

# 1

## Introduction

All scientific investigations are concerned with obtaining a deeper understanding of the world in which we live. Such investigations may be motivated primarily by curiosity, but more often by a recognition that such an understanding is beneficial to the wellbeing of humanity. Environmental science is an area where many would argue that the current level of knowledge pales into insignificance beside the capacity to enact rapid changes on an unprecedented scale, and therefore that it is not only beneficial but essential to understand more clearly the processes at work. Examples of current concerns include the response of climate to greenhouse gas emissions and the knock-on effects in areas such as water resources, agriculture and human health; the effects of industrial activity upon the quality of air and drinking water; the implications of intensive agricultural practices for biodiversity; and the sustainability of industrial-scale fishing operations. In all of these examples, the most compelling grounds for concern are observational: increases in global mean temperatures and various indices of extreme weather (Solomon *et al.*, 2007), increases in the incidence of respiratory diseases associated with particulate matter in the atmosphere (Anderson *et al.*, 1996; Zmirou *et al.*, 1998), declines in the numbers of farmland birds in Europe (Siriwardena *et al.*, 1998) and shrinking fish catches (Pauly *et al.* 2002), to cite just a few examples.

Broadly speaking, to develop an understanding of such phenomena there are two possible approaches. The first is to consider the fundamental processes that are believed to be operating and to build a more or less detailed model of these processes that can be used to make predictions and explore alternative scenarios. Examples of this 'process based' approach include the physical and chemical models of the atmosphere and oceans that are routinely used to provide projections of the earth's climate throughout the twenty-first century (Saunders, 1999; Solomon *et al.*, 2007).

The second approach is to analyse the available data, either to look for relationships that could explain how the system works or to test hypotheses suggested by process based considerations. 'Trend analysis' can be defined as the use of such an empirical approach

to quantify and explain changes in a system over a period of time.<sup>1</sup> The statistical tools required to carry out a trend analysis range from the simple to the very advanced. However, the complexity of most environmental systems, often coupled with difficulties in making accurate observations, ensures that simple methods are rarely adequate for more than a preliminary inspection of the data. At best, such methods may fail to extract all of the available information (which, given the cost of obtaining much environmental data, is a waste of resources) and, at worst, they may yield misleading conclusions. To avoid these pitfalls it is therefore usually necessary to use more advanced methods, such as those described in the following chapters. Many of these have been developed relatively recently, and therefore are unlikely to be encountered in a traditional introductory statistics course for environmental scientists. However, all of them are well established in the statistical literature and have been found to be useful in a wide variety of applications. Furthermore, many of them can be implemented easily using freely available software.

Before proceeding any further, it is worth clarifying the subject matter of the book by defining what is meant by a ‘trend’, examining some of the questions that might lead one to carry out a trend analysis and summarising some of the difficulties and features that are commonly encountered in the analysis of environmental data. The stage will then be set for the statistics.

## 1.1 What is a trend?

We have already defined trend analysis as the investigation of changes in a system over a period of time. However, this is rather a loose definition. The use of quantitative methods requires a precise statement of the scientific question(s) of interest, framed in numerical terms. We therefore consider the behaviour of a system to be encapsulated by the values of some collection of numeric variables (for example the mean global temperature or the numbers of reported incidents of respiratory illness in a particular location) through time. In the simplest case, the data available for the analysis of such a system might consist of a sequence of regularly spaced observations of a single variable taken at equal time intervals:  $y_1, \dots, y_T$ , say. Such data are often analysed using time series analysis techniques. In the time series literature, definitions of trend often refer to changes in the mean level of such a series. Chatfield (2003) defines trend in almost exactly these terms: ‘[Trend] may be loosely defined as “long-term change in the mean level”.’ Kendall and Ord (1990) describe trend as ‘long-term movement’ – again implying a change in the mean level.

Most modern statistical methods require that an observed sequence  $y_1, \dots, y_T$  is regarded as the realised value of a corresponding sequence  $Y_1, \dots, Y_T$  of random variables. Equivalently, if all of the observations are assembled into a single column vector  $\mathbf{y} = (y_1 \cdots y_T)'$  (here and elsewhere, a prime  $'$  is used to denote the transpose of a vector or matrix), then  $\mathbf{y}$  is considered to be the realised value of a random vector  $\mathbf{Y} = (Y_1 \cdots Y_T)'$ . This viewpoint, although perhaps surprising when seen for the first time, enables scientific questions to be framed, in completely unambiguous terms, as questions about the probability distribution from which the observations were drawn. Consider, for example,

---

<sup>1</sup> The term ‘trend’ is also sometimes used to describe the variation of some quantity over a spatial region. In general, the analysis of spatial variation requires different techniques to that of temporal variation: it is therefore not the primary focus of this book. However, tools for the analysis of space–time data are considered briefly in Section 6.1, and several of the contributions to Part II consider both spatial and temporal variation.

the expected values of the random variables  $Y_1, \dots, Y_T$ :

$$E(Y_t) = \mu_t, \text{ say } \quad (t = 1, \dots, T). \quad (1.1)$$

where  $\mu_t$  can be thought of as an ‘underlying’ mean of the process at time  $t$ . In some sense then, the sequence  $\mu_1, \dots, \mu_T$  provides a formal mathematical representation of the notion of ‘change in the mean level’, and this sequence itself could be defined as the trend as in Diggle (1990, Section 1.4). If this definition of trend is accepted then, for example, the rather vague question ‘Is there a trend in my data?’ is equivalent to the much more precise ‘Are  $\mu_1, \dots, \mu_T$  all equal?’.

Although the concept of trend as ‘change in the mean level’ is ubiquitous in the time series literature, it is not universal in the environmental sciences. For example, Robson (2002) distinguishes between ‘trend’ and ‘fluctuation’:

A data series is said to show *trend* if, on average, the series is progressively increasing or decreasing. A data series shows *fluctuation* if the average of a series changes noticeably through time but not in any consistent direction.

Furthermore, environmental problems are not always focused upon the average behaviour of a process. For example, one may be interested in assessing changes in the frequency of ‘extreme’ events such as large floods or dangerously high air pollution episodes. To define ‘trend’ solely in terms of mean levels therefore seems unnecessarily prescriptive: long-term changes in any statistical properties are potentially of interest. However, the exact meaning of ‘long-term’ depends upon the application: a climatologist would probably regard a couple of degrees’ rise in global mean temperature over a period of decades as convincing evidence of a warming trend, whereas a geologist may regard this as uninteresting by comparison with changes in the frequency and severity of glacial epochs.

On the basis of these considerations, we offer the following definition as the focus of the statistical methods to be discussed in this book:

***Definition***

‘Trend’ is long-term temporal variation in the statistical properties of a process, where ‘long-term’ depends on the application.

## 1.2 Why analyse trends?

As indicated above, the use of quantitative methods requires that the objectives of an investigation are specified precisely. In general, the choice of an appropriate analysis method will depend upon the questions of interest. It is therefore worth considering the kinds of situation in which an analysis of trend might be useful. In environmental applications, possible reasons for carrying out a trend analysis include:

- (a) To describe the past behaviour of a process. For example, it may be of interest to quantify the nature and extent of changes in a region’s climate, or in some wildlife population, over a period of time.
- (b) To try and understand the mechanisms behind observed changes. A common goal is to determine whether, or to what extent, such changes are associated with human activity rather than ‘natural’ processes.

## 6 METHODOLOGY

- (c) To make assessments of possible future scenarios, by extrapolating past changes into the future. Such extrapolations are often used to assess the risk of future adverse events such as severe floods or species extinction, and also to justify the introduction of policies designed to reduce this risk if it is judged to be unacceptably high.
- (d) To monitor the effectiveness of environmental control policies. For example, if new controls are introduced to limit industrial emissions, it may be of interest to determine the extent to which a response can be detected in river chemistry and aquatic ecosystems.
- (e) To enable the analysis of systems where long-term changes serve to obscure the aspects of real interest. For example, an ecologist may be interested in studying the interactions between several species that have been steadily increasing or decreasing in abundance due to some 'external' factors; in this case, a first step in the analysis may be to identify and remove the trends so as to see more clearly the species interrelationships.

Such objectives are not unique to environmental applications, of course; however, some of them have perhaps a more central role here than in other areas.

To illustrate some of the issues that may arise in an environmental context, we now consider some simple examples that will be used for illustrative purposes throughout Part I of the book.

### 1.3 Some simple examples

#### 1.3.1 Dutch wind speeds

Our first example relates to records of hourly wind speed from 13 weather stations in the Netherlands, provided by the Royal Netherlands Meteorological Institute (KNMI). The station locations are shown in the left-hand panel of Figure 1.1. Record lengths range from 41 years (at both Beek and Hoek van Holland) to 53 years (at Schiphol); all records ran until the end of 2002 and have been carefully quality controlled and standardised using procedures described in Verkaik (2000a, 2000b). During the quality control procedure, some hourly readings were identified as suspect; some are also missing. The sites with the highest proportions of missing or suspect readings are IJmuiden (3.2%), Hoek van Holland (0.75%), Deelen (0.05%) and Gilze Rijen (0.04%). None of the remaining sites has more than 25 missing or suspect hourly readings during the entire period of record.

We highlight two applications in which the study of these data may be of interest. The first relates to engineering risk assessment. Much of the Netherlands is below sea level and is protected from inundation by dikes. The main cause of dike failure is wave damage, which itself is primarily associated with a combination of storm surges and high wind speeds (Ettema, 2001). An assessment of the wind climate of the country is therefore essential for ensuring the safety of dike systems.

The second application relates to the search for renewable energy sources. Wind power is increasingly being seen as a cheap alternative to fossil fuels. However, to provide a dependable energy supply wind speeds must be high enough to generate the required output, but not so high as to necessitate shutting down the turbines for safety reasons. To determine the long-term viability of a wind power scheme in an area therefore, an analysis of wind speed would be helpful.

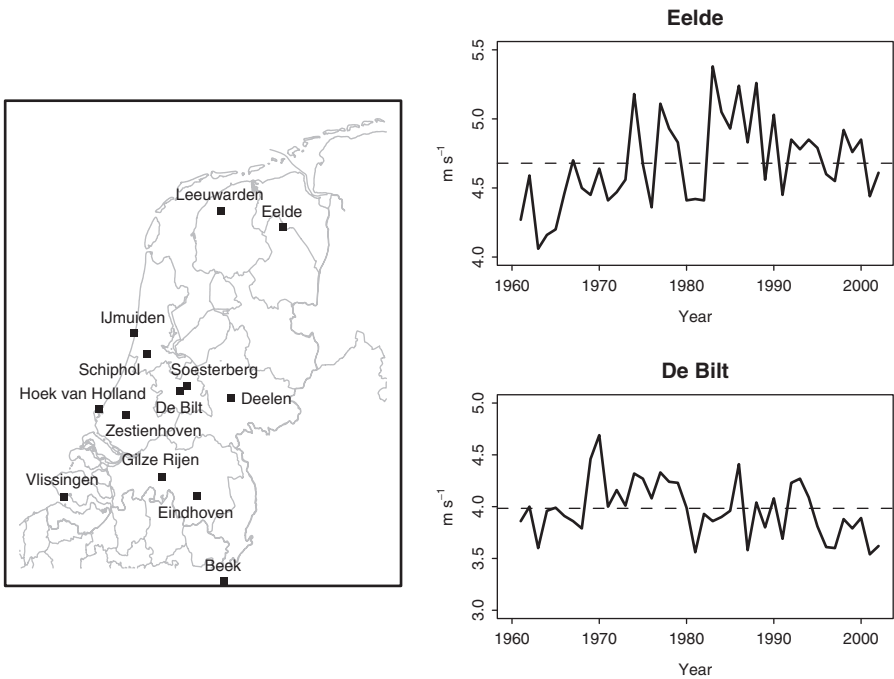


Figure 1.1 Left: locations of Dutch weather stations yielding wind speed data. Right: annual mean wind speeds for two of the stations, 1961–2002 (dashed lines indicate series means).

In both of these applications, it is clearly of interest to detect and quantify trends in wind speeds – and also, if possible, to produce useful extrapolations into the future. The objectives of a trend analysis may therefore be summarised under points (a) to (c) in Section 1.2. In an engineering risk assessment, the focus will be primarily upon the frequency of occurrence of extremely high winds; however, for wind power evaluation both high and low winds will be of interest. Motivated by such considerations, Smits *et al.* (2005) analysed the data considered here, examining trends in the annual numbers of ‘events’ of varying degrees of severity and reporting overall decreases in the frequency of high severity events between 1962 and 2002, although a couple of stations showed increases.

As a simple first step in examining these data, the right-hand panels of Figure 1.1 show the annual mean wind speeds at two of the stations from 1961 to 2002. The graph for De Bilt suggests a decrease over this period; however, there appears to be an upward trend at Eelde, at least from 1960 to the mid 1980s. Both of these findings are in line with the results of Smits *et al.* (2005, Figure 5), although the analysis here is slightly different since Figure 1.1 is concerned with mean wind speed whereas those authors studied trends in ‘severe’ events. In general, it is unwise to overinterpret the results of simple visual inspections; nonetheless, it is worth noting the possibility that trends may vary over the region.

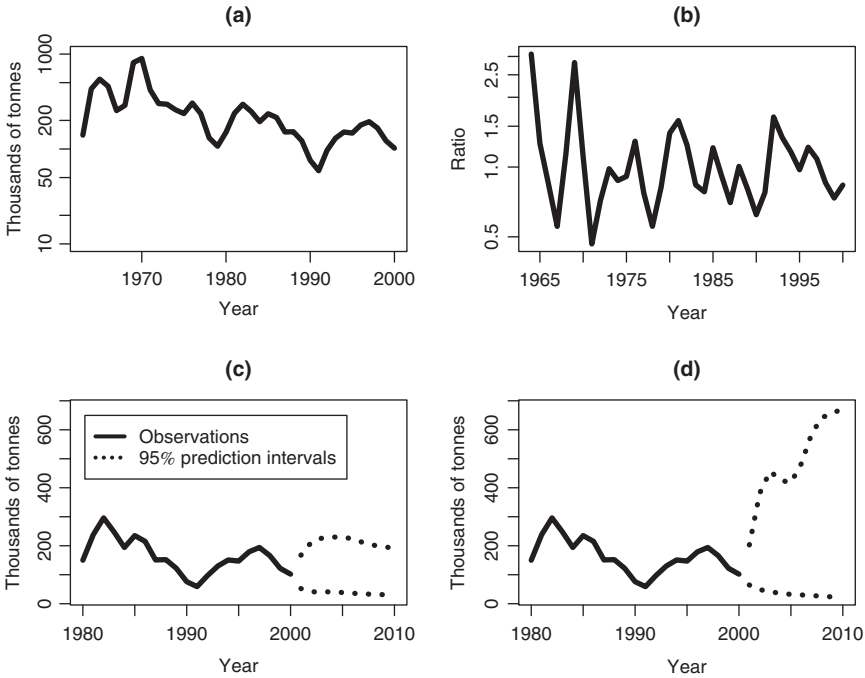


Figure 1.2 Annual North Sea haddock biomass, 1963–2000. (a) Biomass time series ( $Y_t$ ), (b) time series of ratios ( $Y_t/Y_{t-1}$ ), (c) observed time series 1980–2000, along with 95% prediction intervals to 2010 obtained using model (1.2), (d) observed time series 1980–2000, along with 95% prediction intervals to 2010 obtained using model (1.3). Logarithmic scales are used for the y axis in (a) and (b), but not in (c) and (d).

### 1.3.2 North Sea haddock stocks

Figure 1.2 shows some plots relating to annual estimates of spawning stock biomass for North Sea haddock, from 1963 to 2000. These data are from DEFRA (2004). The biomass estimates are based on mathematical models that combine information from international catches and fishing activity, along with research vessel surveys. Over time, there has been some variability in the quality of the data available for fish stock assessments. Furthermore, care needs to be taken when analysing ‘data’ that are themselves produced by a model. A complete analysis of the haddock stocks data would need to account both for the variability in data quality and for the properties of the model used to produce the data, in order to avoid overinterpreting artefacts that may be caused by either of these features (see Section 1.4.4 below). Nonetheless, for illustrative purposes in the first part of the book we will take these data at face value.

Biomass data are used in fisheries management to address, among other things, questions regarding the sustainability of current levels of fishing activity. Interest therefore lies in producing assessments of future biomass, as well as in trying to quantify the effect of fishing activity upon stocks. It is also potentially of interest to identify responses to past changes in the management of the fishery, since the nature of such responses can be used to guide future management strategy. These objectives can be

summarised under points (a) to (d) in Section 1.2. We will introduce the analysis by looking at some simple future scenarios.

Figure 1.2(a) is a time series plot of the annual stock biomass time series from 1963 to 2000, in thousands of tonnes. A logarithmic scale has been used for the  $y$  axis. This is equivalent to plotting the logged biomass time series; the only difference is that the axis is labelled in the original measurement units (which are easier to interpret than their logarithms). The plot shows an apparent linear decrease over the period of record, with constant variation about this overall linear trend. This in turn suggests that the series could be represented using a linear regression model for log biomass:

$$\log Y_t = \beta_0 + \beta_1 t + \varepsilon_t, \quad (1.2)$$

where  $Y_t$  is the biomass in year  $t$  and  $\varepsilon_t$  is an ‘error’. Linear regression models rely on the assumptions that the errors are drawn independently from normal distributions with mean zero and constant variance. We will see in Chapters 3 and 5 that for this particular data set, all of the assumptions seem to be satisfied except that of independence. The dependence between the errors can, however, be represented via a model of the form

$$\varepsilon_t = \phi_1 \varepsilon_{t-1} + \phi_2 \varepsilon_{t-2} + \delta_t,$$

where  $\delta_t$  is a sequence of independent, normally distributed random variables with zero mean and constant variance, and  $\phi_1$  and  $\phi_2$  are extra parameters. Taking time  $t = 1$  at the time of the first observation in 1963 and considering only data up to 2000, the coefficient estimates for this model are  $\hat{\beta}_0 = 5.977$ ,  $\hat{\beta}_1 = -0.034$ ,  $\hat{\phi}_1 = 0.996$  and  $\hat{\phi}_2 = -0.584$ .

An alternative strategy for analysing these data is to study the proportional increase in biomass between years  $t - 1$  and  $t$ :

$$R_t = Y_t / Y_{t-1}.$$

In a stable population, the ratio  $R_t$  is expected to fluctuate around the value 1. Figure 1.2(b) shows the values of these ratios from 1964 to 2000, again on a logarithmic scale. No ratio can be computed for 1963, because data for 1962 are not available. The series does indeed appear to fluctuate around 1 and, apart from a couple of points at the beginning of the series, shows fairly constant variability on the log scale. In Chapter 5, it is shown that the model

$$\log R_t = 0.493 \log R_{t-1} - 0.660 \log R_{t-2} + z_t$$

provides a good fit to the ratios. Here,  $(z_t)$  is another sequence of independent, normally distributed random variables with zero mean and constant variance. Since  $\log R_t = \log(Y_t / Y_{t-1}) = \log Y_t - \log Y_{t-1}$ , this model can be rewritten in terms of the actual biomass values as

$$\log Y_t = 1.493 \log Y_{t-1} - 1.153 \log Y_{t-2} + 0.660 \log Y_{t-3} + z_t. \quad (1.3)$$

In Chapter 5, we will see that models (1.2) and (1.3) both provide an excellent fit to the biomass time series; indeed, on the basis of these data it is very difficult to distinguish between them. However, the models have very different interpretations. The first asserts that over the period of record, biomass has followed a deterministic trend which is linear on the log scale. By contrast, there is no such deterministic component in the second model: here, the current year’s biomass is seen as an adjustment to that of the previous

year, so that any apparent pattern in the observed series is simply an accumulation of year-to-year variation.

The differences between the models are emphasised emphatically when they are used to make future projections. The bottom plots in Figure 1.2 show the last 20 years' observations, along with 95 % prediction intervals for each year from 2001 to 2010 under each model. The plots are drawn to the same scale and do not use logarithmic scaling for the y axes. This emphasises the practical differences between the models: (1.2) implies a continuing gradual decrease in the spawning stock, whereas the prediction intervals from (1.3) encompass scenarios ranging from a more rapid decrease to a population explosion. These differences should cause concern about the use of either model for extrapolation; we will see later on that such concerns are well founded.

This example illustrates nicely the difficulties of extrapolation. We have two models, which both fit very well to the data, but which yield radically different views of the future and hence carry different implications for fishery management. Of course, what is lacking in the analysis so far is any consideration of mechanisms that are known to affect the biomass – the models are purely descriptive. If a model could be built linking biomass to some index of fishing effort, for example, one might have much more faith in its predictions. This idea is pursued later in the book.

### 1.3.3 Alkalinity in the Round Loch of Glenhead

Since the mid 1980s it has been widely accepted that industrial emissions of, in particular, oxides of sulfur and nitrogen can be associated with the acidification of freshwater bodies and consequent damage to the associated ecosystems; see, for example, Battarbee *et al.* (1985). Recognising this, international agreements have led to substantial reductions in sulfur dioxide emissions in many countries since 1980. To monitor the response of water bodies to these emissions reductions in the UK, the United Kingdom Acid Waters Monitoring Network (UKAWMN) was set up in 1988 (Monteith and Evans, 2001). Water samples are taken at regular intervals from 11 lakes and 11 streams, representing some of the more acid sensitive freshwaters in the UK; these are then subject to chemical analysis.

Figure 1.3 shows some data from one of the UKAWMN sites, the Round Loch of Glenhead in southwest Scotland. At this site, samples are taken at roughly three-month intervals; the data in Figure 1.3 run from March 1988 to June 2002. Although there is some variation in the interobservation times, most of them are sufficiently close to three months that the series can be regarded as regularly spaced for practical purposes. The main variable of interest is alkalinity, defined as the capacity of water to neutralise an acid and measured in microequivalents of calcium carbonate per litre ( $\mu\text{eq l}^{-1}$ ). The alkalinity series in Figure 1.3 shows pronounced seasonal oscillation, with a fairly clear increase from 1996 onwards. It is of interest to determine whether this is a response to declining sulfur emissions. This could, in principle, be investigated by relating the alkalinity measurements to sulfur emissions from nearby industrial areas. Unfortunately, however, emissions data are not available at a fine enough scale to support such an analysis. Instead, therefore, sulfate concentrations in the water samples have been taken as a surrogate for sulfur deposition. This introduces a further complication: as well as industrial sulfur emissions, sulfate can be introduced as a neutral salt in sea-spray, which reaches the Round Loch in small quantities since the site is only around 30 km from the coast. The influence of marine deposition at this site is confirmed by the presence of chloride ions in the water; there is no other plausible explanation for these. Assuming that the chloride is entirely marine-derived, the amount of sulfate from marine sources can be

estimated according to the known ratio of sulfate to chloride in sea water (Evans, Monteith and Harriman, 2001). The remainder is taken as a surrogate for industrial sulfur deposition.

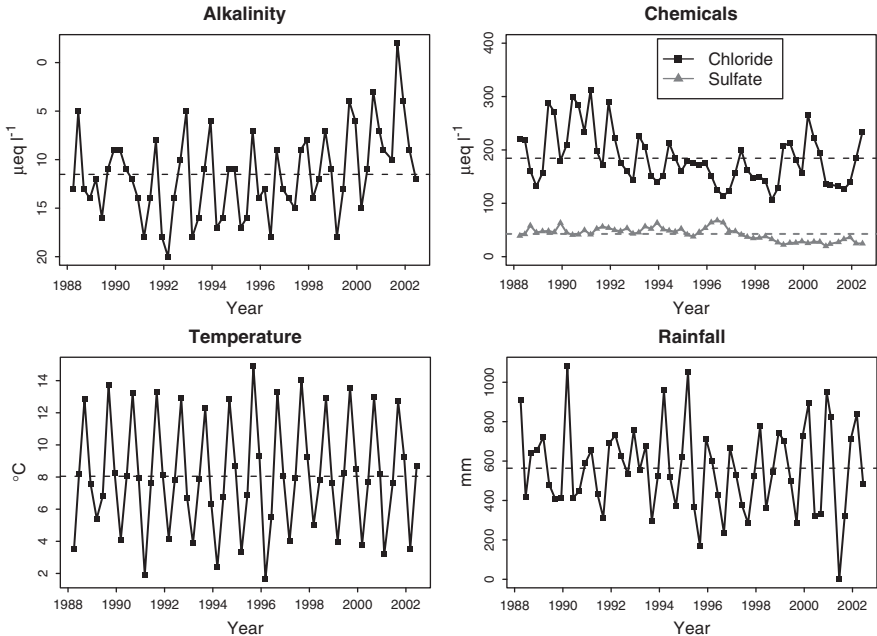


Figure 1.3 Quarterly time series of alkalinity, sulfate and chloride concentrations and meteorological variables at the Round Loch of Glenhead, 1988–2002.

The second panel of Figure 1.3 shows the quarterly time series of both chloride and nonmarine sulfate at the site. The sulfate series appears stable until about 1996, and declines thereafter; this seems consistent with the trend in alkalinity already observed, although the sulfate series shows no obvious seasonality. The chloride series in this panel is of interest because marine deposition has other effects besides the introduction of additional sulfate (Evans, Monteith and Harriman, 2001). It may therefore be worth determining whether there is any relationship between alkalinity and chloride. A quick inspection reveals that the main feature of the chloride series is a period of enhanced deposition during the early 1990s, as well as some indication of seasonality. These are both probably associated with increased rates of marine deposition when weather conditions are favourable.

Weather conditions themselves control surface water chemistry in a variety of ways: for example, weathering rates are dependent on both temperature and rainfall. The bottom two panels in Figure 1.3 show quarterly time series of temperature and rainfall from a weather station 3 km from the Round Loch, for the same period as the water chemistry data. The original data were daily; each temperature in Figure 1.3 is an average over the 91 days prior to sampling, and the corresponding rainfall is a total over the same period. Both series show pronounced seasonality. Apart from this, the temperatures appear fairly stable. The rainfall series, on the other hand, seems to show a sudden drop in the second half of 1996, with a subsequent gradual recovery to the initial level except for an unusually dry summer in 2001.

The primary motivation for this analysis is to determine whether there have been any significant changes in alkalinity at this site, and if so whether they are associated with reductions in industrial sulfur deposition. Clearly, however, the processes controlling alkalinity are complex and it is necessary to disentangle the relative contributions of weather, marine deposition and industrial deposition before we can answer the questions of primary interest. The objectives of the study can therefore be summarised under points (a), (b) and (d) in Section 1.2. The example has been chosen to illustrate a situation in which it is important to discriminate between the effects of different factors upon a quantity of interest. In Chapter 3, we show that rainfall and temperature are strongly associated with alkalinity, as is chloride; however, the existence of a relationship with sulfate is more difficult to establish.

### 1.3.4 Atmospheric ozone in eastern England

Ozone ( $O_3$ ) is generated in the lower atmosphere as a result of reactions between hydrocarbons (generated from the burning of fossil fuels) and oxides of nitrogen ( $NO_x$ ), triggered by exposure to ultraviolet radiation. Ozone is known to pose risks to human health and to be associated with increases in mortality (Anderson *et al.*, 1996); it also damages crops and vegetation (Fowler *et al.*, 1999). It has been identified as a greenhouse gas, with the potential to influence climate change as well as air quality (AQEG, 2007). As a result, many countries and organisations have defined targets that aim to limit atmospheric ozone concentrations for the protection of human health and vegetation. In the European Union (EU), for example, Directive 2008/50/EC of the European Parliament sets ozone targets; it also specifies that member states must collect, exchange and disseminate air quality information. Furthermore the World Health Organisation has issued its own recommendations (WHO, 2000) regarding levels of ozone exposure.

Against this background, the EU-funded GEOMon project<sup>2</sup> aims to collate data on various atmospheric pollutants including ozone, from a network of sites across Europe. Data from different locations have been ‘harmonised’ to ensure that they are comparable (Henne and Fleming, 2008). Figure 1.4 shows a specimen series from one of these sites, the Weybourne Atmospheric Observatory in eastern England. The series is at a daily timescale and runs from January 1989 to December 2008. However, the measurement station was resited in 1992, to a location around 2 km from its original position. This may have induced some inhomogeneity in the series, although the data harmonisation should have alleviated the problem to some extent. As with the haddock stocks example in Section 1.3.2, we will take these data at face value for illustrative purposes. For more details of the data and measurement station, see Penkett *et al.* (1999) and Fleming *et al.* (2006).

Each daily value in Figure 1.4 is an average of eight readings, taken at hourly intervals from 09:00 to 16:00 GMT. However, there are extended periods during which the station did not operate due to shortage of funding and many other days where one or more hourly readings are missing for a variety of reasons including instrument error, meteorological effects or contamination. In Figure 1.4 and all subsequent analyses, data have been used only for days with a full set of eight hourly readings. This is to avoid introducing artificial inhomogeneities, affecting variability in particular, by calculating daily means from different numbers of observations. In principle, such artefacts could be accounted for within a statistical analysis; however, by restricting attention here to days with complete data we aim to keep things reasonably simple. As a result, a total of 2821

---

<sup>2</sup> See <http://www.geomon.eu>.

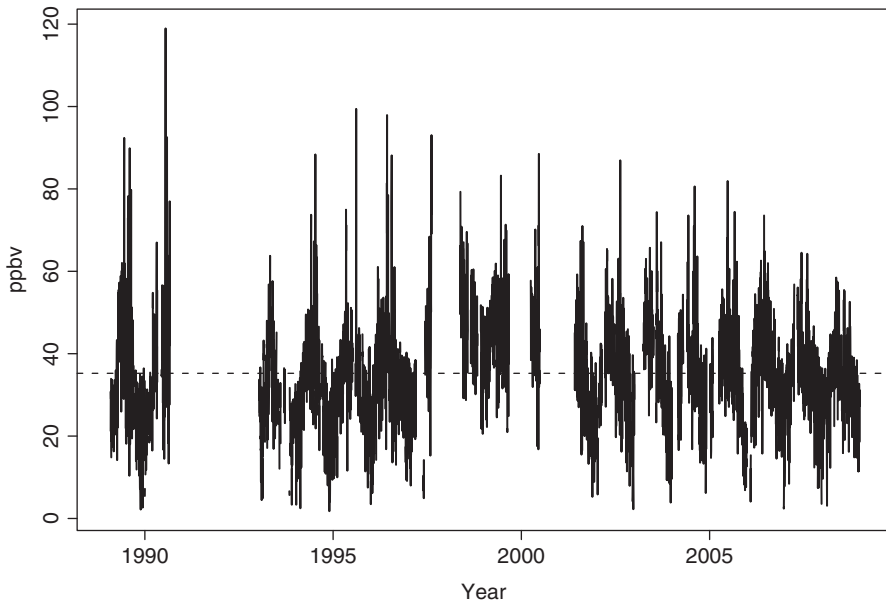


Figure 1.4 Daily ozone concentrations (parts per billion volume, ppbv) at Weybourne, Norfolk, 1989–2008. Dashed line indicates mean of available observations.

of 7305 daily readings are missing from the record as analysed here: Figure 1.4 shows the missing periods clearly. It also shows pronounced seasonality, with highest values in the summer months and an apparent decreasing trend in extreme ozone levels in particular. Overall levels seem particularly high during 1998 and 1999. However, there are many missing values during this period and it is possible that the available measurements are concentrated during the summer months when ozone levels are naturally high: thus the large proportion of missing data makes the plot difficult to interpret.

As discussed above, there is considerable interest in monitoring ozone levels across Europe, as well as in other parts of the world. With respect to Figure 1.4, questions include whether or not there are trends in the data, and if so whether these can be related to legislation that is designed to limit pollutant emissions and hence reduce ozone concentrations in the long term. These correspond to objectives (a) and (d) in Section 1.2. The mechanisms of ozone formation suggest that emissions reductions should lead in particular to declines in summer ozone peaks. Conversely, reductions in  $\text{NO}_x$  emissions are thought to create conditions that are more favourable for ozone formation during the winter months; one might therefore expect increasing ozone trends in winter. Figure 1.4 suggests that there is indeed a gradual decline in peak ozone values over time, although any trends during winter are not immediately apparent. Given that the seasonality is of particular interest, it would be useful to be able to extract a ‘seasonal’ component from the data so as to visualise any changes more clearly. From this perspective, other features of the data – such as irregular episodes or long-term changes in the mean level – may be seen as a nuisance that obscures some of the structure of interest. Thus, objective (e) in Section 1.2 is also relevant: if we can identify any overall trend in the data, we can then remove it and examine the seasonal cycle in more detail.

This example has been chosen primarily because it provides an opportunity to illustrate methods for the analysis of series with large proportions of missing data. This situation is not uncommon in environmental applications.

## 1.4 Considerations and difficulties

The examples above highlight some features that are commonly encountered in environmental studies. These include missing or irregularly spaced observations, data quality issues due to measurement difficulties and the analysis of data from a network of sites. The need to accommodate such features will often be an important consideration when determining an appropriate strategy for analysis, along with several other issues of a statistical nature. We here outline some of the issues that will be discussed in greater depth later in the book. For a perspective on wider considerations that might be relevant in any statistical investigation, the excellent review by Cox (2007) is strongly recommended.

### 1.4.1 Autocorrelation

Most ‘standard’ statistical techniques assume that the available data can be regarded, at some level, as an independent random sample from a ‘population’ of interest. This assumption is critical to the construction of standard hypothesis tests and confidence intervals. Of necessity, however, a trend analysis invariably relies upon the analysis of time series data and, in general, successive observations in a time series will not be independent. Consider, for example, a time series of hourly wind speeds from one of the Dutch weather stations in Figure 1.1. High wind speeds are associated with storms that may last for several hours or even days: therefore, if the wind speed at 9 a.m. today is much higher than average for the time of year, it is likely that the wind speed at 10 a.m. will also be higher than average.

Dependence between successive observations in a time series is referred to as ‘autocorrelation’. In practice, autocorrelation is mostly (but not always) positive, as in the wind speed example: high and low values tend to cluster together more than would be expected in an independent sequence. This clustering can sometimes be mistaken for a trend, especially in relatively short series. A more sophisticated view is that a positively autocorrelated sequence contains less information than the same number of independent observations, so that the ‘effective sample size’ is reduced in the presence of positive autocorrelation. Therefore, techniques based on independent observations will tend to overestimate the precision with which quantities of interest can be estimated. To see this, consider a ‘perfectly autocorrelated’ sequence  $y_1, \dots, y_T$  in which  $y_1$  is drawn from some probability distribution and then  $y_2 \dots, y_T$  are all set equal to  $y_1$  – there is clearly only one observation’s worth of information here.

There are several simple ways to account for autocorrelation in ‘standard’ analyses (for example by studying annual rather than hourly wind speed series because successive annual values are likely to be effectively independent). In general, however, it is preferable to use analysis methods that are specifically designed for use with autocorrelated data. Several such methods will be described in this book: the fact remains, however, that to discriminate between long-term changes and the effects of autocorrelation is often one of the most difficult tasks in a trend analysis.

### 1.4.2 Effect of other variables

Environmental processes do not evolve in isolation. To some extent, therefore, it is not possible to study any environmental variable without considering other aspects of the system to which it belongs. In a trend analysis, failure to do this may lead to genuine trends remaining undetected because they are ‘masked’ by the effects of other variables; or to uninteresting trends being identified because they are merely a response to changes in another variable. The Round Loch water chemistry study in Section 1.3.3 is a good example of this, since trends in the alkalinity of the loch could conceivably be ascribed to changes in industrial emissions, to changing weather conditions or to changes in the frequency of marine deposition events.

The need to allow for competing explanations of an observed trend is fairly obvious. The potential of other variables to obscure trends is perhaps slightly less so. Essentially, the problem is that trends usually contribute a relatively minor amount to the overall variability of a process, by comparison with other factors such as seasonality. ‘Unexplained variability’ is effectively synonymous with ‘uncertainty’ – hence, unless known sources of the variability in a process are acknowledged explicitly, it becomes difficult to make definitive statements about other aspects.

Broadly speaking, there are two ways of accounting for the effects of other variables in an analysis. The first, sometimes referred to as *normalisation*, is to adjust the variable of interest in some way beforehand. The second is to carry out inference within the framework of a statistical model that explicitly represents the possible effects of all relevant factors simultaneously. Normalisation is often used to adjust for seasonality. For example, when analysing a monthly series containing a strong seasonal cycle, a crude procedure (which is not generally to be recommended except for very preliminary purposes, for reasons that will be explained later) is to estimate the seasonal cycle by calculating the mean for each month of the year and to subtract this estimated cycle from the data prior to further analysis.

### 1.4.3 Lack of designed experiments

The emergence of statistical science as a serious discipline in its own right is generally credited to the work of Karl Pearson, Ronald Fisher and others in the first quarter of the twentieth century. The techniques developed at this time include procedures such as the Student  $t$  test, use of the correlation coefficient to quantify and test for association, maximum likelihood estimation and the analysis of variance. These techniques have found their way into almost all areas of quantitative investigation. It is worth bearing in mind, however, that many of them were originally intended for use in very specific and relatively simple situations. To illustrate this, consider the comparison of two groups of observations obtained under experimental conditions that are, as far as possible, identical except for a single factor of interest. Here, it is plausible to write down a mathematical model for the probability distributions generating the data and to postulate that the scientific question of interest (‘Does the factor of interest have any effect on the outcome?’) is directly equivalent to a question about these probability distributions (for example, ‘Do they have different means?’). The most common approach to this problem is the hypothesis test: simplify the model by assuming that the two distributions have the same mean, and

determine whether or not the data are consistent with this simpler model. If not, it is concluded that the factor of interest has a genuine effect upon the outcome.

The argument above is fairly standard in introductory statistics texts and courses, and underpins all hypothesis testing procedures. The basic principle is to compare a ‘simple’ mathematical model with an ‘extended’ version; evidence against the former is then regarded as evidence in support of the latter. However, this logical step is not always valid. Strictly speaking, if the data are not consistent with the simpler model then all we can conclude is that the simpler model may be incorrect. In the example above, the experiment is constructed in such a way that the most plausible alternative explanation is that the factor of interest affects the outcome. In many environmental problems, however, it is not possible to construct experiments in this way (Fisher’s work on the design of agricultural experiments in the 1920s is a notable exception) and analyses are often restricted to available data that may have been collected for an entirely different purpose. Moreover, even if experiments can be designed it is not always possible to follow the protocol exactly: Manly (2001) gives examples of this, as well as a good discussion of general design issues for environmental applications. Finally, the complexity of environmental processes ensures that no model can truly capture the mechanism that generated the data – hence any ‘simple’ model is almost guaranteed to be incorrect!

It would be unduly pessimistic to conclude from this that hypothesis tests and other conventional statistical techniques have no place in environmental investigations. It should be clear, however, that the results of such procedures need to be interpreted carefully and thoughtfully: statistical methods (and hypothesis tests in particular) should not be regarded as a universal panacea for answering questions of interest. For example, it is not uncommon to see an analysis of trends over some region, in which a test for trend has been performed at different locations and a map has been produced showing the areas where ‘significant’ trends have been found. The implication of such a map, intentional or not, is that trends exist in these areas but not elsewhere. In reality, of course, it is much more likely that there are trends everywhere but that they vary over the region: if a trend is statistically insignificant at a particular location, this merely indicates that it is relatively weak.

#### 1.4.4 Consideration of auxiliary information

All statistical analyses are designed to assist in the interpretation of data. Most ‘classical’ procedures operate by taking the recorded values of variables of interest, carrying out some mathematical operations on these values and producing summary information (such as regression coefficients and  $p$ -values) that can be interpreted by the analyst. By definition, the conclusions from such analyses are limited to the information contained in the values analysed. However, these values rarely tell the whole story: they are often accompanied by different types of auxiliary information. This might involve aspects of data quality (for example the knowledge that measurements have been obtained using a variety of different techniques), as well as a more or less detailed understanding of the process being studied.

A simple (nonenvironmental) example serves to illustrate the potential usefulness of auxiliary information. Suppose we wish to determine the probability that a tossed coin will show heads. The coin is tossed 10 times and six heads are obtained. On the basis of these data alone, the estimated probability of obtaining heads is 0.6; the associated standard error is 0.076, so that an approximate 95% confidence interval for the true underlying probability is  $0.6 \pm (1.96 \times 0.076) = (0.45, 0.75)$ . Few people would accept that this confidence interval provides a realistic assessment of uncertainty in this example: centuries of experience, along with the geometry of the situation (a coin is effectively

symmetric so there is no reason to prefer one side over the other), suggest that the probability of obtaining heads is extremely close to 0.5 for most coins. It would be extremely useful to be able to incorporate such information into an analysis.

Of course, environmental problems are much more complex than this. Nonetheless, there are few (if any) cases where the investigator has no understanding of the processes involved prior to seeing the data. In many applications, process based models (discussed at the beginning of this chapter) provide a particularly rich source of auxiliary information. Of course, these models are themselves approximations of reality, and different process based models of the same system can yield rather different outputs (see, for example, the projections of global mean temperature produced by different climate models in Meehl *et al.*, 2007). It is clear, therefore, that neither statistical models based solely on measurements nor process based models based primarily upon physics and chemistry can provide a complete solution to a given problem. In many application areas, it is increasingly being recognised that there is a need for better integration of the two modelling approaches.

In very simple terms, the main challenge in developing an integrated modelling approach is to determine the relative importance to be attached to each source of information (in the coin-tossing example, most people would attach much more importance to their prior understanding of coins than to the observations from a small number of tosses). In fact, this is the main issue to be confronted when dealing with any type of auxiliary information – for example, if some observations are known to be more accurate than others then it is natural to give them more ‘weight’ in an analysis. Some types of auxiliary information can be accommodated straightforwardly, for example by using an appropriate criterion to attach explicit weights to each observation according to its accuracy. In general, however, more sophisticated techniques may be required. In particular, Bayesian methods provide an appealing conceptual framework within which to represent the relationships between different sources of information, as well as the uncertainties involved.

### 1.4.5 The necessity of extrapolation

In Section 1.2, it was noted that one possible reason for carrying out a trend analysis is to gain some insight into the future. Of course, no observations are ever available beyond the present. We are not the first to note that it can be dangerous to stray beyond the limits of the available data – indeed, elementary statistics courses and texts invariably carry a strong warning against doing so. If insight into the future is required, however, extrapolation beyond the available data is unavoidable. It would hardly be appropriate to argue that the design of flood defences is futile because it is dangerous to assess future flood risk on the basis of past observations! What *is* appropriate, however, is to recognise the difficulty of the problem and to proceed extremely carefully when using statistical (or, indeed, any other) methods for extrapolation purposes. A particular challenge is to quantify, reliably and credibly, the uncertainty associated with an extrapolation or forecast.

Quantitative extrapolation, and assessment of the associated uncertainty, is invariably based on models. The main reason for this is that the only alternative is to make a more or less educated guess. However, there are two difficulties with model based extrapolation. Firstly, as in the haddock stocks example described in Section 1.3, there will usually be many models that provide apparently reasonable descriptions of the available data, but that have very different implications for the future; and, secondly, there is always a danger of unforeseen future changes to the system that invalidate the current model. It is almost guaranteed that any model will fail at some point in the future since, as noted

previously, a model is at best an approximation to a complex system. In this context, careful modelling involves:

- Incorporating, as far as possible, knowledge of the mechanism that generated the data, particularly if there are grounds for believing that this mechanism will remain largely unchanged in the future. For example, fishing activity in the North Sea is the primary driver of trends in fish stocks there. Relationships between fishing activity and population growth can be deduced from simple principles that may be expected to hold quite generally (Haddon, 2001); confidence in extrapolations will be increased if they use these relationships.

A potential difficulty with this approach is that to derive extrapolations for the variables of interest, it is necessary to know the future values of other variables as well (in the example above, to forecast fish stocks it will be necessary to know about future fishing activity). There are two potential solutions to this problem. The first is to exploit relationships with variables that can, in principle, be controlled – this enables a variety of scenarios to be presented (the consequences of different fishery management options could be compared, for example). The second is to exploit relationships with variables for which ‘trusted’ extrapolations exist. This is the basis of ‘downscaling’ in climatology (Wilby and Wigley, 1997), in which the aim is to produce future scenarios for variables of interest at a fine spatial scale. Here, large atmosphere–ocean general circulation models (GCMs) are often regarded as producing useful extrapolations of some variables at large spatial scales (e.g. mean global temperature), but the finer-scale structure is generally accepted as less reliable. Downscaling therefore aims to construct plausible models for the relationships between the variables of interest and the large-scale structures, and then to use the GCM outputs to drive the future scenarios.

- Making full use of auxiliary information, as discussed above, to guide the selection of an appropriate model. When building models for medium- or long-term extrapolation, it can be particularly useful to consider what is known about the long-term behaviour of a system. In this respect, environmental problems often yield more information than those in other areas such as economics. This is because many environmental systems are forced to operate within defined limits, which provide some (albeit limited) knowledge of the very long-term future. Few people would disagree, for example, that global mean temperature will remain within tens of degrees of its current value during any timescale of potential interest (which, for some environmental applications such as the safety assessment of nuclear waste repositories, can run into hundreds of thousands of years). By contrast, many of the models commonly used for forecasting and extrapolation have the property that the uncertainty in a forecast grows without bound as the forecast horizon increases. Such models may provide perfectly adequate approximations for short-term extrapolations of global mean temperature, but probably should not be used in the longer term.
- Understanding clearly the limitations of the model being used and, as far as possible, being explicit about the kinds of future event that could lead to failure of the extrapolations or their uncertainty assessments.

To some extent, the last point here is the most important: the limitations of forecasts must be recognised if the information they provide is to be used effectively. Unfortunately, in environmental science as elsewhere, the provision of information regarding

the limitations of future projections is often inadequate at present. There is growing recognition that some assessment of uncertainty needs to be provided, but this on its own is not enough: it is also necessary to demonstrate that the uncertainty assessment is realistic, or at least credible. This can only be achieved by carrying out projections, with uncertainty assessments, for observations that were not used in the model-building process and then using a suitable measure to compare these observations with both the projections and the uncertainty assessment. This topic will not be treated further in this book; there is, however, an extensive literature on the subject. A good starting point, for atmospheric scientists in particular, is Jolliffe and Stephenson (2003). For its insights into the dangers of extrapolation in general, Chatfield (2000) is also worth reading.

## 1.5 Scope of the book

The remainder of Part I is intended as a handbook of modern statistical methods that may be useful for the analysis of environmental trends. The methods are illustrated using simple examples, chosen primarily for clarity of exposition. For a similar reason, Part I focuses mostly on situations in which there is a single series of primary interest (although one might be interested in examining the possibility that trends in this series are associated with changes in other factors). The simultaneous analysis of trends in several series (for example wind speed records from all of the Dutch weather stations shown in Figure 1.1) introduces additional complications that are not helpful at an introductory level. Chapter 6 provides pointers to some more advanced and specialised techniques, and serves as a stepping stone to Part II of the book.

Part II presents four substantial case studies, in which modern statistical methods of trend analysis have been applied to real environmental problems. The problems considered here are more involved than the simple examples presented in Part I: they serve to illustrate how the basic techniques can be used in more complicated situations, as well as to indicate some extensions that may be needed to meet the requirements of a particular application.

The book is aimed at researchers and graduate students in environmental science, as well as at statisticians. The reader is assumed to be familiar, at an operational level, with the basic statistical concepts of estimation, confidence intervals, hypothesis testing and regression. Some exposure to probability distributions and random variables (again at an operational level) would also be helpful, although this is not essential. Most introductory statistics courses will provide the required level of background knowledge. For those wishing to consolidate their statistical background, there are a number of books on the market that give an overview of statistical methods for more or less specialised environmental problems; some of these are summarised in Section 1.6 below.

Throughout Part I of the book, techniques are illustrated where possible using software written in the statistical programming environment R (R Development Core Team, 2004). R is based on the S language, which is designed for easy implementation of a wide range of advanced statistical and graphical procedures. It is rapidly becoming the computing environment of choice within the statistical research community: apart from the attractive price (it is free), this is mainly due to its flexibility and the ease of developing add-on packages to implement new methods. The Comprehensive R Archive Network (CRAN)<sup>3</sup> provides a means of distributing user-contributed packages that extend the basic

---

<sup>3</sup><http://cran.r-project.org/mirrors.html>.

capabilities of the environment. In practice, this means that tested implementations of the latest statistical methods are freely and widely available. Such resources are enormously valuable: without them, it is unlikely that many applied researchers would have the time or the energy to try out many of the methods described in this book. As it is, the difficult work has all been done: all that is required is to know what methods are available, and to experiment with them!

The data sets used in the examples can all be downloaded from the website for the book,<sup>4</sup> as can the R scripts used in the analyses. Those unfamiliar with R may wish to use these scripts as models for their own work. Introductory texts on the S language, and on R in particular, include Dalgaard (2002), Fox (2002) and Maindonald and Braun (2003). Venables and Ripley (1999) is a compact and comprehensive reference source.

## 1.6 Further reading

The techniques covered in the book are largely drawn from the areas of time series analysis and regression modelling: smoothing methods are particularly important in the latter context. Although references are provided throughout the text, at this stage it may be useful to suggest other books that give an accessible overview of these areas. In addition, we indicate some texts that provide an introduction to statistical methods for environmental applications. In the latter category, Manly (2001) provides a clear and accessible overview of a wide variety of topics in environmental statistics; his discussion of the design of experiments for environmental monitoring and trend detection is particularly useful in the current context. More modern statistical developments are covered by Piegorsch and Bailer (2005); the treatment here is slightly more advanced, although still accessible to a general readership. Townend (2003) is another good general introductory text. Oceanic and atmospheric scientists may find Thiebaut (1994) and Wilks (2005) helpful.

For an introduction to time series analysis, Chatfield (2003) is one of the most popular books on the market; it contains an accessible overview of the subject, along with pointers to other relevant literature. For an accessible and detailed discussion of trends from a time series perspective, Kendall and Ord (1990) is hard to beat; unfortunately, this is now out of print, but copies should still be available in libraries. Brockwell and Davis (2002) and Diggle (1990) are also useful references.

The basics of regression analysis are covered by most introductory texts such as those cited already; for a slightly more in-depth treatment it may be necessary to consult a standard statistical text such as Rice (2006) or Wackerly, Mendenhall and Scheaffer (2007). Weisberg (2005) and Draper and Smith (1998) provide detailed accounts of regression methods, starting at an introductory level. Fox (2002) and Faraway (2005) specifically focus on the use of R for regression analyses, while Krzanowski (1998) provides a good overview that includes extensions such as generalised linear models (covered in Section 3.5 of the present volume). In a time series context, the main difficulty is the potential presence of dependence between successive observations. The econometrics literature is probably the best place to look for general information regarding regression methods in the presence of such dependence – Davidson and Mackinnon (2004) and Greene (2003) both deal with the subject. For an introduction to nonparametric regression, which is used extensively in the following chapters, Bowman and Azzalini (1997) is highly recommended: it contains many worked examples using the R environment. Another good book, at a slightly more technical level, is Simonoff (1996).

---

<sup>4</sup>[http://www.wiley.com/go/trend\\_detection](http://www.wiley.com/go/trend_detection).

At several places in Part I, the relevant theory is most easily expressed using matrix notation. We assume familiarity with matrix multiplication, as well as the definitions and properties of matrix transposes and inverses. Readers unfamiliar with these concepts may care to consult a linear algebra text such as Poole (2006) or Cohn (1994), or one of several books that collect together the results that are most useful in statistical applications: Healy (2002) and Chapter 2 of Manly (1994) both contain excellent, compact and nontechnical summaries, whereas Searle (1982) and Schott (1997) are more detailed.

## References

- Anderson, H. R., de Leon, A. P., Bland, J. M., Bower, J. S. and Strachan, D. P. (1996) Air pollution and daily mortality in London: 1987–92. *British Medical Journal*, **312**, 665–669.
- AQEG (2007) Air quality and climate change: a UK perspective Third Report of the UK Air Quality Expert Group. DEFRA Publications, London. Available from <http://www.defra.gov.uk/environment/quality/air/airquality/publications/>.
- Battarbee, R. W., Flower, R. J., Stevenson, A. C. and Rippey, B. (1985) Lake acidification in Galloway: a palaeoecological test of competing hypotheses. *Nature*, **314**, 350–352.
- Bowman, A. W. and Azzalini, A. (1997) *Applied Smoothing Techniques for Data Analysis – The Kernel Approach with S-Plus Illustrations*, vol. 18, Oxford Statistical Science Series. Oxford University Press, Oxford.
- Brockwell, P. J. and Davis, R. A. (2002) *Introduction to Time Series and Forecasting*, 2nd edition. Springer-Verlag, New York.
- Chatfield, C (2000) *Time-Series Forecasting*. Chapman and Hall/CRC, Boca Raton, Florida.
- Chatfield, C. (2003) *The Analysis of Time Series – An Introduction*, 6th edition. Chapman & Hall/CRC Press, Boca Raton, Florida.
- Cohn, P. M. (1994) *Elements of Linear Algebra*. Chapman and Hall/CRC Press, Boca Raton, Florida.
- Cox, D. R. (2007) Applied statistics: a review. *Annals of Applied Statistics*, **1**, 1–16.
- Dalgaard, P. (2002) *Introductory Statistics with R*. Springer-Verlag, New York.
- Davidson, R. and Mackinnon, J. G. (2004) *Econometric Theory and Methods*. Oxford University Press, New York.
- DEFRA (2004) Department for Environment, Food and Rural Affairs: e-Digest of Environmental Statistics. Available from <http://www.defra.gov.uk/environment/statistics/index.htm>.
- Diggle, P. J. (1990) *Time Series: A Biostatistical Introduction*, Oxford University Press, Oxford.
- Draper, N. R. and Smith, H. (1998) *Applied Regression Analysis*, 3rd edition. John Wiley & Sons, Inc., New York.
- Ettema, J. (2001) Analysis of wind fields for wind climate assessment of the Netherlands. Technical Report, Royal Netherlands Meteorological Institute (KNMI), De Bilt, the Netherlands. Available from <http://www.knmi.nl/samenw/hydra/documents/windfields/index.html>.
- Evans, C. D., Monteith, D. T. and Harriman, R. (2001) Long-term variability in the deposition of marine ions at west coast sites in the UK Acid Waters Monitoring Network: impacts on surface water chemistry and significance for trend determination. *Science of the Total Environment* **265**, 115–129.
- Faraway, J. J. (2005) *Linear Models with R*. Chapman & Hall/CRC, Boca Raton, Florida.
- Fleming, Z. L., Monks, P. S., Rickard, A. R., Bandy, B. J., Brough, N., Green, T. J., Reeves, C. E. and Penkett, S. A. (2006) Seasonal dependence of peroxy radical concentrations at a Northern hemisphere marine boundary layer site during summer and winter: evidence for radical activity in winter. *Atmospheric Chemistry and Physics*, **6**, 5415–5433.

- Fowler, D., Cape, J. N., Coyle, M., Flechard, C., Kuylenstierna, J., Hicks, K., Derwent, D., Johnson, C. and Stevenson, D. (1999) The global exposure of forests to air pollutants. *Water, Air, and Soil Pollution*, **116**, 5–32.
- Fox, J. (2002) *An R and S-PLUS Companion to Applied Regression*. Sage Publications, Thousand Oaks, California.
- Greene, W. H. (2003) *Econometric Analysis*, 5th edition. Prentice-Hall, New Jersey.
- Haddon, M. (2001) *Modelling and Quantitative Analysis in Fisheries*. Chapman & Hall/CRC, Boca Raton, Florida.
- Healy, M. J. R. (2002) *Matrices for Statistics*, 2nd edition. Oxford University Press, Oxford.
- Henne, S. and Fleming, Z. (2008) GEOMon harmonized data set of in-situ ground based data of O<sub>3</sub>, NO<sub>2</sub>, CO. Technical Report, GEOMon project. Available from <http://geomon.empa.ch/index.php>. Accessed 1 September 2010.
- Jolliffe, I. T. and Stephenson, D. B. (eds) (2003) *Forecast Verification: a Practitioner's Guide in Atmospheric Science*. John Wiley & Sons, Ltd, Chichester.
- Kendall, M. and Ord, J. (1990) *Time Series*, 3rd edition. Edward Arnold.
- Krzanowski, W. J. (1998) *An Introduction to Statistical Modelling*. Arnold, London.
- Maindonald, J. H. and Braun, J. (2003) *Data Analysis and Graphics Using R: An Example-Based Approach*. Cambridge University Press, Cambridge.
- Manly, B. F. J. (1994) *Multivariate Statistical Methods: A Primer*, 2nd edition. Chapman & Hall/CRC, Boca Raton, Florida.
- Manly, B. F. J. (2001) *Statistics for Environmental Science and Management*. Chapman and Hall/CRC, Boca Raton, Florida.
- Meehl, G. A., Stocker, T. F., Collins, W. D., Friedlingstein, P., Gaye, A. T., Gregory, J. M., Kitoh, A., Knutti, R., Murphy, J. M., Noda, A., Raper, S. C. B., Watterson, I. G., Weaver, A. J. and Zhao, Z. C. (2007) Global climate projections. In *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change* (eds. S. Solomon, D. Qin, M. Manning, Z. Chen, M. Marquis, K. Averyt, M. Tignor, and H. Miller.) Cambridge University Press Cambridge. pp. 747–845.
- Monteith, D. T. and Evans, C. D. (2001) United Kingdom Acid Waters Monitoring Network Summary Report. UK Department of the Environment, Transport and the Regions.
- Pauly, D., Christensen, V., Guenette, S., Pitcher, T. J., Sumaila, U. R., Walters, C. J., Watson, R. and Zeller, D. (2002) Towards sustainability in world fisheries. *Nature*, **418** (6898), 689–695.
- Penkett, S. A., Plane, J. M. C., Comes, F. J., Clemitshaw, K. C. and Coe, H. (1999) The Weybourne Atmospheric Observatory. *Journal of Atmospheric Chemistry*, **33**, 107–110.
- Piegorsch, W. W. and Bailer, A. J. (2005) *Analyzing Environmental Data*. John Wiley & Sons, Ltd, Chichester.
- Poole, D. (2006) *Linear Algebra: A Modern Introduction*, 2nd edition. Thomson Brooks/Cole, Belmont, California.
- R Development Core Team (2004) *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0.
- Rice, J. (2006) *Mathematical Statistics and Data Analysis*, 3rd edition. Duxbury Press, Belmont, California.
- Robson, A. J. (2002) Evidence for trends in UK flooding. *Philosophical Transactions of the Royal Society, London*, **A360**, 1327–1343.
- Saunders, M. A. (1999) Earth's future climate. *Philosophical Transactions of the Royal Society, London*, **A 357**, 3459–3480.
- Schott, J. R. (1997) *Matrix Analysis for Statistics*. John Wiley & Sons, Inc., New York.
- Searle, S. R. (1982) *Matrix Algebra Useful for Statistics*. John Wiley & Sons, Inc., New York.
- Simonoff, J. (1996) *Smoothing Methods in Statistics*. Springer-Verlag, New York.

- Siriwardena, G. M., Baillie, S. R., Buckland, S. T., Fewster, R. M., Marchant, J. H. and Wilson, J. D. (1998) Trends in the abundance of farmland birds: a quantitative comparison of smoothed Common Birds Census indices. *Journal of Applied Ecology*, **35**, 24–43.
- Smits, A., Klein Tank, A. M. G and Können, G. P. (2005) Trends in storminess over the Netherlands, 1962–2002. *International Journal of Climatology*, **25**, 1331–1344.
- Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K. B., Tignor, M. and HLM (eds.) (2007) *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the IPCC*. Cambridge University Press, Cambridge.
- Thiebaut, H. J. (1994) *Statistical Data Analysis for Ocean and Atmospheric Sciences*. Academic Press, New York.
- Townend, J. (2003) *Practical Statistics for Environmental and Biological Scientists*. John Wiley & Sons, Ltd, Chichester.
- Venables, W. N. and Ripley, B. D. (1999) *Modern Applied Statistics with S-Plus*. Springer-Verlag, New York.
- Verkaik, J. (2000a) Documentatie windmetingen in Nederland (documentation on wind speed measurements in the Netherlands). Technical Report, Koninklijk Nederlands Meteorologisch Instituut. Available from <http://www.knmi.nl/samenw/hydra/documents/docum0.htm> (in Dutch).
- Verkaik, J. (2000b) Evaluation of two gustiness models for exposure correction calculations. *Journal of Applied Meteorology*, **39**, 1613–26.
- Wackerly, D., Mendenhall, W. and Scheaffer, R. (2007) *Mathematical Statistics with Applications*, 7th edition. Duxbury Press, Belmont, California.
- Weisberg, S. (2005) *Applied Linear Regression*, 3rd edition. John Wiley & Sons, Inc., Hoboken, New Jersey.
- WHO, (2000) Guidelines for air quality. World Health Organisation, Geneva. Available from [http://whqlibdoc.who.int/hq/2000/WHO\\_SDE\\_OEH\\_00.02\\_pp1-104.pdf](http://whqlibdoc.who.int/hq/2000/WHO_SDE_OEH_00.02_pp1-104.pdf).
- Wilby, R. L. and Wigley, T. M. L. (1997) Downscaling general circulation model output: a review of methods and limitations. *Progress in Physical Geography*, **21**, 530–548.
- Wilks, D. S. (2005) *Statistical Methods in the Atmospheric Sciences*. Academic Press, London.
- Zmirou, D., Schwartz, J., Saez, M., Zanobetti, A., Wojtyniak, B., Touloumi, G., Spix, C., de Leon, AP., Le Moulllec, Y., Bacharova, L., Schouten, J., Ponka, A. and Katsouyanni, K. (1998) Time-series analysis of air pollution and cause-specific mortality. *Epidemiology*, **9**, 495–503.

