Doctoral Thesis

Projecting scenarios of climatic change and future weather for ecosystem models
derivation of methods and their application to forest in the alps

Author(s):
Gyalistras, Dimitrios

Publication Date:
1997

Permanent Link:
https://doi.org/10.3929/ethz-a-001889726

Rights / License:
In Copyright - Non-Commercial Use Permitted

This page was generated automatically upon download from the ETH Zurich Research Collection. For more information please consult the Terms of use.
Projecting Scenarios of Climatic Change and Future Weather for Ecosystem Models: Derivation of Methods and Their Application to Forests In the Alps

A dissertation submitted to the SWISS FEDERAL INSTITUTE OF TECHNOLOGY ZURICH for the degree of Doctor of Natural Sciences

presented by Dimitrios Gyalistras Dipl. El. Ing. ETH born Sept. 17th, 1964 Athens, Greece

accepted on the recommendation of Prof. Dr. H. Flühler, examiner Dr. A. Fischlin, co-examiner Prof. Dr. A. Ohmura, co-examiner

Zurich, 1997
Acknowledgements

My warmest thanks are due to

Dr. Andreas Fischlin
for initiating this research, supporting it with many fruitful ideas and doing the careful supervision.

Prof. Hannes Flühler and Prof. Atsumu Ohmura
for standing by this work, their encouraging support, and the review of the manuscript.

Prof. Martin Beniston, Prof. Hans von Storch and Prof. Heinz Wanner
who helped to establish and pursue this research and took time for many important discussions.

Dr. Harald Bugmann, Prof. Christoph Schär and Prof. Huw Davies
for their stimulating comments and the valuable exchange during different phases of the project.

Jürg Thöny, Dr. Heike Lischke, Frank Thommen, Dr. Olivier Roth,
Dr. Daniel Perruchoud, Hans-Peter Läser, Dr. Thomas Nemecek,
and all other colleagues from the Institute of Terrestrial Ecology ETHZ for their help and the good working atmosphere.

My partner Barbara Davies
for her support and patience.

The financial support of the Swiss Priority Programme Environment, the Swiss National Science Foundation, and the Swiss Federal Institute for Technology is gratefully acknowledged.
Leer - Vide - Empty
# Table of Contents

1. **Introduction** .................................................................................................................. 1

2. **The Spatial Aspect: Statistical Downscaling of GCM-simulated Climatic Changes to the Regional Scale** ................................................. 5
   2.1 Introduction .................................................................................................................. 5
   2.2 Data and Methods ........................................................................................................ 10
       2.2.1 Observations ........................................................................................................ 10
       2.2.2 GCM-Experiments ............................................................................................ 12
       2.2.3 Statistical Procedure ......................................................................................... 13
   2.3 Results and Discussion ................................................................................................. 17
       2.3.1 Model Estimation ............................................................................................... 17
       2.3.2 Model verification .............................................................................................. 22
       2.3.3 Downscaling of GCM-Simulated Climatic Changes ......................................... 30
   2.4 Conclusions ............................................................................................................... 36

3. **The Temporal Aspect: Stochastic Simulation of Monthly Weather** .......................... 38
   3.1 Introduction ............................................................................................................... 38
   3.2 Material and Methods ............................................................................................... 41
       3.2.1 Data .................................................................................................................... 41
       3.2.2 Stochastic Models ............................................................................................ 44
       3.2.3 Parameter Estimation ....................................................................................... 46
       3.2.4 Bioclimatic Variables ....................................................................................... 50
       3.2.5 Statistical Tests ............................................................................................... 52
       3.2.6 Modeling and Simulation Tools ....................................................................... 53
   3.3 Results ...................................................................................................................... 53
   3.4 Discussion ............................................................................................................... 57
   3.5 Conclusions ............................................................................................................... 60

4. **Synthesis and Application: Assessing Impacts of Climatic Change on Forests in the Alps** ................................................................. 61
   4.1 Introduction ............................................................................................................... 61
   4.2 Material and Methods ............................................................................................... 65
       4.2.1 Baseline Climates ............................................................................................. 66
       4.2.2 Climatic Scenarios ......................................................................................... 67
       4.2.3 Forest Model ForClim .................................................................................... 68
   4.3 Results ...................................................................................................................... 69
       4.3.1 Climatic Scenarios ......................................................................................... 69
       4.3.2 Forest Responses ........................................................................................... 72
   4.4 Discussion ............................................................................................................... 74
       4.4.1 Forest Responses ........................................................................................... 77
       4.4.2 Sensitivities and Uncertainties ........................................................................ 80
   4.5 Conclusions ............................................................................................................... 82

5. **Discussion** .................................................................................................................. 84

6. **Conclusions** .............................................................................................................. 88

7. **References** ............................................................................................................... 90
# List of Figures

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.1</td>
<td>Comparison between the climate simulated by the ECHAM1/LSG-GCM in the vicinity of the Alps (averages from three gridpoints) and observations</td>
<td>7</td>
</tr>
<tr>
<td>2.2</td>
<td>Gridpoints of atmospheric fields and case study locations considered for downscaling</td>
<td>10</td>
</tr>
<tr>
<td>2.3</td>
<td>Block diagram of the method used to derive scenarios of local climatic changes from large-scale climatic changes as simulated by GCMs</td>
<td>14</td>
</tr>
<tr>
<td>2.4</td>
<td>CCA model for Bern in winter</td>
<td>18</td>
</tr>
<tr>
<td>2.5</td>
<td>CCA model for Davos in winter</td>
<td>20</td>
</tr>
<tr>
<td>2.6</td>
<td>CCA model for Bern in summer</td>
<td>21</td>
</tr>
<tr>
<td>2.7</td>
<td>Skill of the CCA models as a function of the predictors, season, location and variable considered</td>
<td>24</td>
</tr>
<tr>
<td>2.8</td>
<td>Comparison of skills between the procedure proposed by VON STORCH et al. (1993) and the improved procedure</td>
<td>25</td>
</tr>
<tr>
<td>2.9</td>
<td>Comparison of statistically reconstructed time series of local weather statistics with observations</td>
<td>26</td>
</tr>
<tr>
<td>2.10</td>
<td>1901-1980 linear trends in the large-scale data sets used</td>
<td>29</td>
</tr>
<tr>
<td>2.11</td>
<td>Climatic change scenario for Bern in winter (5 yr running means)</td>
<td>31</td>
</tr>
<tr>
<td>2.12</td>
<td>Statistically downscaled changes in seasonal mean temperatures for the last 20 yr of the &quot;double CO2&quot; experiment and the last 10 yr of the &quot;IPCC Scenario A&quot; experiment</td>
<td>31</td>
</tr>
<tr>
<td>2.13</td>
<td>Statistically downscaled changes in winter precipitation totals and summer probabilities of wet days for the last 10 yr of the &quot;IPCC Scenario A&quot; experiment</td>
<td>32</td>
</tr>
<tr>
<td>3.1</td>
<td>Observed (bio-)climatic parameters at the 89 climatological stations used to test the stochastic simulation of monthly weather</td>
<td>43</td>
</tr>
<tr>
<td>3.2</td>
<td>Comparison of the performance of the Type IV models relative to the Type I-III models</td>
<td>55</td>
</tr>
<tr>
<td>3.3</td>
<td>Comparison of the annual cycles of the diagonal elements $\alpha_{11}$ and $\alpha_{22}$ of the system matrices $A$ of cyclostationary, first-order autoregressive models at selected European locations</td>
<td>56</td>
</tr>
<tr>
<td>4.1</td>
<td>Method used to derive climatic scenarios and simulate forest responses</td>
<td>65</td>
</tr>
<tr>
<td>4.2</td>
<td>Comparison of annual mean temperatures and annual precipitation totals under the present and the assumed scenario climates at the case study sites</td>
<td>70</td>
</tr>
</tbody>
</table>
4.3 Comparison of in period 1931-1980 observed annual cycles for monthly mean temperature and total precipitation with the climatic scenarios derived by statistical downscaling from a "2xCO₂"-experiment with the CCC-GCMII at the case study sites .................................................. 71

4.4 Simulated species compositions at the case study site Bever in the Swiss Alps for current climate (800-2040) and a possible, future "2xCO₂" climate (2060-3200) as downscaled from the CCC-GCMII .................................................. 72

4.5 Simulated equilibrium species compositions at the case study sites in the Alps for current baseline climate (800-2040) .................................................. 73

4.6 Simulated equilibrium species compositions at the case study sites in the Alps for a possible, future "2xCO₂" climate (2060-3200) as downscaled from the CCC-GCMII .................................................. 73

4.7 Using the CLIM SHELL to explore forest dynamics where there are no measurements available .................................................. 75

List of Tables

2.1 Meteorological variables and their seasonal statistics considered .................. 11

2.2 Mean linear trends of weather statistics in the period 1901-1980 as observed and reconstructed from 84 selected CCA models .................. 28

2.3 Projected deviations of weather statistics from their respective 1901-1980 long-term means for the last 20 yr of the "double CO₂" experiment and for the last 10 yr of the "IPCC Scenario A" experiment .................. 33

3.1 Climatological stations used to study the stochastic simulation of monthly weather .................................................. 42

3.2 Types of stochastic models considered .................................................. 44

3.3 Types of output functions considered .................................................. 45

3.4 Output functions used in different variants of stochastic models .................. 45

3.5 Overview of the data used to compare distributions of bioclimatic variables as derived from measured and stochastically simulated weather inputs .................. 52

3.6 Medians of the p-values obtained from the comparison of the distributions of selected bioclimatic variables derived from measured and stochastically simulated monthly weather data at 89 European climatological stations .................. 54

4.1 Characteristics and major current climatic parameters of the case study sites .................. 66
### Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>2mT</td>
<td>2m above ground temperature</td>
</tr>
<tr>
<td>AET</td>
<td>Actual evapotranspiration</td>
</tr>
<tr>
<td>AR(1)</td>
<td>Lag-1 autoregressive model</td>
</tr>
<tr>
<td>CCA</td>
<td>Canonical Correlation Analysis</td>
</tr>
<tr>
<td>CCC</td>
<td>Canadian Climate Centre</td>
</tr>
<tr>
<td>DCO2</td>
<td>&quot;Double CO₂&quot; experiment performed with the ECHAM1/LSG model</td>
</tr>
<tr>
<td>ECHAM</td>
<td>European Centre weather forecasting model, extensively modified at the Max-Planck Institute for Meteorology, Hamburg for climate simulations</td>
</tr>
<tr>
<td>EOF</td>
<td>Empirical Orthogonal Function</td>
</tr>
<tr>
<td>GCM</td>
<td>General Circulation Model</td>
</tr>
<tr>
<td>GHCN</td>
<td>Global Historical Climatology Network</td>
</tr>
<tr>
<td>IPCC</td>
<td>Intergovernmental Panel on Climate Change</td>
</tr>
<tr>
<td>LSG</td>
<td>Ocean model resolving large-scale geostrophic motions, developed at the Max-Planck Institute for Meteorology, Hamburg</td>
</tr>
<tr>
<td>LTM</td>
<td>Long-term mean</td>
</tr>
<tr>
<td>PC</td>
<td>Principal Component</td>
</tr>
<tr>
<td>PCA</td>
<td>Principal Component Analysis</td>
</tr>
<tr>
<td>PET</td>
<td>Potential evapotranspiration</td>
</tr>
<tr>
<td>SCNA</td>
<td>&quot;IPCC Scenario A&quot; experiment performed with the ECHAM1/LSG model</td>
</tr>
<tr>
<td>SLP</td>
<td>Sea-level pressure</td>
</tr>
</tbody>
</table>
Notation and List of Symbols

The following notation is used: \( x, \xi \) or \( \Xi \) denote a scalar, \( X \) denotes a random variable, \( x \) or \( X \) a vector, and \( A \) a matrix. \( X' \) and \( A^T \) denote the transpose of \( X \) and \( A \), respectively. \( A^{-1} \) is the inverse, and \( \alpha_{ij} \) the \((i,j)\)-th element of \( A \). \( \mathbb{E}[X] \), \( \text{STDEV}[X] \), and \( \text{SKEW}[X] \) denote the expected value, standard deviation and skewness of \( X \), respectively, and \( \text{COV}[X,Y] \) denotes the covariance of \( X \) and \( Y \). \( \text{EIGVEC}[A] \) denotes the matrix of the eigenvectors of \( A \), and \( \text{EIGVAL}[A] \) is a diagonal matrix containing the eigenvalues of \( A \). Subscripts (\( t, k \) etc.) are used to denote dependence on time or other dimensions. \( x(1) \) denotes a time series, \( <x(t)> \) its arithmetic mean, and \( \text{MIN}(x(t)) \) its minimum value.

Below follow the most important symbols used in each chapter.

**Symbols Used in Chapter 2**

- \( \text{cof}_i \): i-th empirical orthogonal function
- \( \eta_c \): threshold value for canonical correlations used for prediction
- \( \eta_v \): threshold value for canonical correlations entering the calculation of \( \Psi \)
- \( n_c \): total number of canonical correlations available
- \( n_{cu} \): number of canonical correlations used for prediction
- \( n_x, n_y \): numbers of predictors/predictands entering PCA
- \( N_x, N_y \): number of predictor/predictand PCs retained for CCA
- \( \text{pc}_{i(t)} \): i-th principal component
- \( \mathcal{P}_i, \mathcal{Q}_i \): i-th canonical pattern for the predictors/predictands
- \( \rho_m \): m-th canonical correlation coefficient
- \( s_{i(t)}, t_{i(t)} \): i-th canonical time coefficient for the predictors/predictants
- \( \sigma_{s_i}, \sigma_{t_i} \): standard deviations of the \( s_{i(t)} \) and \( t_{i(t)} \)
- \( t \): index denoting current time (time step = 1 year)
- \( t_{i}^{*}(t) \): i-th estimated canonical time coefficient
- \( v_{i(t)} \): i-th original variable entering PCA
- \( x_{j(t)}, y_{k(t)} \): j-th predictor/k-th predictant entering PCA
- \( y_{k}^{*}(t) \): k-th estimated predictand
- \( \Psi \): index measuring CCA model performance
Symbols Used in Chapter 3

- $a_{\theta i o}$: Annual mean of an $\mu_i$ or $\sigma_i$ ($\theta$ stands for $\mu$ or $\sigma$)
- $a_{\theta ij}, b_{\theta ij}$: Amplitudes of sines/cosines in Fourier expansion of an $\mu_i$ or $\sigma_i$
- $A_{(p)}$: System matrix at phase $p$
- $A$: System matrix in the subspace spanned by the first few Fourier harmonics of the annual cycle
- $B_{(p)}$: Input matrix at phase $p$
- $DSI$: Index of annual drought stress
- $\varepsilon_{(k)}$: Input vector of independent random components from a $N$-dimensional normal distribution $N(0,1)$ at timepoint $k$
- $f_{(i(p)}, g_{(i(p)}, h_{(i(p)}$: Parameters defining log-normal transformation of the state vector element $X_i$ at phase $p$
- $f$: System output function
- $GDD$: Annual growing degree-day total (temperature threshold = 5.5 °C)
- $\Gamma_{v(p)}$: Lag-$v$ covariance matrix of state vector elements at phase $p$
- $i$: Index denoting $i$-th element of the state or output vector
- $k$: Index denoting current simulation time (time step = 1 month)
- $m_{(i(p)}$, $s_{(i(p)}$: Estimated expected value / standard deviation of output $Y_i$ at phase $p$
- $\mu_{(i(p)}$, $\sigma_{(i(p)}$: Expected value / standard deviation of output $Y_i$ at phase $p$
- $M$: Dimension of subspace used to fit phase-averaged cyclostationary models
- $n$: Sample size of measurements
- $n_{\theta i}$: Number of Fourier harmonics used to represent the annual cycle of an $\mu_i$ or $\sigma_i$ ($\theta$ stands for $\mu$ or $\sigma$)
- $N$: Dimension of the state and output vectors
- $p$: Index denoting phase within the year (0=January, 11=December)
- $P$: Monthly total precipitation
- $P$: $P$ standardized to zero mean and unit variance
- $q$: Number of Fourier harmonics used to fit phase-averaged cyclostationary models
- $t$: Index denoting time in measured time series (time step = 1 year)
- $T$: Monthly mean temperature
- $T$: $T$ standardized to zero mean and unit variance
**Symbols Used in Chapter 4**

- **DSI**: index of annual drought stress
- **FC**: field capacity
- **GDD**: annual growing degree-day total (temperature threshold = 5.5 °C)
- **λ**: latitude
- **P**: monthly total precipitation
- **ρ**: correlation between T and P
- **SA_{i}**: slope-aspect index used to correct PET
- **S_{i}**: similarity index used to compare species distributions
- **T**: monthly mean temperature
- **TWinMin**: winter minimum temperature
Leer - Vide - Empty
Abstract


Global climate models are the main source of information on possible future climatic change, whereas local ecosystem models represent important tools to study possible impacts of a changing climate on ecosystems. If one wishes to combine the two kinds of models, however, major problems occur due to the limited horizontal resolution, statistical precision and temporal extension of the global climate simulations. These problems have not been satisfactorily resolved until now. The present thesis deals with the development, testing and application of a method to construct from the output of global climate models climatic scenarios suitable to study ecosystems. The assessment of possible impacts of climatic change on forests in the Alps by means of a forest succession model served as a case study. The method was developed in three steps, as follows.

The first step served to bridge the gap between the spatial scales at which General Circulation Climate Models (GCMs) and ecosystem models operate. Based on the approach proposed by VON STORCH et al. (1993), a statistical downscaling procedure to assess local climatic changes from large-scale climatic changes as simulated by GCMs was developed, verified and applied at five Swiss locations for the summer and winter seasons. According to the very diverse and demanding input requirements of different ecosystem models, at each location 17 seasonal statistics of daily temperatures, precipitation, sunshine duration, air humidity and wind-speed were considered. Year-to-year variations of the local variables were linked by means of Canonical Correlation Analysis to simultaneous anomalies of the North Atlantic/European sea-level pressure and near-surface temperature fields. The statistical models were fitted separately for each season and location for the interval 1901-1940.

In all cases physically plausible statistical relationships were found, which quantified the local effects of changes in major circulation patterns such as the strength of westerly flow in winter and of large-scale subsidence in summer. In the verification interval 1941-1980, most variables were better reconstructed in winter than in summer, and better at the three northern Alpine than at the two southern Alpine locations. The most reliably reconstructed variables were seasonal mean daily temperatures and daily temperature extremes, winter precipitation totals, and winter numbers of days with precipitation above 1 mm. Seasonal mean daily temperature amplitudes, relative humidities, and wind speeds, as well as the within-season standard deviations of most daily variables were generally only poorly reproduced. The procedure of VON STORCH et al. (1993) was, however, generally improved by using in addition to sea-level pressure the near-surface temperature as
a large-scale predictor. Improvement was strongest for temperature related variables, and for the summer season. Application of the statistical models to two simulations of global climatic change with the ECHAM1/LSG-GCM (CUBASCH et al., 1992) yielded for several important ecosystem inputs time-dependent, spatially as well as between the weather variables consistent, and regionally strongly differentiated estimates of possible climatic changes at a spatial resolution far above the resolutions of present global or regional climate models.

The second step focused on the construction of statistically accurate weather inputs over arbitrary time spans, and under any scenarios of time-dependent climatic change. For this purpose investigated was at 89 long-term European climatological stations the performance of 12 stochastic models to simulate monthly mean temperature and precipitation. The models differed in the treatment and estimation of the monthly variables' auto-, and cross-correlation coefficients, the annual cycles of the variables' expected values and standard deviations, and in the use of a skewness-reducing transformation for precipitation. All models were fitted to local measurements from the period 1951-1980. Model performance was evaluated by comparing the distributions of monthly winter minimum temperatures, annual growing degree-days, and an index for the annual drought stress as derived from simulated and independently measured monthly weather data.

It was found that inclusion of a memory term in the stochastic models generally enhances the statistical accuracy of the simulated monthly mean temperatures, winter minimum temperatures and growing degree-day totals. The use of a log-normal transformation strongly improved the simulation of the monthly precipitation totals and the drought stress index. It was shown that cyclostationary autoregressive models can be further improved, and the number of parameters substantially reduced by estimating the monthly system matrices in a sub-space spanned by the first two Fourier harmonics of the annual cycle according to the approach proposed by HASSELMANN & BARNETT (1981). The representation of the annual cycles of the weather variables' expected values and standard deviations by means of their first two (temperature), respectively three (precipitation), Fourier harmonics yielded an improvement mainly for the drought stress index, but not for the two other bioclimatic variables. Based on the above findings a new stochastic model to simulate monthly weather was proposed. Compared to the commonly used models it requires a slightly larger number of climatic parameters, but relies upon more robust methods to estimate these parameters, and produces significantly improved distributions of bioclimatic variables.

In a third step, the previous two steps were combined with the forest succession model FORCLIM (BUGMANN, 1994, 1996; FISCHLIN et al., 1995) into an overall method to project quantitatively possible impacts of climatic change on mountain forests at high temporal (annual cycle), spatial, and qualitative resolution. The method consists of the fol-
lowing steps: (1) Describe weather at the ecosystem location as a stochastic process; (2) estimate the process/climatic parameters for present climate from measurements; (3) use a statistical downscaling procedure to estimate from the output of a GCM time-dependent changes in selected climatic parameters; (4) generate scenarios of monthly weather by means of stochastic simulation; (5) use the simulated weather sequences to drive the forest model.

The method was applied to four representative sites in the Alps, starting from a 2xCO₂ scenario of global climatic change as projected by the the CCC-GCMII climate model (BOER et al., 1992). Similar to the results obtained from the ECHAM1/LSG model the downscaled scenarios showed strong spatial and seasonal variation, and depicted a general warming which was larger at the northern than at the southern slope of the Swiss Alps. A tendency towards increased precipitation was found. However, decreases were obtained for some locations and seasons, with partially dramatic effects on simulated forest compositions. The scenarios appeared physically plausible and spatially consistent. Sharply contrasting forest responses were obtained within short distances under the same 2xCO₂ scenario of radiative forcing. While some forest simulations produced only small changes in tree species composition, others produced major changes even to the point of a complete disappearance of the forest. In some cases new species assemblages emerged without any analogue under present conditions. The forest responses were consistent with current understanding of forest dynamics. They suggest that some mountain forests are sensitive to a 2xCO₂ global change, and that human assistance may be required to help forests to adapt.

In summary, it was found that the proposed method allows to consistently link climatic changes as simulated by global climate models to local ecosystem models. The method is general, flexible, computationally efficient, has intermediate data requirements, and conforms to the IPCC guidelines (CARTER et al., 1994) for impacts assessments. Its main limitation is that the used statistical models may not hold under a changed climate. However, the method allows for extensive sensitivity and uncertainty analyses, and thanks to its modular structure improvements of the individual components can be easily incorporated at a later stage. The overall method used to project forest responses makes good use of existing models and data, integrates current understanding, and is suitable to assess impacts of climatic change on any mid to high latitude forests.
Kurzfassung


tur) bzw. drei (Niederschlag) Fourier-harmonischen Funktionen ergab eine Verbesserung nur für den Trockenheitsstress-Index, jedoch nicht für die beiden anderen bioklimatischen Variablen. Basierend auf den obigen Ergebnissen wurde ein neues stochastisches Modell zur Simulation des monatlichen Wetters vorgeschlagen. Im Vergleich zu den bisher üblichen Modellen benötigt dieses zwar eine etwas grössere Anzahl von Klimaparametern, benutzt jedoch robuster Methoden zu deren Schätzung und produziert signifikant realistischere Verteilungen bioklimatischer Variablen.

In einem dritten Schritt wurden die beiden vorangehenden Schritte mit dem Waldmodell FORCLIM (BUGMANN, 1994, 1996; FISCHLIN et al., 1995) zu einer Gesamtmethode kombiniert, um quantitative Abschätzungen möglicher Klimawirkungen auf Gebirgswälder mit einer hohen zeitlichen (Jahreszyklus), räumlichen und qualitativen Auflösung zu erhalten. Die Methodik besteht aus den folgenden Schritten: (1) Beschreibung des Wetters am Ökosystemstandort als einen stochastischen Prozess; (2) Schätzung der Klima-/Prozessparameter für das heutige Klima anhand von Messungen; (3) Verwendung einer statistischen Herabskalierungsprozedur, um aus einem GCM zeitabhängige Veränderungen ausgewählter Klimaparameter abzuschätzen; (4) Generierung von Szenarien für die monatliche Witterung mittels stochastischer Simulation; (5) Verwendung der simulierten Witterungsvariablen, um das Waldmodell anzutreiben.


Zusammenfassend lässt sich sagen, dass die vorgeschlagene Methodik es ermöglicht, lokale Ökosystemmodelle auf konsistente Weise an die von globalen Klimamodellen
1. Introduction

Since the beginning of the Industrial Revolution the composition of the Earth's atmosphere has been increasingly affected by the activities of man. Steadily rising concentrations of greenhouse-gases and aerosols in the atmosphere have probably already significantly affected the redistribution of solar energy within the climate system (SANTER et al., 1996; HEGERL et al., 1996). According to most projections global climatic change\(^1\) is likely to continue over the next decades to centuries at a rate and magnitude unprecedented in the last 10'000 years (IPCC, 1996a). Such a change can be expected to have wide-ranging, partially irreversible, and potentially adverse effects on ecological systems (IPCC, 1996b).

Global climate models (e.g., GATES et al., 1992) are the main source of information on future climatic change, whereas ecosystem models are of major importance to study possible impacts of climatic change on ecosystems. However, several problems occur if one wishes to combine the two kinds of models for impact assessments: The global models have a very coarse horizontal resolution (several hundreds of km), they simulate weather only with a limited statistical precision (e.g., HULME et al., 1993), and most available simulations cover only relatively short time spans (years to decades). This is in sharp contrast to the needs of ecosystem studies, which often require local, and statistically precise (e.g., NONHEBEL, 1994; FISCHLIN et al., 1995) inputs on weather or climate over several centuries (e.g., PRENTICE et al., 1993) to millenia (e.g., PERRUCHOUD, 1996).

Due to the many uncertainties and unknowns involved in the projection of future climate these inputs can generally not be provided as predictions, but only in the form of scenarios. Climatic scenarios are more or less plausible, internally consistent descriptions of conceivable future space-time evolutions of the climate system. Several methods to construct regional climatic scenarios have been proposed, which are reviewed e.g. in GIORGI & MEARNS (1991), ROBOCK et al. (1993), and CARTER et al. (1994). The advantages and limitations of the various approaches with regard to ecosystem studies are discussed in sections 2.1, 3.1, and 4.1 of this thesis.

---

\(^1\) The present study adopts the classical definitions of "weather" and "climate", according to which the former refers to the short-term (seconds to months) state of the atmosphere at the global to local scales, and the latter to the statistics of weather over decades to centuries. The term "climatic change" is used to refer to a systematic shift in these statistics as caused by changes in the boundary conditions of the climate system (e.g., changing land-surface conditions, or increasing concentrations of radiatively active gases in the atmosphere). "Climatic variability" on the other hand refers to the natural variability of climate as caused by variations in forcings of the climate system (e.g., solar input or volcanic activity) and the internal dynamics of the global and regional climate."
Chapter 1

The production of regional information from the output of global climate models (a process often termed "downscaling") presents a key element in the construction of regional climatic scenarios. A frequently used approach in ecosystem studies (e.g., BURTON & CUMMING, 1995; SAMPSON et al., 1996; BARROW et al., 1996) is to interpolate climatic changes from a few grid points in the vicinity of the region of interest. However, as is discussed below in section 2.1, this procedure gives inconsistent results (see also VON STORCH, 1995). Valid alternatives are the simulation of regional climates with high-resolution global (e.g., CUBASCH et al., 1996) or regional (e.g., GIORGI et al., 1992) climate models; or the utilization of statistical relationships between the large-scale and the regional climate (e.g., VON STORCH et al., 1993).

Regional climate models have the advantage that they are based upon first physical principles. However, their enormous computing requirements severely restrict their usefulness for scenario construction (see section 2.1). Furthermore, even if fast enough computers were available to run a climate model for the time spans and at the horizontal resolution needed by ecosystem studies, some basic limitations would still apply: Firstly, all processes relevant to simulate local climates would have to be sufficiently well known. Secondly, the model would inevitably include empirical approximations of unresolved processes. These must be fitted to finite data sets, such that possible systematic errors could feed into, and be amplified by the model, thus restricting its ability to correctly simulate other climates than the present. Finally, high-resolution models require accurate boundary conditions, and therefore are difficult to test. High-quality forcing fields for the atmosphere and/or the ocean are available for some decades, but long-term data on, e.g., land-surface characteristics are already much more difficult to get.

The statistical downscaling approach appears more suitable since it can provide directly a local resolution, and because it can be expected to be computationally much more efficient. A range of statistical downscaling procedures has been proposed, which are reviewed in KATTENBERG et al. (1996), GYALISTRAS et al. (1998), and in section 2.1 of this thesis. However, the feasibility and suitability of statistical downscaling with regard to ecosystem studies has not been systematically investigated yet.

Moreover, it is also not clear how downscaling should be applied best to provide scenarios with the needed temporal extension and resolution. One possibility would be to directly use downscaled time series of weather variables. However, as is discussed later in section 3.1, this approach has several major limitations.

---

2 The term "weather variable" or "weather statistic" is used to refer to statistics of a meteorological variable over an individual day, month or season (e.g., the average temperature of a particular month, or the number of rainfall events experienced within this month). "Climatic parameter" refers to a statistical
An often used alternative technique to simulate local weather in impact studies (e.g., FISCHLIN et al., 1995; MEARNS et al., 1996) are so-called weather generators (e.g., RICHARDSON, 1981). These are stochastic models of weather variables, which are fitted to local measurements. WILKS (1992), OELSCHLAGEL (1995), and BARROW et al. (1996) have proposed procedures to derive scenarios of daily weather by combining weather generators with the output of global climate models.

However, these studies have demonstrated the construction of scenarios either only based upon general indications from global climate simulations (WILKS, 1992), or only upon very simple downscaling procedures which relied but upon a few climate model grid points (OELSCHLAGEL, 1995; BARROW et al., 1996). Furthermore, as is shown in section 3.1, until now only little work has been done at the monthly resolution, which is particularly important for several ecosystem studies which operate on time scales of centuries to millenia (see e.g. review in PERRUCHoud & FISCHLIN, 1995).

The aim of the present thesis is to develop, test and apply a general method to construct scenarios of future climate and weather suitable for ecosystem studies. The assessment of possible impacts of climatic change on forests in the Alps by means of a forest succession model (SHUGART, 1984; KIRSCHBAUM & FISCHLIN, 1996) serves as a case study to test the method. The forest model poses only medium requirements to the construction of scenarios (see section 4.2.3). However, as is discussed later, several other ecosystem studies have similar needs. Moreover, the method is developed in a modular manner, such that it can be easily extended to meet additional requirements, and that all steps are in principle applicable to any ecosystem model and any region (see Chapter 5).

The main questions addressed are:

- Is it possible to derive new, or improve existing techniques to increase the physical plausibility and consistency of climatic scenarios needed by ecosystem studies?

- Can the scenarios be improved due to
  - the use of statistical procedures to downscale the output of global climate models to the regional scale?
  - an improved stochastic simulation of the driving weather inputs?

- By applying such new, improved techniques, what scenarios of possible future climatic changes and associated forest responses result for selected Alpine locations and how plausible are they?

parameter used to describe weather as a stochastic process (e.g., the expected value of a weather variable or the cross-covariance of two weather variables).
The thesis contains three main chapters which correspond to individual papers already published, or to be published in scientific journals. It is structured as follows:

Chapter 2 focuses on the consistency of climatic scenarios across spatial scales and presents a statistical procedure to downscale climatic changes as simulated by global climate models to the regional scale. This chapter has been published with minor modifications in GYALISTRAS et al. (1994).

Chapter 3 focuses on the temporal aspect of scenario construction. It deals with the simulation of site-specific weather and bioclimatic variables by means of stochastic models.

In Chapter 4 the methods developed in two previous chapters are combined with a forest model into an overall procedure which is applied to project possible impacts of a changing climate on forests in the Alps. This work has been published with minor changes in FISCHLIN & GYALISTRAS (1997).

The proposed methods for scenario construction are discussed in Chapter 5, and the main conclusions of the study are summarized in Chapter 6.
2. The Spatial Aspect: Statistical Downscaling of GCM-simulated Climatic Changes to the Regional Scale

Published as:

2.1 Introduction

In order to study possible impacts of climatic change on particular ecosystems models of these systems are of paramount importance. Although ecosystems and the atmosphere interact on a multitude of temporal and spatial scales, most impact studies consider only the “one-way” forcing of the ecosystems by the atmosphere.

Yet, in ecosystem studies a large variety of climatic input requirements occurs. For example, in order to drive agroecosystem models (PARRY et al., 1988; SPITTERS et al., 1989; ROTH et al., 1995), or insect population models (LISCHKE & BLAGO, 1990) specific combinations of several meteorological variables such as temperature, precipitation, photosynthetically active radiation, wind, and air humidity, with an hourly to daily time step, and for at least the duration of the vegetation season, are needed. On the other hand, forest gap models (SHUGART, 1984) simulating forest succession require realisations of monthly mean temperatures and precipitation totals for every month of the year (FISCHLIN et al., 1995), and SCHRÖDER'S (1976) population dynamics model for red deer requires monthly snow-heights.

To study and assess the impacts of climatic change, a given set of inputs needs to be derived from appropriate climatic change scenarios. A scenario at a particular location and moment should represent an internally consistent picture for changes in at least those climatic parameters which are needed either as direct model inputs (FISCHLIN, 1982; BRZEZIECKI et al., 1993), or to stochastically generate the weather variables that drive the ecosystem model (e.g., MEARNS et al., 1984; SUPIT, 1986; SWARTZMAN & KALUZNY, 1987; WILKS, 1992; FISCHLIN et al., 1995).
Climatic scenarios should extend from the present to an appropriate point in the future, or otherwise cover time spans that are long enough for the purposes considered. In some cases, e.g. agroecosystems, a few decades can be sufficient. When, however, soils or forests are considered, which respond to climate on time scales of several centuries (BUGMANN & FISCHLIN, 1992; 1994), the scenarios should specify the transient behavior of regional climates for at least a few hundred years.

Further, the climatic inputs are typically needed at specific representative locations, i.e. with a spatial resolution of a few kilometres or less. A high spatial resolution is particularly important if ecosystems are studied within a complex topography such as the Alps.

Three basic approaches could be adopted to derive the needed regional climatic change scenarios (GIORGI & MEARNS, 1991): (1) Construct analogues of regional climatic changes from past climatic situations as inferred from proxy data (FLOHN & FANTECHI, 1984; WIGLEY et al., 1986) or instrumental records (e.g., WIGLEY et al., 1980; PITTOCK & SALINGER, 1982; LOUGH et al., 1984; HULME et al., 1990). (2) Use numerical models, such as General Circulation Models (GCMs) or regional climate models (e.g., DICKINSON et al., 1989; GIORGI et al., 1990) embedded in GCMs, to simulate possible future climatic conditions with the best possible spatial detail. (3) Use, as an intermediate solution, semi-empirical approaches establishing a statistical relationship between larger-scale and regional climatic changes (e.g., KIM et al., 1984; WILKS, 1989) which then can be applied to derive climatic scenarios from the outputs of spatially coarse numerical models (KARL et al., 1990; WIGLEY et al., 1990; VON STORCH et al., 1993).

A major advantage of the first, purely empirical, approach is that it is relatively simple to implement. However, paleoclimatic analogues normally provide information only on few parameters, such as mean temperatures and, less often, precipitation (WIGLEY et al., 1986). In addition, the temporal resolution of proxy data is often coarse, and, even if yearly data are available (e.g. from tree rings), the annual cycle may not be well resolved (STOCKTON et al., 1985; SCHWEINGRUBER, 1988). Though this is not the case for instrumental records, there still remains the problem that past climatic changes do not necessarily reflect the effects of increasing greenhouse gas concentrations on climate (GIORGI & MEARNS, 1991). Also, due to the lack of deterministic models it is difficult to formulate gradual shifts in future climates in a physically consistent manner.

The second approach relies upon GCMs. Since GCMs reproduce most large-scale atmospheric and oceanic features, present – and even more so future – climate models are regarded as being capable to reliably simulate at least the broad large-scale aspects of man-made climatic change (DICKINSON, 1986; GATES et al., 1990). Simulations of time-dependent changes for the next 100 years or so become increasingly available (HANSEN et al., 1988; MANABE et al., 1991, 1992; CUBASCH et al., 1992; GATES et
Fig. 2.1: Comparison between the climate simulated by the ECHAM1/LSG-GCM in the vicinity of the Alps (averages from three gridpoints) and observations. (a) Monthly mean temperatures. The following annual mean values were subtracted prior to plotting: "Control": 8.7°C, Bever: 1.5°C, Bern: 8.4°C, Davos: 3.0°C, Lugano: 11.7°C, Saentis: -2.1°C. (b) Differences of the curves shown in (a) from the means of the "Control" experiment. (c) Monthly precipitation totals.
al., 1992), thereby providing vast amounts of physically consistent data with a time step of 1 h or less.

However, a problem occurs due to the coarse horizontal resolution of most currently used climate models, which is in the order of 500 km, and which sharply contrasts with the fine resolution required by ecosystem models. Furthermore, the minimum spatial scale at which GCMs successfully reproduce the observed climate lies above several gridpoint distances. For present GCMs this is at least 2'000 - 4'000 km (von Storch et al., 1993). Climatic changes obtained at individual gridpoints seem even less trustworthy over mountainous areas such as the Alps, which are not well represented in GCMs.

This is illustrated in Fig. 2.1 which compares the performance of the ECHAM1/LSG-GCM (described below in "Data and Methods - GCM Experiments") at three gridpoints in the vicinity of the Alps with measurements from the five case study locations considered in this study. Though in the GCM-"control" experiment (simulation of present climate) the observed annual cycle of temperature is reproduced qualitatively correct, with a flat maximum in July/August and a minimum in January, the GCM generally overestimates the amplitude of the annual cycle by several degrees (Fig. 2.1a). In particular, note that the model error is similar in magnitude to the average changes simulated by the GCM at the three Alpine gridpoints under the "IPCC Scenario A" (IPCC, 1990) for future atmospheric concentrations of greenhouse gases (Fig. 2.1b). Precipitation is severely underestimated at all locations during the summer months. Here the projected changes in gridpoint precipitation under the "Scenario A" are much smaller than the deviations typically found between the observations and the "control" (Fig. 2.1c).

One possibility for improving the simulation of regional climates is to increase the horizontal resolution of the GCMs or, at least, to use them to drive simulation models with enhanced resolution over areas of interest. However, computational costs of climate models increase at least quadratically with the spatial resolution (GiorGI & MEARNS, 1991). It may therefore be expected that, even if more powerful computers become available, the simulation of the full annual cycle over several decades, let alone centuries, by high-resolution models will not be possible for several years to come. Furthermore, even if gridpoint distances for long-term integrations could be reduced to 100 km or less, there would still remain a substantial gap between the scales at which climate models operate reliably and the local detail required by most ecosystem models.

An alternative is to use semiempirical approaches which allow site-specific empirical data to be combined with the physically consistent results of numerical climate models. Semiempirical approaches are particularly attractive, since, in principle, they can be flexibly used at any location and for any variable of interest. Moreover, due to their computational efficiency they would even allow transient scenarios far into the future to be derived.
To date, several semiempirical approaches have been proposed. For example, Wigley et al. (1990) used monthly means of several regionally averaged atmospheric variables to predict variations of monthly mean surface temperature and precipitation at the 32 climate stations within the region considered; Karl et al. (1990) related daily gridpoint data of 22 free-atmosphere variables to daily temperature extrema, precipitation and cloud ceilings from local surface observations; von Storch et al. (1993) used anomalies of large-scale mean sea-level pressure over the Atlantic to predict, using Canonical Correlation Analysis (Barnett & Preisendorfer, 1987) changes in winter mean Iberian precipitation; finally, Werner & von Storch (1993) used basically the same approach to relate January-February mean temperatures from 11 central European stations to the large-scale circulation.

The method of von Storch et al. (1993) appears to be superior, because, unlike the other approaches, it considers the large-scale (several 10^3 km) behavior of a climatic parameter, according to the assumption that predictions of future climates by GCMs are most credible within this resolution. Also, unlike the approach by Karl et al. (1990), the statistical models obtained do not depend on a particular GCM and can thus be applied to other GCMs. However, the method of von Storch et al. (1993) has so far been applied only to predict one climate variable at a time, i.e. rainfall or temperature, and only for winter.

Thus the following questions arise: Is it possible by means of this method to establish plausible statistical relationships which allow multivariate descriptions of local climates, even in a complex orography like the Alps, to be linked to large-scale climatic changes? If yes, for which ecosystem inputs, seasons and locations can the best and for which the poorest results be obtained? What improvements could be gained by modifying the method, for instance by including large-scale near-surface temperature anomalies as an additional predictor? Finally, is it possible to derive regionally varying scenarios from GCM-projected global climatic changes?

Here we use for the first time the method by von Storch et al. (1993) to downscale large-scale climatic changes – at a seasonal resolution, not only for winter, but also for summer – to 17 local ecosystem inputs at several point locations within a complex topography, i.e. at five representative case study locations in the Alps. We show that the method proposed by von Storch et al. (1993) not only yields physically plausible results for all case study locations, but that it can also be substantially improved, in particular for temperature-related variables. Finally, by applying the obtained statistical relationships to two climatic change experiments with a GCM, we demonstrate that our approach allows to derive regionally differentiated, transient climatic scenarios of use in ecosystem studies.
2.2 Data and Methods

2.2.1 Observations

As independent variables (predictors) we tested mean sea-level pressure (SLP) and 2 m above-ground air temperature for which long-term (several decades) observed data sets are available. The independent variables were given on a 5° x 5° latitude by longitude grid containing 153 gridpoints and extending from 40° W to 40° E and 30° N to 70° N (Fig. 2.2a).

Winter (December, January, February) and summer (June, July, August) mean SLP for the years 1901-1980 were calculated at each gridpoint from daily data provided in the NCAR data set (JESSEL, 1991). Seasonal mean near-surface (2 m above-ground) temperatures were derived for the same period from monthly data given on a 10° x 5° latitude by longitude grid (VINNIKOV et al., 1987; JESSEL, 1991), and were then interpolated to the 5° x 5° standard grid. Missing data for some years and gridpoints were replaced by interpolation between adjacent timepoints.

The SLP data were initially given as absolute values, whereas the near-surface temperature data were given as anomalies from the three different basis periods 1881-1935, 1881-1940 and 1881-1960. However, since fitting of the statistical models required data with zero means, anomalies were calculated for both predictors relative to the mean states of the respective years used (see also "Statistical Procedure", below).
On the regional scale, five different locations within Switzerland, representative of north, inner and south alpine climates were considered (Fig. 2.2b): (1) Bern (valley, 565 m above sea level (m.a.s.l.); 7.4° E, 46.9° N) at the northern slope of the Alps; (2) Davos (pronounced valley location, 1590 m.a.s.l.; 9.8° E, 46.8° N) in the central alpine region; (3) Bever (1712 m.a.s.l.; 9.9° E, 46.6° N), located in the Oberengadine valley which is characterized by a central or south alpine climate; (4) Lugano (valley, 273 m.a.s.l.; 9.0° E, 46.0° N) at the southern slope of the Alps; and (5) Saentis (mountain peak, 2500 m.a.s.l.; 9.2° E, 47.2° N) which represents "free-atmosphere" conditions at the northern side of the Alps.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Seasonal Statistics</th>
<th>Explanations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temperature</td>
<td>(a) Tmean, Tmin, Tmax, Tamp1 (b) s(Tmean), s(Tmin), s(Tmax), s(Tamp1)</td>
<td>(a): means, (b): standard deviations of daily mean, minimum and maximum temperatures and of daily temperature amplitude, respectively (in °C).</td>
</tr>
<tr>
<td>Precipitation</td>
<td>(a) Precip (b) s(Precip) (c) Ndays≥1mm</td>
<td>(a): mean, (b): standard deviation of daily precipitation totals (in cm); (c): number of days with total ≥ 1 mm.</td>
</tr>
<tr>
<td>Relative sunshine duration</td>
<td>(a) RelSunsh (b) s(RelSunsh)</td>
<td>(a): mean, (b): standard deviation of daily average from three measurements per day (in %).</td>
</tr>
<tr>
<td>Relative humidity</td>
<td>(a) RelHum (b) s(RelHum)</td>
<td>(a): mean, (b): standard deviation of daily average from three measurements per day (in %).</td>
</tr>
<tr>
<td>Wind speed</td>
<td>(a) Wind (b) s(Wind)</td>
<td>(a): mean, (b): standard deviation of daily average from three measurements per day (in m s⁻¹).</td>
</tr>
</tbody>
</table>

Table 2.1: Meteorological variables and the related seasonal statistics considered in this study.

The dependent variables (predictands) were given at each location by a vector of 17 seasonal weather statistics (Table 2.1). Special emphasis was given to the main weather elements temperature and precipitation, for which 11 variables were defined. Relative sunshine duration was included as a variable allowing us to approximate incoming photosynthetically active radiation, which determines rates of plant growth in many ecosystem models. As additional parameters we considered relative air humidity and wind speed, which are used particularly in agroecosystem models. Within-season standard deviations of all meteorological variables were included, since these parameters are typically needed to simulate daily weather conditions by means of stochastic weather generators. Since precipitation distributions often show considerable skewness, we used, as an additional parameter for the within-season variability of rainfall, the number of days with precipitation ≥ 1 mm, which is proportional to the probability of "wet days" within the season. The threshold value of 1 mm was chosen because it represents a lower limit for the detection of rainfall valid for most measuring devices (cf. UTTINGER, 1970).
All seasonal statistics were derived from daily 1901 to 1980 measurements, extracted from the database of the Swiss Meteorological Institute (SMA), Zurich (SMA, 1901-1980; BANTLE, 1989). Daily mean temperatures, relative sunshine durations, relative humidities and wind speeds, were calculated from three measurements per day, whereas daily temperature minima and maxima were determined as the extrema from the three daily measurements and the evening temperature of the previous day. After 1971 the time at which the evening temperature measurements were taken was changed from 21:30 h to ca. 19:00 h, so daily means for the years 1901-1970 and 1971-1980 were calculated according to different procedures (BANTLE, 1989). The effects of this change in procedure are still under investigation by the SMA; for locations with large daily temperature amplitudes it is likely that, due to the new procedure, daily mean temperatures are overestimated by ca. 0.2° C (A. DE MONTMOLLIN, SMA, personal communication).

2.2.2 GCM-Experiments

Simulated seasonal mean SLP and near-surface temperature were obtained from experiments performed with a fully coupled global atmospheric/oceanic GCM run at the Max-Planck Institute for Meteorology (MPI), Hamburg. The atmosphere component (ECHAM1) of the model is a version of the spectral numerical forecasting model of the European Centre for Medium Range Weather Forecasts, extensively modified at the MPI Hamburg for climate simulations. Its horizontal resolution is limited by a cut-off at wave number 21, corresponding to a gaussian grid with an average spacing of 5.6°, and its vertical resolution is given by 19 levels in a hybrid σ-p coordinate system. The ECHAM1 model simulates the diurnal cycle with a time step of 40 min. The ocean component (LSG), which allows for the calculation of large scale geostrophic motions, is based on 11 variably spaced vertical levels, an effective horizontal grid size of 4° and a basic time step of 30 d, except for the two uppermost ocean layers, where a time step of 1 d is used. A more detailed description of the coupled model is given in CUBASCH et al. (1992).

All GCM-simulated data used in this study were derived from daily GCM-outputs and were interpolated on the 5° x 5° grid of the observed data sets. We considered results from (1) the "control" integration with constant 1985 atmospheric CO2-concentration, (2) the "double CO2" (DCO2) experiment, representing the model system's response to an immediate doubling of greenhouse gas concentrations from 360 to 720 ppm equivalent CO2, and (3) the "IPCC Scenario A" (SCNA) experiment, where the GCM is forced by continuously increasing greenhouse gas concentrations according to the "Business-As-Usual" scenario given by the IPCC (1990). The model's performance in the "control" run and its responses to the greenhouse gas forcings are addressed later.
2.2.3 Statistical Procedure

Our method is based upon a "perfect prognosis" approach (GLAHN, 1985; VON STORCH et al., 1993): a statistical relationship is first established between the large-scale and the local observations, and then applied unmodified to predict changes in the local variables from any large-scale observations or GCM-simulated data sets. For this purpose, we considered each season and location separately.

The overall procedure consists of (1) the selection of two subperiods, one to fit and one to verify the statistical models, (2) the calculation of anomalies, plus the weighting of the predictor and predictand variables, (3) the estimation of a series of differently specified statistical models linking the predictands to the predictors, (4) the verification of all specified models with independent observations, (5) the selection of a subset of the best-performing models, and finally (6) the application of the selected models to GCM anomaly-fields (Fig. 2.3).

In the standard procedure we used the years 1901-1940 for statistical modelling and the years 1941-1980 for model verification. In order to test the sensitivity of the resulting climatic scenarios to the choice of the estimation period, the two subperiods were reversed at a later stage.

All variables were transformed to deviations from the mean states of the years used for model estimation. This is because only anomalies of the large-scale and local variables were related to each other, whereas the long-term means were not affected by the procedure. On the local side, this ensured that climatic change scenarios can be specified in a manner consistent with present long-term mean climate at each location. On the side of the large-scale predictors only the differences occurring between a climatic change experiment and the "control" experiment of a GCM were considered. This avoided the problem that the long-term mean fields simulated by GCMs are normally biased with respect to observations.

The predictor variables were weighted with the square root of their latitude cosine, in order to account for the latitudinal variation of the grid box sizes of the rectangular 5° x 5° grid. When both, SLP and near-surface temperature, were used as predictors, each field was rescaled with a constant factor in order to account for a predefined proportion (e.g. half) of the total predictor variance. For graphical representations of predictor patterns, however, all weightings were removed, such that the same unit applied to all variables of the same kind. The local weather statistics were weighted with their observed standard deviations from the years used for model estimation, thus eliminating the effects of different value ranges.
Chapter 2

Estimation of the statistical models consisted of two steps: First, Principal Component Analysis (PCA; e.g., KUTZBAUGH, 1967; PREISENDORFER, 1988) was used to reduce the dimensionality of the observed data sets and to remove linear dependencies between variables within the same data set. PCA determines from a set of \( n \) variables \( v_{i(t)} \) (\( i=1..n \)) a set of new, mutually uncorrelated variables \( p_{c;i(t)} \) subject to the constraint that the variance of the new variables is subsequently maximized. The new variables are named principal components (PCs) and are given by the coordinate transformation \( p_{c;i(t)} = \).
\( \text{gof}_i \cdot \mathbf{y}(t) \), where \( \mathbf{y}(t) = (y_1(t), \ldots, y_n(t))^\top \). The vectors \( \{\text{gof}_1, \ldots, \text{gof}_n\} \) form an orthogonal basis in \( \mathbb{R}^n \) and are called empirical orthogonal functions (EOFs). The EOFs are given by the eigenvectors of the \( n \times n \) covariance matrix of the \( y_i(t) \). The PCA was performed separately for the \( n_x \) predictors \( x_{j}(t) \) (\( j=1..n_x \)) and the \( n_y \) predictands \( y_{k}(t) \) (\( k=1..n_y \)).

In a second step, the first \( N_x \) predictor and the first \( N_y \) predictand PCs were related by means of Canonical Correlation Analysis to each other (CCA; e.g., ANDERSON, 1984; BARNETT & PREISENDORFER, 1987). Based on the eigenvectors of the squared covariance matrix of all used PCs, CCA identifies \( n_c = \text{Min}(N_x, N_y) \) linear combinations of the predictor PCs which correlate best with respective linear combinations of the predictand PCs. The scalars determining these linear combinations were transformed from the EOF back to the physical space, yielding \( n_c \) canonical patterns \( \mathbf{P}_i \) and \( \mathbf{Q}_i \) (\( i=1..n_c \)) for the predictors and predictands, respectively. Each pair of patterns corresponds to a canonical mode. The canonical patterns were used to infer from the \( x_j \) and \( y_k \) two new sets of variables, the canonical time coefficients \( s_{i}(t) \) and \( t_{i}(t) \) (\( i=1..n_c \)) according to the equations

\[
 s_{i}(t) = \sum_{j=1}^{n_x} \mathbf{P}_{ij} \cdot x_{j}(t),
\]

and

\[
 t_{i}(t) = \sum_{k=1}^{n_y} \mathbf{Q}_{ik} \cdot y_{k}(t),
\]

respectively. The \( \mathbf{P}_i \) and \( \mathbf{Q}_i \) are determined by CCA under the constraint that all \( s_i \) as well as all \( t_i \) are mutually uncorrelated, but that the first pair of time coefficients \( (s_1, t_1) \) shows a maximum canonical correlation \( \rho_1 \). Every further pair \( (s_m, t_m) \) of time coefficients, correlating with a factor \( \rho_m \) (\( m=2..n_c \)), can be used to explain a maximum of the remaining variance of the respective data sets.

When using both, SLP and near-surface temperature, as predictors, the \( x_j \) may be subdivided into SLP anomalies (\( j=1..153 \)) and near-surface temperature anomalies (\( j=154..306 \)). Accordingly, an individual pattern \( \mathbf{P}_i \) was visualised as composed of two separate maps defined by the corresponding elements \( \mathbf{P}_{ij} \). The associated time coefficient \( s_i \) can then be interpreted as the sum of two signals:

\[
 s_{i}(t) = \sum_{j=1}^{153} \mathbf{P}_{ij} \cdot x_{j}(t) + \sum_{j=154}^{306} \mathbf{P}_{ij} \cdot x_{j}(t).
\]
Due to the respective orthogonality of the $s_i$ and $t_i$, the element $P_{ij}$ (or $Q_{ik}$) of the $i$-th canonical pattern represents the covariance between the $j$-th predictor (the $k$-th predictand) and the dimensionless coefficient $s_i$ ($t_i$). Local maxima (minima) in the predictor maps of the $i$-th canonical mode thus represent regions where positive (negative) anomalies in the respective $x_{ij}$ contribute with large positive (negative) anomalies to the coefficient $s_i$ (cf. Eq. 2.1 or 2.1'). Similarly, a large positive (negative) value $Q_{ik}$ denotes that for the $i$-th canonical mode a large positive (negative) anomaly of the $k$-th weather statistic occurs, if the time coefficient $t_i$ takes a positive value. Finally, the canonical correlation $\rho_i$ between $s_i$ and $t_i$ measures the strength with which anomalies in the predictands and predictors are related to each other within the respective canonical mode.

The results of CCA can be used to predict linearly, from any anomaly fields describing changes in the predictors $x_j$, the simultaneous responses of all local weather statistics $y_k$ ($k=1..n_y$), according to

$$ y_{\mathbf{k}}(t) = \sum_{i=1}^{n_{cu}} t_{i}(t) Q_{ik} = \sum_{i=1}^{n_{cu}} \rho_i \frac{\sigma_{s_i}}{\sigma_{t_i}} s_{i}(t) Q_{ik} \quad (2.3) $$

Here, $n_{cu} \leq n_c$ is the number of canonical modes used, $t_{i}^*$ denotes the estimated $i$-th time coefficient of the dependent variables, and $\sigma_{s_i}$, $\sigma_{t_i}$ are the standard deviations of the time coefficients $s_{i}(t)$ and $t_{i}(t)$, respectively. For each CCA model fitted, we chose $n_{cu}$ individually as the number of all canonical correlations $\rho_i$ above the threshold value $\eta_c = 0.33$. For the choice of $\eta_c$, we assumed that serial correlation in the predictors and predictands can be neglected due to the interannual variations considered. Given that CCA systematically overestimates the true $\rho_i$, $\eta_c$ was chosen larger than the critical value of 0.26 (0.31) above which an unbiased estimate of a correlation coefficient would be significantly different from zero at the 90% (95%) confidence level (two-sided t-test, $n=40$; e.g., KREYSZIG, 1977).

Performance of CCA may sensitively depend on the numbers $N_x$ and $N_y$ of EOFs considered. Using too many EOFs will fit the statistical models too strongly to the particular data sets considered, most likely missing an adequate description of the underlying stochastic process. A too small number of EOFs, on the other hand, will omit part of the significant signal, thus resulting in a poorer predictive ability of the overall model. In the present study, instead of retaining a significant, fixed number of EOFs based on EOF-selection rules (e.g., PREISENDORFER et al., 1981) we focused on the effects resulting from possible alternative choices for $N_x$ and $N_y$. To this purpose we performed CCA for the $13^2=169$ combinations resulting when varying $N_x$ and $N_y$ individually within the range of $2..14$. The upper limit of 14 EOFs was chosen because
from this number on typically more than 90% of the total variances of the predictor and predictand data sets could be accounted for, for all seasons and locations considered.

Each of the 169 CCA models was then applied to predict the local variables from the large-scale data not used for model estimation, and model performance was assessed according to

$$\Psi(e_x, e_y) = \frac{1}{n_y} \sum_{k=1}^{n_y} \text{Max} \left( 0, \text{Cor}[y_{k(t)}, y^*_{k(t)}] - \eta_v \right).$$

$$\Psi$$ measures the mean of all correlations above the threshold value $\eta_v = 0.3$ between the observed ($y_k$) and reconstructed ($y^*_k$) weather statistics in the 40-year verification period. The value chosen for $\eta_v$ can be justified similarly as was done for $\eta_c$ above.

The 84 (half of 169) best-performing models were then used to evaluate the performance of the procedure for the individual weather statistics, and to derive scenarios of climatic change from the GCM-experiments.

2.3 Results and Discussion

2.3.1 Model Estimation

We investigated five different variants of predictor data sets, with the SLP and near-surface temperature fields accounting for the total variance of all predictors as given by the ratios 1:0 (i.e., only SLP), 2:1, 1:1, 1:2 and 0:1 (only temperature). For the predictors being SLP alone, SLP and near-surface temperature with equal weight, and temperature alone, respectively, the canonical patterns and time coefficients of individual CCA models were graphically represented and visually compared with each other and between locations.

In this subsection we mainly present results using Bern as an example, since results obtained for Bever, Davos, Lugano and Saentis could be interpreted similarly to those for Bern. We also present only CCA models fitted to a combined predictor data set (SLP and near-surface temperature with equal weight), because the canonical patterns resulting when using only one field were found quite similar to the respective subpatterns of the combined approach. This was generally the case for both seasons considered.
A) WINTER

Fig. 2.4 shows the CCA model obtained for $N_x = N_y = 4$ for Bern in winter. The first predictor pattern consists of a large positive SLP anomaly centered over the United Kingdom, a negative temperature anomaly over land areas, and a positive temperature anomaly over the Atlantic with an increasing amplitude towards the northwest. The two subpatterns give a consistent picture: in winters with on average higher than normal pressure over the UK, mean westerly flow and thus advection of relatively mild maritime air towards the continent are less pronounced, such that temperatures over lands drop below their long-term means. At the same time, advection of polar air into the north-west.
Atlantic is also reduced, resulting in above-normal temperatures in this region. This was the dominant predictor pattern in winter for all locations considered.

The first canonical pattern of the weather statistics in Bern (Fig. 2.4c, solid bars) confirms the above interpretation: temperatures are anomalously low, as are precipitation, its standard deviation, and the number of days where precipitation exceeds 1 mm. The negative responses in the precipitation-related variables are plausible, indicating that advection of maritime air is the main source of winter precipitation in Bern. Since the sign of the canonical patterns is arbitrarily determined by CCA, note that the following interpretation also holds: a negative SLP-anomaly centred over the UK, indicating intensified mean westerly flow, is associated with anomalously high temperatures over the continent, and also implies positive temperature and precipitation anomalies in Bern.

The relevance of the large-scale patterns for the individual weather statistics can be seen from Fig. 2.4d. Shown are the proportions of the variances in the local variables which were explained by the time coefficients $t_1(t)$ (solid bars) and $t_2(t)$ (shaded bars), i.e. the squared correlation coefficients (in percent) between the $y_k(t)$ and $t_1(t)$ for the model estimation period 1901 to 1940.

The second canonical mode mainly explained the variability of winter mean daily temperature extremes and amplitudes, mean relative sunshine duration, and its within-season standard deviation (Fig. 2.4d, shaded bars). The large-scale pattern depicts intensified mean advection of warm air from the west/south-west (Fig. 2.4b, left), and thus elevated temperatures over the continent with a maximum over eastern Europe (Fig. 2.4b, right). For Bern this setting implies slightly milder winters with on average more sunshine and higher-than-normal daily temperature amplitudes (Fig. 2.4c, shaded bars).

The third and fourth canonical modes (not shown) also contributed to explaining the year-to-year variability of the weather statistics. The third predictand pattern denoted predominance of meridional flow from north/northeast, which at Bern was associated with below-normal temperatures and mean wind speed, with higher-than-normal within-season temperature variability, and increased relative humidity. The fourth predictand pattern showed a large positive SLP anomaly over mid-latitude Atlantic and corresponding large-scale positive near-surface temperature anomalies over Finland; it correlated mainly with negative deviations in the within-season standard deviations of daily temperature means and extremes. The third and the fourth mode showed canonical correlations of 0.55 and 0.37, respectively, such that they also contributed to the reconstruction of the weather statistics in the model verification phase.

The canonical correlation patterns obtained for Davos (Fig. 2.5) illustrate the regionally differentiated relationships established by means of CCA. For example, in contrast to
Bern, year-to-year variations of winter mean precipitation, its within-season standard deviation, and of the probability of precipitation events ≥ 1 mm (Fig. 2.5d, shaded bars) were explained in Davos mainly by the second canonical mode (cf. Fig. 2.5b), not by the mean strength of westerly flow. In addition, though the respective SLP and temperature subpatterns are qualitatively similar for Bern and Davos, regional differentiation may also be given by shifts in the locations and/or amplitudes of the pattern's troughs and ridges. Due to sampling uncertainties however, it could be that not all respective patterns are significantly different from each other.

Fig. 2.5: CCA model for Davos in winter. (a) First, (b) second canonical patterns for the predictors. Left sides of (a) and (b): SLP subpatterns, contour interval 1 mb. Right sides: near-surface temperature subpatterns, contour interval 0.2°C. (c) Canonical patterns, (d) explained variances for the local weather statistics. The first seven predictor EOFs and the first four weather statistic EOFs were used, explaining ca. 88% and 73% of the respective total variances. Correlations between time coefficients are 0.91 for the first and 0.79 for the second mode.
B) SUMMER

Fig. 2.6 shows the results of CCA with \( N_x = 4 \) and \( N_y = 3 \) for Bern in summer. Again, the first predictor pattern depicted here for Bern was typical for all other locations as well. Its SLP-subpattern (Fig. 2.6a, left) shows a small positive anomaly over Europe (ca. 0.7 mb) when compared to the 1901-1980 standard deviation of mean summer SLP, which ranges from approximately 0.8 mb over the Mediterranean area to ca. 2 mb over the UK and Scandinavia (not shown). Considering that in the long-term mean the fringe of the Azores high-pressure system reaches Eastern Europe (not shown), the pattern can be in-

---

Fig. 2.6: CCA model for Bern in summer. (a) First, (b) second canonical patterns for the predictors. Left sides of (a) and (b): SLP subpatterns, contour interval 0.5 mb. Right sides: near-surface temperature subpatterns, contour interval: 0.1°C. (c) Canonical patterns, (d) explained variances for the local weather statistics. The first four predictor EOFs and the first four weather statistic EOFs were used, explaining approx. 75% and 77% of the respective total variances. Correlations between time coefficients are 0.89 for the first and 0.75 for the second mode.
terpreted to reflect summers with less pronounced subsidence over the Azores, but with the Azores high extending further than normal into the continent, thus leading to predominantly stable, warm weather conditions over central Europe. An alternative explanation could also be, however, that the SLP-subpattern represents a weak circulation induced by anomalously high temperatures over central and southern Europe.

Consistent with both interpretations, the first canonical mode predicts for Bern positive anomalies for temperature and relative sunshine duration, and a smaller probability for precipitation events \( \geq 1 \text{ mm} \) (Fig. 2.6c, solid bars). Interpreted with opposite signs, the first canonical mode describes summers with a higher-than-normal SLP over the Azores, but a corresponding low SLP over Europe, denoting that the continent is more frequently exposed to intrusions of cold air from west/northwest. This results in anomalously low temperatures at Bern, as well as over large areas southeast of the anomalously low SLP.

The second mode described mainly changes in the precipitation-related variables (Fig. 2.6d, shaded bars): similar to the situation in winter, higher-than-normal SLP centred over the UK (Fig. 2.6b, left) denotes summers with generally weaker westerlies and reduced advection of maritime air into central Europe, whereas the associated intensified northwesterly flow implies negative near-surface temperature anomalies over eastern Europe (Fig. 2.6b, right). In Bern, precipitation-related variables show negative deviations; mean daily temperature amplitudes as well as relative sunshine durations are above their long-term means; and, possibly due to reduced thunderstorm activity, the less pronounced zonal flow leads to negative deviations for summer mean wind speeds (Fig. 2.6c, shaded bars).

Clearly, since summer weather in central Europe is mainly influenced by smaller-scale convective processes, the second canonical mode describes but a relatively small part of the interannual variability of the above mentioned variables (see also "Model Verification" below). Nonetheless, this mode can be interpreted to quantify for Bern the effects resulting from fluctuations in the intensity of the European summer monsoon, i.e. the strength of the enhanced westerly winds over central Europe which typically onset in mid-June (SCHÜEPF & SCHIRMER, 1977).

### 2.3.2 Model verification

For all five variants of SLP/near-surface temperature predictor data sets we determined per season and location, according to Eq. 2.4, the respective best-performing 84 of 169 fitted CCA models. For each set of 84 CCA models, the models' capabilities to predict the individual weather statistics were assessed by comparing the statistically reconstructed
interannual variations of the local variables with the observations. For six main weather statistics we also analysed the resulting 80 yr linear trends.

A) INTERANNUAL VARIABILITY

The skill of the CCA models with regard to the individual variables was measured by the proportions of variance explained (100-\(r^2\), i = 1..84) in the verification period 1941-1980. Under the assumption of a normal distribution, correlations above 0.31, i.e. skills above ca. 10%, suggest a statistically significant link to large-scale climate (\(\alpha=95\%\)).

Fig. 2.7 shows that the skill of the CCA models may vary strongly, depending on the large-scale predictors, the season, location, and weather statistic considered.

Though no combination of predictors could be found which yielded optimal results for all cases, the combined use of SLP and near-surface temperature generally improved the skill of the procedure (predictor data set variants 2-4 in Fig. 2.7). On average over all locations and variables, the mean variances explained when SLP (near-surface temperature) alone was used, amounted to ca. 23% (21%) in winter and to 12% (18%) in summer. An optimum was reached when the two fields were combined with equal weights, such that an average skill of 25% in winter and 19% in summer was attained. Use of the two predictors with equal weights seemed therefore to be a good compromise, which was maintained for the further discussion and for obtaining climatic change estimates from the GCM-experiments.

As can be seen from Fig. 2.8, the most dramatic improvement occurred for the summer, and for temperature-related variables. However, the situation remained, that most variables were better linked to the large-scale state of the atmosphere in winter than in summer.

In both seasons, better results were obtained at the three north alpine locations (Bern, Davos, Saentis) where, on average over all three locations and all variables, the mean skill of the CCA models amounted to 29% in winter and to 21% in summer. At the more southern locations (Bever, Lugano) on average only 20% (winter) and 17% (summer) were attained.

Large differences were found between the individual variables (Fig. 2.8). Temperatures were generally better reproduced than precipitation-related variables, the latter being particularly poorly predicted in summer. For seasonal mean temperatures, mean skills from the respective 84 selected CCA-models were between 44% (Bever) and 67% (Saentis) in winter, and 56% (Bever) and 78% (Saentis) in summer (Fig. 2.7a, predictor
Fig. 2.7: Skill of the CCA models as a function of the predictors, season, location and variable considered. Shown are percentages of variances (=100-$r^2$) explained by the reconstruction of the weather statistics in the verification period 1941-1980. Data points denote the mean variance explained by 84 selected CCA models; error bars are ±1 standard deviation. From left to right (repeated for each location): (1) predictors were SLP anomalies alone, (2) predictors were SLP- and near-surface temperature anomalies accounting for the total variance of the predictor data with the ratios 2:1, (3) 1:1, (4) 1:2, and (5) predictors were near-surface temperature anomalies alone.

variant 3). Mean daily temperature minima, which were better reproduced in summer than in winter at all locations except for Bern (not shown), were predicted with mean skills ranging from 30% (Lugano) to 64% (Saentis) in winter, and from 36% (Lugano) to 73% (Saentis) in summer. Mean daily maximum temperatures were also generally well predicted, with skills ranging in winter from 59% (Bever) to 69% (Bern), and in summer from 33% (Lugano) to 74% (Saentis). Mean daily temperature amplitudes were not well reproduced at any location in winter, but in summer skills of 19%, 24% and 32% were attained at Bever, Saentis, and Bern, respectively. For precipitation, between 29% (Saentis) and 55% (Bern) were reached in winter, and between 10% (Lugano, Saentis) and 28% (Davos) in summer (Fig. 2.7c). Relative sunshine durations, which directly depend on degree of cloudiness, were also less well reproduced; exceptions, however,
were Davos (52%) in winter and Bern (53%) and Lugano (47%) in summer (Fig. 2.7b). Skills for the numbers of days with precipitation above 1 mm ranged from 29% (Davos) to 56% (Bern) in winter, and were 4% (Bever), 18% (Davos), 30% (Saentis), 36% (Lugano), and 42% (Bern) in summer. Seasonal mean wind speeds were not well predicted; the highest skills were attained in winter at Davos (18%) and in summer at Saentis (15%). Mean relative humidities were only well reproduced at Saentis in winter (43%), whereas in summer at no location more than 15% were reached. Within-season standard deviations of daily mean, minimum and maximum temperatures were predicted in winter with skills between 20% and 45%; an exception was Lugano, where skills for all three parameters were below 10%, as was the case for all locations in summer. For the within-season standard deviations of daily precipitation totals, skills above 20% were reached at Bever (24%), Bern (29%), and Lugano (39%) in winter, but, again, at no location in summer. From all remaining within-season standard deviations, a skill above ca. 20% was reached only for relative sunshine durations at Bern (21%) and Davos (20%) in winter, and at Bever (19%) and Lugano (52%) in summer.
In Fig. 2.9, 5 yr running-means of observed (thick lines) and reconstructed (grey areas) time series of weather statistics are compared, showing a generally coherent behavior between the pairs of curves. The better reproduction of temperatures (Figs. 2.9a,c) in contrast to precipitation related variables (Figs. 2.9b,d) also becomes visible in the different widths of the grey areas, i.e. the uncertainties resulting from different choices in the numbers of EOFs used to fit the statistical models.

![Fig 2.9: Comparison of statistically reconstructed time series of local weather statistics with observations (5 yr running means). Solid lines: observations 1901-1980. Grey areas contain 90% of the reconstructed values from 84 selected CCA models fitted separately for each season and location for the years 1901-1940 using a combined SLP/near-surface temperature predictor data set (weights 1:1). Explained variances by the average time series (not shown) of the 84 CCA models in the verification period 1941-1980 were (a) 64%, (b) 55%, (c) 65%, (d) 36%.](image-url)
One main reason for the differences in the predictability of the local variables between the different locations, seasons and variables certainly is that our approach describes only the proportion of the interannual variability of a weather statistic which is controlled by fluctuations of large-scale SLP and near-surface temperature. Differences may thus result from seasonally (winter vs. summer) or regionally (northern vs. southern Alps) varying intensities of smaller-scale convective activity, as well as from different combinations of local factors such as orography, vegetation, and soil characteristics. In particular, these factors may regionally influence local wind systems, snow cover, or energy exchange with the atmosphere, thus uncoupling the variability of individual weather elements from the large-scale circulation. For example, seasonal mean minimum temperatures, which depend on smaller-scale thermal inversions and cold air drainage, were generally less well reconstructed than the seasonal mean and mean maximum temperatures. As could be expected, this was found to be particularly the case for the four valley locations, and for the winter season.

It should be noted that the inclusion of 17 not equally well cross-correlated variables within the same CCA model tended to worsen the prediction of individual variables to the benefit of the ensemble. This is because – despite the standardisation of all predictands to the unit standard deviation (Fig. 2.3) – the relative importance of individual variables was implicitly influenced by typical correlation structures found in the predictand data sets, e.g. a clustering of temperature- or precipitation-related variables. Possibly, due to an alternative choice or weighting of the predictands, the modest performance obtained for e.g. mean relative humidities and wind speeds could be improved.

B) LONG-TERM LINEAR TRENDS

The observed and by means of CCA reconstructed 1901-1980 linear trends of six main weather statistics are summarised in Table 2.2.

Seasonal daily mean, mean minimum and mean maximum temperatures displayed an upward trend at all five stations in winter. The CCA models uniformly failed to reproduce any signs of these trends and instead indicated a decrease of temperature since the beginning of this century. With respect to the interannual variations however, the similarity between reconstructed time series and the in-situ observations was much better (Fig. 2.9a). A similar finding was reported by Werner & von Storch (1993).

CCA indicated a net cooling because of a large-scale trend in SLP (Fig. 2.10a), whereas the spatially less homogeneous trend in the Vinnikov et al. (1987) temperature data (Fig. 2.10b) did not affect the reconstruction of the temperature trends much (see also Eq. 2.1'). The reality of the long-term SLP trend was documented by von Storch et
### Seasonal Statistics

<table>
<thead>
<tr>
<th>Seasonal Statistics</th>
<th>Bever</th>
<th>Bern</th>
<th>Davos</th>
<th>Lugano</th>
<th>Saentis</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Winter</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tmean (°C)</td>
<td>0.78</td>
<td>-0.51</td>
<td>1.34*</td>
<td>-0.49</td>
<td>1.75*</td>
</tr>
<tr>
<td>Tmin (°C)</td>
<td>-1.16</td>
<td>-0.34</td>
<td>2.36*</td>
<td>-0.43</td>
<td>2.64*</td>
</tr>
<tr>
<td>Tmax (°C)</td>
<td>0.60</td>
<td>-0.56</td>
<td>0.36</td>
<td>-0.76</td>
<td>0.77</td>
</tr>
<tr>
<td>Rel. Sunsh. (%)</td>
<td>-11.6*</td>
<td>-2.1</td>
<td>-3.1</td>
<td>-3.4</td>
<td>-6.2</td>
</tr>
<tr>
<td>Precip. (% of LTM)</td>
<td>-20.9</td>
<td>7.4</td>
<td>16.3</td>
<td>6.6</td>
<td>12.2</td>
</tr>
<tr>
<td>Ndays≥1mm (% of LTM)</td>
<td>-9.3</td>
<td>8.0</td>
<td>2.6</td>
<td>3.6</td>
<td>5.2</td>
</tr>
<tr>
<td><strong>Summer</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tmean (°C)</td>
<td>-0.01</td>
<td>0.25</td>
<td>0.50</td>
<td>0.02</td>
<td>0.05</td>
</tr>
<tr>
<td>Tmin (°C)</td>
<td>0.27</td>
<td>0.21</td>
<td>1.24*</td>
<td>0.18</td>
<td>1.22*</td>
</tr>
<tr>
<td>Tmax (°C)</td>
<td>-0.58</td>
<td>0.60</td>
<td>-0.25</td>
<td>-0.12</td>
<td>-0.21</td>
</tr>
<tr>
<td>Rel. Sunsh. (%)</td>
<td>-5.1*</td>
<td>-1.6</td>
<td>-6.6*</td>
<td>-0.6</td>
<td>-7.3*</td>
</tr>
<tr>
<td>Precip. (% of LTM)</td>
<td>7.1</td>
<td>5.8</td>
<td>11.1</td>
<td>-0.8</td>
<td>-1.7</td>
</tr>
<tr>
<td>Ndays≥1mm (% of LTM)</td>
<td>0.9</td>
<td>0.5</td>
<td>-3.1</td>
<td>-0.6</td>
<td>-0.3</td>
</tr>
</tbody>
</table>

Table 2.2: Mean linear trends of weather statistics in the period 1901-1980, both observed (obs.) and reconstructed (rec.) from 84 selected CCA models. The CCA-models were fitted for the years 1901-1940 to a combined SLP/near-surface temperature predictor data set (weights 1:1). Quantities are given in respective units per 80 yr; asterisks denote significance of trends on the 95% level (given for observations only). LTM = long-term (1901-1980) mean.

al. (1993), who found a consistent signal in both ship-of-opportunity observations of SLP and in situ precipitation records on the Iberian Peninsula. When only SLP was used for CCA, the discrepancy between the CCA models and the local observations was increased (mean ± standard deviation of trend from 84 selected CCA models for winter mean temperature in Bern: -1.21±0.28 °C per 80 yr). The differences between the 80-year trends also remained when the 1941-1980 interval was used to fit the CCA models.

There are several candidates that may account for part or all of the discrepancy:

First, the effect of the systematically changing pressure field on the Swiss temperature must have been counteracted by another large-scale feature, presumably representing the thermal structure of the troposphere. One possibility is that, e.g. due to the use of changing reference intervals, a real trend in near-surface temperature is not correctly represented in the VINNIKOV data set. Preliminary calculations with the JONES-data set (JONES & BRIFFA, 1992; BRIFFA & JONES, 1993) actually yielded less negative 80 yr trends for winter mean temperatures, however by only 0.1-0.3 °C. An alternative explanation could thus be a trend in a large-scale parameter not included in our analysis, e.g. 500 mb geopotential height. Due to the lack of data in the first half of this century, however, this hypothesis could not be tested.
A second reason could be that the statistical link between the local temperatures and the large-scale circulation has changed with time. For example, systematic changes in the frequencies of short-lived weather systems, which have a strong effect on the local temperatures may not be adequately represented in the seasonal mean fields. Possibly, the linear CCA models may also have failed to capture any non-linear effects.

Third, it should be noted that the positive trends are significant only for the seasonal mean and mean minimum temperatures at the three urban stations, whereas the two rural stations Bever and Saentis show much smaller trends (Table 2.2). From Fig. 2.9a it becomes obvious that the CCA models failed to reproduce the trend not only in the last 40 years of the verification interval but also in the first 40 years of the analysis interval. We speculate that the positive local trends at the urban stations are overestimated due to the urban heat island effect and increasing air pollution.

In summer, the discrepancy between the indirectly derived and the in situ trends of the three temperature parameters was considerably smaller than in winter. Only the trends of the mean minimum temperatures at the three urban stations were not reproduced. We suggest that these in situ records are contaminated by a significant urbanisation effect. Another major difference was found at Lugano, where the local observations of seasonal mean daily temperature maxima indicate a net cooling of -2.2 °C, whereas the large-scale fields specified a small cooling of only -0.2 °C.

For relative sunshine in winter the statistical models were more successful in reproducing the sign of the trends, even if the absolute values deviated somewhat. The significant reduction in relative sunshine obtained for Bever, as well as its poor reproduction by the CCA models (Fig. 2.7b), probably occurs because measurements for this location were taken from the climate station of St. Moritz 6.9 km away, which furthermore has often been moved.
Trends in summer mean relative sunshine durations were generally underestimated by CCA, but the signs were correct in all five cases. The largest deviations were found for Lugano, where relative sunshine decreased during 1901-1980 by more than 10%, whereas the CCA models estimated a reduction by only 0.7%. Again, this discrepancy could be due to the climate station's being moved (H. BANTLE, SMA, personal communication) or to increased air pollution (see also GENSLER, 1978, p. 9).

Trends of daily mean precipitation and of numbers of days with precipitation exceeding 1 mm were mostly reproduced with an error remaining within 10% of the respective 1901-1980 long-term means. At Bever, observed (-21%) and reconstructed (+7.4%) winter precipitation trends were not consistent, but both numbers are small compared to the 1901-1980 standard deviation which amounts to ca. 49% of the long-term mean. The significant trend found for mean winter precipitation in Saentis, which was also not well reconstructed by means of CCA, is doubtful, since precipitation may not be reliably measured at this peak location.

2.3.3 Downscaling of GCM-Simulated Climatic Changes

GCM-simulated predictors for the climatic change experiments performed with the ECHAM1/LSG-GCM were derived as deviations from the mean SLP and near-surface temperature fields simulated in the first 40 yr of the "control" run. The "control" run shows a drift in the globally and annually averaged near-surface temperature of less than -0.4 °C in 100 yr, which may be attributed to low-frequency variability of the model. In the DCO2 experiment, after one century temperature has increased by 1.7 °C. In the SCNA experiment, global mean temperature rises during the first 40 years by moderate 0.5 °C, which is likely an underestimate due to the "Cold Start"-problem (see HASSEL-MANN et al., 1992). The rate of temperature growth increases then to 0.35 °C per decade, such that by the year 2085, and under greenhouse gas concentrations of ca. 1150 ppm equivalent CO2, global warming reaches 2.6 °C. This result lies between the lowest and best estimates of approx. 2 °C and 3 °C, respectively, given for the same future time-point by the IPCC (1990).

Fig. 2.11 shows time-dependent changes in the temperature and precipitation statistics of Bern, downscaled from the SLP and near-surface temperature anomaly fields of the 100-yr SCNA-experiment. The range of values predicted by the different CCA models using different numbers of EOFs typically increases with time, i.e. with the magnitude of large-scale climatic change. This is because differences in the regression coefficients of Eq. 2.3 become increasingly effective, the more the predictors deviate from the mean state used for CCA model estimation.
Fig. 2.11: Climatic change scenario for Bern (5 yr running means). Changes in the local variables were statistically downscaled from large-scale SLP and near-surface temperature anomalies simulated in the "IPCC Scenario A" experiment performed with the ECHAM1/LSG-GCM. Dashed lines: mean responses of 84 selected CCA models using different numbers of EOFs. Grey areas contain 90\% of the CCA model estimates.

In Figs. 2.12 and 2.13 projected changes in seasonal temperature and precipitation parameters are compared between locations. The regional differentiation obtained is in strong contrast to the homogeneous changes specified at single GCM-gridpoints on a spatial scale of several $10^2$ km. During the last decade of the SCNA experiment, the projected temperature deviations differ between locations by as much as 1.8 °C in winter and 2.0 °C in summer. Similarly pronounced differences occurred for most other variables as well (e.g., Fig. 2.13).

Fig. 2.12: Statistically downscaled changes in seasonal mean temperatures for the last 20 yr of the "double CO$_2$" experiment and for the last 10 years of the "IPCC Scenario A" experiment. Shown are the mean changes obtained from 84 selected CCA models fitted in the period 1901-1940 separately for each season and location. Changes are given relative to the 1901-1940 means.
As can be seen from Fig. 2.12, the DCO2 and the SCNA experiments yielded similar patterns of change between the different locations. Since this was not only the case for temperature (see also Table 2.3), we will focus below on the last decade of the SCNA-experiment, where the most pronounced changes occurred. Further, since for some variables the downscaled changes strongly depended on the data used for CCA model estimation (Fig. 2.13), the mean responses of CCA models fitted in the period 1901-1940, as well as in the complementary period 1941-1980 will be considered.

The results for six main variables are summarised in Table 2.3. For seasonal mean temperatures, the "best estimates" - i.e. the mean changes from all used CCA models per season and location - amounted to 2.0 °C in winter and 2.4 °C in summer, averaged over the three northern locations Bern, Davos, and Saentis, and to 1.2 °C in winter and 2.7 °C in summer, averaged over the two southern locations Bever and Lugano. Winter mean daily temperature extremes showed similar spatial patterns of change to the winter temperature means: winter mean daily minimum temperatures were found to rise at the northern (southern) slope of the Alps by on average 2.2 °C (1.5 °C), whereas for the maxima moderate changes by 1.8 °C (1.0 °C) occurred. Warming was very differently distributed in summer, where a substantial increase by 3.1 °C (3.9 °C) was obtained for the temperature maxima, as opposed to only 2.6 °C (1.7 °C) for the temperature minima.

Projected changes in relative sunshine durations were generally small for winter, whereas in summer changes of +36% were specified at the northern, and +17% at the southern slope of the Alps. Winter precipitation totals changed by only ca. +6% at the northern,
<table>
<thead>
<tr>
<th>Seasonal Statistic</th>
<th>Location</th>
<th>Winter</th>
<th>Summer</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1901-80</td>
<td>DCO2</td>
<td>SCNA</td>
</tr>
<tr>
<td></td>
<td>μ</td>
<td>σ</td>
<td>low b.e. high</td>
</tr>
<tr>
<td>Tmean</td>
<td>Bever</td>
<td>-14.56</td>
<td>1.20</td>
</tr>
<tr>
<td></td>
<td>Bern</td>
<td>-12.01</td>
<td>1.22</td>
</tr>
<tr>
<td></td>
<td>Davos</td>
<td>-15.88</td>
<td>1.81</td>
</tr>
<tr>
<td></td>
<td>Lugano</td>
<td>3.90</td>
<td>1.95</td>
</tr>
<tr>
<td></td>
<td>Saentis</td>
<td>-10.64</td>
<td>1.97</td>
</tr>
<tr>
<td>Tmin</td>
<td>Bever</td>
<td>-1.87</td>
<td>1.04</td>
</tr>
<tr>
<td></td>
<td>Bern</td>
<td>1.35</td>
<td>0.97</td>
</tr>
<tr>
<td></td>
<td>Davos</td>
<td>-0.60</td>
<td>0.46</td>
</tr>
<tr>
<td></td>
<td>Lugano</td>
<td>0.79</td>
<td>0.41</td>
</tr>
<tr>
<td></td>
<td>Saentis</td>
<td>-0.64</td>
<td>0.93</td>
</tr>
<tr>
<td>Tmax</td>
<td>Bever</td>
<td>4.23</td>
<td>1.27</td>
</tr>
<tr>
<td></td>
<td>Bern</td>
<td>2.45</td>
<td>0.79</td>
</tr>
<tr>
<td></td>
<td>Lugano</td>
<td>5.62</td>
<td>0.79</td>
</tr>
<tr>
<td></td>
<td>Saentis</td>
<td>3.82</td>
<td>0.76</td>
</tr>
<tr>
<td>Rel. Sunsh.</td>
<td>Bever</td>
<td>4.5</td>
<td>3.1</td>
</tr>
<tr>
<td></td>
<td>Bern</td>
<td>6.0</td>
<td>3.7</td>
</tr>
<tr>
<td></td>
<td>Davos</td>
<td>6.8</td>
<td>4.0</td>
</tr>
<tr>
<td></td>
<td>Lugano</td>
<td>7.4</td>
<td>5.7</td>
</tr>
<tr>
<td></td>
<td>Saentis</td>
<td>20.7</td>
<td>13.4</td>
</tr>
<tr>
<td>Precip.</td>
<td>Bever</td>
<td>21.6</td>
<td>9.4</td>
</tr>
<tr>
<td></td>
<td>Bern</td>
<td>28.5</td>
<td>12.3</td>
</tr>
<tr>
<td></td>
<td>Davos</td>
<td>26.3</td>
<td>9.4</td>
</tr>
<tr>
<td></td>
<td>Lugano</td>
<td>18.7</td>
<td>10.2</td>
</tr>
<tr>
<td></td>
<td>Saentis</td>
<td>41.8</td>
<td>13.6</td>
</tr>
</tbody>
</table>

Table 2.3: Projected deviations of weather statistics from their respective 1901-1980 long-term means (μ) for the last 20 yr of the "double CO2" experiment (DCO2) and for the last 10 yr of the "IPCC Scenario A" experiment (SCNA). μ = 1901-1980 observed standard deviations of the weather statistics; b.e. = "best estimate" changes, i.e. mean deviations obtained from 168 selected CCA models (84 fitted for the years 1901-1940, and 84 for the years 1941-1980) using a combined SLP/near-surface temperature predictor data set (weights 1:1); low/high = lower and upper limits of empirical intervals containing the responses of 151 (=90% of 168) CCA models 1901-1980 means and standard deviations are given in °C for the temperature parameters, in % for relative sunshine duration, and in cm mo⁻¹ for precipitation. Deviations are given in °C for temperatures and in % of the respective 1901-1980 means for all other variables.

but increased dramatically by 34% (Bever) and 53% (Lugano) at the more southern ones (see also Fig. 2.13a). Summer precipitation was found to increase at all locations by 4% to 30%, except for Saentis, where a strong decrease by 42% was specified; the strongest
increase occurred again at the southern slope of the Alps (average 26%). Winter probabilities of wet days did not change much at the three northern locations, whereas at Bever it increased by 15% and at Lugano by 28%; summer probabilities of wet days were found to change at the three northern locations by -3% to -13%, and, again, to increase at the two southern locations by an average of ca. 12% (see also Fig. 2.13b).

The following "best estimates" were obtained for the weather statistics not considered in Table 2.3: Seasonal mean daily temperature amplitudes decreased in winter quite uniformly by on average -0.4 °C; in summer they increased at the three northern locations by 0.5 °C on average, and at the two southern locations by 2.2 °C. Winter mean daily wind speeds were found to decrease at Bever by 48% and at Davos by 40%, and to increase at Lugano by 9%, of the respective long-term mean; in summer, mean wind speeds decreased again at Bever (-75%) and Davos (-64%), but increased by 35% at Bern, and 61% at Lugano. Seasonal mean relative humidities did not change much in both seasons at all locations, except for Saentis in summer (-15%). Within-season standard deviations of daily mean, minimum and maximum temperatures decreased systematically at all locations, on average by 21%, 21% and 18% in winter and by 11%, 10% and 7% in summer, respectively. Within-season standard deviations of daily temperature amplitudes were generally reduced in winter, by ca. 10%, whereas in summer less coherent changes among the locations, in the order of ±10%, were obtained. Within-season standard deviations of daily precipitation totals increased in winter at Bever and Lugano by 40% and 46%, respectively, and in summer by 5%-24% at all locations, except for Saentis, where a reduction by 41% occurred. Within-season standard deviations of daily relative sunshine durations changed in winter only at Saentis (+10%), whereas in summer they increased at Saentis (+74%) as well as at Bever (+10%), and decreased by 5% to 10% at the remaining locations.

The procedure yielded not only a regionally differentiated but also an internally consistent picture of possible climatic change. Note that plausible changes were even obtained for several variables which were not well predicted in the model verification phase. In some cases however, e.g. for summer precipitation and mean relative sunshine duration at Saentis, the CCA models did not yield sensible results. Possible reasons could be that the linearity assumption (Eq. 2.3) was violated, or that inconsistencies in the local data sets were amplified under the given large-scale climatic change.

All in all, winter climate was specified to be milder and wetter than under present conditions. This suggests an increased probability for nighttime cloud cover, which is consistently mirrored in a stronger rise of the minimum as compared to the maximum temperatures, a general decrease of mean daily temperature amplitudes, and a smaller within-winter temperature variability. The summer was specified to become generally hotter and wetter; in this connection, strong increases in relative sunshine durations, mean daily
maximum temperatures and temperature amplitudes suggested increased irradiation and surface heating. The increases in summer precipitation could correspond to stronger convective activity, or to more intense intrusions of maritime air, which would compensate for the more pronounced ocean-continent temperature contrast as simulated by the GCM. In both seasons, the precipitation increases consistently tended to occur with increased within-season variabilities of daily precipitation totals and increased probabilities of wet days.

It should be noted that the large-scale signals underlying the responses of all weather statistics (Eq. 2.1') were found, in both seasons and for all locations, to be mainly determined by the rising near-surface temperature. In particular, the projected changes depended strongly on the inclusion of near-surface temperature as a large-scale predictor. For example, when SLP was used as the only predictor in winter, anomalously high SLP between 35° N and 50° N in the final decade of the SCNA experiment implied precipitation decreases by 4% to 12% in Bever, Bern and Lugano, and positive changes of a few percent in Saentis and Davos. Yet in Fig. 2.12a precipitation increases are shown which, since they include the information of the temperature field, can be interpreted to be a consequence of the higher moisture content of the air advected towards the Alps, counterbalancing the effect of slightly weakened westerlies. It is possible, that inclusion of additional predictors which show similarly drastic changes to those of near-surface temperature in the GCM, e.g. mid-tropospheric pressure fields, could further modify our results.

The downscaled climatic changes strongly reflected the characteristics of the underlying GCM-simulation. The DCO2- and SCNA experiments yielded qualitatively similar changes in local climates (Fig. 2.12, Table 2.3) because the GCM's large-scale responses for SLP (not shown) as well as for near-surface temperature (CUBASCH et al., 1992) to the respective greenhouse gas forcings show quite similar large-scale patterns in both experiments. In the case of the SCNA experiment, the small changes projected for the first 50 years of the scenario period (Fig. 2.11) reflect the delayed global mean temperature response of the ECHAM1/LSG-GCM. Further, the GCM-downscaled year-to-year fluctuations of the weather statistics were generally smaller than under present climate (Fig. 2.9 vs. Fig. 2.11). This is due to a systematic underestimation of the interannual variability of seasonal mean SLP by the GCM which occurs in the "control" run, as well as in the first decades of the SCNA-experiment for both seasons considered (not shown). A possible reason for this could be the underestimation of mid-latitude cyclonic activity resulting from the model's low spatial resolution (cf. CUBASCH et al., 1992). Finally, it should be noted that the smallest warming occurred for both seasons at the southern slope of the Alps (Lugano). This is possibly because temperatures at the north alpine locations (Bern, Davos and Saentis) and at the more eastwardly located Bever are more strongly determined by advection from higher latitudes and northeastern Europe, which are the regions where the largest warming takes place in the GCM.
2.4 Conclusions

From our case studies at five representative locations in the Alps we conclude:

(1) It is possible to establish plausible statistical relationships which allow the large-scale climatic changes produced by GCMs to be linked to local ecosystem model inputs, even in a complex orography like the Alps. The results obtained were meaningful for winter (Dec., Jan., Feb.) as well as for summer (June, July, Aug.). For each location, the statistical models quantified the effects resulting from changes in major circulation patterns, e.g. from changes in the strengths of large-scale zonal or meridional flow or of subsidence, and from fluctuations in the associated large-scale near-surface temperature distributions.

(2) The strength of the statistical link to the large-scale circulation depends on the season, location, and variable considered. The procedure allows several important ecosystem inputs to be reconstructed on a yearly to decadal timescale reasonably well.

The most reliably reconstructed variables were the seasonal means of daily mean, minimum and maximum temperatures, whereas the poorest results were obtained for seasonal mean temperature amplitudes, relative humidities, wind speeds, and, for summer only, daily precipitation totals, numbers of days with precipitation above 1 mm, plus most within-season standard deviations of daily variables. Some observed 80 yr trends, especially for mean daily temperatures and temperature extrema in winter, and for mean minimum temperatures in summer, could not be correctly reproduced. On the whole, most variables were better reconstructed in winter than in summer.

On average over all variables, the three north alpine locations (Bern, Davos and Saentis) could be better linked to large-scale climate than the two more southern locations (Bever, Lugano). This difference was more pronounced in winter than in summer.

(3) The downscaling procedure originally proposed by von Storch et al. (1993) could be improved by including large-scale near-surface temperature anomalies as an additional large-scale predictor. Improvement was possible for almost all variables and generally for all locations considered in this study. The largest improvements were found for seasonal mean temperatures and mean daily temperature extremes, and for the summer season.

(4) The method presented here allows to flexibly regionally differentiated, time-dependent estimates of climatic change to be flexibly for input variables required by ecosystem models at a much smaller spatial scale than given by the resolution of present GCMs.
However, the following restrictions of this approach must not be overlooked:

- Considerable amounts of data must be available and have to be managed. Required are sufficiently long records of the local variables close enough to the location of interest, simultaneous observations of the large-scale state of the atmosphere in the sector containing this location, as well as corresponding data sets from experiments with GCMs.

- The method assumes that the established statistical relationships remain valid also under future climatic conditions. For example, towards the end of the "IPCC Scenario A" experiment the GCM-simulated fields undergo changes which exceed the range of the observations used to fit the statistical models; thus, towards the end of the next century the projected changes in the local variables represent (linear) extrapolations which might not necessarily hold in the real world.

- The downscaled local climatic changes will not be more reliable than the underlying GCM-experiments. For example, the relatively modest temperature increases obtained in our study at all locations are a consequence of the relatively small sensitivity of the ECHAM1/LSG-GCM to increased greenhouse-gas concentrations. Local climatic changes should therefore be explored for experiments with other GCMs, a procedure which is easy to accomplish with our method.

In spite of these difficulties, the proposed method represents to our knowledge the best approach currently available to consistently link GCM-simulated climatic changes to ecosystem models. In combination with stochastic weather generators it can be used to derive multivariate scenarios of climatic change on a wide range of temporal scales, and yet it allows to attain the high spatial detail particularly required within a mountainous region to be attained. Moreover, our approach can be easily adapted to the specific needs emerging from ongoing ecosystem research. Yet, further improvements can be envisaged, e.g. by downscaling only a reduced set of inputs, by using additional large-scale predictors, and, as recent work showed (GYALISTRAS & FISCHLIN, 1996), by spatial inter- and extrapolation to points with scanty or even no measurements.
3. The Temporal Aspect: Stochastic Simulation of Monthly Weather

3.1 Introduction

Dynamic simulation models present important tools to study possible impacts of future climatic change on ecosystems. Several of these models require site-specific, monthly weather data as an input. For example, biogeochemical models focusing on C/N dynamics, such as MBL-GEM (RASTETTER et al., 1991) or CENTURY Forest (METHERELL et al., 1994), or forest succession models such as FORSKA (PRENTICE et al., 1993) and FORCLIM (BUGMANN, 1994, 1996; FISCHLIN et al., 1995) are driven by different combinations of monthly weather variables related to temperature, precipitation and relative sunshine duration. Simulation studies with such models typically require many, e.g. up to 200 (BUGMANN et al., 1996), realizations of the weather process, and for all months of the year. Furthermore, the inputs must often be provided for time spans covering at least a few decades to millennia.

A straight-forward approach to provide such inputs is to sample weather sequences from the local weather record (e.g., DAVIS & BOTKIN, 1985; BOTKIN & NISBET, 1992). To simulate scenarios of possible future weather the record can be adjusted according to the assumed climatic scenario, for instance by adding a certain fixed amount (e.g., ±2 °C for temperature and ±20% for precipitation) to all elements of the measured time series (e.g., ROBOCK et al., 1993). This approach is computationally efficient and relatively easy to implement. However, it has two major drawbacks: Firstly, if not a very long record is available, the measurements may not cover all possible combinations of regional weather states relevant for the system under investigation. In particular, due to sampling variability the frequencies of events exceeding specific thresholds – such as temperature thresholds that control the survival and growth of organisms – may not be well represented, and this may decrease the robustness of the results obtained with an impact model. Secondly, future climatic change might include changes in global climatic variability (e.g., MEEHL et al., 1994; LUPO et al., 1997), which could strongly affect local precipitation patterns and/or auto- and cross-correlations of regional weather variables (e.g., GREGORY & MITCHELL, 1995; MEARNS et al., 1995a, 1995b; TSONIS, 1996). The direct manipulation of the local weather record allows however mainly for changes in means, and therefore becomes impractical when one wishes to investigate more complex patterns of climatic change.
A second possibility is to use statistical or stochastic models which simulate local weather conditional on the large-scale state of the atmosphere. Several such "downscaling" procedures have been proposed until now, which operate at a seasonal (e.g., VON STORCH et al., 1993; GYALISTRAS et al., 1994) to daily (e.g., BARDOSY & PLATE, 1992; ZORITA et al., 1995; BÜRGER, 1996) temporal resolution. To simulate scenarios of future weather these procedures can be applied to the weather patterns produced in simulation experiments with numerical climate models (e.g., GYALISTRAS et al., 1994; ZORITA et al., 1995; BÜRGER, 1996).

This approach has the advantages that it uses the physically consistent output of the climate models, and that the resulting scenarios reflect possible changes also in the higher-order statistics of weather. Moreover, the use of large-scale weather patterns circumvents the limited regional reliability (GROTCH & MACCRACKEN, 1991; VON STORCH, 1995) of the climate models. However, some major restrictions occur. Firstly, the daily to interannual variability of weather is not very reliably simulated by present-day climate models (e.g., HULME et al., 1993), and this can lead to large errors in the statistics of the simulated local weather (BÜRGER, 1996). Secondly, due to the enormous computing requirements of climate models normally only one realization of large-scale weather is available from climate simulations. This prevents extensive sensitivity analyses and experimentation with many different scenarios, as this is often required in the context of impact studies. Furthermore, simulations with climate models typically extend only over a decade to a century. This restricts the construction of transient scenarios over longer time periods, which again sharply contrasts with the requirements of many ecosystem studies.

An attractive alternative to both above approaches are so-called "weather generators", i.e. stochastic models which simulate the local weather based on site-specific climatic parameters and a pseudo-random number generator. Unlike the direct use of the local weather record, a weather generator allows to describe local climates based on a comparatively small number of well-defined climatic parameters, which may be estimated quite reliably already from relatively short time series by means of appropriate procedures (e.g. RICHARDSON, 1981). Also, differently from the downscaling approaches, which critically depend upon a sufficiently good simulation of the large-scale weather by the climate models, weather generators can be designed to simulate the local weather with a high statistical accuracy. The climatic parameters involved can be easily adjusted — either based on ad-hoc assumptions, or according to estimates of local climatic change as obtained from a downscaling procedure — to experiment with a wide range of climatic scenarios (see e.g. WILKS, 1992). Moreover, the relatively modest computing requirements of this approach make it possible to generate a large number of weather sequences, and under any time-dependent scenarios of climatic change that may extend far into the future.
Though a large body of literature exists on the stochastic simulation of daily (e.g., RICHARDSON, 1981; WILKS, 1992; GREGORY et al., 1993; KATZ, 1996) or hourly (e.g., COWPERTWAIT, 1991; AGUIAR & COLLARES-PEREIRA, 1992; BO et al. 1994; GYALISTRAS et al., 1997) weather variables by means of local weather generators, we are aware only of little work that focuses on the simulation of monthly weather.

BOTKIN & NISBET (1992) investigated the effect of sampling variability in the definition of the baseline climate on forest compositions simulated by means of the JABOWA forest succession model. They resampled monthly weather data from different subperiods of the 1901-1980 record and found generally only small effects on simulated forest compositions. However, they considered but one location, at the transition between boreal and northern hardwoods forests in North America, and did not examine the stochastic simulation of monthly weather variables.

BUGMANN (1994, 1996) proposed in collaboration with the authors of the present paper an improvement of the weather generator commonly used until then to drive forest patch models. In the traditional approach, uncorrelated variates for the monthly weather variables (typically monthly mean temperature and monthly precipitation totals) are drawn from a seasonally varying, bivariate normal distribution (see e.g. FISCHLIN et al., 1995). BUGMANN (1994, 1996) introduced seasonally varying cross-correlation between the monthly temperature and precipitation variables and reported a significant effect on the distribution of a drought stress index (defined as one minus the ratio of actual to potential evapotranspiration) used in many forest simulators. However, according to our knowledge, no systematical analysis of the accuracy and suitability of different stochastic weather generators to simulate monthly weather variables has been carried out until now.

In the present work we present such an analysis using data from 89 European sites reflecting a wide range of climatic conditions. The focus is on the effects of the simulated monthly weather variables on the distributions of three derived bioclimatic variables typically used to drive forest succession models.

Our analysis reveals some shortcomings of the monthly weather generators commonly used to study impacts of climatic change on forests and other systems. We propose an improved stochastic weather generator which requires a comparatively small number of climatic parameters, relies upon more robust methods to estimate these parameters, and produces more realistic distributions of bioclimatic variables.
3.2 Material and Methods

3.2.1 Data

We used monthly mean temperatures and monthly precipitation totals from 89 European stations listed in Table 3.1. The data were extracted from the "Global Historical Climatology Network – GHCN" (VOSE et al., 1992; EISCHEID et al., 1995) data set, and the data base of the Swiss Meteorological Institute (BANTLE, 1989). From both data bases we used only stations within the sector 12° W to 40° E and 42° to 75° N for which at least 20 yrs of simultaneous temperature and precipitation measurements were available in the 30-yr interval 1951-1980, and at least 60 yrs in the 100-yr interval 1894-1993.

Data from the period 1951-1980 were used to define the baseline climates, and to estimate the parameters of all stochastic models. The observed long-term mean annual mean temperatures, annual precipitation totals, annual growing degree-days totals (threshold: 5.5 °C), winter minimum mean temperatures, and annual potential and actual evapotranspiration at the 89 stations are shown in Fig. 3.1. (For the procedures used to compute the various variables see section "Bioclimatic Variables" below). It can be seen that the stations cover a large variety of climates, which range from warm-temperate/lower montane to boreal/subalpine conditions.
Table 3.1: Climatological stations used in this study. Data for stations with ID < 9999 were extracted from the data base of the Swiss Meteorological Institute (BANTLE, 1989), all other data from the "Global Historical Climatology Network – GHCN" (VOSE et al., 1992; EISCHIED et al., 1995) data set. Alt. = altitude in m above sea level, Lon. = longitude (°E), Lat. = latitude (°N); NA = not available.
Fig. 3.1: Observed (bio-)climatic parameters at the 89 climatological stations considered in this study. Shown are long-term means derived from monthly mean temperatures and monthly precipitation totals for the years 1951-1980. Annual growing degree-day totals refer to the temperature threshold 5.5 °C and were calculated according to the procedure given in FISCHLIN et al. (1995). Monthly winter minimum temperatures were defined as Min(TDec, TJan, TFeb), where T denotes a month's mean temperature; PET – annual potential evapotranspiration, calculated from monthly mean temperatures according to THORNTHWAITE & MATHER (1957); AET – annual actual evapotranspiration, computed from PET and monthly precipitation totals by means of the soil water balance model by BUGMANN & CRAMER (1997). For details see section "Bioclimatic Variables".
3.2.2 Stochastic Models

All types of stochastic models considered were given by the discrete time system:

\[ X(k) = A(p)X(k-1) + B(p)\xi(k) \]  \hspace{1cm} (3.1)

\[ Y(k) = f(X(k), u(p)) \]  \hspace{1cm} (3.2)

where \( X \) is the state vector of dimension \( N \), \( k \geq 1 \) denotes the current time (time step = 1 month), \( A \) and \( B \) are the \( N \times N \) system and input matrices, respectively, \( \xi \) is an input vector of independent random components from a \( N \)-dimensional normal distribution \( N(0,1) \), \( Y \) is the \( N \)-dimensional output vector, \( f \) is a vector of non-linear output functions, \( u \) denotes the parameters of \( f \), and \( p \) is the phase within the year, i.e., \( p = \{(k-1) \mod 12\} \), where \( p=0 \) corresponds to January and \( p=11 \) to December.

<table>
<thead>
<tr>
<th>Model Type</th>
<th>Description</th>
<th>Characteristics</th>
<th># Parameters needed in Eq. (3.1)</th>
<th># Param. (( N=q=2 ))</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>Uncorrelated variates ( X_i )</td>
<td>( A = 0, B = I )</td>
<td>12( N )</td>
<td>24</td>
</tr>
<tr>
<td>II</td>
<td>Cross-correlated variates ( X_i )</td>
<td>( A = 0, B \neq 0, \beta_{ij} = \beta_{ji} )</td>
<td>12( N(N+1)/2 )</td>
<td>36</td>
</tr>
<tr>
<td>III</td>
<td>AR(1), fixed-phase cyclostationary</td>
<td>( A \neq 0, B \neq 0 )</td>
<td>12( N^2+12N(N+1)/2 )</td>
<td>84</td>
</tr>
<tr>
<td>IV</td>
<td>AR(1), phase-averaged cyclostationary</td>
<td>( A \neq 0, B \neq 0 )</td>
<td>(1+2q)( N^2+12N(N+1)/2 )</td>
<td>56</td>
</tr>
</tbody>
</table>

Table 3.2: Types of stochastic models considered. \( X_i \): element of state vector \( X \); \( 0, I \): zero and unit matrix, respectively; \( \beta_{ij} \): elements of \( B \); AR(1): lag-1 autoregressive model; \( N \): system order; \( q \): number of Fourier-harmonics used to fit parameters of a Type IV model.

In this study were \( N=2 \) and \( X = (X_1, X_2)' = (T, \bar{P})' \), where \( T \) and \( \bar{P} \) denote monthly mean temperatures (T) and monthly precipitation totals (P), transformed according to Eqs. (3.9a) or (3.9b). Four basic types of models which used different matrices \( A \) and \( B \) (Table 3.2), and four kinds of output functions \( f \) (Table 3.3) were investigated. The procedures used to estimate the two matrices and the various parameter vectors \( u \) are presented under section 3.2.3.

The models of Types I and II were included because they are typically used to generate monthly weather data in the context of climate change studies. The models of Type III were considered to investigate inasmuch the inclusion of temporal autocorrelation (\( A \neq 0 \)) allows to improve the statistical accuracy of the simulated weather sequences. This model requires, however, also more parameters (Table 3.2). Therefore, an additional type of models, Type IV, was also considered. The Type IV models are formally identical to the Type III models, but thanks to a more sophisticated parameter estimation procedure (see later) they require a considerably smaller number of parameters (Table 3.2).
The output function $f_1$ corresponded to the standard output function typically used in monthly weather generators. Function $f_{1L}$ implements a skewness-reducing transformation and was included with the aim to improve the simulation of monthly precipitation totals, which often show strongly skewed distributions (e.g., FLIRI, 1974; GARRIDO et al., 1996). Functions $f_2$ and $f_{2L}$ were similar to $f_1$ and $f_{1L}$, respectively, but aimed at reducing the number of needed parameters by adopting a more parsimonious description of the annual cycles of the output variable's long-term means and standard deviations. For all model Types I-IV we investigated three different model variants (A-C) which were given by different combinations of output functions according to Table 3.4.

<table>
<thead>
<tr>
<th>Model Variant</th>
<th>Temperature</th>
<th>Precipitation</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>$f_1$</td>
<td>$f_1$</td>
</tr>
<tr>
<td>B</td>
<td>$f_1$</td>
<td>$f_{1L}$</td>
</tr>
<tr>
<td>C</td>
<td>$f_2$</td>
<td>$f_{2L}$</td>
</tr>
</tbody>
</table>

Table 3.4: Output functions used in different variants of stochastic models (cf. Table 3.3).

All considered output functions were defined by the equation:

$$Y_{i(k)} = Z_{i(k)} \sigma_{i(p)} + \mu_{i(p)} \quad (3.3)$$

where $Y_i$ denotes the i-th element of the output vector $Y$, $Z_i$ the i-th element of an auxiliary vector $Z$, and $\mu_i$ and $\sigma_i$ are the expected value and standard deviation of an $Y_i$.

In the output functions $f_1$ and $f_{1L}$, the $\mu_i$ and $\sigma_i$ were given as
\[ \mu_i(p) = m_i(p), \quad \sigma_i(p) = s_i(p) \]  

(3.4a)

where the \( m_i \) and \( s_i \) were calculated according to Eqs. (3.6) and (3.7). In output functions \( f_2 \) and \( f_{2L} \), the \( \mu_i(p) \) and \( \sigma_i(p) \) were described by the first few harmonics of their annual cycles according to:

\[ \theta_i(p) = a_{\theta_{00}} + \sum_{j=1}^{n_{\theta_{0}}} \left( a_{\theta_{ij}} \cos\left(\frac{2\pi j p}{12}\right) + b_{\theta_{ij}} \sin\left(\frac{2\pi j p}{12}\right) \right) \]  

(3.4b)

Here \( \theta \) stands for \( \mu \) or \( \sigma \), \( a_{\theta_{00}} \) is the annual mean of \( \theta \), \( n_{\theta_{0}} \) is the number of harmonics used to represent its annual cycle, and \( a_{\theta_{ij}} \) and \( b_{\theta_{ij}} \) are parameters estimated according to Eqs. (3.6) to (3.8c). In the present study were used throughout \( n_{\mu_1} = n_{\sigma_1} = 2 \) for \( T \), and \( n_{\mu_2} = n_{\sigma_2} = 3 \) for \( P \).

For the output functions \( f_1 \) and \( f_2 \) we used

\[ Z_i(k) = X_i(k) \]  

(3.5a)

whereas in functions \( f_{1L} \) and \( f_{2L} \), which assume a log-normal distribution for skewed outputs \( Y_i \), we used the back-transformation

\[ Z_{i(k)} = \begin{cases}  
+\exp\left\{ f_{i(p)} X_{i(k)} + g_{i(p)} \right\} + h_{i(p)} & \text{if } \text{SKEW}\left[Y_{i(p)}\right] > 0 \\
X_{i(k)} & \text{if } \text{SKEW}\left[Y_{i(p)}\right] = 0 \\
-\exp\left\{ f_{i(p)} X_{i(k)} + g_{i(p)} \right\} + h_{i(p)} & \text{if } \text{SKEW}\left[Y_{i(p)}\right] < 0 
\end{cases} \]  

(3.5b)

Here \( f_{i(p)} \), \( g_{i(p)} \), and \( h_{i(p)} \) are parameters estimated according to Eqs. (3.11)-(3.14), \( p \) is the phase within the year, and \( \text{SKEW}[V] \) the skewness of the random variable \( V \).

### 3.2.3 Parameter Estimation

All model parameters were determined for the period 1951-1980, and separately for each location.

Estimates \( m_i(p) \) and \( s_i(p) \) for the expected values \( \mu_i(p) \) and standard deviations \( \sigma_i(p) \) of the output variables \( Y_{i(p)} \) (\( i=1..2 \) for \( T \) and \( P \), respectively) were obtained according to:

\[ m_i(p) = \langle y_{i(p,t)} \rangle = E\left[Y_{i(p)}\right] \]  

(3.6)

\[ s_i(p) = \left( \frac{1}{n-1} \sum_{t=1}^{n} \left( y_{i(p,t)} - m_i(p) \right)^2 \right)^{1/2} = \text{STDEV}\left[Y_{i(p)}\right] \]  

(3.7)
where $y_{i(p,t)}$ denotes a measured time series, $\langle y_{i(p,t)} \rangle$ is the arithmetic mean over all timepoints $t$, and $n$ is the sample size. The parameters $a_{0i}$ and $b_{0i}$ of the output functions $f_2$ and $f_2L$ were estimated according to (see e.g. BOX & JENKINS, 1976, p. 36):

$$a_{0i} = \frac{1}{12} \sum_{p=1}^{12} v_i(p)$$

$$a_{0ij} = \frac{1}{12} \sum_{p=1}^{12} v_i(p) \cos(2\pi j p/12)$$

$$b_{0ij} = \frac{1}{12} \sum_{p=1}^{12} v_i(p) \sin(2\pi j p/12)$$

for $j \leq 5$, where $\theta$ and $v_i(p)$ stand for $\mu$ and $m_i(p)$, or $\sigma$ and $s_i(p)$, respectively.

The matrices $A$ and $B$ were estimated using transformed monthly time series $\bar{y}_{i(p,t)}$ or $\bar{y}_{i(p,t)}$. The transformations applied were as follows. For the output functions $f_1$ or $f_2$ used was

$$\bar{y}_{i(p,t)} = \frac{y_{i(p,t)} - \mu_i(p)}{\sigma_i(p)}$$

where the $\mu_i(p)$ and $\sigma_i(p)$ were obtained according to Eqs. (3.4a) for $f_1$ and (3.4b) for $f_2$. Note that a $\bar{y}_{i(p,t)}$ had exactly zero mean and unit variance only when output function $f_1$ was used. For the output functions $f_{1L}$ and $f_{2L}$ used was:

$$\bar{y}_{i(p,t)} = \left\{ \begin{array}{ll}
\frac{\ln \{+y_{i(p,t)} - h_{i(p)}\}}{f_{i(p)}} - g_{i(p)} & \text{if skew}_{i(p)} \gg 0 \\
\bar{y}_{i(p,t)} & \text{if skew}_{i(p)} \text{small} \\
\frac{\ln \{-y_{i(p,t)} - h_{i(p)}\}}{f_{i(p)}} - g_{i(p)} & \text{if skew}_{i(p)} \ll 0
\end{array} \right.$$  (3.9b)

where

$$\text{skew}_{i(p)} = \frac{5}{3} \langle y_{i(p,t)} - \bar{y}_{i(p,t)} \rangle^3 = \text{SKEW} [\bar{Y}_{i(p)}]$$

Here $\bar{m}_{i(p)}$ and $\bar{s}_{i(p)}$ are the estimated (Eqs. 3.6 and 3.7) mean and standard deviation of $\bar{y}_{i(p,t)}$ respectively. The condition "skew$_{i(p)}$ small" was defined to be true if a $\chi^2$-test (e.g., KREYSZIG 1977, p. 229) yielded at least a 10% probability ($p$-value $\geq 0.1$) that the measurements $\bar{y}_{i(p,t)}$ stemmed from a normal distribution. Otherwise (first or third case in Eq. 3.9b) a log-normal distribution for the random variable $\bar{Y}_{i(p)}$ was assumed.
We discuss the parameter estimation only for the case skew, \( \alpha \ll 0 \), since a formally identical procedure was also applied in the case of a negative skewness. The only difference was that, in order to obtain a positively skewed variable with the same mean as the original variable, all negatively skewed \( \tilde{y}_{i(p,t)} \) were replaced by \( 2 \cdot (\tilde{m}_{i(p)} - \tilde{y}_{i(p,t)}) \).

If \( h_{i(p)} \) is known, the maximum likelihood estimators for \( g_{i(p)} \) and \( f_{i(p)} \) are (JOHNSON & KOTZ, 1970, p. 120):

\[
g_{i(p)} = \frac{1}{n} \sum_{t} \tilde{y}_{i(p,t)}
\]

\[
f_{i(p)} = \left( \frac{1}{n} \sum_{t} \left( \tilde{y}_{i(p,t)} - g_{i(p)} \right)^{2} \right)^{1/2}
\]

For \( h_{i(p)} \), we considered the range of values given by

\[
h_{i(p)} = \text{MIN}(\tilde{y}_{i(p,t)}) - \kappa \cdot \tilde{y}_{i(p)}
\]

when \( \kappa \) was varied within \([0.05 \ldots 5.0]\). Here \( \text{MIN}(\tilde{y}_{i(p,t)}) \) denotes the minimum value in the time series \( \tilde{y}_{i(p,t)} \). For each \( h_{i(p)} \) we estimated the associated \( g_{i(p)} \) and \( f_{i(p)} \) according to Eqs. (3.11) and (3.12), and then selected the combination of parameters \( f_{i(p)}, g_{i(p)}, h_{i(p)} \) which maximized the likelihood function

\[
\lambda_{i(p)} = \langle \ln \{ p_{\kappa}(\tilde{y}_{i(p,t)}) \} \rangle
\]

where \( \langle \cdot \rangle \) is again the averaging operator, and \( p_{\kappa(x)} \) is the log-normal probability density function \( p \) obtained for a given \( \kappa \), evaluated at point \( x \).

The system matrices were estimated as follows. For models of Type II was

\[
B_{i(p)} = \text{EIGVEC}[\Gamma_{0(p)}] \text{Sqrt}(\text{EIGVAL}[\Gamma_{0(p)}])
\]

where \( \text{EIGVEC}[M] = [E_{1}, E_{2}, \ldots, E_{N}] \) denotes the \( N \times N \) matrix of the eigenvectors of \( M \), \( \text{EIGVAL}[M] \) is a \( N \times N \) diagonal matrix containing the eigenvalues of \( M \), and \( \Gamma_{0(p)} \) is the lag-zero covariance matrix of the \( \tilde{y}_{i} \) (respectively \( \tilde{y}_{i} \)) at phase \( p \). The elements \( \gamma_{i,j(p)} \) of the lag-\( V \) covariance matrix were estimated as

\[
\gamma_{i,j(p)}^{V} = \frac{1}{n-V} \left( v_{i(p,t)} - m_{i(p)} \right) \cdot \left( v_{j(p-V,t)} - m_{j(p-V)} \right) = \text{COV}[V_{i(p)}, V_{j(p-V)}]
\]

where \( v_{i(p,t)} \) stands for \( \tilde{y}_{i(p,t)} \) or \( \tilde{y}_{i(p,t)} \), \( \cdot \) is the vector product, and \( m_{i(p)} \) is the mean of \( v_{i(p,t)} \). When output function \( f_{1} \) was used for all output variables, \( \Gamma_{v(p)} \) corresponded to the lag-\( V \) correlation matrix of the observed time series \( y_{i(p,t)} \).
For the models of Type III the matrices $A(p)$ and $B(p)$ were given according to the generalized Yule-Walker equations (e.g., BOX & JENKINS, 1976, p. 55) as:

$$A(p) = \Gamma_{1(p)} \Gamma_{0(p)}^{-1}$$

(3.17)

$$B(p)B_p^T = \Gamma_{0(p)} - \Gamma_{1(p)} \Gamma_{0(p)}^{-1} \Gamma_{1(p)}^T = \Gamma_{0(p)} - A(p)A(p)^T$$

(3.18)

Similarly to the case of $\Gamma_{0(p)}$ in Eq. (3.15), since $Q = B(p)B(p)^T$ is real and symmetric there exists a decomposition $E \text{Sqrt}(L) \text{Sqrt}(L) E^T$ with $E = \text{EIGVEC}[Q]$ and $L = \text{EIGVAL}[Q]$, such that $B(p) = E \text{Sqrt}(L)$.

The matrices $A(p)$ of the of Type IV models were determined according to the procedure proposed by HASSELMANN & BARNETT (1981; see also GARDNER, 1994). Following this procedure, the original variables – which define a $N \times 12$-dimensional ($i=1..N$, $p=0..11$) state space – are first projected onto a $M=N \times (1+2q)$-dimensional sub-space spanned by the first $q$ Fourier harmonics of the fundamental frequency $1/12$:

$$J_{i,1(k)} = V_{i(k)}$$

(3.19a)

$$J_{i,2\xi(k)} = V_{i(k)} \cos(2\pi \xi k/12)$$

(3.19b)

$$J_{i,2\xi+1(k)} = V_{i(k)} \sin(2\pi \xi k/12)$$

(3.19c)

Here the $J_{i,\xi}$, with $\xi$ running from 1 to $q$, denote the new variables, $k$ is the current time step, and $V_i$ stands for an $\hat{X}_i$ or $\tilde{X}_i$. In the present study we used throughout $q = 2$, i.e. $M$ equaled 10.

The variables $J_{i,j}$ define a new, phase-independent, $M$-dimensional state vector $\mathbf{J} = [J_{1,1(k)}, J_{1,2(k)}, J_{1,3(k)}, \ldots, J_{N,1+2q-1(k)}, J_{N,1+2q(k)'}]$. The $M \times M$ system matrix $\mathbf{A}$ of the corresponding AR(1) process [cf. Eq. (3.1)] was determined according to Eq. (3.17). The matrices $A(p)$ were then obtained by projecting $\mathbf{A}$ back to the original state space according to

$$\alpha_{ij(p)} = \hat{\alpha}_{kl} + \sum_{\xi=1}^q \hat{\alpha}_{kl} [\cos(2\pi \xi p/12) + \sin(2\pi \xi p/12)]$$

(3.20)

where $k = q(i-1)+1$, $l = q(j-1)$, and $q > 0$. The $B(p)$ were finally determined by solving Eq. (3.18) using the $A(p)$ obtained from Eq. (3.20).
3.2.4 Bioclimatic Variables

The performance of the stochastic models was assessed by considering three bio-climatic variables derived from monthly weather data: monthly winter minimum temperature (T\text{WinMin}), annual growing degree-day totals over the temperature threshold of 5.5 °C (GDD) and an index for the annual drought stress (DSI) applicable to forest vegetation (cf. Fig. 3.1). These variables were chosen because each one of them covers a distinct aspect of the annual weather, and because they are of interest to many ecosystem and biogeographical studies.

Monthly winter minimum temperature for year $y$ was computed as

$$T_{\text{WinMin}} = \min(T_{\text{Dec}}^{(y)}, T_{\text{Jan}}^{(y)}, T_{\text{Feb}}^{(y)})$$

(3.21)

Due to the non-linearity introduced by the minimum function, T\text{WinMin} is particularly sensitive to the accurate simulation of $T$ in the winter months.

Annual growing degree-day totals were computed according to the procedure given by FISCHLIN et al. (1995) as:

$$GDD^{(y)} = \sum_{m=\text{Jan}}^{\text{Dec}} GDD^{(m)(y)}$$

(3.22a)

$$GDD^{(m)(y)} = 30.5 \cdot \max(T^{(m)}^{(y)} - T_{\text{thresh}}, 0) + \delta(T^{(m)}^{(y)})$$

(3.22b)

where $T_{\text{thresh}} = 5.5^\circ$. $\delta(T)$ is an empirically derived function which corrects for the bias introduced by the monthly resolution; the largest values (~60 °Cd) are returned for $T$ close to $T_{\text{thresh}}$ (for details see BUGMANN, 1994). GDD\textit{y} is sensitive to the simulation of $T$ in summertime, where the largest contributions to the annual GDD sum occur, and in the transition seasons, where at mid-latitude locations $T$ is typically close to $T_{\text{thresh}}$.

The drought stress index used was defined following BUGMANN & CRAMER (1997) as:

$$DSI^{(y)} = 1 - \frac{\sum_{m=\text{Jan}}^{\text{Dec}} E_{\text{offSoil}}^{(m)(y)}}{\sum_{m=\text{Jan}}^{\text{Dec}} M_{\text{Demand}}^{(m)(y)}}$$

(3.23)

where $E_{\text{offSoil}}^{(m)(y)}$ is an estimate of the water transpired by the vegetation, and $M_{\text{Demand}}^{(m)(y)}$ is an estimate of the demand for moisture from the soil.
The Temporal Aspect: Stochastic Simulation

The DSI was used to assess the stochastic model's ability to simulate precipitation and its interaction with temperature. It was calculated according to the simple "bucket"-type model for the soil water balance proposed by BUGMANN & CRAMER (1997), as follows. The available soil moisture at time step $k$ was determined as (indices $m$ and $y$ are omitted for clarity):

$$SM(k) = \text{Max}( 0, \text{Min}( SM(k-1) + P_{\text{toSoil}} - E_{\text{offSoil}}, b ))$$  \hspace{1cm} (3.24a)

where $k$ denotes the current time (time step 1 month), $b$ is the "bucket" size, and

$$P_{\text{toSoil}} = P - E_{\text{offVeg}}$$  \hspace{1cm} (3.24b)

$$E_{\text{offVeg}} = \text{Min}( k_{\text{icpt}} \cdot P, \text{PET} )$$  \hspace{1cm} (3.24c)

$$M_{\text{Demand}} = \text{PET} - E_{\text{offVeg}}$$  \hspace{1cm} (3.24d)

$$M_{\text{Supply}} = \frac{k_{\text{cw}} \cdot SM(k-1)}{b}$$  \hspace{1cm} (3.24e)

$$E_{\text{offSoil}} = \text{Min}( M_{\text{Supply}}, M_{\text{Demand}} )$$  \hspace{1cm} (3.24f)

$$\text{AET} = E_{\text{offVeg}} + E_{\text{offSoil}}$$  \hspace{1cm} (3.24g)

Here $P_{\text{toSoil}}$ is the proportion of monthly precipitation $P$ which reaches the soil, $E_{\text{offVeg}}$ is the evaporative loss due to interception, as controlled by the parameter $k_{\text{icpt}}$, PET is the monthly potential evapotranspiration (see below), $M_{\text{Supply}}$ is the monthly supply of water from the soil, which is controlled by the maximum evapotranspiration rate $k_{\text{cw}}$, and AET is the monthly actual evapotranspiration in mm/month. PET was computed according to THORNTHWAITE & MATHER (1957) as:

$$\text{PET} = \{ \alpha_{(m)} + \beta_{(m)} \cdot \text{MIN}(\lambda, 50) \} \cdot \left( \frac{10}{h} \cdot \text{MAX}(0, T)^{a} \right)$$  \hspace{1cm} (3.25a)

$$h = \sum_{m=\text{Jan}}^{\text{Dec}} \text{MAX}(0, 0.2 \cdot T_{(m)})^{1.514}$$  \hspace{1cm} (3.25b)

$$a = 6.75 \cdot 10^{-7} \cdot h^{3} - 7.71 \cdot 10^{-5} \cdot h^{2} + 1.792 \cdot 10^{-2} \cdot h + 49.239 \cdot 10^{-3}$$  \hspace{1cm} (3.25c)

where $\alpha = 1$ and $\beta = O(10^{-2})$ are parameters used to correct for sun angle and day length depending on latitude $\lambda$, and $h$ is a "heat index" calculated from long-term monthly mean temperatures $T$.

The following parameter values were used for all simulations: $b = 150$ mm, $k_{\text{cw}} = 120$ mm/month, and $k_{\text{icpt}} = 0.3$. The parameter $h$ was calculated at each location for its 1951-1980 baseline climate. The initial condition for the soil water model was $SM(0) = b$. 
3.2.5 Statistical Tests

The data base used to assess the performance of the stochastic models was generated as follows. Firstly, all available measured monthly weather data were used to derive time series of bioclimatic variables at the 89 locations considered. Secondly, for each location, type of stochastic model (I-IV), and variant of output functions (A-C) 100 years of weather data were generated by means of stochastic simulation. All simulations started in January, and the initial conditions $X(0)$ for the models of Types III and IV were given by the long-term mean climate of December. Finally, the simulated weather data were used to compute corresponding time series of bioclimatic variables.

<table>
<thead>
<tr>
<th>Data Period</th>
<th>Definition</th>
<th># Years</th>
<th>MinYrs</th>
<th># Stations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>1951 - 1980</td>
<td>30</td>
<td>20</td>
<td>89</td>
</tr>
<tr>
<td>Test Period 1</td>
<td>1921 - 1950</td>
<td>30</td>
<td>20</td>
<td>87</td>
</tr>
<tr>
<td>Test Period 2</td>
<td>1884 - 1950 ∪ 1981 - 1993</td>
<td>70</td>
<td>50</td>
<td>59</td>
</tr>
</tbody>
</table>

Table 3.5: Overview of the data used to compare distributions of bioclimatic variables as derived from measured and stochastically simulated weather inputs. # Years: number of years within period; MinYrs: minimum years of data required to use a station for the comparison of distributions; # Stations: number of stations with at least MinYrs of data.

Model performance was measured by comparing the distributions of stochastically simulated bioclimatic variables with distributions derived from measured weather data in the two test periods defined in Table 3.5. Note that none of the test periods overlapped with the baseline period (1951-1980, see also Fig. 3.1), which had originally been used to fit the stochastic models. The simulated distributions used for comparison with Test Periods 1 and 2 were defined by the first 30, respectively last 70 years of simulated data.

To measure the similarity of any two distributions of bioclimatic variables we considered the p-values obtained from two non-parametric tests, the Mann-Whitney U-Test (U) and the Kolmogorov-Smirnov test (KS). For either test the p-value gives the probability that the two compared data sets stem from the same parent distribution. The U-Test is sensitive to differences of the medians, less sensitive to differences in skewness, and insensitive to differences in variance (e.g., SACHS, 1984, p. 293). The KS-test is the sharpest homogeneity test and covers differences in the mean, the median, the dispersion, the skewness, and the excess of two distributions (SACHS, 1984, p. 291).

The following summary results over all locations were computed: Firstly, average model performance was assessed by computing separately for each combination of bioclimatic variables, types of stochastic models (I-IV), variants of output functions (A-C), test periods (1 or 2), and statistical tests (U or KS) the median p-value ($p_{\text{med}}$) from all
locations. In order to assess the representativity of the baseline climate, the pv$_{\text{med}}$ were also computed for the distributions of bioclimatic variables which were derived from measured weather data in the baseline period 1951-1980.

Secondly, in order to assess the performance of the different types (I-IV) of models relative to each other we determined the numbers N of cases in which a model of a given type yielded a larger p-value than each other type of model. The N were determined using the p-values from both test periods. The significance of a given N was assessed based on the following reasoning: if the two types of models were equally good (null hypothesis), N would be binomially distributed with p = q = 0.5 and n = 87+59 = 146 (cf. Table 3.5), and, since npq = 36.5 ≥ 9, approximately normally distributed with μ = np = 73 and σ = $\sqrt{npq} = 6$. Evaluation of the normal probability density function then yields that if the value 100·N/n deviates by more than 5.3% (8.2%) from 50%, the two types of models perform significantly different at the 90% (95%) confidence level (one-sided test).

3.2.6 Modeling and Simulation Tools

Two main computer programs were used, which were both written by the authors. For the management and analysis of monthly weather data, the calculation of bioclimatic variables, and the estimation of the parameters of the stochastic models we used the program CLIMSHELL V1.4d. The stochastic simulation of bioclimatic variables was carried out with the program BCSIM V1.0. Both programs were developed based on the modular software development and modeling environments "Dialog Machine" (FISCHLIN, 1986; FISCHLIN & SCHAUFELBERGER, 1987), "RAMSES" (Research Aids for the Modeling and Simulation of Environmental Systems; FISCHLIN, 1991; FISCHLIN et al. 1994) and "RASS" (RAMSES Simulation Server; THOENY et al., 1994; 1995). The Mann-Whitney and Kolmogorov-Smirnov tests were computed with the software package Splus V3.3.

3.3 Results

The median p-values (pv$_{\text{med}}$) obtained from all tests are shown in Table 3.6. It can be seen that model performance generally increased with increasing sophistication of the models, and that the models of Type IV and III yielded generally the best results.

The model's capability to reproduce the test distributions depended on the variable considered: The mean pv$_{\text{med}}$ values (averaged over all model types and output function variants) were 0.31 for TWinMin, 0.12 for GDD, and 0.17 for DSI. The pv$_{\text{med}}$ values for the distributions of bioclimatic variables that were derived from stochastically simulated weather inputs were mostly below the ones that were computed from measured weather
### Table 3.6: Medians of the p-values (pv<sub>med</sub>) obtained from the comparison of the distributions of bioclimatic variables as derived from measured and stochastically simulated monthly weather data at 89 European climatological stations (cf. Table 3.1). TWinMin – monthly winter minimum temperature; GDD – annual growing degree-day totals; DSI – annual drought stress index. Test Period 1/2: periods of measured weather data used to derive test distributions of bioclimatic variables (cf. Table 3.5). U: pv<sub>med</sub> refers to p-values obtained from the Mann-Whitney U-Test; KS: pv<sub>med</sub> refers to p-values obtained from the Kolmogorov-Smirnov test; I-IV: types of stochastic models considered (cf. Table 3.2); A-C: variants of functions used to calculate outputs of stochastic models (cf. Table 3.4); Baseline: distributions from test periods 1/2 were compared with distributions for the baseline period 1951-1980. The highest value(s) obtained within a column for each model variant A-C is printed in bold.

<table>
<thead>
<tr>
<th></th>
<th>Test Period 1</th>
<th>Test Period 2</th>
<th>Test Period 1</th>
<th>Test Period 2</th>
<th>Test Period 1</th>
<th>Test Period 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>A I</td>
<td>.40 .39</td>
<td>.17 .14</td>
<td>.11 .19</td>
<td>.10 .04</td>
<td>.33 .03</td>
<td>.16 .00</td>
</tr>
<tr>
<td>II</td>
<td>.31 .39</td>
<td>.37 .26</td>
<td>.09 .09</td>
<td>.06 .06</td>
<td>.30 .02</td>
<td>.19 .01</td>
</tr>
<tr>
<td>III</td>
<td>.44 .44</td>
<td>.29 .24</td>
<td>.17 .16</td>
<td>.13 .12</td>
<td>.36 .03</td>
<td>.28 .00</td>
</tr>
<tr>
<td>IV</td>
<td>.44 .50</td>
<td>.34 .31</td>
<td>.17 .24</td>
<td>.14 .16</td>
<td>.37 .03</td>
<td>.23 .01</td>
</tr>
<tr>
<td>B I</td>
<td>.29 .24</td>
<td>.30 .16</td>
<td>.16 .20</td>
<td>.08 .05</td>
<td>.24 .06</td>
<td>.27 .05</td>
</tr>
<tr>
<td>II</td>
<td>.36 .39</td>
<td>.31 .21</td>
<td>.13 .07</td>
<td>.06 .03</td>
<td>.37 .04</td>
<td>.33 .07</td>
</tr>
<tr>
<td>III</td>
<td>.36 .39</td>
<td>.31 .25</td>
<td>.12 .16</td>
<td>.09 .10</td>
<td>.32 .03</td>
<td>.23 .09</td>
</tr>
<tr>
<td>IV</td>
<td>.41 .39</td>
<td>.33 .40</td>
<td>.18 .24</td>
<td>.07 .10</td>
<td>.33 .03</td>
<td>.26 .05</td>
</tr>
<tr>
<td>C I</td>
<td>.23 .24</td>
<td>.21 .09</td>
<td>.17 .20</td>
<td>.05 .03</td>
<td>.25 .06</td>
<td>.22 .08</td>
</tr>
<tr>
<td>II</td>
<td>.28 .33</td>
<td>.24 .15</td>
<td>.13 .11</td>
<td>.06 .02</td>
<td>.35 .03</td>
<td>.34 .06</td>
</tr>
<tr>
<td>III</td>
<td>.31 .39</td>
<td>.36 .24</td>
<td>.16 .20</td>
<td>.09 .08</td>
<td>.41 .07</td>
<td>.35 .08</td>
</tr>
<tr>
<td>IV</td>
<td>.34 .39</td>
<td>.42 .30</td>
<td>.14 .17</td>
<td>.09 .08</td>
<td>.34 .05</td>
<td>.31 .05</td>
</tr>
<tr>
<td>Baseline</td>
<td>.40 .46</td>
<td>.50 .44</td>
<td>.23 .39</td>
<td>.21 .21</td>
<td>.43 .09</td>
<td>.48 .14</td>
</tr>
</tbody>
</table>

Data: the mean pv<sub>med</sub>-values in the "Baseline" case were 0.45 for TWinMin, 0.26 for GDD, and 0.29 for DSI.

From Table 3.6 can be seen that for TWinMin the Type IV models yielded for all except one case (Period 2/U-test) the best result. The variants A and B gave generally higher pv<sub>med</sub>-values than variant C: compared to variant A, performance in variant C was better only for the Test Period 2 (U-test) for model Types I, III and IV, but was otherwise less good in 12 out of 16 (= 2 test periods × 2 statistical tests × 4 model types) cases. Compared to variant B, variant C was worse in 11, and better only in two cases.

For GDD, the test distributions were under variant A in all cases most successfully reproduced by the Type IV models (Table 3.6). Under variant B, for two cases the best results were obtained with the Type III models. Variant C appeared again to perform less well than variants A and B. Compared to these variants it gave lower pv<sub>med</sub> values in 10 respectively 7 out of 16 cases, whereas better results were obtained only in 5 cases each.

For DSI, under variant A for three out of four cases the best result was obtained with the Type IV models. However, for variants B and C the highest pv<sub>med</sub> values were obtained
Fig 3.2: Comparison of the performance of the Type IV models relative to the Type I-III models (cf. Table 3.2). Each panel shows the percentage of cases (relative to the 50% line) in which a Type IV model reproduced for a given output function variant (A-C, cf. Table 3.4) a test distribution of a bioclimatic variable better than the respective other type of model. For each comparison were used a total of 146 test distributions, as derived from independently measured weather data at 89 European climatological stations (cf. Table 3.1), and for two different test periods (cf. Table 3.5). Bars above the dashed lines indicate significantly better performance of the Type IV models at the 95% confidence level (one sided test). Black bars: comparisons with the test distributions were based upon the Mann-Whitney U test. Grey bars: Kolmogorov-Smirnov test. TWinMin = monthly winter minimum temperature; GDD = annual growing degree-day totals; DSI = annual drought stress index.

with model Types I-III. Under the variant B performance increased in 10 out of 16 cases as compared to variant A. Improvement was even more pronounced under variant C, where in all except two (Test Period 2/U-test) cases higher $p_{\text{med}}$ values were obtained than for variant A.

The $p_{\text{med}}$-values presented random variables, such that some of the found differences between variants or model types may not be significant. The overall picture obtained from Table 3.6 is however confirmed in Fig. 3.2, which compares the performance of the Type IV models relative to the three other types of models.

It can be seen that for TWinMin the Type IV models performed according to both, the U- and the KS-tests, significantly better than the Type I models. The Type IV models appeared to perform also systematically better than the Type II models, but this result was
Fig 3.3: Comparison of the annual cycles of the diagonal elements $\alpha_{11}$ and $\alpha_{22}$ of the system matrices $A$ (cf. Eq. 3.1) of cyclostationary, first-order autoregressive stochastic models of monthly weather variables at selected European locations. The $\alpha_{ij}$ refer to the state vector $X = (X_1, X_2)' = (T, P)'$, where $T$ and $P$ denote standardized monthly mean temperatures (T) and monthly precipitation totals (P). Thin lines: matrix elements were estimated by considering each month separately ("Type III" models); thick lines: matrix elements were estimated in a subspace spanned by the first two Fourier harmonics of the annual cycle according to the approach proposed by HASSELMANN & BARNETT (1981) ("Type IV" models). All values are given in standard deviations of the respective variable. Analysis interval was 1951-1980.

generally not significant at the 95% level (cf. dashed lines in Fig. 3.6). With regard to GDD, the Type IV models performed significantly better than the Type I models only according to the sharper KS-test. However, according to both tests, they clearly performed better than the Type II models. For DSI no clear improvement was obtained due to the use of Type IV models. Note, however, that the general improvement obtained under variants B and C as compared to variant A can not be discerned from Fig. 3.2, since in this figure the different types of models are compared only relative to each other. Except for two cases (U-tests for TWinMin, model III/A, and DSI, model III/B), no significant differences in the performance of the Type III and Type IV models were found.
Fig. 3.3 compares for selected locations the annual cycles of the diagonal elements $\alpha_{11}$ and $\alpha_{22}$ of the system matrices $A$ (see Eqs. 3.1, 3.17, 3.20) used in the Type III and Type IV models. It can be seen that the $\alpha_{ii}$ of the Type IV models followed smoothly the annual cycles that were obtained for the Type III models. The memory terms were generally larger for temperature ($i=1$) than for precipitation ($i=2$). Further it can be seen that the amplitude and form of the annual cycles of the $\alpha_{ii}$ varied across locations. However, for temperature in all cases distinct minima were obtained in the transition seasons. Not shown in Fig. 3.3 are the elements $\alpha_{12}$ and $\alpha_{21}$, which were generally of same magnitude as the $\alpha_{22}$. The $\alpha_{ii}$ of the Type III models were very close to the respective lag-1 autocorrelation coefficients (not shown; cf. Eqs. 3.9a, 3.16) of the two variables.

### 3.4 Discussion

Temporal autocorrelation on the monthly time scale appears to be a non-neglectable feature of mid-latitude weather. The autocorrelation found in local weather variables on the one hand relates to persistent anomalies in the large-scale circulation, such as blocking events or long-lasting periods of zonal flow (e.g., JACOBEIT, 1988; KLAUS, 1993). The larger autocorrelation coefficients obtained for temperature as compared to precipitation (Fig. 3.3) probably reflected the generally stronger dependence of local temperatures on the large-scale circulation. On the other hand, autocorrelation depends also on smaller-scale processes, which may enhance (e.g., long-lasting inversions in valley locations) as well as reduce (e.g., convective precipitation, or unsteady flow in the lee of a mountain range) the temporal stability of the local weather. Such processes may also have contributed to the found differences between variables, seasons and locations (Fig. 3.3).

The generally better performance of the Type III and IV models as compared to the simpler Type I and II models (Table 3.6, Fig. 3.2) demonstrated that inclusion of a memory term in stochastic models of monthly weather allows to enhance the statistical accuracy of simulated weather sequences and bioclimatic variables. The proposed autoregressive models thus presented an improvement compared to existing solutions, which discard autocorrelations (e.g., FISCHLIN et al., 1995), or generally any correlations (e.g., SOLOMON & WEST, 1987; KRÄUCHI, 1994) between monthly weather variables. Some authors (e.g., KRÄUCHI, 1994) have argued that these correlations can be neglected because they are generally too small to be statistically significant. Though this may be true for individual months, our analysis revealed distinct annual cycles for the auto- (Fig. 3.3), or cross-correlation (not shown) coefficients, and these would not occur if the correlations were purely random. Furthermore, our tests with independent data (Table 3.5) clearly showed that in the majority of the cases the correlations carry valid
information (see e.g. comparison with the Type I models in Fig. 3.2), and hence significantly help to improve stochastic weather generation.

The improvements obtained due to the use of Type III or IV models were largest for TWinMin and GDD. This was because these variables depended strongly on the joint probability distributions of monthly mean temperatures (see Eqs. 3.21, 3.22), and these joint distributions were much better represented when correlations between successive months (Fig. 3.3) were included in the stochastic models. In contrast, for DSI the inclusion of monthly autocorrelations yielded a clear improvement only under the output function variant A. However, this improvement was small when compared to the improvement achieved due to the use of a log-normal transformation for precipitation in variants B and C (Table 3.6). This was because DSI depended mainly on precipitation (Eqs. 3.24), and this variable showed generally only small autocorrelation (Fig 3.3), but was otherwise found to be strongly skewed (see also discussion below).

The use of different variants of output functions (Table 3.4) showed contrasting effects for the different bioclimatic variables. The use of variant B did not appear to have any systematic effect on the simulation of TWinMin and GDD. This appears plausible since this variant mainly affected the simulation of precipitation (Table 3.4). The found differences between variants A and B therefore probably reflected but sampling variability of the $p_{\text{med}}$. Under variant C, however, the $p_{\text{med}}$ for TWinMin and GDD quite clearly deteriorated. This result reflected the threshold-effects that entered the calculation of TWinMin and GDD (Eqs. 3.21, 3.22), and suggests that stochastic simulation of these two variables strongly depends on an accurate representation of the annual cycles of the expected values and variances of monthly mean temperature.

A different result was obtained with regard to precipitation, where variants B and C yielded a strong improvement as compared to variant A (Table 3.6). The main reason was that the monthly precipitation data used for the calculation of this variable were strongly skewed: from the 1089 (= 89 stations x 12 months) 30-yr distributions investigated, 85% (4%) were positively (negatively) skewed and differed significantly from a normal distribution ($\alpha = 90\%$). This result conforms with the findings by other authors (e.g., FLIRI, 1974) and suggests that a skewness-reducing transformation should be generally used in stochastic models of monthly precipitation. The equally good (or even slightly better) results obtained for variant C as compared to variant B (Table 3.6) further indicated that the annual cycle of precipitation is generally better represented by means of its first few Fourier harmonics rather than twelve monthly values.

Which types/variants of stochastic models should be used best to simulate the three bioclimatic variables considered in this study? The results obtained for TWinMin and GDD (Table 3.6, Fig. 3.2) clearly ruled out the Type I and II models. For DSI the best re-
results were obtained under variant C, and this would favour the Type III models (Fig. 3.2). However, these models required much more parameters than the Type IV models (cf. Table 3.1). Furthermore, variant C appeared suboptimal with regard to TWinMin and GDD (Table 3.6). This lead to the definition of a new variant, variant D, in which for precipitation we still used the output function \( f_{2L} \) (see Table 3.2), but for temperature only output function \( f_1 \) (as in variants A and B). Indeed, simulations under variant D yielded for the Type IV models and the four statistical tests \( p_{\text{med}} \)-values (cf. Table 3.6) of 0.37, 0.39, 0.30, and 0.25 for TWinMin, 0.15, 0.24, 0.07, and 0.08 for GDD, and 0.36, 0.03, 0.39, and 0.11 for DSI. Hence, compared to variant C, variant D yielded for TWinMin a slightly reduced, but otherwise for GDD and DSI a generally improved performance. Moreover, under this new variant the Type IV models performed again equally good as the Type III models, and in several cases significantly better than the Type I and II models (results not shown, cf. Fig. 3.2).

Hence, use of the Type IV models in combination with the output function variant D appears to be a good compromise if all three bioclimatic variables are needed simultaneously. On the other hand, if only TWinMin and/or GDD are needed, we recommend the use of the Type IV models in combination with the output function variant A (cf. Table 3.6).

However, it should be noted that even the best stochastic models did not yield as good results as the direct use of the "Baseline" weather record (Table 3.6). A closer analysis showed that the "Baseline" distributions yielded for TWinMin in 55%, for GDD in 65%, and for DSI in 60% of all cases better results than the the Type IV models. This was mainly because the simulated bioclimatic variables showed a too small variability. The stochastic models per definition (Eq. 3.3) reproduced the variance of the monthly weather variables. Hence, additional improvements would probably require a more accurate simulation of further higher-order moments (such as the skewness and curtosis) of the weather variables' distributions. This could possibly be accomplished by using a second-order autoregressive process for temperature and/or a more sophisticated skewness-reducing procedure for precipitation. Even better results might also be obtained by optimizing for each location the numbers of harmonics used to fit the system matrices of the Type IV models and to represent the weather variables' annual cycles.

Our results demonstrated that the choice of weather generation scheme involves a trade-off between the statistical accuracy that can be attained, and the parsimony of the simulation approach. The optimal choice further depends on data availability: if only a relatively short record (say, 20 years or less) is available, use of a stochastic simulation approach may be superior to the direct use of the weather record. This is because the stochastic models require much less parameters, and thus can be expected to be more robust (cf. Fig. 3.3). For example, note that if 20 years of measurements are used to describe a
location's temperature and precipitation climate this corresponds to \(2 \times 12 \times 20 = 480\) parameters. In contrast, the Type IV models (variant D) required a maximum of only 99 parameters (the exact number depended on the number of fitted log-normal distributions).

Simulation experiments with impact models can be used to determine the optimal weather generation approach with regard to a particular application. For instance, preliminary simulations with the forest succession model FORCLIM (BUGMANN, 1994; FISCHLIN et al., 1995) at four Alpine locations (Basel, Bern, Bever and Sion; cf. Table 3.1) revealed sensitivity to an improved simulation of the driving weather inputs: simulated forest compositions at Bever and Sion differed significantly when the Type III and IV instead of the Type I and II models were used. The sensitivities appeared realistic since in at least one case (Bever) the more accurate weather generators also yielded more realistic forest compositions. Additional experiments where the forest model is driven with measured weather data could be conducted to determine in as far the Type IV models are actually sufficient. One possibility to construct realistically auto- and cross-correlated input time series for such experiments would be to sample at random annual cycles of monthly temperature/precipitation pairs from the weather record.

3.5 Conclusions

From our stochastic simulations and analyses at 89 European long-term climatological stations we concluded:

1. The inclusion of a memory term in stochastic models of monthly weather generally improves the statistical accuracy of simulated monthly mean temperatures, whereas use of a log-normal transformation strongly improves the simulation of monthly precipitation totals.

2. By estimating the monthly system matrices in a sub-space spanned by the first two Fourier harmonics of the annual cycle, according to the approach proposed by HASSEL-MANN & BARNETT (1981), cyclostationary autoregressive models of monthly weather can be further improved, and the number of needed parameters substantially reduced.

3. To accurately simulate monthly winter minimum temperatures, annual growing degree-day totals, and the studied annual index of drought stress, the input data should be generated with a stochastic model, which, in addition to the above properties (1) and (2), uses a smoothed representation of the annual cycle of precipitation by means of its first three Fourier harmonics.

Published as:

4.1 Introduction

In a world subject to global change, mountain forests may play an increasingly important role: They moderate the water cycle, stabilise soils, protect human settlements, shape the landscape, provide wood and other products, and begin playing a key role in preserving biodiversity while current trends of low-elevation deforestation continue. Assessing possible impacts of climatic change on these important ecosystems poses a particular scientific challenge, owing to the complex effects of mountainous topography both on local climates and on their forests.

Neither ecological theory (e.g., SOLOMON, 1988) nor experimental approaches (e.g., KÖRNER, 1993) enable us to predict precisely the consequences of particular climatic changes on ecosystems. On the other hand carefully designed simulation models (e.g., FISCHLIN, 1991), which embrace what is known from theory and experiments, not only make it possible to trace the consequences of a given set of assumptions, but also render the underlying theory and experimental data accessible for scrutiny. Thus it may be argued that models currently provide the most comprehensive means to assess impacts of climatic change on ecosystems and are likely to remain so for some time.

Simulation models are also essential tools for impact assessments according to the IPCC Guidelines (CARTER et al., 1994), which distinguish these basic methods: experimentation; impact projections; empirical analogue studies; and expert judgement. In the case of forests, experimentation is often impractical due to the longevity of the dominant tree species; to follow conventional experimental approaches, forests would need to be investigated over several centuries. Forest ecosystem models are therefore essential, although the question remains "How much can they actually accomplish?"
Several modelling approaches are currently available to assess the impact of climatic changes (e.g., SHUGART, 1990; KIRSCHBAUM & FISCHLIN, 1996), offering varying advantages or disadvantages, depending on emphasis plus resolution in time, space, and structure.

In the first of these approaches, climate and vegetation are empirically correlated by assuming equilibrium conditions (HOLDRIDGE, 1947; 1967; BOX, 1978; 1981). If such relationships can be quantified, efficient tools to project vegetation responses in space result (e.g., EMANUEL et al., 1985; KIENAST et al., 1987; BOX & MEENTEMEYER, 1991; BRZEZIECKI et al., 1993; CRAMER & LEEMANS, 1993, 1995). This approach assumes a static relationship between climate and climax vegetation, however, which may be perfectly adequate to predict a potential natural vegetation in an undisturbed, distant future world, but not necessarily the real, near-future vegetation.

The second approach is to use ecophysiological models (e.g., SCHIMEL et al., 1990; RASTETTER et al., 1991; McGUIRE et al., 1993; MELILLO et al., 1993; PARTON et al., 1993) which offer the advantages of being dynamic and able to reproduce ecosystem responses to climatic forcings at a high temporal and sometimes relatively high spatial (e.g., MELILLO et al., 1996) or qualitative resolution (e.g., KIRSCHBAUM et al., 1994). These models, however, often focus on particular chemical elements such as C or N (e.g., RAICH et al., 1991; RAICH & SCHLESINGER, 1992) or on ecophysiological processes that lump together properties, such as species composition (e.g., SCHIMEL et al., 1990; PARTON et al., 1993) or canopy structure, hence providing only poor qualitative resolution. The associated up-scaling problems limit the usefulness of these approaches, since feed-backs to the atmosphere by structural changes in an ecosystem must be ignored unless the latter are modelled explicitly. For instance, if the species composition in a mixed-deciduous forest changes, this may greatly affect winter albedo, an effect which can only be modelled if species composition is modelled explicitly. Similar arguments can be put forward for other structural properties of forests, such as age structure, stem density or dispersion, all affecting surface roughness.

Some additional problems often apply to the above approaches. In many instances paleoecological studies of the effects of climatic change on ecosystems have demonstrated that structural properties such as the species composition are of essential relevance (DAVIS, 1986, 1989, 1990). This has been confirmed particularly for forests (e.g., DAVIS, 1981; HUNTLEY & BIRKS, 1983; HUNTLEY, 1990; OVERPECK et al., 1991; PRENTICE et al., 1991; SOLOMON & BARTLEIN, 1992; WEBB III, 1992; WRIGHT et al., 1993). Since most phytosociological as well as ecophysiological approaches ignore species composition (PERRUCHOUD & FISCHLIN, 1995), their usefulness for studies of climatic change impacts appears to be limited.
The third and perhaps most promising approach is the use of patch dynamic models, which have already proved relatively successful in mimicking forest succession (e.g., Shugart, 1984). By operating at an intermediate level (high spatial, medium temporal, and medium qualitative resolution) they allow the relevant time constants of forest dynamics to be included while still simulating important structural characteristics of forests such as species composition or age structure.

Patch models are able to mimic broad characteristics of real forests under a wide range of climates (e.g., West et al., 1981; Shugart et al., 1992; Smith et al., 1992) and are thus of relatively high predictive power (Shugart, 1984). Patch models have also been successfully used to study forest responses to (i) past climatic changes (Solomon et al., 1980; Solomon & Webb III, 1985; Lotter & Kienast, 1992; Solomon & Bartlein, 1992; Fischlin et al., 1998a, 1998b), (ii) direct effect of CO₂ (Solomon, 1986; Pastor & Post, 1988; Kienast, 1991), or (iii) possible future climatic changes (Solomon et al., 1981; Shugart et al., 1986; Overpeck et al., 1990; Botkin & Nisbet, 1992; Smith et al., 1994).

With regard to the Alps, several authors have conducted modelling and evaluation studies (Forece, Kienast, 1987; Kienast & Kuhn, 1989; Forclim, Bugmann, 1994; Forsum, Krauchi, 1994) and have studied possible impacts of a changing climate on Alpine forests (Kienast, 1991; Krauchi & Kienast, 1993; Bugmann, 1994; Bugmann & Fischlin, 1994, 1996; Fischlin, 1995).

These studies have shown that Alpine forests may be sensitive to climatic change. However, they all relied upon relatively coarse climatic scenarios, which may have hampered the internal consistency and potential realism of the results. Indeed, the highly variable topography of the Alps, their location in the transitional zone between the temperate, Mediterranean and continental climatic regimes, the complexity of forests, and the high input and precision requirements of forest patch models render the construction of appropriate climatic scenarios a challenging task.

A simple method often adopted is to adjust climatic parameters on an ad hoc basis, e.g. by assuming a temperature increase of 1-4 °C within the next, say, 50-100 years (e.g., IPCC, 1990; Ozenda & Borel, 1990). While this approach may be useful for initial sensitivity studies, its main disadvantage is that differences between possible patterns of global climatic change, as well as the regionally differentiated responses to such patterns must be completely ignored. In complex terrain like the Alps, this approach is therefore particularly likely to yield inconsistent results (Gyalistras et al., 1994).

An often recommended approach with fewer shortcomings (Carter et al., 1994) is to rely upon simulations with global climate models, in particular three-dimensional,
coupled general circulation models of the atmosphere (WASHINGTON & PARKINSON, 1986) and the oceans (SEMTNER, 1995) ("AO-GCMs"). At least three different strategies to construct scenarios of regional climatic changes from GCMs have been proposed:

First, GCM-output at a few gridpoints in the vicinity of the region of interest may be used (e.g., KARL et al., 1990; SANTER et al., 1990). For instance BUGMANN & FISCHLIN (1996) directly interpolated climatic scenarios from GCM grids to assess the impacts of these scenarios on Alpine forests. However, GCMs typically show very large errors at individual model gridpoints (e.g., GROTCH & MacCRACKEN, 1991). This is particularly true over a complex topography such as the Alps (GYALISTRAS et al., 1994).

The second approach is to use a physically-based regional climate model (RegCM) driven by boundary conditions taken from a GCM (e.g., GIORGI et al., 1992). A major limitation is that even if a RegCM is run at very high horizontal resolution (say ~20 km, MARI-NUCCI et al., 1995), the simulated climatic changes can only be trusted at a spatial scale above several RegCM-gridpoint distances (cf. VON STORCH, 1995). Hence, many mountain features (ridges, valleys, slopes), can not be adequately resolved. Further, the huge computational requirements of RegCMs severely restrict the construction of time-dependent scenarios over the time spans needed to assess forest responses, i.e. several centuries.

The third approach is based on the interpretation of large-scale climatic changes as simulated by GCMs (or RegCMs) using expert knowledge (e.g., ROBOCK et al., 1993) or statistical models that relate regional climates to the large-scale atmospheric state (e.g., VON STORCH et al., 1993). The latter approach appears to be practical, offering the potential to satisfy all requirements simultaneously (GYALISTRAS et al., 1994). Several authors have demonstrated that the application of empirical "downscaling" relationships can yield physically plausible and internally consistent first-order estimates of possible climatic changes at least at regional scales (for reviews see e.g., KATTENBERG et al., 1996; GYALISTRAS et al., 1998). BUGMANN (1994), BUGMANN & FISCHLIN (1994), and FISCHLIN (1995) have used statistically downscaled scenarios to assess forest responses in the Alps, but they have used scenarios (GYALISTRAS et al., 1994) which considered only winter and summer seasons instead of the entire annual cycle.

This paper presents a general method to estimate possible impacts of climatic change on forests in the complex Alpine terrain by combining global climate models, downscaling techniques, and patch models. For several carefully selected sites, each representing a typical forest ecosystem, it will be shown that: the proposed method provides consistent and plausible (and otherwise unavailable) quantitative projections of possible changes in key structural characteristics such as species composition of mountain forests; many forests in the Alps are sensitive to these downscaled climatic scenarios given at a monthly
resolution, and; forests within a relatively small distance may show a surprisingly wide range of responses to the same pattern of global climatic change.

4.2 Material and Methods

Climatic change impacts were assessed at four study sites in the Alps (Table 4.1). For each site CLIMSHELL (GYALISTRAS et al., 1994; GYALISTRAS & FISCHLIN, 1996) was used to define baseline climates and to derive climatic scenarios from GCM simulation results, and FORCLIM (BUGMANN, 1994; FISCHLIN et al., 1995) was used to simulate forests' responses to the obtained climatic scenarios (Fig. 4.1).

![Diagram](image)

Fig. 4.1: Method used to derive climatic scenarios (CLIMSHELL, GYALISTRAS et al., 1994; GYALISTRAS & FISCHLIN, 1996) and simulate forest responses (FORCLIM, BUGMANN, 1994; FISCHLIN et al., 1995). Arrows represent data flow: large — vectors or matrices, thin — scalar variable or parameter. GHGSc: greenhouse gas emission scenario (in this study 2xCO₂-equilibrium); GCM, General Circulation Model (simulation results used in this study from CCC-GCMII, BOER et al., 1992); MObs, meteorological large-scale (JESSEL, 1991; JONES & BRIFFA, 1992; BRIFFA & JONES, 1993) and local (BANTLE, 1989) observations; DTM, digital terrain model (in this study ARC/INFO data describing Swiss Alps); curC, current climate data; CC, data describing climatic change; T, climatic parameters $E[T_m]$, $\text{VAR}[T_m]$ for monthly temperatures $T_m$; $P$, climatic parameters $E[P_m]$, $\text{VAR}[P_m]$ for monthly total precipitation $P_m$; $\rho$, COV[$T_m$, $P_m$]; $SA_l$, slope-aspect index; $FC$, field capacity; $\lambda$, latitude; $T\text{WinMin}$, winter minimum temperature; GDD, annual growing degree-day totals; AET, actual evapotranspiration; DSI, annual drought stress index; $Ps$, matrix of species parameters; $FD$, forest dynamics (e.g., age distribution, species compositions, leaf area index etc.). Downscaling is described in Gyalistras et al. (1994): Interpolation attempts to make best use of local/regional meteorological measurements and digital terrain model; submodel FORCLIM-C controls climatic change within FORCLIM; submodel FORCLIM-E computes the abiotic environment; submodel FORCLIM-P simulates tree dynamics.

Each case study site (Table 4.1) represents a particular ecoregion from North to South: Bern located on the Swiss Plateau is a typical submontane site, Bever represents subalpine forests, St. Gotthard represents an alpine site, currently above the timberline, and Sion represents colline belt conditions (cf. ELLENBERG, 1988).
4.2.1 Baseline Climates

The large-scale observations used to fit the downscaling models were gridded (5° x 5° latitude by longitude) anomalies of monthly mean sea-level pressure (SLP, provided by NCAR, see JESSEL, 1991) and near-surface air temperature (2mT, from the data set of JONES & BRIFFA, 1992; BRIFFA & JONES, 1993) over the North-Atlantic/European sector (40°W–40°E and 30°N–70°N). Local climatological observations were extracted from the data base of the Swiss Meteorological Institute (BANTLE, 1989).

<table>
<thead>
<tr>
<th>Site</th>
<th>Location</th>
<th>Elevation (m above sea level)</th>
<th>annual mean temperature (°C)</th>
<th>annual total precipitation (cm)</th>
<th>Current potential natural vegetation (Ellenberg &amp; Klotzli, 1972)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Bern</td>
<td>Swiss Plateau (Northern Alps)</td>
<td>570</td>
<td>8.6</td>
<td>99 Submontane mixed deciduous forests dominated by beech (Fagus silvatica L.) and silver fir (Abies alba Miller)</td>
</tr>
<tr>
<td>B</td>
<td>Bever</td>
<td>Central/Southern Alps</td>
<td>1712</td>
<td>1.6</td>
<td>82 Subalpine coniferous forests dominated by larch (Larix decidua Miller) and arolla pine (Pinus cembra L.)</td>
</tr>
<tr>
<td>C</td>
<td>St. Gotthard</td>
<td>Transition zone Northern to Southern Alps</td>
<td>2300</td>
<td>−1.0</td>
<td>207 Alpine belt, above current timberline</td>
</tr>
<tr>
<td>D</td>
<td>Sion</td>
<td>Central Alps</td>
<td>542</td>
<td>9.9</td>
<td>60 Colline mixed-deciduous oak forest</td>
</tr>
</tbody>
</table>

Table 4.1: Characteristics and major current climatic parameters of the case study sites.

The forest model FORCLIM uses a stochastic weather generator to simulate annual cycles of monthly mean temperature (T) and precipitation totals (P) based on the following set of site-specific, climatic input parameters: expected values of monthly mean temperatures (E[T]) and precipitation totals (E[P]), and monthly 2x2 cross-covariance matrices (COV[T,P]) for each month of the year (FISCHLIN et al., 1995).

For Bever, Bern and Sion all climatic parameters were computed from daily measurements for the period 1931-1980 (BANTLE, 1989). For St. Gotthard, which is ~0.6 km away from the nearest climatological station (at 2090 m a.s.l.), E[T] and E[P] were interpolated using a further 39 stations for T (25 for P) up to a distance of 80 km (60 km for P), whereas COV[T,P] was taken directly from the nearest station. To interpolate we applied a linear regression separately for each month to predict E[T] and E[P] from elevation, and then adjusted the result based upon an inverse distance-weighted (IDW)
interpolation of elevation-detrended expected values from the surrounding stations (cf. GYALISTRAS & FISCHLIN, 1995; GYALISTRAS & FISCHLIN, 1996). We used for E[P] a linear, and for E[T] a piecewise linear, seasonally varying dependency on elevation with a breakpoint at 1450 m.

4.2.2 Climatic Scenarios

All climatic scenarios were derived from a "2xCO₂" global climate change experiment simulated by the Canadian Climate Centre CCC-GCMII (BOER et al., 1992). The scenarios were constructed based on the statistical downscaling method of GYALISTRAS et al. (1994; GYALISTRAS & FISCHLIN, 1995; GYALISTRAS & FISCHLIN, 1996) as follows:

(a) For each month Principal Component Analysis (PCA, PREISENDORFER, 1988) was used to construct a smaller number of new, large-scale variables (so-called principal components, PCs), from the 306 variables contained in the SLP- and 2mT-fields of the period 1931-1980. Between 8 (winter months) and 14 (summer months) PCs were retained, which explained ~90% of the total interannual large-scale variability for all months.

(b) Canonical Correlation Analysis (CCA, BARNETT & PREISENDORFER, 1987), again performed for 1931-1980, was used to establish separately for each location and month a multivariate regression model to predict from the PCs simultaneous anomalies of local monthly mean T and monthly √P from their respective long-term means. The CCA regression parameters define pairs of large-scale patterns and corresponding local responses (see VON STORCH et al., 1993; GYALISTRAS et al., 1994), which were all plotted to allow inspection of the statistical relationships.

(c) The monthly downscaling models derived from the CCA were applied to five years of monthly mean large-scale anomalies as simulated by the CCC-GCMII under "2xCO₂" conditions relative to the long-term mean fields from a five year control ("1xCO₂") simulation. Changes in the seasonal (winter = December, January, February; spring = March, April, May; summer = June, July, August; and autumn = September, October, November) mean SLP- and 2mT-fields were plotted to examine the downscaled scenarios.

(d) Site-specific changes in E[T] and E[P] were estimated by averaging the five downscaled anomalies for each month. Since these changes showed jagged annual cycles at all locations, annual cycles were smoothed using a moving average of the downscaled changes of the month itself and the preceding and subsequent months. The climatic scenario for St. Gotthard was obtained by IDW interpolation of the downscaled monthly changes from the same surrounding stations as were used to derive the present climate.
Since the downscaled changes showed no strong dependency on altitude, no correction for elevation was applied. At all sites the covariance matrices COV[T,P] were held constant at present (baseline) values.

### 4.2.3 Forest Model FORCLIM

From the modularized (FISCHLIN, 1991) forest model FORCLIM (version 2.4.0.4, BUGMANN, 1994; FISCHLIN et al., 1995) we used three submodels (Fig. 4.1). FORCLIM-C (climate) simulates location-specific climatic changes as discrete events. FORCLIM-E (environment) simulates the abiotic environment of a patch from the climatic parameters as produced by FORCLIM-C. FORCLIM-P (plants) is a discrete time (1 year time step) patch dynamics model simulating the fate of tree cohorts populating a patch of 1/12 ha in a species specific manner.

FORCLIM-E contains the stochastic weather generator which simulates interannual variability in monthly temperature and precipitation. From the location-specific parameters SAI, FC, and λ (Fig. 4.1) FORCLIM-E then computes the winter minimum temperature TWinMin, the annual growing degree-day totals GDD, and the annual drought stress index DSI for input to FORCLIM-P. TWinMin is the minimum of the variates of T for December, January, and February. GDD is computed by correcting for biases and discretization errors (for a discussion cf. FISCHLIN et al., 1995) according to the method developed by BUGMANN (1994). Following a simple bucket-model approach, actual (AET) and potential (PET) evapotranspiration are computed according to THORNTHWAITE & MATHER (1957), where calculations depend not only on the usual site-specific parameters field capacity FC (in this study at all sites 30 cm) and latitude λ (site A: 46.9°N; B, C: 46.6°N; and D: 46.2°N), but also on the slope-aspect index SAI. The latter was used to correct the PET for the slope and aspect dependent radiation plus wind effects (cf. BUGMANN, 1994). The drought stress index DSI is the difference between annual PET and AET divided by the PET (PRENTICE & HELMISAARI, 1991; BUGMANN, 1994; FISCHLIN et al., 1995).

FORCLIM-P simulates three basic processes, which determine annual changes in the tree cohorts currently existing within a patch: (i) establishment of saplings, (ii) death of individual trees [both (i) and (ii) formulated as Poisson processes], and (iii) tree growth, formulated deterministically based on an improved growth equation (MOORE, 1989; BUGMANN, 1994), which mimics explicitly inter- and intraspecific competition for light and implicitly for water and nutrients. Establishment and growth are directly affected by weather. However, since slow growth lasting over a series of years increases the probability of tree deaths, weather may also contribute indirectly to mortality.
Full definitions of all equations forming FORCLIM can be found in BUGMANN (1994, FORCLIM-P) and FISCHLIN et al. (1995, FORCLIM-E).

Simulation results were obtained according to the Monte-Carlo technique by sampling for each site 200 variates (BUGMANN et al., 1996). Always assuming an empty patch as the initial condition, each variate was obtained by sampling the state vector every 20th year within the simulation period 800 till 3200. FORCLIM-C simulated climatic changes as a step change in the year 2050. All simulations were performed on Macintosh computers (68040 CPU) and Sun workstations using the interactive RAMSES simulation environment (FISCHLIN, 1991; FISCHLIN et al., 1994) and the RAMSES simulation server RASS (THOENY et al., 1994; THOENY et al., 1995).

Steady state estimates under current and future climates were computed from the 200 variates by averaging species abundances from biomasses over 400-year periods, under the baseline climate (1840-2040), and under future equilibrium conditions assumed to be reached after 2800 (cf. BUGMANN et al., 1996).

To summarize effects of climatic change on species compositions similarity indices, $S_{ij}$, were computed between pairs of steady state estimates (see above) according to the formula $S_{ij} = 1 - \frac{\sum |x_k - y_k|}{\sum (x_k + y_k)}$ where $x_k$ and $y_k$ are abundances of species $k$ in the current ($x_k$) and the future ($y_k$) climate, respectively.

### 4.3 Results

#### 4.3.1 Climatic Scenarios

At all four study sites (Table 4.1) the GCM-based future scenarios showed an increase in annual mean temperature and a tendency towards wetter conditions compared to the present climate. The direction and magnitude of the changes (Fig. 4.2) differed from site to site. Annual mean temperatures increased by 2.4 °C at Sion and St. Gotthard, by 2.5 °C at Bern, and by 2.6 °C at Bever. Precipitation showed no significant change at Sion (+0.9 cm or +1%), whereas increases of 8.6 cm (+11%), 18 cm (+31%), and 42 cm (+20%) were obtained at Bern, Bever and St. Gotthard, respectively.

The downscaling models provided plausible linkages between observed interannual variability of the local weather variables and large-scale anomalies in (i) the strength of the westerlies in winter; (ii) the intensity of more meridional (i.e. north-south) flow patterns in the transition seasons; and (iii) the strength of large-scale subsidence in summer (see
also GYALISTRAS et al., 1994; GYALISTRAS et al., 1998). The proportions of total variances of the local variables explained in the fitting interval 1931-1980 averaged over all locations and winter half-year (October–March) amounted to 58% for temperature and 36% for precipitation. For the summer half-year (April–September), the mean variances were 65% and 32% for temperature and precipitation, respectively.

![Graph showing temperature and precipitation](image)

**Fig. 4.2**: Comparison of annual mean temperatures and annual precipitation totals under the present (●) and the assumed scenario climates (○) at the case study sites (Table 4.1). ● means for 1931-1980 computed from daily measurements (BANTLE, 1989); ○ scenario values derived by statistical downscaling (GYALISTRAS et al., 1994; GYALISTRAS & FISCHLIN, 1996) from a "2xCO₂"-experiment with the CCC-GCMII (BOER et al., 1992).

Comparison of the annual cycles of temperature and precipitation under present-day and the simulated future climate shows (Fig. 4.3) that the shifts in the annual means (Fig. 4.2) were not equally distributed throughout the year and that the seasonal patterns vary from site to site. Averaged over all locations warming was smallest in spring and autumn (+2.2 °C) and largest in summer (+2.8 °C) and precipitation increased in all seasons (+9% to +30%) except for summer (-5%). Among sites the warming differed the least in autumn (0.3°C) and the most in summer (0.9°C) and the changes in precipitation differed again the least in autumn (20%) and the most in spring (44%).

These results conform to the underlying circulation changes simulated by the CCC-GCM. In winter the GCM-projected enhanced mean westerly flow over Europe would produce stronger temperature changes at the more north-westerly sites (Bern and Sion) and a gen-
Fig. 4.3: Comparison of in period 1931-1980 observed (thick lines) annual cycles for monthly mean temperature (left) and total precipitation (right) (BANTLE, 1989) with the climatic scenarios (broken lines) derived by statistical downscaling (GYALISTRAS et al., 1994; GYALISTRAS & FISCHLIN, 1996) from a "2xCO₂"-experiment with the CCC-GCMII (BOER et al., 1992) at the four case study sites (see also Table 4.1). Note the different scale for precipitation at St. Gotthard.

eral precipitation increase. The smaller warming at all locations during spring is associated with a distinct strengthening of the northerly flow component simulated by the GCM. In summer, increased anticyclonic activity over central Europe in combination with strong mid-continental heating produced greater temperature increases at the more easterly locations (St. Gotthard, Bever). A strengthening of the north-easterly flow in autumn was associated with a smaller warming and a slight increase in precipitation at all sites, except for the more sheltered location at Sion.
4.3.2 Forest Responses

A general response to climatic change, probably typical for many mountain forests in the Alps (BUGMANN, 1994; BUGMANN & FISCHLIN, 1994), is that observed at the Bever site (Fig. 4.4). The primary succession starting in year 800 lasts about six centuries, after which European larch (Larix decidua MILL.), a pioneer species, is substantially replaced by the late-successional species arolla pine (Pinus cembra L.). The climax community is the larch-arolla pine forest often found in the central subalpine belt of the Alps (Table 4.1). At this site the simulated step change in climate (cf. Figs. 4.2, 4.3) produced a sharp transient response in the forest. It then initiated a secondary succession resembling a primary one, which eventually lead to a completely new climax community containing none of the previously dominant species. Only larch and Scots pine (P. sylvestris L.) from the earlier climax community appear as early successional species.

Fig. 4.4: Simulated species compositions at the case study site Bever (B, Table 4.1) in the Swiss Alps for current climate (800-2040) and a possible, future 2xCO₂ climate (2060-3200) as down-scaled (GYALISTRAS et al., 1994) from the CCC-GCMII (BOER et al., 1992). All simulations were made with the forest model FORCLIM (BUGMANN, 1994; FISCHLIN et al., 1995). Accumulatively shown mean species abundances in t/ha were averaged from 200 variates sampled according to the Monte-Carlo-technique from the stochastic process described by FORCLIM (cf. Fig. 4.5 and 4.6). “∑ all other species” is total of the following low abundance species: Salix alba L., Sorbus aria (L.) CRANTZ, S. aucuparia L., Tilia cordata MILLER, T. platyphyllos SCOP., Quercus pubescens WILLO., Populus tremula L., Corylus avellana L., Betula pendula ROTH, Carpinus betulus L., Alnus glutinosa (L.) GAERTNER, A. incana (L.) MOENCH, A. viridis (CHAIX) DC., Taxus baccata L., Acer campestre L., and Pinus montana MILLER.
Fig. 4.5: Simulated equilibrium species compositions at the case study sites (see also Table 4.1, Fig. 4.4, and Fig. 4.7 bottom) in the Alps for current baseline climate (800-2040). All simulations made with FORCLIM (BUGMANN, 1994; FISCHLIN et al., 1995). Depicted are mean species abundances averaged from 200 variates sampled according to the Monte-Carlo-technique from the stochastic process described by FORCLIM (cf. Fig. 4.6). All other settings as described under Fig. 4.4.

Fig. 4.6: Simulated equilibrium species compositions at the case study sites (see also Table 4.1, Fig. 4.4, and Fig. 4.7 bottom) in the Alps for a possible, future 2xCO₂ climate (2060-3200) as downscaled (GYALISTRAS et al., 1994) from the CCC-GCMII (BOER et al., 1992). All other settings as described under Figs. 4.4 and 4.5.
The steady-state biomass densities for all four sites (Table 4.1) are depicted for current climate in Fig. 4.5 and for the projected future equilibrium climates (Figs. 4.2, 4.3), in Fig. 4.6. At Bern the climatic change caused no significant changes in the climax communities \((S_i = 0.92)\). Contrastingly, the steady states at Bever differ sharply \((S_i = 0.07)\). A similar dramatic change \((S_i = 0.002)\) was obtained at St. Gotthard where a forest appears above the current timberline (cf. Fig. 4.7 bottom). At Sion we obtained a quite different response, i.e. the collapse of the forest canopy: Only very low tree biomass remains in the climax community under the changed climate \((S_i = 0.07)\).

The flexibility of the new technique (CLIMSHEll combined with FORCLIM, cf. Fig. 4.1) is demonstrated in Fig. 4.7. The technique makes it possible to simulate the behaviour of forests at locations different from those at which weather records are available, for instance along an altitudinal gradient. This is possible not only for current, but also for downscaled, future projected climatic scenarios (Fig. 4.7 top, middle, bottom; steady-states from bottom simulation also shown in Figs. 4.5 and 4.6).

### 4.4 Discussion

For a far-future "2xCO₂" equilibrium world, the CCC-GCMII projects a warming in the mean annual global near-surface air temperature of 3.5 °C (BOER et al., 1992), approximately at the centre of the 2.1 - 4.6 °C range projected by state-of-the-art GCMs (KAT-TENBERG et al., 1996). Transient experiments with coupled GCMs (with climatic sensitivities in the range noted above) under steadily increasing concentrations of greenhouse-gases showed a warming of 1.3 - 3.8 °C at the time of doubled CO₂, with an average of only 2.0 °C. Such a delay was not considered in our simple, step-like scenarios, but, as has been shown by BUGMANN (1994), it is probably of minor relevance for the mid and long-term response of forests.

Several reasons indicate that the regional scenarios of climatic change used here are plausible and spatially consistent: (i) The scenarios plausibly reflect the effects of changes in the spatial distributions of large-scale monthly mean sea-level pressure and near-surface temperature as projected by the CCC-GCMII (analysis of CCA model response). (ii) The projected warming is to be expected, since it seems unlikely that any changes in regional climate forcings (which could lead to e.g. increased frequency of thermal inversions or of cold air drainage) could override the strong, general warming prescribed by the CCC-GCM. (iii) The projected increases in precipitation are consistent with the general increases in globally averaged precipitation of ca. 2%-15% projected by GCMs under a CO₂-doubling (IPCC, 1990, 1992), as well as with indications from an experiment with a regional climate model (SCHÄR et al., 1996). (iv) The average ratio
Fig. 4.7: Using the CLIMSHELL (GYALISTRAS & FISCHLIN, 1996) to explore forest dynamics where there are no measurements available (top - 2100, middle - 2200, bottom - 2300 m a.s.l.). The applied technique allows to interpolate baseline climates and climatic scenarios by combining measurements from long-term "base stations" (this study: station of St. Gotthard at 2090 m a.s.l.), with measurements from auxiliary climatological stations (this study: up to additional 39 stations), a digital terrain model, and regionalized GCM-output (for bottom cf. Fig. 4.5 and 4.6). All other settings as described under Fig. 4.4 and 4.5.
between projected changes in annual temperature and precipitation (5.4%/°C) is consistent with the theoretical value (e.g., ROEDEL, 1992, p.65) obtained under the assumption that the relative humidity of the atmosphere would remain unaltered (e.g., MITCHELL & INGRAM, 1992). (v) The variability in the regionalized patterns of change appears realistic, in view of the seasonally and spatially strongly varying link between Alpine and large-scale climate (e.g., SCHUEPP, 1968; FLIRI, 1974; GENSLER & SCHUEPP, 1991; GYALISTRAS et al., 1994; SCHAR et al., 1998). (vi) The projected changes were spatially more uniform for temperature than for precipitation, in agreement with patterns observed in the Alpine region (FLIRI, 1974; EHRENDORFER, 1987; AUER & BÖHM, 1994; BENISTON et al., 1994). (vii) The scenarios are consistent with climatic changes obtained at a coarser spatial scale from physically-based regional climate models (for a detailed comparison of model-based and empirically-downscaled scenarios for the Alpine region, see GYALISTRAS et al., 1998).

In present climates FORCLIM normally produces realistic species compositions as is shown not only by our own results (cf. Table 4.1 with Figs. 4.4 to 4.7), but also by other studies, which have analysed and validated the behaviour of this model in Europe, North America, present, and past (e.g., BUGMANN, 1994; BUGMANN & FISCHLIN, 1994; BUGMANN & SOLOMON, 1995; FISCHLIN, 1995; FISCHLIN et al., 1998a). From all this evidence we claim that the model FORCLIM has considerable predictive power and is generally capable of projecting "realistic" results.

Similarly, sensitivity analyses at the four study sites (not shown), agree with results from former studies (e.g., BUGMANN, 1994) and suggest that the projected new equilibria for the species compositions are relatively robust, i.e. that small changes in the climatic scenarios of the order of ±0.5 °C or ±5% for precipitation would show only little effect (FISCHLIN et al., 1995).

Although all study sites were affected by the same global pattern of climatic change, the projected forest responses differed significantly, ranging from enhanced growing conditions, to no effect, to complete disappearance of the forest (cf. Figs. 4.5 and 4.6). All simulations assumed an identical species pool disregarding any phytogeographic history. Thus, observed differences among the sites can be explained, at least partly, by the site specific climatic parameters for monthly temperature and precipitation. Since the scenarios of local climatic change contained also a strong shared component, however, the dramatic differences found in the forest responses cannot be explained only by the physical environment. To fully understand the obtained patterns, we have to consider also the intrinsic mechanics of the ecosystem model, which form a complex network of non-linear, interdependent causes behind the projected forest responses.
4.4.1 Forest Responses

A) BERN

Bern shows a remarkable insensitivity to the projected changes. It is the only site where the similarity index is close to one, whereas all other sites show very small, near zero indices (see "Results"), indicating sharp changes in species compositions under current vs. new equilibrium conditions. Although other studies (e.g., NILSSON & PITT, 1991) have projected similarly small changes for this zone (Swiss Plateau) our result contrasts with that obtained by BRZIEIECKI et al. (1995), who have applied a statistical, steady-state model based on correlations between zonal forest communities, temperature, and edaphic factors (BRZIEIECKI et al., 1993; BRZIEIECKI et al., 1995). Their model uses temperature as the only climatic factor determining plant communities. Although temperature may serve in some instances as a useful indicator for the water balance regime, this can not be expected to be the case in general (HOLDRIDGE, 1947, 1967; BOX, 1981; WOODWARD, 1987; BOX & MEENTEMEYER, 1991), which may explain some of the differences between their and our results.

Moreover, the Bern site is currently characterized by few periods of drought stress, whereas in the southern Alpine areas (which BRZIEIECKI et al. have used as an analogue for the future conditions on the Swiss Plateau) precipitation and, hence, drought stress, show greater high intra- and interseasonal variability. For example, Bern receives under present climate in summer (winter) a mean total precipitation of 35 cm (18 cm) distributed over 35 (28) days, whereas at the southern Alpine location of Lugano a far larger amount of 55 cm (23 cm) falls within only 32 (20) days.

A further explanation for this difference lies in our use of seasonal climatic scenarios, which projected the strongest warming at Bern during winter, which has only a minor effect on the vegetation. Moreover, BRZIEIECKI et al. have assumed no changes in precipitation, whereas the downscaled scenarios showed increased precipitation during winter, spring, and fall, partly compensating for the projected increases in temperature.

Unless the insubrian climate typical of the southern Alps should really prevail on the Swiss Plateau, the projections by FORCLIM appear to be more plausible for the given climatic scenario. The small sensitivity at Bern to warming is further corroborated by the temperature requirements of the presently dominant tree species, since the projected climatic changes do not push any of these species far from their ecophysiological optima, allowing them to remain within the centre of their realized niches. However, the statistical model by BRZIEIECKI et al. might again become superior, in cases of extreme warming scenarios, where patch models like FORCLIM – e.g., due to the use of simpli-
fied schemes to compute the local water balance (THORNTHWAITE & MATHER, 1957; FISCHLIN et al., 1995) – tend to underestimate the sensitivity of forest responses (KIENAST, 1991; BUGMANN, 1994; BUGMANN & FISCHLIN, 1994).

B) BEVER

At the subalpine site Bever, the projected climatic changes cause major changes in species composition (Fig. 4.4), also expressed in the extremely low similarity index. The new forest composition simulated under a changed climate represents a completely new community with no present analogue (ELLENBERG & KLÖTZLI, 1972; ELLENBERG, 1988). This result conforms with the individual species responses postulated by several authors to explain the patterns found during past climatic changes (e.g., DAVIS, 1981; HUNTLEY & BIRKS, 1983; DAVIS, 1990; HUNTLEY, 1990).

The climatic changes projected for Bever vary considerably with season. For instance, summer warms by ~0.7 °C more than winter, while precipitation in summer remains unchanged, but increases 12 to 55% in other seasons.

Not surprisingly, the annually averaged changes in climate at Bever (Fig. 4.3) distributed equally over all months cause a forest response (results not shown here) which differs significantly in its transient as well as equilibrium species compositions ($S_t = 0.62$). Consistent with increased water availability and less warming during summer, Acer pseudoplatanus was found to be less abundant in the non-seasonal scenario than under our original, monthly resolved scenario (Fig. 4.4); instead, Picea abies produces ca. 30% of the total biomass. The high abundance of $P. abies$ moves this new forest composition closer to that found under present conditions. Hence, we conclude that using annually averaged scenarios may lead to an overestimation of such a forest's ability to adapt to potential climatic change.

Bever is located in the centre of the Alps and the omnipresence of species, e.g., of sweet chestnut ($C. sativa$) or European beech ($Fagus silvatica$), as assumed in the model, cannot be expected to be the case in reality. Therefore, the transition to a new equilibrium, is likely to be further hampered by the migrational barriers posed by mountains. This inference is corroborated by phytogeographic evidence from the past, which shows that the Alps have functioned as an insurmountable barrier for slow-migrating species in the present-day climate (HUNTLEY & BIRKS, 1983; HUNTLEY, 1990; OZENDA & BOREL, 1990).
C) ST. GOTTHARD

At St. Gotthard tree growth is completely suppressed under the current climate, whereas in the projected new climate trees can form a forest canopy (cf. Figs. 4.5, 4.6, and 4.7). This site is located just above the current tree line (cf. Fig. 4.7 top and middle vs. 4.7 bottom) where forests are believed to be mainly limited by temperature, since precipitation is abundant (WOODWARD, 1987; ELLENBERG, 1988).

The forest responses projected by FORCLIM are consistent with ecological expectations, which require particular temperature regimes for tree growth, i.e., a growing season of at least 30 days with daily mean temperature above 10°C and fewer than 8 months with mean daily minima below 0°C (WALTER & BRECKLE, 1986, 1991). At St. Gotthard the present climate is characterised by no months with a daily mean temperature above 10°C, but in the projected new climate (cf. Fig. 4.3) there are more than 30 days exceeding this threshold. Furthermore, the period with daily minima below freezing decreases from almost 8 months under the present climate to less than 7 months under the projected, future climate.

Hence, the forest establishment projected by the model appears plausible, although some details of the initial succession may not be realistic. Firstly, existing soils may not be fully colonizable (RENNER, 1982) requiring a long phase of development. Secondly, growth at the tree line may be reduced because of adverse local conditions such as diseases, strong winds, browsing by cattle and game, or physical instability on steep slopes. Thirdly, the models ignore the form of the precipitation (tree growth might also be hampered by mechanical or drought stress due to snow and ice), and changes in incoming solar radiation and in the duration of snow cover. For instance, increases in temperature and/or its variance during spring may produce warm periods which can melt the snow cover earlier than at present. Since occasional invasions of cold air into central Europe during spring can be expected to occur also in the future, an early retreat of the protective snow cover may increase the exposure of plants to frost damage. The strengthening of the northerly flow component over Europe as projected by the CCC-GCMII during spring (mainly April) even suggests the possibility for an increase of this risk under a "2xCO₂"-climate.

Even though high latitude tree lines can not be compared directly with high altitude Alpine tree lines (e.g., because of the different radiation regime), some recent observations from boreal tree lines (TAUBES, 1995) appear to suggest similar effects of at least transiently reduced growth under warming conditions.
D) SION

The Sion site presents an opposite case from that of St. Gotthard: the current climate allows for tree growth, whereas in the projected new climate, trees can no longer form a forest canopy (cf. Figs. 4.5, 4.6).

The disappearance of the forest vegetation appears to be plausible, considering the present-day low mean annual precipitation of 600 mm (cf. Table 4.1), which places this xeric site close to the drought tree line (HOLDRIDGE, 1967; WALTER & BRECKLE, 1983, 1984, 1986, 1991; WOODWARD, 1987). Using the FORECE model (KIENAST, 1987; KIENAST et al., 1987; KIENAST & KUHN, 1989) KIENAST (1991) has obtained similar results for this site.

An analysis of the growth factor that quantifies the effect of soil moisture deficits in FORCLIM (BUGMANN, 1994; FISCHLIN et al., 1995) revealed the simulated degradation of growth conditions were due to enhanced drought stress. In the projected climate, growth was reduced to a range between 4% and 10% (upper and lower 95% confidence limits) of the maximum growth potential. This increased drought stress was caused not only by the general rise in temperature, but also by the simultaneous 28% decrease in summer precipitation. The downscaled changes for summer precipitation are particularly uncertain (e.g., GYALISTRAS et al., 1994), but it is worth-noticing that other experiments with FORCLIM (not shown here) – where we assumed only warming and no changes in annual precipitation – still lead to a collapse of the forest canopy.

4.4.2 Sensitivities and Uncertainties

The sensitivity of Alpine forests to human interference with the climate system directly depends on the underlying sensitivities of the global and regional climate. We note that in this study we used a global climate model with an intermediate sensitivity to increased concentrations of greenhouse gases, and that the downscaling procedure adopted may over- or underestimate the response of the local climates to the simulated changes in global climate (GYALISTRAS et al., 1998). The forest responses obtained then revealed a potential for greatly differing sensitivities to the same global scenario of climatic change, a result which must be interpreted carefully. Despite many recent efforts to improve FORCLIM (BUGMANN & FISCHLIN, 1992, 1994; BUGMANN, 1994; FISCHLIN et al., 1995; BUGMANN et al., 1996), this model may not always adequately reflect the sensitivities of the real forests.
For instance, the disappearance of the forest at Sion may overestimate the true sensitivity, since this result depends, amongst others, on the particular and limited pool of species used in the simulations. Olive trees (Olea europaea L.), oaks such as the cork oak (Q. suber L.), holly oak (Q. ilex L.), or Pyrenean oak (Q. pyrenaica Willd.) could probably produce higher tree biomasses than those simulated by FORCLIM. Similarly, if we were to accept the oak species now included in FORCLIM, i.e. Q. robur L., Q. petrea, and Q. pubescens, could possess the characteristics of Mediterranean provenances of these species, we would obtain a similar effect (FISCHLIN et al., 1998b). Without human assistance, however, it is unlikely that such provenances could quickly migrate to Sion, leaving the site vulnerable to a transitory, yet long-lasting forest disappearance.

Moreover, FORCLIM may have overestimated the sensitivity at all sites, since, the greater the genetic plasticity of today's tree species in terms of tolerance to abiotic forcings such as drought, the lower is their expected sensitivity to a given climatic change. Such a buffering effect, now completely ignored by FORCLIM, might be further enhanced if climatic change were to trigger novel selection and thus alter the gene pools of the tree species by affecting gene frequencies. Considering such effects would require additional simulations which include new species or to adjust the corresponding species parameters within FORCLIM.

Conversely FORCLIM may overestimate the robustness of forest compositions at the Bern site, since various simulations under even stronger warming (not shown here) still showed little effect. Nevertheless, as already discussed, for the ranges of climatic change used in this study, the low sensitivity obtained at Bern is likely to be generally realistic.

FORCLIM may also underestimate the sensitivity close to the timberline limited by temperature. This is because it ignores possible additional effects resulting from decreases in the duration of the snow cover, from increases in photosynthetic efficiency, or from improved nutrient allocation (cf. e.g. KÖRNER, 1995).

The projections represent no forecasts: they merely describe the forest succession if all prescribed assumptions hold or become actually true. Consequently, many unavoidable and in some instances eventually irreducible uncertainties accompany the projections. For instance the arbitrary selection of particular reference points in a large space of abiotic and other environmental parameters like the selection of the 2xCO₂ radiative forcing scenario, the CCC-GCMII, the 1931-1980 baseline climate, the species parameters, etc. all generate uncertainties.

Thanks to the modular structure of our method it is easy to explore uncertainties, because modules can simply be exchanged for others: e.g., the CLIMSHELL can be switched to any other GCM, or FORCLIM can be easily simulated with any combination of sub-
models (FISCHLIN, 1991; FISCHLIN et al., 1994). In some cases this allows quantification of uncertainties: For instance based on a random resampling procedure (EFRON, 1979) we obtained ca. ±0.5 °C for temperature and ±20% for precipitation relative to the "best estimate" scenario values obtained from the 2xCO₂ experiment with the CCC-GCMII (averaged over 22 Alpine locations and all months of the year by determining 95% percentiles, for details see GYALISTRAS & FISCHLIN, 1995).

4.5 Conclusions

This study demonstrated the feasibility and viability of a new method to assess possible transient responses and equilibrium states of forests in a topographically complex region such as the Alps. In combining results from a GCM-experiment with a downscaling technique and a forest patch model (Fig. 4.1) we obtained regionally differentiated, integrated, reproducible, quantitatively consistent assessments of climatic change and their associated impacts on mountain forests at a relatively high temporal and spatial resolution. The method is spatially flexible and general and has the potential to be applied directly without modification in the mid and high latitudes of the Northern Hemisphere (BUGMANN & SOLOMON, 1995) at every location of ecological interest. Finally, it conforms to the IPCC guidelines for impact assessments (CARTER et al., 1994) and is modular and efficient. The latter is important for exploring sensitivities and uncertainties and provides a basic framework for replacing modules with better variants or enhancing the method as new procedures or submodels become available.

The climatic scenarios obtained and the associated forest responses appeared reasonable in light of current knowledge of the climate system and the local ecology. It mattered for the forest responses that we used climatic scenarios resolving the annual cycle, indicating that annually averaged scenarios may yield misleading results. We obtained highly variable forest sensitivities within close vicinity: Insensitivity was found for low-altitude deciduous forests, whereas high sensitivities were found at the water- and temperature-tree lines. These results indicate that mountain forests will be highly sensitive to climatic change. At present little is known about the proportions of sensitive vs. insensitive forests in a region such as the Alps. Consequently, the relative importances of critical forest responses (e.g., temporary die-back during phases of major changes in species composition or even complete disappearance) versus beneficial effects (e.g., establishment above the current timber-line) remain to be studied further. If climatic change should occur in the patterns suggested here, it is likely to result in severe local damage, even if the total area affected is relatively small. Once more the results of this study indicate that tree populations respond individually and not as a community, and that
without human assistance new steady states are reached only after several centuries or millennia, especially in the presence of migrational barriers.

The results ought not be confounded with actual forecasts: they represent mere projections which give possible answers to "what if" scenarios. The validity some of these projections may hold, only the future can reveal. We believe that they represent valid first-order estimates of possible impacts of climatic change on forests in the Alps if greenhouse gas forcing doubles.
5. Discussion

The demanding input requirements of ecosystem models present a particular challenge for the construction of climatic scenarios. The present work demonstrated that by combining global and local measurements with simulation results by GCMs it is possible to derive appropriate and physically plausible (sections 2.3.3, 4.4) scenarios at comparatively small expenses. The use of a downscaling procedure in particular allowed linkage of local ecosystem responses to in principle any given scenario for the future radiative forcing of the global climate system (Fig. 4.1). Thus, in contrast to simpler approaches, such as ad-hoc adjustments and analogue techniques, the proposed method provides a mean to explore precisely the propagation of uncertainties (amplification vs. damping) through climatic scenarios and ecosystem models.

A commonly used approach in impact studies is to interpolate the climatic scenarios from a few climate model gridpoints in the vicinity of the region of interest. The pronounced spatial gradients found in the present study (Figs. 2.12, 2.13, 4.3), however, were in strong contrast to the smooth patterns of change (e.g., BACH et al., 1985; OZENDA & BOREL, 1990) that result from this climatologically inconsistent (cf Fig. 2.1; VON STORCH, 1995) procedure. In particular, as shown by GYALISTRAS & FISCHLIN (1995), application of gridpoint-interpolated scenarios would have yielded in some cases misleading forest responses – at least in a complex terrain such as the Alps.

Different from regional climate models the proposed method provided a very high (local) resolution. This resolution was obtained based on a conceptually and technically relatively simple procedure (Eqs. 2.1-2.4 and 3.1-3.4), and at medium data requirements. Hence, it appears feasible that with the aid of two newly developed computer programs, ClimShell and MonWeathGen, a graduate student could construct a first iteration of scenarios already within a few days. Quite differently, simulation experiments with a regional climate model would have required to develop considerable expertise, and would have depended on the availability of large data sets for model initialization, testing, and application. All this would have required a considerably larger amount of time.

The here proposed procedure was also found to be computationally efficient. For example, downscaling of hundred years of global climate model output to a particular location (Fig. 2.11) took only ~1 min on a modern workstation. The stochastic simulation of 200 x 1'400 years of monthly weather data (section 4.2.3, Fig. 4.4) required only an additional ~10 min per location. In contrast, simulations with e.g. the NCAR
second generation regional climate model would have required at a resolution of 60 km per simulated year 60 hours of CPU time on a Cray Y-MP (Giorgi, 1996).

A further advantage of the proposed procedure was that it matched the limited precision of GCMs. This was achieved by using a local weather generator instead of GCM-simulated time series (Fig. 4.1), by removing GCM biases prior to downscaling, and by using but the first few EOFs of monthly to seasonally averaged fields (Fig. 2.3). Quite differently, in regional climate simulations the errors of the driving model are directly propagated into, and in some instances even amplified by the high-resolution model. For example, based on similar boundary conditions to the ones which we used to construct the "ECHAM 2xCO2" scenario in section 2.3.3, Rotach et al. (1997) obtained in a simulation experiment with a high-resolution regional climate model over the Alps a summer warming of 4-6 °C. This result was probably unrealistic since it was mainly caused by shortcomings in the simulation of the jet stream by the driving GCM in combination with an inappropriate representation of the regional soil moisture (Beniston et al., 1995; Marinucci et al., 1995). Our downscaling procedure yielded a smaller, much more plausible warming in the order of 1-3 °C (Fig. 2.12, Table 2.3). This, however, does not defy the use of regional models in principle; it only demonstrates that it is easier to obtain plausible scenarios with our method. Thus, our result may have again to be revised as improved high-resolution simulations under similar boundary conditions become available.

All scenarios were based on the critical assumption that the statistical models used for downscaling and stochastic weather generation would also hold under a changed climate. The validity of this assumption can not be strictly proven. Generally, the errors of the downscaling procedure can be expected to increase with increasing strength of climatic change (cf. Fig. 2.11). One may argue that for the near future, i.e. the next few decades, the use of first-order terms (Eq. 2.3) could be sufficient. This view is to some extent supported by analyses of GCM-experiments which suggest that future climate might not show basically new circulation types, but only a redistribution of situations already found in this century's weather record (e.g., Zorita et al., 1995). Moreover, a recent comparison of statistically downscaled changes in Romanian precipitation with results from dynamic simulations (Busuioc & von Storch, 1997) suggested that a simple linear model like the one used in the present study can correctly capture regional first-order effects of changes in the large-scale circulation. Further studies should investigate in as far this could apply also to the climatically much more complex Alpine region.

For several variables, such as summertime precipitation, performance of downscaling was relatively poor (Fig. 2.8). Possibly, better results could have been obtained by including additional large-scale predictors (such as upper-level and moisture fields), optimizing the size of the large-scale sector used for downscaling, and using a higher
(e.g., daily) temporal resolution. However, regional climatic changes also depend on systematic changes in smaller-scale climate forcings (e.g., land use), or feedbacks to the regional climate system (e.g., due to changes in vegetation cover). Such effects were not considered by the here proposed method. Nevertheless, indications from simulation studies addressing these issues (e.g., GiorGi, 1996) could be included at any time in our method by adjusting the corresponding parameters used for weather generation (cf. sensitivity analyses in section 4.4.1, sites Bever and Sion).

The used global models were far from perfect and thus also imposed their limitations upon the derived scenarios. The monthly to seasonally averaged fields used for downscaling were nevertheless reasonably well reproduced by both used models for "1xCO2" conditions (Von Storch et al., 1993; Zorita et al., 1995; McFarlane et al., 1992; and own analyses). However, the "2xCO2" responses of the two models differed considerably: for example, the change in global mean near-surface temperature in the ECHAM1/LSG model was only 1.7 °C, whereas in the CCC-GCMII it was 3.5 °C. These uncertainties in the simulation of global climate were found to affect mainly the magnitudes and seasonal patterns of the downscaled scenarios, whereas the spatial patterns of change were quite similar (sections 2.3.2 and 4.3.1). The stability of this latter result should be studied further based on the use of additional global simulations and more sophisticated downscaling procedures.

All derived scenarios were based upon specific assumptions on the future radiative forcing of the global climate. For instance, more recent projections of global climatic change, which included the cooling effect of aerosols, showed a much reduced summer warming over Europe (Kattenberg et al., 1996). This can be expected to have a strong effect on forest responses. The proposed procedure is certainly flexible enough (Fig. 4.1) to investigate such alternative scenarios as soon as they become available.

It could be argued that the suitability of the proposed method was tested but in the context of one case study. However, this completely independent case study pursued its own research goals (Chapter 4) and was therefore considered to represent a realistic research situation. Furthermore, the input requirements of the FORCLIM model (monthly mean temperature and precipitation at a resolution of ~100 m, and for at least several centuries) were representative for an entire family of models, including JABOWA (Botkin & Nisbet, 1992), FORSKA (Prentice et al., 1993), or PNt-II (Aber et al., 1995). Finally, the results of the presented analyses and the general conclusions depended only to a small extent on the case study.

More detailed dynamic models than FORCLIM would have required additional weather variables, and/or a daily temporal resolution (section 2.1). The downscaling procedure was however shown to be applicable to in principle arbitrary combinations of weather
variables (Chapter 2). For some of these variables downscaling involved large uncer-
tainties (Fig. 2.7), but these were at least quantifiable (Fig. 2.11, Table 2.3; see also
GYALISTRAS & FISCHLIN, 1995). In order to provide scenarios at a high temporal
resolution, the monthly weather generator could have been easily extended by a second
weather generator which simulates daily or even hourly weather based on monthly input
data (GYALISTRAS et al., 1997).

Static models of climate-vegetation relationships (e.g., STEPHENSON, 1990; BRZEZIECKI
et al., 1995) would have had generally less demanding requirements in terms of temporal
resolution, but they would have required spatially extended scenarios. These could have
been derived by applying the spatial interpolation procedure (Figs. 4.1, 4.7; GYALIS-
TRAS & FISCHLIN, 1996) on a regular grid. The feasibility of this approach was demon-

Hence the proposed method appears to be generally applicable to a wider range of eco-
system studies. In particular, its application to modelling studies dealing with possible
impacts of climatic change on grasslands (RJEDO et al., 1997), snow cover (ABEGG,
1996), and run-off (STADLER et al., 1997) suggest that it can be useful also in other
sectors of climate impact research.
6. Conclusions

The proposed method to derive climatic scenarios enables consistent assessments of possible impacts of global climatic change on local ecosystems. It bridges the gap between the spatial scales at which global climate models and local ecosystem models operate, and yet allows to derive transient scenarios at a high temporal resolution and over arbitrary time spans. The method is general, flexible, and efficient, and conforms to the IPCC guidelines for impact assessments (CARTER et al., 1994). Thanks to its modular structure improvements of the individual components can be easily incorporated at a later stage.

Downscaling

Use of a statistical downscaling procedure enhances the consistency of local climatic scenarios. For all Alpine locations considered and for all seasons physically plausible statistical downscaling models were found. The model's reliability varied however with the time of the year, the variable and the region considered, and was partly low for some ecologically important variables (such as growing season precipitation). The downscaled scenarios depended plausibly on the large-scale climatic changes simulated by two global climate models, they appeared realistic in view of current understanding of the involved physics, and were consistent between locations. Compared to the use of regional climate models statistical downscaling is easy to test, computationally efficient, and provides sufficient spatial detail far above the resolution of these models.

Stochastic Weather Generation

The newly proposed stochastic weather generator improves the simulation of monthly weather variables and relies upon more robust procedures to estimate the needed climatic parameters. Inclusion of autocorrelation mattered for a statistically more accurate simulation of winter minimum temperatures and growing degree-day totals, whereas use of a skewness reducing procedure for precipitation improved the simulation of a commonly used index for annual drought stress. Compared to the direct use of output from climate models the local weather generator circumvents the presently limited temporal precision of these models, is more flexible, and provides a concise description of local climates. Preliminary investigations indicated sensitivity of simulated forest compositions to changes in higher-order statistics of climate. The weather generator provided a good starting point for extensive sensitivity studies.
Conclusions

Climatic Scenarios
The application of downscaling to three model-generated scenarios of global climatic change yielded significant, complex, and spatially as well as seasonally highly variable climatic changes in the Alpine region. The scenarios depended on the choice of large-scale predictors, were dominated by changes in the large-scale temperature field, and reflected the global climate sensitivities of the driving climate models. All scenarios depicted a general warming, which was larger at the northern than at the southern slope of the Swiss Alps. A tendency towards increased precipitation was found. However, decreases were found for some locations and seasons, with partially dramatic effects on simulated forest compositions. The consistency of the climatic scenarios should be assessed further based on comparisons with alternative statistical downscaling procedures and simulations with regional climate models.

Forest Responses
The downscaled scenarios and the weather generator were combined with a forest succession model to assess possible impacts of climatic change on forests in the Alps. It was shown that under one and the same 2xCO2 scenario of global climatic change within short distances sharply contrasting forest responses may occur: minor changes in tree species composition, major changes with temporary die-back, complete disappearance of the forest, or the establishment of a new forest. The forest responses were consistent with current understanding of forest dynamics. In some cases they depended on the use of seasonally resolved scenarios. It was once more found that completely new species compositions may emerge under a changing climate, and that human assistance may be needed to help some forests to adapt.

The above results appeared reasonable in light of current knowledge of the climate system and the ecology of forests. However, they are no forecasts. They represent only projections of possible future developments which are likely to occur if the assumed global scenarios plus a series of further assumptions (Fig. 4.1; sections 2.4 and 4.4.2) would hold or actually come true. Nevertheless, our findings clearly demonstrate the potential for drastic changes in Alpine climate and forests. The here proposed methods could contribute to the development of corresponding mitigation and adaptation strategies.
7. References


References


References 95


References


References


References


Curriculum Vitae

I was born in Athens, Greece, on Sept. 17th, 1964. In 1975 my family emigrated to Munich where I visited the secondary school. In 1983 I graduated from high-school, and in the same year I began studying Electrical Engineering at the Swiss Federal Institute of Technology, ETH Zurich. In 1987 I did a semester work on modelling the response of glaciers to climatic change under the supervision of Prof. A. Ohmura, Geographical Institute ETHZ. After receiving my Diploma in 1988 I worked until 1991 part time as a software engineer, and part time as a research associate and teaching assistant at the Systems Ecology Group ETHZ, directed by Dr. A. Fischlin. From 1991 to 1992 I worked as a full-time research scientist, and from 1993 to 1995 as a self-employed scientific contractor associated with the Systems Ecology Group ETHZ. From 1991 on to the present I have been working on the derivation of climatic scenarios and their application to assess possible impacts of climatic change on forests, grasslands and snow cover in the Alpine region. Since eight years I live with my partner Barbara Davies in Zurich.