Uncertainty in Remote Sensing and GIS

Edited by

GILES M. FOODY and PETER M. ATKINSON

Department of Geography, University of Southampton, UK
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FORWARD WITH UNCERTAINTY

'It is certain because it is impossible' (Tertullianus, 210, Ch5).

This much quoted paradox describes one end of an uncertainty continuum. For instance, we are certain that we will not be able to measure cows jumping over the moon. However, if we knew from previous measurements that 1% of all cats were co-located with fiddles then we could say how uncertain any of our measurements of cat-fiddle pairings would be. These two measurement uncertainty examples, although apparently trivial, are also examples of uncertainty in understanding and so are worth exploring further. In the former we think we understand the processes involved (cows can’t jump that high) while in the latter we do not understand the processes involved (why are some cats co-located with fiddles?). The world we think we understand we can try to manage or even control via such disciplines as engineering and planning. The world we do not understand spans from reasonably certain to very uncertain (May, 2001a) and falls within the realm of science (Krebs, 2002). To avoid confusion between uncertainty in measurement and uncertainty in understanding it is helpful to first define uncertainty in understanding in no uncertain (although rather gender-specific) terms.

‘When a scientist doesn’t know the answer to a problem he is ignorant. When he has a hunch as to what the result is, he is uncertain. And when he is pretty darn sure of what the result is going to be, he is still in some doubt. We have found it of paramount importance that in order to progress we must recognise our ignorance and leave room for doubt. Scientific knowledge is a body of statements of varying degrees of certainty – some most unsure, some nearly sure, but none absolutely certain’ (Feynman, 1988, p. 245).

Regardless of our degree of understanding the knowledge upon which our understanding is built is derived increasingly from measurement. However, measurement alone is not enough:

‘to serve the purposes of science the measurements must be susceptible to comparison. And comparability of measurement requires some common
understanding of their accuracy, some way of measuring and expressing the uncertainty in their values and the inferential statements derived from them’ (Stigler, 1986, p. 1).

This measurement uncertainty can be described probabilistically by ascribing either the degree of uncertainty (e.g. error) or degree of certainty (e.g. accuracy) to measurements we make (Foody, 2001; Zhang and Goodchild, 2002). This is relatively simple to do for that part of the world that can be described by laws (e.g. gravity in cow illustration) or where that part has been measured already (e.g. cat and fiddle illustration). Paradoxically though, the poorly understood and the unmeasured parts of our world are where remote sensing and geographical information systems (GIS) are likely to be of most practical value. For example, remotely sensed data may provide ‘measurements’ of sea-surface temperature (SST), and GIS, via spatial data modelling, may provide socioeconomic ‘measurements’ for a region. In both cases we have no known data at the same location, time and size of support with which to determine the uncertainty of these remote sensing or GIS ‘measurements’. In practice, we can predict uncertainty by comparing remote sensing and GIS measurement data to known measurement data from other locations. For example, without a law to help, information on the uncertainty of our remotely sensed SST measurements can be provided by the difference between remotely sensed SST ‘measurements’ and buoy SST measurements for a different time, place and size of support. Likewise, without a law to help, information on the uncertainty of our socioeconomic ‘measurements’ can be provided by the difference between these socioeconomic measurements and surrogate measurements (e.g. average income) made again, for a different time, place and size of support.

To turn again to issues of uncertainty in understanding: some of the most exciting areas in remote sensing are where our understanding is uncertain and other measurements (i.e. ground data or sea data) are not available. This is where remote sensing can be used as an inductive tool of exploration to ‘find things’ and to provide a base on which to develop a deterministic understanding of how the world works (Curran, 1987). Remote sensing is one of the few fields that make vastly (orders of magnitude) more measurements than are needed. These huge sets of measurements are, like library archives, meteorological records or space x-ray data repositories, just ripe for mining. However, for reasons outlined before, the uncertainty associated with these archives of remotely sensed ‘measurements’ of our environment is unknown. For example, the influential papers that have used global time series of AVHRR NDVI data to understand how our planet functions are based on measurements of vegetation characteristics with unknown levels of accuracy.

So far this Foreword has treated measurement uncertainty and understanding uncertainty as if they were separate. This is the stance taken by many disciplines. Economists, since the early part of the twentieth century, have given the name risk to measurement uncertainty (or chance) and uncertainty to understanding uncertainty (or the unexpected) (Knight, 1921; Keynes, 1936). In environmental impact studies risk is measurement uncertainty when you ‘know the odds’ and uncertainty is understanding uncertainty when you ‘don’t know the odds’ and are ignorant (Wynne, 1992). By way of illustration, we know that the chance of the average...
A westerner dying in any one year of heart disease is currently 1:385, compared to 1:519 for cancer and 1:1752 for stroke (HCRA, 2002) but we have no idea what the chances are of there being a catastrophic international event of some sort during our lifetime. Likewise, the measurement uncertainty associated with the release of dichlorodiphenyltrichloroethane (DDT) and chlorofluorocarbons (CFCs) into our environment was reasonably low but the understanding uncertainty was alarmingly high (Hoffmann-Riem and Wynne, 2002). However, in remote sensing, GIS and a wide range of related fields (e.g. those covered by the *International Journal of Uncertainty, Fuzzyness and Knowledge-Based Systems*) the term uncertainty, often seeks to incorporate measurement uncertainty and understanding uncertainty as it is their interplay that determines the efficacy of what we are trying to do (Goodchild and Case, 2001). It is not just error in $x$, $y$ (location) but also understanding of $z$ (variable) that is important. One of the better documented environmental examples of the interplay between the two forms of uncertainty occurred in the UK following the 1986 Chernobyl nuclear accident. Very accurate chemical immobilization measurements (made previously on lowland soil in the UK) were used to predict that the radioactive material would be immobilized within three weeks and as a result upland sheep sales were banned for that period. However, the underpinning understanding was uncertain. Organic upland soil did not respond like lowland soil and the soil immobilization of radioactive material and the reopening of a market in sheep took not weeks but years (Wynne, 1992). In this case, measurements with little and known levels of uncertainty were not that useful! However, in many of the cases we face in remote sensing and GIS both the measurement and understanding are uncertain. For example, the 2000 talks on mechanisms for implementing the Kyoto Protocol collapsed due to uncertainty in both our measurement and understanding of terrestrial carbon sinks (Read *et al.*, 2001; Bégni *et al.*, 2002). What was required was an accurate means of predicting carbon sink strength over land. These predictions needed to be accurate enough to enable them to be both traded in a world market and input to models of future carbon sink strength. The only practical methods are a judicious mix of remote sensing, carbon flux measurements, GIS and ecosystem simulation models. The outputs of such methods are therefore subject to both measurement uncertainty and understanding uncertainty, as we not only have difficulty in measuring accurately (e.g. standing biomass of forest) but also we do not understand many of the processes involved (e.g. interactions between vegetation, soil and climate). This mix of measurement uncertainty and understanding uncertainty is difficult to deal with as the former can be quantified readily while the latter is unquantifiable. As a result,

‘the uncertainties associated with estimates (of carbon sink strength) derived from all of these methods is considerable. A further fundamental problem is that the magnitude of this uncertainty is unknown’ (Read *et al.*, 2001, p. 12).

A way around the problem is to treat the phenomena we are interested in as a model and understanding uncertainty as a model imperfection. Therefore, understanding uncertainty can be quantified as the difference between measurement and model prediction once allowance has been made for measurement uncertainty. This
is very difficult to implement in practice as understanding uncertainty has a considerably greater magnitude but (fortunately) a considerably lower frequency than measurement uncertainty. In climate change research an alternative solution has been to use ‘expert opinion’ to ascribe probabilities to the degree of understanding uncertainty (Schneider, 2001). However, this neat solution whilst popular with policy makers remains controversial (Grübler and Nakicenovik, 2001; Pittock et al., 2001).

This Foreword has focused on the two types of uncertainty that are of most concern. In addition, these uncertainties are underpinned by a range of task-specific uncertainties. Uncertainty may arise because of incomplete information – what will the climate of China be in 2005? or because of disagreement over information sources – what was the DN to radiance calibration for a given sensor and date? Uncertainty may arise from linguistic imprecision – what exactly is meant by Case II water? or the inappropriate use of jargon – ‘validating the retrieval of large scale parameters’. It may refer to variability – what exactly is the atmospheric ozone concentration over the poles? Uncertainty may be about a quality – slope of the variogram, or the type of model – shape of a variogram. Even if we were to have no measurement uncertainty we may still be uncertain because of simplifications or approximations used to make the analysis feasible – global NDVI data sets. If that were not enough we also add uncertainty by how we decide to analyse and then represent any analysis we do and as a result we are always uncertain, even about our uncertainty (Morgan and Henrion, 1992). Perhaps not surprisingly discussions of uncertainty in remote sensing and GIS have tended to focus on that which is tractable (i.e. has a relatively small magnitude but relatively large frequency). As a result much of what will follow in this book is a discussion of probability applied to random error, systematic error and thereby measurement uncertainty. This focus on measurement uncertainty, as has been noted earlier, is very necessary although not sufficient if measurements are to be the building blocks for understanding.

‘Difficulties arise when the uncertainties are not caused by probabilistic predictions, but rather derive from a fundamental lack of understanding of a new phenomenon at or beyond the frontiers of present knowledge’ (May, 2001b, p. 891).

or to put it more bluntly,

‘we need to recognise and address the crucial distinction between uncertainty and ignorance’ (Hoffmann-Riem and Wynne, 2002, p. 123).

In remote sensing and GIS we are striving to refine and better characterize our probabilistic predictions of such variables as land cover and biomass, ocean temperature and chlorophyll concentration and understand for example, how measurement uncertainties in inputs are propagated through spatial models (Heuvelink and Burrough, 2002). A clear focus on measurement uncertainty has, until recently, been neglected in the environmental (although not statistical/mathematical) literature. Such a focus will be an aid to ensuring the vitality/credibility of remote sensing and GIS and is the aim of what I anticipate will be a most influential book.
Individually, the chapters that follow serve to highlight impressive strides that are being made in the study of measurement uncertainty over a wide range of scales. Collectively, these chapters set down both an uncertainty research agenda and an intriguing challenge for the future. This challenge, and the topic of this Foreword, is that of not being lulled into believing that confidence of our measurement uncertainty (however important), is the same as confidence of our understanding uncertainty (Morgan and Henrion, 1992; Gupta, 2001). A sentiment that is captured most elegantly by the (very) recently deceased Douglas Adams.

'It sounded quite a sensible voice, but it just said, “Two to the power of one hundred thousand to one against and falling,” and that was all.

Ford skidded down a beam of light and spun around but could see nothing he could seriously believe in.

“What was that voice?” shouted Arthur.

“I don’t know,” yelled Ford, “I don’t know. It sounded like a measurement of probability.”

“Probability? What do you mean?”

“Probability. You know, like two to one, three to one, five to four against. It said two to the power of one hundred thousand to one against. That’s pretty improbable, you know.”

A million-gallon vat of custard unended itself over them without warning.

“But what does it mean?” cried Arthur.

“What, the custard?”

“No, the measurement of improbability?”

“I don’t know. I don’t know at all.”'


References


May, R. M., 2001b, Risking uncertainty: at the frontiers of science we don’t always know what may happen, *Nature*, 411, 891.


Paul J. Curran
University of Southampton
Uncertainty is a topic of considerable importance but one which has only recently attracted major attention within the remote sensing and GIS communities. We, therefore, felt that a short conference to bring together researchers in remote sensing and GIS to discuss uncertainty would be useful. The conference was held at the University of Southampton in July 2001 and designed to fulfil two major objectives. First, it was to encourage a dialogue on uncertainty and provide a guide to the current status of uncertainty related research within remote sensing and GIS. Here, it is worth noting that, like others, we use the term GIS to mean both geographical information systems and geographical information science. In general the distinction between these two meanings is made where appropriate in the book but sometimes either interpretation is valid. Second, saddened by the decay in short, highly focused, research meetings in the UK, we wanted to run a meeting that was academically strong, fun and involved contributions from junior researchers through to the established leaders in the field that were drawn from a variety of backgrounds and nationalities to help plug a gap that appears to have arisen in our calendars. In total 25 papers were presented at the conference that was attended by 61 delegates from eight countries.

Our attempt to achieve the key objectives was aided greatly by sponsorship that allowed us to attract the involvement of a large number of postgraduate students as well as three keynote speakers, Jennifer Dungan (NASA, USA), Curtis Woodcock (Boston University, USA) and Gerard Heuvelink (Amsterdam University, The Netherlands). Perhaps more importantly, the sponsorship also ensured we could have an informal social evening at the Mill Arms public house. From the feedback we received after the conference this seems to have been a great success, with far more social interaction amongst delegates than normal. Indeed the evening went so well that nobody seemed to mind that the skittles competition was won by a team from Southampton! Most important of all, however, the conference contained some excellent material on uncertainty in remote sensing and GIS. All of the presenters were encouraged to write up their paper for possible publication as a means of extending and communicating the material discussed at the conference and this book contains some of those papers together with contributions to fill apparent gaps in coverage. Each article received was rigorously reviewed and edited. Typically, each chapter was reviewed by three people: a delegate with relevant expertise, an established researcher in the specific topic discussed as well as at least one of the editors. Those articles that appeared to both fit the general aims of the conference and pass the quality criteria set were accepted and follow. Several
articles did not get past the review stage. In most cases, the articles that we were unable to include were judged to require further work that was not compatible with our strict timetable. We confidently hope and expect that many of these articles will appear in the open literature in the near future as the work matures.

Staging a conference and producing a book are large tasks and cannot be achieved without the inputs of a vast and varied team of helpers. Here, we wish to thank those who have helped us. This is not out of any formal requirement to do so but rather a genuine desire to thank the many people and organizations that provided invaluable assistance. Five groups deserving explicit thanks can be identified. First, we are extremely grateful to our various sponsors. We received kind and generous support from a number of sources, notably: the Remote Sensing and Photogrammetry Society’s Edinburgh Award, Ordnance Survey, Taylor and Francis, Erdas (UK), PCI Geomatics, Research Systems, Wiley and the Quantitative Methods Research Group of the Royal Geographical Society (with the Institute of British Geographers). Our gratitude to these bodies is very real. Without them we simply could not have staged the meeting and undoubtedly the warm feedback we received from delegates after the conference is in part a reflection of the support we received to stage it. Second, many people helped us with the organization and smooth running of the conference. In particular we wish to thank Karen Anderson, Reno Choi, Adam Corres, Aidy Muslim, Nick Hamm, Tatiana Kuplich, Gary Llewellyn, Nick Odoni, Michael Riedmann, Valeria Salvatori, Isabel Sargent, Caiti Steele, Andy Tatem, Debbie Wilson and Matt Wilson (for those who attended the meeting, many of these were the folk in the yellow tee-shirts who provided invaluable assistance before, during and after the conference – perhaps that is why we forgave them for winning the skittles competition that they helped organize?). Third, the production of the book benefited enormously from the inputs of the referees. Refereeing book chapters is an important task and one that we believe should be recognized publicly. As we must, however, maintain their confidentiality we will not identify the referees but simply express here our genuine gratitude for their constructive input. Fourth, we are grateful to the authors themselves. Not only for providing the chapters to a tight schedule but also for their positive attitude, most noticeable when responding to sometimes sharp comment from the referees. Fifth, we wish to thank all others who have played a role in bringing this book to print. These include Lyn Roberts, Susan Barclay and Keily Larkins of Wiley for guidance, Matt Wilson for help in constructing the index and Denise Pompa in our Departmental Office who had the horrible job of converting a pile of annotated manuscripts from us into something the publishers could handle.

We hope that this book provides an interesting and useful guide to uncertainty in remote sensing and GIS and that all of those connected with it in any way are pleased with its final form.

Finally, it is with much sadness that we must report the death in August 2002 of Anna Jakomulska, lead author of Chapter 7 and a valued colleague and friend. Anna worked tirelessly in the fields of remote sensing and GIS, often going beyond even the highest expectations to support her research. Anna will be greatly missed. We dedicate this book to her memory.

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1

Uncertainty in Remote Sensing and GIS: Fundamentals

P. M. Atkinson and G. M. Foody

1 Introduction

Uncertainty has been an important topic in geographical information science for over a decade (e.g. Goodchild and Gopal, 1989; Veregin, 1996; Kiiveri, 1997; Heuvelink, 1998; Zhang and Goodchild, 2002). This focus has led researchers to recommend over many years that the spatial output of a geographical information system (GIS) should be (at least) twofold: (i) a map of the variable of interest and (ii) some assessment of uncertainty in that map. Uncertainty has also been the subject of much research in remote sensing (e.g. Congalton, 1991; Fisher, 1994; Canters, 1997; Foody, 2002) with the main focus of such work being the assessment (and increase) of prediction or classification accuracy. However, uncertainty in remote sensing seems to have been a less explicit focus of research effort than uncertainty in GIS, with perhaps fewer calls for the production of maps depicting uncertainty.

This book aims to (i) discuss the nature of uncertainty; its interpretation, assessment and implications, (ii) assemble a range of up-to-date research on uncertainty in remote sensing and geographical information science to show the current status of the field and (iii) indicate future directions for research. We seek, in this introductory chapter, to define uncertainty and related terms. Such early definition of terms should help to (i) provide a common platform upon which each individual chapter can build, thus, promoting coherence and (ii) avoid duplication of basic material, thus, promoting efficiency in this book. We have done this also in the hope that others will adopt and use the definitions provided here to avoid confusion in publications in the future. We start with uncertainty itself.
Uncertainty arises from many sources ranging from ignorance (e.g. in understanding), through measurement to prediction. The *Oxford English Dictionary* gives the following definition of the word uncertain: 'not known or not knowing certainly; not to be depended on; changeable'. Uncertainty (the noun) is, thus, a general concept and one that actually conveys little information. For example, if someone is uncertain, we know that they are not 100% sure, but we do not know more than that, for example, how uncertain they are or should be. If uncertainty is our general interest then clearly we shall need a vocabulary that provides greater information and meaning, and facilitates greater communication of that information. The vocabulary that we use in this chapter involves clearly defined terms such as error, accuracy, bias and precision. Before defining such terms, two distinctions need to be made.

First, and paradoxically, to be uncertain one has to know something (Hoffman-Riem and Wynne, 2002). It is impossible to ascribe an uncertainty to something of which you are completely ignorant. This interesting paradox is explored by Curran in the Preface to this book. Essentially, it is possible to distinguish that which is known (and to which an uncertainty can be ascribed) and that which is simply not known. In this book, we deal with uncertainty and, therefore, that which is known (but not perfectly).

Second, dealing solely with that which is known, it is possible to divide uncertainty into ambiguity and vagueness (Klir and Folger, 1988). Ambiguity is the uncertainty associated with crisp sets. For example, in remote sensing, land cover is often mapped using hard classification (in which each pixel in an image is allocated to one of several classes). Each hard allocation is made with some ambiguity. This ambiguity is most often (and most usefully) expressed as a probability. Vagueness relates to sets that are not crisp, but rather are fuzzy or rough. For example, in remote sensing, land cover often varies continuously from place to place (e.g. ecotones, transition zones). In these circumstances, the classes should be defined as fuzzy, not crisp. This fuzziness is an expression of vagueness. In this opening chapter, following the majority of chapters in this book, we concentrate on ambiguity.

# 2 Error

An error $e(x_0)$ at location $x_0$ may be defined as the difference between the true value $z(x_0)$ and the prediction $\hat{z}(x_0)$

$$e(x_0) = \hat{z}(x_0) - z(x_0)$$

such that

$$\hat{z}(x_0) = z(x_0) + e(x_0).$$

Thus, errors relate to individual measured or predicted values (equations 1 and 2) and are essentially data-based. There is no statistical model involved. Thus, if we measure the soil pH at a point in two-dimensional space and obtain a value $\hat{z}(x_0)$ of 5.6, where the true value $z(x_0)$ is 5.62, the error $e(x_0)$ is $-0.02$.

Further, error has a very different meaning to uncertainty. In the example above, consider that both the predicted value (5.6) and the error ($-0.02$) are known per-
fectly. Then, an error exists, but there is no uncertainty. Uncertainty relates to what is 'not known or not known certainly'. Thus, uncertainty is associated with (statistical) inference and, in particular, (statistical) prediction. Such statistical prediction is most often of the unknown true value, but it can equally be of the unknown error. Attention is now turned to three properties that do relate information on uncertainty: accuracy, bias and precision.

3 Accuracy, Bias and Precision

Accuracy may be defined in terms of two further terms: bias and precision (Figure 1.1). Accuracy, bias and precision are frequently misused terms. For example, researchers often use precision to mean accuracy and vice versa. Therefore, it is important to define these terms clearly. Let us, first, deal with bias and precision, before discussing accuracy.

3.1 Bias

Unlike error, bias is model-based in that it depends on a statistical model fitted to an ensemble of data values. Bias is most often predicted by the mean error, perhaps the simplest measure of agreement between a set of known values $z(x_i)$ and a set of predicted values $\hat{z}(x_i)$

*Figure 1.1  Bull’s eye target, represented by the set of concentric rings, with four sets of predictions, only one of which is accurate: (triangles) biased and imprecise, therefore, inaccurate; (squares) unbiased but imprecise, therefore, inaccurate; (diamonds) biased but precise, therefore, inaccurate; (circles) unbiased and precise, therefore, accurate*
Thus, bias is an *expectation* of over- or under-prediction based on some statistical model. The larger the (systematic) errors, the greater the bias.

Take a single measured value with a given error (equation 2). Suppose that the error is +0.1 units. True, the measurement has over-predicted the true value. However, this does not imply bias: nor can bias be inferred from a single over-prediction. In simple terms, bias is what we might expect for a long run of measurements, or in the long term. Therefore, bias is a statistical expectation and to predict it, generally, we need an ensemble of values. If for a large sample the true value was consistently over-predicted we could infer that the measurement process was biased. Such inference is based on a statistical model.

### 3.2 Precision

Like bias, precision is model-based in that it depends on a statistical model fitted to an ensemble of values. Precision is most often predicted using some measure of the spread of errors around the mean error, for example, the standard deviation of the error, often termed the prediction error (where the prediction error is the square root of the prediction variance).

The standard deviation of the error can be predicted directly from the errors themselves if they are known

\[
se = \sqrt{\frac{\sum_{i=1}^{n} (\hat{e}_i - \bar{e}_i)^2}{n-1}}. \tag{4}
\]

Thus, (im)precision is an expectation of the spread of errors. The smaller the (random) errors, the greater the precision. Such statistical inference is, again, model-based.

### 3.3 Accuracy

Accuracy is the sum of unbias (i.e. the opposite of bias) and precision:

\[
\text{Accuracy} = \text{Unbias} + \text{Precision} \tag{5}
\]

This simple equation defining accuracy in terms of unbias and precision is fundamentally important in research into uncertainty.

Where an independent data set is used to assess uncertainty, accuracy may be predicted directly. In particular, the root mean square error (RMSE) which is sensitive to both systematic and random errors, can be used to predict accuracy

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{n} (z_i - \hat{z}_i)^2}{n}}. \tag{6}
\]
Accuracy, like bias and precision, depends on a statistical model. It is an expectation of the overall error.

It is important to distinguish between error and accuracy. Essentially, error relates to a single value and is data-based. Accuracy relates to the average (and, thereby, statistical expectation) of an ensemble of values: it is model-based. An actual observed error depends on no such underlying model. This distinction between model and data is fundamental to statistical analysis.

4 Model-based Prediction and Estimation

In this book, and more generally in the literature relating to remote sensing and geographical information science, it is acknowledged that many authors use both estimation and prediction in relation to variables. However, in this chapter, a distinction is made between the terms prediction and estimation. Prediction is used in relation to variables and estimation is used in relation to parameters. This is the scheme adopted by most statisticians and we shall adopt it here in the hope of promoting consistency in the use of terms.

4.1 Variables and parameters

Variables are simply measured or predicted properties such as leaf area index (LAI) and the normalized difference vegetation index (NDVI). Parameters are either constants (in a classical statistical framework) or vary (in a Bayesian framework), but in both cases define models. For example, two parameters in a simple regression model are the slope, $\beta$, and intercept, $\alpha$. In the classical framework, once a regression model is fitted to data, $a$ and $b$, which estimate $\alpha$ and $\beta$, are fixed and are referred to as model coefficients (i.e. estimated parameters). However, it is possible to treat parameters as varying. For example, within a Bayesian framework, parameters vary and their statistical distributions (i.e. their cumulative distribution functions, cdfs) are estimated. Thus, in the Bayesian framework, the distinction between estimation (of parameters) and prediction (of variables) disappears.

It is very difficult to achieve standardization on the use of the terms prediction and estimation. For example, authors often use estimate in place of predict. Such interchange of terms has been tolerated in this book.

4.2 Prediction variance

Much effort has been directed at designing techniques for predicting efficiently, that is, with the greatest possible accuracy (unbiased prediction with minimum prediction variance). An equally large effort has been directed at predicting the prediction variance and other characteristics of the error cdf. Let us concentrate on the prediction of continuous variables. In particular, consider the prediction of the mean of some variable, to illustrate the basic concept of prediction variance.
Given a sample $\hat{z}(x_i)$ for all $i = 1, 2, 3, \ldots, n$ of some variable $z$, the unknown mean $\mu$ may be predicted using

$$m = \frac{\sum_{i=1}^{n} \hat{z}(x_i)}{n}$$  \hspace{1cm} (7)

The above model (equation 7) has been fitted to the available sample data, and the model used to predict the unknown mean.

From central limit theorem, for large sample size $n$ the conditional cdf (i.e. the distribution of the error) should be approximately Gaussian (or normal) (see Figure 1.2) meaning that it is possible to predict the prediction error (and, therefore, imprecision) using the standard error, SE

$$SE = \frac{s}{\sqrt{n}}$$  \hspace{1cm} (8)

Figure 1.2  Schematic representation of probability density function for prediction of the mean $\mu$, with given standard error (SE)
where,

\[
s = \sqrt{\frac{\sum_{i=1}^{n} (z_i - \hat{z}_i)^2}{n-1}}
\]  

(9)

where, \( s \) is the standard deviation of the variable \( z \) and \( n \) is the number of data used to predict, in this case, the mean value (Figure 1.2). The prediction variance is simply the square of the standard error. As stated above, the standard error, and the prediction variance, are measures of precision. More strictly, in statistical terms, precision may be defined as the inverse of the prediction variance, although the term precision is more often used (and is used in this chapter) less formally.

For a Gaussian model (i.e. a normal distribution), the mean and variance are the only two parameters. Therefore, given:

1. unbiasedness (i.e. the predicted mean tends towards the true mean as the sample size increases, such that the error can be assumed to be random) and
2. that the conditional cdf (i.e. the error distribution) is known to be Gaussian (e.g. via central limit theorem above)

then

3. the prediction variance (equivalent to the square of the standard error) is sufficient to predict the full distribution of the error.

For most statistical analyses, it is this error distribution (i.e. the full conditional cdf) that is the focus of attention.

It is useful to note that generally most statistical models can be used to infer precision, but not bias (and, therefore, not accuracy). For the example above involving predicting the mean, the SE conveys information only on precision. Nothing can be said about bias (or, therefore, accuracy) because we do not have any information by which to judge the predicted mean relative to the true mean (we can only look at the spread of values relative to the predicted mean). Statistical models are often constructed for unbiased prediction, meaning that the prediction error (or its square, the prediction variance), which measures imprecision (not bias), is sufficient to assess accuracy.

The example above involving predicting the regional mean can be extended to other standard statistical predictors. For example, linear regression (prediction of continuous variables) and maximum likelihood classification, MLC (prediction of categorical variables) are now common in remote sensing and geographical information science (Thomas et al., 1987; Tso and Mather, 2001). In both cases (i.e. regression or classification), the objective is prediction (of a continuous or categorical variable), but the model can be used to predict also the prediction error. The model must, first, be fitted to ‘training’ data. In regression, for example, the regression model is fitted to the scatterplot of the predicted variable \( y \) on the explanatory
variable $z$ (or more generally, $z$) in the sense that the sum of the squared differences between the line and the data (in the $y$-axis direction) is minimized (the least-squares regression estimator). For MLC, the multivariate Gaussian distribution is fitted to clusters of pixels representing each class in spectral feature space. Once the model has been fitted it may be used to predict unknown values given $z$ (simple regression) or unknown classes given the multispectral values $z$ (classification). However, the (Gaussian) model may be used (in both cases) to predict the prediction error. As with the SE, the prediction error is based on the variance in the original data that the models are fitted to.

There is not space here to elaborate further on standard statistical predictors. However, several of the chapters in this book deal with the geostatistical analysis of spatial data (e.g. Dungan, Chapter 3; Warr et al., Chapter 14; Lloyd, Chapter 15). Therefore, a brief introduction to geostatistical prediction is provided here for the reader who may be unfamiliar with the field.

### 4.3 Spatial prediction

In geostatistics, the variogram is a central tool. Generally, the experimental variogram is predicted from sample data and a continuous mathematical model is fitted to it (Figure 1.3). This variogram model can then be used in the geostatistical technique for spatial prediction known as kriging (i.e. best linear unbiased prediction, BLUP). The variogram can, alternatively, be used in conditional simulation (Journel, 1996) or for a range of related objectives (e.g. optimal sampling design, van Groenigen et al., 1997; van Groenigen and Stein, 1998; van Groenigen, 1999).

Kriging is often used within a GIS framework to predict unknown values spatially from sample data; that is, to interpolate. Kriging has several important properties that distinguish it from other interpolators such as inverse distance weighting. In particular, since kriging is a least-squares regression-type predictor (Goovaerts, 1997; Deutsch and Journel, 1998; Chiles and Delfiner, 1999), it is able to predict with minimum prediction variance (referred to as kriging variance). Kriging predicts this kriging variance as a byproduct of the least-squares fitting (i.e. the regression). The kriging variance for a given predicted value, therefore, plays the same role as the square of the standard error for the predicted mean of a sample. However, the kriging variance is predicted for all locations (usually constituting a map). Thus, kriging is able to provide both (i) a map of the predicted values and (ii) a map of prediction variance: exactly what is required by users of GIS. A caveat is that the prediction variance is only minimum for the selected linear model (i.e. it is model-based).

A problem with the kriging variance is that it depends only on the variogram and the spatial configuration of the sample in relation to the prediction: it is not dependent on real local data values. However, for situations where local spatial variation is similar from place to place, the kriging variance provides a valuable tool for optimizing sampling design (Burgess et al., 1981). For example, for a fixed variogram, the sample configuration can be optimized for a given criterion without actual sample or
Figure 1.3 Exponential variogram model (line) fitted to an experimental variogram (symbols). The experimental variogram was obtained from an unconditional simulation of a random function model parameterized with an exponential covariance. The estimated exponential model parameters are as follows: non-linear parameter, $r_1$, is 3.5 pixels; sill variance, $c_1$, is 1.06 units. The model was fitted without a nugget variance, $c_0$.

survey data (van Groenigen, 1999). Wameling provides an example of the use of the kriging variance in Chapter 13 of this book.

4.4 A note on confidence intervals

Knowledge of the standard error allows the researcher to make statements about the limits within which the true value is expected to lie. In particular, the true value is expected to lie within $\pm 1$ SE with a 68% confidence, within $\pm 2$ SE with a 95% confidence and within $\pm 3$ SE with (approximately) a 99% confidence.

There has been a move within statistics in recent years away from the use of confidence intervals. This is partly because confidence intervals are chosen arbitrarily. The problem arises mostly in relation to statistical significance testing. For example, in the case of the simple $t$-test for a significant difference between the means of two data sets the result of the test (is there a significant difference?) depends entirely on the (essentially arbitrary) choice of confidence level. A confidence of 68% may lead to a significant difference whereas one of 95% may not. Statistical significance testing is increasingly being replaced by probability statements.
5 Accuracy Assessment

The methods discussed so far for predicting the prediction error (e.g. SE of the mean) have been model-based. Thus, they depend on model choice (the particular model chosen and fitted). Approaches for assessing the accuracy of predictions based primarily on data and, in particular, an ‘independent’ testing data set (i.e. data not used to fit the model and estimate its parameters) are now considered.

5.1 Retrieval, verification and validation

Before examining accuracy assessment it is important to highlight the misuse of some terms. First, it is common, particularly in the literature relating to physical modelling, to read of parameters being ‘retrieved’. This term is misleading (implying that a parameter is known a priori and that it has somehow been lost and must be ‘fetched’ or ‘brought back’). Parameters are estimated. Second, it is common in the context of accuracy assessment to read the words ‘verify’ and ‘validate’. To verify means to show to be true (i.e. without error). This is rarely the case with modelling in statistics and even in physical modelling (strictly, verification is scientifically impossible). No one model is the ‘correct’ model. Rather, all models compete in terms of various criteria. One model may be the preferred model in terms of some criterion, but nothing more. For example, if we define the RMSE as a criterion on which models are to be judged, then it should be possible to select a model that has the smallest RMSE. However, this does not imply that the selected model (e.g. simple regression) is in any sense ‘true’.

To validate has a similar, although somewhat less strict meaning (it is possible for something to be valid without being ‘true’). Its use is widespread (e.g. in relation to remote sensing, researchers often refer to ‘validation data’ and physical models are often ‘validated’ against real data). This use of the word validation is often inappropriate. For example, we do not show a classification to be valid. Rather, we assess its accuracy. In these circumstances, the correct term is ‘accuracy assessment’, and that is the subject to which we now return.

Once a model has been fitted and used to predict unknown values, it is important that an accuracy assessment is executed, and there are various ways that this can be achieved. The following sections describe some of the alternatives.

5.2 Cross-validation

A popular method of assessing accuracy that requires no independent data set is known as cross-validation. This involves fitting a model to all available data and then predicting each value in turn using all other data (that is, omitting the value to be predicted). The advantage of this approach is that all available data are used in model fitting (training). The main disadvantage is that the assessment is biased in favour of the model. That is, cross-validation may predict too high an accuracy because there is an inherent circularity in using the same data to fit and test the model.