Haan L, Peng L (2003) On optimising the estimation of high quantiles of a probability distribution. *Statistics* 37(5): 401–434.

Ferro CAT, Segers J (2003) Inference for clusters of extreme values. *Journal of the Royal Statistical Society, Series B* 65(2): 545–556.

Fieller EC, Hartley HO, Pearson ES (1957) Tests for rank correlation coefficients I. *Biometrika* 44(3–4): 470–481.

Findley DF (1986) On bootstrap estimates of forecast mean square errors for autoregressive processes. In: Allen DM (Ed) *Computer Science and Statistics*. North-Holland, Amsterdam, pp 11–17.

Fine TL (1983) Foundations of probability. In: Kotz S, Johnson NL, Read CB (Eds) *Encyclopedia of statistical sciences*, volume 3. Wiley, New York, pp 175–184.

Fischer H (1997) *Räumliche Variabilität in Eiskernzeitreihen Nordostgrönlands*. Ph.D. Dissertation. University of Heidelberg, Heidelberg, 188 pp.

Fischer K (1907) Die Sommerhochwasser der Oder von 1813 bis 1903. *Jahrbuch für die Gewässerkunde Norddeutschlands, Besondere Mitteilungen* 1(6): 1–101.

Fisher DA, Reeh N, Clausen HB (1985) Stratigraphic noise in time series derived from ice cores. *Annals of Glaciology* 7(1): 76–83.

Fisher RA (1915) Frequency distribution of the values of the correlation coefficient in samples from an indefinitely large population. *Biometrika* 10(4): 507–521.

Fisher RA (1921) On the “probable error” of a coefficient of correlation deduced from a small sample. *Metron* 1(4): 3–32.

Fisher RA (1922) On the mathematical foundations of theoretical statistics. *Philosophical Transactions of the Royal Society of London, Series A* 222: 309–368.

Fisher RA (1929) Tests of significance in harmonic analysis. *Proceedings of the Royal Society of London, Series A* 125(796): 54–59.

Fisher RA, Tippett LHC (1928) Limiting forms of the frequency distribution of the largest or smallest member of a sample. *Proceedings of the Cambridge Philosophical Society* 24(2): 180–190.

Fishman GS (1996) *Monte Carlo: Concepts, Algorithms, and Applications*. Springer, New York, 698 pp.

Fleitmann D (2001) *Annual to millennial Indian Ocean monsoon variability recorded in Holocene and Pleistocene stalagmites from Oman*. Ph.D. Dissertation. University of Bern, Bern, 236 pp.

Fleitmann D, Burns SJ, Mangini A, Mudelsee M, Kramers J, Villa I, Neff U, Al-Subbary AA, Buettner A, Hippler D, Matter A (2007a) Holocene ITCZ and Indian monsoon dynamics recorded in stalagmites from Oman and Yemen (Socotra). *Quaternary Science Reviews* 26(1–2): 170–188.

Fleitmann D, Burns SJ, Mudelsee M, Neff U, Kramers J, Mangini A, Matter A (2003) Holocene forcing of the Indian monsoon recorded in a stalagmite from southern Oman. *Science* 300(5626): 1737–1739.

Fleitmann D, Burns SJ, Neff U, Mudelsee M, Mangini A, Matter A (2004) Paleoclimatic interpretation of high-resolution oxygen isotope profiles derived from annually laminated speleothems from southern Oman. *Quaternary Science Reviews* 23(7–8): 935–945.

Fleitmann D, Cheng H, Badertscher S, Edwards RL, Mudelsee M, Göktürk OM, Fankhauser A, Pickering R, Raible CC, Matter A, Kramers J, Tüysüz O (2009) Timing and climatic impact of Greenland interstadials recorded in stalagmites from northern Turkey. *Geophysical Research Letters* 36(19): L19707. [doi:10.1029/2009GL040050]

Fleitmann D, Dunbar RB, McCulloch M, Mudelsee M, Vuille M, McClanahan TR, Cole JE, Eggins S (2007b) East African soil erosion recorded in a 300 year old coral colony from Kenya. *Geophysical Research Letters* 34(4): L04401. [doi:10.1029/2006GL028525]

Fleitmann D, Mudelsee M, Burns SJ, Bradley RS, Kramers J, Matter A (2008) Evidence for a widespread climatic anomaly at around 9.2 ka before present. *Paleoceanography* 23(1): PA1102. [doi:10.1029/2007PA001519]

Fligge M, Solanki SK, Beer J (1999) Determination of solar cycle length variations using the continuous wavelet transform. *Astronomy and Astrophysics* 346(1): 313–321.

Fodor IK, Stark PB (2000) Multitaper spectrum estimation for time series with gaps. *IEEE Transactions on Signal Processing* 48(12): 3472–3483.

Foias C, Frazho AE, Sherman PJ (1988) A geometric approach to the maximum likelihood spectral estimator for sinusoids in noise. *IEEE Transactions on Information Theory* 34(5): 1066–1070.

Folland CK, Sexton DMH, Karoly DJ, Johnson CE, Rowell DP, Parker DE (1998) Influences of anthropogenic and oceanic forcing on recent climate change. *Geophysical Research Letters* 25(3): 353–356.

Forster P, Ramaswamy V, Artaxo P, Berntsen T, Betts R, Fahey DW, Haywood J, Lean J, Lowe DC, Myhre G, Nganga J, Prinn R, Raga G, Schulz M, Van Dorland R (2007) Changes in atmospheric constituents and in radiative forcing. In: Solomon S, Qin D, Manning M, Marquis M, Averyt K, Tignor MMB, Miller Jr HL, 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, pp 129–234.

Foster G (1996a) Time series analysis by projection. I. Statistical properties of Fourier analysis. *The Astronomical Journal* 111(1): 541–554.

Foster G (1996b) Wavelets for period analysis of unevenly sampled time series. *The Astronomical Journal* 112(4): 1709–1729.

Foster G, Annan JD, Schmidt GA, Mann ME (2008) Comment on "Heat capacity, time constant, and sensitivity of Earth's climate system" by S. E. Schwartz. *Journal of Geophysical Research* 113(D15): D15102. [doi:10.1029/2007JD009373]

Foutz RV (1980) Estimation of a common group delay between two multiple time series. *Journal of the American Statistical Association* 75(372): 779–788.

Fraedrich K, Blender R (2003) Scaling of atmosphere and ocean temperature correlations in observations and climate models. *Physical Review Letters* 90(10): 108501. [doi:10.1103/PhysRevLett.90.108501]

Fraedrich K, Blender R (2004) Fraedrich and Blender reply. *Physical Review Letters* 92(3): 039802. [doi:10.1103/PhysRevLett.92.039802]

Francisco-Fernández M, Opsomer J, Vilar-Fernández JM (2004) Plug-in bandwidth selector for local polynomial regression estimator with correlated errors. *Nonparametric Statistics* 16(1–2): 127–151.

Francisco-Fernández M, Vilar-Fernández JM (2005) Bandwidth selection for the local polynomial estimator under dependence: A simulation study. *Computational Statistics* 20(4): 539–558.

Frangos CC, Schucany WR (1990) Jackknife estimation of the bootstrap acceleration constant. *Computational Statistics and Data Analysis* 9(3): 271–281.

Franke J, Neumann MH (2000) Bootstrapping neural networks. *Neural Computation* 12(8): 1929–1949.

Franklin LA (1988) A note on approximations and convergence in distribution for Spearman's rank correlation coefficient. *Communications in Statistics—Theory and Methods* 17(1): 55–59.

Fraser AM, Swinney HL (1986) Independent coordinates for strange attractors from mutual information. *Physical Review A* 33(2): 1134–1140.

Fréchet M (1927) Sur la loi probabilité de l'écart maximum. *Annales de la Société Polonaise de Mathématique* 6: 93–116.

Freedman D (1984) On bootstrapping two-stage least-squares estimates in stationary linear models. *The Annals of Statistics* 12(3): 827–842.

Freedman DA (1981) Bootstrapping regression models. *The Annals of Statistics* 9(6): 1218–1228.

Freedman DA, Peters SC (1984) Bootstrapping an econometric model: Some empirical results. *Journal of Business & Economic Statistics* 2(2): 150–158.

Frei C, Schär C (2001) Detection probability of trends in rare events: Theory and application to heavy precipitation in the Alpine region. *Journal of Climate* 14(7): 1568–1584.

Freund RJ, Minton PD (1979) *Regression Methods: A Tool for Data Analysis.* Marcel Dekker, New York, 261 pp.

Friis-Christensen E, Lassen K (1991) Length of the solar cycle: An indicator of solar activity closely associated with climate. *Science* 254(5032): 698–700.

Fuller WA (1987) *Measurement Error Models.* Wiley, New York, 440 pp.

Fuller WA (1996) *Introduction to Statistical Time Series.* Second edition. Wiley, New York, 698 pp.

Fuller WA (1999) Errors in variables. In: Kotz S, Read CB, Banks DL (Eds) *Encyclopedia of statistical sciences*, volume U3. Wiley, New York, pp 213–216.

Galambos J (1978) *The Asymptotic Theory of Extreme Order Statistics.* Wiley, New York, 352 pp.

Gallant AR (1987) *Nonlinear Statistical Models.* Wiley, New York, 610 pp.

Galton F (1888) Co-relations and their measurement, chiefly from anthropometric data. *Proceedings of the Royal Society of London* 45(245): 135–145.

Gardenier JS, Gardenier TK (1988) Statistics of risk management. In: Kotz S, Johnson NL, Read CB (Eds) *Encyclopedia of statistical sciences*, volume 8. Wiley, New York, pp 141–148.

Gasser T, Kneip A, Köhler W (1991) A flexible and fast method for automatic smoothing. *Journal of the American Statistical Association* 86(415): 643–652.

Gasser T, Müller H-G (1979) Kernel estimation of regression functions. In: Gasser T, Rosenblatt M (Eds) *Smoothing Techniques for Curve Estimation.* Springer, Berlin, pp 23–68.

Gasser T, Müller H-G (1984) Estimating regression functions and their derivatives by the kernel method. *Scandinavian Journal of Statistics* 11(3): 171–185.

Gayen AK (1951) The frequency distribution of the product-moment correlation coefficient in random samples of any size drawn from non-normal universes. *Biometrika* 38(1–2): 219–247.

Gençay R, Selçuk F, Ulugülyağci A (2001) EVIM: A software package for extreme value analysis in MATLAB. *Studies in Nonlinear Dynamics & Econometrics* 5(3): 213–239.

Gentle JE (1998) *Numerical Linear Algebra for Applications in Statistics.* Springer, New York, 221 pp.

Genton MG, Hall P (2007) Statistical inference for evolving periodic functions. *Journal of the Royal Statistical Society, Series B* 69(4): 643–657.

Geyh MA, Schleicher H (1990) *Absolute Age Determination: Physical and Chemical Dating Methods and Their Application.* Springer, Berlin, 503 pp.

Ghil M, Allen MR, Dettinger MD, Ide K, Kondrashov D, Mann ME, Robertson AW, Saunders A, Tian Y, Varadi F, Yiou P (2002) Advanced spectral methods for climatic time series. *Reviews of Geophysics* 40(1): 1003. [doi:10.1029/2000RG000092]

Giaiotti D, Stel F (2001) A comparison between subjective and objective thunderstorm forecasts. *Atmospheric Research* 56(1–4): 111–126.

Gibbons JD, Chakraborti S (2003) *Nonparametric Statistical Inference.* Fourth edition. Marcel Dekker, New York, 645 pp.

Giese H-J, Albeverio S, Stabile G (1999) Stochastic and deterministic methods in the analysis of the δ^{18}O record in the core V28-239. *Chemical Geology* 161(1–3): 271–289.

Gijbels I, Goderniaux A-C (2004a) Bandwidth selection for changepoint estimation in nonparametric regression. *Technometrics* 46(1): 76–86.

Gijbels I, Goderniaux A-C (2004b) Bootstrap test for change-points in nonparametric regression. *Nonparametric Statistics* 16(3–4): 591–611.

Gijbels I, Hall P, Kneip A (2004) Interval and band estimation for curves with jumps. *Journal of Applied Probability* 41A: 65–79.

Gil-Alana LA (2008) Time trend estimation with breaks in temperature time series. *Climatic Change* 89(3–4): 325–337.

Gillieson D (1996) *Caves: Processes, Development and Management.* Blackwell, Oxford, 324 pp.

Gilman DL, Fuglister FJ, Mitchell Jr JM (1963) On the power spectrum of "red noise." *Journal of the Atmospheric Sciences* 20(2): 182–184.

Giordano F, La Rocca M, Perna C (2005) Neural network sieve bootstrap prediction intervals for hydrological time series. *Geophysical Research Abstracts* 7: 02801.

Giordano F, La Rocca M, Perna C (2007) Forecasting nonlinear time series with neural network sieve bootstrap. *Computational Statistics and Data Analysis* 51(8): 3871–3884.

Girardin M-P, Tardif JC, Flannigan MD, Bergeron Y (2006a) Synoptic-scale atmospheric circulation and boreal Canada summer drought variability of the past three centuries. *Journal of Climate* 19(10): 1922–1947.

Girardin MP, Ali AA, Carcaillet C, Mudelsee M, Drobyshev I, Hély C, Bergeron Y (2009) Heterogeneous response of circumboreal wildfire risk to climate change since the early 1900s. *Global Change Biology* 15(11): 2751–2769.

Girardin MP, Bergeron Y, Tardif JC, Gauthier S, Flannigan MD, Mudelsee M (2006b) A 229-year dendroclimatic-inferred record of forest fire activity for the Boreal Shield of Canada. *International Journal of Wildland Fire* 15(3): 375–388.

Girardin MP, Mudelsee M (2008) Past and future changes in Canadian boreal wildfire activity. *Ecological Applications* 18(2): 391–406.

Glaser R (2001) *Klimageschichte Mitteleuropas.* Wissenschaftliche Buchgesellschaft, Darmstadt, 227 pp.

Gleissberg W (1944) A table of secular variations of the solar cycle. *Terrestrial Magnetism and Atmospheric Electricity* 49(4): 243–244.

Gleissberg W (1965) The eighty-year solar cycle in auroral frequency numbers. *Journal of the British Astronomical Association* 75(4): 227–231.

Gluhovsky A, Agee E (1994) A definitive approach to turbulence statistical studies in planetary boundary layers. *Journal of the Atmospheric Sciences* 51(12): 1682–1690.

Glymour C (1998) Causation (update). In: Kotz S, Read CB, Banks DL (Eds) *Encyclopedia of statistical sciences*, volume U2. Wiley, New York, pp 97–109.

Gnedenko B (1943) Sur la distribution limite du terme maximum d'une série aléatoire. *Annals of Mathematics* 44(3): 423–453. [English translation in: Kotz S, Johnson NL (Eds) (1992) *Breakthroughs in Statistics*, volume 1. Springer, New York, pp 195–225]

Goel AL (1982) Cumulative sum control charts. In: Kotz S, Johnson NL, Read CB (Eds) *Encyclopedia of statistical sciences*, volume 2. Wiley, New York, pp 233–241.

Goldenberg SB, Landsea CW, Mestas-Nuñez AM, Gray WM (2001) The recent increase in Atlantic hurricane activity: Causes and implications. *Science* 293(5529): 474–479.

Goldstein RB (1973) Algorithm 451: Chi-square quantiles. *Communications of the ACM* 16(8): 483–485.

Good PI (2005) *Resampling Methods: A Practical Guide to Data Analysis.* Third edition. Birkhäuser, Boston, 218 pp.

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, pp 59–78.

Goodman LA (1953) A simple method for improving some estimators. *Annals of Mathematical Statistics* 24(1): 114–117.

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

Goossens C, Berger A (1986) Annual and seasonal climatic variations over the northern hemisphere and Europe during the last century. *Annales Geophysicae, Series B* 4(4): 385–399.

Gordon C, Cooper C, Senior CA, Banks H, Gregory JM, Johns TC, Mitchell JFB, Wood RA (2000) The simulation of SST, sea ice extents and ocean heat transports in a version of the Hadley Centre coupled model without flux adjustments. *Climate Dynamics* 16(2–3): 147–168.

Goreau TJ (1980) Frequency sensitivity of the deep-sea climatic record. *Nature* 287(5783): 620–622.

Gosse JC, Phillips FM (2001) Terrestrial in situ cosmogenic nuclides: Theory and application. *Quaternary Science Reviews* 20(14): 1475–1560.

Götze F, Künsch HR (1996) Second-order correctness of the blockwise bootstrap for stationary observations. *The Annals of Statistics* 24(5): 1914–1933.

Govindan RB, Vyushin D, Bunde A, Brenner S, Havlin S, Schellnhuber H-J (2002) Global climate models violate scaling of the observed atmospheric variability. *Physical Review Letters* 89(2): 028501. [doi:10.1103/PhysRevLett.89.028501]

Gradshteyn IS, Ryzhik IM (2000) *Tables of Integrals, Series, and Products.* Sixth edition. Academic Press, San Diego, 1163 pp.

Gradstein FM, Ogg JG, Smith AG (Eds) (2004) *A Geologic Time Scale 2004.* Cambridge University Press, Cambridge, 589 pp.

Granger C, Lin J-L (1994) Using the mutual information coefficient to identify lags in nonlinear models. *Journal of Time Series Analysis* 15(4): 371–384.

Granger CW, Maasoumi E, Racine J (2004) A dependence metric for possibly nonlinear processes. *Journal of Time Series Analysis* 25(5): 649–669.

Granger CWJ (1969) Investigating causal relations by econometric models and cross-spectral methods. *Econometrica* 37(3): 424–438.

Granger CWJ (1980) Long memory relationships and the aggregation of dynamic models. *Journal of Econometrics* 14(2): 227–238.

Granger CWJ, Hyung N (2004) Occasional structural breaks and long memory with an application to the S&P 500 absolute stock returns. *Journal of Empirical Finance* 11(3): 399–421.

Granger CWJ, Joyeux R (1980) An introduction to long-memory time series models and fractional differencing. *Journal of Time Series Analysis* 1(1): 15–29.

Grassberger P (1986) Do climatic attractors exist? *Nature* 323(6089): 609–612.

Graybill FA, Iyer HK (1994) *Regression Analysis: Concepts and Applications.* Duxbury Press, Belmont, CA, 701 pp.

Greenwood JA, Landwehr JM, Matalas NC, Wallis JR (1979) Probability weighted moments: Definition and relation to parameters of several distributions expressable in inverse form. *Water Resources Research* 15(5): 1049–1054.

Gregory JM, Stouffer RJ, Raper SCB, Stott PA, Rayner NA (2002) An observationally based estimate of the climate sensitivity. *Journal of Climate* 15(22): 3117–3121.

Grenander U (1958) Bandwidth and variance in estimation of the spectrum. *Journal of the Royal Statistical Society, Series B* 20(1): 152–157.

Grenander U, Rosenblatt M (1956) *Statistical Analysis of Stationary Time Series.* Almqvist & Wiksell, Stockholm, 300 pp.

Grieger B (1992) *Orbital tuning of marine sedimentary cores: An automatic procedure based on a general linear model.* Max Planck Institute for Meteorology, Hamburg, 30 pp. [Report No. 79]

Grieger B, Latif M (1994) Reconstruction of the El Niño attractor with neural networks. *Climate Dynamics* 10(6–7): 267–276.

Grün R (1989) *Die ESR-Altersbestimmungsmethode.* Springer, Berlin, 132 pp.

Grünewald U, Chmielewski R, Kaltofen M, Rolland W, Schümberg S, Ahlheim M, Sauer T, Wagner R, Schluchter W, Birkner H, Petzold R, Radczuk L, Eliasiewicz R, Bjarsch B, Paus L, Zahn G (1998) *Ursachen, Verlauf und Folgen des Sommer-Hochwassers 1997 an der Oder sowie Aussagen zu bestehenden Risikopotentialen. Eine interdisziplinäre Studie — Langfassung.* Deutsches IDNDR-Komitee für Katastrophenvorbeugung e.V., Bonn, 187 pp.

Grünewald U, Kaltofen M, Schümberg S, Merz B, Kreibich H, Petrow T, Thieken A, Streitz W, Dombrowsky WR (2003) *Hochwasservorsorge in Deutschland: Lernen aus der Katastrophe 2002 im Elbegebiet.* Deutsches Komitee für Katastrophenvorsorge, Bonn, 144 pp. [Schriftenreihe des DKKV 29]

Grunwald GK, Hyndman RJ (1998) Smoothing non-Gaussian time series with autoregressive structure. *Computational Statistics and Data Analysis* 28(2): 171–191.

Guiot J, Tessier L (1997) Detection of pollution signals in tree-ring series using AR processes and neural networks. In: Subba Rao T, Priestley MB, Lessi O (Eds) *Applications of Time Series Analysis in Astronomy and Meteorology.* Chapman and Hall, London, pp 413–426.

Gumbel EJ (1958) *Statistics of Extremes.* Columbia University Press, New York, 375 pp.

Haam E, Huybers P (2010) A test for the presence of covariance between time-uncertain series of data with application to the Dongge cave speleothem and atmospheric radiocarbon records. *Paleoceanography* 25(2): PA2209. [doi:10.1029/2008PA001713]

Hagelberg T, Pisias N, Elgar S (1991) Linear and nonlinear couplings between orbital forcing and the marine δ^{18}O record during the late Neogene. *Paleoceanography* 6(6): 729–746.

Haldane JBS (1942) Moments of the distributions of powers and products of normal variates. *Biometrika* 32(3–4): 226–242.

Hall P (1985) Resampling a coverage pattern. *Stochastic Processes and their Applications* 20(2): 231–246.

Hall P (1986) On the bootstrap and confidence intervals. *The Annals of Statistics* 14(4): 1431–1452.

Hall P (1988) Theoretical comparison of bootstrap confidence intervals (with discussion). *The Annals of Statistics* 16(3): 927–985.

Hall P (1992) On bootstrap confidence intervals in nonparametric regression. *The Annals of Statistics* 20(2): 695–711.

Hall P, Horowitz JL, Jing B-Y (1995a) On blocking rules for the bootstrap with dependent data. *Biometrika* 82(3): 561–574.

Hall P, Jing B-Y, Lahiri SN (1998) On the sampling window method for long-range dependent data. *Statistica Sinica* 8(4): 1189–1204.

Hall P, Lahiri SN, Polzehl J (1995b) On bandwidth choice in nonparametric regression with both short- and long-range dependent errors. *The Annals of Statistics* 23(6): 1921–1936.

Hall P, Ma Y (2007) Testing the suitability of polynomial models in errors-in-variables problems. *The Annals of Statistics* 35(6): 2620–2638.

Hall P, Martin MA (1988) On bootstrap resampling and iteration. *Biometrika* 75(4): 661–671.

Hall P, Martin MA (1996) Comment on “Bootstrap confidence intervals” by DiCiccio TJ and Efron B. *Statistical Science* 11(3): 212–214.

Hall P, Martin MA, Schucany WR (1989) Better nonparametric bootstrap confidence intervals for the correlation coefficient. *Journal of Statistical Computation and Simulation* 33(3): 161–172.

Hall P, Peng L, Tajvidi N (2002) Effect of extrapolation on coverage accuracy of prediction intervals computed from Pareto-type data. *The Annals of Statistics* 30(3): 875–895.

Hall P, Tajvidi N (2000) Nonparametric analysis of temporal trend when fitting parametric models to extreme-value data. *Statistical Science* 15(2): 153–167.

Hall P, Titterington DM (1988) On confidence bands in nonparametric density estimation and regression. *Journal of Multivariate Analysis* 27(1): 228–254.

Hall P, Turlach BA (1997) Interpolation methods for nonlinear wavelet regression with irregularly spaced design. *The Annals of Statistics* 25(5): 1912–1925.

Hall P, Weissman I (1997) On the estimation of extreme tail probabilities. *The Annals of Statistics* 25(3): 1311–1326.

Hall P, Wilson SR (1991) Two guidelines for bootstrap hypothesis testing. *Biometrics* 47(2): 757–762.

Hamed KH (2008) Trend detection in hydrologic data: The Mann–Kendall trend test under the scaling hypothesis. *Journal of Hydrology* 349(3–4): 350–363.

Hamed KH (2009a) Effect of persistence on the significance of Kendall's tau as a measure of correlation between natural time series. *European Physical Journal Special Topics* 174(1): 65–79.

Hamed KH (2009b) Enhancing the effectiveness of prewhitening in trend analysis of hydrologic data. *Journal of Hydrology* 368(1–4): 143–155.

Hammer C, Mayewski PA, Peel D, Stuiver M (Eds) (1997) *Greenland Summit Ice Cores GISP2/GRIP*, volume 102(C12) of *Journal of Geophysical Research*. [Special issue]

Hamon BV, Hannan EJ (1974) Spectral estimation of time delay for dispersive and non-dispersive systems. *Applied Statistics* 23(2): 134–142.

Hampel FR (1985) The breakdown points of the mean combined with some rejection rules. *Technometrics* 27(2): 95–107.

Hann J (1901) *Lehrbuch der Meteorologie*. Tauchnitz, Leipzig, 805 pp.

Hannan EJ (1960) *Time Series Analysis*. Methuen, London, 152 pp.

Hannan EJ (1961) Testing for a jump in the spectral function. *Journal of the Royal Statistical Society, Series B* 23(2): 394–404.

Hannan EJ, Quinn BG (1989) The resolution of closely adjacent spectral lines. *Journal of Time Series Analysis* 10(1): 13–31.

Hannan EJ, Robinson PM (1973) Lagged regression with unknown lags. *Journal of the Royal Statistical Society, Series B* 35(2): 252–267.

Hannan EJ, Thomson PJ (1974) Estimating echo times. *Technometrics* 16(1): 77–84.

Hansen AR, Sutera A (1986) On the probability density distribution of planetary-scale atmospheric wave amplitude. *Journal of the Atmospheric Sciences* 43(24): 3250–3265.

Hansen JE, Lacis AA (1990) Sun and dust versus greenhouse gases: An assessment of their relative roles in global climate change. *Nature* 346(6286): 713–719.

Hardin JW, Schmiediche H, Carroll RJ (2003) The regression–calibration method for fitting generalized linear models with additive measurement error. *The Stata Journal* 3(4): 361–372.

Härdle W (1990) *Applied nonparametric regression*. Cambridge University Press, Cambridge, 333 pp.

Härdle W, Bowman AW (1988) Bootstrapping in nonparametric regression: Local adaptive smoothing and confidence bands. *Journal of the American Statistical Association* 83(401): 102–110.

Härdle W, Chen R (1995) Nonparametric time series analysis, a selective review with examples. *Bulletin of the International Statistical Institute* 56(1): 375–394.

Härdle W, Marron JS (1991) Bootstrap simultaneous error bars for nonparametric regression. *The Annals of Statistics* 19(2): 778–796.

Härdle W, Steiger W (1995) Optimal median smoothing. *Applied Statistics* 44(2): 258–264.

Hare FK (1979) Climatic variation and variability: Empirical evidence from meteorological and other sources. In: Secretariat of the World Meteorological Organization (Ed) *Proceedings of the World Climate Conference*. World Meteorological Organization, Geneva, pp 51–87. [WMO Publication No. 537]

Hargreaves JC, Annan JD (2002) Assimilation of paleo-data in a simple Earth system model. *Climate Dynamics* 19(5–6): 371–381.

Harris FJ (1978) On the use of windows for harmonic analysis with the discrete Fourier transform. *Proceedings of the IEEE* 66(1): 51–83.

Harrison RG, Stephenson DB (2006) Empirical evidence for a nonlinear effect of galactic cosmic rays on clouds. *Proceedings of the Royal Society of London, Series A* 462(2068): 1221–1233.

Hartley HO (1949) Tests of significance in harmonic analysis. *Biometrika* 36(1–2): 194–201.

Haslett J, Parnell A (2008) A simple monotone process with application to radiocarbon-dated depth chronologies. *Applied Statistics* 57(4): 399–418.

Hasselmann K (1976) Stochastic climate models: Part I. Theory. *Tellus* 28(6): 473–485.

Hasselmann K (1993) Optimal fingerprints for the detection of time-dependent climate change. *Journal of Climate* 6(10): 1957–1971.

Hasselmann K (1997) Multi-pattern fingerprint method for detection and attribution of climate change. *Climate Dynamics* 13(9): 601–611.

Hasselmann K (1999) Linear and nonlinear signatures. *Nature* 398(6730): 755–756.

Haug GH, Ganopolski A, Sigman DM, Rosell-Mele A, Swann GEA, Tiedemann R, Jaccard SL, Bollmann J, Maslin MA, Leng MJ, Eglinton G (2005) North Pacific seasonality and the glaciation of North America 2.7 million years ago. *Nature* 433(7028): 821–825.

Haug GH, Sigman DM, Tiedemann R, Pedersen TF, Sarnthein M (1999) Onset of permanent stratification in the subarctic Pacific Ocean. *Nature* 401(6755): 779–782.

Hays JD, Imbrie J, Shackleton NJ (1976) Variations in the Earth's orbit: Pacemaker of the ice ages. *Science* 194(4270): 1121–1132.

Heegaard E, Birks HJB, Telford RJ (2005) Relationships between calibrated ages and depth in stratigraphical sequences: An estimation procedure by mixed-effect regression. *The Holocene* 15(4): 612–618.

Hegerl GC, Crowley TJ, Allen M, Hyde WT, Pollack HN, Smerdon J, Zorita E (2007a) Detection of human influence on a new, validated 1500-year temperature reconstruction. *Journal of Climate* 20(4): 650–666.

Hegerl GC, Crowley TJ, Hyde WT, Frame DJ (2006) Climate sensitivity constrained by temperature reconstructions over the past seven centuries. *Nature* 440(7087): 1029–1032.

Hegerl GC, Hasselmann K, Cubasch U, Mitchell JFB, Roeckner E, Voss R, Waszkewitz J (1997) Multi-fingerprint detection and attribution analysis of greenhouse gas, greenhouse gas-plus-aerosol and solar forced climate change. *Climate Dynamics* 13(9): 613–634.

Hegerl GC, North GR (1997) Comparison of statistically optimal approaches to detecting anthropogenic climate change. *Journal of Climate* 10(5): 1125–1133.

Hegerl GC, von Storch H, Hasselmann K, Santer BD, Cubasch U, Jones PD (1996) Detecting greenhouse-gas-induced climate change with an optimal fingerprint method. *Journal of Climate* 9(10): 2281–2306.

Hegerl GC, Zwiers FW, Braconnot P, Gillett NP, Luo Y, Marengo Orsini JA, Nicholls N, Penner JE, Stott PA (2007b) Understanding and attributing climate change. In: Solomon S, Qin D, Manning M, Marquis M, Averyt K, Tignor MMB, Miller Jr HL, 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, pp 663–745.

Heisenberg W (1969) *Der Teil und das Ganze*. Piper, Munich, 334 pp.

Henderson GM (2002) New oceanic proxies for paleoclimate. *Earth and Planetary Science Letters* 203(1): 1–13.

Henze FH-H (1979) The exact noncentral distributions of Spearman's r and other related correlation coefficients. *Journal of the American Statistical Association* 74(366): 459–464. [Corrigendum: 1980 Vol. 75(371): 765]

Herrmann E (1997) Local bandwidth choice in kernel regression estimation. *Journal of Computational and Graphical Statistics* 6(1): 35–54.

Herterich K, Sarnthein M (1984) Brunhes time scale: Tuning by rates of calcium-carbonate dissolution and cross spectral analyses with solar insolation. In: Berger A, Imbrie J, Hays J, Kukla G, Saltzman B (Eds) *Milankovitch and Climate*, volume 1. D. Reidel, Dordrecht, pp 447–466.

Heslop D, Dekkers MJ (2002) Spectral analysis of unevenly spaced climatic time series using CLEAN: Signal recovery and derivation of significance levels using a Monte Carlo simulation. *Physics of the Earth and Planetary Interiors* 130(1–2): 103–116.

Hewa GA, Wang QJ, McMahon TA, Nathan RJ, Peel MC (2007) Generalized extreme value distribution fitted by LH moments for low-flow frequency analysis. *Water Resources Research* 43(6): W06301. [doi:10.1029/2006WR004913]

Hidalgo J (2003) An alternative bootstrap to moving blocks for time series regression models. *Journal of Econometrics* 117(2): 369–399.

Hill BM (1975) A simple general approach to inference about the tail of a distribution. *The Annals of Statistics* 3(5): 1163–1174.

Hinkley DV (1970) Inference about the change-point in a sequence of random variables. *Biometrika* 57(1): 1–17.

Hinkley DV (1971) Inference about the change-point from cumulative sum tests. *Biometrika* 58(3): 509–523.

Hinkley DV (1988) Bootstrap methods. *Journal of the Royal Statistical Society, Series B* 50(3): 321–337.

Hinnov LA, Schulz M, Yiou P (2002) Interhemispheric space–time attributes of the Dansgaard–Oeschger oscillations between 100 and 0 ka. *Quaternary Science Reviews* 21(10): 1213–1228.

Hlaváčková-Schindler K, Paluš M, Vejmelka M, Bhattacharya J (2007) Causality detection based on information-theoretic approaches in time series analysis. *Physics Reports* 441(1): 1–46.

Hocking RR, Smith WB (1968) Estimation of parameters in the multivariate normal distribution with missing observations. *Journal of the American Statistical Association* 63(321): 159–173.

Holland GJ (2007) Misuse of landfall as a proxy for Atlantic tropical cyclone activity. *Eos, Transactions of the American Geophysical Union* 88(36): 349–350.

Holton JR, Curry JA, Pyle JA (Eds) (2003) *Encyclopedia of Atmospheric Sciences*, volume 1–6. Academic Press, Amsterdam, 2780 pp.

Holtzman WH (1950) The unbiased estimate of the population variance and standard deviation. *American Journal of Psychology* 63(4): 615–617.

Holzkämper S, Mangini A, Spötl C, Mudelsee M (2004) Timing and progression of the last interglacial derived from a high Alpine stalagmite. *Geophysical Research Letters* 31(7): L07201. [doi:10.1029/2003GL019112]

Hopley PJ, Weedon GP, Marshall JD, Herries AIR, Latham AG, Kuykendall KL (2007) High- and low-latitude orbital forcing of early hominin habitats in South Africa. *Earth and Planetary Science Letters* 256(3–4): 419–432.

Horne JH, Baliunas SL (1986) A prescription for period analysis of unevenly sampled time series. *The Astrophysical Journal* 302(2): 757–763.

Hornstein C (1871) Über die Abhängigkeit des Erdmagnetismus von der Rotation der Sonne. *Sitzungsberichte der Kaiserlichen Akademie der Wissenschaften, Mathematisch-Naturwissenschaftliche Classe, Zweite Abtheilung* 64(6): 62–74.

Horowitz LL (1974) The effects of spline interpolation on power spectral density. *IEEE Transactions on Acoustics, Speech, and Signal Processing* 22(1): 22–27.

Hosking JRM (1981) Fractional differencing. *Biometrika* 68(1): 165–176.

Hosking JRM (1984) Modeling persistence in hydrological time series using fractional differencing. *Water Resources Research* 20(12): 1898–1908.

Hosking JRM (1985) Maximum-likelihood estimation of the parameters of the generalized extreme-value distribution. *Applied Statistics* 34(3): 301–310.

Hosking JRM (1990) L-moments: Analysis and estimation of distributions using linear combinations of order statistics. *Journal of the Royal Statistical Society, Series B* 52(1): 105–124.

Hosking JRM, Wallis JR (1987) Parameter and quantile estimation for the generalized Pareto distribution. *Technometrics* 29(3): 339–349.

Hosking JRM, Wallis JR (1997) *Regional Frequency Analysis: An Approach Based on L-Moments*. Cambridge University Press, Cambridge, 224 pp.

Hosking JRM, Wallis JR, Wood EF (1985) Estimation of the generalized extreme value distribution by the method of probability-weighted moments. *Technometrics* 27(3): 251–261.

Hotelling H (1953) New light on the correlation coefficient and its transforms (with discussion). *Journal of the Royal Statistical Society, Series B* 15(2): 193–232.

Houghton JT, Ding Y, Griggs DJ, Noguer M, van der Linden PJ, Dai X, Maskell K, Johnson CA (Eds) (2001) *Climate Change 2001: The Scientific Basis. Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, 881 pp.

Houseman EA (2005) A robust regression model for a first-order autoregressive time series with unequal spacing: Application to water monitoring. *Applied Statistics* 54(4): 769–780.

Hoyt DV, Schatten KH (1997) *The Role of the Sun in Climate Change*. Oxford University Press, New York, 279 pp.

Hoyt DV, Schatten KH (1998) Group sunspot numbers: A new solar activity reconstruction. *Solar Physics* 179(1): 189–219. [Corrigendum: 1998 Vol. 181(2): 491–512]

Hsieh WW, Tang B (1998) Applying neural network models to prediction and data analysis in meteorology and oceanography. *Bulletin of the American Meteorological Society* 79(9): 1855–1870.

Hsu DA (1977) Tests for variance shift at an unknown time point. *Applied Statistics* 26(3): 279–284.

Huber PJ (1964) Robust estimation of location parameter. *Annals of Mathematical Statistics* 35(1): 73–101.

Huber PJ (1981) *Robust Statistics*. Wiley, New York, 308 pp.

Hudson DJ (1966) Fitting segmented curves whose join points have to be estimated. *Journal of the American Statistical Association* 61(316): 1097–1129.

Huet S, Bouvier A, Poursat M-A, Jolivet E (2004) *Statistical Tools for Nonlinear Regression: A Practical Guide With S-PLUS and R Examples*. Second edition. Springer, New York, 232 pp.

Hurrell JW (1995) Decadal trends in the North Atlantic Oscillation: Regional temperatures and precipitation. *Science* 269(5524): 676–679.

Hurst HE (1951) Long-term storage capacity of reservoirs (with discussion). *Transactions of the American Society of Civil Engineers* 116: 770–808.

Hurvich CM, Tsai C-L (1989) Regression and time series model selection in small samples. *Biometrika* 76(2): 297–307.

Huybers P (2002) *Depth and Orbital Tuning: A New Chronology of Glaciation and Nonlinear Orbital Climate Change*. M.Sc. Thesis. Massachusetts Institute of Technology, Cambridge, MA, 119 pp.

Huybers P, Denton G (2008) Antarctic temperature at orbital timescales controlled by local summer duration. *Nature Geoscience* 1(11): 787–792.

Huybers P, Wunsch C (2004) A depth-derived Pleistocene age model: Uncertainty estimates, sedimentation variability, and nonlinear climate change. *Paleoceanography* 19(1): PA1028. [doi:10.1029/2002PA000857]

Huybers P, Wunsch C (2005) Obliquity pacing of the late Pleistocene glacial terminations. *Nature* 434(7032): 491–494.

Hwang S (2000) The effects of systematic sampling and temporal aggregation on discrete time long memory processes and their finite sample properties. *Econometric Theory* 16(3): 347–372.

Imbrie J, Berger A, Boyle EA, Clemens SC, Duffy A, Howard WR, Kukla G, Kutzbach J, Martinson DG, McIntyre A, Mix AC, Molfino B, Morley JJ, Peterson LC, Pisias NG, Prell WL, Raymo ME, Shackleton NJ, Toggweiler JR (1993) On the structure and origin of major glaciation cycles 2. The 100,000-year cycle. *Paleoceanography* 8(6): 699–735.

Imbrie J, Boyle EA, Clemens SC, Duffy A, Howard WR, Kukla G, Kutzbach J, Martinson DG, McIntyre A, Mix AC, Molfino B, Morley JJ, Peterson LC, Pisias NG, Prell WL, Raymo ME, Shackleton NJ, Toggweiler JR (1992) On the structure and origin of major glaciation cycles 1. Linear responses to Milankovitch forcing. *Paleoceanography* 7(6): 701–738.

Imbrie J, Hays JD, Martinson DG, McIntyre A, Mix AC, Morley JJ, Pisias NG, Prell WL, Shackleton NJ (1984) The orbital theory of Pleistocene climate: Support from a revised chronology of the marine δ^{18}O record. In: Berger A, Imbrie J, Hays J, Kukla G, Saltzman B (Eds) *Milankovitch and Climate*, volume 1. D. Reidel, Dordrecht, pp 269–305.

Inclán C, Tiao GC (1994) Use of cumulative sums of squares for retrospective detection of changes of variance. *Journal of the American Statistical Association* 89(427): 913–923.

Ivanovich M, Harmon RS (Eds) (1992) *Uranium-series Disequilibrium: Applications to Earth, Marine, and Environmental Sciences.* Second edition. Clarendon Press, Oxford, 910 pp.

Jansson M (1985) A comparison of the detransformed logarithmic regressions and power function regressions. *Geografiska Annaler* 67A(1–2): 61–70.

Jarrett RF (1968) A minor exercise in history. *The American Statistician* 22(3): 25–26.

Jefferys WH (1980) On the method of least squares. *The Astronomical Journal* 85(2): 177–181. [Corrigendum: 1988 Vol. 95(4): 1299]

Jefferys WH (1981) On the method of least squares. II. *The Astronomical Journal* 86(1): 149–155. [Corrigendum: 1988 Vol. 95(4): 1300]

Jenkins GM, Watts DG (1968) *Spectral Analysis and its Applications.* Holden-Day, San Francisco, 525 pp.

Jenkinson AF (1955) The frequency distribution of the annual maximum (or minimum) values of meteorological elements. *Quarterly Journal of the Royal Meteorological Society* 81(348): 158–171.

Jennen-Steinmetz C, Gasser T (1988) A unifying approach to nonparametric regression estimation. *Journal of the American Statistical Association* 83(404): 1084–1089.

Jiménez-Moreno G, Anderson RS, Fawcett PJ (2007) Orbital- and millennial-scale vegetation and climate changes of the past 225 ka from Bear Lake, Utah–Idaho (USA). *Quaternary Science Reviews* 26(13–14): 1713–1724.

Johns TC, Carnell RE, Crossley JF, Gregory JM, Mitchell JFB, Senior CA, Tett SFB, Wood RA (1997) The second Hadley Centre coupled ocean–atmosphere GCM: Model description, spinup and validation. *Climate Dynamics* 13(2): 103–134.

Johnsen SJ, Dahl-Jensen D, Gundestrup N, Steffensen JP, Clausen HB, Miller H, Masson-Delmotte V, Sveinbjörnsdottir AE, White J (2001) Qxygen isotope and palaeotemperature records from six Greenland ice-core stations: Camp Century, Dye-3, GRIP, GISP2, Renland and NorthGRIP. *Journal of Quaternary Science* 16(4): 299–307.

Johnson NL, Kotz S, Balakrishnan N (1994) *Continuous Univariate Distributions*, volume 1. Second edition. Wiley, New York, 756 pp.

Johnson NL, Kotz S, Balakrishnan N (1995) *Continuous Univariate Distributions*, volume 2. Second edition. Wiley, New York, 719 pp.

Johnson NL, Kotz S, Kemp AW (1993) *Univariate Discrete Distributions.* Second edition. Wiley, New York, 565 pp.

Johnson RG (1982) Brunhes–Matuyama magnetic reversal dated at 790,000 yr B.P. by marine–astronomical correlations. *Quaternary Research* 17(2): 135–147.

Jones MC, Lotwick HW (1984) A remark on algorithm AS 176. Kernel density estimation using the Fast Fourier Transform. *Applied Statistics* 33(1): 120–122.

Jones PD, Moberg A (2003) Hemispheric and large-scale surface air temperature variations: An extensive revision and an update to 2001. *Journal of Climate* 16(2): 206–223.

Jones PD, Raper SCB, Bradley RS, Diaz HF, Kelly PM, Wigley TML (1986) Northern hemisphere surface air temperature variations: 1851–1984. *Journal of Climate and Applied Meteorology* 25(2): 161–179.

Jones RH (1981) Fitting a continuous time autoregression to discrete data. In: Findley DF (Ed) *Applied Time Series Analysis II*. Academic Press, New York, pp 651–682.

Jones RH (1985) Time series analysis with unequally spaced data. In: Hannan EJ, Krishnaiah PR, Rao MM (Eds) *Handbook of Statistics*, volume 5. Elsevier, Amsterdam, pp 157–177.

Jones RH (1986) Time series regression with unequally spaced data. *Journal of Applied Probability* 23A: 89–98. [Special volume]

Jones RH, Tryon PV (1987) Continuous time series models for unequally spaced data applied to modeling atomic clocks. *SIAM Journal on Scientific and Statistical Computing* 8(1): 71–81.

Jones TA (1979) Fitting straight lines when both variables are subject to error. I. Maximum likelihood and least-squares estimation. *Mathematical Geology* 11(1): 1–25.

Jouzel J, Masson-Delmotte V, Cattani O, Dreyfus G, Falourd S, Hoffmann G, Minster B, Nouet J, Barnola JM, Chappellaz J, Fischer H, Gallet JC, Johnsen S, Leuenberger M, Loulergue L, Luethi D, Oerter H, Parrenin F, Raisbeck G, Raynaud D, Schilt A, Schwander J, Selmo E, Souchez R, Spahni R, Stauffer B, Steffensen JP, Stenni B, Stocker TF, Tison JL, Werner M, Wolff EW (2007) Orbital and millennial Antarctic climate variability over the past 800,000 years. *Science* 317(5839): 793–796.

Julious SA (2001) Inference and estimation in a changepoint regression problem. *The Statistician* 50(1): 51–61.

Jun M, Knutti R, Nychka DW (2008) Spatial analysis to quantify numerical model bias and dependence: How many climate models are there? *Journal of the American Statistical Association* 103(483): 934–947.

Kahl JD, Charlevoix DJ, Zaitseva NA, Schnell RC, Serreze MC (1993) Absence of evidence for greenhouse warming over the Arctic Ocean in the past 40 years. *Nature* 361(6410): 335–337.

Kallache M (2007) *Trends and Extreme Values of River Discharge Time Series*. Ph.D. Dissertation. University of Bayreuth, Bayreuth, 125 pp.

Kallache M, Rust HW, Kropp J (2005) Trend assessment: Applications for hydrology and climate research. *Nonlinear Processes in Geophysics* 12(2): 201–210.

Kandel ER (2006) *In Search of Memory: The Emergence of a New Science of Mind*. W. W. Norton, New York, 510 pp.

Kant I (1781) *Critik der Reinen Vernunft*. Hartknoch, Riga, 856 pp.

Kantz H, Schreiber T (1997) *Nonlinear time series analysis*. Cambridge University Press, Cambridge, 304 pp.

Karl TR, Knight RW, Plummer N (1995) Trends in high-frequency climate variability in the twentieth century. *Nature* 377(6546): 217–220.

Karl TR, Riebsame WE (1984) The identification of 10- to 20-year temperature and precipitation fluctuations in the contiguous United States. *Journal of Climate and Applied Meteorology* 23(6): 950–966.

Karl TR, Williams Jr CN (1987) An approach to adjusting climatological time series for discontinuous inhomogeneities. *Journal of Climate and Applied Meteorology* 26(12): 1744–1763.

Kärner O (2002) On nonstationarity and antipersistency in global temperature series. *Journal of Geophysical Research* 107(D20): 4415. [doi:10.1029/2001JD002024]

Karr AF (1986) *Point Processes and Their Statistical Inference*. Marcel Dekker, New York, 490 pp.

Katz RW, Parlange MB, Naveau P (2002) Statistics of extremes in hydrology. *Advances in Water Resources* 25(8–12): 1287–1304.

Kaufmann RK, Stern DI (1997) Evidence for human influence on climate from hemispheric temperature relations. *Nature* 388(6637): 39–44.

Kawamura K, Parrenin F, Lisiecki L, Uemura R, Vimeux F, Severinghaus JP, Hutterli MA, Nakazawa T, Aoki S, Jouzel J, Raymo ME, Matsumoto K, Nakata H, Motoyama H, Fujita S, Goto-Azuma K, Fujii Y, Watanabe O (2007) Northern Hemisphere forcing of climatic cycles in Antarctica over the past 360,000 years. *Nature* 448(7156): 912–916.

Kay SM, Marple Jr SL (1981) Spectrum analysis—a modern perspective. *Proceedings of the IEEE* 69(11): 1380–1419.

Keigwin LD (1996) The Little Ice Age and Medieval Warm Period in the Sargasso Sea. *Science* 274(5292): 1504–1508.

Kendall M, Gibbons JD (1990) *Rank Correlation Methods*. Fifth edition. Edward Arnold, London, 260 pp.

Kendall MG (1938) A new measure of rank correlation. *Biometrika* 30(1–2): 81–93.

Kendall MG (1954) Note on bias in the estimation of autocorrelation. *Biometrika* 41(3–4): 403–404.

Kennett JP (1982) *Marine Geology*. Prentice-Hall, Englewood Cliffs, NJ, 813 pp.

Kernthaler SC, Toumi R, Haigh JD (1999) Some doubts concerning a link between cosmic ray fluxes and global cloudiness. *Geophysical Research Letters* 26(7): 863–865.

Khaliq MN, Ouarda TBMJ, Gachon P, Sushama L (2008) Temporal evolution of low-flow regimes in Canadian rivers. *Water Resources Research* 44(8): W08436. [doi:10.1029/2007WR006132]

Khaliq MN, Ouarda TBMJ, Ondo J-C, Gachon P, Bobée B (2006) Frequency analysis of a sequence of dependent and/or non-stationary hydro-meteorological observations: A review. *Journal of Hydrology* 329(3–4): 534–552.

Khaliq MN, St-Hilaire A, Ouarda TBMJ, Bobée B (2005) Frequency analysis and temporal pattern of occurrences of southern Quebec heatwaves. *International Journal of Climatology* 25(4): 485–504.

Kharin VV, Zwiers FW (2005) Estimating extremes in transient climate change simulations. *Journal of Climate* 18(8): 1156–1173.

Kiktev D, Sexton DMH, Alexander L, Folland CK (2003) Comparison of modeled and observed trends in indices of daily climate extremes. *Journal of Climate* 16(22): 3560–3571.

King T (1996) Quantifying nonlinearity and geometry in time series of climate. *Quaternary Science Reviews* 15(4): 247–266.

Klemeš V (1974) The Hurst phenomenon: A puzzle? *Water Resources Research* 10(4): 675–688.

Klemeš V (1978) Physically based stochastic hydrologic analysis. *Advances in Hydroscience* 11: 285–356.

Knuth DE (2001) *The Art of Computer Programming*, volume 2. Third edition. Addison-Wesley, Boston, 762 pp.

Knutson TR, McBride JL, Chan J, Emanuel K, Holland G, Landsea C, Held I, Kossin JP, Srivastava AK, Sugi M (2010) Tropical cyclones and climate change. *Nature Geoscience* 3(3): 157–163.

Knutti R, Krähenmann S, Frame DJ, Allen MR (2008) Comment on "Heat capacity, time constant, and sensitivity of Earth's climate system" by S. E. Schwartz. *Journal of Geophysical Research* 113(D15): D15103. [doi:10.1029/2007JD009473]

Kodera K (2004) Solar influence on the Indian Ocean monsoon through dynamical processes. *Geophysical Research Letters* 31(24): L24209. [doi:10.1029/2004GL020928]

Koen C, Lombard F (1993) The analysis of indexed astronomical time series — I. Basic methods. *Monthly Notices of the Royal Astronomical Society* 263(2): 287–308.

Koenker R, Bassett Jr G (1978) Regression quantiles. *Econometrica* 46(1): 33–50.

Koenker R, Hallock KF (2001) Quantile regression. *Journal of Economic Perspectives* 15(4): 143–156.

Kolmogoroff A (1933) Grundbegriffe der Wahrscheinlichkeitsrechnung. *Ergebnisse der Mathematik und ihrer Grenzgebiete* 2(3): 195–262.

Köppen W (1923) *Die Klimate der Erde: Grundriss der Klimakunde.* de Gruyter, Berlin, 369 pp.

Koscielny-Bunde E, Bunde A, Havlin S, Goldreich Y (1996) Analysis of daily temperature fluctuations. *Physica A* 231(4): 393–396.

Koscielny-Bunde E, Bunde A, Havlin S, Roman HE, Goldreich Y, Schellnhuber H-J (1998a) Indication of a universal persistence law governing atmospheric variability. *Physical Review Letters* 81(3): 729–732.

Koscielny-Bunde E, Kantelhardt JW, Braun P, Bunde A, Havlin S (2006) Long-term persistence and multifractality of river runoff records: Detrended fluctuation studies. *Journal of Hydrology* 322(1–4): 120–137.

Koscielny-Bunde E, Roman HE, Bunde A, Havlin S, Schellnhuber H-J (1998b) Long-range power-law correlations in local daily temperature fluctuations. *Philosophical Magazine B* 77(5): 1331–1340.

Kotz S, Balakrishnan N, Johnson NL (2000) *Continuous Multivariate Distributions*, volume 1. Second edition. Wiley, New York, 722 pp.

Kotz S, Johnson NL, Read CB (Eds) (1982a) *Encyclopedia of statistical sciences*, volume 1. Wiley, New York, 480 pp.

Kotz S, Johnson NL, Read CB (Eds) (1982b) *Encyclopedia of statistical sciences*, volume 2. Wiley, New York, 613 pp.

Kotz S, Johnson NL, Read CB (Eds) (1983a) *Encyclopedia of statistical sciences*, volume 3. Wiley, New York, 722 pp.

Kotz S, Johnson NL, Read CB (Eds) (1983b) *Encyclopedia of statistical sciences*, volume 4. Wiley, New York, 657 pp.

Kotz S, Johnson NL, Read CB (Eds) (1985a) *Encyclopedia of statistical sciences*, volume 5. Wiley, New York, 741 pp.

Kotz S, Johnson NL, Read CB (Eds) (1985b) *Encyclopedia of statistical sciences*, volume 6. Wiley, New York, 758 pp.

Kotz S, Johnson NL, Read CB (Eds) (1986) *Encyclopedia of statistical sciences*, volume 7. Wiley, New York, 714 pp.

Kotz S, Johnson NL, Read CB (Eds) (1988a) *Encyclopedia of statistical sciences*, volume 8. Wiley, New York, 870 pp.

Kotz S, Johnson NL, Read CB (Eds) (1988b) *Encyclopedia of statistical sciences*, volume 9. Wiley, New York, 762 pp.

Kotz S, Johnson NL, Read CB (Eds) (1989) *Encyclopedia of statistical sciences*, volume S. Wiley, New York, 283 pp.

Kotz S, Nadarajah S (2000) *Extreme value distributions: Theory and applications.* Imperial College Press, London, 187 pp.

Kotz S, Read CB, Banks DL (Eds) (1997) *Encyclopedia of statistical sciences*, volume U1. Wiley, New York, 568 pp.

Kotz S, Read CB, Banks DL (Eds) (1998) *Encyclopedia of statistical sciences*, volume U2. Wiley, New York, 745 pp.

Kotz S, Read CB, Banks DL (Eds) (1999) *Encyclopedia of statistical sciences*, volume U3. Wiley, New York, 898 pp.

Koutsoyiannis D (2002) The Hurst phenomenon and fractional Gaussian noise made easy. *Hydrological Sciences Journal* 47(4): 573–595.

Koutsoyiannis D (2005a) Hydrological persistence and the Hurst phenomenon. In: Lehr JH, Keeley J (Eds) *Water Encyclopedia: Surface and Agricultural Water*. Wiley, New York, pp 210–220.

Koutsoyiannis D (2005b) Uncertainty, entropy, scaling and hydrological stochastics. 2. Time dependence of hydrological processes and time scaling. *Hydrological Sciences Journal* 50(3): 405–426.

Koutsoyiannis D (2006) Nonstationarity versus scaling in hydrology. *Journal of Hydrology* 324(1–4): 239–254.

Koyck LM (1954) *Distributed Lags and Investment Analysis*. North-Holland, Amsterdam, 111 pp.

Kraemer HC (1974) The non-null distribution of the Spearman rank correlation coefficient. *Journal of the American Statistical Association* 69(345): 114–117.

Kraemer HC (1982) Biserial correlation. In: Kotz S, Johnson NL, Read CB (Eds) *Encyclopedia of statistical sciences*, volume 1. Wiley, New York, pp 276–280.

Kreiss J-P (1992) Bootstrap procedures for AR(∞)-processes. In: Jöckel K-H, Rothe G, Sendler W (Eds) *Bootstrapping and Related Techniques*. Springer, Berlin, pp 107–113.

Kreiss J-P, Franke J (1992) Bootstrapping stationary autoregressive moving-average models. *Journal of Time Series Analysis* 13(4): 297–317.

Kristjánsson JE, Staple A, Kristiansen J, Kaas E (2002) A new look at possible connections between solar activity, clouds and climate. *Geophysical Research Letters* 29(23): 2107. [doi:10.1029/2002GL015646]

Kruskal WH (1958) Ordinal measures of association. *Journal of the American Statistical Association* 53(284): 814–861.

Kuhn TS (1970) *The Structure of Scientific Revolutions*. Second edition. University of Chicago Press, Chicago, 210 pp.

Kullback S (1983) Fisher information. In: Kotz S, Johnson NL, Read CB (Eds) *Encyclopedia of statistical sciences*, volume 3. Wiley, New York, pp 115–118.

Kumar KK, Rajagopalan B, Cane MA (1999) On the weakening relationship between the Indian monsoon and ENSO. *Science* 284(5423): 2156–2159.

Künsch HR (1989) The jackknife and the bootstrap for general stationary observations. *The Annals of Statistics* 17(3): 1217–1241.

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(1–2): 187–195.

Kürschner WM, van der Burgh J, Visscher H, Dilcher DL (1996) Oak leaves as biosensors of late Neogene and early Pleistocene paleoatmospheric CO_2 concentrations. *Marine Micropaleontology* 27(1–4): 299–312.

Kutner MH, Nachtsheim CJ, Neter J, Li W (2005) *Applied Linear Statistical Models*. Fifth edition. McGraw-Hill/Irwin, Boston, 1396 pp.

Kwon J, Min K, Bickel PJ, Renne PR (2002) Statistical methods for jointly estimating the decay constant of ^{40}K and the age of a dating standard. *Mathematical Geology* 34(4): 457–474.

Kyselý J (2002) Temporal fluctuations in heat waves at Prague–Klementinum, the Czech Republic, from 1901–97, and their relationships to atmospheric circulation. *International Journal of Climatology* 22(1): 33–50.

Kyselý J (2008) A cautionary note on the use of nonparametric bootstrap for estimating uncertainties in extreme-value models. *Journal of Applied Meteorology and Climatology* 47(12): 3236–3251.

Lahiri SN (1993) On the moving block bootstrap under long range dependence. *Statistics & Probability Letters* 18(5): 405–413.

Lahiri SN (1999) Theoretical comparisons of block bootstrap methods. *The Annals of Statistics* 27(1): 386–404.

Lahiri SN (2003) *Resampling Methods for Dependent Data*. Springer, New York, 374 pp.

Lakatos I, Musgrave A (Eds) (1970) *Criticism and the Growth of Knowledge*. Cambridge University Press, Cambridge, 282 pp.

Lanczos C (1964) A precision approximation of the gamma function. *SIAM Journal on Numerical Analysis* 1: 86–96.

Landsea CW (1993) A climatology of intense (or major) Atlantic hurricanes. *Monthly Weather Review* 121(6): 1703–1713.

Landsea CW (2007) Counting Atlantic tropical cyclones back to 1900. *Eos, Transactions of the American Geophysical Union* 88(18): 197, 202.

Landsea CW, Glenn DA, Bredemeyer W, Chenoweth M, Ellis R, Gamache J, Hufstetler L, Mock C, Perez R, Prieto R, Sánchez-Sesma J, Thomas D, Woolcock L (2008) A reanalysis of the 1911–20 Atlantic hurricane database. *Journal of Climate* 21(10): 2138–2168.

Landsea CW, Nicholls N, Gray WM, Avila LA (1996) Downward trends in the frequency of intense Atlantic hurricanes during the past five decades. *Geophysical Research Letters* 23(13): 1697–1700.

Landsea CW, Nicholls N, Gray WM, Avila LA (1997) Reply. *Geophysical Research Letters* 24(17): 2205.

Landsea CW, Pielke Jr RA, Mestas-Nuñez AM, Knaff JA (1999) Atlantic basin hurricanes: Indices of climatic changes. *Climatic Change* 42(1): 89–129.

Landsea CW, Vecchi GA, Bengtsson L, Knutson TR (2010) Impact of duration thresholds on Atlantic tropical cyclone counts. *Journal of Climate* 23(10): 2508–2519. [doi:10.1175/2009JCLI3034.1]

Landwehr JM, Matalas NC, Wallis JR (1979) Probability weighted moments compared with some traditional techniques in estimating Gumbel parameters and quantiles. *Water Resources Research* 15(5): 1055–1064.

Lang M, Ouarda TBMJ, Bobée B (1999) Towards operational guidelines for over-threshold modeling. *Journal of Hydrology* 225(3–4): 103–117.

Lanyon BP, Barbieri M, Almeida MP, Jennewein T, Ralph TC, Resch KJ, Pryde GJ, O'Brien JL, Gilchrist A, White AG (2009) Simplifying quantum logic using higher-dimensional Hilbert spaces. *Nature Physics* 5(2): 134–140.

Lanzante JR (1996) Resistant, robust and non-parametric techniques for the analysis of climate data: Theory and examples, including applications to historical radiosonde station data. *International Journal of Climatology* 16(11): 1197–1226.

Lassen K, Friis-Christensen E (2000) Reply. *Journal of Geophysical Research* 105(A12): 27493–27495.

Laurmann JA, Gates WL (1977) Statistical considerations in the evaluation of climatic experiments with Atmospheric General Circulation Models. *Journal of the Atmospheric Sciences* 34(8): 1187–1199.

Laut P (2003) Solar activity and terrestrial climate: An analysis of some purported correlations. *Journal of Atmospheric and Solar-Terrestrial Physics* 65(7): 801–812.

Laut P, Gundermann J (2000) Solar cycle lengths and climate: A reference revisited. *Journal of Geophysical Research* 105(A12): 27489–27492.

Lawrence KD, Arthur JL (Eds) (1990) *Robust Regression: Analysis and Applications.* Marcel Dekker, New York, 287 pp.

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

Leadbetter MR, Rootzén H (1988) Extremal theory for stochastic processes. *The Annals of Probability* 16(2): 431–478.

Ledford AW, Tawn JA (2003) Diagnostics for dependence within time series extremes. *Journal of the Royal Statistical Society, Series B* 65(2): 521–543.

Ledolter J (1986) Prediction and forecasting. In: Kotz S, Johnson NL, Read CB (Eds) *Encyclopedia of statistical sciences*, volume 7. Wiley, New York, pp 148–158.

Lees JM, Park J (1995) Multiple-taper spectral analysis: A stand-alone C-subroutine. *Computers and Geosciences* 21(2): 199–236.

Lehmann EL, Casella G (1998) *Theory of Point Estimation.* Second edition. Springer, New York, 589 pp.

Lehmann EL, Romano JP (2005) *Testing Statistical Hypotheses.* Third edition. Springer, New York, 784 pp.

Leith CE (1973) The standard error of time-average estimates of climatic means. *Journal of Applied Meteorology* 12(6): 1066–1069.

Leith NA, Chandler RE (2010) A framework for interpreting climate model outputs. *Applied Statistics* 59(2): 279–296.

LePage R, Billard L (Eds) (1992) *Exploring the Limits of Bootstrap.* Wiley, New York, 426 pp.

Li H, Maddala GS (1996) Bootstrapping time series models (with discussion). *Econometric Reviews* 15(2): 115–195.

Linden M (1999) Time series properties of aggregated AR(1) processes with uniformly distributed coefficients. *Economics Letters* 64(1): 31–36.

Linder E, Babu GJ (1994) Bootstrapping the linear functional relationship with known error variance ratio. *Scandinavian Journal of Statistics* 21(1): 21–39.

Lindley DV (1947) Regression lines and the linear functional relationship. *Journal of the Royal Statistical Society, Supplement* 9(2): 218–244.

Lindley DV (1965) *Introduction to Probability and Statistics.* Cambridge University Press, Cambridge, 259 pp.

Linnell Nemec AF, Nemec JM (1985) A test of significance for periods derived using phase-dispersion-minimization techniques. *The Astronomical Journal* 90(11): 2317–2320.

Lisiecki LE, Lisiecki PA (2002) Application of dynamic programming to the correlation of paleoclimate records. *Paleoceanography* 17(4): 1049. [doi:10.1029/2001PA000733]

Lisiecki LE, Raymo ME (2005) A Pliocene–Pleistocene stack of 57 globally distributed benthic δ^{18}O records. *Paleoceanography* 20(1): PA1003. [doi:10.1029/2004PA001071]

Liu RY, Singh K (1992) Moving blocks jackknife and bootstrap capture weak dependence. In: LePage R, Billard L (Eds) *Exploring the Limits of Bootstrap.* Wiley, New York, pp 225–248.

Loader CR (1992) A log-linear model for a Poisson process change point. *The Annals of Statistics* 20(3): 1391–1411.

Lockwood M, Fröhlich C (2007) Recent oppositely directed trends in solar climate forcings and the global mean surface air temperature. *Proceedings of the Royal Society of London, Series A* 463(2086): 2447–2460.

Loh W-Y (1987) Calibrating confidence coefficients. *Journal of the American Statistical Association* 82(397): 155–162.

Loh W-Y (1991) Bootstrap calibration for confidence interval construction and selection. *Statistica Sinica* 1(2): 477–491.

Lomb NR (1976) Least-squares frequency analysis of unequally spaced data. *Astrophysics and Space Science* 39(2): 447–462.

Lomnicki ZA (1967) On the distribution of products of random variables. *Journal of the Royal Statistical Society, Series B* 29(3): 513–524.

Lorenz EN (1963) Deterministic nonperiodic flow. *Journal of the Atmospheric Sciences* 20(2): 130–141.

Lorenz EN (1991) Dimension of weather and climate attractors. *Nature* 353(6341): 241–244.

Lovelock JE, Kump LR (1994) Failure of climate regulation in a geophysiological model. *Nature* 369(6483): 732–734.

Lu L-H, Stedinger JR (1992) Variance of two- and three-parameter GEV/PWM quantile estimators: Formulae, confidence intervals, and a comparison. *Journal of Hydrology* 138(1–2): 247–267.

Ludwig KR (2003) *User's Manual for Isoplot 3.00: A Geochronological Toolkit for Microsoft Excel.* Berkeley Geochronology Center, Berkeley, CA, 70 pp. [Special Publication No. 4]

Lund R, Wang XL, Lu Q, Reeves J, Gallagher C, Feng Y (2007) Changepoint detection in periodic and autocorrelated time series. *Journal of Climate* 20(20): 5178–5190.

Luterbacher J, Rickli R, Xoplaki E, Tinguely C, Beck C, Pfister C, Wanner H (2001) The late Maunder Minimum (1675–1715)—A key period for studying decadal scale climatic change in Europe. *Climatic Change* 49(4): 441–462.

Lüthi D, Le Floch M, Bereiter B, Blunier T, Barnola J-M, Siegenthaler U, Raynaud D, Jouzel J, Fischer H, Kawamura K, Stocker TF (2008) High-resolution carbon dioxide concentration record 650,000–800,000 years before present. *Nature* 453(7193): 379–382.

Lybanon M (1984) A better least-squares method when both variables have uncertainties. *American Journal of Physics* 52(1): 22–26.

Maasch KA (1988) Statistical detection of the mid-Pleistocene transition. *Climate Dynamics* 2(3): 133–143.

MacDonald GJ (1989) Spectral analysis of time series generated by nonlinear processes. *Reviews of Geophysics* 27(4): 449–469.

Macdonald JR, Thompson WJ (1992) Least-squares fitting when both variables contain errors: Pitfalls and possibilities. *American Journal of Physics* 60(1): 66–73.

Macleod AJ (1989) A remark on algorithm AS 215: Maximum-likelihood estimation of the parameters of the generalized extreme-value distribution. *Applied Statistics* 38(1): 198–199.

Madansky A (1959) The fitting of straight lines when both variables are subject to error. *Journal of the American Statistical Association* 54(285): 173–205.

Madden RA, Jones RH (2001) A quantitative estimate of the effect of aliasing in climatological time series. *Journal of Climate* 14(19): 3987–3993.

Maidment DR (Ed) (1993) *Handbook of Hydrology.* McGraw-Hill, New York, 1400 pp.

Mandelbrot BB (1983) Fractional Brownian motions and fractional Gaussian noises. In: Kotz S, Johnson NL, Read CB (Eds) *Encyclopedia of statistical sciences*, volume 3. Wiley, New York, pp 186–189.

Mandelbrot BB, Wallis JR (1969) Some long-run properties of geophysical records. *Water Resources Research* 5(2): 321–340.

Mankinen EA, Dalrymple GB (1979) Revised geomagnetic polarity time scale for the interval 0–5 m.y. B.P. *Journal of Geophysical Research* 84(B2): 615–626.

Manley G (1974) Central England temperatures: Monthly means 1659 to 1973. *Quarterly Journal of the Royal Meteorological Society* 100(425): 389–405.

Mann HB (1945) Nonparametric tests against trend. *Econometrica* 13(3): 245–259.

Mann ME, Emanuel KA (2006) Atlantic hurricane trends linked to climate change. *Eos, Transactions of the American Geophysical Union* 87(24): 233, 238, 241.

Mann ME, Emanuel KA, Holland GJ, Webster PJ (2007a) Atlantic tropical cyclones revisited. *Eos, Transactions of the American Geophysical Union* 88(36): 349–350.

Mann ME, Lees JM (1996) Robust estimation of background noise and signal detection in climatic time series. *Climatic Change* 33(3): 409–445.

Mann ME, Sabbatelli TA, Neu U (2007b) Evidence for a modest undercount bias in early historical Atlantic tropical cyclone counts. *Geophysical Research Letters* 34(22): L22707. [doi:10.1029/2007GL031781; corrigendum: 2007 Vol. 34(24): L24704 (doi:10.1029/2007GL032798)]

Mann ME, Woodruff JD, Donnelly JP, Zhang Z (2009) Atlantic hurricanes and climate over the past 1,500 years. *Nature* 460(7257): 880–883.

Maraun D, Rust HW, Timmer J (2004) Tempting long-memory—on the interpretation of DFA results. *Nonlinear Processes in Geophysics* 11(4): 495–503.

Markowitz E (1968a) Minimum mean-square-error estimation of the standard deviation of the normal distribution. *The American Statistician* 22(3): 26.

Markowitz E (1968b) Priority acknowledgement to "Minimum mean-square-error estimation of the standard deviation of the normal distribution." *The American Statistician* 22(4): 42.

Marquardt DW, Acuff SK (1982) Direct quadratic spectrum estimation from unequally spaced data. In: Anderson OD, Perryman MR (Eds) *Applied Time Series Analysis*. North-Holland, Amsterdam, pp 199–227.

Marriott FHC, Pope JA (1954) Bias in the estimation of autocorrelations. *Biometrika* 41(3–4): 390–402.

Marron JS (1987) What does optimal bandwidth selection mean for nonparametric regression estimation? In: Dodge Y (Ed) *Statistical Data Analysis Based on the L_1-Norm and Related Methods*. North-Holland, Amsterdam, pp 379–392.

Marron JS (1988) Automatic smoothing parameter selection: A survey. *Empirical Economics* 13(3–4): 187–208.

Martin MA (1990) On bootstrap iteration for coverage correction in confidence intervals. *Journal of the American Statistical Association* 85(412): 1105–1118.

Martin MA (2007) Bootstrap hypothesis testing for some common statistical problems: A critical evaluation of size and power properties. *Computational Statistics and Data Analysis* 51(12): 6321–6342.

Martin RJ (1998) *Irregularly sampled signals: Theories and techniques for analysis*. Ph.D. Dissertation. University College London, London, 158 pp.

Martins ES, Stedinger JR (2000) Generalized maximum-likelihood generalized extreme-value quantile estimators for hydrologic data. *Water Resources Research* 36(3): 737–744.

Martins ES, Stedinger JR (2001) Generalized maximum likelihood Pareto–Poisson estimators for partial duration series. *Water Resources Research* 37(10): 2551–2557.

Martinson DG, Menke W, Stoffa P (1982) An inverse approach to signal correlation. *Journal of Geophysical Research* 87(B6): 4807–4818.

Martinson DG, Pisias NG, Hays JD, Imbrie J, Moore Jr TC, Shackleton NJ (1987) Age dating and the orbital theory of the ice ages: Development of a high-resolution 0 to 300,000-year chronostratigraphy. *Quaternary Research* 27(1): 1–29.

Masry E (1984) Spectral and probability density estimation from irregularly observed data. In: Parzen E (Ed) *Time Series Analysis of Irregularly Observed Data.* Springer, New York, pp 224–250.

Matalas NC, Langbein WB (1962) Information content of the mean. *Journal of Geophysical Research* 67(9): 3441–3448.

Matteucci G (1990) Analysis of the probability distribution of the late Pleistocene climatic record: Implications for model validation. *Climate Dynamics* 5(1): 35–52.

Matyasovszky I (2001) A nonlinear approach to modeling climatological time series. *Theoretical and Applied Climatology* 69(3–4): 139–147.

Mayewski PA, Meeker LD, Twickler MS, Whitlow S, Yang Q, Lyons WB, Prentice M (1997) Major features and forcing of high-latitude northern hemisphere atmospheric circulation using a 110,000-year-long glaciochemical series. *Journal of Geophysical Research* 102(C12): 26345–26366.

McAvaney BJ, Covey C, Joussaume S, Kattsov V, Kitoh A, Ogana W, Pitman AJ, Weaver AJ, Wood RA, Zhao Z-C (2001) Model evaluation. In: Houghton JT, Ding Y, Griggs DJ, Noguer M, van der Linden PJ, Dai X, Maskell K, Johnson CA (Eds) *Climate Change 2001: The Scientific Basis. Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change.* Cambridge University Press, Cambridge, pp 471–523.

McGuffie K, Henderson-Sellers A (1997) *A Climate Modelling Primer.* Second edition. Wiley, Chichester, 253 pp.

McMillan DG, Constable CG, Parker RL (2002) Limitations on stratigraphic analyses due to incomplete age control and their relevance to sedimentary paleomagnetism. *Earth and Planetary Science Letters* 201(3–4): 509–523.

Meehl GA, Stocker TF, Collins WD, Friedlingstein P, Gaye AT, Gregory JM, Kitoh A, Knutti R, Murphy JM, Noda A, Raper SCB, Watterson IG, Weaver AJ, Zhao Z-C (2007) Global climate projections. In: Solomon S, Qin D, Manning M, Marquis M, Averyt K, Tignor MMB, Miller Jr HL, 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, pp 747–845.

Meehl GA, Tebaldi C (2004) More intense, more frequent, and longer lasting heat waves in the 21st century. *Science* 305(5686): 994–997.

Meehl GA, Washington WM, Wigley TML, Arblaster JM, Dai A (2003) Solar and greenhouse gas forcing and climate response in the twentieth century. *Journal of Climate* 16(3): 426–444.

Meehl GA, Zwiers F, Evans J, Knutson T, Mearns L, Whetton P (2000) Trends in extreme weather and climate events: Issues related to modeling extremes in projections of future climate change. *Bulletin of the American Meteorological Society* 81(3): 427–436.

Meeker LD, Mayewski PA, Grootes PM, Alley RB, Bond GC (2001) Comment on "On sharp spectral lines in the climate record and the millennial peak" by Carl Wunsch. *Paleoceanography* 16(5): 544–547.

Menzefricke U (1981) A Bayesian analysis of a change in the precision of a sequence of independent normal random variables at an unknown time point. *Applied Statistics* 30(2): 141–146.

Mesa OJ, Poveda G (1993) The Hurst effect: The scale of fluctuation approach. *Water Resources Research* 29(12): 3995–4002.

Meyer MC, Faber R, Spötl C (2006) The WinGeol Lamination Tool: New software for rapid, semi-automated analysis of laminated climate archives. *The Holocene* 16(5): 753–761.

Miao X, Mason JA, Johnson WC, Wang H (2007) High-resolution proxy record of Holocene climate from a loess section in southwestern Nebraska, USA. *Palaeogeography, Palaeoclimatology, Palaeoecology* 245(3–4): 368–381.

Michener WK, Blood ER, Bildstein KL, Brinson MM, Gardner LR (1997) Climate change, hurricanes and tropical storms, and rising sea level in coastal wetlands. *Ecological Applications* 7(3): 770–801.

Miller DM (1984) Reducing transformation bias in curve fitting. *The American Statistician* 38(2): 124–126.

Mills TC (2007) Time series modelling of two millennia of northern hemisphere temperatures: Long memory or shifting trends? *Journal of the Royal Statistical Society, Series A* 170(1): 83–94.

Milly PCD, Wetherald RT (2002) Macroscale water fluxes 3. Effects of land processes on variability of monthly river discharge. *Water Resources Research* 38(11): 1235. [doi:10.1029/2001WR000761]

Milne AE, Lark RM (2009) Wavelet transforms applied to irregularly sampled soil data. *Mathematical Geosciences* 41(6): 661–678.

Mitchell JFB, Wilson CA, Cunnington WM (1987) On CO_2 climate sensitivity and model dependence of results. *Quarterly Journal of the Royal Meteorological Society* 113(475): 293–322.

Mondal D, Percival DB (in press) Wavelet variance analysis for gappy time series. *Annals of the Institute of Statistical Mathematics*. [doi:10.1007/s10463-008-0195-z]

Monnin E, Indermühle A, Dällenbach A, Flückiger J, Stauffer B, Stocker TF, Raynaud D, Barnola J-M (2001) Atmospheric CO_2 concentrations over the last glacial termination. *Science* 291(5501): 112–114.

Monro DM (1975) Complex discrete Fast Fourier Transform. *Applied Statistics* 24(1): 153–160.

Monro DM (1976) Real discrete Fast Fourier Transform. *Applied Statistics* 25(2): 166–172.

Montanari A (2003) Long-range dependence in hydrology. In: Doukhan P, Oppenheim G, Taqqu MS (Eds) *Theory and Applications of Long-Range Dependence*. Birkhäuser, Boston, pp 461–472.

Montanari A, Rosso R, Taqqu MS (1997) Fractionally differenced ARIMA models applied to hydrologic time series: Identification, estimation, and simulation. *Water Resources Research* 33(5): 1035–1044.

Montgomery DC, Peck EA (1992) *Introduction to Linear Regression Analysis*. Second edition. Wiley, New York, 527 pp.

Montgomery DC, Peck EA, Vining GG (2006) *Introduction to Linear Regression Analysis*. Fourth edition. Wiley, Hoboken, NJ, 612 pp.

Moore MI, Thomson PJ (1991) Impact of jittered sampling on conventional spectral estimates. *Journal of Geophysical Research* 96(C10): 18519–18526.

Moore PD, Webb JA, Collinson ME (1991) *Pollen analysis*. Second edition. Blackwell, Oxford, 216 pp.

Moran PAP (1948) Rank correlation and product-moment correlation. *Biometrika* 35(1–2): 203–206.

Mosedale TJ, Stephenson DB, Collins M, Mills TC (2006) Granger causality of coupled climate processes: Ocean feedback on the North Atlantic Oscillation. *Journal of Climate* 19(7): 1182–1194.

Moss RH, Edmonds JA, Hibbard KA, Manning MR, Rose SK, van Vuuren DP, Carter TR, Emori S, Kainuma M, Kram T, Meehl GA, Mitchell JFB, Nakicenovic N, Riahi K, Smith SJ, Stouffer RJ, Thomson AM, Weyant JP, Wilbanks TJ (2010) The next generation of scenarios for climate change research and assessment. *Nature* 463(7282): 747–756.

Mostafa MD, Mahmoud MW (1964) On the problem of estimation for the bivariate lognormal distribution. *Biometrika* 51(3–4): 522–527.

Mudelsee M (1999) *On an interesting statistical problem imposed by an ice core*. Institute of Mathematics and Statistics, University of Kent, Canterbury, 12 pp. [Technical Report UKC/IMS/99/21]

Mudelsee M (2000) Ramp function regression: A tool for quantifying climate transitions. *Computers and Geosciences* 26(3): 293–307.

Mudelsee M (2001a) Note on the bias in the estimation of the serial correlation coefficient of AR(1) processes. *Statistical Papers* 42(4): 517–527.

Mudelsee M (2001b) The phase relations among atmospheric CO_2 content, temperature and global ice volume over the past 420 ka. *Quaternary Science Reviews* 20(4): 583–589.

Mudelsee M (2002) TAUEST: A computer program for estimating persistence in unevenly spaced weather/climate time series. *Computers and Geosciences* 28(1): 69–72.

Mudelsee M (2003) Estimating Pearson's correlation coefficient with bootstrap confidence interval from serially dependent time series. *Mathematical Geology* 35(6): 651–665.

Mudelsee M (2005) A new, absolutely dated geomagnetic polarity timescale for the Late Pliocene to Early Pleistocene. In: Berger A, Ercegovac M, Mesinger F (Eds) *Milutin Milankovitch Anniversary Symposium: Paleoclimate and the Earth Climate System*. Serbian Academy of Sciences and Arts, Belgrade, pp 145–149.

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(1): 141–144.

Mudelsee M (2007) Long memory of rivers from spatial aggregation. *Water Resources Research* 43(1): W01202. [doi:10.1029/2006WR005721]

Mudelsee M (2009) Break function regression: A tool for quantifying trend changes in climate time series. *European Physical Journal Special Topics* 174(1): 49–63.

Mudelsee M, Alkio M (2007) Quantifying effects in two-sample environmental experiments using bootstrap confidence intervals. *Environmental Modelling and Software* 22(1): 84–96.

Mudelsee M, Börngen M, Tetzlaff G, Grünewald U (2003) No upward trends in the occurrence of extreme floods in central Europe. *Nature* 425(6954): 166–169. [Corrigendum: Insert in Eq. (1) on the right-hand side a factor h^{-1} before the sum sign.]

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(D23): D23101. [doi:10.1029/2004JD005034; corrigendum: Eq. (5): replace $n^\dagger$ by n, Eq. (6): replace $K(t - T^\dagger(j))$ by $h^{-1}K([t - T^\dagger(j)]h^{-1})$.]

Mudelsee M, Deutsch M, Börngen M, Tetzlaff G (2006) Trends in flood risk of the River Werra (Germany) over the past 500 years. *Hydrological Sciences Journal* 51(5): 818–833.

Mudelsee M, Raymo ME (2005) Slow dynamics of the Northern Hemisphere Glaciation. *Paleoceanography* 20(4): PA4022. [doi:10.1029/2005PA001153]

Mudelsee M, Scholz D, Röthlisberger R, Fleitmann D, Mangini A, Wolff EW (2009) Climate spectrum estimation in the presence of timescale errors. *Nonlinear Processes in Geophysics* 16(1): 43–56.

Mudelsee M, Schulz M (1997) The Mid-Pleistocene Climate Transition: Onset of 100 ka cycle lags ice volume build-up by 280 ka. *Earth and Planetary Science Letters* 151(1–2): 117–123.

Mudelsee M, Stattegger K (1994) Plio-/Pleistocene climate modeling based on oxygen isotope time series from deep-sea sediment cores: The Grassberger–Procaccia algorithm and chaotic climate systems. *Mathematical Geology* 26(7): 799–815.

Mudelsee M, Stattegger K (1997) Exploring the structure of the mid-Pleistocene revolution with advanced methods of time-series analysis. *Geologische Rundschau* 86(2): 499–511.

Mueller M (2003) Damages of the Elbe flood 2002 in Germany—A review. *Geophysical Research Abstracts* 5: 12992.

Müller H-G (1992) Change-points in nonparametric regression analysis. *The Annals of Statistics* 20(2): 737–761.

Muller RA, MacDonald GJ (1995) Glacial cycles and orbital inclination. *Nature* 377(6545): 107–108.

Muller RA, MacDonald GJ (1997a) Glacial cycles and astronomical forcing. *Science* 277(5323): 215–218.

Muller RA, MacDonald GJ (1997b) Simultaneous presence of orbital inclination and eccentricity in proxy climate records from Ocean Drilling Program Site 806. *Geology* 25(1): 3–6.

Muller RA, MacDonald GJ (1997c) Spectrum of the 100 kyr glacial cycle: Orbital inclination, not eccentricity. *Proceedings of the National Academy of Sciences of the United States of America* 94(16): 8329–8334.

Muller RA, MacDonald GJ (2000) *Ice Ages and Astronomical Causes: Data, spectral analysis and mechanisms*. Springer, London, 318 pp.

Mullis CT, Scharf LL (1991) Quadratic estimators of the power spectrum. In: Haykin S (Ed) *Advances in Spectrum Analysis and Array Processing*, volume 1. Prentice-Hall, Englewood Cliffs, NJ, pp 1–57.

Munk W, Hasselmann K (1964) Super-resolution of tides. In: Yoshida K (Ed) *Studies on Oceanography: A Collection of Papers dedicated to Koji Hidaka*. University of Washington Press, Seattle, WA, pp 339–344.

Münnich KO, Östlund HG, de Vries H (1958) Carbon-14 activity during the past 5,000 years. *Nature* 182(4647): 1432–1433.

Musekiwa A (2005) *Estimating the slope in the simple linear errors-in-variables model*. M.Sc. Thesis. University of Johannesburg, Johannesburg, South Africa, 85 pp.

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

Nakagawa S, Niki N (1992) Distribution of the sample correlation coefficient for non-normal populations. *Journal of the Japanese Society of Computational Statistics* 5(1): 1–19.

Naveau P, Nogaj M, Ammann C, Yiou P, Cooley D, Jomelli V (2005) Statistical methods for the analysis of climate extremes. *Comptes Rendus Geoscience* 337(10–11): 1013–1022.

Neff U, Burns SJ, Mangini A, Mudelsee M, Fleitmann D, Matter A (2001) Strong coherence between solar variability and the monsoon in Oman between 9 and 6 kyr ago. *Nature* 411(6835): 290–293.

Negendank JFW, Zolitschka B (Eds) (1993) *Paleolimnology of European Maar Lakes.* Springer, Berlin, 513 pp.

Neuendorf KKE, Mehl Jr JP, Jackson JA (2005) *Glossary of Geology.* Fifth edition. American Geological Institute, Alexandria, VA, 779 pp.

Neumann MH, Kreiss J-P (1998) Regression-type inference in nonparametric autoregression. *The Annals of Statistics* 26(4): 1570–1613.

Newton HJ, North GR, Crowley TJ (1991) Forecasting global ice volume. *Journal of Time Series Analysis* 12(3): 255–265.

Nicolis C, Nicolis G (1984) Is there a climatic attractor? *Nature* 311(5986): 529–532.

Nielsen MA, Chuang IL (2000) *Quantum Computation and Quantum Information.* Cambridge University Press, Cambridge, 676 pp.

Nierenberg WA (Ed) (1992) *Encyclopedia of Earth System Science*, volume 1–4. Academic Press, San Diego, 2825 pp.

Nievergelt Y (1998) Total least squares. In: Kotz S, Read CB, Banks DL (Eds) *Encyclopedia of statistical sciences*, volume U2. Wiley, New York, pp 666–670.

Niggemann S, Mangini A, Mudelsee M, Richter DK, Wurth G (2003) Sub-Milankovitch climatic cycles in Holocene stalagmites from Sauerland, Germany. *Earth and Planetary Science Letters* 216(4): 539–547.

Nogaj M, Yiou P, Parey S, Malek F, Naveau P (2006) Amplitude and frequency of temperature extremes over the North Atlantic region. *Geophysical Research Letters* 33(10): L10801. [doi:10.1029/2005GL024251]

Nordgaard A (1992) Resampling stochastic processes using a bootstrap approach. In: Jöckel K-H, Rothe G, Sendler W (Eds) *Bootstrapping and Related Techniques.* Springer, Berlin, pp 181–185.

North Greenland Ice Core Project members (2004) High-resolution record of northern hemisphere climate extending into the last interglacial period. *Nature* 431(7005): 147–151.

Nuttall AH (1981) Some windows with very good sidelobe behavior. *IEEE Transactions on Acoustics, Speech, and Signal Processing* 29(1): 84–91.

Nyberg J, Malmgren BA, Winter A, Jury MR, Kilbourne KH, Quinn TM (2007) Low Atlantic hurricane activity in the 1970s and 1980s compared to the past 270 years. *Nature* 447(7145): 698–701.

Ocean Drilling Program (Ed) (1986–2004) *Proceedings of the Ocean Drilling Program, Initial Reports*, volume 101–210. Ocean Drilling Program, College Station, TX.

Ocean Drilling Program (Ed) (1988–2007) *Proceedings of the Ocean Drilling Program, Scientific Results*, volume 101–210. Ocean Drilling Program, College Station, TX.

Odeh RE, Evans JO (1974) The percentage points of the normal distribution. *Applied Statistics* 23(1): 96–97.

Odell PL (1983) Gauss–Markov theorem. In: Kotz S, Johnson NL, Read CB (Eds) *Encyclopedia of statistical sciences*, volume 3. Wiley, New York, pp 314–316.

Oeschger H, Langway Jr CC (Eds) (1989) *The Environmental Record in Glaciers and Ice Sheets*. Wiley, Chichester, 401 pp.

Oh H-S, Nychka D, Brown T, Charbonneau P (2004) Period analysis of variable stars by robust smoothing. *Applied Statistics* 53(1): 15–30.

Otten A (1973) The null distribution of Spearman's S when $n = 13(1)16$. *Statistica Neerlandica* 27(1): 19–20.

Packard NH, Crutchfield JP, Farmer JD, Shaw RS (1980) Geometry from a time series. *Physical Review Letters* 45(9): 712–716.

Page ES (1954) Continuous inspection schemes. *Biometrika* 41(1–2): 100–115.

Palm FC, Smeekes S, Urbain J-P (2008) Bootstrap unit-root tests: Comparison and extensions. *Journal of Time Series Analysis* 29(2): 371–401.

Paluš M, Vejmelka M (2007) Directionality of coupling from bivariate time series: How to avoid false causalities and missed connections. *Physical Review E* 75(5): 056211. [doi:10.1103/PhysRevE.75.056211]

Pankratz A (1991) *Forecasting with Dynamic Regression Models*. Wiley, New York, 386 pp.

Paparoditis E (2002) Frequency domain bootstrap for time series. In: Dehling H, Mikosch T, Sørensen M (Eds) *Empirical Process Techniques for Dependent Data*. Birkhäuser, Boston, pp 365–381.

Paparoditis E, Politis DN (2001) Tapered block bootstrap. *Biometrika* 88(4): 1105–1119.

Paparoditis E, Politis DN (2002) Local block bootstrap. *Comptes Rendus Mathematique* 335(11): 959–962.

Pardo-Igúzquiza E, Chica-Olmo M, Rodríguez-Tovar FJ (1994) CYSTRATI: A computer program for spectral analysis of stratigraphic successions. *Computers and Geosciences* 20(4): 511–584.

Parent E, Bernier J (2003a) Bayesian POT modeling for historical data. *Journal of Hydrology* 274(1–4): 95–108.

Parent E, Bernier J (2003b) Encoding prior experts judgments to improve risk analysis of extreme hydrological events via POT modeling. *Journal of Hydrology* 283(1–4): 1–18.

Park E, Lee YJ (2001) Estimates of standard deviation of Spearman's rank correlation coefficients with dependent observations. *Communications in Statistics—Simulation and Computation* 30(1): 129–142.

Park J (1992) Envelope estimation for quasi-periodic geophysical signals in noise: A multitaper approach. In: Walden AT, Guttorp P (Eds) *Statistics in the Environmental & Earth Sciences*. Edward Arnold, London, pp 189–219.

Park SK, Miller KW (1988) Random number generators: Good ones are hard to find. *Communications of the ACM* 31(10): 1192–1201.

Parrenin F, Barnola J-M, Beer J, Blunier T, Castellano E, Chappellaz J, Dreyfus G, Fischer H, Fujita S, Jouzel J, Kawamura K, Lemieux-Dudon B, Loulergue L, Masson-Delmotte V, Narcisi B, Petit J-R, Raisbeck G, Raynaud D, Ruth U, Schwander J, Severi M, Spahni R, Steffensen JP, Svensson A, Udisti R, Waelbroeck C, Wolff E (2007) The EDC3 chronology for the EPICA Dome C ice core. *Climate of the Past* 3(3): 485–497.

Parthasarathy B, Munot AA, Kothawale DR (1994) All-India monthly and seasonal rainfall series: 1871–1993. *Theoretical and Applied Climatology* 49(4): 217–224.

Parzen E (Ed) (1984) *Time Series Analysis of Irregularly Observed Data*. Springer, New York, 363 pp.

Patel JK, Read CB (1996) *Handbook of the Normal Distribution.* Second edition. Marcel Dekker, New York, 431 pp.

Paul A, Schäfer-Neth C (2005) How to combine sparse proxy data and coupled climate models. *Quaternary Science Reviews* 24(7–9): 1095–1107.

Pauli F, Coles S (2001) Penalized likelihood inference in extreme value analyses. *Journal of Applied Statistics* 28(5): 547–560.

Pearson K (1896) Mathematical contributions to the theory of evolution—III. Regression, heredity, and panmixia. *Philosophical Transactions of the Royal Society of London, Series A* 187: 253–318.

Pearson K (1901) On lines and planes of closest fit to systems of points in space. *Philosophical Magazine* 2(11): 559–572.

Pearson K (1907) Mathematical contributions to the theory of evolution—XVI. On further methods for determining correlation. *Drapers' Company Research Memoirs, Biometric Series* 4: 1–39.

Pearson K (1924) *The Life, Letters and Labours of Francis Galton*, volume 2. Cambridge University Press, Cambridge, 425 pp.

Pelletier JD, Turcotte DL (1997) Long-range persistence in climatological and hydrological time series: Analysis, modeling and application to drought hazard assessment. *Journal of Hydrology* 203(1–4): 198–208.

Peng C-K, Buldyrev SV, Havlin S, Simons M, Stanley HE, Goldberger AL (1994) Mosaic organization of DNA nucleotides. *Physical Review E* 49(2): 1685–1689.

Peng C-K, Havlin S, Stanley HE, Goldberger AL (1995) Quantification of scaling exponents and crossover phenomena in nonstationary heartbeat time series. *Chaos* 5(1): 82–87.

Penner JE, Andreae M, Annegarn H, Barrie L, Feichter J, Hegg D, Jayaraman A, Leaitch R, Murphy D, Nganga J, Pitari G (2001) Aerosols, their direct and indirect effects. In: Houghton JT, Ding Y, Griggs DJ, Noguer M, van der Linden PJ, Dai X, Maskell K, Johnson CA (Eds) *Climate Change 2001: The Scientific Basis. Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change.* Cambridge University Press, Cambridge, pp 289–348.

Percival DB, Walden AT (1993) *Spectral Analysis for Physical Applications: Multitaper and Conventional Univariate Techniques.* Cambridge University Press, Cambridge, 583 pp.

Percival DB, Walden AT (2000) *Wavelet Methods for Time Series Analysis.* Cambridge University Press, Cambridge, 594 pp.

Perron P (2006) Dealing with structural breaks. In: Mills TC, Patterson K (Eds) *Palgrave Handbook of Econometrics*, volume 1. Palgrave Macmillan, Houndmills, Basingstoke, pp 278–352.

Pestiaux P, Berger A (1984) Impacts of deep-sea processes on paleoclimatic spectra. In: Berger A, Imbrie J, Hays J, Kukla G, Saltzman B (Eds) *Milankovitch and Climate*, volume 1. D. Reidel, Dordrecht, pp 493–510.

Peters SC, Freedman DA (1984) Some notes on the bootstrap in regression problems. *Journal of Business & Economic Statistics* 2(4): 406–409.

Peterson TC, Easterling DR, Karl TR, Groisman P, Nicholls N, Plummer N, Torok S, Auer I, Boehm R, Gullett D, Vincent L, Heino R, Tuomenvirta H, Mestre O, Szentimrey T, Salinger J, Førland EJ, Hanssen-Bauer I, Alexandersson H, Jones P, Parker D (1998a) Homogeneity adjustments of *in situ* atmospheric climate data: A review. *International Journal of Climatology* 18(13): 1493–1517.

Peterson TC, Vose R, Schmoyer R, Razuvaëv V (1998b) Global Historical Climatology Network (GHCN) quality control of monthly temperature data. *International Journal of Climatology* 18(11): 1169–1179.

Petit JR, Jouzel J, Raynaud D, Barkov NI, Barnola J-M, Basile I, Bender M, Chappellaz J, Davis M, Delaygue G, Delmotte M, Kotlyakov VM, Legrand M, Lipenkov VY, Lorius C, Pépin L, Ritz C, Saltzman E, Stievenard M (1999) Climate and atmospheric history of the past 420,000 years from the Vostok ice core, Antarctica. *Nature* 399(6735): 429–436.

Pettitt AN (1979) A non-parametric approach to the change-point problem. *Applied Statistics* 28(2): 126–135.

Pfister C (1999) *Wetternachhersage*. Paul Haupt, Bern, 304 pp.

Pickands III J (1975) Statistical inference using extreme order statistics. *The Annals of Statistics* 3(1): 119–131.

Pielke Jr RA, Landsea C, Mayfield M, Laver J, Pasch R (2005) Hurricanes and global warming. *Bulletin of the American Meteorological Society* 86(11): 1571–1575.

Pielke Jr RA, Landsea CW (1998) Normalized hurricane damages in the United States: 1925–95. *Weather and Forecasting* 13(3): 621–631.

Pirie W (1988) Spearman rank correlation coefficient. In: Kotz S, Johnson NL, Read CB (Eds) *Encyclopedia of statistical sciences*, volume 8. Wiley, New York, pp 584–587.

Pisias NG, Mix AC (1988) Aliasing of the geologic record and the search for long-period Milankovitch cycles. *Paleoceanography* 3(5): 613–619.

Pittock AB (1978) A critical look at long-term Sun–weather relationships. *Reviews of Geophysics and Space Physics* 16(3): 400–420.

Polansky AM (1999) Upper bounds on the true coverage of bootstrap percentile type confidence intervals. *The American Statistician* 53(4): 362–369.

Polanyi M (1958) *Personal Knowledge: Towards a Post-Critical Philosophy*. University of Chicago Press, Chicago, 428 pp.

Politis DN (2003) The impact of bootstrap methods on time series analysis. *Statistical Science* 18(2): 219–230.

Politis DN, Romano JP (1992a) A circular block-resampling procedure for stationary data. In: LePage R, Billard L (Eds) *Exploring the Limits of Bootstrap*. Wiley, New York, pp 263–270.

Politis DN, Romano JP (1992b) A general resampling scheme for triangular arrays of α-mixing random variables with application to the problem of spectral density estimation. *The Annals of Statistics* 20(4): 1985–2007.

Politis DN, Romano JP (1994) The stationary bootstrap. *Journal of the American Statistical Association* 89(428): 1303–1313.

Politis DN, Romano JP, Lai T-L (1992) Bootstrap confidence bands for spectra and cross-spectra. *IEEE Transactions on Signal Processing* 40(5): 1206–1215.

Politis DN, Romano JP, Wolf M (1999) *Subsampling*. Springer, New York, 347 pp.

Politis DN, White H (2004) Automatic block-length selection for the dependent bootstrap. *Econometric Reviews* 23(1): 53–70.

Popper K (1935) *Logik der Forschung: Zur Erkenntnistheorie der modernen Naturwissenschaft*. Julius Springer, Wien, 248 pp.

Powell JL (1986) Censored regression quantiles. *Journal of Econometrics* 32(1): 143–155.

Prais SJ, Winsten CB (1954) *Trend Estimators and Serial Correlation*. Cowles Commission, Yale University, New Haven, CT, 26 pp. [Discussion Paper No. 383]

Preisendorfer RW (1988) *Principal Component Analysis in Meteorology and Oceanography.* Elsevier, Amsterdam, 425 pp.

Prell WL, Imbrie J, Martinson DG, Morley JJ, Pisias NG, Shackleton NJ, Streeter HF (1986) Graphic correlation of oxygen isotope stratigraphy application to the late Quaternary. *Paleoceanography* 1(2): 137–162.

Prescott P, Walden AT (1980) Maximum likelihood estimation of the parameters of the generalized extreme-value distribution. *Biometrika* 67(3): 723–724.

Press WH, Teukolsky SA, Vetterling WT, Flannery BP (1992) *Numerical Recipes in Fortran 77: The Art of Scientific Computing.* Second edition. Cambridge University Press, Cambridge, 933 pp.

Press WH, Teukolsky SA, Vetterling WT, Flannery BP (1996) *Numerical Recipes in Fortran 90: The Art of Parallel Scientific Computing.* Second edition. Cambridge University Press, Cambridge, pp 935–1486.

Press WH, Teukolsky SA, Vetterling WT, Flannery BP (2007) *Numerical Recipes: The Art of Scientific Computing.* Third edition. Cambridge University Press, Cambridge, 1235 pp. [C++ code]

Prichard D, Theiler J (1995) Generalized redundancies for time series analysis. *Physica D* 84(3–4): 476–493.

Priestley MB (1962a) The analysis of stationary processes with mixed spectra—I. *Journal of the Royal Statistical Society, Series B* 24(1): 215–233.

Priestley MB (1962b) Analysis of stationary processes with mixed spectra—II. *Journal of the Royal Statistical Society, Series B* 24(2): 511–529.

Priestley MB (1981) *Spectral Analysis and Time Series.* Academic Press, London, 890 pp.

Priestley MB (1988) *Non-linear and Non-stationary Time Series Analysis.* Academic Press, London, 237 pp.

Priestley MB (1996) Wavelets and time-dependent spectral analysis. *Journal of Time Series Analysis* 17(1): 85–103.

Priestley MB (1997) Detection of periodicities. In: Subba Rao T, Priestley MB, Lessi O (Eds) *Applications of Time Series Analysis in Astronomy and Meteorology.* Chapman and Hall, London, pp 65–88.

Priestley MB, Chao MT (1972) Non-parametric function fitting. *Journal of the Royal Statistical Society, Series B* 34(3): 385–392.

Prieto GA, Parker RL, Vernon III FL (2009) A Fortran 90 library for multitaper spectrum analysis. *Computers and Geosciences* 35(8): 1701–1710.

Prieto GA, Thomson DJ, Vernon FL, Shearer PM, Parker RL (2007) Confidence intervals for earthquake source parameters. *Geophysical Journal International* 168(3): 1227–1234.

Prokopenko AA, Hinnov LA, Williams DF, Kuzmin MI (2006) Orbital forcing of continental climate during the Pleistocene: A complete astronomically tuned climatic record from Lake Baikal, SE Siberia. *Quaternary Science Reviews* 25(23–24): 3431–3457.

Prueher LM, Rea DK (2001) Volcanic triggering of late Pliocene glaciation: Evidence from the flux of volcanic glass and ice-rafted debris to the North Pacific Ocean. *Palaeogeography, Palaeoclimatology, Palaeoecology* 173(3–4): 215–230.

Pujol N, Neppel L, Sabatier R (2007) Regional tests for trend detection in maximum precipitation series in the French Mediterranean region. *Hydrological Sciences Journal* 52(5): 956–973.

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

Pyper BJ, Peterman RM (1998) Comparison of methods to account for autocorrelation in correlation analyses of fish data. *Canadian Journal of Fisheries and Aquatic Sciences* 55(9): 2127–2140. [Corrigendum: 1998 Vol. 55(12): 2710]

Quinn BG (1989) Estimating the number of terms in a sinusoidal regression. *Journal of Time Series Analysis* 10(1): 71–75.

Quinn BG, Hannan EJ (2001) *The Estimation and Tracking of Frequency*. Cambridge University Press, Cambridge, 266 pp.

Rahmstorf S (2003) Timing of abrupt climate change: A precise clock. *Geophysical Research Letters* 30(10): 1510. [doi:10.1029/2003GL017115]

Ramesh NI, Davison AC (2002) Local models for exploratory analysis of hydrological extremes. *Journal of Hydrology* 256(1–2): 106–119.

Ramsey CB (2008) Deposition models for chronological records. *Quaternary Science Reviews* 27(1–2): 42–60.

Randall DA, Wood RA, Bony S, Colman R, Fichefet T, Fyfe J, Kattsov V, Pitman A, Shukla J, Srinivasan J, Stouffer RJ, Sumi A, Taylor KE (2007) Climate models and their evaluation. In: Solomon S, Qin D, Manning M, Marquis M, Averyt K, Tignor MMB, Miller Jr HL, 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, pp 589–662.

Rao AR, Hamed KH (2000) *Flood Frequency Analysis*. CRC Press, Boca Raton, FL, 350 pp.

Raymo ME (1997) The timing of major climate terminations. *Paleoceanography* 12(4): 577–585.

Raymo ME, Huybers P (2008) Unlocking the mysteries of the ice ages. *Nature* 451(7176): 284–285.

Raynaud D, Jouzel J, Barnola JM, Chappellaz J, Delmas RJ, Lorius C (1993) The ice record of greenhouse gases. *Science* 259(5097): 926–934.

Reed BC (1989) Linear least-squares fits with errors in both coordinates. *American Journal of Physics* 57(7): 642–646. [Corrigendum: 1990 Vol. 58(2): 189]

Reed BC (1992) Linear least-squares fits with errors in both coordinates. II: Comments on parameter variances. *American Journal of Physics* 60(1): 59–62.

Reimer PJ, Baillie MGL, Bard E, Bayliss A, Beck JW, Bertrand CJH, Blackwell PG, Buck CE, Burr GS, Cutler KB, Damon PE, Edwards RL, Fairbanks RG, Friedrich M, Guilderson TP, Hogg AG, Hughen KA, Kromer B, McCormac G, Manning S, Ramsey CB, Reimer RW, Remmele S, Southon JR, Stuiver M, Talamo S, Taylor FW, van der Plicht J, Weyhenmeyer CE (2004) INTCAL04 terrestrial radiocarbon age calibration, 0–26 cal kyr BP. *Radiocarbon* 46(3): 1029–1058.

Reinsel GC (2002) Trend analysis of upper stratospheric Umkehr ozone data for evidence of turnaround. *Geophysical Research Letters* 29(10): 1451. [doi:10.1029/2002GL014716]

Reinsel GC, Miller AJ, Weatherhead EC, Flynn LE, Nagatani RM, Tiao GC, Wuebbles DJ (2005) Trend analysis of total ozone data for turnaround and dynamical contributions. *Journal of Geophysical Research* 110(D16): D16306. [doi:10.1029/2004JD004662]

Reinsel GC, Weatherhead EC, Tiao GC, Miller AJ, Nagatani RM, Wuebbles DJ, Flynn LE (2002) On detection of turnaround and recovery in trend for ozone. *Journal of Geophysical Research* 107(D10): 4078. [doi:10.1029/2001JD000500]

Reis Jr DS, Stedinger JR (2005) Bayesian MCMC flood frequency analysis with historical information. *Journal of Hydrology* 313(1–2): 97–116.

Reiss R-D, Thomas M (1997) *Statistical Analysis of Extreme Values.* Birkhäuser, Basel, 316 pp.

Resnick SI (1987) *Extreme Values, Regular Variation, and Point Processes.* Springer, New York, 320 pp.

Rimbu N, Lohmann G, Lorenz SJ, Kim JH, Schneider RR (2004) Holocene climate variability as derived from alkenone sea surface temperature and coupled ocean–atmosphere model experiments. *Climate Dynamics* 23(2): 215–227.

Rind D (2002) The Sun's role in climate variations. *Science* 296(5568): 673–677.

Ripley BD, Thompson M (1987) Regression techniques for the detection of analytical bias. *Analyst* 112(4): 377–383.

Ritson D (2004) Comment on "Global climate models violate scaling of the observed atmospheric variability." *Physical Review Letters* 92(15): 159803. [doi:10.1103/PhysRevLett.92.159803]

Roberts DH, Lehár J, Dreher JW (1987) Time series analysis with CLEAN. I. Derivation of a spectrum. *The Astronomical Journal* 93(4): 968–989.

Robinson PM (1977) Estimation of a time series model from unequally spaced data. *Stochastic Processes and their Applications* 6(1): 9–24.

Robinson PM (Ed) (2003) *Time Series with Long Memory.* Oxford University Press, Oxford, 382 pp.

Robock A (2000) Volcanic eruptions and climate. *Reviews of Geophysics* 38(2): 191–219.

Rodionov SN (2004) A sequential algorithm for testing climate regime shifts. *Geophysical Research Letters* 31(9): L09204. [doi:10.1029/2004GL019448]

Rodionov SN (2006) Use of prewhitening in climate regime shift detection. *Geophysical Research Letters* 33(12): L12707. [doi:10.1029/2006GL025904]

Rodó X, Baert E, Comín FA (1997) Variations in seasonal rainfall in southern Europe during the present century: Relationships with the North Atlantic Oscillation and the El Niño–Southern Oscillation. *Climate Dynamics* 13(4): 275–284.

Rodriguez RN (1982) Correlation. In: Kotz S, Johnson NL, Read CB (Eds) *Encyclopedia of statistical sciences*, volume 2. Wiley, New York, pp 193–204.

Rodriguez-Iturbe I, Rinaldo A (1997) *Fractal River Basins: Chance and Self-Organization.* Cambridge University Press, Cambridge, 547 pp.

Roe GH, Steig EJ (2004) Characterization of millennial-scale climate variability. *Journal of Climate* 17(10): 1929–1944.

Rohling EJ, Pälike H (2005) Centennial-scale climate cooling with a sudden cold event around 8,200 years ago. *Nature* 434(7036): 975–979.

Röthlisberger R, Bigler M, Hutterli M, Sommer S, Stauffer B, Junghans HG, Wagenbach D (2000) Technique for continuous high-resolution analysis of trace substances in firn and ice cores. *Environmental Science & Technology* 34(2): 338–342.

Röthlisberger R, Mudelsee M, Bigler M, de Angelis M, Fischer H, Hansson M, Lambert F, Masson-Delmotte V, Sime L, Udisti R, Wolff EW (2008) The southern hemisphere at glacial terminations: Insights from the Dome C ice core. *Climate of the Past* 4(4): 345–356.

Rothman DH (2001) Global biodiversity and the ancient carbon cycle. *Proceedings of the National Academy of Sciences of the United States of America* 98(8): 4305–4310.

Rothman DH (2002) Atmospheric carbon dioxide levels for the last 500 million years. *Proceedings of the National Academy of Sciences of the United States of America* 99(7): 4167–4171.

Rousseeuw PJ, Leroy AM (1987) *Robust Regression and Outlier Detection.* Wiley, New York, 329 pp.

Rubin DB (1976) Inference and missing data (with discussion). *Biometrika* 63(3): 581–592.

Ruddiman WF, Raymo ME (2003) A methane-based time scale for Vostok ice. *Quaternary Science Reviews* 22(2–4): 141–155.

Ruelle D (1990) Deterministic chaos: The science and the fiction. *Proceedings of the Royal Society of London, Series A* 427(1873): 241–248.

Ruiz NE, Vargas WM (1998) 500 hPa vorticity analyses over Argentina: Their climatology and capacity to distinguish synoptic-scale precipitation. *Theoretical and Applied Climatology* 60(1–4): 77–92.

Ruppert D, Carroll RJ (1980) Trimmed least squares estimation in the linear model. *Journal of the American Statistical Association* 75(372): 828–838.

Rust HW, Maraun D, Osborn TJ (2009) Modelling seasonality in extreme precipitation: A UK case study. *European Physical Journal Special Topics* 174(1): 99–111.

Rust HW, Mestre O, Venema VKC (2008) Fewer jumps, less memory: Homogenized temperature records and long memory. *Journal of Geophysical Research* 113(D19): D19110. [doi:10.1029/2008JD009919]

Rutherford S, D'Hondt S (2000) Early onset and tropical forcing of 100,000-year Pleistocene glacial cycles. *Nature* 408(6808): 72–75.

Rützel E (1976) Zur Ausgleichsrechnung: Die Unbrauchbarkeit von Linearisierungsmethoden beim Anpassen von Potenz- und Exponentialfunktionen. *Archiv für Psychologie* 128(3–4): 316–322.

Rybski D, Bunde A, Havlin S, von Storch H (2006) Long-term persistence in climate and the detection problem. *Geophysical Research Letters* 33(6): L06718. [doi:10.1029/2005GL025591]

Saltzman B (2002) *Dynamical Paleoclimatology: Generalized Theory of Global Climate Change.* Academic Press, San Diego, 354 pp.

Saltzman B, Verbitsky MY (1993) Multiple instabilities and modes of glacial rhythmicity in the Plio–Pleistocene: A general theory of late Cenozoic climatic change. *Climate Dynamics* 9(1): 1–15.

Sankarasubramanian A, Lall U (2003) Flood quantiles in a changing climate: Seasonal forecasts and causal relations. *Water Resources Research* 39(5): 1134. [doi:10.1029/2002WR001593]

Scafetta N (2008) Comment on "Heat capacity, time constant, and sensitivity of Earth's climate system" by S. E. Schwartz. *Journal of Geophysical Research* 113(D15): D15104. [doi:10.1029/2007JD009586]

Scafetta N, West BJ (2007) Phenomenological reconstructions of the solar signature in the northern hemisphere surface temperature records since 1600. *Journal of Geophysical Research* 112(D24): D24S03. [doi:10.1029/2007JD008437]

Scargle JD (1982) Studies in astronomical time series analysis. II. Statistical aspects of spectral analysis of unevenly spaced data. *The Astrophysical Journal* 263(2): 835–853.

Scargle JD (1989) Studies in astronomical time series analysis. III. Fourier transforms, autocorrelation functions, and cross-correlation functions of unevenly spaced data. *The Astrophysical Journal* 343(2): 874–887.

Scargle JD (1997) Wavelet methods in astronomical time series analysis. In: Subba Rao T, Priestley MB, Lessi O (Eds) *Applications of Time Series Analysis in Astronomy and Meteorology.* Chapman and Hall, London, pp 226–248.

Schiffelbein P (1984) Effect of benthic mixing on the information content of deep-sea stratigraphical signals. *Nature* 311(5987): 651–653.

Schiffelbein P (1985) Extracting the benthic mixing impulse response function: A constrained deconvolution technique. *Marine Geology* 64(3–4): 313–336.

Schrage L (1979) A more portable Fortran random number generator. *ACM Transactions on Mathematical Software* 5(2): 132–138.

Schreiber T, Schmitz A (2000) Surrogate time series. *Physica D* 142(3–4): 346–382.

Schulz M (1996) *SPECTRUM und ENVELOPE: Computerprogramme zur Spektralanalyse nicht äquidistanter paläoklimatischer Zeitreihen.* Sonderforschungsbereich 313, University of Kiel, Kiel, 131 pp. [Report No. 65]

Schulz M (2002) On the 1470-year pacing of Dansgaard–Oeschger warm events. *Paleoceanography* 17(2): 1014. [doi:10.1029/2000PA000571]

Schulz M, Berger WH, Sarnthein M, Grootes PM (1999) Amplitude variations of 1470-year climate oscillations during the last 100,000 years linked to fluctuations of continental ice mass. *Geophysical Research Letters* 26(22): 3385–3388.

Schulz M, Mudelsee M (2002) REDFIT: Estimating red-noise spectra directly from unevenly spaced paleoclimatic time series. *Computers and Geosciences* 28(3): 421–426.

Schulz M, Paul A (2002) Holocene climate variability on centennial-to-millennial time scales: 1. Climate records from the North-Atlantic realm. In: Wefer G, Berger W, Behre K-E, Jansen E (Eds) *Climate Development and History of the North Atlantic Realm.* Springer, Berlin, pp 41–54.

Schulz M, Stattegger K (1997) SPECTRUM: Spectral analysis of unevenly spaced paleoclimatic time series. *Computers and Geosciences* 23(9): 929–945.

Schulze U (1987) *Mehrphasenregression.* Akademie-Verlag, Berlin, 178 pp.

Schuster A (1898) On the investigation of hidden periodicities with application to a supposed 26 day period of meteorological phenomena. *Terrestrial Magnetism* 3(1): 13–41.

Schuster A (1906) On the periodicities of sunspots. *Philosophical Transactions of the Royal Society of London, Series A* 206: 69–100.

Schwartz SE (2007) Heat capacity, time constant, and sensitivity of Earth's climate system. *Journal of Geophysical Research* 112(D24): D24S05. [doi:10.1029/2007JD008746]

Schwartz SE (2008) Reply to comments by G. Foster et al., R. Knutti et al., and N. Scafetta on "Heat capacity, time constant, and sensitivity of Earth's climate system." *Journal of Geophysical Research* 113(D15): D15105. [doi:10.1029/2008JD009872]

Schwarzacher W (1964) An application of statistical time-series analysis of a limestone–shale sequence. *Journal of Geology* 72(2): 195–213.

Schwarzacher W (1975) *Sedimentation Models and Quantitative Stratigraphy.* Elsevier, Amsterdam, 382 pp.

Schwarzacher W (1991) Milankovitch cycles and the measurement of time. In: Einsele G, Ricken W, Seilacher A (Eds) *Cycles and Events in Stratigraphy.* Springer, Berlin, pp 855–863.

Schwarzacher W (1993) *Cyclostratigraphy and the Milankovitch Theory.* Elsevier, Amsterdam, 225 pp.

Schwarzacher W (1994) Searching for long cycles in short sections. *Mathematical Geology* 26(7): 759–768.

Schweingruber FH (1988) *Tree Rings: Basics and Applications of Dendrochronology.* Kluwer, Dordrecht, 276 pp.

Scott DW (1979) On optimal and data-based histograms. *Biometrika* 66(3): 605–610.

Seber GAF, Wild CJ (1989) *Nonlinear Regression.* Wiley, New York, 768 pp.

Seibold E, Berger WH (1993) *The Sea Floor.* Second edition. Springer, Berlin, 356 pp.

Seidel DJ, Lanzante JR (2004) An assessment of three alternatives to linear trends for characterizing global atmospheric temperature changes. *Journal of Geophysical Research* 109(D14): D14108. [doi:10.1029/2003JD004414]

Seleshi Y, Demarée GR, Delleur JW (1994) Sunspot numbers as a possible indicator of annual rainfall at Addis Ababa, Ethiopia. *International Journal of Climatology* 14(8): 911–923.

Selley RC, Cocks LRM, Plimer IR (Eds) (2005) *Encyclopedia of Geology*, volume 1–5. Elsevier, Amsterdam, 3297 pp.

Sen A, Srivastava M (1990) *Regression Analysis: Theory, Methods, and Applications.* Springer, New York, 347 pp.

Sercl P, Stehlik J (2003) The August 2002 flood in the Czech Republic. *Geophysical Research Abstracts* 5: 12404.

Shackleton N (1967) Oxygen isotope analyses and Pleistocene temperatures reassessed. *Nature* 215(5096): 15–17.

Shackleton NJ (2000) The 100,000-year ice-age cycle identified and found to lag temperature, carbon dioxide, and orbital eccentricity. *Science* 289(5486): 1897–1902.

Shackleton NJ, Backman J, Zimmerman H, Kent DV, Hall MA, Roberts DG, Schnitker D, Baldauf JG, Desprairies A, Homrighausen R, Huddlestun P, Keene JB, Kaltenback AJ, Krumsiek KAO, Morton AC, Murray JW, Westberg-Smith J (1984) Oxygen isotope calibration of the onset of ice-rafting and history of glaciation in the North Atlantic region. *Nature* 307(5952): 620–623.

Shackleton NJ, Berger AL, Peltier WR (1990) An alternative astronomical calibration of the lower Pleistocene timescale based on ODP Site 677. *Transactions of the Royal Society of Edinburgh, Earth Sciences* 81(4): 251–261.

Shackleton NJ, Crowhurst S, Hagelberg T, Pisias NG, Schneider DA (1995a) A new late Neogene time scale: Application to Leg 138 sites. In: Pisias NG, Mayer LA, Janecek TR, Palmer-Julson A, van Andel TH (Eds) *Proc. ODP, Sci. Results*, volume 138. Ocean Drilling Program, College Station, TX, pp 73–101.

Shackleton NJ, Fairbanks RG, Chiu T-c, Parrenin F (2004) Absolute calibration of the Greenland time scale: Implications for Antarctic time scales and for Δ^{14}C. *Quaternary Science Reviews* 23(14–15): 1513–1522.

Shackleton NJ, Hall MA (1984) Oxygen and carbon isotope stratigraphy of Deep Sea Drilling Project hole 552a: Plio–Pleistocene glacial history. In: Roberts DG, Schnitker D, Backman J, Baldauf JG, Desprairies A, Homrighausen R, Huddlestun P, Kaltenback AJ, Krumsiek KAO, Morton AC, Murray JW, Westberg-Smith J, Zimmerman HB (Eds) *Init. Repts. DSDP*, volume 81. U.S. Govt. Printing Office, Washington, DC, pp 599–609.

Shackleton NJ, Hall MA, Pate D (1995b) Pliocene stable isotope stratigraphy of Site 846. In: Pisias NG, Mayer LA, Janecek TR, Palmer-Julson A, van Andel TH (Eds) *Proc. ODP, Sci. Results*, volume 138. Ocean Drilling Program, College Station, TX, pp 337–355.

Shaman P, Stine RA (1988) The bias of autoregressive coefficient estimators. *Journal of the American Statistical Association* 83(403): 842–848.

Shapiro HS, Silverman RA (1960) Alias-free sampling of random noise. *Journal of the Society for Industrial and Applied Mathematics* 8(2): 225–248.

Shenton LR, Johnson WL (1965) Moments of a serial correlation coefficient. *Journal of the Royal Statistical Society, Series B* 27(2): 308–320.

Sherman M, Speed Jr FM, Speed FM (1998) Analysis of tidal data via the blockwise bootstrap. *Journal of Applied Statistics* 25(3): 333–340.

Shumway RH, Stoffer DS (2006) *Time Series Analysis and Its Applications: With R Examples.* Second edition. Springer, New York, 575 pp.

Siegel AF (1980) Testing for periodicity in a time series. *Journal of the American Statistical Association* 75(370): 345–348.

Siegenthaler U, Stocker TF, Monnin E, Lüthi D, Schwander J, Stauffer B, Raynaud D, Barnola J-M, Fischer H, Masson-Delmotte V, Jouzel J (2005) Stable carbon cycle–climate relationship during the late Pleistocene. *Science* 310(5752): 1313–1317.

Sievers W (1996) Standard and bootstrap confidence intervals for the correlation coefficient. *British Journal of Mathematical and Statistical Psychology* 49(2): 381–396.

Silverman BW (1982) Kernel density estimation using the Fast Fourier Transform. *Applied Statistics* 31(1): 93–99.

Silverman BW (1986) *Density Estimation for Statistics and Data Analysis.* Chapman and Hall, London, 175 pp.

Silverman BW (1999) Wavelets in statistics: Beyond the standard assumptions. *Philosophical Transactions of the Royal Society of London, Series A* 357(1760): 2459–2473.

Silverman BW, Young GA (1987) The bootstrap: To smooth or not to smooth? *Biometrika* 74(3): 469–479.

Simonoff JS (1996) *Smoothing Methods in Statistics.* Springer, New York, 338 pp.

Singer BS, Pringle MS (1996) Age and duration of the Matuyama–Brunhes geomagnetic polarity reversal from ^{40}Ar/^{39}Ar incremental heating analyses of lavas. *Earth and Planetary Science Letters* 139(1–2): 47–61.

Singh K (1981) On the asymptotic accuracy of Efron's bootstrap. *The Annals of Statistics* 9(6): 1187–1195.

Slepian D (1978) Prolate spheroidal wave functions, Fourier analysis, and uncertainty—V: The discrete case. *Bell System Technical Journal* 57(5): 1371–1430.

Smith AFM (1975) A Bayesian approach to inference about a change-point in a sequence of random variables. *Biometrika* 62(2): 407–416.

Smith RL (1985) Maximum likelihood estimation in a class of nonregular cases. *Biometrika* 72(1): 67–90.

Smith RL (1987) Estimating tails of probability distributions. *The Annals of Statistics* 15(3): 1174–1207.

Smith RL (1989) Extreme value analysis of environmental time series: An application to trend detection in ground-level ozone (with discussion). *Statistical Science* 4(4): 367–393.

Smith RL (2004) Statistics of extremes, with applications in environment, insurance, and finance. In: Finkenstädt B, Rootzén H (Eds) *Extreme Values in Finance, Telecommunications, and the Environment.* Chapman and Hall, Boca Raton, FL, pp 1–78.

Smith RL, Shively TS (1994) *A Point Process Approach to Modeling Trends in Tropospheric Ozone Based on Exceedances of a High Threshold.* National Institute of Statistical Sciences, Research Triangle Park, NC, 20 pp. [Technical Report Number 16]

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

Smith RL, Shively TS (1995) Point process approach to modeling trends in tropospheric ozone based on exceedances of a high threshold. *Atmospheric Environment* 29(23): 3489–3499.

Smith RL, Tawn JA, Coles SG (1997) Markov chain models for threshold exceedances. *Biometrika* 84(2): 249–268.

Smith RL, Tebaldi C, Nychka D, Mearns LO (2009) Bayesian modeling of uncertainty in ensembles of climate models. *Journal of the American Statistical Association* 104(485): 97–116.

Sokal A, Bricmont J (1998) *Intellectual Impostures*. Profile Books, London, 274 pp.

Solanki SK, Usoskin IG, Kromer B, Schüssler M, Beer J (2004) Unusual activity of the Sun during recent decades compared to the previous 11,000 years. *Nature* 431(7012): 1084–1087.

Solomon S, Qin D, Manning M, Marquis M, Averyt K, Tignor MMB, Miller Jr HL, Chen Z (Eds) (2007) *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, 996 pp.

Solow AR (1987) Testing for climate change: An application of the two-phase regression model. *Journal of Climate and Applied Meteorology* 26(10): 1401–1405.

Solow AR (1991) An exploratory analysis of the occurrence of explosive volcanism in the northern hemisphere, 1851–1985. *Journal of the American Statistical Association* 86(413): 49–54.

Spall JC (Ed) (1988) *Bayesian Analysis of Time Series and Dynamic Models*. Marcel Dekker, New York, 536 pp.

Spearman C (1904) The proof and measurement of association between two things. *American Journal of Psychology* 15(1): 72–101.

Spearman C (1906) 'Footrule' for measuring correlation. *British Journal of Psychology* 2(1): 89–108.

Spötl C, Mangini A, Richards DA (2006) Chronology and paleoenvironment of Marine Isotope Stage 3 from two high-elevation speleothems, Austrian Alps. *Quaternary Science Reviews* 25(9–10): 1127–1136.

Squire PT (1990) Comment on "Linear least-squares fits with errors in both coordinates," by B. C. Reed [Am. J. Phys. 57, 642–646 (1989)]. *American Journal of Physics* 58(12): 1209.

Stainforth DA, Allen MR, Tredger ER, Smith LA (2007) Confidence, uncertainty and decision-support relevance in climate predictions. *Philosophical Transactions of the Royal Society of London, Series A* 365(1857): 2145–2161.

Stanley SM (1989) *Earth and life through time*. Second edition. Freeman, New York, 689 pp.

Stattegger K (1986) Die Beziehungen zwischen Sediment und Hinterland: Mathematisch-statistische Modelle aus Schwermineraldaten rezenter fluviatiler und fossiler Sedimente. *Jahrbuch der Geologischen Bundesanstalt* 128(3–4): 449–512.

Stedinger JR, Crainiceanu CM (2001) Climate variability and flood-risk analysis. In: Haimes YY, Moser DA, Stakhiv EZ (Eds) *Risk-Based Decision Making in Water Resources IX*. American Society of Civil Engineers, Reston, VA, pp 77–86.

Steele JH, Thorpe SA, Turekian KK (Eds) (2001) *Encyclopedia of Ocean Sciences*, volume 1–6. Academic Press, San Diego, 3399 pp.

Steffensen JP, Andersen KK, Bigler M, Clausen HB, Dahl-Jensen D, Fischer H, Goto-Azuma K, Hansson M, Johnsen SJ, Jouzel J, Masson-Delmotte V, Popp T, Rasmussen SO, Röthlisberger R, Ruth U, Stauffer B, Siggaard-Andersen M-L, Sveinbjörnsdóttir ÁE, Svensson A, White JWC (2008) High-resolution Greenland ice core data show abrupt climate change happens in few years. *Science* 321(5889): 680–684.

Stensrud DJ (2007) *Parameterization Schemes: Keys to Understanding Numerical Weather Prediction Models*. Cambridge University Press, Cambridge, 459 pp.

Stephenson DB, Pavan V, Bojariu R (2000) Is the North Atlantic Oscillation a random walk? *International Journal of Climatology* 20(1): 1–18.

Stern DI, Kaufmann RK (1999) Econometric analysis of global climate change. *Environmental Modelling and Software* 14(6): 597–605.

Stern DI, Kaufmann RK (2000) Detecting a global warming signal in hemispheric temperature series: A structural time series analysis. *Climatic Change* 47(4): 411–438.

Stine RA (1987) Estimating properties of autoregressive forecasts. *Journal of the American statistical association* 82(400): 1072–1078.

Stine RA (1997) Nonlinear time series. In: Kotz S, Read CB, Banks DL (Eds) *Encyclopedia of statistical sciences*, volume U1. Wiley, New York, pp 430–437.

Storey JD (2007) The optimal discovery procedure: A new approach to simultaneous significance testing. *Journal of the Royal Statistical Society, Series B* 69(3): 347–368.

Stott PA, Tett SFB, Jones GS, Allen MR, Mitchell JFB, Jenkins GJ (2000) External control of 20th century temperature by natural and anthropogenic forcings. *Science* 290(5499): 2133–2137.

Strupczewski WG, Kaczmarek Z (2001) Non-stationary approach to at-site flood frequency modelling II. Weighed least squares estimation. *Journal of Hydrology* 248(1–4): 143–151.

Strupczewski WG, Singh VP, Feluch W (2001a) Non-stationary approach to at-site flood frequency modelling I. Maximum likelihood estimation. *Journal of Hydrology* 248(1-4): 123–142.

Strupczewski WG, Singh VP, Mitosek HT (2001b) Non-stationary approach to at-site flood frequency modelling. III. Flood analysis of Polish rivers. *Journal of Hydrology* 248(1–4): 152–167.

Stuart A (1983) Kendall's tau. In: Kotz S, Johnson NL, Read CB (Eds) *Encyclopedia of statistical sciences*, volume 4. Wiley, New York, pp 367–369.

Stuiver M, Braziunas TF (1993) Sun, ocean, climate and atmospheric $^{14}CO_2$: An evaluation of causal and spectral relationships. *The Holocene* 3(4): 289–305.

Stuiver M, Reimer PJ, Bard E, Beck JW, Burr GS, Hughen KA, Kromer B, McCormac G, van der Plicht J, Spurk M (1998) INTCAL98 radiocarbon age calibration, 24,000–0 cal BP. *Radiocarbon* 40(3): 1041–1083.

Subba Rao T, Gabr MM (1984) *An Introduction to Bispectral Analysis and Bilinear Time Series Models*. Springer, New York, 280 pp.

Suess HE (1965) Secular variations of the cosmic-ray-produced carbon 14 in the atmosphere and their interpretations. *Journal of Geophysical Research* 70(23): 5937–5952.

Suess HE, Linick TW (1990) The ^{14}C record in bristlecone pine wood of the last 8000 years based on the dendrochronology of the late C. W. Ferguson. *Philosophical Transactions of the Royal Society of London, Series A* 330(1615): 403–412.

Sura P, Newman M, Penland C, Sardeshmukh P (2005) Multiplicative noise and non-Gaussianity: A paradigm for atmospheric regimes? *Journal of the Atmospheric Sciences* 62(5): 1391–1409.

Svensmark H, Friis-Christensen E (1997) Variation of cosmic ray flux and global cloud coverage—a missing link in solar–climate relationships. *Journal of Atmospheric and Solar-Terrestrial Physics* 59(11): 1225–1232.

Sweldens W, Schröder P (2000) Building your own wavelets at home. In: Klees R, Haagmans R (Eds) *Wavelets in the Geosciences*. Springer, Berlin, pp 72–130.

Tachikawa K, Vidal L, Sonzogni C, Bard E (2009) Glacial/interglacial sea surface temperature changes in the southwest Pacific over the past 360 ka. *Quaternary Science Reviews* 28(13–14): 1160–1170.

Talkner P, Weber RO (2000) Power spectrum and detrended fluctuation analysis: Application to daily temperatures. *Physical Review E* 62(1): 150–160.

Tate RF (1954) Correlation between a discrete and a continuous variable. Point-biserial correlation. *Annals of Mathematical Statistics* 25(3): 603–607.

Taylor RE (1987) *Radiocarbon Dating: An Archaeological Perspective*. Academic Press, Orlando, FL, 212 pp.

Tebaldi C, Sansó B (2009) Joint projections of temperature and precipitation change from multiple climate models: A hierarchical Bayesian approach. *Journal of the Royal Statistical Society, Series A* 172(1): 83–106.

Theiler J, Eubank S, Longtin A, Galdrikian B, Farmer JD (1992) Testing for nonlinearity in time series: The method of surrogate data. *Physica D* 58(1–4): 77–94.

Thiébaux HJ, Zwiers FW (1984) The interpretation and estimation of effective sample size. *Journal of Climate and Applied Meteorology* 23(5): 800–811.

Thompson DWJ, Kennedy JJ, Wallace JM, Jones PD (2008) A large discontinuity in the mid-twentieth century in observed global-mean surface temperature. *Nature* 453(7195): 646–649.

Thomson DJ (1982) Spectrum estimation and harmonic analysis. *Proceedings of the IEEE* 70(9): 1055–1096.

Thomson DJ (1990a) Quadratic-inverse spectrum estimates: Applications to palaeoclimatology. *Philosophical Transactions of the Royal Society of London, Series A* 332(1627): 539–597.

Thomson DJ (1990b) Time series analysis of Holocene climate data. *Philosophical Transactions of the Royal Society of London, Series A* 330(1615): 601–616.

Thomson DJ (1997) Dependence of global temperatures on atmospheric CO_2 and solar irradiance. *Proceedings of the National Academy of Sciences of the United States of America* 94(16): 8370–8377.

Thomson DJ, Chave AD (1991) Jackknifed error estimates for spectra, coherences, and transfer functions. In: Haykin S (Ed) *Advances in Spectrum Analysis and Array Processing*, volume 1. Prentice-Hall, Englewood Cliffs, NJ, pp 58–113.

Thomson J, Cook GT, Anderson R, MacKenzie AB, Harkness DD, McCave IN (1995) Radiocarbon age offsets in different-sized carbonate components of deep-sea sediments. *Radiocarbon* 37(2): 91–101.

Thomson PJ, Robinson PM (1996) Estimation of second-order properties from jittered time series. *Annals of the Institute of Statistical Mathematics* 48(1): 29–48.

Thywissen K (2006) *Components of Risk: A Comparative Glossary*. United Nations University, Institute for Environment and Human Security, Bonn, 48 pp. [Studies of the University: Research, Counsel, Education No. 2]

Tjøstheim D, Paulsen J (1983) Bias of some commonly-used time series estimates. *Biometrika* 70(2): 389–399.

Tol RSJ, de Vos AF (1993) Greenhouse statistics—time series analysis. *Theoretical and Applied Climatology* 48(2–3): 63–74.

Tol RSJ, de Vos AF (1998) A Bayesian statistical analysis of the enhanced greenhouse effect. *Climatic Change* 38(1): 87–112.

Tomé AR, Miranda PMA (2004) Piecewise linear fitting and trend changing points of climate parameters. *Geophysical Research Letters* 31(2): L02207. [doi:10.1029/2003GL019100]

Tomé AR, Miranda PMA (2005) Continuous partial trends and low-frequency oscillations of time series. *Nonlinear Processes in Geophysics* 12(4): 451–460.

Tong H (1990) *Non-linear Time Series.* Clarendon Press, Oxford, 564 pp.

Tong H (1992) Some comments on a bridge between nonlinear dynamicists and statisticians. *Physica D* 58(1–4): 299–303.

Tong H (1995) A personal overview of non-linear time series analysis from a chaos perspective (with discussion). *Scandinavian Journal of Statistics* 22(4): 399–445.

Tong H, Lim KS (1980) Threshold autoregression, limit cycles and cyclical data (with discussion). *Journal of the Royal Statistical Society, Series B* 42(3): 245–292.

Tong H, Yeung I (1991) Threshold autoregressive modelling in continuous time. *Statistica Sinica* 1(2): 411–430.

Torrence C, Compo GP (1998) A practical guide to wavelet analysis. *Bulletin of the American Meteorological Society* 79(1): 61–78.

Trauth MH (1998) TURBO: A dynamic-probabilistic simulation to study the effects of bioturbation on paleoceanographic time series. *Computers and Geosciences* 24(5): 433–441.

Trauth MH (2007) *MATLAB® Recipes for Earth Sciences.* Second edition. Springer, Berlin, 288 pp.

Trauth MH, Larrasoaña JC, Mudelsee M (2009) Trends, rhythms and events in Plio–Pleistocene African climate. *Quaternary Science Reviews* 28(5–6): 399–411.

Traverse A (2007) *Paleopalynology.* Second edition. Springer, Dordrecht, 813 pp.

Trenberth KE (1984a) Some effects of finite sample size and persistence on meteorological statistics. Part I: Autocorrelations. *Monthly Weather Review* 112(12): 2359–2368.

Trenberth KE (1984b) Some effects of finite sample size and persistence on meteorological statistics. Part II: Potential predictability. *Monthly Weather Review* 112(12): 2369–2379.

Triacca U (2001) On the use of Granger causality to investigate the human influence on climate. *Theoretical and Applied Climatology* 69(3–4): 137–138.

Triacca U (2007) Granger causality and contiguity between stochastic processes. *Physics Letters A* 362(4): 252–255.

Tsay RS (1988) Outliers, level shifts, and variance changes in time series. *Journal of Forecasting* 7(1): 1–20.

Tsonis AA, Elsner JB (1995) Testing for scaling in natural forms and observables. *Journal of Statistical Physics* 81(5–6): 869–880.

Tsonis AA, Elsner JB (Eds) (2007) *Nonlinear Dynamics in Geosciences.* Springer, New York, 604 pp.

Tukey JW (1977) *Exploratory Data Analysis.* Addison-Wesley, Reading, MA, 688 pp.

Udelhofen PM, Cess RD (2001) Cloud cover variations over the United States: An influence of cosmic rays or solar variability? *Geophysical Research Letters* 28(13): 2617–2620.

Ulbrich U, Brücher T, Fink AH, Leckebusch GC, Krüger A, Pinto JG (2003a) The central European floods of August 2002: Part 1 – Rainfall periods and flood development. *Weather* 58(10): 371–377.

Ulbrich U, Brücher T, Fink AH, Leckebusch GC, Krüger A, Pinto JG (2003b) The central European floods of August 2002: Part 2 – Synoptic causes and considerations with respect to climatic change. *Weather* 58(11): 434–442.

Urban FE, Cole JE, Overpeck JT (2000) Influence of mean climate change on climate variability from a 155-year tropical Pacific coral record. *Nature* 407(6807): 989–993.

Usoskin IG, Marsh N, Kovaltsov GA, Mursula K, Gladysheva OG (2004) Latitudinal dependence of low cloud amount on cosmic ray induced ionization. *Geophysical Research Letters* 31(16): L16109. [doi:10.1029/2004GL019507]

van der Linden P, Mitchell JFB (Eds) (2009) *ENSEMBLES: Climate change and its impacts at seasonal, decadal and centennial timescales.* Met Office Hadley Centre, Exeter, 160 pp.

van de Wiel MA, Di Bucchianico A (2001) Fast computation of the exact null distribution of Spearman's ρ and Page's L statistic for samples with and without ties. *Journal of Statistical Planning and Inference* 92(1–2): 133–145.

VanDongen HPA, Olofsen E, VanHartevelt JH, Kruyt EW (1997) *Periodogram analysis of unequally spaced data: The Lomb method.* Leiden University, Leiden, 66 pp. [ISBN 9080385115]

Van Dongen HPA, Olofsen E, VanHartevelt JH, Kruyt EW (1999) A procedure of multiple period searching in unequally spaced time-series with the Lomb–Scargle method. *Biological Rhythm Research* 30(2): 149–177.

Van Montfort MAJ, Witter JV (1985) Testing exponentiality against generalised Pareto distribution. *Journal of Hydrology* 78(3–4): 305–315.

Vecchi GA, Knutson TR (2008) On estimates of historical North Atlantic tropical cyclone activity. *Journal of Climate* 21(14): 3580–3600.

Verdes PF (2005) Assessing causality from multivariate time series. *Physical Review E* 72(3): 026222. [doi:10.1103/PhysRevE.72.026222]

Vidakovic B (1999) *Statistical Modeling by Wavelets.* Wiley, New York, 382 pp.

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

von Weizsäcker CF (1985) *Aufbau der Physik.* Deutscher Taschenbuch Verlag, Munich, 662 pp.

Vyushin D, Bunde A, Brenner S, Havlin S, Govindan RB, Schellnhuber H-J (2004) Vjushin et al. reply. *Physical Review Letters* 92(15): 159804. [doi:10.1103/PhysRevLett.92.159804]

WAFO group (2000) *WAFO: A Matlab Toolbox for Analysis of Random Waves and Loads.* Lund Institute of Technology, Lund University, Lund, 111 pp.

Wagenbach D (1989) Environmental records in Alpine glaciers. In: Oeschger H, Langway Jr CC (Eds) *The Environmental Record in Glaciers and Ice Sheets.* Wiley, Chichester, pp 69–83.

Wagenbach D, Preunkert S, Schäfer J, Jung W, Tomadin L (1996) Northward transport of Saharan dust recorded in a deep Alpine ice core. In: Guerzoni S, Chester R (Eds) *The Impact of Desert Dust Across the Mediterranean.* Kluwer, Dordrecht, pp 291–300.

Wald A (1940) The fitting of straight lines if both variables are subject to error. *Annals of Mathematical Statistics* 11(3): 284–300.

Walden AT (1992) Asymptotic percentage points for Siegel's test statistic for compound periodicities. *Biometrika* 79(2): 438–440.

Walker GT (1914) Correlation in seasonal variations of weather, III. On the criterion for the reality of relationships or periodicities. *Memoirs of the Indian Meteorological Department* 21(9): 13–15.

Walker M (2005) *Quaternary Dating Methods.* Wiley, Chichester, 286 pp.

Wand MP, Jones MC (1995) *Kernel Smoothing.* Chapman and Hall, London, 212 pp.

Wanner H, Beer J, Bütikofer J, Crowley TJ, Cubasch U, Flückiger J, Goosse H, Grosjean M, Joos F, Kaplan JO, Küttel M, Müller SA, Prentice IC, Solomina O, Stocker TF, Tarasov P, Wagner M, Widmann M (2008) Mid- to late Holocene climate change: An overview. *Quaternary Science Reviews* 27(19–20): 1791–1828.

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

Wasserman L (2006) *All of Nonparametric Statistics.* Springer, New York, 268 pp.

Weedon GP (2003) *Time-Series Analysis and Cyclostratigraphy.* Cambridge University Press, Cambridge, 259 pp.

Weikinn C (1958) *Quellentexte zur Witterungsgeschichte Europas von der Zeitwende bis zum Jahre 1850: Hydrographie, Teil 1 (Zeitwende–1500).* Akademie-Verlag, Berlin, 531 pp.

Weikinn C (1960) *Quellentexte zur Witterungsgeschichte Europas von der Zeitwende bis zum Jahre 1850: Hydrographie, Teil 2 (1501–1600).* Akademie-Verlag, Berlin, 486 pp.

Weikinn C (1961) *Quellentexte zur Witterungsgeschichte Europas von der Zeitwende bis zum Jahre 1850: Hydrographie, Teil 3 (1601–1700).* Akademie-Verlag, Berlin, 586 pp.

Weikinn C (1963) *Quellentexte zur Witterungsgeschichte Europas von der Zeitwende bis zum Jahre 1850: Hydrographie, Teil 4 (1701–1750).* Akademie-Verlag, Berlin, 381 pp.

Weikinn C (2000) *Quellentexte zur Witterungsgeschichte Europas von der Zeitwende bis zum Jahr 1850: Hydrographie, Teil 5 (1751–1800).* Gebrüder Borntraeger, Berlin, 674 pp. [Börngen M, Tetzlaff G (Eds)]

Weikinn C (2002) *Quellentexte zur Witterungsgeschichte Europas von der Zeitwende bis zum Jahr 1850: Hydrographie, Teil 6 (1801–1850).* Gebrüder Borntraeger, Berlin, 728 pp. [Börngen M, Tetzlaff G (Eds)]

Welch PD (1967) The use of Fast Fourier Transform for the estimation of power spectra: A method based on time averaging over short, modified periodograms. *IEEE Transactions on Audio and Electroacoustics* 15(2): 70–73.

White JS (1961) Asymptotic expansions for the mean and variance of the serial correlation coefficient. *Biometrika* 48(1–2): 85–94.

Whittle P (1952) The simultaneous estimation of a time series harmonic components and covariance structure. *Trabajos de Estadística* 3(1–2): 43–57.

Wigley TML, Santer BD, Taylor KE (2000) Correlation approaches to detection. *Geophysical Research Letters* 27(18): 2973–2976.

Wilks DS (1995) *Statistical Methods in the Atmospheric Sciences.* Academic Press, San Diego, 467 pp.

Wilks DS (1997) Resampling hypothesis tests for autocorrelated fields. *Journal of Climate* 10(1): 65–82.

Wilks DS (2006) *Statistical Methods in the Atmospheric Sciences.* Second edition. Elsevier, Amsterdam, 627 pp.

Williams DA (1970) Discrimination between regression models to determine the pattern of enzyme synthesis in synchronous cell cultures. *Biometrics* 26(1): 23–32.

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

Willson RC, Hudson HS (1988) Solar luminosity variations in solar cycle 21. *Nature* 332(6167): 810–812.

Wilson RM (1997) Comment on "Downward trends in the frequency of intense Atlantic hurricanes during the past 5 decades" by C. W. Landsea et al. *Geophysical Research Letters* 24(17): 2203–2204.

Witt A, Schumann AY (2005) Holocene climate variability on millennial scales recorded in Greenland ice cores. *Nonlinear Processes in Geophysics* 12(3): 345–352.

Witte HJL, Coope GR, Lemdahl G, Lowe JJ (1998) Regression coefficients of thermal gradients in northwestern Europe during the last glacial–Holocene transition using beetle MCR data. *Journal of Quaternary Science* 13(5): 435–445.

Wolff E, Kull C, Chappellaz J, Fischer H, Miller H, Stocker TF, Watson AJ, Flower B, Joos F, Köhler P, Matsumoto K, Monnin E, Mudelsee M, Paillard D, Shackleton N (2005) Modeling past atmospheric CO_2: Results of a challenge. *Eos, Transactions of the American Geophysical Union* 86(38): 341, 345.

Wolff EW, Fischer H, Röthlisberger R (2009) Glacial terminations as southern warmings without northern control. *Nature Geoscience* 2(3): 206–209.

Woods TN, Lean J (2007) Anticipating the next decade of Sun–Earth system variations. *Eos, Transactions of the American Geophysical Union* 88(44): 457–458.

Worsley KJ (1986) Confidence regions and tests for a change-point in a sequence of exponential family random variables. *Biometrika* 73(1): 91–104.

Wu CFJ (1986) Jackknife, bootstrap and other resampling methods in regression analysis (with discussion). *The Annals of Statistics* 14(4): 1261–1350.

Wu P, Wood R, Stott P (2005) Human influence on increasing Arctic river discharges. *Geophysical Research Letters* 32(2): L02703. [doi:10.1029/2004GL021570]

Wu WB, Zhao Z (2007) Inference of trends in time series. *Journal of the Royal Statistical Society, Series B* 69(3): 391–410.

Wu Y (2005) *Inference for Change-Point and Post-Change Means After a CUSUM Test.* Springer, New York, 158 pp.

Wunsch C (2000) On sharp spectral lines in the climate record and the millennial peak. *Paleoceanography* 15(4): 417–424.

Wunsch C (2001) Reply. *Paleoceanography* 16(5): 548.

Wunsch C (2003) The spectral description of climate change including the 100 ky energy. *Climate Dynamics* 20(4): 353–363.

Wunsch C (2006) *Discrete Inverse and State Estimation Problems.* Cambridge University Press, Cambridge, 371 pp.

Wunsch C, Gunn DE (2003) A densely sampled core and climate variable aliasing. *Geo-Marine Letters* 23(1): 64–71.

Yamamoto R, Iwashima T, Sanga NK, Hoshiai M (1986) An analysis of climatic jump. *Journal of the Meteorological Society of Japan* 64(2): 273–281.

Yashchin E (1995) Estimating the current mean of a process subject to abrupt changes. *Technometrics* 37(3): 311–323.

Yee TW, Wild CJ (1996) Vector generalized additive models. *Journal of the Royal Statistical Society, Series B* 58(3): 481–493.

Yiou P, Ribereau P, Naveau P, Nogaj M, Brázdil R (2006) Statistical analysis of floods in Bohemia (Czech Republic) since 1825. *Hydrological Sciences Journal* 51(5): 930–945.

York D (1966) Least-squares fitting of a straight line. *Canadian Journal of Physics* 44(5): 1079–1086.

York D (1967) The best isochron. *Earth and Planetary Science Letters* 2(5): 479–482.

York D (1969) Least squares fitting of a straight line with correlated errors. *Earth and Planetary Science Letters* 5(5): 320–324.

Young GA (1988) A note on bootstrapping the correlation coefficient. *Biometrika* 75(2): 370–373.

Yu K, Lu Z, Stander J (2003) Quantile regression: Applications and current research areas. *The Statistician* 52(3): 331–350.

Yule GU (1927) On a method of investigating periodicities in disturbed series, with special reference to Wolfer's sunspot numbers. *Philosophical Transactions of the Royal Society of London, Series A* 226: 267–298.

Zalasiewicz J, Williams M, Smith A, Barry TL, Coe AL, Brown PR, Brenchley P, Cantrill D, Gale A, Gibbard P, Gregory FJ, Hounslow MW, Kerr AC, Pearson P, Knox R, Powell J, Waters C, Marshall J, Oates M, Rawson P, Stone P (2008) Are we now living in the Anthropocene? *GSA Today* 18(2): 4–8.

Zar JH (1978) Approximations for the percentage points of the chi-squared distribution. *Applied Statistics* 27(3): 280–290.

Zeileis A, Leisch F, Hornik K, Kleiber C (2002) strucchange: An R package for testing for structural change in linear regression models. *Journal of Statistical Software* 7(2): 1–38.

Zhang X, Zwiers FW, Li G (2004) Monte Carlo experiments on the detection of trends in extreme values. *Journal of Climate* 17(10): 1945–1952.

Zheng Zg, Yang Y (1998) Cross-validation and median criterion. *Statistica Sinica* 8(3): 907–921.

Zielinski GA, Mayewski PA, Meeker LD, Whitlow S, Twickler MS (1996) A 110,000-yr record of explosive volcanism from the GISP2 (Greenland) ice core. *Quaternary Research* 45(2): 109–118.

Zielinski GA, Mayewski PA, Meeker LD, Whitlow S, Twickler MS, Morrison M, Meese DA, Gow AJ, Alley RB (1994) Record of volcanism since 7000 B.C. from the GISP2 Greenland ice core and implications for the volcano-climate system. *Science* 264(5161): 948–952.

Zolitschka B (Ed) (1999) *High-resolution records from European lakes*, volume 18(7) of *Quaternary Science Reviews*. [Special issue]

Zou GY (2007) Toward using confidence intervals to compare correlations. *Psychological Methods* 12(4): 399–413.

Zwiers FW, von Storch H (1995) Taking serial correlation into account in tests of the mean. *Journal of Climate* 8(2): 336–351.

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

Subject Index

K

L

M

N

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

Author Index

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0

Mudelsee M (2010) Climate Time Series Analysis: Classical Statistical and Bootstrap Methods. Springer, Dordrecht. *** This is from 2nd proofs (July 2010), final version: September 2010. *** ISBN: 978-90-481-9481-0; URL: http://www.manfredmudelsee.com/book; full content available from http://www.springer.com/environment/global+change+-+climate+change/book/978-90-481-9481-0