CHARLES UNIVERSITY
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HABILITATION THESIS

SPATIOTEMPORAL LINKS AND VARIABILITY IN CLIMATE TIME SERIES

JIŘÍ MIKŠOVSKÝ

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CONTENTS

CHAPTER 1

INTRODUCTION

Earth's climate system consists of a multitude of components, active on a range of temporal and spatial scales, interrelated and subject to external influences from the planetary interior or outer space as well as to the effects of human activity. The intricacy of the resulting structure marks it as one of the most challenging targets for study in – and beyond – the field of physics, and no current scientific technique is able to provide its complete, accurate description. Even so, much understanding about climate system's behavior can be gained through its simplified representations. Since analytical solutions do only exist for the most minimalistic embodiments of the related dynamics, numerical simulations have become the prime research tool in meteorology and climatology. Nevertheless, even the most sophisticated state-of-the-art models still fail to deliver a completely realistic reproduction of the climate system or its individual components. This applies not only to the prognostic simulations, limited in their ability to reliably forecast weather by the inherently chaotic nature of the atmosphere, but also to their climatic counterparts, struggling to provide a fully satisfactory approximation of the complex weave of processes forming the Earth's climate. Consequently, many of the real-world features are misrepresented or absent in the simulated climates, or captured with substantial uncertainty. As illustrated for instance by the summary assessment by the Intergovernmental Panel on Climate Change (STOCKER ET AL. 2013), steady improvement of the performance of climate models has been achieved over the past years, gradually alleviating many of their imperfections. Yet, even in their current advanced state, numerical simulations do still not offer a completely dependable picture of the climate and other approaches are needed to support, complement and validate them. This role is filled in a large part by statistical methods, ranging from basic descriptive and exploratory techniques to complex nonlinear algorithms for investigation of the variability patterns in multidimensional data.

A substantial part of the knowledge about the climate system comes from the study of its direct or indirect manifestations, recorded in the form of univariable or multivariable time series. Main role of statistical techniques then consists in extraction, refinement and interpretation of information contained in such signals. Obviously, this brief thesis does not attempt to provide a full treatise of the extensive array of statistical methods used in the climate research, or to deliver a comprehensive synopsis of their numerous applications to the observed and simulated data. Rather, it aims to highlight several topics pertaining to my past research in the field of statistical climatology, to deliver selected examples of the related results, and to connect them in a unifying frame.

The thesis has been created as summary, amalgamation and evolution of materials published in selected papers authored or co-authored by me since 2005. Its core is built upon nine stand-alone publications with my major participation, provided in the appendices and exploring various applications of time series analysis in meteorology and climatology:

- **MIKŠOVSKÝ & RAIDL (2006)** → **(Appendix I, p. 45)**
  MIKŠOVSKÝ, J., AND A. RAIDL (2006), Testing for nonlinearity in European climatic time series by the method of surrogate data, Theoretical and Applied Climatology, 83(1-4), 21-33, doi:10.1007/s00704-005-0130-7.
- **MIKŠOVSKÝ ET AL. (2008)** → **(Appendix II, p. 59)**
  MIKŠOVSKÝ, J., P. PIŠOFT, AND A. RAIDL (2008), Global Patterns of Nonlinearity in Real and GCM-Simulated Atmospheric Data, in: Nonlinear Time Series Analysis in the Geosciences: Applications in Climatology, Geodynamics and Solar-Terrestrial Physics (Eds.: Donner, R. V., and S. M. Barbosa), Lecture Notes in Earth Sciences, 112, 17-34, doi:10.1007/978-3-540-78938-3_2.
- **MIKŠOVSKÝ & RAIDL (2005)** → **(Appendix III, p. 78)**
  MIKŠOVSKÝ, J., AND A. RAIDL (2005), Testing the performance of three nonlinear methods of time series analysis for prediction and downscaling of European daily temperatures, Nonlinear Processes in Geophysics, 12(6), 979-991, doi:10.5194/npg-12-979-2005.
- **HUTH ET AL. (2015)** → **(Appendix IV, p. 92)**
  HUTH, R., J. MIKŠOVSKÝ, P. ŠTĚPÁNEK, M. BELDA, A. FARDA, Z. CHLÁDOVÁ, AND P. PIŠOFT (2015), Comparative validation of statistical and dynamical downscaling models on a dense grid in central Europe: temperature, Theoretical and Applied Climatology, 120(3-4), 533-553, doi:10.1007/s00704-014-1190-3.
- **MIKŠOVSKÝ ET AL. (2014)** → **(Appendix V, p. 114)**
  MIKŠOVSKÝ, J., R. BRÁZDIL, P. ŠTĚPÁNEK, P. ZAHRADNÍČEK, AND P. PIŠOFT (2014), Long-term variability of temperature and precipitation in the Czech Lands: an attribution analysis, Climatic Change, 125(2), 253-264, doi:10.1007/s10584-014-1147-7.
- **BRÁZDIL ET AL. (2015B)** → **(Appendix VI, p. 127)**
  BRÁZDIL, R., M. TRNKA, J. MIKŠOVSKÝ, L. ŘEZNÍČKOVÁ, AND P. DOBROVOLNÝ (2015B), Spring-summer droughts in the Czech Land in 1805-2012 and their forcings, International Journal of Climatology, 35, 1405-1421, doi:10.1002/joc.4065.
- **MIKŠOVSKÝ ET AL. (2016A)** → **(Appendix VII, p. 145)**
  MIKŠOVSKÝ, J., E. HOLTANOVÁ, AND P. PIŠOFT (2016A), Imprints of climate forcings in global gridded temperature data, Earth System Dynamics, 7, 231-249, doi:10.5194/esd-7-231-2016.
- **BRÁZDIL ET AL. (2019)** → **(Appendix VIII, p. 165)**
  BRÁZDIL, R., J. MIKŠOVSKÝ, P. ŠTĚPÁNEK, P. ZAHRADNÍČEK, L. ŘEZNÍČKOVÁ, AND P. DOBROVOLNÝ (2019), Forcings and projections of past and future wind speed over the Czech Republic, Climate Research, 77, 1-21, doi:10.3354/cr01540.
- **MIKŠOVSKÝ ET AL. (2019)** → **(Appendix IX, p. 187)**
  MIKŠOVSKÝ, J., R. BRÁZDIL, M. TRNKA, AND P. PIŠOFT (2019), Long-term variability of drought indices in the Czech Lands and effects of external forcings and large-scale climate variability modes, Climate of the Past, 15, 827-847, doi:10.5194/cp-15-827-2019.

Further materials have also been used or referenced from the following books and proceedings papers, not enclosed within the thesis, but topically close to its main themes:

- **BRÁZDIL ET AL. (2012A)**
  BRÁZDIL, R., M. BĚLÍNOVÁ, P. DOBROVOLNÝ, J. MIKŠOVSKÝ, P. PIŠOFT, L. ŘEZNÍČKOVÁ, P. ŠTĚPÁNEK, H. VALÁŠEK, AND P. ZAHRADNÍČEK (2012A), Temperature and precipitation fluctuations in the Czech Lands during the instrumental period, Masaryk University, Brno, 236 pp., ISBN 978-80-210-6052-4.
- **MIKŠOVSKÝ & PIŠOFT (2015)**
  MIKŠOVSKÝ, J., AND P. PIŠOFT (2015), Attribution of European temperature variability during 1882-2010: A statistical perspective, in: Global Change: A Complex Challenge (Ed.: Urban O.), Global Change Research Centre AS CR, Brno, 10-13, ISBN: 978-80-87902-10-3.
- **BRÁZDIL ET AL. (2015A)**
  BRÁZDIL, R., M. TRNKA, L. ŘEZNÍČKOVÁ, J. BALEK, L. BARTOŠOVÁ, I. BIČÍK, P. CUDLÍN, P. ČERMÁK, P. DOBROVOLNÝ, M. DUBROVSKÝ, A. FARDA, M. HANEL, J. HLADÍK, P. HLAVINKA, B. JANSKÝ, P. JEŽÍK, K. KLEM, J. KOCUM, T. KOLÁŘ, O. KOTYZA, E. KRKOŠKA LORENCOVÁ, J. MACKŮ, J. MIKŠOVSKÝ, M. MOŽNÝ, R. MUZIKÁŘ, I. NOVOTNÝ, A. PÁRTL, P. PAŘIL, R. POKORNÝ, M. RYBNÍČEK, D. SEMERÁDOVÁ, E. SOUKALOVÁ, Z. STACHOŇ, P. ŠTĚPÁNEK, P. ŠTYCH, P. TREML, O. URBAN, D. VAČKÁŘ, H. VALÁŠEK, A. VIZINA, R. VLNAS, J. VOPRAVIL, P. ZAHRADNÍČEK, AND Z. ŽALUD (2015A), Sucho v českých zemích: Minulost, současnost, budoucnost / Drought in the Czech Lands: Past, present and future, Centrum výzkumu globální změny AV ČR, Brno, 400 pp., ISBN 978-80-87902-11-0 (in Czech with English summary).
- **MIKŠOVSKÝ ET AL. (2016B)**
  MIKŠOVSKÝ, J., M. TRNKA, AND R. BRÁZDIL (2016B), Manifestations of climatic teleconnections in Czech drought characteristics, in: Global Change & Ecosystems, Vol 2 (Eds.: Vačkář D., and D. Janouš), Global Change Research Institute, Czech Academy of Sciences, Brno, 15-26, ISBN 978-80-87902-17-2.

To provide a more complete picture of some of the issues discussed, additional unpublished results were also included. To facilitate identification of publications with my contribution (and with my explicit authorship or co-authorship), the respective references are followed by an asterisk (*) in the rest of the text.

While the topics covered here vary substantially in terms of methods employed, datasets examined, as well as the general purpose of the particular analyses, some joint themes stand out. Besides the general subject of spatiotemporal relationships, and application of statistical techniques for their characterization, the issue of manifestations of nonlinearity in the climate data is particularly pervasive in my past research, from early attempts to quantify the magnitude of nonlinear behavior in univariable and multivariable series (MIKŠOVSKÝ & RAIDL 2005*, 2006*; MIKŠOVSKÝ ET AL. 2008*), to use of nonlinear functions for downscaling of large-scale data (MIKŠOVSKÝ & RAIDL

2005*; HUTH ET AL. 2015*), or application of regression models connecting the observed variability to various climate forcings and variability modes (BRÁZDIL ET AL. 2012A*; MIKŠOVSKÝ ET AL. 2014*; BRÁZDIL ET AL. 2015B*). The issue of attribution also permeates through much of my past work, whether focused on identification of factors shaping temporal variability of basic climate variables such as temperature (BRÁZDIL ET AL. 2012A*; MIKŠOVSKÝ ET AL. 2014*; MIKŠOVSKÝ & PIŠOFT 2015*; MIKŠOVSKÝ ET AL. 2016A*), precipitation (MIKŠOVSKÝ ET AL. 2014*) or wind speeds (BRÁZDIL ET AL. 2019*), assessment of variability in the ozone amounts and other characteristics of the middle atmosphere (KRIŽAN ET AL. 2011*; KUCHAŘ ET AL. 2015*; ŠÁCHA ET AL. 2018*), or imprints of climate forcings and large-scale variability modes in the series of drought indices (BRÁZDIL ET AL. 2015A*, 2015B*; MIKŠOVSKÝ ET AL. 2016B*, 2019*).

Despite the obvious topical diversity of the issues addressed, there are some general lessons to be learned. This unifying commentary is therefore not organized by individual publications. Instead, the text is structured into several topically focused (though still partly overlapping and interrelated) sections. Two of them concentrate on technical, yet critical issues: Chapter 2 briefly illustrates the diversity of data available for statistical analyses in the climate sciences in general and in the works presented here in particular; Chapter 3 shows selected representatives of linear and nonlinear regression mappings, as the primary methodological common point of the publications assembled within this thesis. The subsequent sections then summarize specific results pertaining to the three basic categories of problems tackled here: Chapter 4 explores the manifestations of nonlinear behavior related to short-term prediction of atmospheric variables; Chapter 5 is devoted to spatial relationships within and among different datasets, with particular focus on the issue of statistical downscaling (Chap. 5.1) and an additional example demonstrating approximation of temperature values from other concurrently measured records (Chap. 5.2); Chapter 6 shows outcomes of statistical attribution analysis for various forms of temperature and precipitation data (Chap. 6.1), wind speed records (Chap. 6.2), and series of drought indices (Chap. 6.3). Finally, summarizing and concluding remarks are given in Chapter 7.

CHAPTER 2
CLIMATE DATA: OBSERVATIONS & SIMULATIONS

Various measured and simulated time series are a key source of information about the climate system and its evolution, but their origins and properties do vary substantially. To briefly illustrate the variety of datasets used in our past research, some of the prominent classes of observational and simulated data are highlighted in this section, and a mention is given to their most prominent representatives employed in the studies discussed in Chapters 4-6.

The basic – and most traditional – form of climate records comes from the measurements taken at land-based stations, often established specifically for weather observations. The resulting series of meteorological variables such as temperature, precipitation totals or air pressure can span several decades, with longest of them covering multiple centuries. Length of these signals makes them a valuable source for examining the climate variability at various time scales. On the other hand, records of this extent are also prone to presence of non-climatic breaks and inhomogeneities and they are often in need of quality control and homogenization (e.g. BRÁZDIL ET AL. 2012B). In the contributions within this thesis, numerous series of daily temperature, precipitation, pressure or wind speed from Czech weather stations were used, obtained from the observational network maintained by the Czech Hydrometeorological Institute (CHMI - http://www.chmi.cz/). Data for the downscaling tests targeting European daily temperatures in MIKŠOVSKÝ & RAIDL (2005*) were supplied from the European Climate Assessment & Dataset (ECA&D - http://eca.knmi.nl/; KLEIN TANK ET AL. 2002). Daily temperatures employed in HUTH ET AL. (2015*) were provided by various partners within the CECILIA project (Central and Eastern Europe Climate Change Impact and Vulnerability Assessment - http://www.cecilia-eu.org/). Monthly temperature and precipitation series from several secular Czech weather stations and their areal averages (BRÁZDIL ET AL. 2012B) were studied in BRÁZDIL ET AL. (2012A*) and MIKŠOVSKÝ ET AL. (2014*), and they also served as a basis for calculation of the drought indices analyzed in BRÁZDIL ET AL. (2015A*, 2015B*) and MIKŠOVSKÝ ET AL. (2016B*). Delving even deeper into the past, central European temperature, precipitation and drought indices reconstructions spanning more than five centuries were then studied in MIKŠOVSKÝ ET AL. (2019*), derived from a combination of documentary and instrumental data.

While the nature of the records taken at individual weather stations makes them useful for assessing local climate, they are not necessarily representative of a larger neighborhood of their site of origin. Furthermore, mutual comparability of the series of direct measurements may be compromised by technical factors, particularly by differences among the measuring and record keeping practices of individual data gatherers (such as national weather services). For these reasons, composite datasets are often created from local measurements, through interpolation/extrapolation techniques supported by various quality-control and homogenization algorithms (e.g. ŠTĚPÁNEK ET AL. 2011). The resulting data are then typically provided in the form of spatiotemporal fields, often on a regular longitude-latitude geographic grid. Several such gridded datasets were employed within this thesis. Gridded versions of daily minimum and maximum temperature created within the CECILIA project (ŠTĚPÁNEK ET AL. 2011) were used in HUTH ET AL. (2015*). Gridded monthly temperature anomalies from GISTEMP (HANSEN ET AL. 2010) and Berkeley Earth (ROHDE ET AL. 2013A, 2013B) datasets were utilized in the attribution studies MIKŠOVSKÝ ET AL. (2014*), MIKŠOVSKÝ & PIŠOFT (2015*), along with the series of their continental and global means. For the global-scale attribution analysis in MIKŠOVSKÝ ET AL. (2016A*), these were further complemented by the MLOST (SMITH ET AL. 2008) and HadCRUT (MORICE ET AL. 2012) datasets.

As primarily physical disciplines, meteorology and climatology rely heavily on mathematical representations of their respective systems of interest. Over the past decades, these numerical simulations have evolved from simple, low-resolution models into complex, multi-component structures, capturing much of the large-scale weather/climate dynamics and its responses to external forcings. The current generation of global climate models (GCMs) not only serves as the main tool for generating outlooks of climate future, but provides valuable insights into its past as well. While the GCM-type simulations do not follow the historical trajectory of the climate system, they are constructed to preserve its general statistical characteristics – at least in theory, as this goal is still just partly fulfilled, and even the best state-of-the-art simulations suffer from numerous deficiencies (e.g. STOCKER ET AL. 2013). Outcomes of the HadCM3 model (GORDON ET AL. 2000) were used as a source of the simulated geopotential height data for the analysis of nonlinear behavior in MIKŠOVSKÝ ET AL. (2008*).

Being inherently world-wide simulations, GCMs do generally provide outputs on a relatively coarse spatial grid. The resolution gap between GCM-generated data and fine-scale inputs needed in local-oriented studies can be bridged by regional climate models (RCMs): High-resolution simulations over a geographically limited area, embedded into the global model or other suitable source of boundary conditions (such as global reanalysis). Of the numerous RCMs in existence, outputs of the RegCM3 (HALENKA ET AL. 2006) and ALADIN-Climate/CZ (FARDA ET AL. 2010) models were used in our works, and subjected to the performance comparison with their statistical downscaling alternatives in HUTH ET AL. (2015*). Several Euro-CORDEX RCMs were also employed for wind speed analysis in BRÁZDIL ET AL. (2019*).

Direct climate measurements (and their gridded versions) provide records of the past climate variability, but are available for just some periods and locations. GCM simulations can deliver a complete data coverage over their integration period, yet they do not track the historical trajectory of the real climate system, and they suffer from various systematic biases. Outcomes of atmospheric reanalyses can then be considered an intermediate form between these two data types: Created by assimilation of actual measurements into a numerical model-like framework, a reanalysis can provide a formally complete account of the state of the atmosphere, while still following the past trajectory of the real climate system. Two representatives of modern-era reanalysis products were used in the entries to this thesis: NCEP/NCAR reanalysis (with data since the year 1948; KISTLER ET AL. 2001) and ERA-40 reanalysis (covering the period 1957-2002; UPPALA ET AL. 2005). Of particular interest for investigation of longer-term climate variations is also the 20th Century Reanalysis (COMPO ET AL. 2011), providing data from the year 1851 onward (version V2c), and employed in some of our works.

The range of data characterizing past climate is obviously immense, regarding both the general type of the dataset and its specific representatives. Often multiple options are available as potential analysis inputs when a particular problem is to be studied. In theory, data from different sources should conform to the same, historical, evolution of the climate system at all relevant spatial and temporal scales (or, in the case of GCM/RCM simulations, the general dynamical and statistical features should be captured in a manner consistent with observed climate). In reality, however, differences between individual datasets can be substantial, and so can be distinctions between results stemming from their use.

A simple demonstration of possible contrasts among individual representatives of atmospheric variables is shown in Fig. 2.1. Czech temperature anomalies at monthly and annual time step are compared in four versions: a series derived directly from local observations, two specimen of gridded temperature data and the 20th Century Reanalysis. All the signals show similar (though not completely identical) variability at the monthly time scale over the years 1980-2010 (Fig. 2.1a). On the other hand, systematic differences appear in the long-term trends, with noticeable discrepancy detected especially between the reanalysis and the rest of the observational datasets (Fig. 2.1b). When match of the temperature series provided by various data sources is investigated globally, strong regional specifics emerge – see the correlation-based comparison of several gridded temperature datasets in Fig. 2.2 and notice, for instance, their generally good agreement in Europe, contrasting with rather loosened similarity in parts of Africa or South America. These distinctions may then translate into discrepancies between outcomes of otherwise identical analysis procedures applied to data from different sources.

In the frame of the topics addressed within this thesis, issues related to the problem of inter-dataset differences have been tackled to some extent. Possible manifestations of nonlinearity in short-term prediction of (pseudo)observational data were compared for direct meteorological measurements and their reanalysis-based counterparts (MIKŠOVSKÝ & RAIDL 2006*). Reanalysis data were also compared to the outputs of a global climate model, in terms of the geographical patterns of nonlinearity detectable from local multivariable systems (MIKŠOVSKÝ ET AL. 2008*). Performance of dynamical downscaling was studied for two different representatives of regional climate models in HUTH ET AL. (2015*), both of them driven by the ERA-40 reanalysis. The effects of using alternative versions of the input data were also considered in our early analyses concerned with statistical attribution; a brief summary of the respective conclusions was included in the papers themselves (MIKŠOVSKÝ ET AL. 2014*; BRÁZDIL ET AL. 2015B*). More specific attention to the matter of inter-dataset contrasts was then paid in MIKŠOVSKÝ & PIŠOFT (2015*), and especially in MIKŠOVSKÝ ET AL. (2016A*), focused on identification of forcing-related patterns in several gridded temperature datasets. Another aspect of this problem was recently addressed in MIKŠOVSKÝ ET AL. (2019*), this time with regard to sensitivity of the outcomes of statistical attribution analysis to the choice of proxy-based explanatory variables. Clearly, even from the limited sample of results presented here, it should be evident that the problem of data-specific features and uncertainties needs to be treated with great care. Questions of whether directly measured climate variables can be replaced by their gridded/reanalyzed/simulated counterparts (and which specific dataset should be used) must be carefully considered, and assessment of the effects of input data choice should be a crucial part of the studies dealing with spatiotemporal relations and variability in the climate system.

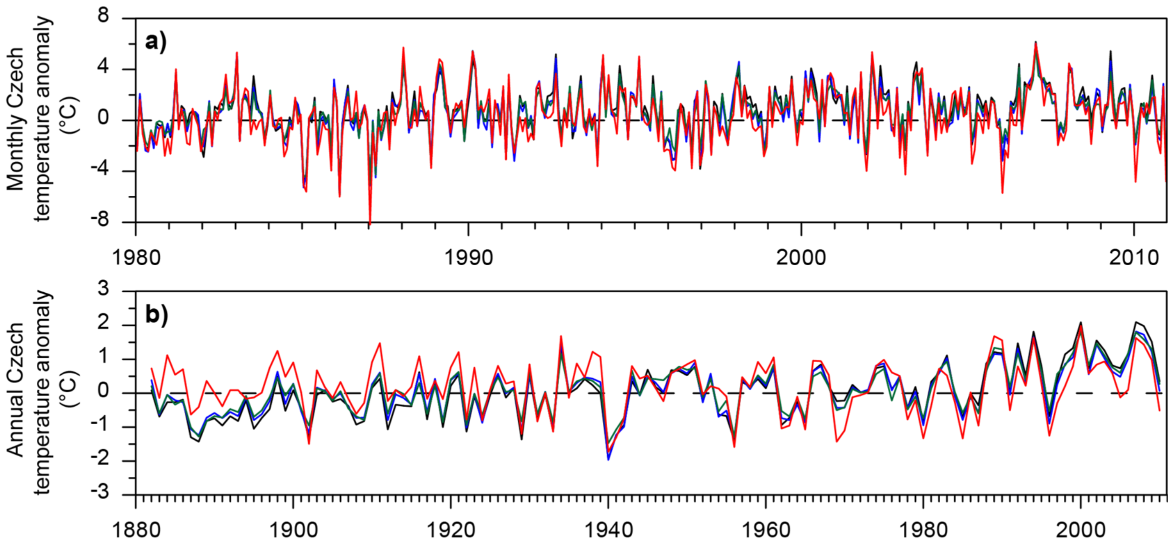


FIGURE 2.1: Time series of monthly **(a)** and annual **(b)** temperature anomalies for the area of the Czech Republic derived from data obtained from various sources: mean areal temperature created from measurements at 10 Czech weather stations (**black:** BRÁZDIL ET AL. 2012A*); GISTEMP dataset (**green:** HANSEN ET AL. 2010); Berkeley Earth dataset (**blue:** ROHDE ET AL. 2013A, 2013B); 20th Century Reanalysis (**red:** COMPO ET AL. 2011). The anomalies are expressed relative to the 1951-1980 period and shown for the years 1980-2010 (monthly series) and 1882-2010 (annual series).

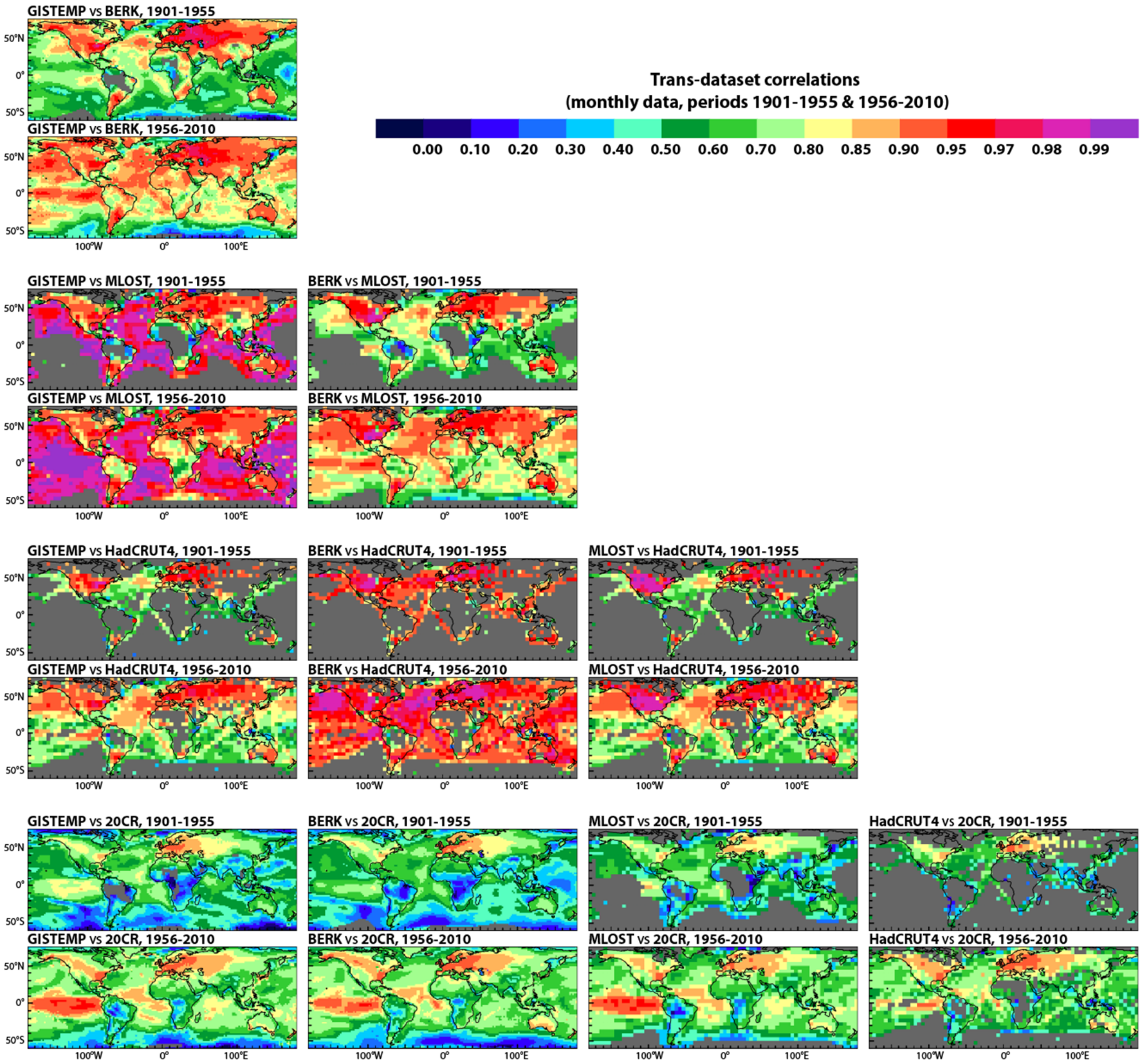


Figure 2.2: Local values of Pearson correlation coefficient between time series of monthly temperature anomalies from selected global gridded datasets: GISTEMP (Hansen et al. 2010); Berkeley Earth (BERK; Rohde et al. 2013a, 2013b); MLOST (Smith et al. 2008); HadCRUT4 (Morice et al. 2012); 20th Century Reanalysis (20CR; Compo et al. 2011). The correlations were calculated over the 1901-1955 and 1956-2010 periods; grey areas mark regions with insufficient amount of data available (more than 10% of missing temperature pairs in the analysis period). Adapted from the supplementary materials to Mikšovský et al. (2016a*).

CHAPTER 3
(NON)LINEAR REGRESSION TECHNIQUES

A wide range of statistical techniques was used to investigate individual problems presented throughout this text, from estimation of elementary descriptive statistics, to dimensionality reduction and clustering algorithms and an assortment of statistical significance tests. One particular topic, however, permeates through most of the analyses presented here: Application of various forms of linear and nonlinear regression, connecting values of a univariable predictand $y(t)$ to one or more predictors $p_i(t), i = 1, \dots, M$. Index t distinguishes between individual cases in the datasets studied (out of the total of N available), and it mostly pertains to time here. While straightforward in their basic purpose, regression mappings can be employed to fulfill various objectives, determined by the character of variables assigned to the role of predictand and predictors. Within the range of problems tackled here, regression was used for predictive tasks (i.e., predictand estimated from predictors preceding it in time), approximation of spatial relations (with concurrent predictand and predictors originating from different geographic locations), trend estimation (matching the target variable against time) or as a basis for attribution-seeking models (decomposing predictand into components associated with explanatory variables representing various external climate forcings and internal variability modes). In this chapter, selected classes of regression models are very briefly outlined, with regard to their basic structure as well as some details concerning their implementation in the works gathered within this thesis.

A prominent (and historically dominant) place among the regression techniques is held by multiple linear regression (MLR). The respective mapping between predictors and predictand takes a form of a simple weighted averaging formula,

$$y(t) = \hat{y}(t) + \varepsilon(t) = a_0 + \sum_{i=1}^{M} a_i p_i(t) + \varepsilon(t)\,, \tag{1}$$

with regression coefficients a_i calculated to obtain a model of desired properties – typically one that minimizes the sum of squared regression residuals ε, calculated as differences between the actual values of y and their regression-based estimates $\hat{y}$. This so-called 'least squares method' of a_i calculation was employed in all applications of linear regression here.

While simple, fast and open to easy interpretation of its outcomes, linear regression suffers from an obvious limitation: In its basic form, it is only able to capture strictly linear links, embodying direct proportionality between the predictors and individual components in the predictand. However, it has been shown that linear mappings can be used to approximate dynamics of even strongly nonlinear systems, providing that linear models are applied locally for just small sections of the phase space or space of predictors (see, e.g., contributions in OTT ET AL. 1994). This approach, dubbed method of local linear models (LLM) here, relies on calculation of the regression coefficients a_i individually for each instance of t. The coefficients can then no longer be considered globally valid constants, but rather t-dependent functions:

$$y(t) = \hat{y}(t) + \varepsilon(t) = a_0(t) + \sum_{i=1}^{M} a_i(t)p_i(t) + \varepsilon(t). \qquad (2)$$

To achieve the local specificity of the regression coefficients, their calculation is carried out for just a limited number $L \ll N$ of cases from the calibration part of the data, representing situations with the closest resemblance to the one being processed (i.e., to the one pertaining to t). The similarity of individual cases can be measured by the distance of the respective M-dimensional vectors of predictors $\mathbf{p}(t) = (p_1(t), \dots, p_M(t))$, quantified by a suitable metric (often Euclidean). The optimum size and structure of the local neighborhood is subject to the specifics of the task investigated, including dimensionality of the system studied, type of time series involved and their eventual contamination by noise. Details on the design of the local linear models employed in our analyses are given in the individual papers in the appendices.

Over the past years, great popularity among nonlinear regression techniques has been attained by various architectures of artificial neural networks (NNs) (see, e.g., HAYKIN 1999). The perhaps most prominent of them, multilayer perceptron (MLP), was employed in several of our studies, in a form with a single hidden layer,

$$y(t) = \hat{y}(t) + \varepsilon(t) = b_0 + \sum_{i=1}^{L_{MLP}} b_i\, \varphi\left(b_{0i} + \sum_{j=1}^{M} b_{ji}\, p_j(t) \right) + \varepsilon(t), \qquad (3)$$

where b_{ji} and b_i represent weights of connections between neurons in the input and hidden layer and in the hidden and output layer, respectively, and L_{MLP} denotes number of neurons in the hidden layer (specifying complexity of the network). Of the possible forms of the (generally nonlinear) transfer function φ, either logistic function (used in MIKŠOVSKÝ & RAIDL 2005*, 2006*) or hyperbolic tangent (BRÁZDIL ET AL. 2012A*; MIKŠOVSKÝ ET AL. 2014*; BRÁZDIL ET AL. 2015B*; HUTH ET AL. 2015*) were applied in the examples here. The learning algorithms (i.e., procedures used to calculate weights b from the calibration data) were based on various forms of error backpropagation.

An alternative type of neural networks built around radial basis functions (RBFs) (see, e.g., HAYKIN 1999) was also applied in some of our studies. The respective mapping can be captured by the formula

$$y(t) = \hat{y}(t) + \varepsilon(t) = c_0 + \sum_{i=1}^{L_{RBF}} c_i\, \rho(\|\mathbf{p}(t) - \mathbf{d}_i\|) + \varepsilon(t), \qquad (4)$$

with M-dimensional vector $\mathbf{d}_i$ representing center of the radial function assigned to the i-th of L_{RBF} neurons in the hidden layer. In our analysis setups, Gaussian-style RBFs were used, $\rho(\|\mathbf{p}(t) - \mathbf{d}_i\|) = \exp(-\|\mathbf{p}(t) - \mathbf{d}_i\|^2/2\sigma^2)$, with parameter σ

controlling the width of the radial functions. Simple subsampling of the centers $\mathbf{d}_i$ from the training part of the datasets was typically employed, although more sophisticated methods (e.g., pre-processing through clustering algorithms) were also tested. The weights c_i were then calculated to minimize the sum of squared errors, in a fashion analogous to multiple linear regression.

The above introduced regression techniques share a common purpose: to capture relations between the explanatory variables and the target signal. Intuitively, one might expect nonlinear mappings to be more universal in their ability to approximate the respective links, and thus automatically superior to linear regression. As exemplified in the following chapters, such presumption often turns out to be unsupported: Despite the inherently nonlinear and deterministically chaotic nature of the Earth's climate system, deviations from purely linear behavior are not always detectable in the time series it spawns. Moreover, application of nonlinear algorithms typically comes with increased demands on computational power, more difficult interpretation of the regression outcomes and more complicated evaluation of their statistical significance. The question therefore remains how beneficial nonlinear techniques really are and whether gain from their application outweighs the extra demands and interpretational challenges.

Even in the presence of nonlinearities strong enough to uphold the application of nonlinear regression, another choice has to be made: Selection of the most suitable form of nonlinear mapping. The three examples above, embodied by Equations 2-4, represent different approaches to this problem. The method of local linear models builds upon an ensemble of individual, formally independent regression functions, pertaining to specific (and typically mutually overlapping) segments of the space of predictors. Multilayer perceptrons, on the other hand, can be considered a global mapping, without a specific link of individual neurons to particular states of the system (or vectors of the predictors). RBF-based neural networks form a middle ground between these two approaches: While the mapping is formally global, individual hidden neurons are associated with specific vectors in the space of predictors, and their activation is reduced for inputs more distant from their assigned centers. The general form of the regression function is not the only important factor determining the behavior of the nonlinear models: Their individuality is subject to the selection of the structure-defining descriptors (such as the complexity-controlling parameters L, L_{MLP} or L_{RBF} above), and finding the optimum setup is as critical as it is nontrivial. Some specific aspects of these problems are illustrated in the following chapters and in the respective publications in the appendices.

CHAPTER 4
NONLINEARITY IN PREDICTIVE MAPPINGS

Over the past decades, various methods have been developed for assessing the presence – and potentially magnitude – of nonlinear and chaotic behavior in univariable or multivariable time series. Numerous attempts have also been made to apply these techniques in the atmospheric and climate sciences (see, for instance, the overview by SIVAKUMAR 2004 for specific examples, or the references discussed by MIKŠOVSKÝ ET AL. 2008*). The emergence of global- or continental-scale datasets of climate data (particularly outcomes of various reanalysis projects) provided an opportunity for an even more systematic investigation of this problem, including the evaluation of the geographic and seasonal patterns of nonlinearity. However, the variety of results in the existing studies also demonstrates that degree to which deviations from strictly linear behavior manifest depends on a number of factors, related to the datasets analyzed as well as task performed. Outcomes of nonlinearity tests are therefore subject to the choice of the testing criterion, reflecting the particular form of nonlinear interaction of interest. Prediction errors represent one of the natural choices of the testing statistic: Due to their relation to the information transfer between consequent states of the climate system, tests based on short-term predictive mappings can provide useful information about the local properties of the atmosphere, related to its chaoticity and predictability. In this chapter, our experiments dealing with this topic are outlined, published in the papers MIKŠOVSKÝ & RAIDL (2006* - APPENDIX I), MIKŠOVSKÝ ET AL. (2008* - APPENDIX II) and MIKŠOVSKÝ & RAIDL (2005* - APPENDIX III). Some of the relevant materials were also previously included in my dissertation thesis (MIKŠOVSKÝ 2004*).

Our initial attempts at nonlinearity detection were focused on identification of rules governing the manifestations of nonlinear behavior in short-term forecasts of daily temperature and pressure, as documented in MIKŠOVSKÝ & RAIDL (2006*). The tests applied were built upon the method of surrogate data, employing the Iterative Amplitude Adjusted Fourier Transform (IAAFT) technique (SCHREIBER & SCHMITZ 1996, 2000). Implementation of the respective algorithms from the TISEAN software package was used (HEGGER ET AL. 1999). Both univariable and multivariable time series were investigated for the presence of nonlinearities, using either the method of time delays (e.g. PACKARD ET AL. 1980) or the multivariable approach (e.g. KEPPENNE & NICOLIS 1989) to reconstruct the phase space of the local climate system (or, more accurately, to provide its approximate representation, and a set of predictors to enter the predictive regression mappings). Series of daily temperature (mean, minimum and maximum) and daily pressure measured at the weather station Prague-Ruzyně (Czech Republic) served as predictands, and they were complemented by their counterparts adopted from the NCEP/NCAR reanalysis. The reanalysis also supplied potential predictors for the multivariable analysis setups, with step-wise screening used to identify the best subset of explanatory variables.

Figure 4.1 provides an illustrative example of the outcomes of the surrogate data-based analysis in MIKŠOVSKÝ & RAIDL (2006*), comparing errors of prediction carried out by the method of local linear models for the original data and for an ensemble of their IAAFT-randomized versions. It was demonstrated that nonlinear behavior does indeed manifest in the predictive mappings, but only in some test configurations and in greatly varying degree. Only mild to no detectable nonlinearity (i.e., small difference between the prediction errors in the original data and in the surrogates) was indicated for the setups with predictors generated by the method of time delays. On the other hand, a distinct nonlinear component was typically uncovered in predictive mappings employing multivariable predictors. Nonlinearity was generally stronger for longer signals (30-year-long series) than for their shortened (10-year-long) versions. It was also comparably most noticeable for the shortest-term prediction (lead time of 1 day), weakening and eventually disappearing as the lead time increased. Generally, our results suggested that nonlinear behavior manifests more strongly in setups with higher amount of information available within the data analyzed, provided that a deterministic link between predictand and predictors exists. The information content in individual scalar signals seemed insufficient to capture the complex dynamics of the local climate system beyond simple linear links, and application of nonlinear predictive mappings was thus largely baseless for the univariable settings (at least for the particular type of time series studied in our tests).

While the surrogate data-based tests can deliver statistically well founded conclusions about the presence of specific forms of nonlinearity, they are somewhat cumbersome and computationally demanding. From the perspective of applied time series analysis, a more direct question regarding nonlinear behavior may be of interest: What is the actual improvement achieved by application of a specific nonlinear method over its linear counterpart? This issue was only very briefly touched upon in MIKŠOVSKÝ & RAIDL (2006*), but we focused on it more specifically in MIKŠOVSKÝ & RAIDL (2005*). Comparison of the short-term predictive skill of linear regression and local linear models was carried out for daily temperatures across the European region, supplied from the NCEP/NCAR reanalysis. Multivariable predictors were used, arranged in a pre-defined geographic pattern. In addition to the method of local linear models, MLP and RBF neural networks were also applied, to assess the sensitivity of the results to the choice of the nonlinear model. Relatively strong nonlinear behavior (i.e., superiority of nonlinear methods over linear regression) was generally indicated, especially during boreal winter. Distinct geographic variations of nonlinearity were found, but just rudimentary explanation of their spatial patterns could be provided. Mostly minor differences between the predictive skills of individual types of nonlinear mappings were found.

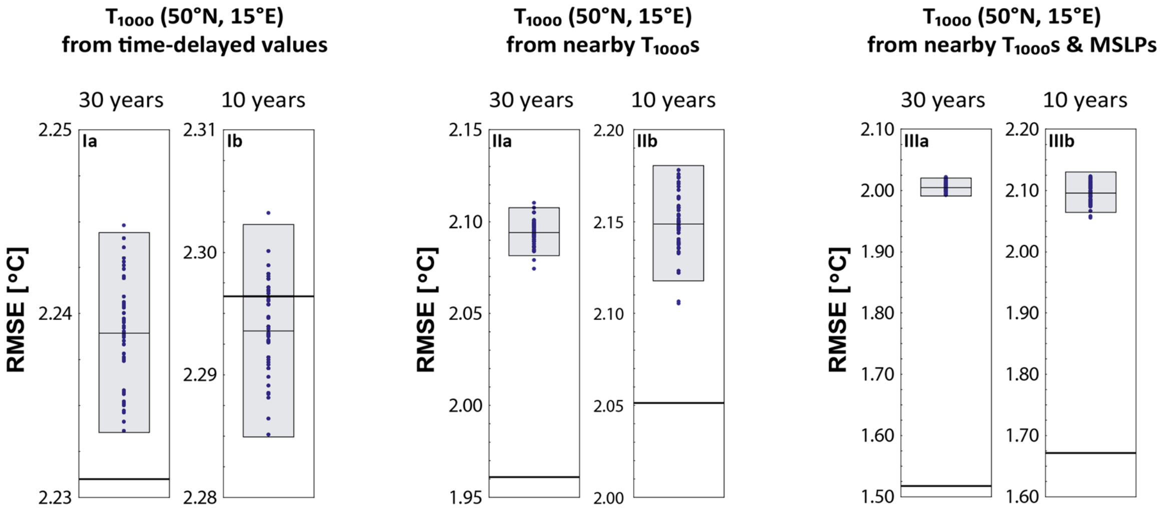


FIGURE 4.1: Manifestations of nonlinear behavior in univariable and multivariable time series. Root mean squared error (RMSE) of NCEP/NCAR daily temperature series (50°N, 15°E, 1000 hPa level) forecast 1 day ahead is shown, obtained by the method of local linear models for the original series (long horizontal line) and 49 instances of the corresponding IAAFT-generated surrogates (dots). Individual setups pertain to phase space reconstruction by the method of time delays **(I)**, multivariable reconstruction employing 1000 hPa temperatures from a region between 60°N, 0°E and 40°N, 30°E **(II)** and multivariable reconstruction employing 1000 hPa temperatures as well as mean sea level pressures from the same region **(III)**. Results are shown for approximately 30-year-long **(a)** and 10-year-long **(b)** versions of the series. The embedded rectangle with shorter inset horizontal line shows average RMSE for the surrogates and the matching 2σ range. See MIKŠOVSKÝ & RAIDL (2006*) for more details on the analysis setup, other related results and their interpretation.

In MIKŠOVSKÝ & RAIDL (2005*) and MIKŠOVSKÝ & RAIDL (2006*), we focused on nonlinearity manifestations within just a geographically limited region, and only observational time series were studied (either direct measurements or series originating from a reanalysis). In MIKŠOVSKÝ ET AL. (2008*), a global scope of the analysis was embraced, and outcomes of the HadCM3 global climate model were investigated along with data originating from the NCEP/NCAR reanalysis. The primary method of nonlinearity quantification in MIKŠOVSKÝ ET AL. (2008*) was based on direct comparison of the 1-day-ahead prediction error achieved by multiple linear regression and by the local linear models method, with multivariable predictors arranged in a regular pattern, centered on the location of the predictand (Fig. 4.2a). The role of predictand belonged to the relative topography of the 850-500 hPa layer (i.e., a quantity proportional to the average air temperature between the 850 and 500 hPa pressure levels) or to the geopotential height of the 850 hPa level.

The global nonlinearity patterns in the NCEP/NCAR data revealed a distinct contrast between relatively strong (and generally statistically significant) nonlinearities in the midlatitudes and largely negligible and statistically non-significant improvement from application of a nonlinear predictive model in the equatorial regions (Fig. 4.2b).

Besides this basic latitudinal pattern, areas with the strongest manifestations of nonlinearity in the higher latitudes were identified and linked to the atmospheric zones with the most intensive synoptic activity. Our analysis also confirmed presence of distinct seasonal variations of the results, with nonlinearity typically intensified during the cold part of the year in the extratropical regions.

By comparing the nonlinearity patterns for the NCEP/NCAR reanalysis (approximating the actual historical variability within the climate system) and for the HadCM3 model (global numerical simulation, generating a trajectory uncorrelated with the historical one), we confirmed that the model is capable of reproducing the basic character of the observed nonlinearity patterns, although differences appeared in both the finer details of the structures detected and in their magnitude (Fig. 4.2c). Our analysis thus served as an advanced validation tool of a general circulation model and suggested the ability of numerical climate simulations to replicate not only the elementary statistical characteristics of the climate data, but also their properties related to the nonlinear and chaotic structures.

Finally, nonlinearity tests based on assessing the ratio between the prediction errors from multiple linear regression and local linear models method were also compared to the approach employing surrogate data. Relatively good match between the respective geographic patterns of nonlinearity was found (see Figs. 3a and 6 in MIKŠOVSKÝ ET AL. 2008*). This suggests that comparing errors from linear and nonlinear mappings may be used as an alternative to the computationally more expensive surrogate-assisted testing (with some reservations, discussed in MIKŠOVSKÝ ET AL. 2008*). However, such conclusion should not be mistaken for complete invariance regarding the analysis setup: Choice of the specific form of the nonlinear model (and of its design parameters) can still affect the results to some extent, which needs to be taken into account when interpreting the outcomes of the nonlinearity tests.

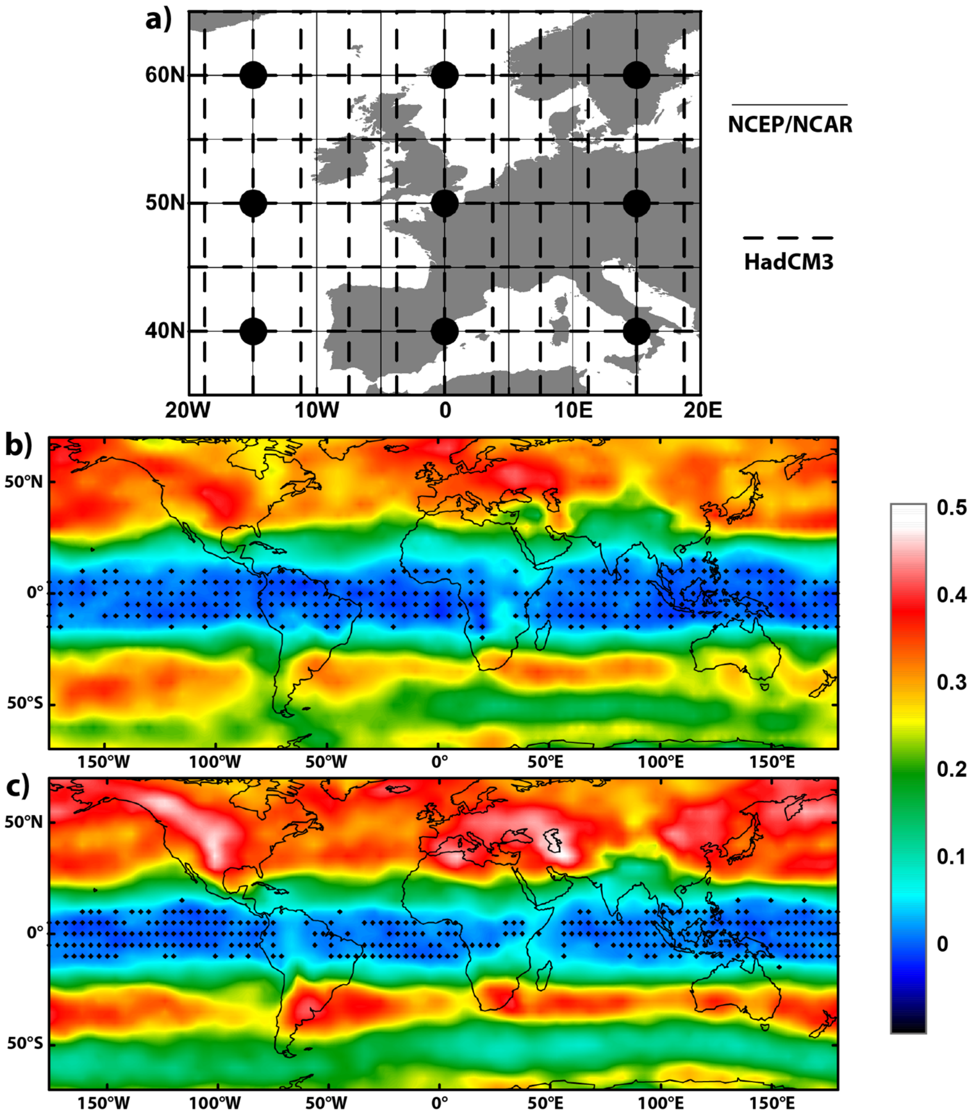


FIGURE 4.2: Global distribution of estimated regional magnitude of nonlinearity, associated with prediction of relative topography 850-500 hPa 1 day ahead. Multivariable vector of predictors was used, consisting of 9 values of relative topography 850-500 hPa and 9 values of geopotential height of the 850 hPa level, arranged in a pattern shown in **(a)** for the predictand series located at 50°N, 0°E. Nonlinearity was quantified by a skill score defined as $SS = 1 - (R_{LLM}/R_{MLR})^2$, with R_{LLM} and R_{MLR} representing root mean squared error (RMSE) of the forecast by the method of local linear models and multiple linear regression, respectively (by this definition, $SS = 0$ pertains to situations with both methods performing identically in terms of RMSE, and thus no detectable nonlinearity, while positive values of SS indicate nonlinear mapping outperforming its linear counterpart). Results are shown for the NCEP/NCAR reanalysis data **(b)** and for the outputs of the HadCM3 global climate model **(c)**, with the forecast mappings calibrated over the 1961-1990 period and validated for the years 1991-2000. Locations with statistically non-significant improvement from application of the method of local models over linear regression are marked by black diamonds (one-sided paired sign test, 95% confidence level). See MIKŠOVSKÝ ET AL. (2008*) for more details on the analysis setup and additional results.

CHAPTER 5
SPATIAL RELATIONS IN CLIMATE DATA

It is typical for climate variables characterizing geographically close locations to share a portion of their temporal variability, and for the respective time series to be connected to some degree. These associations often manifest through simple linear correlations, but their nature may also be more complex. Regression techniques can be used to identify, extract and quantify the inter-variable dependencies; they can also help to reveal and capture connections between different datasets (for instance, to estimate station-specific series from large-scale data available from a reanalysis or global climate model). In this section, examples are given of our results related to approximation of spatial relations within and among various datasets of climate data: downscaling of large-scale atmospheric fields (Chap. 5.1; MIKŠOVSKÝ & RAIDL 2005* - APPENDIX III; HUTH ET AL. 2015* - APPENDIX IV), and estimation of temperature measurements from nearby concurrent records (Chap. 5.2).

5.1 STATISTICAL DOWNSCALING OF DAILY TEMPERATURES

As already mentioned in Chap. 2, spatial resolution of global climate models (as well as of global reanalyses) is often insufficient for local-oriented studies, and the resolution gap can be bridged by dynamical downscaling (i.e., through a high-resolution regional climate model embedded into the global simulation or reanalysis). As an alternative to such cascade of numerical simulations, statistical methods can also be used to approximate the connections between large-scale model outputs and more site-specific data (such as observations at individual weather stations). Of the various techniques of statistical downscaling in existence, we focused on direct mappings between large-scale data (predictors) and local measurements or their gridded versions (predictands) in our works.

In MIKŠOVSKÝ & RAIDL (2005*), our main aim was to assess the suitability of different forms of empirical regression functions to provide downscaled versions of daily temperature. Using NCEP/NCAR reanalysis data as predictors, the four regression mappings introduced in Chap. 3 (MLR, LLM, MLP NN, RBF NN) were used to generate estimates of daily mean, minimum and maximum temperature, recorded at 25 sites across Europe and obtained from the ECA&D database (KLEIN TANK ET AL. 2002). A pre-defined pattern of predictors was employed (Fig. 5.1a). The regression models were calibrated using data from the 1961-1990 period and then validated for the years 1991-2000, separately for each location. Distinct differences between the temperature estimation errors for individual stations were found (see the examples for daily maximum temperature in Figs. 5.1b,c, as well as figures and tables in MIKŠOVSKÝ & RAIDL 2005*). No clear geographic pattern of the error magnitudes was identified, suggesting a dominant influence of the local specifics of each of the target sites. The analysis also highlighted an inclination towards stronger nonlinearity during boreal winter, though exceptions from this tendency were detected for some combinations of temperature type and location. Downscaling skills of the three nonlinear regression techniques (LLM, MLP NN, RBF NN) were found to be mutually similar.

The problem of daily temperature downscaling was later revisited in HUTH ET AL. (2015*), this time to provide a detailed comparison of the performance of various dynamical and statistical downscaling methods. The analysis utilized a high-resolution dataset of daily maximum and minimum temperature series, assembled within the CECILIA project (http://www.cecilia-eu.org/; ŠTĚPÁNEK ET AL. 2011) and providing both station-specific records and their versions interpolated onto a regular grid, for a geographically limited region along the joint borders of Austria, Czech Republic, Hungary and Slovakia. In addition to multiple linear regression and the three representatives of nonlinear regression (LLM, MLP NN, RBF NN), method of analogues (e.g. ZORITA & VON STORCH 1999) was also employed and compared to the other downscaling approaches. Predictors were supplied from the ERA-40 reanalysis and pre-selected through a step-wise screening procedure based on linear regression. Calibration of the regression mappings was carried out for the years 1961-1990, and their validation performed over the 1991-2000 period. The dynamical downscaling models were represented by the ERA-40-driven integrations of the RegCM3 (HALENKA ET AL. 2006) and ALADIN-Climate/CZ (FARDA ET AL. 2010) regional climate models.

In Fig. 5.2, performance of some of the downscaling techniques applied in HUTH ET AL. (2015*) is illustrated, through root mean squared error (RMSE) of winter minimum daily temperature estimates. Superiority of nonlinear regression over MLR was once again indicated, though exceptions were detected for some combinations of season, location and temperature type. Unlike in MIKŠOVSKÝ & RAIDL (2005*), however, RMSE did not serve as the primary validation criterion in HUTH ET AL. (2015*). Instead, emphasis was on evaluating the ability of the statistical and dynamical downscaling models to realistically reproduce the extreme quantiles of the statistical distributions, their higher moments (skewness, kurtosis), autocorrelation structures in the time series, spatial correlations between temperatures from different locations and long-term temporal trends in the series. As individual sections in HUTH ET AL. (2015*) show, no downscaling technique was found to be universally superior to the others. Subject to the type of temperature, location, season and validation criterion, the relative skill rank of individual downscaling approaches varied greatly: In some cases, statistical downscaling techniques out-performed the (arguably more popular) regional climate models, but the opposite was also occasionally true. Also, despite the relative superiority of nonlinear empirical models over linear regression in terms of RMSE, their advantage did not automatically extend to the above mentioned validation criteria related to statistical distributions or spatiotemporal correlations.

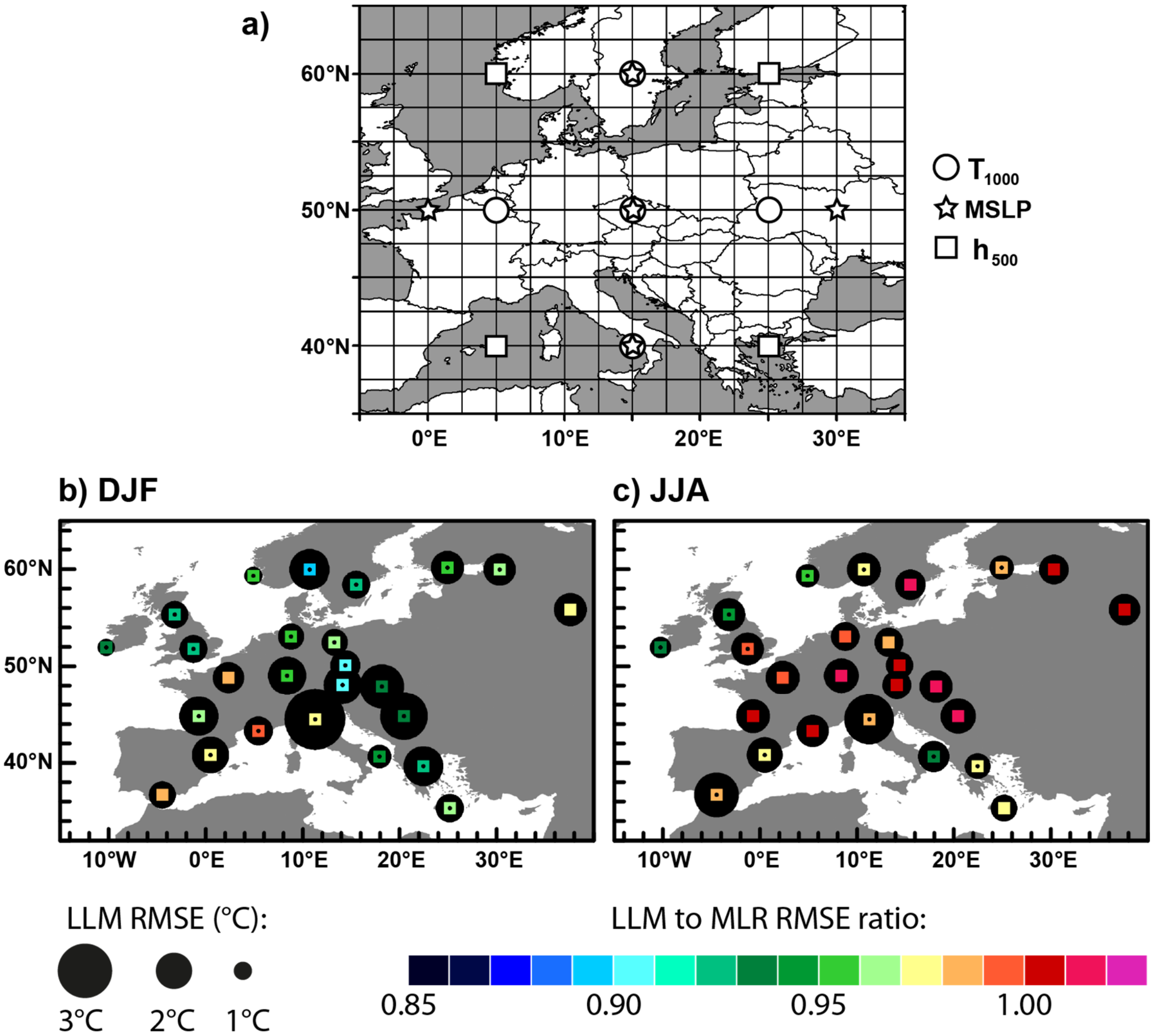


FIGURE 5.1: Results of maximum daily temperature downscaling for 25 European locations. A set of NCEP/NCAR reanalysis predictors consisting of the series of 1000 hPa level temperature (T_{1000}), mean sea level pressure (MSLP) and 500 hPa level geopotential height (h_{500}) was used. The predictors were arranged in a pre-defined pattern centered on the grid point closest to the target station, as illustrated in **(a)** for predictand located near coordinates 50°N, 15°E. Outcomes of the analysis are shown for boreal winter **(b)** and summer **(c)**. Root mean squared error (RMSE) of the temperature estimate is displayed through the size of the circle at the station's location, along with the ratio of RMSEs obtained by the method of local linear models (LLM) and multiple linear regression (MLR) (color of the embedded square). Presence of a central dot indicates statistically significant (confidence level 95%) difference between the series downscaled by the LLM and MLR methods, according to the paired Wilcoxon test. See MIKŠOVSKÝ & RAIDL (2005*) for more details on the test setup and additional results.

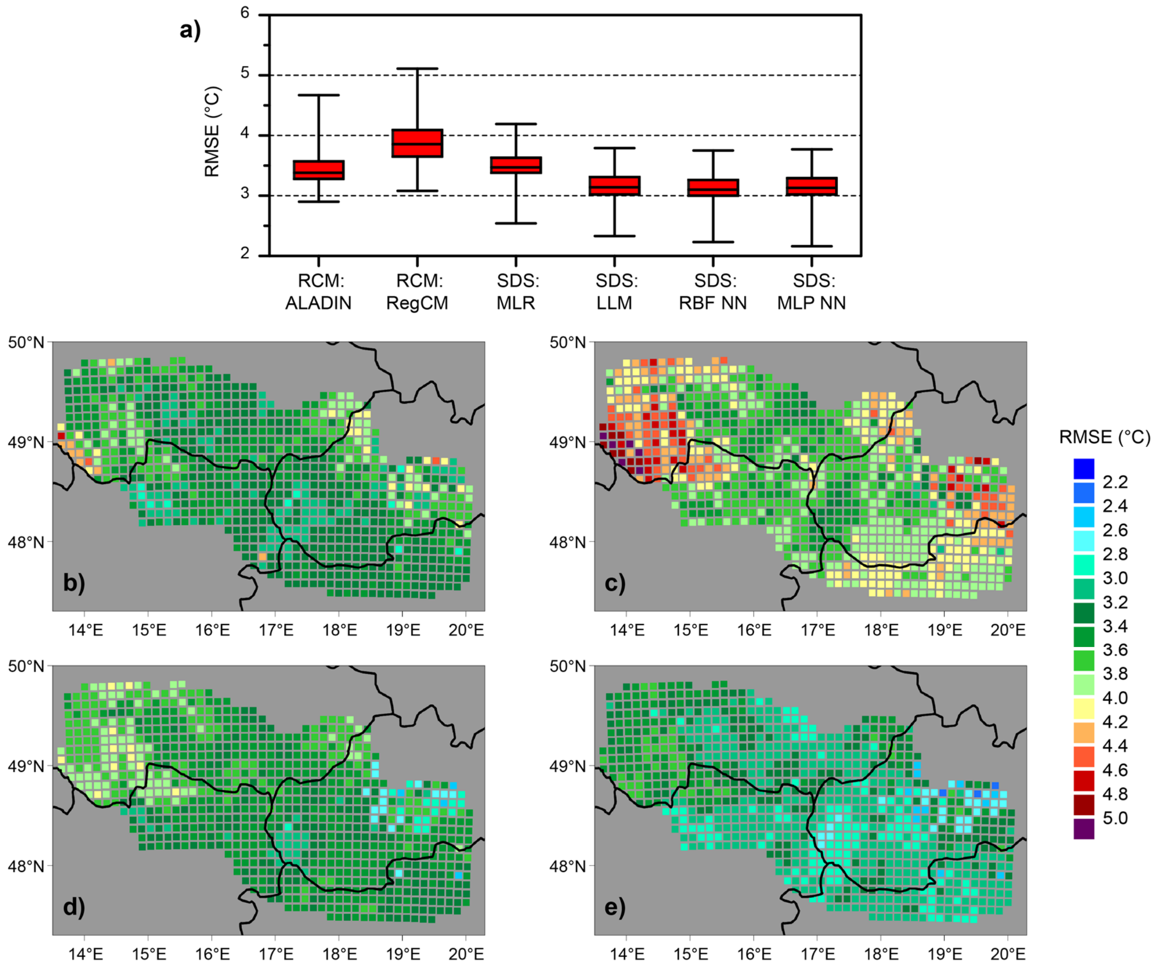


FIGURE 5.2: Root mean squared error (°C) of minimum daily temperature estimates in boreal winter (December, January, February), obtained by different methods of dynamical (RCM) and statistical (SDS) downscaling, using ERA-40 reanalysis data as inputs. Statistical distribution of errors within the target area is displayed in the form of boxplots, showing min-max range of the values, their inter-quartile range and median **(a)**. Geographic pattern of the errors is visualized for the ALADIN regional climate model **(b)**, RegCM climate model **(c)**, statistical downscaling by multiple linear regression **(d)**, and statistical downscaling by the method of local linear models **(e)**. Adapted from the outcomes of the analysis presented in HUTH ET AL. (2015*), where more details on the test setup can be found.

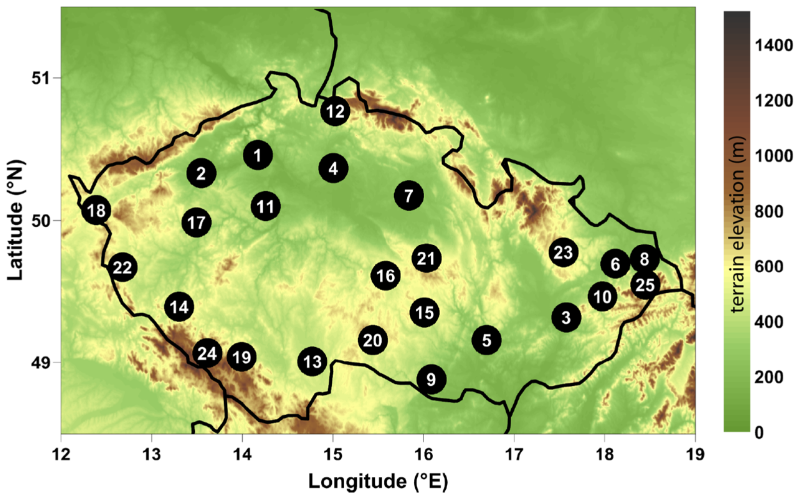
5.2 Estimation of daily temperatures from other concurrent records

While the series of meteorological measurements from land-based weather stations represent one of the basic types of data in the atmospheric research, it is not uncommon for these records to be incomplete, interrupted by shorter or longer periods of missing values. Often, such gaps need to be filled before a subsequent analysis can be performed, and records from other nearby sites are commonly used for this purpose. In this section, outcomes of our experiments with estimating daily temperature data from other concurrent measurements are briefly presented, with an emphasis again on comparing the performance of linear and nonlinear regression techniques. Although these results were not published as a stand-alone paper, their sample was included here to demonstrate yet another application of regression mappings for approximation of the spatial relations among climate time series.

The tests were conducted on a dataset comprising daily mean, minimum and maximum temperature from 25 Czech weather stations (Fig. 5.3). Linear and nonlinear regression were used to generate estimates of each of these temperature series from the temperature records at the rest of the weather stations and from the temperatures and geopotential heights provided by the ERA-40 reanalysis. The regression mappings included multiple linear regression, method of local linear models and MLP and RBF neural networks, as introduced in Chap. 3. The pool of potential predictors consisted of mean, minimum and maximum temperature from the remaining 24 stations, as well as ERA-40 series of temperature and geopotential height at the 1000 hPa and 850 hPa levels from the area bounded by 40°N, 60°N, 0°E and 30°E. A step-wise screening procedure based on multiple linear regression was applied to identify the 20 most influential predictors, individually for each temperature type and location. These were then used as inputs for all four empirical models. The regression mappings were calibrated for the years 1961-1990 and validated for the 1991-2000 period. Other technical details of the tests were similar to those in Huth et al. (2015*). The temperature estimates by different regression models were compared mutually and also to the outcomes of inverse distance weighting (IDW), one of the most common geostatistical interpolation techniques (e.g. Jarvis & Stuart 2001).

Figure 5.4 summarizes root mean squared errors of the temperature estimates obtained for individual weather stations and temperature types. On average, all nonlinear models outperformed multiple linear regression. Gain from considering the nonlinear components of the spatial relations was generally strongest for the high-elevation weather stations, which can be considered atypical sites in their local geographic neighborhood. At locations with another station of similar character situated nearby, differences between outputs of linear and nonlinear mappings tended to be smaller, as did total error. RBF neural networks and the method of local linear models were found mutually comparable in their performance. Multilayer perceptrons, although no worse on average than the other two nonlinear methods, have produced substantially greater dispersion of errors relative to linear regression, sometimes even giving less accurate temperature estimates than MLR. This intermittent performance loss did not seem to be related to MLP's sensitivity to the initialization of its training procedure (which was found to be quite low). Rather, it was traced to greater vulnerability of multilayer perceptrons to inhomogeneities in the input data, present in some of the series of station-based measurements. All regression techniques (including MLR) distinctly outperformed IDW interpolation. Experiments were also performed using ERA-40 series alone as the regression inputs, essentially creating a downscaling-like setup (Fig. 5.4d). Unsurprisingly, use of reanalysis-only predictors increased the error of temperature estimation. However, the loosening of the predictors-predictand links also resulted in generally greater relative improvement from application of nonlinear regression models, which now outperformed multiple linear regression by an even greater margin.

While not shown here, regression models' ability to realistically reproduce statistical distributions of observed temperatures was investigated as well. The validation statistics included standard deviation, as well as skewness and kurtosis. Performance of all regression techniques was found to be generally good and mutually comparable in this regard, with only mild advantage occasionally indicated for the nonlinear mappings. On the other hand, all regression models, linear and nonlinear alike, displayed just limited ability to realistically reproduce individual temporal trends in the temperature series, largely due to mismatch of long-term components in temperature records from different sites.



Station no.	Station name	Longitude (°E)	Latitude (°N)	Elevation (m)
1	Doksany	14.17	50.46	158
2	Žatec	13.54	50.33	201
3	Holešov	17.57	49.32	224
4	Semčice	15	50.37	234
5	Brno-Tuřany	16.69	49.16	241
6	Mošnov	18.12	49.69	251
7	Hradec Králové	15.84	50.17	278
8	Lučina	18.44	49.73	300
9	Kuchařovice	16.09	48.88	334
10	Valašské Meziříčí	17.97	49.46	334
11	Praha-Ruzyně	14.26	50.1	364
12	Liberec	15.02	50.77	398
13	Třeboň	14.77	49.01	429
14	Klatovy	13.3	49.39	430
15	Velké Meziříčí	16.01	49.35	452
16	Havlíčkův Brod	15.58	49.61	455
17	Královice	13.49	49.99	468
18	Cheb	12.39	50.07	471
19	Husinec	13.99	49.04	536
20	Kostelní Myslová	15.44	49.16	569
21	Svratouch	16.03	49.74	737
22	Přimda	12.68	49.67	742
23	Červená	17.54	49.77	750
24	Churáňov	13.61	49.07	1118
25	Lysá Hora	18.44	49.54	1324

FIGURE 5.3: Locations of the Czech weather stations (maintained by the Czech Hydrometeorological Institute; http://www.chmi.cz/) providing data for the experiments with estimation of daily temperatures from other concurrent records. Numerical identifiers of the stations correspond to their ranks in the elevation-ordered list on the right.

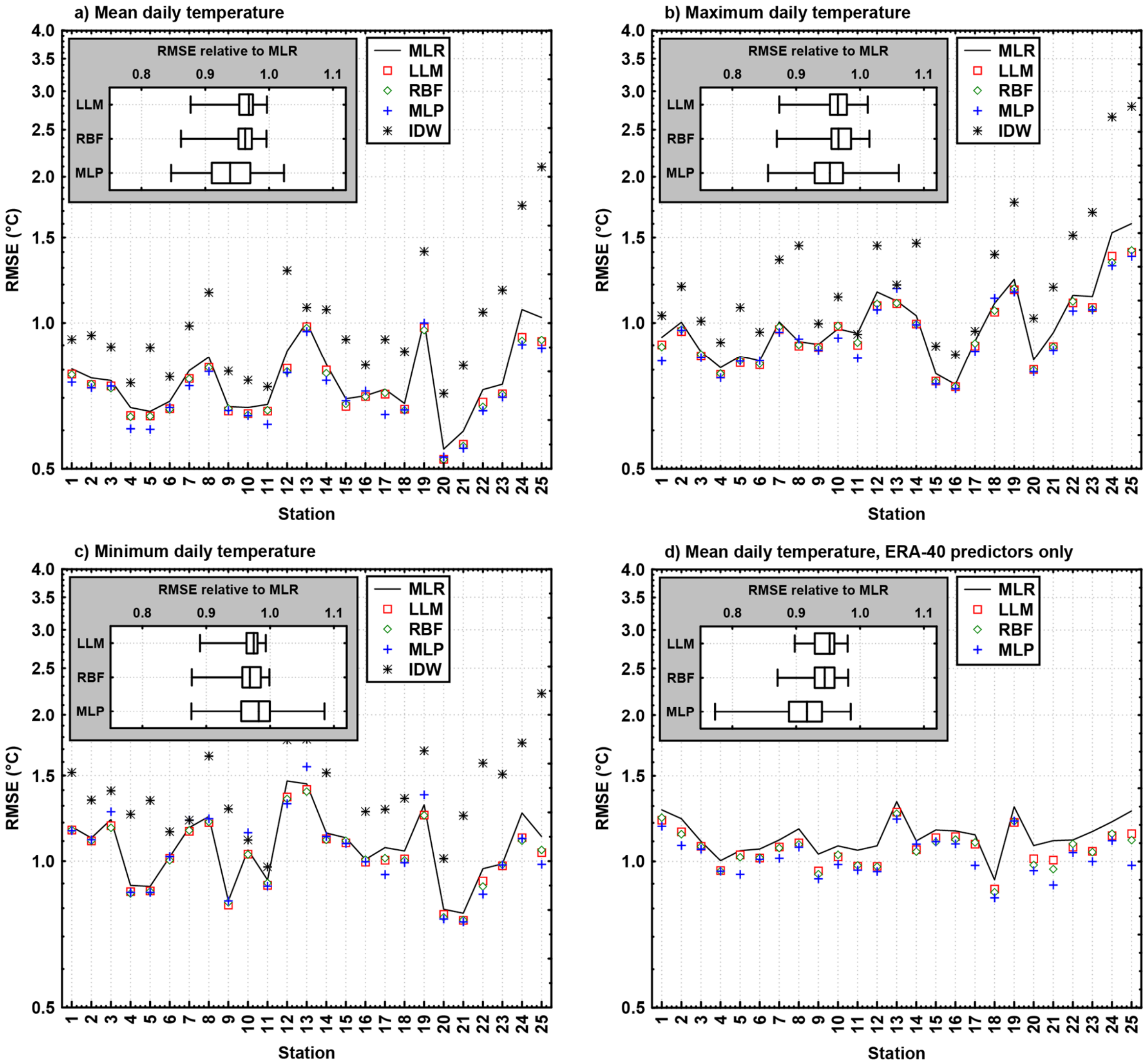


FIGURE 5.4: Root mean squared error (RMSE) of daily temperature estimation, carried out for 25 Czech weather stations by different regression techniques (multiple linear regression: MLR; local linear models: LLM; RBF neural network: RBF; multilayer perceptron neural network: MLP), as well as by inverse distance weighting interpolation (IDW). The results are shown for daily mean **(a)**, maximum **(b)** and minimum **(c)** temperature computed using temperature series from the other observational sites and ERA-40 data as potential predictors, as well as for daily mean temperature computed from ERA-40 data only **(d)**. Identifiers of individual stations correspond to their numerical IDs in Fig. 5.3. The embedded boxplots show distributions of RMSE achieved by the nonlinear regression methods relative to linear regression in the set of all 25 stations: whiskers represent min-max range of the values, the box encloses values between lower and upper quartile, the central line corresponds to the median.

CHAPTER 6
STATISTICAL ATTRIBUTION ANALYSIS

Among the problems studied by contemporary climatology, a prominent place is held by the issue of attribution, i.e. linking the observed spatiotemporal variability in the climate system to individual internal and external factors responsible. In this chapter, several examples of our contributions to the related problems are given, including analyses of temporal and geographical variability in temperature or precipitation series (Chap. 6.1; BRÁZDIL ET AL. 2012A*; MIKŠOVSKÝ ET AL. 2014* - APPENDIX V; MIKŠOVSKÝ & PIŠOFT 2015*; KUCHAŘ ET AL. 2015*; MIKŠOVSKÝ ET AL. 2016A* - APPENDIX VII), in wind speeds across the Czech Republic (Chap. 6.2; BRÁZDIL ET AL. 2019* - APPENDIX VIII), and in the series of various drought indices (Chap. 6.3), both over the instrumental era (BRÁZDIL ET AL. 2015A*, 2015B* - APPENDIX VI; MIKŠOVSKÝ ET AL. 2016B*) and during more distant past (MIKŠOVSKÝ ET AL. 2019* - Appendix IX).

6.1 ATTRIBUTION OF TEMPERATURE AND PRECIPITATION VARIABILITY

Of variables defining the state of the climate system, air temperature is perhaps the most intensely studied. Yet, despite the concentrated attention aimed at various thermal characteristics of the atmosphere, their behavior and its causes still remain only partly understood. Even temporal variability in a single series of local temperature can be quite complicated (as shown in Fig. 2.1 for Czech temperature), and it becomes yet more intricate when spatial structures are taken into account. Identifying and quantifying the effects of individual climate-affecting agents (and their eventual interactions) is a process often approached by statistical methods, including various forms of regression mappings (see, e.g., the introductory sections in MIKŠOVSKÝ ET AL. 2014* and MIKŠOVSKÝ ET AL. 2016A*). Several examples of our efforts in this field are presented here, demonstrating the application of statistical analysis to various local and global temperature series and the insights that can obtained about the role of external climate forcings and large-scale climate variability modes.

Our first take on the issue of statistical attribution of temperature variability was aimed at the series of mean annual Czech temperature over the 1860-2008 period, with the results published as a part of the monograph BRÁZDIL ET AL. (2012A*). The temperature series investigated was created from measurements gathered at 10 Czech weather stations, quality-controlled and subjected to a homogenization procedure (BRÁZDIL ET AL. 2012A*, 2012B). Motivated by the prior attribution studies concerned with identification of the imprints of natural and anthropogenic factors in the temperature data (particularly by SCHÖNWIESE ET AL. 2010), we used multiple linear regression and multilayer perceptron neural network to detect temperature components related to the concentration of greenhouse gases (GHGs), amounts of sulfate aerosols and solar activity, as well as to the effects of the Southern Oscillation (SO) and the North Atlantic Oscillation (NAO). Relatively prominent slow-variable components formally correlated with greenhouse gases concentration and sulfate amounts were found, along with a weaker imprint of solar activity. NAO proved to be an important driver of the inter-annual temperature variability, whereas the component attributed to SO was substantially weaker. Attention was also paid to the possible nonlinearities in the links studied: Application of MLP neural network instead of basic linear regression resulted in just about 2% decrease of total RMSE (using the same set of predictors for both techniques), and the respective regression-based temperature estimates were found to be quite similar (Fig. 6.1).

The conclusions of BRÁZDIL ET AL. (2012A*) highlighted some possible connections of Czech temperature to external climate forcings and large-scale internal variability modes. However, the underlying analysis was somewhat rudimentary, and it neglected potentially critical aspects of the attribution problem such as assessment of the statistical significance of the relations, possibility of time-delayed responses or seasonal specifics of the links. In MIKŠOVSKÝ ET AL. (2014*), we therefore revisited the matter of regression-based attribution analysis in more depth. Monthly series of temperature were studied alongside their annual means, and results for the Czech Lands were also compared to their counterparts derived from pan-European and global land temperature series (supplied from the Berkeley Earth dataset: ROHDE ET AL. 2013A, 2013B). Statistical significance of the regression coefficients was tested by moving block bootstrap (e.g. FITZENBERGER 1998). Our results confirmed the existence of a strong formal match between the long-term warming trends in temperature and concentration of greenhouse gases, and a weaker (and typically statistically non-significant) cooling tendency associated with sulfate aerosols. Only weak effects of solar activity were detected in any of the temperature series investigated. We also found no clear imprint of volcanic activity in the Czech (or European) temperatures, in contrast to a distinct temporary post-eruption cooling in global land temperature. Of the internal climate oscillations, NAO was confirmed to be one of the dominant sources of shorter-term variability in the European region, whereas contributions from the Southern Oscillation, albeit noticeable, were only borderline statistically significant. A weakly significant component in the Czech temperature was also detected for the phase of the Atlantic Multidecadal Oscillation (AMO).

In addition to the temperature data, Czech precipitation series and their possible relations to the climate forcings and variability modes were also investigated. The respective results in BRÁZDIL ET AL. (2012A*) and MIKŠOVSKÝ ET AL. (2014*) demonstrated that, unlike for temperatures, only very small fraction of total variance could be explained by any form of the regression model (7% or less, compared to up to 53 % for Czech annual temperature and 20% for Czech monthly temperature). NAO index was found to be the only predictor contributing a statistically significant component to the Czech precipitation series.

In MIKŠOVSKÝ ET AL. (2014*), too, nonlinear regression models were applied in addition to multiple linear regression, to detect and quantify eventual nonlinear interactions among the predictors and temperature/precipitation. None of the nonlinear mappings did, however, distinctly outperform multiple linear regression in terms of the fraction of variance explained. Hence, while some of the climate responses to the forcing factors may be inherently nonlinear, their manifestations in the monthly and annual series of temperature seem to be approximated quite well by purely linear superposition. A similar conclusion was also reached in our analysis of temperature and other variables in the middle atmosphere (KUCHAŘ ET AL. 2015*). In the follow-up work, we therefore turned our attention to the analysis of various forms of gridded temperature data, using multiple linear regression alone as the tool for separating components associated with individual climate-affecting factors.

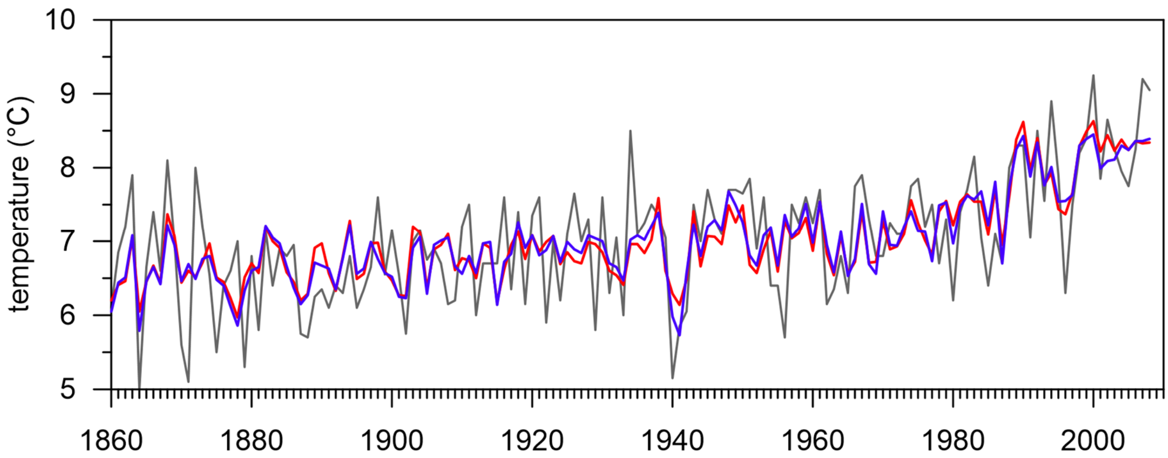


FIGURE 6.1: Annual mean areal Czech temperature in the 1860-2008 period, observed (**grey line**) and approximated by multiple linear regression (**red line**) and multilayer perceptron neural network (**blue line**) from a set of explanatory variables representing various climate forcings, described in BRÁZDIL ET AL. (2012A*) and based on the setup by SCHÖNWIESE ET AL. (2010). Adapted from BRÁZDIL ET AL. (2012A*).

In MIKŠOVSKÝ & PIŠOFT (2015*), we investigated presence of imprints of various climate forcings and internal variability modes in the series of gridded monthly temperature anomalies throughout the European region, supplied from the GISTEMP (HANSEN ET AL. 2010) and Berkeley Earth (ROHDE ET AL. 2013A, 2013B) datasets. Multiple linear regression was applied to identify links between local temperature anomalies and selected explanatory variables with established or suspected influence on the European weather and climate (Fig. 6.2). Statistical significance of the regression coefficients was assessed by moving block bootstrap. While not included in MIKŠOVSKÝ & PIŠOFT (2015*), the tests were also carried out for temperatures adopted from the 20th Century Reanalysis (COMPO ET AL. 2011). This allowed for a comparison of the predictor imprints in the gridded observations and in a reanalysis dataset (which, in the particular case of the 20th Century Reanalysis, does not use temperatures from the land-based stations as inputs). In Fig. 6.3, our results are summarized in the form of temperature responses to pre-selected characteristic variations of the predictors, specified in the caption of Fig. 6.2. Some of the previously established links have been confirmed by our analysis. These included the universally strong, yet locally variable correlation between GHGs concentration and the long-term temperature component, or presence of a distinct response pattern related to the North Atlantic Oscillation. Some interesting outcomes regarding the effects of external forcings or teleconnections projected by internal variability modes also appeared, particularly the association between the Pacific Decadal Oscillation (PDO) and temperatures in Scandinavia. Furthermore, our analysis highlighted some of the uncertainties potentially stemming from the choice of the target temperature dataset. Of particular interest was the notable difference between components correlated with the greenhouse gases concentration in the GISTEMP and Berkeley Earth datasets and in the 20th Century Reanalysis. This contrast, symptomatic of potential mis-representation of long-term temperature trends in the 20th Century Reanalysis (COMPO ET AL. 2013), served as a cautionary example of the specifics of the reanalysis-type data, frequently employed as proxies of direct climate measurements, yet often carrying a distinct signature of the numerical model involved in their creation and of the selection of its inputs.

To further pursue the issue of temperature variability attribution, and to closer investigate the associated uncertainties related to input data selection, four gridded observational datasets (GISTEMP, Berkeley Earth, MLOST and HadCRUT4) were employed alongside the 20th Century Reanalysis in our follow-up analysis, presented in MIKŠOVSKÝ ET AL. (2016A*). The study focused on identification of global imprints of external forcings and large-scale climate variability modes in the temperature fields, but also on the issues of their statistical significance and on the possibility of time-lagged temperature responses. The results highlighted various long-range teleconnections associated with the activity of NAO, SO, AMO and PDO, including, for instance, a noteworthy PDO link to northern European temperature, or relationship between AMO phase and temperatures in large regions over the Indian and Pacific Oceans. Local direct effects of natural external climate forcings (solar and volcanic activity) were found to be rather weak and largely statistically non-significant over most of the globe; on the other hand, strong episodic volcanism-induced cooling was confirmed in the globally averaged temperature series. Resemblance of the response patterns obtained from individual gridded temperature datasets was found to be generally strong, although notably weakened in areas with limited raw data availability, such as some African regions. Noteworthy contrasts have also been confirmed between the 20th Century Reanalysis and the analysis-type temperature datasets, particularly over land.

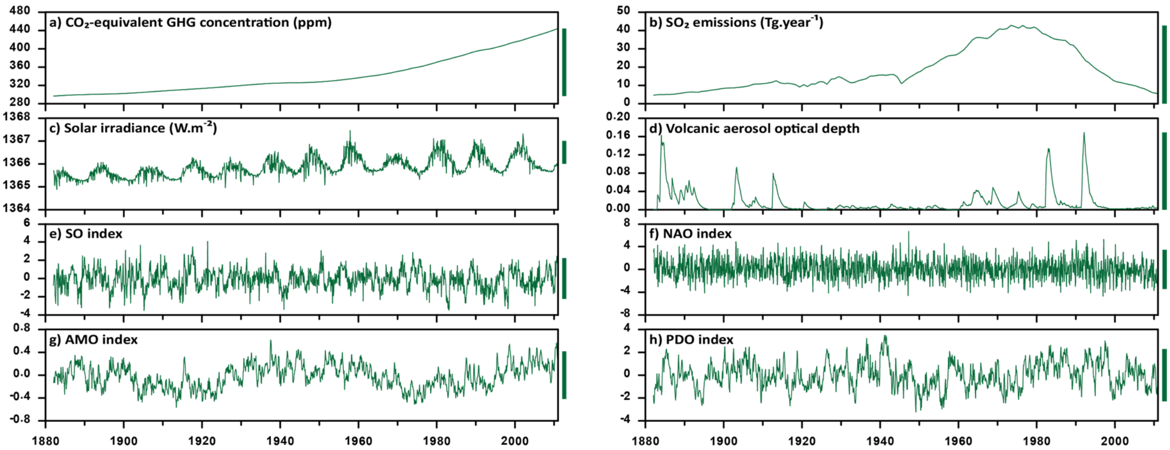
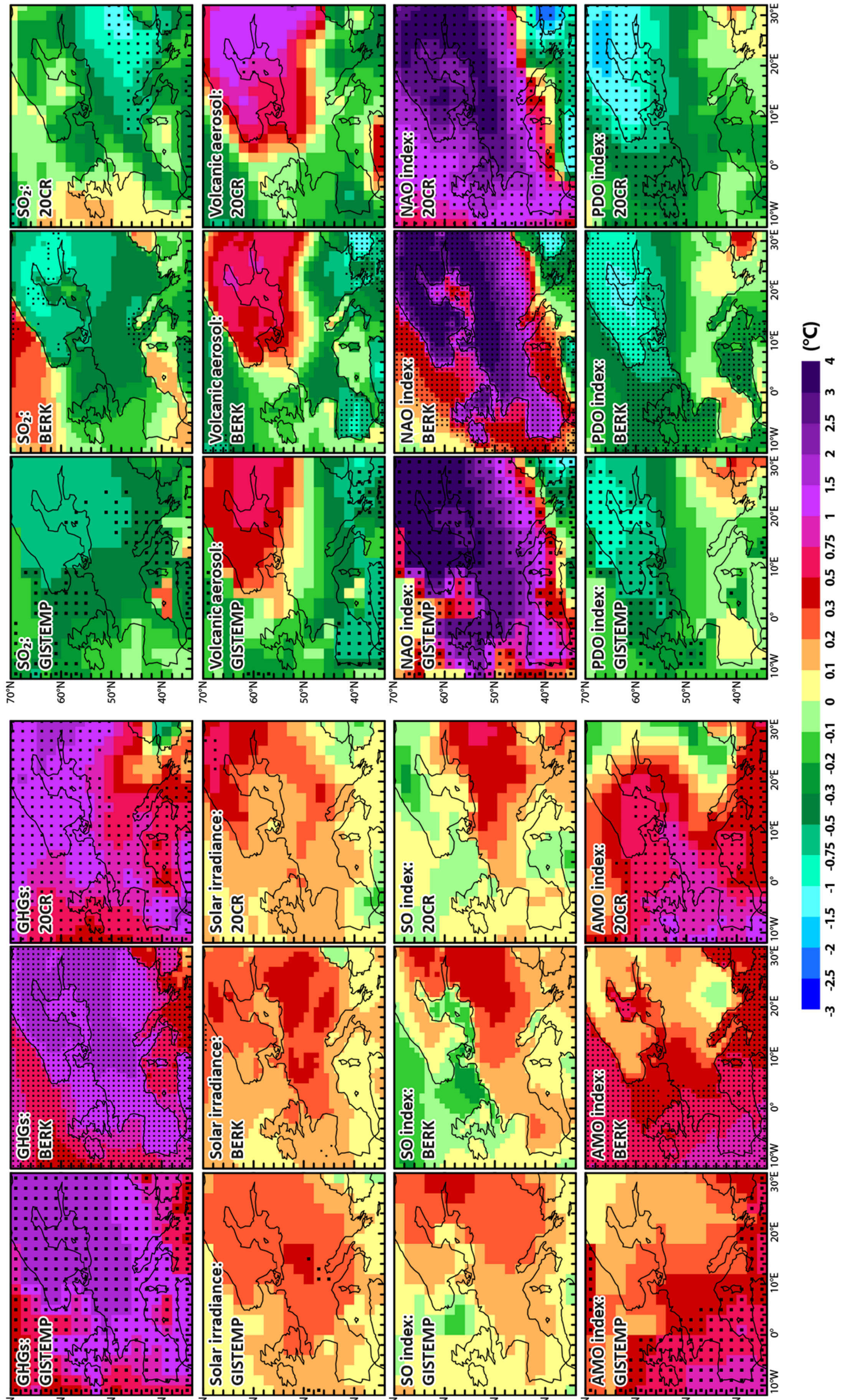


FIGURE 6.2: Time series of explanatory variables employed in the attribution analysis in MIKŠOVSKÝ & PIŠOFT (2015*): CO_2-equivalent concentration of Kyoto protocol-controlled greenhouse gases (GHGs), obtained from http://www.pik-potsdam.de/~mmalte/rcps/ (MEINSHAUSEN ET AL. 2011) **(a)**; European SO_2 emissions adapted from the data by SMITH ET AL. (2011) as a proxy for the amounts of anthropogenic sulfate aerosols **(b)**; monthly solar irradiance from http://climexp.knmi.nl/data/itsi_wls_mon.dat (WANG ET AL. 2005) **(c)**; volcanic aerosol optical depth from http://data.giss.nasa.gov/modelforce/strataer/ (SATO ET AL. 1993) **(d)**; Southern Oscillation (SO) index (ROPELEWSKI & JONES 1987) **(e)** and North Atlantic Oscillation (NAO) index (JONES ET AL. 1997) **(f)** from the CRU database at http://www.cru.uea.ac.uk/cru/data/pci.htm; Atlantic Multidecadal Oscillation (AMO - e.g. ENFIELD ET AL. 2001) index from https://www.esrl.noaa.gov/psd/data/timeseries/AMO/ **(g)**; Pacific Decadal Oscillation (PDO - e.g. ZHANG ET AL. 1997) index from http://climexp.knmi.nl/data/ipdo_erssta.txt **(h)**. Green bars to the right of individual panels illustrate the size of the characteristic variation Δp_i of the predictor, used for calculation of the temperature responses shown in Fig. 6.3: Increase of the CO_2-equivalent GHGs concentration between 1882 and 2010 (+148 ppm); peak value of the European SO_2 emissions (43 $Tg.year^{-1}$); increase of the solar irradiance by 1 $W.m^{-2}$; Mt. Pinatubo-sized volcanic event; increase of SO, NAO, AMO and PDO indices by four times their standard deviation. Modified from MIKŠOVSKÝ & PIŠOFT (2015*).

FIGURE 6.3 (➔): Geographic patterns of local temperature response (°C) associated with various explanatory variables, calculated as a product of the regression coefficient a_i (computed individually for each grid point by multiple linear regression) and the characteristic variation Δp_i of the respective predictor (specified in Fig. 6.2). Monthly temperature anomalies from the GISTEMP (HANSEN ET AL. 2010), Berkeley Earth (BERK: ROHDE ET AL. 2013A, 2013B) and 20th Century Reanalysis (20CR: COMPO ET AL. 2011) datasets were analyzed, for the 1882-2010 period. Statistical significance of the components associated with individual predictors was evaluated by moving block bootstrap – black dots mark grid points with response statistically significant at the 99% level. Modified from MIKŠOVSKÝ & PIŠOFT (2015*) and expanded with the 20CR-based results.


GHGs: GISTEMP
GHGs: BERK
GHGs: 20CR
Solar irradiance: GISTEMP
Solar irradiance: BERK
Solar irradiance: 20CR
SO index: GISTEMP
SO index: BERK
SO index: 20CR
AMO index: GISTEMP
AMO index: BERK
AMO index: 20CR
SO2: GISTEMP
SO2: BERK
SO2: 20CR
Volcanic aerosol: GISTEMP
Volcanic aerosol: BERK
Volcanic aerosol: 20CR
NAO index: GISTEMP
NAO index: BERK
NAO index: 20CR
PDO index: GISTEMP
PDO index: BERK
PDO index: 20CR
(°C)
-3 -2.5 -2 -1.5 -1 -0.75 -0.5 -0.3 -0.2 -0.1 0 0.1 0.2 0.3 0.5 0.75 1 1.5 2 2.5 3 4

6.2 Attribution of wind speed variability

As the most direct manifestation of atmospheric circulation, wind speeds constitute another prominent weather and climate descriptor. In the case of near-ground wind, a complex interaction between large-scale air flow and local terrain is typically responsible for the observed variability patterns. To study and attribute these, wind speed records from 119 Czech weather stations were analyzed over the 1961-2015 period in Brázdil et al. (2019*), and presence of components related to natural or anthropogenic forcings and selected climate or circulation indices was assessed. A distinct anti-correlation was found between the long-term wind speed components and anthropogenic GHGs concentration; however, no such connection was detected for the free-atmosphere wind speeds, adopted from the NCEP/NCAR reanalysis. The stilling in the Czech wind speeds was therefore found unlikely to be directly associated with global climate change and its effect on large-scale circulation over Europe. Other factors, such as local surface roughness changes, may be responsible for the observed wind speed decrease trend.

Regarding the short-to-mid-term oscillatory components in the Czech wind speeds, our analysis highlighted not only seasonally and geographically variable imprints of the NAO index and the Central European Zonal Index, but also notable links to the East Atlantic/Western Russia Pattern. In the future, understanding of these relationships will help to construct more reliable statistical models replicating wind variability patterns over central Europe and complementing dynamical simulations of the region. This objective may be particularly desirable considering the mismatch of the observed wind speed trends and their RCM-simulated counterparts, documented in Brázdil et al. (2019*) for outputs of several Euro-CORDEX models.

6.3 Attribution of drought variability

While temperature, precipitation sums or wind speeds are among the basic – and most intensely studied – climate descriptors, more intricate composite characteristics are often used to capture interaction of weather/climate with other Earth systems. Drought indices, constructed to measure the degree of wet or dry conditions within some locality of interest, are one particular class of such impact-focused quantities. In Brázdil et al. (2015b*), we examined various aspects of several short- and long-term indices (SPI, SPEI, Z-index, PDSI) quantifying meteorological droughts in the Czech Republic during the instrumental era. The analysis focused on spring and summer as the seasons most relevant to the drought impacts on agriculture. As a part of this assessment, presence of links between the time series of individual drought indices and explanatory variables related to climate forcings was investigated. Attention was paid to the possible manifestations of man-induced changes to the atmospheric composition (particularly increasing concentrations of the greenhouse gases) as well as to the effects of natural external forcings (solar and volcanic activity). Presence of components correlated with the phase of the North Atlantic Oscillation, Southern Oscillation or Atlantic Multidecadal Oscillation was also assessed. Statistically significant formal connection between drought indices and anthropogenic forcing was found for the indices involving temperature or evapotranspiration in their definition. Links to NAO were generally strong and a tendency towards drier conditions has been confirmed for the positive NAO phase. Possible influence of the Southern Oscillation was detected as well, though only statistically significant for some of the indices and seasons. Again, nonlinear regression techniques were used alongside multiple linear regression, but, just as in the case of annual and monthly temperature and precipitation, only minor gain from application of nonlinear statistical models was generally indicated.

In our subsequent analysis of the spatiotemporal variability of Czech droughts, incorporated into the monograph BRÁZDIL ET AL. (2015A*), we paid attention to both short-term (monthly time scale) and long-term (annual time scale) drought indices, with extra emphasis on seasonal and geographical specifics of their responses to various climate drivers. Of the results obtained, the spatially intermittent, yet often statistically significant links of long-term droughts to the Southern Oscillation index were of particular interest. A similar analysis, but specifically targeting mid-term droughts, was therefore subsequently conducted with an increased focus on connections of Czech droughts to climate variability modes originating from the Pacific area (MIKŠOVSKÝ ET AL. 2016B*). Unlike in BRÁZDIL ET AL. (2015A*), Pacific Decadal Oscillation index was also considered in the analysis, along with the previously employed index of the Southern Oscillation. Due to a link between these two climate variability modes (e.g. NEWMAN ET AL. 2003), and the resulting correlation between their respective indices, partial regression models were applied to better capture their individual influences. PDO index was ultimately found to be more influential predictor of Czech drought variability than its SO counterpart, with statistically significant PDO imprints detected in drought indices from multiple Czech locations.

Finally, in MIKŠOVSKÝ ET AL. (2019*), the analysis of Czech drought variability patterns and their components has been extended beyond the instrumental era. Reconstructions of temperature, precipitation and various drought indices, spanning more than five centuries and based on a combination of instrumental and documentary data, were studied and compared to proxy-based reconstructions of several large-scale climate variability modes and external climate forcings. Notable influence of AMO- and PDO-related temperature variations on multi-decadal variability of Czech droughts was indicated by the outcomes of regression and wavelet analysis, along with marked NAO-linked oscillations at shorter time scales. Colder and wetter episodes were found to coincide with large volcanic eruptions, especially during summer. Moreover, the results in MIKŠOVSKÝ ET AL. (2019*) once again underscored the role of uncertainties related to the selection of the input data, particularly evident from the distinct contrasts between drought responses estimated for three different versions of proxy-based PDO reconstruction.

CHAPTER 7
CONCLUDING REMARKS

The individual pieces of analyses shown throughout this text have demonstrated a few examples of the wide range of possible applications of statistical – and especially regression – techniques in the atmospheric and climate sciences. The results achieved, diverse in their aims, methods used and datasets involved, can obviously not be summarized by a simple, universal conclusion. There are, however, a few points worthy of mentioning, related to the individual topics here as well as their common aspects.

First, our experiments have affirmed that nonlinearity, while inherent to the climate system, manifests with varying level of intensity in the climate time series. It would be too daring to try to formulate specific guidelines pinpointing scenarios suitable for application of nonlinear techniques. Our results as well as those of other studies devoted to this topic (see, for instance, references in the introduction of MIKŠOVSKÝ ET AL. 2008*) have highlighted numerous factors potentially affecting the level of discernible nonlinearity. Additional ambiguity can be brought by technical specifics or imperfections of the data themselves, such as the presence of non-climatic inhomogeneities. Still, there seem to be some general factors preconditioning superiority of the nonlinear approach (or lack thereof). In the absence of nontrivial, low-dimensional links between predictors and predictand (for instance when forecasting daily temperatures more than a few days ahead), no benefit stemmed from the use of nonlinear models. On the other hand, diminished degree of detectable nonlinearity was also characteristic of setups with very high linear correlation between the predictand and the predictor(s), when most of the information could be transmitted through a purely linear function, leaving only small fraction of total variance unexplained and available for the extra contribution from a nonlinear mapping. Of the tasks studied in this thesis, some degree of superiority of nonlinear techniques was typically indicated for multi-predictor regression setups at daily time scales, especially for relationships involving a spatial component. Even then, the gain was not automatically guaranteed for each individual test configuration. This means that the key problem – reliable identification of scenarios suitable for the application of nonlinear methods – needs to be treated on case-by-case basis. Sometimes, pointers are available that can help to make the decision. In particular, presence of markers of low-dimensional chaotic behavior in the data, such as existence of a well-defined strange attractor, is a likely indicator of capturable nonlinear links. Dominant, unambiguous manifestations of low-dimensional chaotic dynamics are however rare in climate data, and their presence usually difficult to establish from the observational time series (at least at the spatiotemporal scales investigated here). As a result, conclusions about the feasibility of nonlinear techniques typically need to be obtained by direct tests focused on the specific performance criteria of interest. The same then also applies to the selection of the best performing type of the nonlinear mapping.

As shown in Chap. 5.1 for series of daily temperature, statistical downscaling tasks do often benefit from the nonlinear approach to the construction of the regression functions. However, the gain is not automatically assured, and some validation statistics show no systematic improvement from the use of a nonlinear regression model, as we demonstrated (HUTH ET AL. 2015*) and as was also suggested by other studies with similar focus (e.g. HUTH ET AL. 2008). There are, however, additional matters in need of attention. Besides the critical – yet occasionally neglected – issue of predictor selection (e.g. HUTH 2004), stability of the downscaling mappings must be carefully verified. This becomes particularly crucial when GCM outputs for the future time periods are downscaled, with predictors possibly falling outside the range of values typical for the past climate, and thus unprecedented in the data employed for calibration of the downscaling models. Bearing these caveats in mind, statistical downscaling – regardless of the specific methodology – remains a valuable tool for bypassing the resolution gap between global climate simulations and local-scale data. With further improvement of the spatial step of the climate models, and reduction of their still considerable biases, need for statistical downscaling (and also for statistical postprocessing, reducing the systematic errors in the GCM/RCM simulations – e.g. DÉQUÉ 2007; THEMEßL ET AL. 2012) may eventually disappear. Today, however, statistical downscaling models do still represent a viable alternative (or a useful complement) to their dynamical counterparts.

In our attribution-seeking analyses, only minor gain from application of nonlinear mappings was generally detected (BRÁZDIL ET AL. 2012A*; MIKŠOVSKÝ ET AL. 2014*; BRÁZDIL ET AL. 2015B*; KUCHAŘ ET AL. 2015*). Even in the prior studies concerned with comparable problems, and reporting presence of nonlinearities, magnitude of the nonlinear components was rather variable and inferiority of linear models not guaranteed for every test setting (PASINI ET AL. 2006; SCHÖNWIESE ET AL. 2010). But even though it may seem that approaching the problem of statistical attribution analysis via purely linear methods does not impose excessive oversimplification, such conclusion can not be automatically generalized to all types of forcings, teleconnections or variables of interest. As suggested, for instance, by our most recent experiments with nonlinearity detection (presented at the European Meteorological Society 2019 meeting – http://www.miksovsky.info/EMS2019.pptx), nonlinear components can be noteworthy for some more complex teleconnection setups, from both formal and practical perspective. Additional focus on such relationships, and on the dynamical principles behind them, is therefore quite desirable in the future research of links and responses within the climate system.

Finally, it should be emphasized that despite the benefits of the statistical approach to attribution, such as its relative speed and flexibility, one should always be aware of its limitations as well. Aside from suffering from potential uncertainties related to the choice of data employed for the analysis, and to the selection of a suitable analytical framework, purely statistical techniques only consider formal similarities among the time series, oblivious of the underlying physical dependencies or their absence. Dangers of misrepresentation of the outcomes of the statistical approach to attribution have been highlighted in the past (e.g. BENESTAD & SCHMIDT 2009); we also touched upon this subject in MIKŠOVSKÝ ET AL. (2014*), BRÁZDIL ET AL. (2015B*), MIKŠOVSKÝ ET AL. (2016A*), BRÁZDIL ET AL. (2019*) or MIKŠOVSKÝ ET AL. (2019*). In particular, caution is needed when interpreting formal links of climate variables to trend-like predictors such as greenhouse gases-induced forcing, due to very limited number of degrees of freedom in the relevant signals. Whenever possible, statistical answers to the question of attribution should therefore be considered along with other information sources, especially simulations by general circulation models, inherently more universal than purely statistical methodologies, even though still only partly successful in completely reproducing the observed features of the climate system (e.g. STOCKER ET AL. 2013). By combining the statistical and dynamical approaches, mutually compensating for their individual limitations, more complete and dependable picture of variability in the climate system and its causes may then ultimately be gained.

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