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Applications of complex adaptive systems approaches to coastal systems

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Applications of Complex Adaptive Systems Approaches to Coastal Systems

By

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To Jenna

Applications of Complex Adaptive Systems Approaches to Coastal Systems

Kenneth Samuel Kingston

Abstract: This thesis investigates the application of complex adaptive systems approaches (e.g. Artificial Neural Networks and Evolutionary Computation) to the study of coastal hydrodynamic and morphodynamic behaviour. Traditionally, nearshore morphological coastal system studies have developed an understanding of those physical processes occurring on both short temporal, and small spatial scales with a large degree of success. The associated approaches and concepts used to study the coastal system at these scales have primarily been linear in nature. However, when these approaches to studying the coastal system are extended to investigating larger temporal and spatial scales, which are commensurate with the aims of coastal management, results have had less success. The lack of success in developing an understanding of large scale coastal behaviour is to a large extent attributable to the complex behaviour associated with the coastal system. This complexity arises as a result of both the stochastic and chaotic nature of the coastal system. This allows small scale system understanding to be acquired but prevents the larger scale behaviour to be predicted effectively.

This thesis presents four hydro-morphodynamic case studies to demonstrate the utility of complex adaptive system approaches for studying coastal systems. The first two demonstrate the application of Artificial Neural Networks, whilst the latter two illustrate the application of Evolutionary Computation. Case Study #1 considers the nature of the discrepancy between the observed location of wave breaking patterns over submerged sandbars and the actual sandbar locations. Artificial Neural Networks were able to quantitatively correct the observed locations to produce reliable estimates of the actual sand bar locations. Case Study #2 considers the development of an approach for the discrimination of shoreline location in video images for the production of intertidal maps of the nearshore region. In this case the system modelled by the Artificial Neural Network is the nature of the discrimination model carried out by the eye in delineating a shoreline feature between regions of sand and water. The Artificial Neural Network approach was shown to robustly recognise a range of shoreline features at a variety of beaches and hydrodynamic settings. Case Study #3 was the only purely hydrodynamic study considered in the thesis. It investigated the use of Evolutionary Computation to provide means of developing a parametric description of directional wave spectra in both reflective and non-reflective conditions. It is shown to provide a unifying approach which produces results which surpassed those achieved by traditional analysis approaches even though this may not strictly have been considered as a fully complex system. Case Study #4 is the most ambitious application and addresses the need for data reduction as a precursor when trying to study large scale morphodynamic data sets. It utilises Evolutionary Computation approaches to extract the significant morphodynamic variability evidenced in both directly and remotely sampled nearshore morphologies. Significant data reduction is achieved whilst retaining up to 90% of the original variability in the data sets.

These case studies clearly demonstrate the ability of complex adaptive systems to be successfully applied to coastal system studies. This success has been shown to equal and sometimes surpass the results that may be obtained by traditional approaches. The strong performance of Complex Adaptive System approaches is closely linked to the level of complexity or non-linearity of the system being studied. Based on a qualitative evaluation, Evolutionary Computation was shown to demonstrate an advantage over Artificial Neural Networks in terms of the level of new insights which may be obtained. However, utility also needs to consider general ease of applicability and ease of implementation of the study approach. In this sense, Artificial Neural Networks demonstrate more utility for the study of coastal systems. The qualitative assessment approach used to evaluate the case studies in this thesis, may be used as a guide for choosing the appropriateness of either Artificial Neural Networks or Evolutionary Computation for future coastal system studies.

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Glossary

(The purpose of this brief glossary is to provide an overview of some specific terminology which may not commonly be used within the coastal research community)

Architecture	A description of the number of the layers in a neural network, each layer's transfer function, the number of neurons per layer, and the connections between layers.
Chaotic behaviour	A system which displays the following traits is deemed to be chaotic; 1) Aperiodic bounded dynamics. 2) Sensitive dependence on initial conditions. A criterion which may be used to estimate the level of complexity of a phenomenon is the quantity of information required to define it and the associated practical difficulty in obtaining the information.
Coastal community	The body of researchers; oceanographers, geomorphologists, coastal engineers, who are primarily interested in furthering knowledge about the coastal system. Also included are those people; coastal managers, and policy makers, who have a vested interest in the coastal system
Coastal system	For the purposes of this thesis the description of a coastal system is deemed to comprise a description of the physical behaviour of those objects/features observed at the interface between the land and the sea.
Determinism	A deterministic system is one in which there is a definite rule with no random terms governing the dynamics of the system. Therefore knowledge of the state of a system at any time t implies the knowledge of the state of the system at any time $t + \tau$. Determinism is also strongly linked with the concept of causality i.e. nothing occurs without a cause or a *determining* reason. Thus if a stimulus for change is provided to a deterministic system the corresponding response is predetermined.
Epoch	The presentation of the set of training (input and/or target) vectors to a network and the calculation of new weights and biases.
Generalisation	An attribute of a network whose output for a new input vector tends to be close to outputs for similar input vectors in its training set.
Large Scale Coastal Behaviour	The dynamics of the coastal system on temporal and spatial scales of months to decades and kilometres. These time and length scales tend to be commensurate with those scales which are of interest to coastal managers.
Over-fitting	Over-fitting of a model occurs when the model is biased to reproduce specific characteristics of the training data set rather than identifying the true system behaviour of which the data set is representative.
Perceptron	The basic processing element of a neural network. Includes weights and bias, a summing junction and an output transfer function. Artificial neurons are abstractions of biological neurons.
Performance function	A measure of discrepancy between network output and desired goal. Commonly the mean squared error of the network outputs.
Regularisation	Involves modifying the performance function, which is normally chosen to be the sum of squares of the network errors on the training set, by adding some fraction of the squares of the network weights.
Sigmoid	Monotonic S-shaped function mapping numbers in the interval $(-\infty, \infty)$ to a finite interval such as (-1,+1) or (0,1).
System	A set of connected things or parts that form a whole or work together

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One of the enjoyable things about doing a PhD is that it brings you into contact with many people who also share a similar interest in research. I feel I have been very fortunate to during the course of this thesis to have been able to collaborate on a number of publications and projects with a number of talented and inspiring researchers. Thanks to **Stefan Aarninkhof** for sharing many hours of work and play in Corvallis and more recently in Plymouth and the Netherlands. Thanks to **Gerben Ruessink** for launching a most successful trilogy of papers. Thanks to **Nathaniel Plant** for infecting me with his enthusiasm and eye for detail. Thanks also to **Howard (Speedy) Southgate** for being a researcher who is not afraid to be an independent scientist and for his valuable comments having read an early draft of this thesis.

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Author's Declaration

At no time during the registration for the degree of Doctor of Philosophy has the author been registered for any other University award.

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Regular departmental seminars were attended and at which the author presented work on a number of occasions.

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IAHR Symposium on River Coastal and Estuarine Modelling, Genoa, Italy, 1999.
3rd Argus Workshop, Corvallis, Oregon 2000.
NICOP Workshop, Plymouth, UK, 2000.
Coastal Dynamics '01, ASCE, Lund, Sweden, 2001.
NICOP Workshop, Lund, Sweden, 2001.
4th Argus Workshop, Corvallis, Oregon, 2001.
28th International Conference on Coastal Engineering, ICCE, Cardiff, UK, 2002.

Publications:

Davidson, M.A., **Kingston, K.S.** and Huntley, D.A., 2000, 'New Solution for Directional Wave Analysis in Reflective Wave Fields', Journal of Waterway, Port, Coastal and Ocean Engineering, Vol. 126, No. 4, pp 173-181

Kingston, K.S. and Davidson, M.A., 1999, 'Artificial Neural Network Model of Sand Bar Location for a Macro-Tidal Beach, Perranporth, UK', *IAHR Symposium on River Coastal and Estuarine Modelling*, Genoa, Italy, pp 227-236

Kingston, K.S. and Davidson, M.A., 2001, 'A Parametric Morphologic Descriptor for Nearshore Sandbar Features', *Proceedings of 4th Conference* on Coastal Dynamics '01, ASCE, Lund, June 11-15, pp 673-682

Kingston, K.S. and Davidson, M.A., 2002, 'Observed Evolution of Directional Spectra in an Estuarine Environment over a Tidal Cycle', Proceedings of 28th International Conference on Coastal Engineering, 2002, ICCE, Cardiff, UK, (in press)

Kingston, K.S., Mallet, C., Plant, N.G. and Davidson, M.A., 2002, 'Intertidal Mapping of Morphological Features From Remotely Sensed Data', *Marine Geology*, (submitted)

Kingston, K.S., Ruessink, B.G., Van Enckevort, I.M.J. and Davidson, M.A., 2000, 'Artificial Neural Network Correction of Remotely Sensed Sandbar Location', Marine Geology, Vol. 169, No. 1-2, pp 137-160

Mallet, C., **Kingston, K.S.**, Davidson, M.A. and Huntley, D.A., 2000, 'The Use of Video in the Study of Sandbar Dynamics, *International Workshop "Marine Sandwave Dynamics"*, 23-25 March 2000, Lille, France.

Kingston, K.S., Ruessink, B.G., Van Enckevort, I.M.J. and Davidson, M.A., 2002, 'Artificial Neural Network Correction of Video Estimates of Sandbar Location', in '*Coast3D – Egmond. The Behaviour of a Straight Sandy Coast on the Time Scale of Storms and Seasons*', Edited by Van Rijn, L.C., Ruessink, B.G. and Mulder, J.P.M., Aqua Publications, Amsterdam, The Netherlands.

Ruessink, B.G., van Enckevort, I.M.J. and **Kingston, K.S.**, 1999, 'Characteristics of Alongshore Non-uniform Sandbar Behaviour', Published as a supplement to *EOS*, Transactions, AGU, Vol. 80, No. 46, pp F538

Ruessink, B.G., Van Enckevort, I.M.J., **Kingston, K.S.**, and Davidson, M.A., 2000, 'Analysis of Observed Two- and Three-Dimensional Nearshore Bar Behaviour', *Marine Geology*, Vol. 169, No. 1-2, pp 161-183

Woodd-Walker, R.S., **Kingston, K.S.** and Gallienne, C.P., 2001, 'Using Neural Networks to Predict Surface Zooplankton Biomass Along a 50°N to 50°S Transect of the Atlantic, *Journal of Plankton Research*, Vol. 23, No. 8, pp 875-888

Signed ....Kenneth Kingston -....

Date ....15/04/2003....

Chapter 1 Introduction

1.1 Introduction

"Gathering information about the sea, its chemistry, physics, and biology and their interacting mechanisms, should come right at the top of mankind's list of priorities. The more we know, the better we shall understand how far we can safely go in availing ourselves of the sea's resources and the consequences of abusing our present powers as a dominant species and recklessly plundering or exploiting its most fruitful regions."

James Lovelock, 'Gaia. A New Look at Life on Earth', 1995

When considering the nearshore region along our coasts, one is immediately struck by the rich complexity of the interactions and the continuous evolution of the coupled hydrodynamic – sediment dynamic system. The diversity of this morphodynamic coastal system is reflected in the broad range of temporal and spatial scales of observed behaviour. Over the past few decades there have been major advances in the general understanding of the mechanisms governing the behaviour of the hydrodynamics of this coastal system and to a lesser extent the nature of sediment dynamics (Komar, 1998; Thornton *et al.*, 2000). Yet we are still at the infancy of unravelling the behaviour of the morphodynamic coastal system.

A significant proportion of our acquired knowledge on coastal systems has stemmed from a form of scientific methodology, such as that presented in figure 1.1. It follows a cyclical path linking observation, interpretation and simulation or modelling. A starting point for interpretation of the methodology may be taken to be that of observation. This is the main source of evidence as to why the coastal system behaves as it does. This is as close as we get to the true nature of the morphodynamic evolution and interactions.

Observation is typically followed by interpretation. At this point the following questions are typically raised. Do the measurements make any sense in light of current concepts of the system's behaviour ? What potential additional information about the system may be derived from the observations ? This interpretation then leads to the development of models which try to implement any new insights and to simulate the observations which have been previously obtained.

Modelling is a juncture when it is possible to ascertain to some degree the validity of the interpretative stage. Direct comparison with observation allows validation of that sample of the system's behaviour. However, as it is only a sample, it does not guarantee that all the system dynamics have been captured in the interpretation. Therefore there are levels of understanding of system behaviour which may be revealed which mirror the levels of behaviour of the actual system itself. For example, understanding the nature of suspension events over ripples does not lead directly to an understanding of rhythmic bar formation.

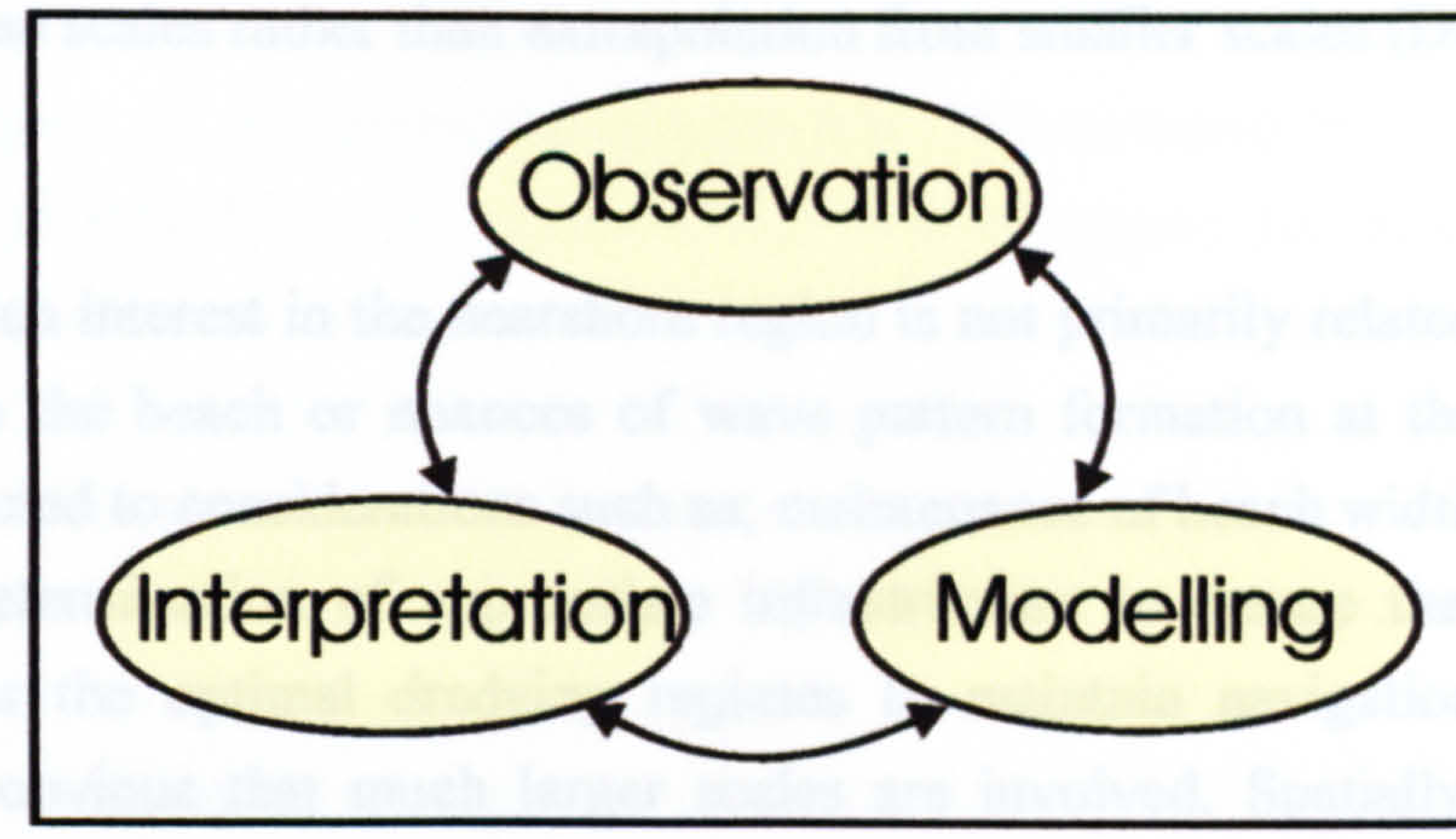


Figure 1.1 Process of understanding system behaviour

The extent of understanding may be established by extrapolating our knowledge outside the parameter space of the original measurements to allow comparison with other measurements. The extent of this predictive capability is an intrinsic mechanism whereby the gaps in our knowledge tend to be highlighted and suggest re-evaluation of assumptions of system behaviour at the interpretation stage. This quite often leads to a requirement for further observations and thus the cycle perpetuates itself.

Much emphasis to date, has been placed on understanding small-intermediate scale phenomenology in considerable detail. Processes and interactions occurring at small scales [Small Scale Coastal Behaviour, SSCB $O(10^{-1} - 10^{1})$ sec, $O(10^{-3} - 10^{1})$ m] govern the nature of breaking waves, boundary layer interactions and the initiation of sediment suspension events (Battjes and Stive, 1985; Fredsøe and Deigaard, 1992). Intermediate scale processes [Medium Scale Coastal Behaviour, MSCB $O(10^{1} - 10^{2})$ sec, $O(10^{1} - 10^{2})$ m] tend to be predominant in the characterisation of nearshore waves and currents (Dean and Dalrymple, 1993). Intuitively variations in these waves and currents cause spatial gradients in the local sediments fluxes resulting in changes in the overall topography (Large Scale Coastal Behaviour, LSCB [$O(10^{3} - 10^{5})$ sec, $O(10^{2} - 10^{4})$ m]) of the nearshore region (Komar, 1998). Processes occurring at any given scale can be seen to impact on and be affected by processes occurring at other scales through various feedback mechanisms (Cowell and Thom, 1994).

Hence, it had been hoped that knowledge at the small and intermediate scale would facilitate a capability of both understanding and predicting larger scale behaviour. This has been shown not to be the case (Roelvink and Broker, 1993; Schoones and Theron, 1995). Both these references are related to the alongshore averaged behaviour of cross-shore models. To date, this evaluation of modelling capability has not been extended in detail to the 3-dimensional case of area morphodynamic models. However it is likely that the best approach to understanding morphodynamics on larger scales will be based on processes occurring at those scales rather than extrapolation from smaller scales (De Vriend, 1997).

Yet much of the societal driven interest in the nearshore region is not primarily related to grain by grain changes in the beach or nuances of wave pattern formation at the shore. Instead, interest is directed to considerations such as; maintenance of beach width for recreational purposes, determination of appropriate infrastructure to ensure that erosion will be alleviated or the optimal dredging regimes to maintain navigation channels. Immediately it is obvious that much larger scales are involved. Spatially, entire beach regions are affected and the impact of either hard or soft beach protection schemes typically are not fully felt for a period of years to decades. At longer time scales, if one considers the impact such phenomena as sea level rise may have at our shorelines, it is obvious that building up an understanding of nearshore behaviour at larger scales is of paramount importance. Therefore the major motivation for this thesis is the desire to develop an understanding of coastal system behaviour at larger temporal and spatial scales. The thesis seeks to elucidate techniques and approaches which will be useful for the interpretation and modelling of such systems. To this end, this thesis advocates a change in the underpinning philosophies that have been adopted in the study of coastal systems to date.

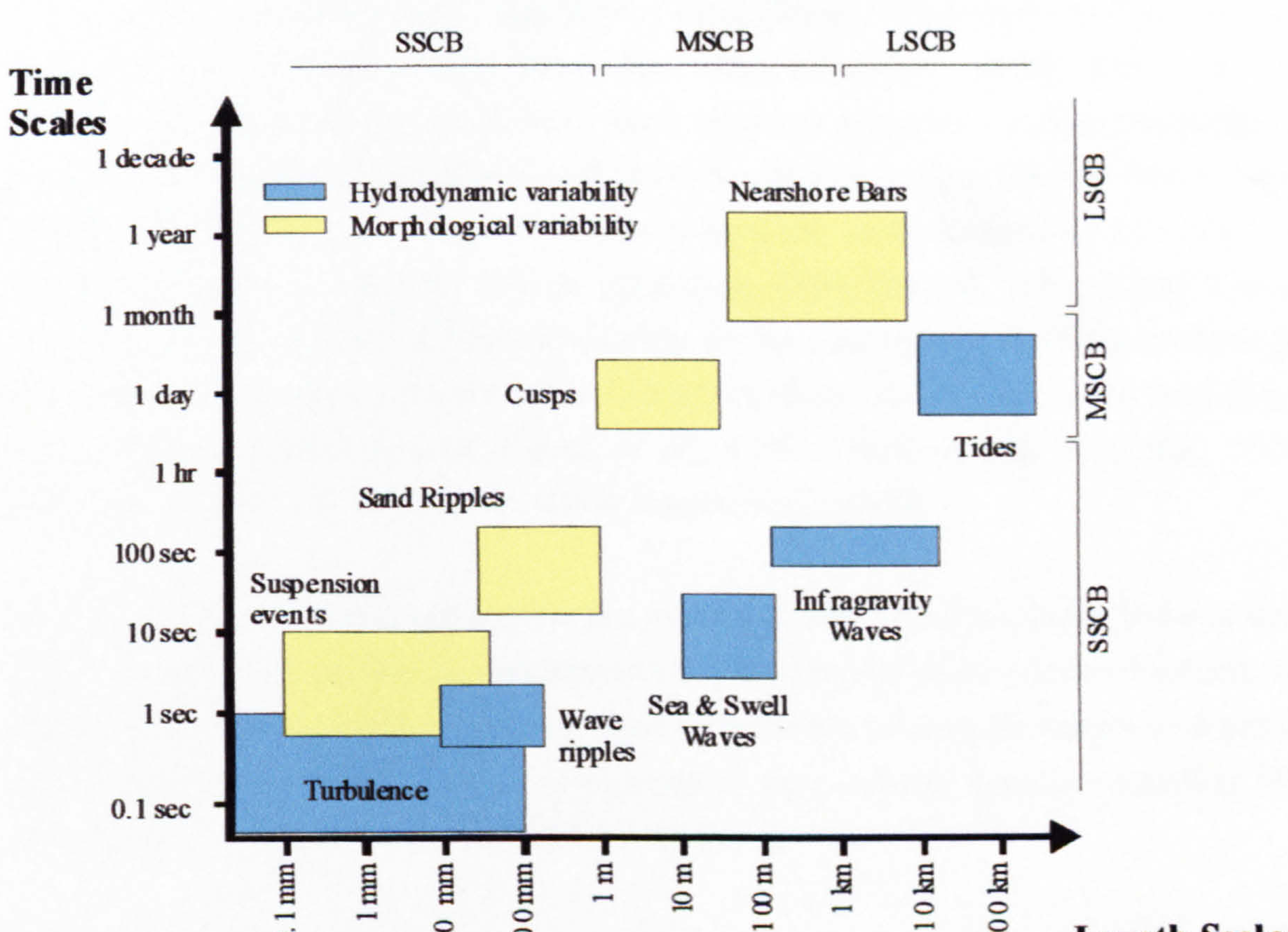


Figure 1.2 Temporal and spatial scales of coastal system behaviour

The range of scales of behaviour presented in figure 1.2 highlight the different scales of behaviour in the nearshore region. At any given spatial scale it is often assumed that the morphological features are generated by the corresponding hydrodynamic processes which exists at that scale. If this is true, there is a discrepancy between their temporal scales of behaviour, as was highlighted by Ruessink (1998). This results in a much slower response time of evolution of the morphological feature compared to the hydrodynamic process. Thus the forcing and morphological scales may exist on different levels as for example is the case for sand ripples in a tidal channel. The challenge facing the nearshore research community, therefore, is not only to try to develop an understanding of larger scale behaviour, but also to gain insight on how different scales of behaviour are inter-related.

Two questions therefore arise. Firstly, is there any particular reason as to why insight has been gained on relatively small scale coastal processes rather than the larger scale processes which impact more directly on the majority of people ? Secondly, what alternative approaches may be considered useful to bring new insights on coastal system behaviour in general and especially an understanding of the larger scale coastal system behaviour ?

1.2 Aim and objectives of the thesis

The purpose of this thesis is to consider alternative approaches to the general study of complex dynamic systems and investigate how they may be applied to coastal systems. The aim of this thesis is to identify methodologies, new to the field of nearshore processes, that have the capability of achieving one of the following goals ...

a) produce insight into coastal systems equivalent to those achieved by traditionally accepted analysis and modelling techniques.
b) to provide new insights into the behaviour of coastal systems, as a result of taking a new view of the system, even though it may be possible with hindsight to achieve similar information from traditional approaches.
c) to provide new insights into the behaviour of coastal systems, as a result of taking a new view of the system, which are unlikely to have been achieved by other means.

Specifically, those approaches developed in the area of **Complex Adaptive Systems** are considered. Complex adaptive systems are macroscopic collections of simple (and typically non-linearly) interacting units that have the ability to evolve and adapt to a changing environment. These systems display complex and quite often unexpected behaviour. The motivation for adopting this approach is that in the past the various branches of science have tended to be quite insular. This has resulted in techniques and methodologies (mathematical, statistical, etc.) being developed which, though applicable in a broader sense, have seen little migration outside their area of development. However, many scientists have begun to recognise that the transposition of approaches to problem solving in one discipline to a new discipline can lead to new insights. An example of this is the class of analysis tools comprising of empirical orthogonal functions and their variants (Hotelling, 1936; Barnett, 1983; Horel, 1984). Originally developed and utilised extensively in the atmospheric sciences to develop insight into correlations between sets of variables, there have been several successful applications to coastal systems (Liang *et al.*, 1992; Wijnberg and Terwindt, 1995; Larson *et al.*, 1999; Ruessink, *et al.*, 2000; Larson *et al.*, 2000).

The successful transposition of approaches to solving problems leads to the premise that the success is due to underlying characteristics in the areas of study which are inherently similar. This is an essential part of the ethos of the study of complex adaptive systems, which expounds the consideration of systems in their entirety thereby exploiting the underlying common characteristics between systems.

As already stated, the major task facing the nearshore research community is to develop a better understanding of the large scale behaviour of the coastal system. Whilst this is an admirable goal, it is felt that it is beyond the realms of any one thesis to address all the issues it presents. Instead a more conservative objective is deemed appropriate. The purpose of this thesis is to examine some of the approaches adopted in the study of complex adaptive systems and demonstrate their application to coastal systems.

Specifically the objectives of this thesis are to:

1. Present a brief overview of the current understanding of coastal system behaviour.
2. Indicate techniques, taken from the field of complex adaptive systems, which have the potential to lead to significant insight for the study of coastal systems.
3. Give examples of applications of complex adaptive system techniques to coastal system problems.
4. Demonstrate whether adopting complex adaptive system approaches for the study of coastal systems leads to useful insights in understanding coastal systems
5. Address the more general question of whether there is a 'correct' approach to studying coastal systems.

1.3 Thesis Outline

Chapter 2 starts by presenting a synopsis of the extent of the Coastal system which is considered in this thesis. Rather than giving an outline of specific processes occurring in coastal systems, the focus of the chapter is a consideration of the generic characteristics of coastal systems. This has the aim of indicating the broad categories of types of knowledge acquisition necessary for the study of these systems. This is followed by a brief overview of measurements and modelling techniques that have been adopted to date in understanding coastal systems. Chapter 2 concludes by highlighting the areas in which significant gaps in our knowledge of coastal systems still exist.

Chapter 3 proceeds to introduce concepts related to Complex Adaptive Systems. The general concepts of complexity and chaotic behaviour are presented, followed by a review of some of the more popular approaches to knowledge acquisition that permeate this field. This chapter concludes with a summary of the argument for considering coastal morphodynamic systems as complex adaptive systems.

The structural layouts of Chapter 4 and Chapter 5, which form the main body of the thesis, are identical. These chapters consider a range of applications of complex adaptive systems approaches to studying problems in coastal systems. The former chapter considers Artificial Neural Networks and the latter Evolutionary Computation. Each chapter initially presents a detailed overview of the operation and application of the particular technique, before presenting two specific case studies which apply the technique to coastal systems. Each of these case studies consists of the presentation of a specific problem taken from coastal systems, a proposed solution utilising the relevant complex adaptive system approach and incorporates a discussion specific to the problem.

The specific applications chosen for this study reflect the large range of scales of interest inherent in coastal systems. They range from an hydrodynamic problem occurring at a specific point over the duration of a few minutes, to a combined hydrodynamic/morphodynamic problem with alongshore length scale covering a region of shoreline of 3 km extending over a temporal scale of 15 months. The intention is to demonstrate a variety of applications utilising complex adaptive systems approaches which may indicate routes to insight of large scale morphodynamic behaviour for future studies.

Chapter 6 considers the applications of the complex adaptive approaches presented in the two previous chapters. Initially attention is paid to specific merits the complex adaptive systems approaches had for the applications considered. This is followed by a discussion of more general attributes of the techniques and their merits. Chapter 7 summarises by presenting the main conclusions of the thesis.

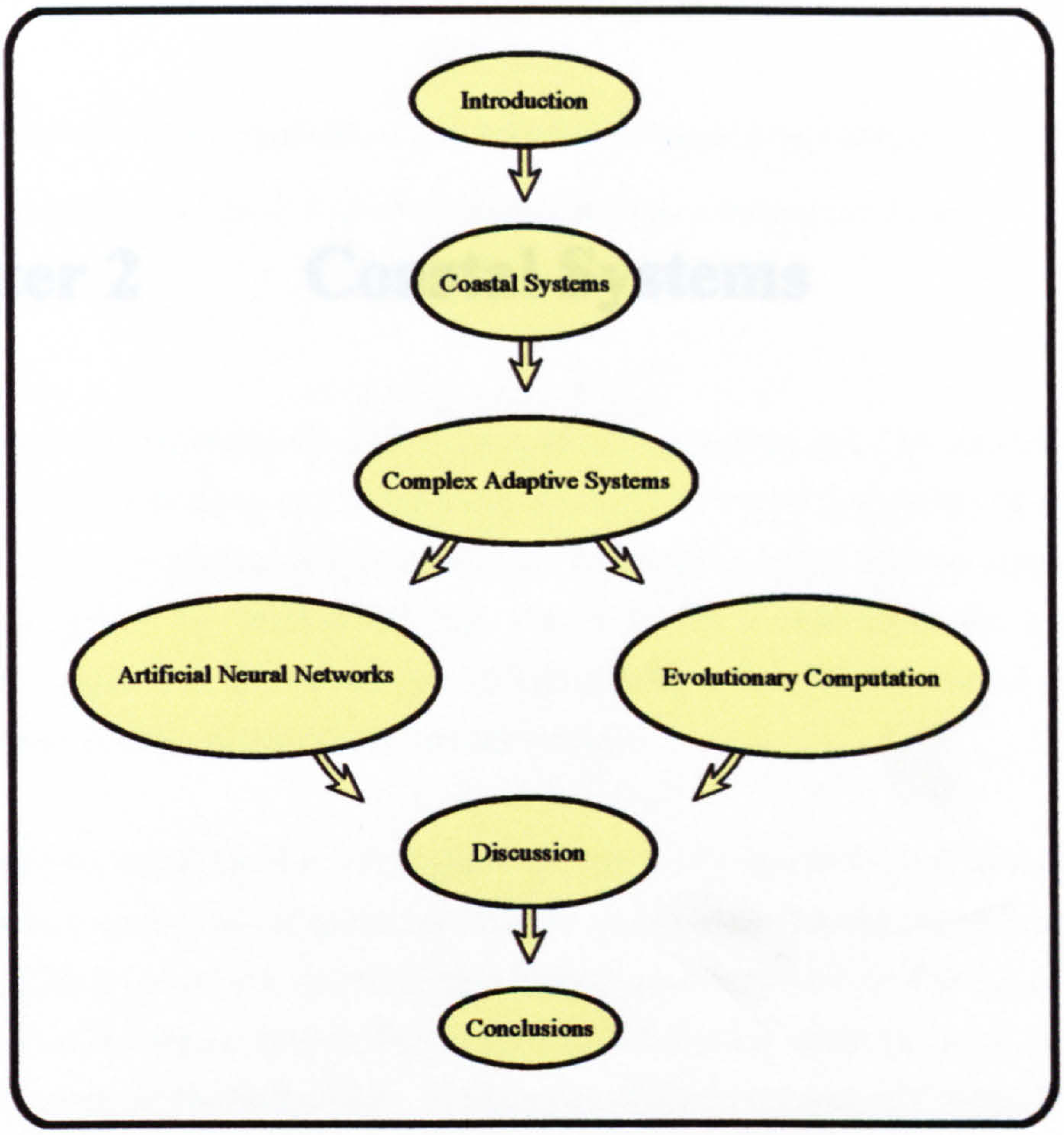


Figure 1.3 Thesis structure outline

Figure 1.3 presents an overview of the layout of the thesis. As can be seen the chapters do not necessarily follow sequentially. Chapters 4 and 5 are presented in parallel as there is no preferred order of occurrence. Similarly their respective contents and layout are mirrored.

To summarise, the goal of this thesis is to highlight the importance of taking a lateral view of approaching the study of coastal systems and to give a range of examples where this has proved to be worthwhile.

Chapter 2 Coastal Systems

2.1 Introduction to Coastal Systems

"About 20% of the world's coast is sandy and backed by ridges, dunes or other sandy depositional terrain. Of this, more than 70% has shown net erosion over the past decade."

Bird, 1985

"Fifty percent of the population of the industrialised world lives within one kilometre of a coast. This population will grow at about 1.5 percent per year over the next decade."

Goldberg, 1994

The term coastal system covers a vast range of not only physical, but also biological and chemical interactions along our shorelines. It would be naïve to expect any one thesis to be able to present a treatise which considers this system in its entirety with any detail. The coastal system of interest for this thesis is the morphodynamic system along sedimentary coasts. For the remainder of this thesis, references to coastal systems will implicitly refer to this subset of the overall system.

Coastal systems consider the interaction of the hydrodynamic and sedimentological subsystems at a variety of temporal and spatial scales in the nearshore region. Figure 2.1 summarises the cross-shore extent of this system as considered in this study. It extends from the offshore region outside the depth limited breaker zone (as may be defined by the depth of closure; Nicholls *et al.*, 1998) to the backshore area of the upper beach face beyond the influence of the hydrodynamic regime. This is only a subset of the cross-shore extent of the coastal region, which extend beyond the depth-limited breaker zone and into deeper water. As morphological response times become larger with progression

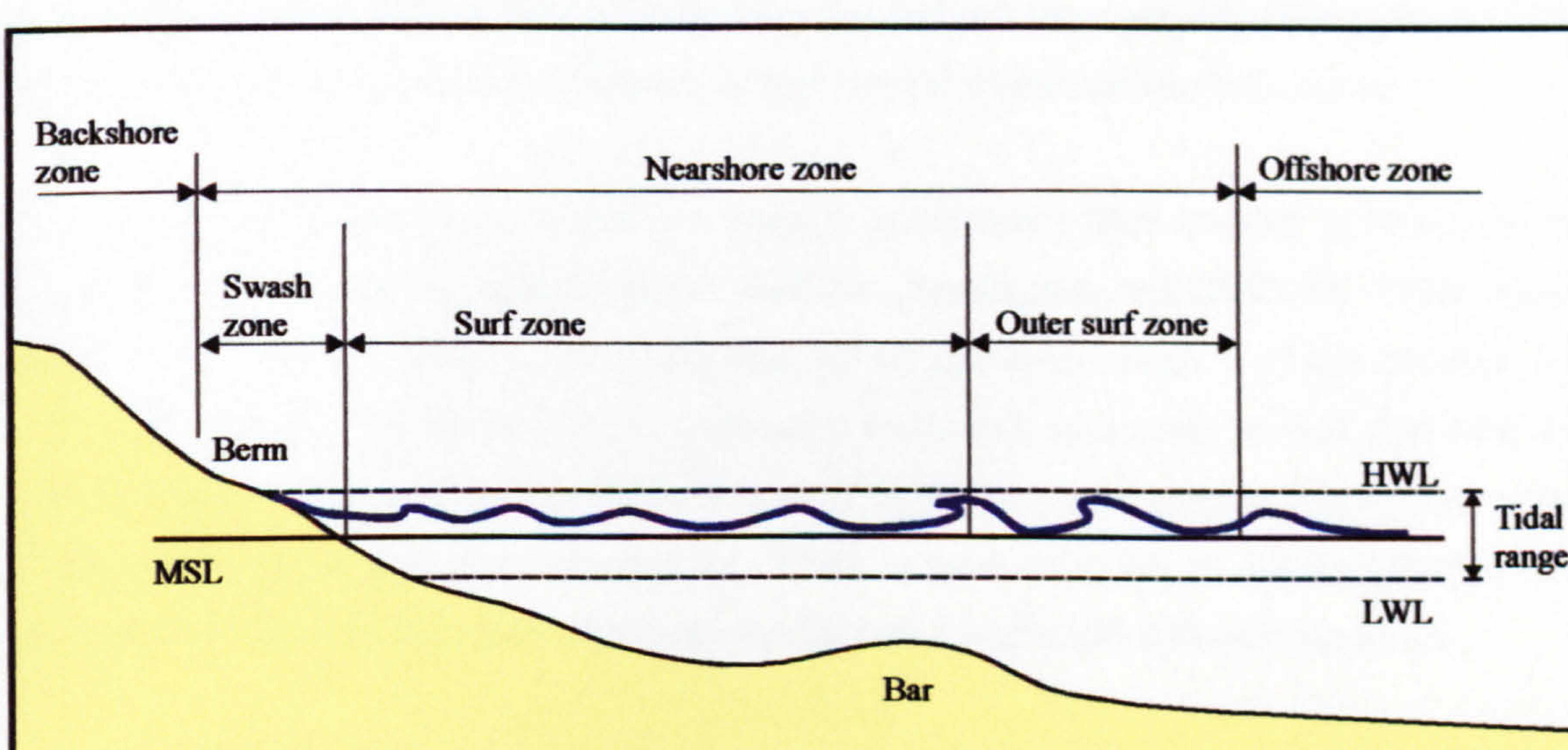


Figure 2.1 Cross-shore extent of the morphodynamic coastal system.

offshore, the effect of neglecting this outer area is to omit consideration of a region which will never be able achieve an equilibrium state due to hydrodynamic forcing. In the longshore direction, consideration is given to behaviour occurring over uniform or enclosed stretches of beach, known as littoral cells (List and Terwindt, 1995; Komar, 1998). Examples of these littoral cells are quasi-linear stretches of beach exposed to uniform hydrodynamic forcing or pocket beaches where behaviour is bounded by headland features. Even though the system of interest is located in the nearshore region, consideration of the boundary conditions for this system suggest the significance of the non-local hydrodynamic forcing system.

Rather than enumerate the various accepted physical processes which occur within the coastal system, this chapter will focus on presenting a description of the system as a whole. This will be followed by a summary of important observations and current methodologies adopted for both the understanding and the modelling of the coastal system behaviour.

2.2 Characteristics of coastal systems

Coastal systems are examples of dissipative energy systems. Wave and tidal energy are continually input and subsequently dissipated, predominantly through the process of wave breaking. It is expected that such a system would evolve towards a state of dynamic equilibrium under steady forcing conditions. Many researchers have attempted to use these concepts of equilibrium states, both to characterise (Dean, 1991; Wright and Short, 1984) and to model coastal system behaviour (Hanson, 1989; Nairn and Southgate, 1993). It was assumed that the morphological system was trying to head towards a state of equilibrium, but due to changes in the forcing boundary conditions, this state was not reached. The concept of coastal systems achieving a state of equilibrium assumes that the system is to a large extent deterministic i.e. the system is dominated by forced behaviour. Pilkey *et al.*, (1993) question the application of models based on equilibrium concepts as many of these concepts are based on theoretical or laboratory based considerations which are not justified when applied to field conditions.

However, in high dimensional systems such as coastal systems, where many of the interactions are non-linear in nature, states of dynamic equilibrium are not always fixed or achieved. It is possible for chaotic, self-organised responses to occur, leading to a divergence from an equilibrium state. The chaotic behaviour of the system, under certain circumstances, allows transitions to occur in observed morphological behaviour. In fact it is possible for these systems to be maintained in a state which is far from equilibrium (Southgate and Beltran, 1996; Southgate and Möller, 2000). These transitions in system state (sometimes termed as bifurcation points in system behaviour) have been observed both spatially and temporally. For example, two spatially distinct regimes of cyclical bar behaviour have been observed along the Dutch coast (Wijnberg, 1995). At Duck, N.C. in the USA, differing offshore bar migration rates were observed to occur north and south of FRF pier during two distinct time periods (Plant *et al.*, 1999) demonstrating a combination of temporal and spatial transitions in behaviour.

Increasingly in recent years there has been a acceptance that coastal systems do not necessarily behave in a deterministic fashion (Southgate and Beltran, 1996; Coco, 1999). This view is enforced by consideration of the non-linearity of the system. The system of coupled hydrodynamic - sediment transport equations which describe bed level evolution as given by equations 2.1 –2.8 highlight the complex non-linear nature of the sub-systems and their interaction. They consist of a set of hydrodynamic flow equations, a selected sediment transport model and a sediment balance equation.

Hydrodynamic flow equations

$$\frac{\partial u}{\partial t}+u\frac{\partial u}{\partial x}+v\frac{\partial u}{\partial y}+w\frac{\partial u}{\partial z}-fv+g\frac{\partial(h+\zeta-z_b)}{\partial x}=\frac{\partial}{\partial z}\left(\mu\frac{\partial u}{\partial z}\right) \qquad 2.1$$

$$\frac{\partial v}{\partial t}+u\frac{\partial v}{\partial x}+v\frac{\partial v}{\partial y}+w\frac{\partial v}{\partial z}+fu+g\frac{\partial(h+\zeta-z_b)}{\partial y}=\frac{\partial}{\partial z}\left(\mu\frac{\partial v}{\partial z}\right) \qquad 2.2$$

$$\frac{\partial u}{\partial x}+\frac{\partial v}{\partial y}+\frac{\partial w}{\partial z}=0 \qquad 2.3$$

where (u, v, w) are the components of flow velocity averaged over turbulence at time t and location (x, y, z). h is the mean water depth, ζ is the elevation of the free surface with respect to mean water level ($z = 0$). z_b is the bottom elevation with respect to the mean bottom elevation ($z = -h$). g is the acceleration due to gravity, f the Coriolis parameter and μ the molecular eddy viscosity.

Sediment balance equation

$$\frac{\partial h}{\partial t}+\vec{\nabla}.\vec{S}_t+\frac{S_*}{\rho_s(1-p)}=0 \qquad 2.4$$

where ∂h is the change in bed elevation for a time step ∂t and ρ_s and p are the sediment density and the porosity. One possible sediment transport model formulation (in this case for unidirectional flow) is given by

$\vec{S}_t$ *is the volumetric sediment flux* given by

$$\vec{S}_t=\sigma\left[\frac{|\vec{\tau}|-\tau_{c0}}{\tau_{c0}}\right]^b\left[\frac{\vec{\tau}}{|\vec{\tau}|}-\lambda.\vec{\nabla}h\right] \qquad 2.5$$

where σ, b and the tensor λ depend on sediment properties. τ is the actual bed shear stress and τ_{c0} is the threshold shear stress for erosion on a flat bed.

S_* *is the erosion deposition flux* given by

$$S_*=w_s c_a-w_s c_o \qquad 2.6$$

where w_s is the settling velocity, c_a and c_0 are a reference concentration and the concentration near to the bottom. c_a is parameterised on terms of flow conditions. A typical parameterisation is given by Dyer and Soulsby (1988);

$$c_a = \rho_s(1-p)\left[\frac{\gamma_o s}{1+\gamma_o s}\right] \qquad 2.7$$

$$s = \frac{\tau - \tau_c}{\tau_c} \qquad 2.8$$

τ_c is the critical shear stress for erosion.

The main point to note about these equations is that the behaviour of the hydrodynamic and sediment transport sub-systems in themselves are non-linear in nature. This non-linearity is commonly associated with unpredictability. The hydrodynamic components manifest themselves in the generation of radiation stress terms which are highly non-linear Therefore, when this is extended to the interaction of the coupled system, it is unreasonable to expect a predictable behaviour of the system as a whole.

Concepts of non-linearity, which we have seen to be an intrinsic part of the morphological coastal system, and others such as the impacts of feedback and of the chronology of hydrodynamic forcing on the coastal system will now be considered in more detail.

2.2.1 Non-linearity

Non-linear systems are characterised by behaviour in which the output of the system is not in constant proportion to the input (Cowell and Thom, 1994; Cowell *et al.*, 1995). Thus a system in which the output, Y, is a function of its inputs, X, such that

$$Y = G(X) \qquad 2.9$$

is non-linear if

$$G \neq constant \qquad 2.10$$

Non-linearity of behaviour in morphodynamic systems is inherent because the interactions between the morphodynamic components are not weak (von Bertalanffy, 1968). In addition to this, many of the subsystems comprising the coastal systems themselves are strongly non-linear in nature as indicated previously. This is especially true for hydrodynamic systems where the behaviour becomes increasingly non-linear as water depth decreases. Waves undergo shoaling as they approach the coastline. This results in a steepening of water surface slopes which causes increasing interactions between different fluid-dynamic processes.

Increasing non-linearity in wave flows is significant because it allows the possibility of transfer of energy between these flows, often at different frequencies (Guza and Thornton, 1981; De Vriend, 1991). These flows and interactions have been identified as possible mechanisms leading to complex bar-trough topographies (Bowen and Guza, 1978; Huntley *et al.*, 1981; Holman and Bowen, 1982).

2.2.2 Chronology

Beach morphology response to hydrodynamic forcing is strongly non-linear as may be inferred by the high power law relationship between sediment dynamics and wave orbital velocities (Fredsøe and Deigaard, 1992; Van Rijn, 1993). This non-linearity necessitates that the morphological response may be highly dependent on the sequencing of wave events (Southgate, 1995). Periods of high energy will raise more sediment into suspension, thereby allowing other processes (e.g. infragravity wave motion) the opportunity to transport this larger volume of sediment, resulting in significant morphological change. Therefore morphodynamic response is dependent on the sequencing of periods of significant energy levels.

Morphodynamic change cannot be explained by just considering the hydrodynamic inputs to the coastal system. These systems are also influenced by their antecedent state (Wright and Thom, 1977). Beaches are typified by periods of rapid erosion followed by extended times of accretional recovery. Southgate (1995) showed, based on a reordering of wave events in a numerical study, that beach response is most strongly dependent on its antecedent state during lower energy events. Beach response following a high energy event showed little dependence on prior morphological state. This latter case is an example of forced behaviour i.e. the hydrodynamic boundary conditions dominating the morphological outcome.

Dong and Chen (2001) carried out a similar analysis to Southgate. They concluded that shoreline erosion statistics are sensitively dependent on the wave climate, predominantly because of the cross-shore transport response to extreme events. This again highlights the significance of the non-linear nature of the coastal system as the cumulative effects of beach response over a period of time is highly dependent on the ordering of extreme hydrodynamic events.

2.2.3 Complexity and feedback mechanisms

Coastal systems have been shown to display non-deterministic or complex behaviour as a result of being strongly non-linear. Phillips (1992) suggests two possible types of complexity which may be prevalent in coastal systems. Firstly, stochastic complexity arises from the cumulative effects of multiple interacting components. Such random components may be too numerous, and interact at such widely varying time and spatial scales, to make it possible to account for the overall resulting behaviour. A second type of complexity arises from the non-linear dynamics of relatively simple systems of equations (Lorenz, 1963; Reeve and Fleming, 1997). This deterministic complexity has the appeal that, at least within a certain time scale or horizon, behaviour predictions are still feasible, whilst over longer timescales the statistical properties of the system are still understood, even if absolute description of the system state is no longer possible.

Feedback mechanisms are intrinsic to the study of non-linear systems. The hydrodynamic forcing changing the beach topography will in turn be altered by the morphological changes (Howd *et al.*, 1992). Hence their significance is related to their role in which they govern the evolution of the system towards an equilibrium state. Equilibrium is a product of negative feedback. This has the effect of damping perturbation growth to maintain the current state of equilibrium. This equilibrium can take three forms (Phillips, 1992) ... a) steady state, b) periodic and c) chaotic. The case of steady state equilibrium occurs for coastal systems when the sediment flux either averages to zero or there is no gradient in the sediment flux vector (Cowell and Thom, 1994). Mathematically this may be expressed by the continuity equation for sediment transport as given by

$$\frac{\partial h}{\partial t}=\varepsilon\left(\frac{\partial C}{\partial t}+\frac{\partial q_x}{\partial x}+\frac{\partial q_y}{\partial y}\right)-\frac{\partial V}{\partial t}=0 \qquad 2.11$$

where h is the bed elevation, ε accounts for sediment density and porosity. C and q_x, q_y are the depth integrated total concentration of suspended sediment and the sediment mass fluxes perpendicular and parallel to the shoreline, respectively. V accounts for autogenic sediment production and losses as well as human interventions such as beach nourishments or sand mining. The spatial terms in equation 2.11 define source or sink terms according to

$$\frac{\partial q_x}{\partial x}+\frac{\partial q_y}{\partial y}\left|\begin{array}{l}<0, \text{ sink}\\ =0, \text{ pathway}\\ >0, \text{ source}\end{array}\right. \qquad 2.12$$

Positive feedback is responsible for the enhancement of minor perturbations. If the level of feedback is strong these perturbations will be reinforced. The study of the stability of the dynamical equations (either linear or the more complicated non-linear case) in the presence of minor perturbations show that positive feedback can lead to the development of rhythmic features over a wide range of scales i.e. from sand ripples [O(cm - m)] to transverse welded bars [O(10 – 100 m)] to crescentic bars [O(100 m)] (Vittori and Blondeaux, 1990; Falques *et al.*, 1996; Deigaard *et al.*, 1999). Positive feedback is also the basis for self organised behaviour. This will be discussed in more detail in §3.4.1.

Plant *et al.* (2001) attempted to establish the role of feedback for the case of sandbars at the Duck site. They related the detrended bar response to a breaker index over the bar crest. As expected, low breaker index values were associated with onshore bar migration with a reduction in bar amplitude. For high values, bars migrated offshore with little change in amplitude. The bar migration was associated with a stabilising feedback mechanism (negative feedback) with bars tending towards an equilibrium position. There was also a suggestion that feedback could have a destabilising effect on bar amplitude causing decay of amplitude associated with conditions of low wave breaking activity.

Even though it is accepted that feedback mechanisms exist in coastal systems and that they have a role to play, it is still not widely understood what their contribution to system evolution is relative to the forced behaviour contribution from hydrodynamic boundary conditions. This is complicated by the fact that the level of significance of feedback will be dependent on the temporal duration of interest.

2.3 Acquisition of knowledge about coastal systems

If one recalls the simplistic model of knowledge acquisition presented in figure 1.1, the key stages outlined were observation, interpretation and modelling. As interpretation is in some sense the goal for both the development of understanding and acquisition of knowledge, focus here will be directed towards the observational and modelling stages.

2.3.1 Coastal system measurements

Most of the recent insights into coastal system behaviour have come as a result of extensive field measurement campaigns. "Extensive" in this context needs to be considered in both the spatial and temporal sense with correspondingly dense sampling densities. An ideal measurement campaign incorporates both an intensive measurement regime coupled with a long temporal duration. The scales of the measurement regime should be at least commensurate with the scales of expected behaviour if not of finer resolution. Having a long term data set, which has both high temporal and high spatial resolution, allows the possibility of addressing the issue of linkages in scales of behaviour. To date these data sets are still quite rare (Southgate *et al.*, 2002).

The following are a selection of some of the more successful observational morphological field campaigns and the insights which they have revealed. In many cases, the existence of a major morphological field campaign has inspired the additional initiation of shorter term, more intensive field campaigns.

JARKUS ... The JARKUS data set consists of the results of yearly surveys of the bathymetry along the Dutch coast over the period 1963-1990. The longshore and cross-shore resolution were 250 m and 10-20 m respectively. Profiles extended up to 750 m seaward, well outside the surf zone of 200-300 m. Supplementary information is available from the TAW data set consisting of a few profiles which are surveyed more frequently and a number of other additional surveys.

Ruessink and Kroon (1994) investigated the behaviour of the multiple bar system for a site at Terschelling in the North of the Netherlands, using the Jarkus and additional data sets. They identified a sequence of stages during the bars existence; a) generation close to the shore, b) seaward migration and c) degeneration of the bar at the outer margin of the nearshore bar zone.

Wijnberg and Terwindt (1995) analysed the JARKUS data set using empirical orthogonal functions for the entire Dutch coast. A clear difference in behaviour was evident in the large scale morphological behaviour between the North and South Holland regions. North of Ijmuiden, a location which appears to behave as a spatial morphological bifurcation point, nearshore breaker bars migrate seaward and show a cyclic behaviour with the outer bar fading away and a new bar forming near the coast, thereby confirming the findings of Ruessink and Kroon. The period of the cycle was about 15 years. South of Ijmuiden, the bars are smaller and appear to migrate faster with the bar cycle being about 4 years. Further analysis by Wijnberg (1995) suggests that the morphology in the North region tends to be rhythmic in nature in the longshore direction. In the southern region, rthymic longshore bar behaviour is less pronounced.

Duck ... Duck is located on the Atlantic seaboard of the US. The US Army Corp of Engineers established a field research facility as a national centre for coastal research in the early 1980's. Over the period from 1990 – 1999 a series of intensive field measurement campaigns were undertaken

Delilah ...	low frequency and incident band longshore and cross-shore hydrodynamics.
Duck 94 ...	fundamental understanding and modelling of surf zone dynamics and nearshore morphology. Duck 94 was planned as a pilot experiment for the SandyDuck experiment.
SandyDuck ...	sediment transport and morphologic evolution at bed form scales from ripples to nearshore bars.

One of the most significant findings from Duck was the verification of the existence of oscillations in the longshore current (Oltman-Shay *et al.*, 1989), known as shear waves. There have been numerous other studies carried out based on the Duck data sets. One of the more recent ones by Larson *et al.* (2000) used a variant of the empirical orthogonal function approach, Canonical Correlation Analysis, to investigate the relationship between the beach profiles and the incident wave climate for a period of 11 years duration. Profile response was more strongly correlated with nearshore rather than offshore conditions. A strong correlation was also found for profile shape and the mean ratio of breaking waves for time preceding the profile survey. This suggests that cumulative energy is associated with a particular profile configuration.

Argus ... the Argus programme is an initiative established by Prof. Rob Holman of Oregon State University (Holman and Sallenger Jr., 1986; Lippmann and Holman, 1989). It consists of a number of stations established at beaches at a variety of locations around the world. Sites were chosen to incorporate a wide range of hydrodynamic and morphologic conditions. Each station consists of a number of video cameras, which overlook the nearshore region, gathering information on the hydrodynamic and morphologic environment. A variety of image types, including snapshots, time exposure and time variance images, highlight both the instantaneous and the time averaged patterns of hydrodynamic variability in the nearshore. These hydrodynamic patterns in themselves may be directly related to the underlying morphology (Lippmann and Holman, 1989; Lippmann *et al.*, 1993; Kingston *et al.*, 2000).

A particular strength of the video monitoring technique is the ability to transform the qualitative information content observed in the images into world co-ordinates (Lippmann and Holman 1989; Holland *et al.* 1997). This allows subsequent quantification of many of the observed features and processes evident in the images. These systems are unique in that they have large spatial coverage (km) with high resolution (~ 2-5 m cross-shore, 5-10 m longshore, depending on distance from cameras) collected on an hourly basis during daylight hours.

Perhaps one of the most remarkable findings of the Argus programme is the insight it has provided on morphological variability. This is not just from the point of view of intra-site variability but perhaps more significantly, observed variability at a given site (Lippmann and Holman, 1990). In addition to this general observation, there have been a range of more specific insights into nearshore behaviour arising from the Argus programme. Much of the Argus related research to date has focussed on converting the qualitative information observed in the video imagery into a quantifiable form which greatly enhanced the value of the data sets. For example, applications have included: phase speed and angle of breaking waves (Lippmann and Holman, 1991), mapping intertidal morphology (Plant and Holman, 1997; Davidson *et al.*, 1997; Aarninkhof *et al.*, 1997; Kingston *et al.*, 2002), indirect measurements of subaerial bathymetry (Stockdon and Holman, 2000). This data is then available for subsequent analysis and interpretation.

Lippmann and Holman (1990) utilised the Argus video data to develop an objective classification scheme of morphological behaviour of the nearshore region. This refinement of the Wright and Short (1984) scheme classified beach state into 8 categories based on 4 distinct classification criteria. For single barred coasts (or the inner-most bar on multi-bar coasts) the classification is unique.

2.3.2 Data reduction

The ultimate goal of studying large scale coastal behaviour data sets is to increase understanding of the processes which govern long term morphological evolution. It is therefore necessary to extract those characteristics which comprehensively describe the features which comprise the significant variance of these data sets. Traditionally at the smaller scales that have been considered, the emphasis has been on obtaining more resolution in the data sets. However the study and modelling of LSCB data sets requires a change in approach. Even though a high resolution is often maintained in the collection scheme, it may be necessary to consider this as noise when considering large scale processes. This has lead to the suggestion of aggregated models which at a given scale incorporate averaged processes from smaller scales (De Vriend, 1997). This approach inherently assumes that it is possible to identify those small scale processes which are likely to be significant at larger scales. It also follows that this approach is representative of bottom-up modelling as it does not explicitly take account of feedback or of any emergent phenomena (Southgate and Beltran, 1996).

Before it is possible to identify the physical processes linking the different scales of behaviour and attempt to develop models describing their morphological evolution, it is firstly necessary to be able to identify the behaviour itself. One of the main issues which faces the research community is how to transform LSCB data sets into useful information both in a spatial and a temporal sense. A typical realisation of a bathymetry obtained from in-situ measurements may consist of $O(10^3\text{-}10^5)$ individual estimates of elevation. For realisations obtained from remotely sensed data, the quantity of data may be significantly more $O(10^4\text{-}10^6)$. Tracking the temporal behaviour of such data is therefore a daunting task in terms of computational expense.

This feature simplification has been done with reasonable success in the cross-shore direction with the aid of power law profiles (Dean, 1991) and the superposition of bar-like features (Plant *et al.*, 1999). It is also possible to reduce regional spatial patterns with the use of empirical orthogonal functions - EOF's, (Aubrey, 1979; Lippmann and Holman, 1990), which explain different levels of variance present. EOF techniques suffer from the limitation of only being able to describe standing wave features. It is possible to extend this to the identification of progressive wave patterns of behaviour by using complex empirical orthogonal functions - CEOF's (Horel, 1984; Ruessink *et al.*, 2000), or Principle Interaction Patterns - PIP's (or its linearised version ... Principal Oscillation Patterns - POP's) (Hasselmann, 1988; Larson *et al.*, 2002) which have been shown mathematically to be equivalent to CEOF's.

On a more subjective level, attempts to describe large scale behaviour have resulted in general classification schemes such as those by Wright and Short (1984) and Lippmann and Holman (1990). These classification schemes endeavour to produce morphological beach descriptors based on the presence or absence of sand bars, the nature of their longshore variability as well as the degree to which the underlying profile is dissipative or reflective. Lippmann and Holman carried out a statistical analysis of the bar system at Duck in terms of their classification. However, in general these classification schemes have revealed limited insight on the underlying dynamics of these systems.

2.3.3 Modelling of coastal systems

Coastal morphological system change occurs on a variety of spatial and temporal scales as we have seen earlier. Modelling and prediction of these systems is restricted to a number of scales typically related to the discipline of interest (sedimentologists are interested in small scale processes, coastal engineers are interested in scales commensurate with the lifespan and extent of the infrastructure, whilst geologists are interested in centuries to millennia time scales of evolution). It is therefore a daunting task to provide a predictive capability across this range of behaviour. Most process based understanding of coastal systems to date focussed on the small to medium scales (waves, currents, ripples, sediment transport (Fredsøe and Deigaard, 1992)) rather than the larger scales of morphological behaviour. However, societal interest is increasingly driving the research community to develop a large-scale predictive capability (Thornton *et al.*, 2000).

The issue of scales of behaviour has lead to the concept of aggregated models of coastal evolution (De Vriend, 1997) where distinction is made between the different levels or scales of system knowledge. It is assumed that the prediction of behaviour at a given scale should primarily involve the modelling of those processes which occur at that particular scale. Processes occurring at scales larger than that of interest appear as long term trends which may need to be filtered out. Processes occurring at smaller scales, appear at what can be considered a 'noise' level. This noise will have a net effect which will need to be incorporated in the modelling of the process of interest, yet will not have to be modelled explicitly itself. For example, if the time scale of interest is of the order of minutes to hours, the larger scale processes may include tidal forcing or interannual morphological variability. Small scale processes to be considered as noise may include various nuances of turbulence induced by wave breaking processes.

A challenge presented by this approach to large scale system prediction is to find appropriate techniques to integrate processes occurring at both larger and smaller scales into models at the actual scale of interest. There are various approaches which may be taken to this problem including formal averaging of equations and statistical averaging of process results (De Vriend *et al.*, 1993). However, this particular area is still open for much additional research, especially when transition from small and medium scale systems to larger scales is the goal.

Two distinct classes of morphodynamic models may be identified, namely engineering and science driven models. The former class are primarily interested in achieving a practical predictive capability. Whilst a predictive capability is also the goal of science driven models, the predictability tends to be more general in nature rather than site-specific as is the case for engineering models. For scientific models, prediction of general trends of morphological behaviour are equally as valid as absolutes. The following sections present a selection of approaches that have been adopted for modelling coastal systems.

2.3.3.1 Process based modelling

Typical governing equations of a purely hydrodynamic – sediment dynamic coupled morphologic model have already been presented in equations 2.1 – 2.6. Many of the models in this class fall into both the engineering and scientific categories of interest. These models tend to have the practical objective of prediction and are based on scientifically accepted processes. Their practicality is limited by the distance into the future which predictions remain valid (typically of the order of a sequence of wave energy events). The following is a brief overview of some applications of this approach to modelling coastal systems.

There are two broad categories of process based models; profile models which consider cross-shore transport and area models based on fully 3-d or vertically averaged 2-d flow models which considers both longshore and cross-shore behaviour.

In process based profile models the sediment transport distribution over the profile is computed as a function of the cross-shore profile, sediment properties and the seaward boundary conditions. Roelvink and Broker (1993) present a review of the main characteristics of these models. Forcing is considered to be stationary over the duration of the morphological time step. These models have been developed to address the following questions. How much erosion will a beach suffer during a given storm ? Will the beach recover and how quickly ? Can anthropogenic influence abate erosion or other negative effects ? Hence these models are designed to be effective over durations corresponding to wave energy events. The models are seen to perform reasonably when the coastal system is dominated by cross-shore phenomenology.

De Vriend *et al.* (1993) present a review of medium-term coastal area modelling. Their main conclusions were that whilst significant development had been achieved in this type of model, much work was required to validate the models and make them robust for practical applications. They were most applicable to short-term evolution problems where there was a fast response to a large interference of the system. In a later review, Nicholson *et al.* (1997) also compare coastal area morphodynamic models. These 2DH models were developed at a number of different institutes The choice of sediment transport formulation was shown to have a large influence on the resulting morphology. In addition the requirement of a high accuracy of the components of the models is highlighted to combat the build-up of errors, especially over longer runs.

A variation on this modelling approach compared to the previous sediment transport formulations is the so called energetics based approach (Bowen, 1980; Bailard, 1981). The energetics approach expresses the sediment transport rate as a function of various velocity moments. A variety of models have adopted this approach (Guza and Thornton, 1985; Roelvink and Stive, 1989; Nairn and Southgate, 1993; Russell and Huntley, 1999, etc.) These models have been shown to perform well for erosive conditions (Schoones and Theron, 1995), but their main limitation being an inability to correctly simulate accretion during times of low energy (Gallagher *et al.*, 1998).

Detailed process models have reached the stage in their development where they are capable of producing reasonable results over short to medium term time scales. It would be tempting to let these models run for longer periods of time to cater for larger scale behaviour, especially considering the rapid advances being made in the computational capacity of modern computers. However, De Vriend (1997) highlights the following serious problems with this approach .

- Even though the computational power is advancing rapidly, models run times comparable to prototype times are still required for detailed process models. This is not a viable option for long-term modelling.
- Detailed process models have the inherent danger of build up of numerical errors which would ultimately lead to erroneous answers.
- As already mentioned extrapolation of small – medium scale processes to larger scales may not be appropriate as emergent behaviour at larger scales will not necessarily have been taken into account.
- There are inherent limits on predictability which will limit the prediction horizon for a particular scale of process.

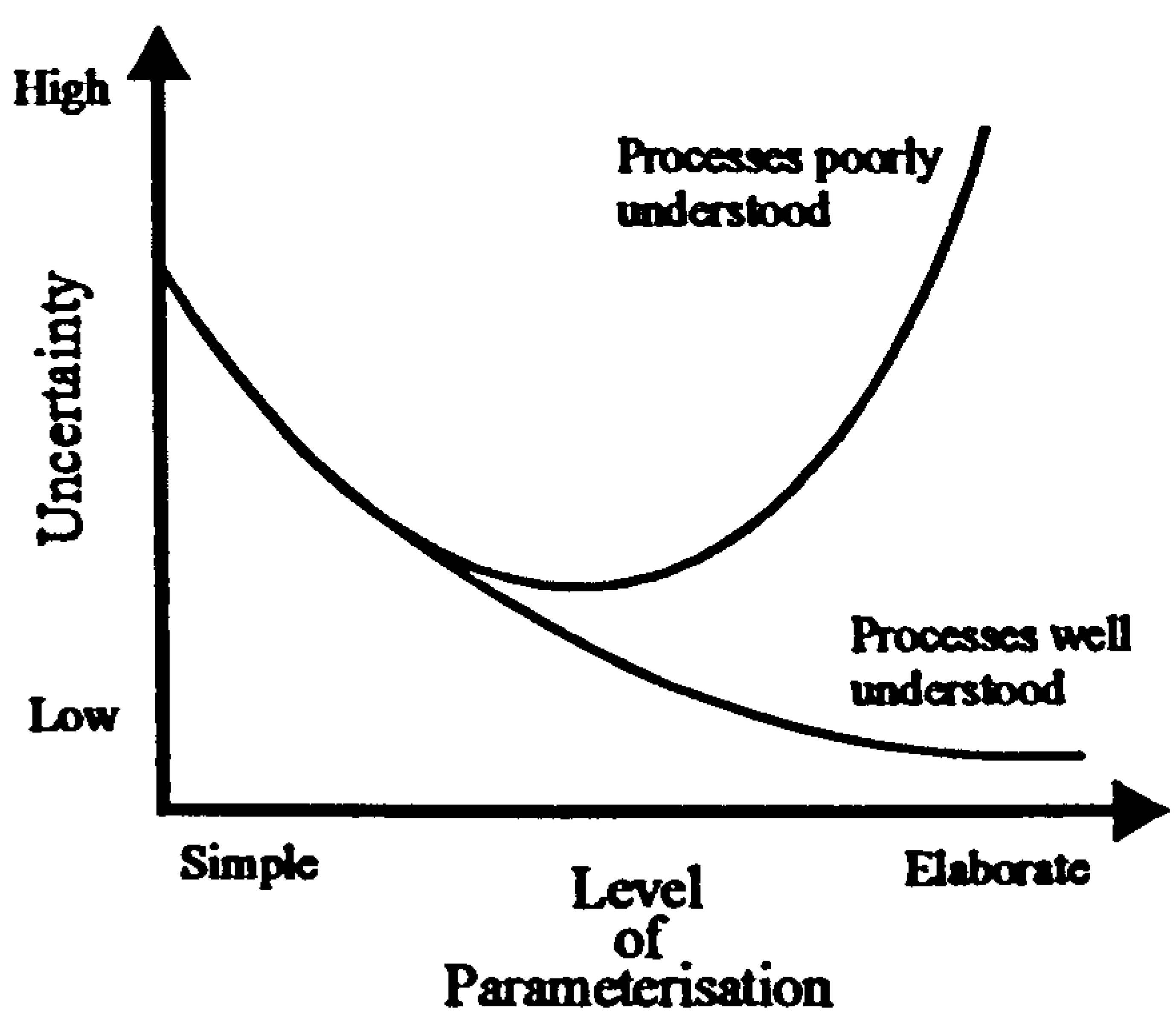


Figure 2.2 Uncertainty of mathematical models (after Cowell et al., 1995)

From a practical point of view, the inherent uncertainty in knowledge of process details suggests that a simplified parameterisation for modelling coastal systems would be most effective (Cowell *et al.*, 1995). However as the level understanding of processes increase increasing levels of complexity are acceptable in the model formulation as shown in Figure 2.2. Consideration of these limitations has forced researchers to find alternative approaches to modelling coastal systems.

One final class of models, which essentially falls under the heading of process based models, are those which attempt to utilise observations to provide corrections to parameterisations of dynamic models via data assimilation. Such models have been used extensively in meteorological applications and to some extent in global ocean modelling. To date, however, data assimilation has not been used extensively for modelling coastal morphological systems, primarily due to the computational expense of the approach.

2.3.3.2 Behaviour-oriented modelling ...

A recent trend in the development of morphological models has been an interest in investigating the minimum quantity of process knowledge which is required to produce a model which produces the correct behaviour. These so called behaviour-oriented models aim at describing the general behaviour of a phenomenon without going into the details of the underlying physical processes (De Vriend *et al.*, 1993). These models map the observed behaviour of a coastal system (obtained from either field data or process based model runs) onto simple mathematical models which exhibit similar behaviour (Capobianco *et al.*, 1999). The model does not need in principle to be based on the underlying physical processes, only to exhibit certain behavioural characteristics as defined by the model developer. As simplicity tends to be a key element of these models, they have tended to be predominantly of cross-shore profile rather than area models.

Cowell *et al.* (1995) outline a large scale coastal behaviour morphological model based only on principles of sand mass conservation and geometric rules for shoreface and sand body morphology. Physical processes are incorporated as parameters which describe the geometry of the cross-shore profile. Their study suggests the importance of small residual sand movements that accumulate through time in causing large scale coastal behaviour.

Plant *et al.* (1999) present a simplified bar migration model based on concepts of equilibrium. The bar is constrained to migrate towards a time dependent equilibrium position at a rate governed by both a response time and instantaneous distance of the bar from the equilibrium position. The response time and the equilibrium position are both assumed to be dependent on the time varying wave height. The model was calibrated and subsequently evaluated on an alongshore averaged, 16 year, field data set from Duck. It was able to explain up to 80% of the bar position variability. This model is significant in that it had only two free parameters yet was capable of capturing the essential dynamics of the bar position variability.

In one-line models the changes in shoreline position are assumed to be produced by spatial and temporal differences in the longshore sand transport rate (Hanson, 1989). This type of model is used for changes that occur over a period of years to decades. The models are best suited to scenarios where there is a systematic trend in the longshore shoreline change behaviour. Cross-shore variability is assumed to average out over the typical simulation periods. It has been attempted to extend these engineering oriented models to n-line models which attempt to cater for cross-shore processes (Hanson and Larson, 2000). This extension demonstrated a capability of resolving seasonal cross-shore variability but was not able to resolve change due to the impact of storm events.

Due to the inherent limitations of predictability of process based cross-shore profile models, i.e. the coastal system is always in a transitional state due to the discrepancy in response time of the morphology to the forcing, Stive and De Vriend (1995), proposed a simple "panel type" model to map long term cross-shore behaviour. This was based on the assumption that it is possible to schematise the profile into distinct morphological zones; the upper shoreface incorporating the dune face, beach and surf zone; the lower shoreface reaching out to the continental shelf; the middle shoreface forming a transition zone. A limitation of the model was that forcing was only due to short waves. The authors point out that the simplicity of the model would result in answers which were valid as estimates of order of magnitude rather than absolutes.

The potential contribution that behaviour-oriented models make to developing a predictive capability for coastal systems can be seen to be two fold: firstly, developing insight into the significance of processes and their contribution to the overall morphological evolution. For example, Cowell *et al.* (1995) highlight the significance of uncertainty in estimating the contribution of longshore sediment flux to large scale coastal behaviour.

Secondly, a potential benefit of behaviour oriented models, which has not necessarily been capitalised on, is to exploit their simplistic nature. As they tend to have a significantly lower computational overhead, compared to their process-oriented model counterparts, it is possible to adopt techniques of Monte Carlo simulation to develop probabilistic models of the coastal system. Multiple runs in which the boundary conditions governing model parameters are varied in line with their uncertainty are used to build a statistical assessment of the most likely outcome (Vrijling and Meijer, 1992). This approach would be beneficial when long term prediction is required to establish the impact of human intervention on coastal systems.

2.4 Requirements for Further Insights into Coastal System Behaviour

This section is aimed to address the following question. What are the stumbling blocks that are holding back the development of understanding of coastal system behaviour ? Addressing this question helps to clarify the key requirements for future research into coastal systems.

It is evident that gaps in knowledge about the processes occurring in coastal systems exist. This becomes especially prevalent as we move to larger scales. There appears to be a strong link between the level of knowledge of process behaviour and the scales at which observations are readily available. The examples presented in §2.3.1 highlight the importance of large scale measurement campaigns for revealing new insights into coastal system behaviour. Augmenting such existing data sets is perhaps the most cost effective way of establishing large scale coastal behaviour data sets. The Argus programme is perhaps one of the most appropriate data sets for this consideration. From these arguments, the continuation of implementation of field measurement campaigns is a prerequisite for achieving further insight into coastal system behaviour.

Data rich observations lead to the necessity for data reduction. This extraction of the key variance of data sets lends itself to the development of simple models. Due to their simplicity, these models will have a greater possibility of achieving robustness. Closely linked to this objective is the issue of scales of behaviour. More research needs to be conducted on the evaluation of the concepts of scale cascades (the hierarchical transition of modelling from one scale level to the next). The alternative to this hypothesis is the development of phenomenological models appropriate to the scale of interest which essentially ignores linkages between scales (Werner, 1999).

One important issue which has not been addressed with regards to modelling of coastal systems is methods of assessing the success of particular approaches or models. Reading through the literature we are repeatedly confronted with model evaluations where model results compare 'well' with observations. A stringent and objective evaluation would be more appropriate. An objective measure is even more important when inter-comparison of models is being considered, as quite often direct comparison of model results is difficult. Peet *et al.* (2002), present an application of the Brier Skill Score as an objective measure for the evaluation of model performance. Atger (1999), showed that this particular measure of model skill may be broken down into reliability and resolution components. However, model evaluation for coastal systems is an area which still requires further work.

The conclusion which may be drawn from the above arguments is that the over-riding challenge facing the nearshore research community is to establish techniques to facilitate both the interpretation of data sets and to aid in the modelling processes of these increasingly large and complex data sets. The next chapter will proceed to give an overview of some of the techniques which show potential for these component stages of gaining insight into coastal systems.

Chapter 3 Complex Adaptive Systems

3.1 Introduction to Complexity

"The slenderest knowledge that may be obtained of the highest things is more desirable than the most certain knowledge obtained of lesser things"

St. Thomas Aquinas

Complex Adaptive Systems may be considered to be collections of simple units which evolve as a result of interaction, both between the components and the components and their environment. Many natural systems (e.g., the brain, immune systems, ecologies, societies) and increasingly, many artificial systems (parallel and distributed computing systems, artificial intelligence systems, artificial neural networks, evolutionary programs) are characterised by apparently complex behaviour. This complex behaviour manifests itself as chaotic, seemingly unpredictable dynamics. These characteristics emerge as a result of non-linear, spatio-temporal interactions among a large number of component systems at different levels of organisation. As the above quotation implies, detailed knowledge of the behaviour of any of the components of such a system does not necessarily prescribe knowledge of behaviour at the level of the full system.

Consequently, researchers in a large number of disparate areas (including computer science, artificial intelligence, neural networks, cognitive science, computational economics, mathematics, optimisation, complexity theory, control systems, biology, neuroscience, psychology, engineering, etc.) have begun to address, through a combination of basic, applied, theoretical and experimental research, the analysis and modelling of complex systems. Collectively these studies are termed the study of complex adaptive systems (alternatively known as General Systems Theory or the 'Sciences of Complexity'). This multi-disciplinary area of research investigates both the principles common to all complex entities, and the mathematical models which can be used to describe them. The base level operations that these mathematical models typically perform tend to be simplistic in nature. However, often the resulting level of complexity which they can model is surprising (Babovic and Minns, 1994). This emergent functionality leads to the important point that many of the adopted mathematical models themselves may be considered as complex systems in their own right.

This chapter will continue by outlining the historical development of this area of enquiry. It will then proceed to present some characteristics of complex adaptive systems and approaches that have been taken to studying them. The list of concepts presented here is by no means intended to be exhaustive, but rather a representative selection. The chapter concludes by presenting a summary of reasons why it is valid to consider coastal systems as complex adaptive systems. Where appropriate, arguments will be backed up with examples from coastal systems. However, as the application of complex adaptive systems approaches to coastal systems is still in its infancy these are still relatively sparse.

3.2 A New Paradigm in Thinking

The recognition of complex adaptive systems marked the beginning of a new paradigm in the approaches taken to the investigation of system behaviour. The implementation of this new approach to investigating systems can be traced back to the development of operations research during World War II. Its pragmatic approach, with the aim of winning the war, may be summarised as follows (Skyttner, 1996) ...

- It is not necessary to understand everything, rather to have it under control. Ask what happens rather than why.
- Do not collect more information than is necessary for the job. Concentrate on the main consequences of the task, the small details are of little significance.
- Solve the problems of today and be aware that prerequisites and solutions soon become obsolete.

Whilst these guidelines may not be completely appropriate to the scientific study of systems, operations research marked the first successful methodology where complex problems were not disassembled into their component parts but could be treated as a single entity by different researchers.

A more scientific emphasis on the holistic approach to the study of systems was advocated in the 1940's by the biologist Ludwig von Bertalanffy (von Bertalanffy, 1968). Traditionally, systems or entities were reduced to the properties of their parts or elements. This reductionistic approach to the analysis of biological systems ignored the their interaction with their environment. Von Bertalanffy emphasised the necessity of a holistic approach as systems can acquire new properties through emergent behaviour. This behaviour typically is not evident or even expected from a consideration of the components of the system. For example an understanding of the firing of individual neurons in the brain cannot begin to explain the higher level functions of the brain such as reasoning, memory or self-awareness. Von Bertalanffy believed that a general systems theory would offer an ideal conceptual framework for unifying various scientific disciplines that had become isolated and fragmented.

An explosion of interest in complex adaptive systems was instrumental in the establishment of the Santa-Fe Institute. Here, scientists from various disciplines gathered together to share experience and ideas for the study of complex adaptive systems. This establishment has flourished to date and has become one of the leading centres for complex adaptive systems research. For general references to the emergence of the study of complex adaptive systems, a good overview is provided by Waldrop (1992) and Gell-Mann (1994). Books such as those by Gleick (1987) and Bak (1997) provide a broad summary of many of the concepts and topics permeating the complex adaptive systems field.

3.3 Characteristics of Complex Adaptive Systems

The most striking characteristic of complex adaptive systems is their ability to demonstrate unexpected or emergent behaviour. This behaviour is strongly linked to the non-linear interactions that occur between the component elements of the system. This behaviour manifests itself as dynamical patterns which have no apparent foundation in the dynamical equations describing the motion of the elementary particles. For example aeolian sand ripples display rhythmic patterns which are not immediately explained by the processes governing the sand transport (Anderson, 1990). The emergent behaviour can be considered to occur due to the two forms of complexity previously considered in §2.2.3, namely, stochastic and/or chaotic complexity.

In a morphodynamic system, one may consider each spatial location in the nearshore region as an extra dimension (Southgate *et al.*, 2002). Systems of such extremely high dimensionality readily lend themselves to stochastic complexity. As the systems become more complicated with multiple interacting components their apparent behaviour also increases in complexity. Yet stochastic complexity, prevalent in coastal systems, does not completely hide the underlying dynamics of the systems. It is relieved to some extent by a high level of system redundancy as the behaviour of nearby locations will be strongly correlated. To build on the idea of system dynamics operating on a reduced dimensionality, Patil *et al.* (2001), in the field of atmospheric sciences, reiterate, that whilst the atmospheric system phase space is of high dimension, the dynamics of that system take place on an attractor of significantly lower dimension (see §3.4.2 for a discussion of phase space representations and attractors).

However stochastic complexity alone is not responsible for all the observed chaotic behaviour. As previously shown, coastal systems are characterised by non-linear governing equations. Feedback, positive or negative, is therefore an essential factor in the evolution of such systems. It is the case of positive feedback which results in emergent behaviour. Often these systems behaviours are considered to fall into the category of deterministic chaos. Deterministic chaos lies between the two extremes of determinism and randomness (Abarbanel, 1996) in terms of the level of predictability associated with the system. Perhaps it is best to introduce a few definitions relevant to chaotic systems...

- A deterministically chaotic system is one which displays aperiodic bounded dynamics with sensitive dependence on initial conditions. This is true even for simple systems where the dynamics are governed by a limited number of equations.
- Deterministic means that there is a definite rule with no random terms governing the dynamics of the system. Therefore knowledge of the state of a system at any time t implies the knowledge of the state of the system at any time $t + \tau$. Determinism is

also strongly linked with the concept of causality i.e. nothing occurs without a cause or a *determining* reason. Thus if a stimulus for change is provided to a deterministic system the corresponding response is predetermined.

- Sensitive dependence on initial conditions, means that two points that are initially close in a system will drift apart as time proceeds. For example consider a system whose dynamics depend on the choice of a particular parameter. If this initial parameter is perturbed a small amount, then for a chaotic system, the evolving dynamics of the system will be seen to diverge for the two starting conditions. This is an essential aspect of chaos and is a key element in the identification of chaotic systems.

A criterion for judging the level of complexity of a phenomenon is the quantity of information required to define it and the associated practical difficulty in obtaining the information. Linear phenomena will require just two known points whereas a phenomenon such as turbulence will require many thousands of samples to capture the dynamics.

Deterministic chaos is usually thought of in terms of temporal evolution. However, unless a system is in a perfectly isotropic state at its initial conditions, temporal chaos will lead to spatial chaos (Phillips, 1999), manifesting as increasing spatial complexity over time. Phillips (1993) shows that traditional spatial statistics are unable to distinguish deterministic chaos from random noise. Thus trying to decipher system behaviour is made increasingly difficult.

When the source of a system's signal is linear a standard means of classification is the use of a Fourier spectrum (Priestley, 1981). The system dynamics may be inferred from the location and magnitude of the peaks in the spectrum. On the other hand, chaotic non-linear systems produce continuous broadband spectra (Abarbanel, 1996). Whilst this allows inference of emergent behaviour via measures such as fractal dimension, this approach is not able to reveal any significant information about the underlying process dynamics of the system. Alternative approaches are therefore required to characterise chaotic systems. These will be outlined in more detail in the following sections.

3.3.1 Analytic versus systemic approaches

When considering approaches to investigating systems there are two major perspectives on how this may be achieved. These are the analytical and the systemic approaches to the characterisation and modelling of systems. This is sometimes also termed as bottom-up and top-down modelling. The analytic approach seeks to reduce a system to its elementary components in order to study in detail and understand the types of interaction that exist between them. From this understanding of processes on a microscopic level it is assumed that by extrapolation to larger spatial and temporal scales it is feasible to predict behaviour on a macroscopic level. Systemic approaches on the other hand advocate system investigation as a whole with emphasis being placed on global system patterns of behaviour rather than specific details.

To make a predictive capability viable, analytical approaches rely on invoking the laws of the additivity of elementary properties. This is the case in homogenous systems, i.e. those composed of similar elements and having weak interactions (such as loose sand grains being poured from a bucket). Traditional models try to anticipate as many factors as possible in as much detail as possible. Even though typically these models are based on sensible underlying physical principles, they invariably incorporate a certain level of parameterisation. The values taken for these parameters tend to be calibrated on limited and sometimes abstracted data sets (e.g. laboratory data). Thereby they become very inflexible and practically useless when new regions of parameter space are being explored as these models are typically not very adaptive.

The laws of additivity of elementary properties do not apply in the case of highly complex systems composed of a large number of elements linked together by strong interactions (for example, fluid particles interacting with each other and also with sand grains). These systems need to be approached by new methods such as those which the systemic approach group together. The purpose of the new methods is to consider a system in its totality.

Systemic approaches tend to adhere to the following principles ...

System Holism Principle: A system as a whole works differently than the parts of the system. The parts alone cannot do what the system can.
Complementarity law: Differing perspectives on the same system are neither 100% independent nor 100% compatible. Together, they reveal more information about the system than any perspective in isolation.
Universality Principle: Certain mechanisms and laws hold for many different kinds of systems studied in diverse areas.

Evidence for universality comes from empirical patterns of behaviour (including, for example, fractals, 1/f noise) that are common to a large range of systems. For example, fractals patterns have been shown to occur in systems as diverse as measures of coastlines, highway traffic, flow of the river Nile and quasars. The principle of universality requires that general features cannot be sensitive to small scale details (Bak, 1997), as the details for each system would intrinsically be different. Therefore, if the behaviour of a large class of systems is similar as this suggests then it should be sufficient to study the simplest system to gain insight into a large range of systems. For example, Feigenbaum, (1980), used an overly simplified model to study transitions to chaos. Subsequently this model has been used to describe disparate problems such as the dynamics behind a forced pendulum or a liquid with rotating convective rolls (Bak, 1997). One potential flaw with the models based on universality is that they, to some extent, assume stationarity of forcing (Werner, 1999). This typically is not the case especially for coastal systems where the forcing occurs over a large range of temporal scales.

Table 3.1 presents a summary of the general traits of both approaches to studying systems. Even though the goal of both analytical and systemic approaches is essentially the same, namely, to shed light on the behaviour and characteristics of a given system as was identified in Chapter 1, it is not always possible or obvious as to how to reconcile both approaches.

Table 3.1 Analytic vs. systemic approaches to studying systems

Analytic Approach	Systemic Approach
Emphasises the precision of details	Emphasises global perception
Isolates, and then concentrates on the elements	Unifies and concentrates on the interaction between elements
Studies the nature of the interaction	Studies the effects of the interactions
Modifies one variable at a time	Modifies groups of variables simultaneously
Validates facts by means of experimental proof within the framework of a theory	Validates facts through comparison of the behaviour of the model with reality

3.4 Approaches to Studying Complex Adaptive Systems

A significant proportion of effort invested in the study of complex adaptive systems has been in the development of appropriate techniques for the investigation of their behaviour and modelling. The more popular examples of these are Artificial Neural Networks, Evolutionary Computation and Cellular Automata. These approaches in themselves are complex adaptive systems which have adopted ideas from other systems and much research has been conducted into the mechanisms which govern their behaviour. In addition to these complex adaptive systems techniques, the field of non-linear dynamics has also given many insights into the behaviour of complex adaptive systems. In particular, this is in relation to concepts of system characterisation and predictability.

This thesis will concentrate on investigating the utility of the two former approaches, Artificial Neural Networks and Evolutionary Computation, for the analysis and modelling of coastal systems. To date the application of these techniques to coastal systems is very limited and has tended to concentrate on hydrodynamic aspects of coastal systems rather than morphodynamic considerations. A brief overview of the other complex adaptive system techniques is now given. Artificial Neural Networks and Evolutionary Computation will be revisited in significant detail in the following chapters.

3.4.1 Cellular Automata

Cellular Automata are simple, mathematical models of systems. They consist of a grid upon which elements at each grid point are updated at each time step according to simple rules. The rules by which these elements are updated are explicitly dependent on the state of adjacent neighbouring grid locations. All grid locations are updated synchronously. The evolution of such systems tend to be highly dependent on initial state, yet, evolved statistical properties are similar irrespective of initial state. Therefore even though cellular automata models tend to evolve from different starting points in parameter space, the evolved systems attain a specific 'organised' configuration. Hence these models are sometimes termed as models of self-organisation (Bak, 1997).

As previously suggested, Cellular automata are an example of a complex adaptive system whereby their inherent complex behaviour may be used to describe and model other complex adaptive systems. Cellular automata have been used widely to investigate complex behaviour in areas such as biology, chemistry, environmental science (for an overview, see for example, Bak, 1997; Science, 1999).

Cellular automata have already been used extensively to further understanding of the behaviour of geomorphological systems. These studies have concentrated on producing models which, whilst considering micro-scale behaviour such as that of sand grains or water particles, result in models which produce patterns of behaviour at much larger scales such as ripple formation. Hallet (1990) presents an early review of geomorphological applications of cellular automata. More recently, further geomorphological applications have included phenomena such as aeolian ripples (Anderson, 1990; Ouchi and Nishimori, 1995); braided rivers (Murray and Paola, 1994); and eolian dunes (Werner, 1995).

In the context of coastal morphodynamic systems, Werner and Fink (1993) demonstrated that a cellular automata type model is capable of simulating beach cusp features. This model was capable of producing results which were indistinguishable from a process based model where the features are generated by edge wave motions in the alongshore (Bowen and Huntley, 1984). Coco (1999) extended this work to show that the beach cusps formed due to feedback processes between the flow and the topography. The beach cusp topography developed to exhibit a wavelength proportional to the swash excursion. Self organisation processes were shown to be capable of reshaping the pre-existing topography to allow for cusp development unless the topography was exaggerated enough to drive the flow circulation.

Werner and Kocurek (1997) investigate the dynamics of bed-forms and suggests that these features may be simulated by only investigating the defects (end of the bed-form crests) in the pattern. This was motivated by the hypothesis that the defects will respond more immediately to changes in the dynamical forcing conditions.

Murray and Reydellet, (2001) present a self organised model for rip currents. They show that their model is capable of producing quantifiably accurate results and produced plausible explanations for a range of rip-current phenomena. At larger scales of morphological behaviour, Ashton *et al.* (2001) suggest that instabilities in longshore currents generated by oblique wave approach could lead to self-organised large scale shorelines features such as cuspate forelands and large scales capes such as those along the south-eastern coast of North America. Cellular automata, therefore, have proven themselves to be an example of a complex adaptive systems approach which have given valuable insight into the behaviour of coastal systems.

3.4.2 Non-linear dynamics

Whilst not strictly a class of complex adaptive system in themselves, non-linear dynamical systems, and their study, are intrinsically linked to many of the concepts pervading the field of complex adaptive systems and systemic study in general. Of the immediate questions which may be raised when studying a system perhaps the most significant is the following; how can we recognise when we are dealing with a complex system ? This may be rephrased as; what are the characteristics of complex systems as opposed to those of more predictable systems, which the majority of traditional analysis techniques assume ? Non-linear dynamics techniques provide a window of insight into the behaviour of these chaotic systems and allows us to try to answer these questions. Much of the following discussion is derived from the publications of Kaplan and Glass (1995) and Abarbanel (1996).

The central concept behind non-linear dynamics is that of the phase space representation of a system. The typical presentation of a representative time series, $f_i(t)$, from a system, D; is a plot of the dynamics of the measure, $f_i(t)$, as a function of time, t. However this is only one form of representation. It is also possible to represent the dynamics of a system by plotting the trajectory of the dynamics as given by their n-dimensional co-ordinates. This is termed the state space representation of the dynamics. As typically we do not know the all the components of a system we refer to a phase space representation of dimension, m (m < n) embedded within the state space. A characterisation of phase space representations is that for dissipative systems the volume of phase space taken up by a systems dynamics will contract due to losses in energy (Gleick, 1987). This is not true however for systems characterised by white noise, as completely random processes will eventually occupy all regions of phase space.

Adequate information is seldom available to generate these representations of systems, especially if systems of large dimensionality are being considered, as is the typical case for coastal systems. However it is possible to 'reconstruct' the dynamics of a system from a given time series of the system. This is known as the time delay embedding of a time series. A time series may be embedded in a space of dimension, D_E by taking D_E co-ordinates given by

$$D_E = \left(D_t, D_{t-\tau}, D_{t-2\tau}, \ldots, D_{t-(D_L-1)\tau}\right) \qquad 3.1$$

where τ is the time delay. Typically the actual dimension of the system, D_L, is unknown and so it is necessary to estimate D_E. Key issues for time delay embedding are estimation of the time delay, τ, and the embedding dimension, D_E. The details of these tasks will not be presented here but further information may be obtained from Abarbanel (1996).

The heart of non-linear dynamics lies with an important theorem; Takens embedding theorem (Takens, 1981). This theorem states that the reconstructed dynamics are geometrically similar to the original system dynamics for both continuous and discrete systems. Hence one does not require complete knowledge of a system to be able to predict its future behaviour. If it is possible to measure one system variable it should be possible to reconstruct the dynamics of the entire system. This in turn will facilitate the development of phase space models of the system.

To illustrate the above concepts consider the much referenced Lorenz equations (Lorenz, 1963).

$$\begin{aligned} \frac{dx}{dt} &= \sigma(y-x) \\ \frac{dy}{dt} &= rx - y - xz \\ \frac{dz}{dt} &= xy - bz \end{aligned} \qquad 3.2$$

This system of equations have been shown to display chaotic behaviour for certain ranges of the constants σ, r, and b. Figure 3.1a plots a measured signal from the Lorenz system (in this case, x). The state space representation of the system is given in figure 3.1b. The trajectory or orbit of the system dynamics are plotted as a function of the system variables (x, y, z). The orbits can be seen to inhabit 2 quasi-periodic regions of phase space yet no point is actually revisited.

Figure 3.1c gives an example of the reconstructed phase space representation of the system. The embedding dimension in this case was taken to be 3 which is the actual system dimension. The lag is 8 sampling points. Whilst the reconstructed dynamics are not identical to the original phase space representation they can be seen to be quite similar with 2 distinct regions of phase space being occupied.

One of the most important insights non-linear dynamics gives us on system characteristics is an estimate of the dimensionality of the system i.e. the minimum number of discrete measurements required to encapsulate the behaviour of the system. If the reconstructed dynamics do not match that of the original system then a higher dimensional representation is required. However extrapolation of D_E to dimensions greater than a certain threshold does not provide any additional information on the system dynamics.

The power of non-linear dynamic techniques lies in the capability to extract underlying dynamics from chaotic signals. The techniques are not limited to the analysis of chaotic

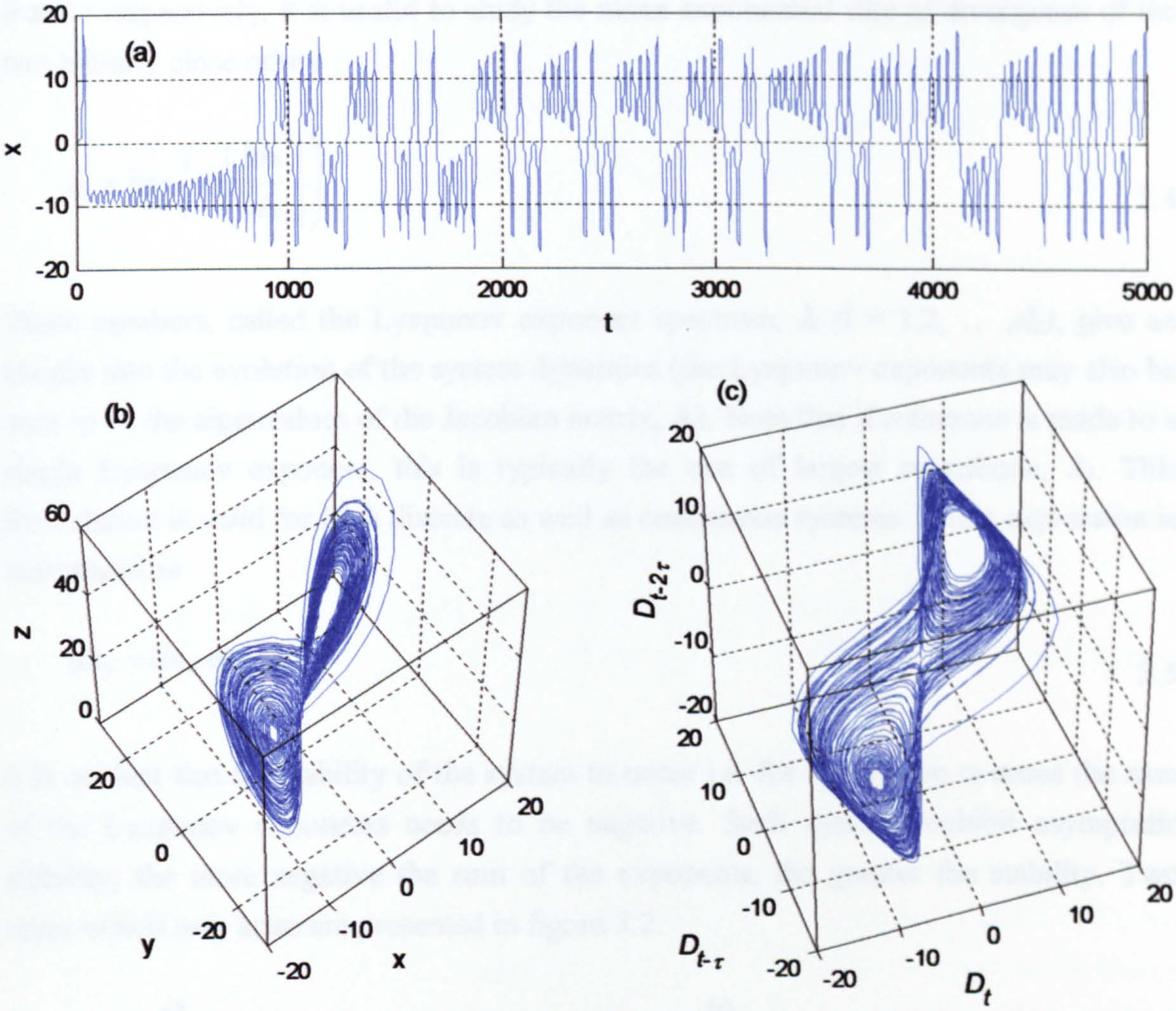


Figure 3.1 Lorenz equation system dynamics

signals and have also proved to be very powerful for the case of gravity waves (Frison and Abarbanel, 1997) and tidal signals which are predominantly deterministic (Frison *et al.*, 1999a; Frison *et al.*, 1999b). The following sections outline some of the specific non-linear dynamic techniques which have proved useful for system interpretation.

3.4.2.1 Lyapunov Exponents

Consider the following general case of a differential system of equations

$$\frac{d\mathbf{x}(t)}{dt} = \mathbf{A} \cdot \mathbf{x}(t) \qquad 3.3$$

If we consider two initially close starting points in a phase space each of which will generate an orbit in that space as time evolves, the dynamics, $\mathbf{x}(t)$, will be governed by the eigenvalues of the Jacobian matrix **A**. If $d\mathbf{x}_0$ and $d\mathbf{x}_t$ are the orbit separations at times

0 and *t* respectively, it is useful to study the mean exponential rate of divergence of the two initially close orbits

$$\lambda_i = \lim_{t \to \infty} \frac{1}{t} \ln\left(\frac{|d\mathbf{x}_t|}{|d\mathbf{x}_0|}\right) \qquad 3.4$$

These numbers, called the Lyapunov exponent spectrum, λ_i $(i = 1,2, \ldots ,d_L)$, give an insight into the evolution of the system dynamics (the Lyapunov exponents may also be seen to be the eigenvalues of the Jacobian matrix, A). Note that if reference is made to a single Lyapunov exponent, this is typically the one of largest magnitude, λ_1. This formulation is valid for both discrete as well as continuous systems. If this expression is rearranged as

$$d\mathbf{x}_t = d\mathbf{x}_0 \exp\{\lambda t\} \qquad 3.5$$

it is evident that for stability of the system to occur i.e. for dissipative systems the sum of the Lyapunov exponents needs to be negative. Such systems exhibit asymptotic stability; the more negative the sum of the exponents, the greater the stability. Two cases which may arise are presented in figure 3.2.

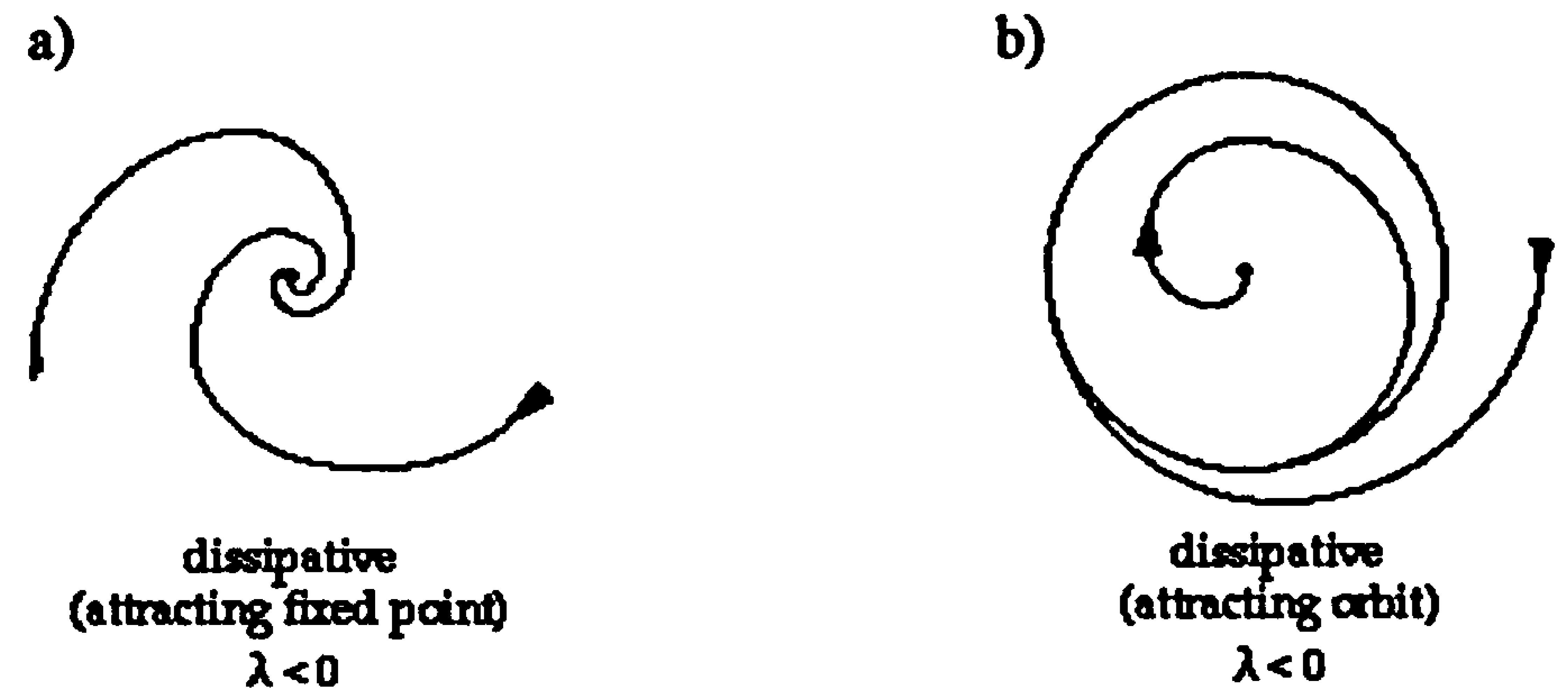


Figure 3.2 Lyapunov orbits for dissipative systems

For chaotic systems it is also possible to have positive Lyapunov exponents, in fact a positive Lyapunov exponent is an essential requirement for a chaotic system. If $\lambda > 0$, the orbit separations will grow exponentially with time resulting in an unstable and chaotic orbit. Nearby points, no matter how close, will diverge to any arbitrary separation. $\lambda > 0$ suggests the possibility of orbits going to infinity, however in practice this does not occur with the orbits remaining bounded due to dissipation processes. A final characteristic revealed by the spectrum of Lyapunov exponents occurs if the observed system is characterised by a flow (conservative system) which is associated with one of the Lyapunov exponents having to be zero.

3.4.2.2 Prediction Horizons

One of the most important insights which non-linear dynamic techniques gives is an indication of the limits of predictability of a system. This is not possible with traditional signal analysis approaches which assume underlying predictability.

The prediction horizon for chaotic systems is linked to the magnitude of the largest positive Lyapunov exponent. As seen previously, separation of orbits grows exponentially at a rate dictated by the largest Lyapunov exponent, λ_1. Correspondingly, if this is thought of as the amount of variability which may be expected from the range of all possible starting locations, it can be seen the expected error of a predictive model of a chaotic system will initially be small and after a while start to increase significantly. This point known as the prediction horizon will prevent accurate predictions of system behaviour after this time has elapsed. If two points are close together in phase space at time t_1, their distance at time t_2 ($t_2 > t_1$) is the original distance multiplied by

$$e^{\lambda_1(t_2-t_1)} \tag{3.6}$$

When this product has dimensions of the same order as the attractor, predictability in a global sense is lost (Frison and Abarbanel, 1997). It is also possible that some regions of an attractor are more predictable than the global average given by λ_1. For example, Abarbanel (1996, p98) gives the following expression for the estimated rms error in prediction of a local polynomial model of phase space dynamics as

$$N^{\frac{-(P+1)}{d_L}} e^{L\lambda_1} \tag{3.7}$$

where N is the required number of prediction steps and P is the polynomial order.

3.4.2.3 Average Mutual Information

An important aspect of non-linear chaotic systems is the issue of how much information knowledge of one region of a system's behaviour tells us about behaviour in another region. Shannon (1948) in his classical work on information theory provides a measure, the average mutual information, for quantifying exactly this.

Consider two series of measurements; $a_1, a_2, a_3, \ldots, a_m$ and $b_1, b_2, b_3, \ldots, b_n$. We want to know how much information we can gain about one series from the other. The average mutual information is given by the expression

$$I_{AB} = \sum_{a_m, b_n} P_{AB}(a_m, b_n) \log_2 \left[\frac{P_{AB}(a_m, b_n)}{P_A(a_m) P_B(b_n)} \right] \qquad 3.7$$

where $P_A(a_m)$ and $P_B(b_n)$ are the normalised histograms of observed values in the two series respectively. $P_{AB}(a_m, b_n)$ is the joint distribution for both measurements. This is a type of non-linear 'correlation' function and hence gives an indication of the level of independence of different regions of an orbit's trajectory. The average mutual information is useful for determining levels of redundancy in a system, in that it addresses the question - how much of the system dynamics have to be sampled before we are confident we can satisfactorily identify the dynamical behaviour?

3.4.2.4 Coastal System Applications of Non-Linear Dynamics

To date there have been very few treatments of coastal systems directly as non-linear systems, thereby adopting the range of techniques available for non-linear dynamical system characterisation and modelling. This has been predominantly due to two reasons. Firstly the field of non-linear dynamics is still relatively in its infancy and is only just starting to permeate into other fields of application. Secondly as non-linear dynamics considers the invariant long-term properties of systems, it typically requires prohibitively large quantities of data for analysis purposes. This is of the order of 10^n data points, where n is the dimensionality of the system (Ruelle, 1990). Coastal system time series typically are at best 10^4 samples in length. Fluid turbulence is an exception as it is possible to make measurements in controlled laboratory conditions with very high sampling rates.

However, a few examples of non-linear dynamic approaches have started to permeate the coastal system literature. Frison and Abarbanel (1997) used non-linear dynamics to analyse a number of gravity wave data sets. These data sets showed a consistent behaviour of having 6 or 7 active dynamical degrees of freedom. Frison *et al.* (1999a) investigate chaos and predictability of ocean water level. This work was extended by Frison *et al.* (1999b) to look at prediction models capable of making inter-station water level predictions. This assumed that the underlying attractor at the chosen stations was similar, therefore knowledge of the dynamics at one station by default gave insight into the dynamics at all stations.

Holland *et al.*, (1999) compared a process-based and a non-linear forecasting model for the evolution of sand bars at Duck. In the non-linear approach the modelling is conducted in phase space rather than the standard physical representation used in process-based modelling. The non-linear dynamics approach was shown to have greater skill in forecasting with a prediction horizon of the order of 5 days compared with only a few days for the deterministic model. Whilst this is a comparatively small improvement, it demonstrates the capability of the non-linear approach to capture more of the system dynamics.

3.5 Coastal Morphodynamic Systems as Complex Adaptive Systems

Already from the preceding discussions it should be apparent that coastal systems have many of the characteristics required to allow them to be considered as complex adaptive systems. A summary of the main requirements of complex adaptive systems and an assessment of the corresponding coastal system characteristics are now presented in Table 3.2.

Table 3.2 Coastal systems as complex adaptive systems

Complex Adaptive Systems	Coastal Systems
Multiple interacting components	Coastal systems comprise wave forms of differing periods and amplitudes, variable sediment types
Dissipative systems with constant influx of energy	Energy supplied by stochastic wave forcing. Dissipation occurs due to bottom friction and wave breaking
Deterministic chaos characterised by low-dimensional system	Coastal systems are typically high dimensional, however, the dynamics operate on a lower dimensional subset
Dynamics governed by systems of non-linear equations	Coastal systems comprised of hydrodynamic and sediment dynamic sub-systems both of which are intrinsically non-linear
Multiple attractors with potential bifurcation (jumps between attractor basins)	Evidence for multiple attractors comes from scenarios where more than one system state is possible for the same boundary conditions. Evidence is also available for temporal and spatial bifurcation.

To conclude, it is postulated that consideration of coastal systems as complex adaptive systems should, at the very least, shed light on many of their general characteristics. The following chapters will demonstrate applications which will attempt to show this.

Chapter 4 Artificial Neural Networks

4.1 Introduction

"When man reasoneth, he does nothing else but conceive a sum total, from addition of parcels; or conceive a remainder, from subtraction of one sum from another: which, if it be done by words, is conceiving of the consequence of the names of all the parts, to the name of the whole; or from the names of the whole and one part, to the name of the other part. And though in some things, as in numbers, besides adding and subtracting, men name other operations, as multiplying and dividing; yet they are the same: for multiplication is but adding together of things equal; and division, but subtracting of one thing, as often as we can. These operations are not incident to numbers only, but to all manner of things that can be added together, and taken one out of another. For as arithmeticians teach to add and subtract in numbers, so the geometricians teach the same in lines, figures (solid and superficial), angles, proportions, times, degrees of swiftness, force, power, and the like; the logicians teach the same in consequences of words, adding together two names to make an affirmation, and two affirmations to make a syllogism,"

Hobbes, 1651

A desire to capture some essence of the human brain, the most powerful computational machine known to man, has been the goal and dream of many researchers in Artificial Intelligence for a large part of the 20th century. The rich and complex range and variety of functional tasks, perception and interaction with the environment which this organ allows has intrigued scientists. In the early part of the 1960s, a surge in interest arose in the development of an appreciation of the functional behaviour of the brain. This led to the premise that it should be possible to emulate the cognitive functionality of the brain simply be reproducing the physical mechanisms of the brain. Whilst this premise may have been somewhat misguided, it has lead to many fascinating insights and whole new areas of knowledge.

A branch of this research investigated the possibility of developing simple models of individual brain cells or neurons. These basic building blocks were to launch a myriad of conceptual insights into operation of both biological and artificial units. More importantly the research highlighted the significance of the connectionist nature of the brain. Only when many of the building blocks are connected together in some larger body does the extent of the functional capability of the structure become realised.

The following paragraphs present a brief synopsis of the current understanding of the behaviour of the biological neuron and its theoretical counterpart, the perceptron.

4.1.1 Neuron

The main body of a brain cell or Neuron is called the soma. Attached to the soma is a tree-like network of fibres called dendrites. The dendrites carry signals to the soma in the form of electrical pulses that have originated from other neurons. The axon is a sort of non-linear threshold device that is 'fired' when the potential within the soma rises above a certain threshold level. The soma processes the incoming information and may produce an output signal in the axon in the form of another electrical pulse or action

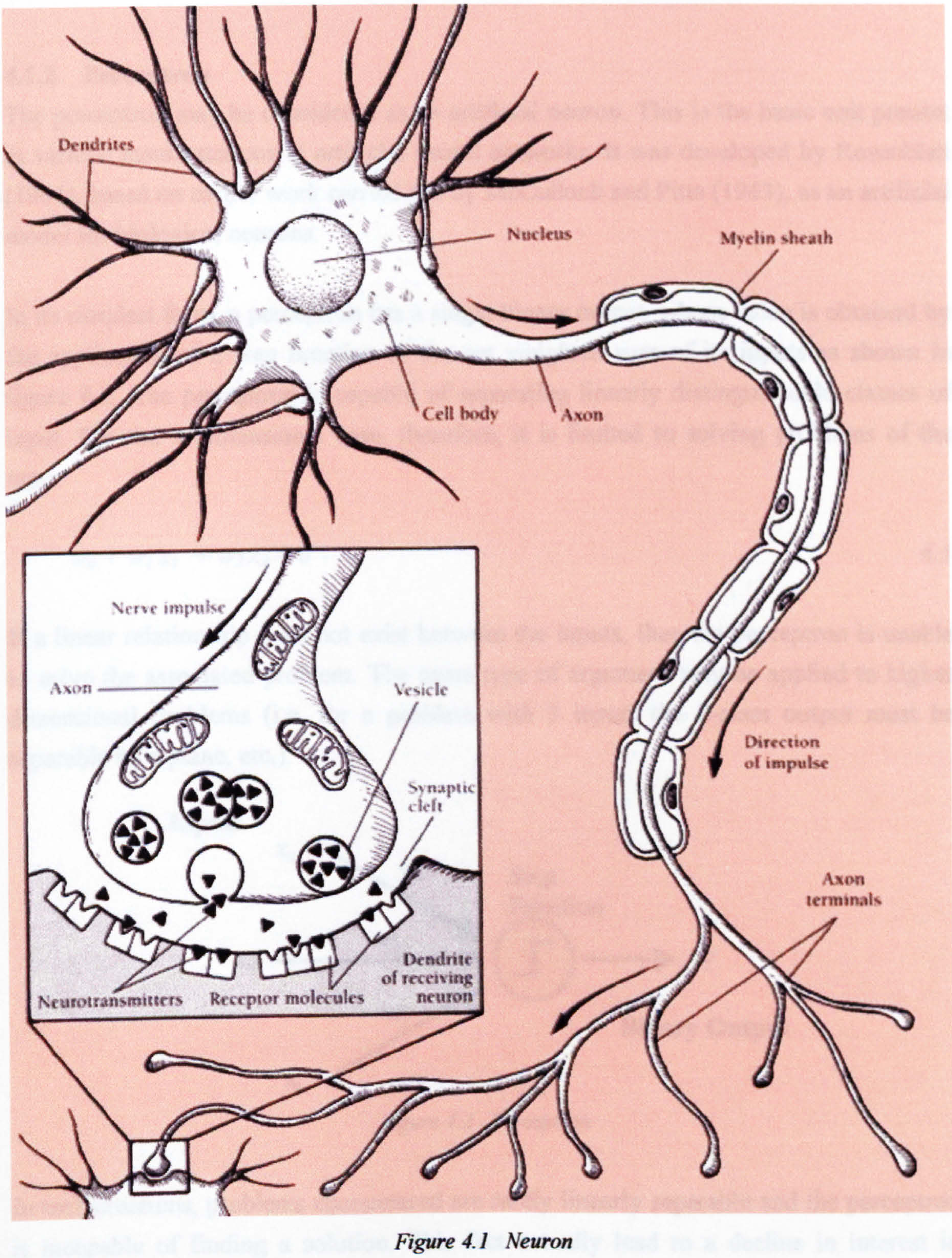


Figure 4.1 Neuron

potential. The axon divides into various branches that make connections (synapses) onto the dendrites and somas of other neurons.

Chemicals called neuro-transmitters are released from the synapse when the potential of the synapse has been sufficiently raised by the action potential in the axon. The effect of the neurotransmitters on the receiving dendrite of the soma is to raise or lower the electrical potential inside the body of the receiving cell.

4.1.2 Perceptron

The perceptron may be considered as an artificial neuron. This is the basic unit present in various manifestations in artificial neural networks. It was developed by Rosenblatt (1961), based on earlier work carried out by McCulloch and Pitts (1943), as an artificial model for biological neurons.

In its simplest form, a perceptron has a single binary output, whose value is obtained by the application of a step function to the net weighted sum of its inputs as shown in figure 4.2. The perceptron is capable of separating linearly distinguishable classes of input. For the 2 dimensional case, therefore, it is limited to solving problems of the type:

$$w_o + w_1 x_1 + w_2 x_2 = 0 \qquad 4.1$$

If a linear relationship does not exist between the inputs, then the perceptron is unable to solve the associated problem. The same type of argument may be applied to higher dimensional problems (i.e. for a problem with 3 inputs the 2-class output must be separable by a plane, etc.).

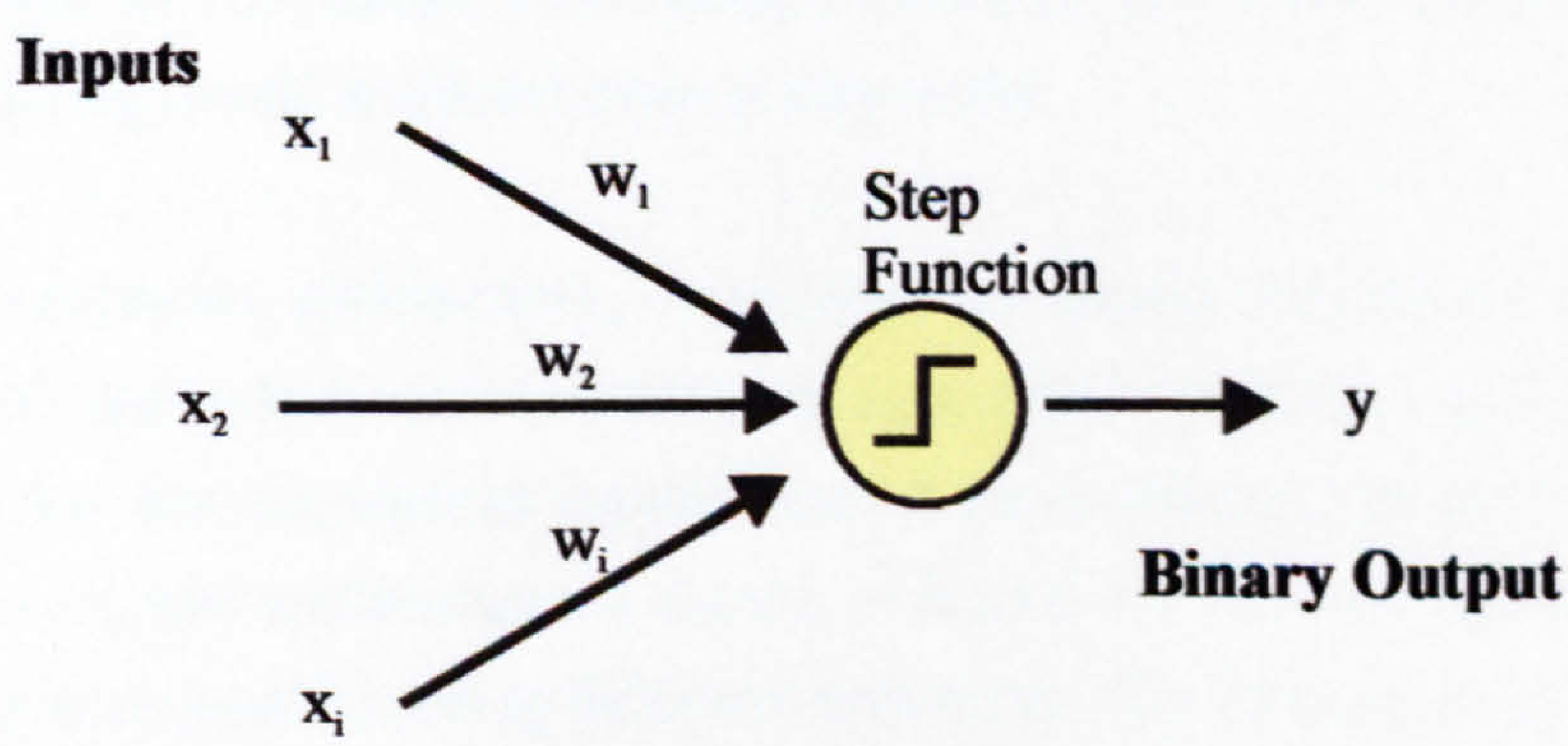


Figure 4.2 Perceptron

In real situations, problems encountered are rarely linearly separable and the perceptron is incapable of finding a solution. This fact actually lead to a decline in interest in Artificial Neural Networks in the late 1960s and 1970s. The significance of the perceptron is that, whilst it is a very simplistic model of the neuron, it laid the groundwork for much of the work which was to follow in the development of much more powerful Artificial Neural Network models, heralded by the work of Rumelhart and McClelland (1986). These advanced models use variants of the perceptron as a basic building block to produce systems which are capable of solving a variety of complex problems. The contribution of Rumelhart and McClelland was to provide a successful learning algorithm for automatically adjusting the weights in all layers of the network. The next section proceeds to give details on the typical characteristics of an Artificial Neural Network model.

4.2 Artificial Neural Networks

Artificial Neural Networks may be considered as a class of models which from a numerical modelling point of view, are a general framework for representing non-linear mappings between multi-dimensional spaces in which the form of the mapping is governed by a number of adjustable parameters. It is by the modification of the adjustable parameters that the Artificial Neural Network model '*learns*' or identifies the mapping. There are 4 functional characteristics of which a typical Artificial Neural Network model will comprise.

1) Types of Neurons ... Before the output of a neuron is passed on to subsequent neurons or a network output, the weighted sum of the inputs is passed through an activation function. This governs the magnitude of the resulting output signal. This activation function takes a variety of forms some of which are shown in figure 4.3. The activation function in the perceptron consists of a step function, with values

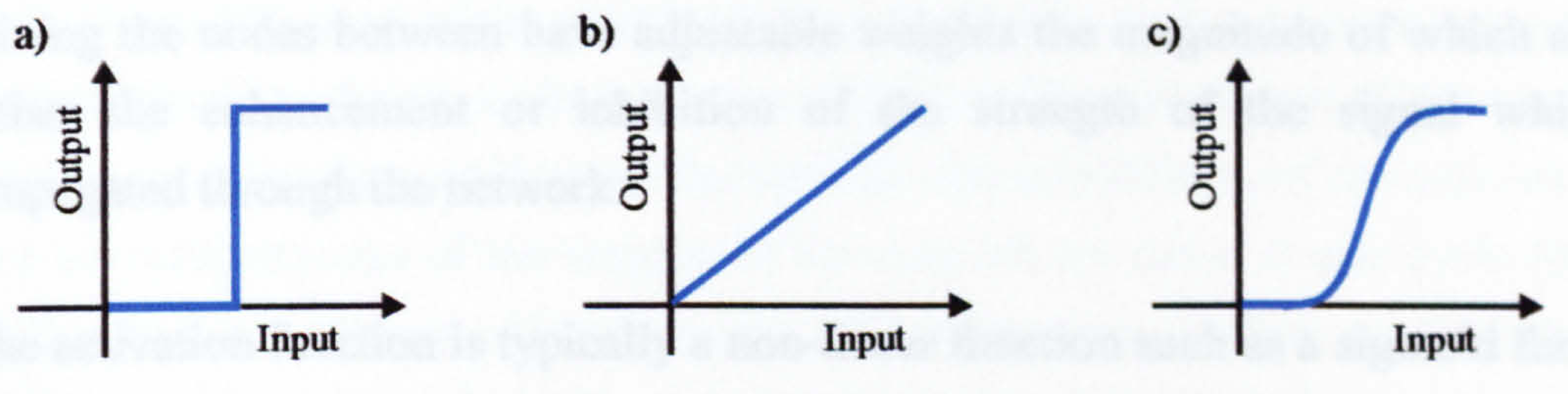


Figure 4.3 Examples of activation functions a) step function b) linear c) sigmoidal

above a certain threshold resulting in a 'firing' of the perceptron. However, typically it is advantageous to have the magnitude of the activation function's output related to a larger range of the magnitude of the weighted summed inputs. The sigmoid (s-shaped) activation function is particularly important as it allows the development of non-linear relationships between input and output. This is one of the main strengths of Artificial Neural Networks.

2) Connectionist architecture ... as was previously mentioned it is not until a number of individual perceptrons are connected together into some organised structure that the processing capabilities of an Artificial Neural Network become realised. A typical architecture is shown in figure 4.4. The architecture consists of a number of layers each having different functions. The first layer consists of a set of inputs to the network. No actual processing is performed at this stage. This input layer is connected to a series of one or more hidden layers. It is these layers where the processing power of the model is developed. Each hidden layer performs a transformation of its input parameter space to a space where different classes or patterns are more readily differentiable.

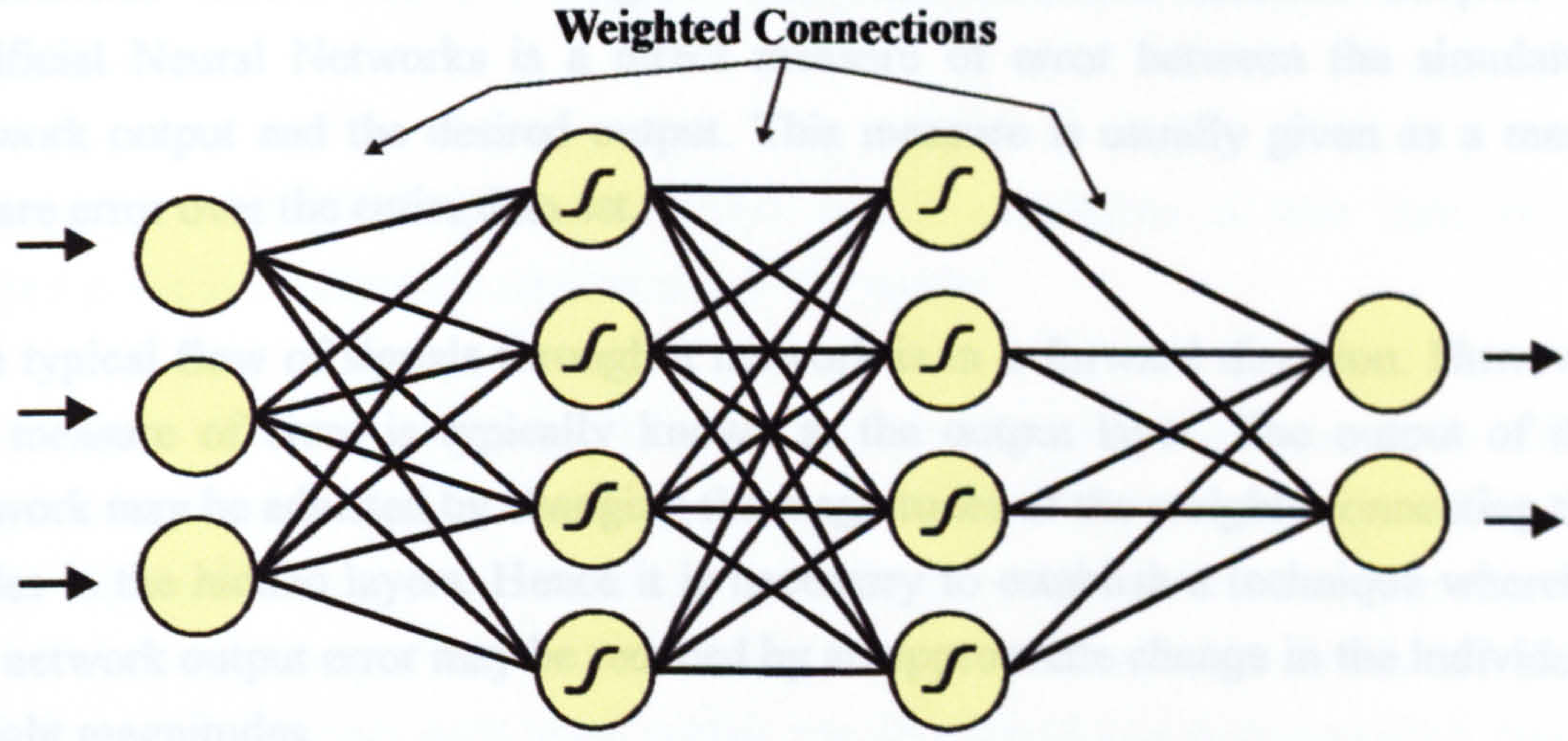


Figure 4.4 Typical artificial neural network architecture

Each node or unit in a hidden layer consists of a perceptron. The connections joining the nodes between have adjustable weights the magnitude of which allows either the enhancement or inhibition of the strength of the signal which is propagated through the network.

The activation function is typically a non-linear function such as a sigmoid function which transforms the weighted sum of the inputs to the unit to a corresponding output. The output layer performs a linear summation of the input from the previous hidden layer to produce the final output.

The network presented in figure 4.4 is an example of a fully connected feed forward network. All inputs or signals are fed through the model in a forward direction. It is also possible to have network models (recurrent networks) which allow feedback. This is done by allowing the output from a given processing layer to loop back as an input to the same or previous hidden layers. This has the effect allowing a time delay in the input sequence. This is especially important when considering models of time series. Recurrent networks are not only capable of learning spatial patterns in a given input, but also temporal patterns. This is a form of memory and allows the recall of previously learned patterns in the input signals.

3) Learning algorithm … The objective in training an Artificial Neural Network model is to establish the appropriate weights in the network which most closely allow a match between the model output and a corresponding desired output for a given training data set. This requirement in itself necessitates two features, firstly a measure of error which describes how closely the simulated model output matches the desired output and secondly a technique which determines the appropriate

adjustments to the network weights. The most common measure adopted in Artificial Neural Networks is a direct measure of error between the simulated network output and the desired output. This measure is usually given as a mean square error over the entire data set.

The typical flow of signals through a network is in a forward direction. However the measure of error is typically known at the output layer. The output of the network may be adjusted by changing the magnitudes of the weights connecting the nodes in the hidden layers. Hence it is necessary to establish a technique whereby the network output error may be reduced by an appropriate change in the individual weight magnitudes.

The standard approach to this is the use of the backpropagation algorithm (Rumelhart *et al.*, 1986). As the name suggests the error is propagated backwards through the network to establish the relative contribution of each node to the overall error. A modification of the weights is then applied in such a manner as to reduce the contribution of each node to the overall error. The simulation of the model by passing the input data set through the network, the establishing of the network error and the readjustments of the weights in the network are taken as one cycle (epoch) of the training process. Many epochs of training are applied to the network. Reduction in error tends to be quite rapid at first but then slows down as the network reaches a stagnation level where the training algorithm is no longer able to reduce the magnitude of the error.

The backpropagation algorithm mentioned above is just one of many algorithms used in training Artificial Neural Networks. It is a form of gradient descent algorithm. While it gives good results, its convergence to optimal network tends to be rather slow. An alternative algorithm proposed by Hagan and Menhaj (1994) known as the Levenberg-Marquardt algorithm (a quasi-Newton approach) gives much quicker convergence at the cost of more intensive computational requirements. This is the algorithm used in all the applications presented in this thesis. The reader is referred to Hagan and Menhaj (1994) for details of the implementation of both the back-propagation and the Levenberg-Marquardt algorithms.

4) Recall algorithm ... this is the final requirement of an Artificial Neural Network modelling paradigm. Having established an optimal network architecture, and trained the model on a sample data set, it is necessary to be able to simulate the model on previously unseen data. The assumption made here is that the training data used is characteristic of the system being investigated. Hence any new data

sets having similar characteristics presented to the network model will also produce realistic output.

The quality of Artificial Neural Network model simulation of new data sets is related to the generalisation capabilities of the model

Artificial Neural Networks fall into 2 broad categories, related to the manner in which they acquire knowledge about the data set being investigated, namely supervised and non-supervised networks. In supervised networks the training examples comprise inputs vectors **x** and desired output vectors y. Training is performed until the Artificial Neural Network learns to associate each input vector x to its desired and corresponding output vector y, i.e. it learns to approximate a function of the form ... $\mathbf{y} = f(\mathbf{x})$. The feed forward neural network is an example of a supervised network.

In unsupervised networks only input vectors x are supplied. The Artificial Neural Network model learns some internal features of the whole set of input vectors presented to it. Examples of this type of model are the Self Organising Maps (SOM's) proposed by Kohonen (1990). These models are beyond the scope of this thesis.

The following section will outline, in some detail, probably the most popular form of Artificial Neural Network model; the feed-forward neural network (also referred to as the multilayer perceptron). This is the type of model used to address the case studies in this thesis.

4.2.1 Artificial Neural Network Theory

One of the most widely used types of neural network is the feed-forward neural network. This type of network model is equivalent to a multivariate multiple non-linear regression model and is the type used in this study. Its structure or architecture is presented in schematic form in figure 4.5. It consists of a layer of nodes that accept various inputs. These inputs, depending on the complexity of the network architecture, are fed to further layers of nodes and ultimately to a layer of outputs which produce a response. The aim of the technique is to 'train' the network such that the response to a given set of inputs corresponds as closely as possible to a desired output. Multi-layer feed-forward networks have the property that they can approximate to arbitrary accuracy any continuous function defined on a domain, provided that the number of internal hidden nodes is sufficient.

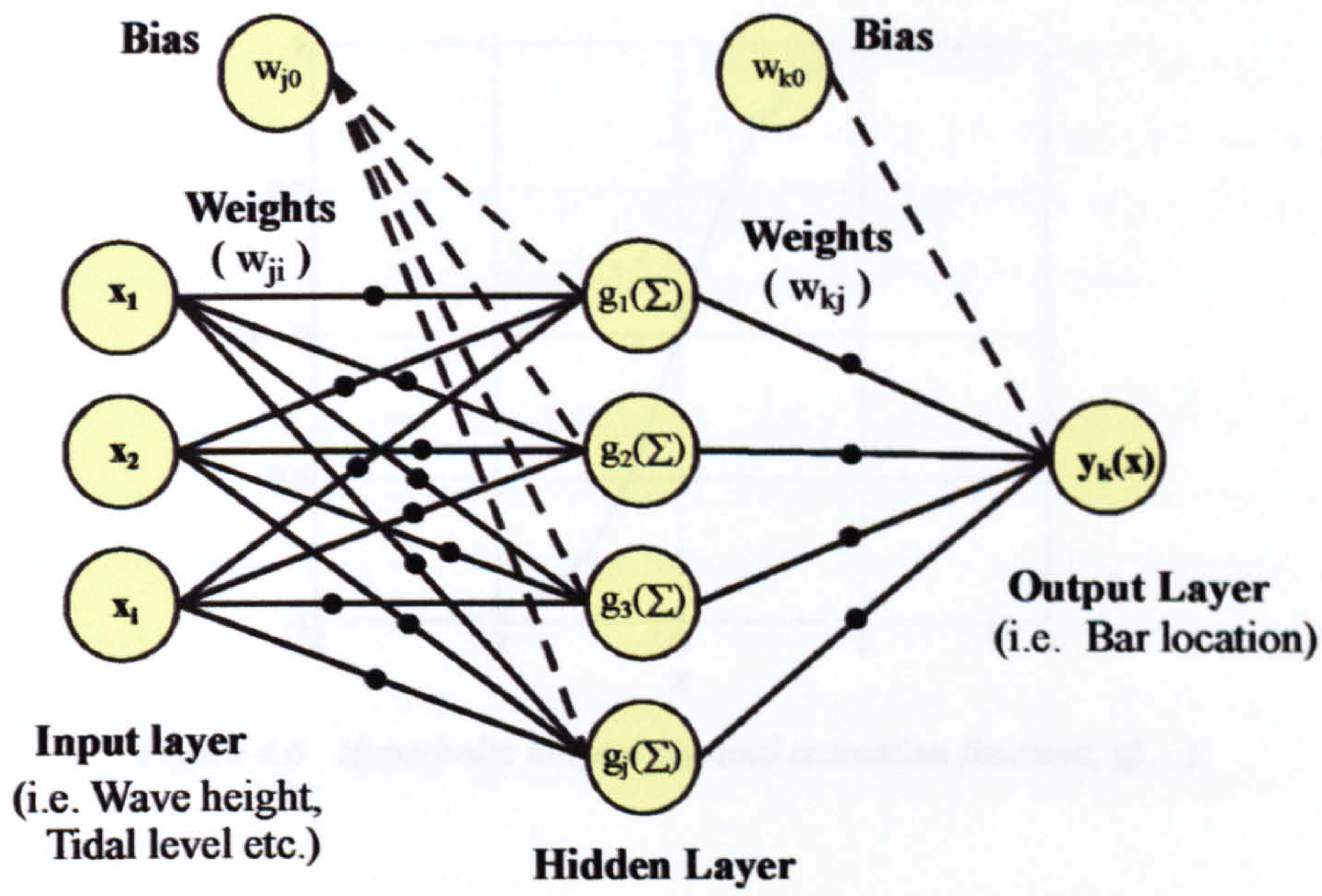


Figure 4.5 Feed Forward Artificial Neural Network Architecture

Mathematically, the feed-forward artificial neural network is a multivariate non-linear function, (see for example Bishop, 1995; Jordan and Bishop, 1996) that is expressed in the form:

$$y_k(x) = \sum_{j=1}^{M} w_{kj} g\left(\sum_{i=1}^{D} w_{ji} x_i + w_{j0}\right) + w_{k0} \qquad 4.2$$

where x is considered to be the original parameter space of dimension D, w_{ji} and w_{kj} are weighting parameters, w_{j0} and w_{k0} are bias parameters, M is the number of nodes in the hidden layer and $g(...)$ is the activation function. This activation function allows a non-linear conversion of the summed inputs. It has the form of a hyperbolic tangent sigmoid function as given in equation 4.3 and is presented graphically in figure 4.6.

$$g = \frac{2}{1+e^{-2z}} - 1 \qquad 4.3$$

In equation 4.3, z corresponds to the summed weighted input from the input layer. This is a key element of the model. If this non-linear transformation of the summation of weighted inputs were removed, the model would be reduced to a linear summation of linear summations, which also would be linear. The bias parameters for the hidden and output layers allow offsets to be introduced. The weights to both the hidden and output layers need to be adjusted to minimise the error between the Artificial Neural Network's simulated output and the actual output.

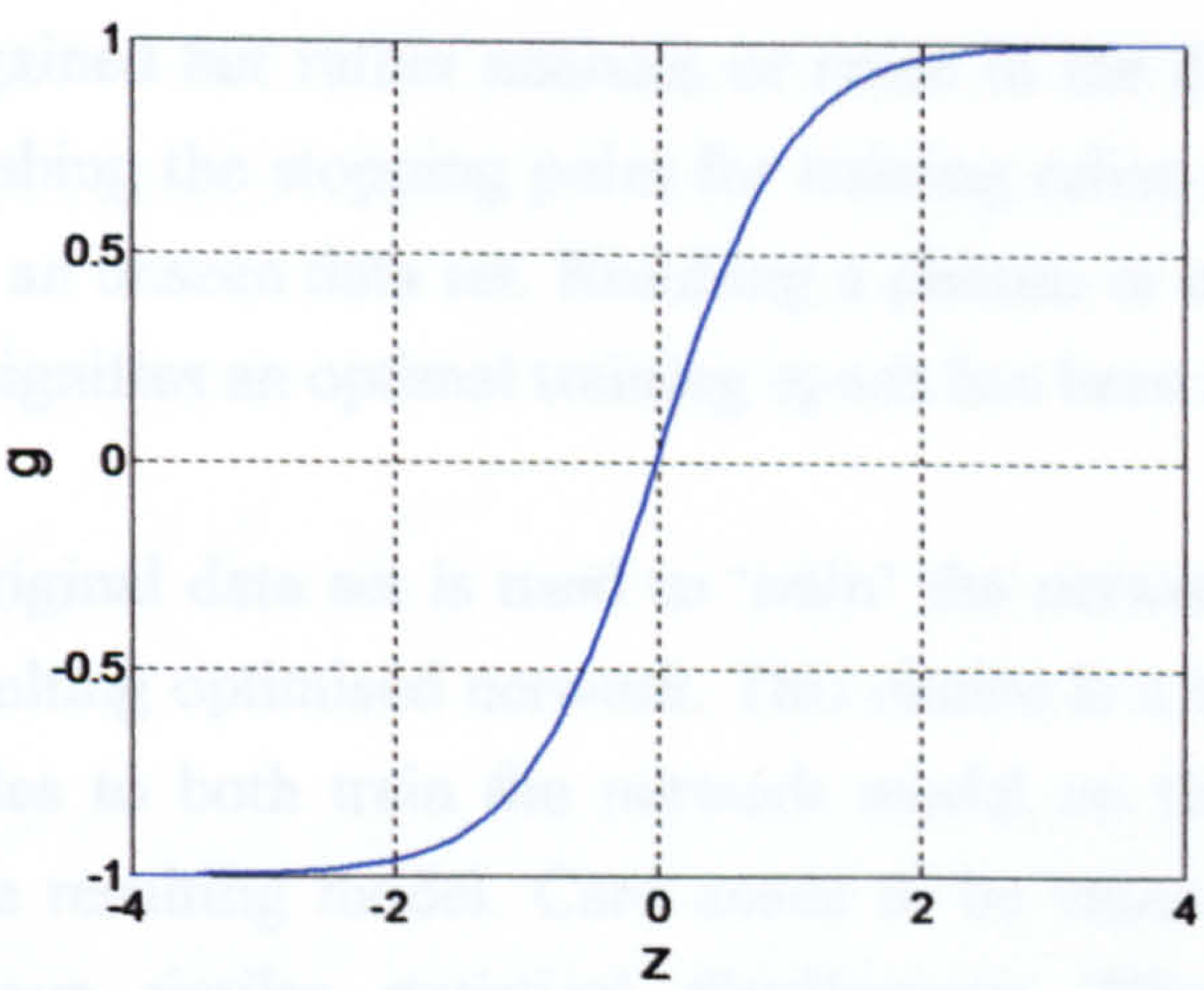


Figure 4.6 Hyperbolic tangent sigmoid activation function, g(...)

4.2.1.1 Generalisation of Artificial Neural Network Models

Even though an optimised network may have been achieved for the training and testing data set, it is possible that this model may overfit the training sample space resulting in poor generalisation capabilities on unseen data. This is because the unseen data may be from a different region of parameter space than that covered by the training/testing data set. The optimal model fits the training sample points well but oscillates wildly between these points. This is analogous to fitting a high order polynomial to a lesser number of data points.

A suggested method of improving generalisation, known as regularisation, involves modifying the Artificial Neural Network performance function. Normally, as mentioned above, this is taken to be the mean sum of the squares of the network residuals. Generalisation may be improved if the performance function also incorporates the mean sum of the squares of the network weights and biases as outlined by MacKay (1992). A Bayesian approach is used to determine the relative contribution of each to the performance function. Regularisation has the effect of reducing the magnitudes of the weights and the biases thereby producing a smoother model. This may result in a slight reduction in performance of the developed Artificial Neural Network model on the training data set, but better performance on the testing or other unseen data sets. This is especially important if the developed model is to be used in regions of the parameter space not covered by the training data set.

An alternative to regularisation as a means of improving the generalisation capabilities of Artificial Neural Networks is a process known as early stopping. In this process, training on a given data set is stopped prematurely before an optimal solution is obtained. The idea behind this is that if training is continued the generalisation capabilities of the model will diminish, as at some point additional 'knowledge' of the system will not be gained but rather nuances or noise in the data set considered. The technique for establishing the stopping point for training relies on testing the model as training proceeds on an unseen data set. Reaching a plateau or a decrease in the trained model performance signifies an optimal training epoch has been reached.

Normally half the original data set is used to 'train' the network and the other half is used to '*test*' the resulting optimised network. This choice is a balance between having adequate data samples to both train the network model on the parameter space and subsequently test the resulting model. Care needs to be taken that both training and testing data sets have similar statistical distributions. This helps to ensure the generalisation capabilities of the network to produce correct output based on previously unseen inputs.

4.2.1.2 Artificial Neural Network Model Confidence Intervals

It is useful to try to quantify the reliability of the Artificial Neural Network model outputs based on new input vectors, i.e. data which has not been used in either the training or testing of the Artificial Neural Network model. Van Gent and van den Boogaard (1998) present a methodology for estimating the reliability of Artificial Neural Network output. They initially determine how the data used to train the Artificial Neural Network model is distributed over its domain using multivariate Gaussian probability density functions. Then the probability density of a new data pattern, for which the Artificial Neural Network output is required, relative to the original data patterns is determined. This approach provides information on how far a new data pattern is located from original data patterns and whether the new data pattern is for instance within a 95% reliability interval of lying in the same region of parameter space occupied by the original data pattern.

The multivariate Gaussian probability density function $\varphi(\vec{\xi})$, for a given training input vector, $\vec{\xi}$ (i.e. $[H_{rms}, T_{1/3}, \theta, \eta]$), is given by equation 4.4. This function is also known as a point spread function as it is essentially 'spreading' the domain of influence over a multi-dimensional region.

$$\varphi(\vec{\xi})=\frac{1}{\left(\sqrt{2\pi}\right)^{D}\sqrt{\left|\Sigma_{p}\right|}}\exp\left[-\frac{1}{2}\left(\vec{\xi}-\vec{\mu_{p}}\right)^{T}.\Sigma_{p}^{-1}.\left(\vec{\xi}-\vec{\mu_{p}}\right)\right] \qquad 4.4$$

where D is the number of input parameters, μ_p is a D-dimensional vector denoting the mean of $\vec{\xi}$, Σ_p is the covariance matrix of $\vec{\xi}$, and $|\Sigma_p|$ is the determinant of the covariance matrix Σ_p. T is the matrix transpose operator. The superposition of the point spread functions provides the most accurate estimate of the probability density function, $f\left(\vec{\xi'}\right)$, of a new data input vector, $\vec{\xi'}$, for which the Artificial Neural Network prediction is required.

$$f\left(\vec{\xi'}\right)=\frac{1}{N}\sum_{n=1}^{N}\varphi\left(\vec{\xi'}-\vec{X_n}\right) \qquad 4.5$$

where $\vec{X_n}$ denotes the n[th] input training pattern and N is the number of input patterns. If this probability density function exceeds a certain threshold, δ, then the new input pattern may be considered to be 'close' to the training input pattern and the Artificial Neural Network will produce a reliable output. To obtain a proper threshold value for which a prediction may be accepted, a level of significance, α (i.e. 95%) is introduced. The region of significance is formed by a D-dimensional ellipsoid of critical radius, R_α given by

$$R_\alpha=\sqrt{\left(\vec{\xi}-\vec{\mu_p}\right)^T\cdot\sum_p^{-1}\cdot\left(\vec{\xi}-\vec{\mu_p}\right)} \qquad 4.6$$

δ is related to R_α by

$$\delta=\varphi(\xi_\alpha)=\frac{1}{N\left(\sqrt{2\pi}\right)^D\sqrt{\left|\Sigma_p\right|}}\exp\left[-\frac{1}{2}R_\alpha^2\right] \qquad 4.7$$

Having determined whether an Artificial Neural Network output for a given input is acceptable or not by comparing the input with the training input parameter space, it is useful to estimate the confidence interval, *ci*, of the resulting Artificial Neural Network output, $y(\vec{\xi'})$. This is done by considering the distribution of the output values of the training data set which correspond to or are deemed to be close in parameter space. Assuming the outputs are Normally distributed, the following range may be taken as an estimate of the 95% confidence interval around $y(\vec{\xi'})$.

$$y(\vec{\xi'})-1.96\sigma_{(T)},\ y(\vec{\xi'})+1.96\sigma_{(T)} \qquad 4.8$$

where $\sigma_{(T)}$ is the standard deviation of those training outputs whose corresponding inputs, $\vec{\xi}$ are deemed close to $\vec{\xi'}$.

4.2.2 Implementation of an Artificial Neural Network Model

This section outlines briefly the steps involved in the implementation of a feed forward neural network model. The synopsis is placed in the context of the following sample problem. Consider the scenario where we have been given a data set consisting of a time series of mean water level (i.e. the tidal signal). Hence consideration is only given to contributions to surface elevation which are outside the influence of gravity and infra-gravity waves). This signal consists of a deterministic component, the astronomical tide, (typically 85-90% of the variance) and a fluctuating component consisting of predominantly atmospheric contributions. The data for this example is taken from an estuarine environment with the measured water level taken in limited water depth (1.5 - 4 m). This problem therefore has an additional level of complexity in that shallow water effects will also make a contribution to the remaining unexplained variance in the signal.

The objective for the sample problem will be to establish an Artificial Neural Network model which will be able to predict the actual tidal level given information on the astronomical tide and the major atmospheric factors such as atmospheric pressure and wind speed and direction.

1. Generation of a data set. The data set consists of both input and output components. The outputs are those measures of the system which we are interested in being able to predict, i.e. the measured tide level. The inputs are those measures of the system to which we believe the outputs are strongly correlated. Careful consideration of an appropriate input set is required to establish an adequate model of the system. In our case the inputs will be the astronomical tide, atmospheric pressure and wind speed/direction (the wind data will be input as the North-South, East-West vector components).

2. Selection of network architecture. For the purpose of this sample application a two-layer feed-forward neural network model will be used to model the system as will also be the case for latter applications. The choice of the input and output data sets predetermines the number of nodes in the input and output layers as specified previously

3. That leaves the question as to how many nodes are required in the hidden layer. The number of nodes may be taken as a measure of the processing power of the model. Too few nodes will result in a model which will not be able to establish the mapping between the inputs and outputs. Too many nodes results in a model which will have a much longer training time and will have poor generalisation capabilities. For the applications in this thesis, 10-15 nodes were typically used in the hidden layer depending on the level of complexity of the problem. In the sample problem, 10

nodes are used. These suggestions given here for the level of processing power in the hidden layer are based on experience of application to coastal models.

4. Partition of data set into training and testing subsets. A key element in the training paradigm is the provision of both a data set for the training of the Artificial Neural Network model and a second data set to evaluate the efficacy of the trained model of the system. The simplest approach is to divide the data set into 2 blocks or take alternate samples for the training and testing data sets.

   However certain considerations should be observed. It is assumed that the data set is representative of the system being investigated, hence, the objective needs to be to partition the data set in such a manner that both parts are statistically equivalent. Secondly, it is assumed that the samples are independent and that there are no chronological influences present in the data set. If these criteria are true, and the data set is sufficiently large, the best approach to this is to build up both data sets by picking samples at random from the original data set. If chronology is an important consideration an Artificial Neural Network architecture which considers feedback would be more appropriate, combined with block division of the data set. Assuming chronology is not significant, a suggested procedure for partitioning the data set is as follows. Initially select samples at random from the original data set for both training and testing subsets. Histograms of the input parameters for both data subsets are then generated. The histogram bin counts of the training data set are plotted versus those of the testing data set. If the two data sets have identical distributions this will result with a plot with an R^2 value of 1. The procedure of selecting data sets at random is repeated a number of times and those data sets with the highest R^2 value are taken to be the training and testing data sets.

5. Normalisation of input data. In general there will not be any reason why the inputs and outputs to the network will have similar magnitudes and ranges. Hence it is usual to normalise the inputs such that they have a zero mean and unit standard deviation. This leads to Artificial Neural Network models which generally are better behaved.

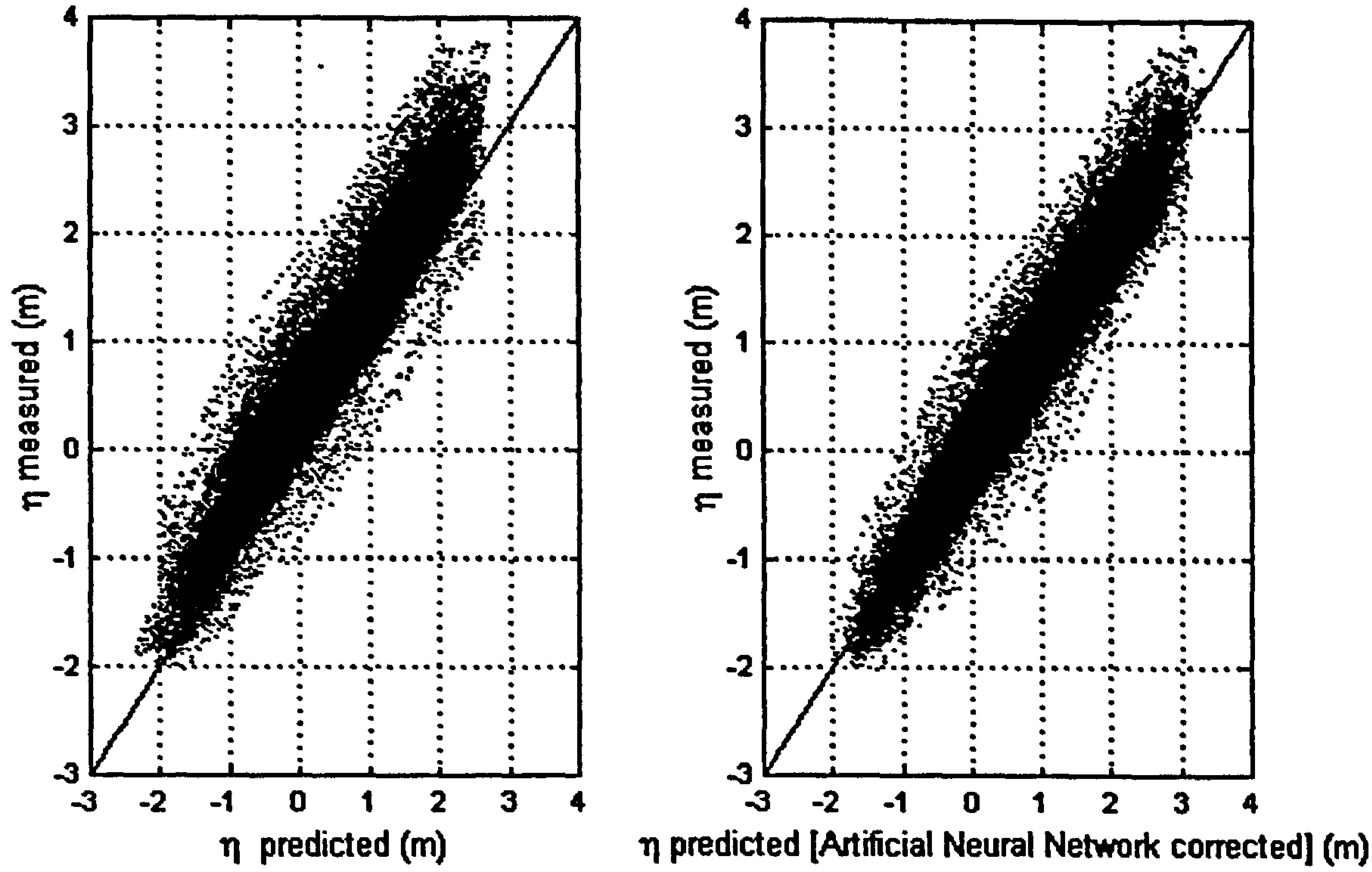
6. Choice of model parameters. The other model parameters required include the number of epochs for which training should be conducted and the nature of the termination criteria. Typically 40-50 epochs are appropriate for the applications presented in this thesis. At this point the Artificial Neural Network begins to stagnate, i.e. it is unable to reduce the discrepancy between the simulated and required output by further application of the training algorithm. The maximum number of epochs is the main termination criterion that is typically encountered. The other termination criterion is a permissible training error. If this minimum level of error is achieved during the training then the Artificial Neural Network is deemed to have been successful in modelling the data set.

One would hope that in detailing the application of a technique that it would be possible to give a definitive description. However, when it comes to detailing Artificial Neural Networks there is some uncertainty as to the appropriate level of computational power which needs to be built into the hidden layer. This is where the art of designing successful Artificial Neural Network models comes into play. To achieve an optimal architecture it is necessary, in the absence of other guidance, to apply a trial and error approach to investigating the number of nodes used in the architecture and number of epochs used in training the Artificial Neural Network model.

The goal is to achieve the appropriate number of nodes in the hidden layer which allow convergence onto a set of weights to give an optimal solution, whilst not incorporating so many nodes that the Artificial Neural Network model will tend to find a solution and then proceed to extract nuances of noise in the training data set. This latter scenario can be identified by looking at the evolution of the performance measure (discrepancy between Artificial Neural Network model output and desired output) as a function of epoch. In general the trace will display an initial decrease in error which will tend to reach a constant plateau. At this point, the ANN model will have established a solution to the system and from there on will be extracting noise form the data set.

The complexity of achieving an optimal solution may be further compounded if consideration of the appropriate set of input parameters is to be taken into account. This is where the user knowledge of the system under investigation is the key to a successful model. Even so a little experimentation with the input parameter set has the potential to produce a more global optimal Artificial Neural Network model. This may be attributed to level of independence of the input parameters. This may be alleviated by initially considering a cross-correlation matrix of the input parameters to identify those signals which may not be considered as being independent. Care still needs to be taken to establish whether one of these parameters may be dropped from the input parameter set or if the parameter has a more subtle but significant impact on the overall system behaviour.

Getting back to the sample problem, figure 4.7a presents the relationship between the actual and predicted tide level for a 1 year period from a site located at Teignmouth in the Southwest of the UK. As can be seen the astronomical tide does a reasonable job at estimating the actual water level (almost 90% of the variance is modelled). However there still appears to be a residual offset. After applying the Artificial Neural Network model to produce a corrected tidal prediction, as shown in figure 4.7b, the apparent offset has been removed and an additional 5% of the variance has been catered for. Whilst this is still not perfect (some structure is still apparent in the remaining residuals), it represents a significant improvement at this level of skill. This is especially true considering that the shallow water effects will have a significant contribution to the overall measurements.



a) $R^2 = 0.89$ *b)* $R^2 = 0.94$

Figure 4.7 Sample Artificial Neural Network application. Correction of predicted tide level

4.3 Application of Artificial Neural Networks

Artificial Neural Networks have been used in three main ways ...

- as models of biological nervous systems and intelligence. This has been considered in detail in the introduction to this chapter.
- as real-time adaptive signal processors or controllers implemented in hardware for applications such as industrial robots.
- as data analysis methods. These methods are of specific interest for this thesis. It has been shown (Sarle, 1994) that many Artificial Neural Network models designed for specific tasks such as pattern recognition or time series prediction have counterparts in the realm of statistics. Indeed, the approach to the development of a statistical and an Artificial Neural Network model of a process share many similar traits. A disadvantage of statistical models however is the requirement for the choice of an appropriate model for the task at hand which is not necessarily always obvious.

Artificial Neural Networks, not surprisingly, have also found application in geo-scientific areas. Typically these applications fall into 2 broad categories, those applications concerned with signal analysis or pattern recognition to extract specific information and those applications which are used to forecast the future behaviour of some aspect of a system. Artificial Neural Networks have been most widely applied in the fields of hydraulics and hydrology: forecasting of rainfall (French *et al.*, 1992), rain runoff levels (Crespo and Mora, 1993) and river flow (Karunanithi *et al.*, 1994; Corne *et al.*, 1998). Other interesting applications include the retrieval of wind vectors from scatterometer data (Thiria *et al.*, 1993, Richaume *et al.*, 2000).

In the area of hydrodynamics and in coastal engineering areas a few applications of Artificial Neural Networks have emerged. Generally, topics considered have included applications in signal processing problems, such as wave forecasting by Deo and Sridar Naidu (1999), directional wave estimates by Deo *et al.* (2002) and tidal level forecasting by Tsai and Lee (1999). Applications in pattern recognition have included the estimation of ocean surface currents from satellite imagery (Cote and Tatnall, 1997) and the classification of side scan sonar imagery (Stewart *et al.* 1994). Dibike *et al.* (1999) presented an interesting analysis of the manner in which Artificial Neural Networks may be used to encapsulate the knowledge contained in numerical-hydraulic models.

In coastal engineering applications of Artificial Neural Networks, Mase *et al.* (1995) showed that Artificial Neural Networks can produce equivalent estimates of breakwater stability compared to those obtained from conventional empirical formulae. Van Gent and van de Boogaard (1998) investigated the utility of using Artificial Neural Networks to predict wave forces on coastal structures. Due to the complexity of the phenomenon of wave interaction with structures it is not always possible to assess the impact of the relevant parameters in design formulae. They showed that Artificial Neural Networks can satisfactorily predict horizontal loads on vertical structures with a greater degree of reliability and accuracy than the equivalent process based models.

To date, Artificial Neural Networks have not been applied extensively to the study of hydro-morphodynamic systems. In one of the few examples, Kingston and Davidson (1999) used Artificial Neural Networks to develop a model for sandbar migration at a macro-tidal site. The investigation indicated that performance obtained by the Artificial Neural Network model was capable of exceeding that given by a multiple regression model. The next sections will proceed to give details of two further case studies of applications of Artificial Neural Networks to the study of hydro-morphodynamic systems.

4.4 Case Study # 1: Artificial Neural Network Correction of Video Estimates of Sand Bar Location[1],

Sandbar systems provide a natural defence mechanism for the coastline, play an important role in the budget of nearshore sediments and considerably affect the dynamics of most surf zone processes. However, the development, migration and degeneration of sandbar systems are still poorly understood. This fact has prompted the coastal research community to try and improve our current predictive capabilities for long-term, large-scale coastal evolution. Accordingly, there is the need for long-term (weeks, months, years, decades), and large-scale (10^2-10^3 m) field measurements. The collection of data with sufficient spatial and temporal resolution is not possible with traditional in-situ process style measurements, due to the cost and vulnerability of in-situ instruments. For this reason there is a growing emphasis on the use of remote sensing techniques like video (Holland *et al.*, 1997) and radar (Bell, 1999), to monitor coastal processes.

Holman and Sallenger (1986) first reported the use of video remote sensing (the Argus system) for the analysis of nearshore processes. Since this time these video methods have been used to quantify coastal morphology in a number of ways. First, it is possible to evaluate the intertidal morphology by mapping tidally modulated shoreline features (Plant and Holman, 1997, Davidson *et al.*, 1997, Aarninkhof *et al.*, 1997). Indirect measurements of bathymetry have been made using measurements of the phase-velocity of gravity waves (Stockdon and Holman, 2000). Finally, the location and morphology of bar-systems can be inferred from wave breaking patterns. Whilst many approaches have been attempted to extract bathymetric information from video, this remains a difficult and on-going issue. It is the latter application of sand bar morphology which is of interest in this case study.

Lippmann and Holman (1989) showed that the location of shallow submerged sandbar features are correlated with the locations of frequent wave breaking. These wave breaking patterns are most evident in time-averaged images. Typically, 600 images

[1] A version of this section has been published as Kingston, K.S., Ruessink, B.G., van Enckevort, I.M.J. and Davidson, M.A., 2000, 'Artificial Neural Network Correction of Remotely Sensed Sandbar Location', *Marine Geology*, Vol. 169, No. 1-2, pp 137-160. The inspiration for this study came about when Gerben Ruessink was on sabbatical at the University of Plymouth. He was investigating the relationships between bar migration and forcing from a variety of data sources as part of the Coast3d project. From discussions with Gerben, it became apparent to me Artificial Neural Networks seemed an appropriate avenue of discovery for establishing links between direct and indirect measurements of nearshore morphology, resulting in a very fruitful collaboration.

My contribution to this study was in the development of the Artificial Neural Network model of the sand bar system. Gerben Ruessink contributed the numerical data set and the WESP field data set. Irene van Enckevort contributed the Argus image data set. Mark Davidson added valuable comments and insight into the structure and layout of the case study.

Figure 4.8 Argus video image showing wave breaking intensity patterns over submerged sandbars at Egmond aan Zee, Netherlands. (a) snapshot, (b) 10 minute time average.

recorded at 1 Hz will be averaged over a 10-minute period. Examples of a snapshot and corresponding time-average image are shown in figures 1a,b respectively. Notice the clearly defined intensity maxima associated with waves which break frequently over submerged bars.

The oblique images shown in figure 4.8 are routinely transformed into real-world co-ordinates on an undistorted horizontal scale using the method known as rectification, outlined by Holland *et al.* (1997). An example rectification of figure 4.8b is given in figure 4.9. It is often assumed that the intensity maxima seen in these images provides an estimate of the location of sandbar positions, the location of which can be quantified in terms of real world co-ordinates after the rectification process (Lippmann and Holman, 1989; Lippmann *et al.*, 1993). Figure 4.10a shows an example from a beach with an outer and inner bar. Superimposed on this are shown intensity profiles as obtained from rectified time average video images. The maxima in the intensity profiles are clearly seen to occur in the vicinity of the underlying bar features.

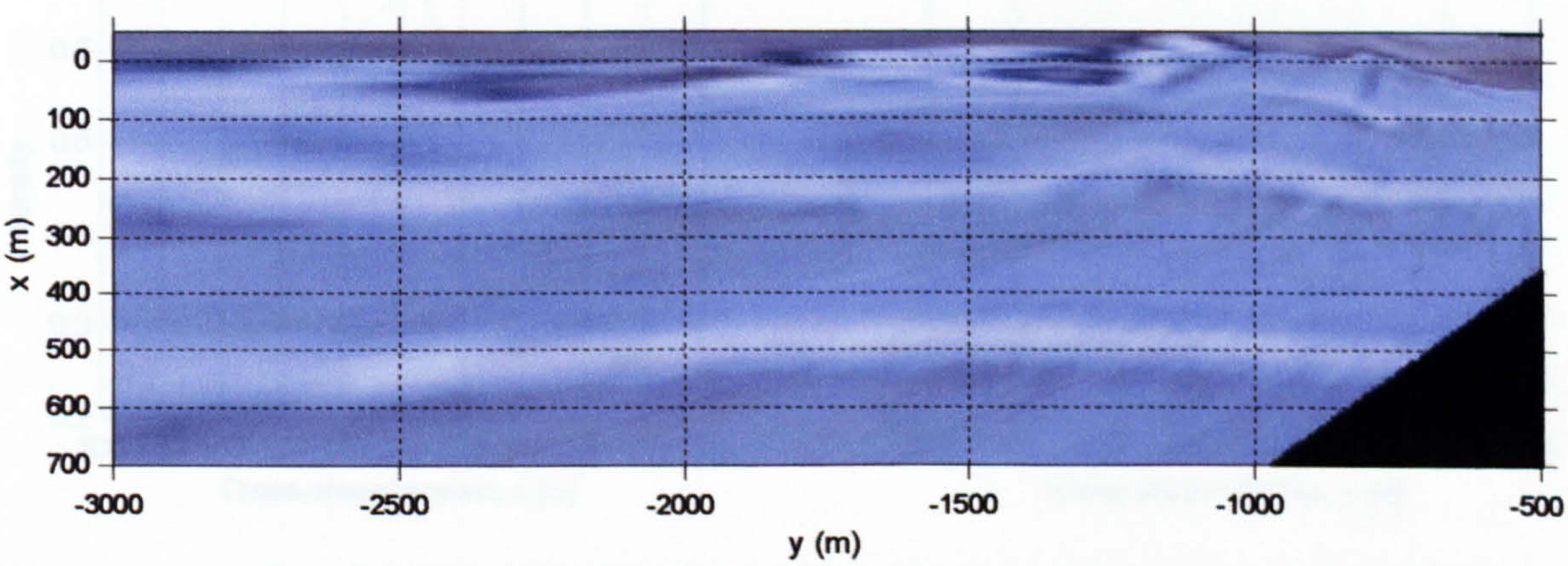


Figure 4.9 A rectified view of figure 4.8 in real-world co-ordinates.

Recent studies carried out by Van Enckevort and Ruessink (2001) have shown that there may be very significant differences between the cross-shore location of the intensity maximum x_i and the actual bar position x_p. The actual measured bar location, x_p is defined as the region of maximum deviation from the long-term (34 years) barless mean profile as shown in figure 4.10a. Van Enckevort and Ruessink (2001) have shown this measurement to be more strongly correlated to the breaker location rather than the location of the minimum depth over the bar.

From their analysis, it is evident that the difference between the measured bar locations and the intensity maxima extracted from the video images can be in the order of 30 to 40 m. It is also apparent that there are much higher frequency fluctuations in x_i than are observed in x_p. The dominant frequency observed in x_i correlates closely to the tidal frequency. As might be expected, the breakpoint is effectively being modulated by the tide, with waves breaking further offshore during the lower tidal elevations. This is shown effectively in figures 4.10b and 4.10c which zoom in on the inner and outer bar regions respectively, shown in figure 4.10a. Van Enckevort and Ruessink (2001) also show that wave height has a similar effect, with the breakpoint moving seaward with increasing wave energy until the wave field near the crest is saturated.

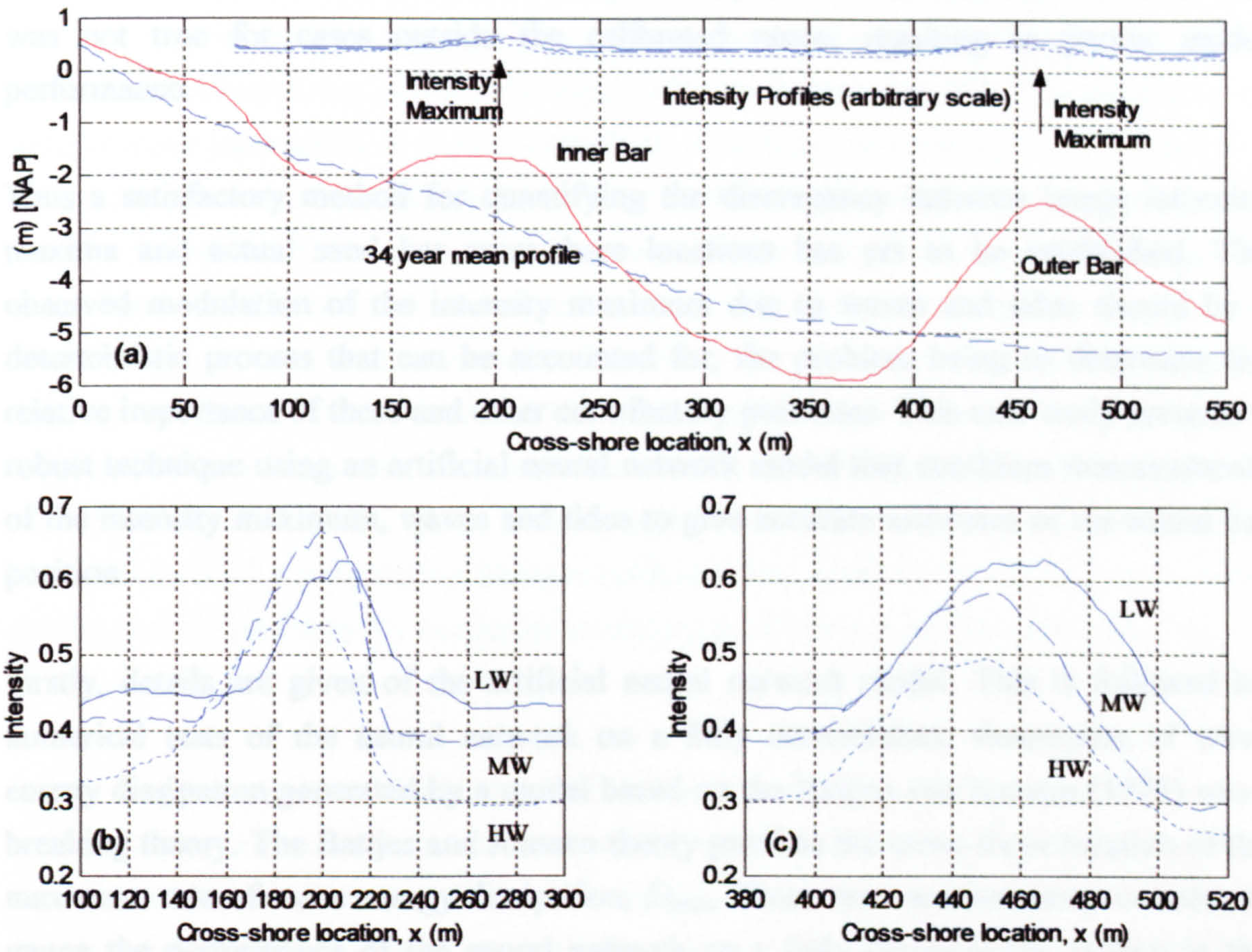


Figure 4.10 (a) Sample beach profile showing correlation between image intensity profiles with location of the outer and inner sand bars. The 34 year mean profile is shown as a dashed line. (b, c) fluctuation of location of wave breaking maximum with water level

Plant and Holman (1998) show that the image estimates of intensity maxima are strongly correlated with the bar positions ($R^2 = 0.8$), for the case of a micro-tidal beach at Duck, North Carolina. They attribute the discrepancies between the measurements to changes in wave height and also a strong dependence on bar amplitude. They point to the need for the reconciliation of the bar locations by means of either empirical or process based models. An example of an empirical approach is that adopted by Bailey and Shand (1997). They give a simple correction of the location of the intensity maximum which is related to depth over the bar. This necessitates information on profile shape which is generally unavailable. In addition it does not take into account other processes, such as tide and wave height which may determine the location of the intensity maximum.

Aarninkhof *et al.* (1997) adopt a process-based approach of trying to estimate nearshore bathymetry. They use an inverse model of a wave breaking parameter through the surf zone, coupled with Argus image intensity patterns to identify the cross shore bathymetric profile. When performing validation of the technique, they found that for cases in which the wave breaker parameter was within the range for which the model was calibrated, reliable estimates of bathymetric profile were obtained. However this was not true for cases outside the calibrated range, resulting in poorer model performance.

Thus a satisfactory method for quantifying the discrepancy between image intensity maxima and actual sand bar cross-shore locations has yet to be established. The observed modulation of the intensity maximum due to waves and tides should be a deterministic process that can be accounted for, the problem being to determine the relative importance of these and other contributory processes. This case study presents a robust technique using an artificial neural network model that combines measurements of the intensity maximum, waves and tides to give accurate estimates of the actual bar position.

Firstly, details are given of the artificial neural network model. This is followed by numerical tests of the neural network on a fully deterministic time-series of wave energy dissipation generated by a model based on the Battjes and Janssen (1978) wave breaking theory. The Battjes and Janssen theory predicts the cross-shore location of the maximum rate of wave energy dissipation, D_{max}. These tests are necessary in order to gauge the performance of the neural network on a fully deterministic system in the absence of noise. Following this the Artificial Neural Network model is trained and tested on field data collected at Egmond aan Zee, the Netherlands, as part of the Coast3D project, with the results being compared with those from equivalent multiple regression models. The resulting Artificial Neural Network models are subsequently applied to predict the sandbar locations during storm periods where physical surveys were not possible.

4.4.1 Artificial Neural Networks

The network structure used in this study consists of a layer of input nodes, which correspond to those signals (wave height, tidal level) that are considered to be significant in the determination of the output signals which in this case is the sand bar location. A sample set of inputs is presented to the network to produce a set of simulated outputs. For the purpose of this study the Levenberg-Marquardt algorithm (Hagan and Menhaj, 1994) is used to update the network weights.

A 2-layer feed forward Artificial Neural Network architecture is used throughout this study. The hidden layer has 15 nodes with hyperbolic tangent sigmoid transfer functions. Linear transfer functions are used in the output layer. The model was trained for 40 epochs (an epoch is one iteration of evaluating a network output and updating the network weights with the chosen algorithm). Statistical equivalence of the training and testing data sets was optimised by adapting the procedure outlined in section.

The first step in applying the Artificial Neural Network in this model is to investigate the inherent correlations between the input and output data sets. This aids the choice of suitable input parameters. It is also possible to investigate redundancy of information in the input parameters from this analysis. This can be done by simple linear regression. It must be remembered, however, that these correlations in themselves only highlight the linear dependencies between variables. As the performance of an optimised Artificial Neural Network model is somewhat dependent on the original choice of weights, repeated training does not result in the same model. Hence the performance of the Artificial Neural Network was tested statistically by repeating the training / testing procedure 100 times. This gives a better indication of the behaviour of the Artificial Neural Network for the problem being considered. The Artificial Neural Network model chosen was the one with the maximum evaluated performance on the testing data set.

4.4.2 Application of Artificial Neural Network to Numerical Data

In this section, numerical tests are conducted in order to evaluate the performance of the neural network work on a realistic, fully deterministic system. The numerical system chosen is taken to have similar characteristics to, but not necessarily represent, the field data case. For the purpose of the numerical tests, the wave energy dissipation, D, over irregular bathymetry, modelled according to Battjes and Janssen (1978), is used in order to predict the location of the intensity maximum, D_{max}. Following Lippmann and Holman (1989), it is assumed here that the region of maximum wave energy dissipation, D_{max}, behaves in a similar manner to the intensity maximum seen in the video images, x_i, thereby providing a numerical simulation which is similar in nature to the field data. The model equations are given in Appendix A1. The cross-shore location of D_{max}, x_{Dmax} is a function of the following parameters:

$$x_{D\max} \approx x_i = f\left(H, T, \theta, \eta, d(x)\right) \qquad 4.9$$

Here, H, T and θ are measures of the offshore wave height, period and direction, η is the water surface elevation and $d(x)$ is the local evolving seabed profile. The offshore input parameters required by the Battjes and Janssen model are shown graphically in figure 4.11. This data consists of sequential hourly samples taken over a 21 day period for the Egmond aan Zee field campaign. Onshore/offshore bar migration was simulated (i.e.,

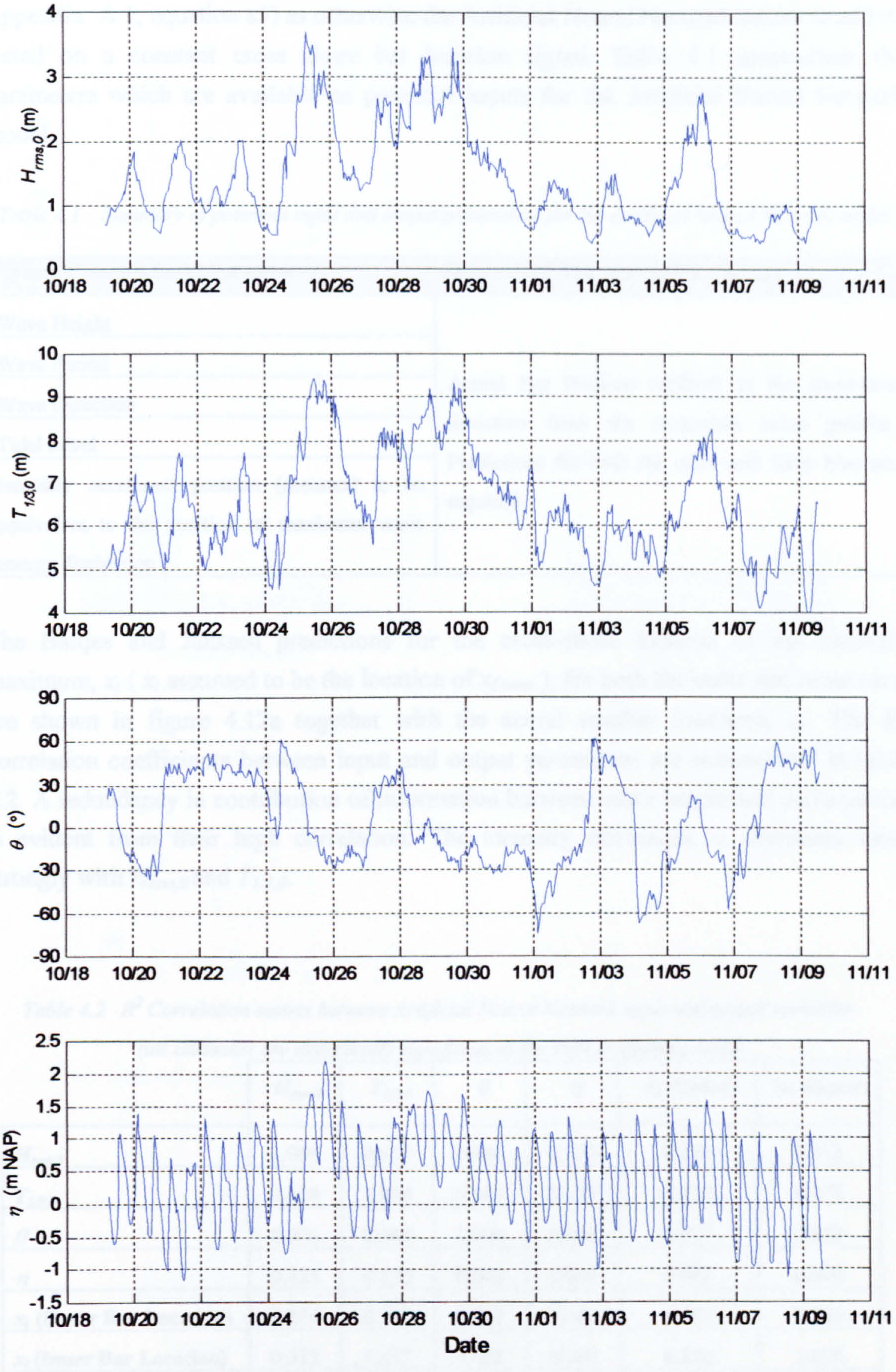


Figure 4.11 Wave climate input parameters for numerical model. $H_{rms,0}$ is the offshore root mean square wave height (m). $T_{1/3,0}$ is the significant offshore wave period (s). θ is the wave direction (degrees relative to the shore-normal). η is the offshore water surface elevation (m, NAP)

Appendix A.1, equation a5) as otherwise the Artificial Neural Network model would be tested on a constant cross shore bar location signal. Table 4.1 summarises the parameters which are available as potential inputs for the Artificial Neural Network model.

Table 4.1 Summary of potential input and output parameters for the Artificial Neural Network model

Neural Network Input Parameters	Neural Network Output Parameters
Wave Height	Actual Bar Position (defined as the maximum deviation from the long-term mean profile). Predictions for both the outer and inner bars are required.
Wave Period	
Wave Direction	
Tidal Level	
Intensity maximum position (assumed to be equivalent to the position of maximum wave energy dissipation)	

The Battjes and Janssen predictions for the cross-shore location of the intensity maximum, x_i (x_i assumed to be the location of x_{Dmax}), for both the outer and inner bars, are shown in figure 4.12a together with the actual sandbar locations, x_p. The R^2 correlation coefficients between input and output parameters are summarised in table 4.2. A redundancy in contribution of information between wave height and wave period is evident from their high correlation. The intensity maximum, x_i correlates most strongly with $H_{rms,0}$ and $T_{1/3,0}$.

Table 4.2 R^2 Correlation matrix between Artificial Neural Network input and output variables. (all estimates are statistically significant at the 99% confidence level)

	$H_{rms,0}$	$T_{1/3,0}$	θ	η	x_i (Outer)	x_i (Inner)
$H_{rms,0}$	1.000	0.819	0.006	0.223	0.274	0.312
$T_{1/3,0}$	0.819	1.000	0.064	0.170	0.219	0.277
θ	0.006	0.064	1.000	0.043	0.037	0.022
η	0.223	0.170	0.043	1.000	0.043	0.000
x_i (Outer Bar Location)	0.274	0.219	0.037	0.043	1.000	0.810
x_i (Inner Bar Location)	0.312	0.277	0.022	0.000	0.810	1.000
x_p (Outer Bar Location)	0.012	0.009	0.043	0.004	0.769	0.646
x_p (Inner Bar Location)	0.015	0.009	0.037	0.004	0.788	0.660

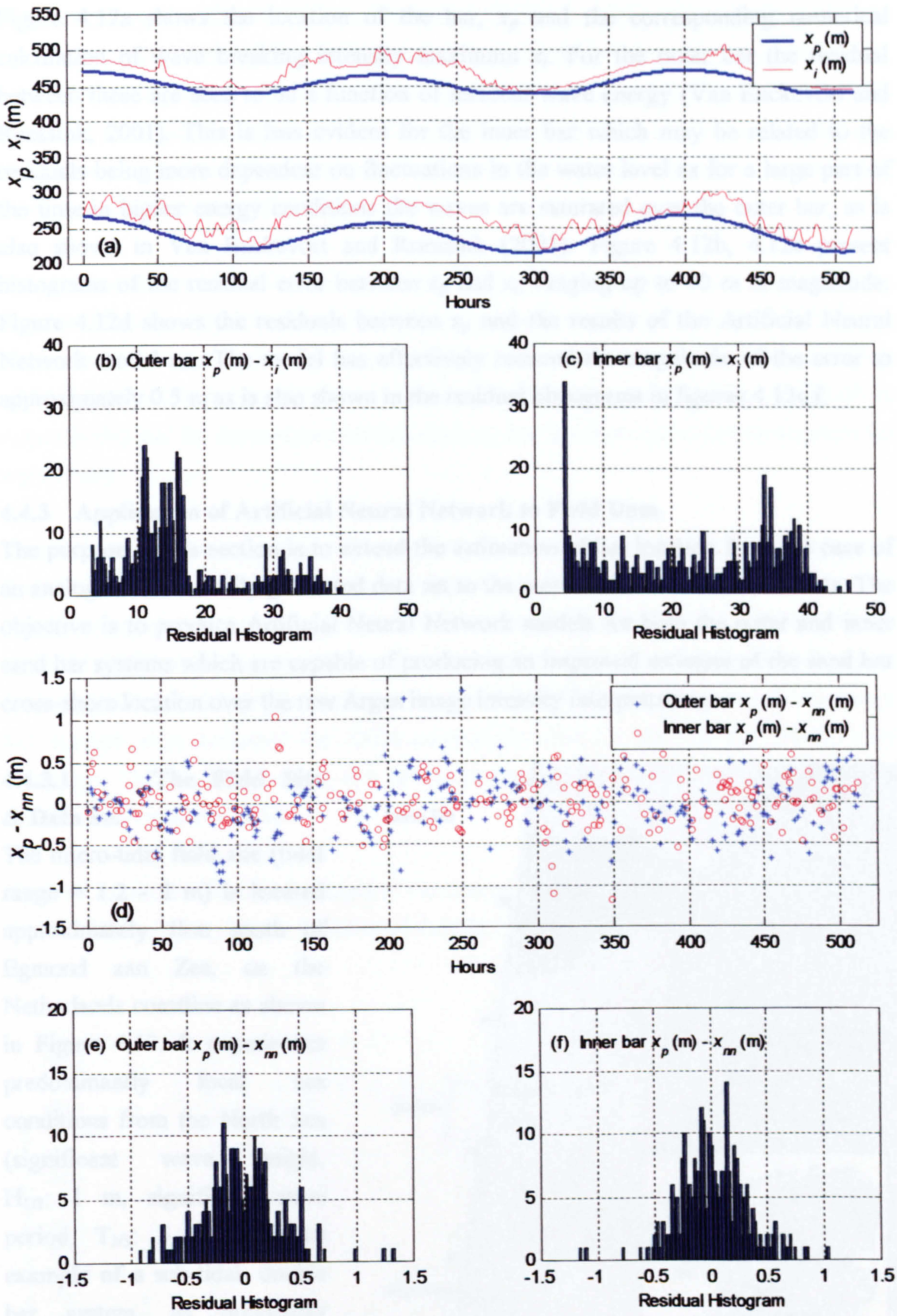


Figure 4.12 (a) Plot of actual bar position (outer and inner) x_p plus the location of the Battjes and Janssen output x_i. (b, c) Histograms of outer and inner bar residual error (x_p-x_i). (d) Differences between x_p and x_{nn} (inner and outer bars on one graph) (e, f) Histograms of outer and inner bar residual error (x_p-x_{nn}).

Figure 4.12a shows the location of the bar, x_p and the corresponding numerical calculation of wave breaking intensity maximum x_i. For the outer bar the residual between these are seen to be a function of incident wave energy (Van Enckevort and Ruessink, 2001). This is less evident for the inner bar which may be related to the residuals being more dependent on fluctuations in the water level as for a large part of the time in higher energy conditions the waves are saturated over the outer bar, as is also shown in Van Enckevort and Ruessink (2001). Figure 4.12b, 4.12c present histograms of the residual error between x_p and x_i, ranging up to 40 m in magnitude. Figure 4.12d shows the residuals between x_p and the results of the Artificial Neural Network model x_{nn}. The model has effectively reduced the magnitude of the error to approximately 0.5 m as is also shown in the residual histograms in figures 4.12e,f.

4.4.3 Application of Artificial Neural Network to Field Data

The purpose of this section is to extend the estimation of bar location from the case of an analogous numerically generated data set to the more realistic case of field data. The objective is to produce Artificial Neural Network models for both the outer and inner sand bar systems which are capable of producing an improved estimate of the sand bar cross-shore location over the raw Argus image intensity interpretation.

4.4.3.1 The Field Site & Data Set

The micro-tidal field site (tidal range = 1.2 - 2 m) is located approximately 1km south of Egmond aan Zee, on the Netherlands coastline as shown in Figure 4.13. It experiences predominantly local sea conditions from the North Sea (significant wave height, $H_{1/3}$: 1 m, significant wave period, $T_{1/3}$: 5 s). It is an example of a sub-tidal, double bar system, as previously shown in figure 4.10a.

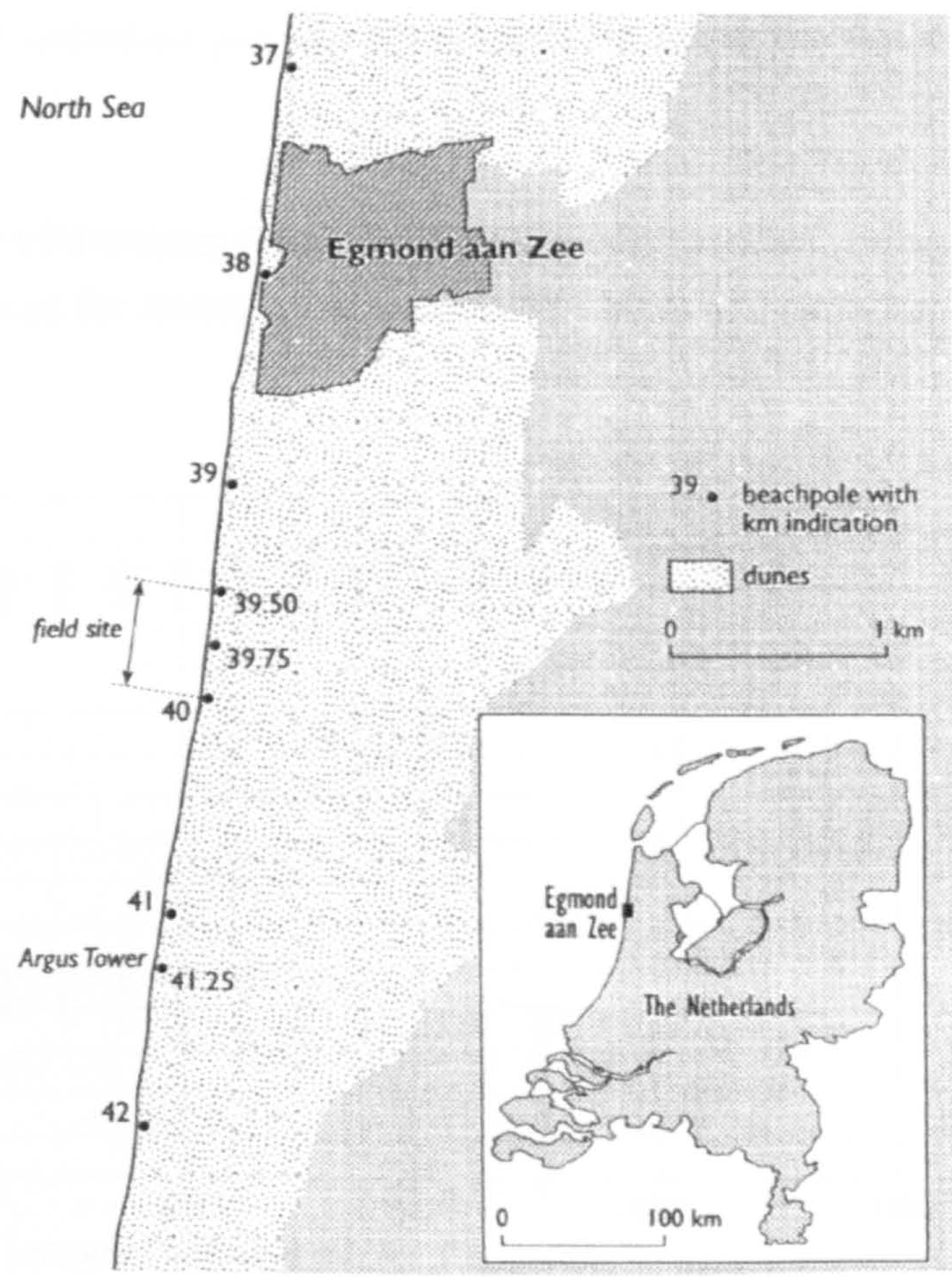


Figure 4.13 Location map, Egmond aan Zee, the Netherlands

During the COAST 3D field campaign an extensive bathymetric data set was obtained using the WESP (Water En Strand Profiler) during a six week period in October/November 1998. The WESP is an approximately 15 m high amphibious 3-wheel vehicle equipped with a kinematic differential global positioning system (DGPS) with a 95% accuracy in the horizontal and vertical of about 3 and 5 cm, respectively. This converts to a maximum error of 10-20 cm in the vertical when tilt over a sloping bed is taken into account (De Hilster, 1998).

The data set consisted of 21 cross-shore profiles taken along a 500 m section of the coast at 25 m spacing. Weather permitting, one survey was conducted per day. The bar migration rates were considered to be small (the mean outer bar migration/day is 0.13 m with a standard deviation of 5.05 m; for the inner bar these are –0.41 m and 6.85 m respectively) and for the purposes of this data set, bar location was assumed constant for a given day.

In addition to the bathymetric data set, the cross shore bar locations were estimated from the location of breaker patterns in Argus video images. The images were recorded hourly using a two camera system. The resolution (pixel footprint) obtained was typically 10-20 m in the cross-shore direction and 30-60 m in the longshore direction for the outer bar and 2-4 m in the cross-shore and 12-25 m in the longshore for the inner bar. Images were collected for ~78% of daylight time for the duration of the field campaign. This results in up to 8-9 estimates per day were available when the wave conditions were favourable.

Figure 4.14 shows a typical example of the cross-shore location of a surveyed bar, using the WESP, together with the location of the intensity maxima for the inner and outer bar systems.

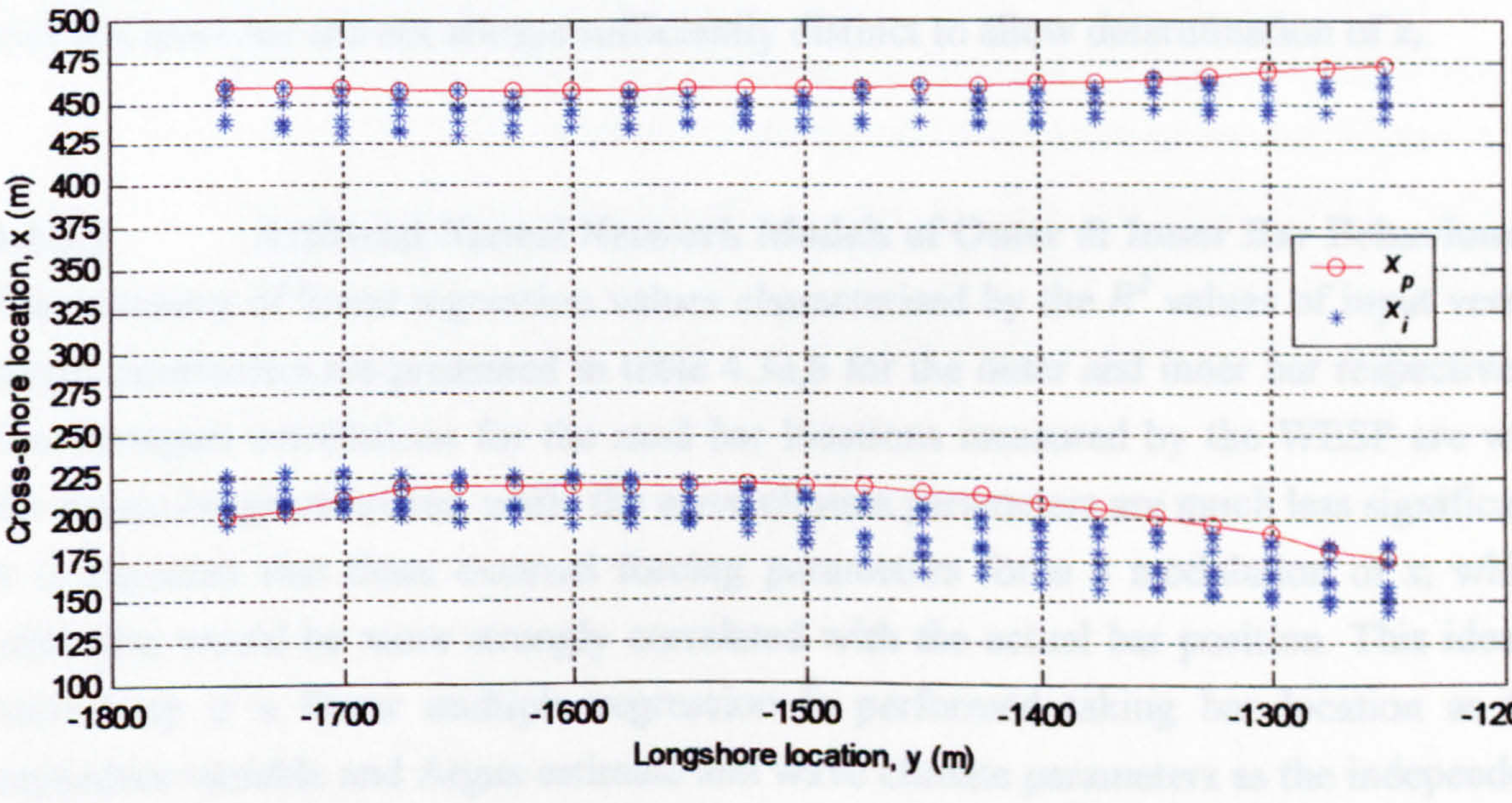


Figure 4.14 Longshore variation of x_i and x_p for a given day

It can be seen that x_p tends to act as an outer bound to the extent of x_l. The tendency for the wave breaking to be located shoreward of the sand bars has been attributed to a combination of breaker delay and roller effects as mentioned in Roelvink *et al.* (1995). This figure also shows how the location of the maximum intensity relative to the bar crest is not constant in the alongshore direction highlighting the influence of the local profile on the breaker location.

Egmond is characterised by a semi-diurnal tidal regime. Offshore root-mean-square wave heights, significant wave periods and wave directions were measured using a directional wave buoy in 15 m water depth. Offshore water levels were measured at tidal stations 20 km north and south of Egmond respectively. The water level at Egmond was taken to be the average of these two values. Typical root-mean-square wave heights ranged from 0.5 to 3.5 m with wave periods of 5 to 9 seconds. Waves predominantly approached the shore from either the North West or the south west. The water level signal has a spring-neap range of 1.8 m to 1.3 m respectively. The first 500 hours of this data set has already been used as input to the numerical study in section 4.4.3 as shown in figure 4.11.

Two data sets have been compiled for the outer and inner bars respectively over the six week period. For the purpose of training the Artificial Neural Network it is only those samples which have both Argus estimates of bar location, x_l and actual WESP measurements, x_p which are of interest. There is substantially more data available for the inner bar (1407 samples have both Argus and WESP measurements out of a total of 3339 samples) than the outer bar (819/1806 samples). This is primarily because WESP measurements of the inner bar were possible in more extreme wave conditions. However, not all those times when WESP measurements of the outer bar were available correspond to data also being available for the inner bar, as the wave breaking patterns over the inner bar are not always sufficiently distinct to allow determination of x_l.

4.4.3.2 Artificial Neural Network Models of Outer & Inner Bar Behaviour

The summary of linear regression values characterised by the R^2 values of input versus output parameters are presented in table 4.3a,b for the outer and inner bar respectively. The strongest correlations for the sand bar locations measured by the WESP are with the Argus image estimates, while the wave climate parameters are much less significant. It is expected that these external forcing parameters force a modulation of x_l which otherwise would be more strongly correlated with the actual bar position. This idea is backed up if a linear multiple regression is performed taking bar location as the dependent variable and Argus estimate and wave climate parameters as the independent variables. R^2 values of 0.588 and 0.643 (adjusted for the number of input parameters) are obtained for the outer and inner bars respectively. A perfect correlation is not expected as firstly the multiple regression is linear in nature and secondly the set of parameters on which the multiple regression is performed act on a different timescale to that of the bar location signal. These multiple regression R^2 values may be considered as a baseline by which to gauge the Artificial Neural Network performance.

Table 4.3 R^2 correlation matrix between Artificial Neural Network inputs and output variables (Field Data) (all estimates are statistically significant at the 99% confidence level)

(a) Outer Bar Location

	$H_{rms,0}$	$T_{1/3,0}$	θ	η	x_i
$H_{rms,0}$	1.000	0.407	0.149	0.027	0.124
$T_{1/3,0}$	0.407	1.000	0.301	0.097	0.117
θ	0.149	0.301	1.000	0.127	0.199
η	0.027	0.097	0.127	1.000	0.080
x_i	0.124	0.117	0.199	0.080	1.000
x_p	0.207	0.068	0.098	0.000	0.513

(b) Inner Bar Location

	$H_{rms,0}$	$T_{1/3,0}$	θ	η	x_i
$H_{rms,0}$	1.000	0.459	0.052	0.117	0.027
$T_{1/3,0}$	0.459	1.000	0.023	0.024	0.016
θ	0.052	0.023	1.000	0.012	0.023
η	0.117	0.024	0.012	1.000	0.275
x_i	0.027	0.016	0.023	0.275	1.000
x_p	0.014	0.017	0.010	0.000	0.448

Using the procedure outlined in Section 2, Artificial Neural Network models to correct the video estimates of sand bar location were generated for both the outer and inner bar. The inputs to the network consisted of x_i, $H_{rms,0}$, $T_{1/3,0}$, θ and η. The results of the Artificial Neural Network models are presented in figure 4.15. For the sake of clarity, samples from only one of the cross shore profiles (-1600m) are presented. Figure 4.15a shows the original discrepancies between x_p and x_i. The Artificial Neural Network corrected version is presented in figure 4.15b with the corresponding residuals magnitude ($x_p - x_{nn}$) presented in figure 4.15c. Both models perform well reducing the residuals magnitude to 10m or less.

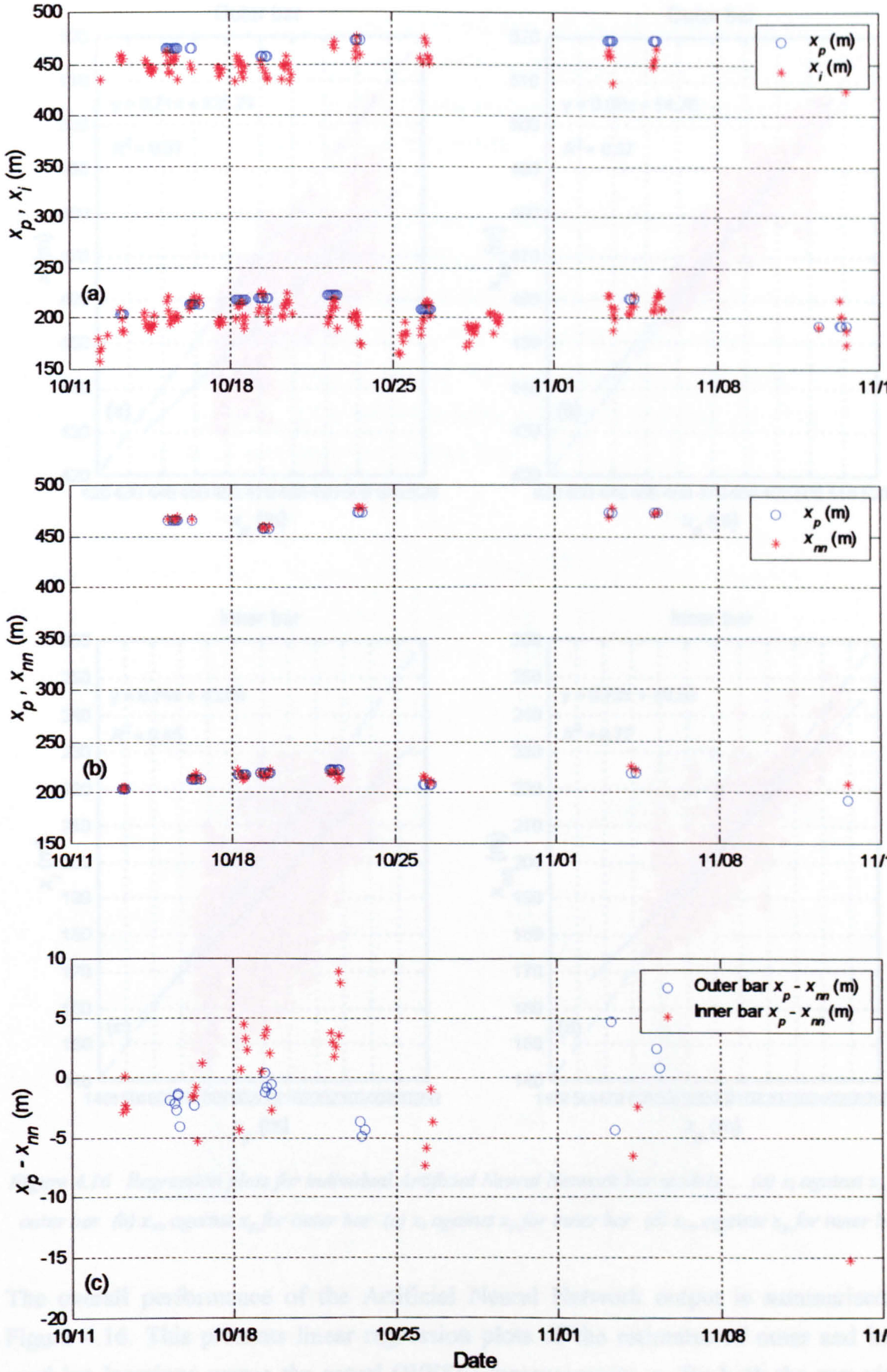


Figure 4.15 (a) Plot of actual bar position (inner and outer) x_p *plus the location of the Battjes and Janssen output* x_i. *(b) Plot of actual inner and outer bar position* (x_p) *plus NN prediction* (x_{nn}). *(c) Differences between* x_p *and* x_{nn} *(inner and outer bars on one graph)*

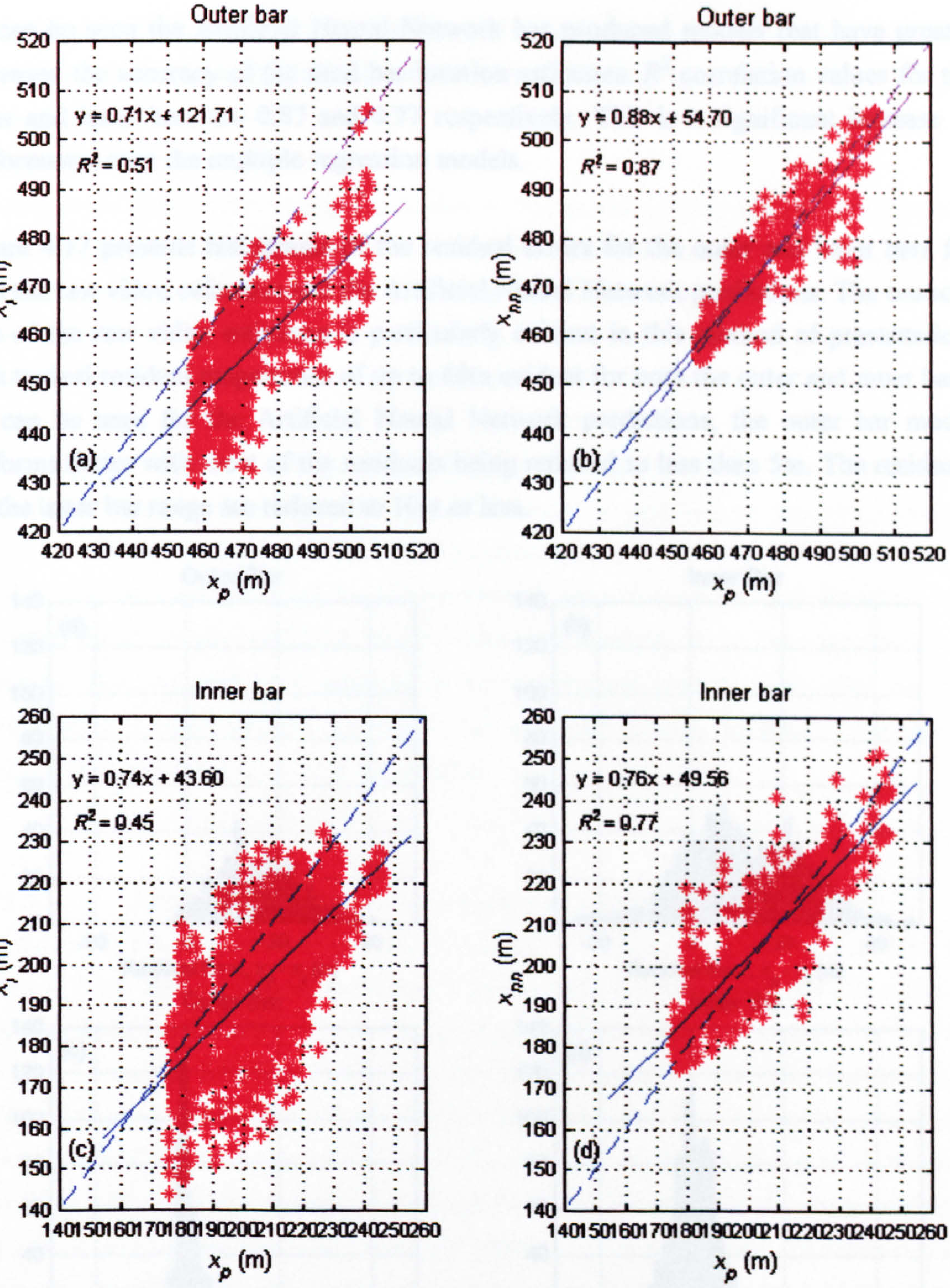


Figure 4.16 Regression plots for individual Artificial Neural Network bar models ... (a) x_i against x_p for outer bar (b) x_{nn} against x_p for outer bar (c) x_i against x_p for inner bar (d) x_{nn} against x_p for inner bar

The overall performance of the Artificial Neural Network output is summarised in Figure 4.16. This presents linear regression plots of the estimates of outer and inner sand bar locations versus the actual (WESP) measurements, x_p for both the raw video image estimates, x_i in figures 4.16a,c and also the Artificial Neural Network improved estimate, x_{nn} in figures 4.16b,d. The objective of the technique is to try to produce models which will produce regression lines (shown as solid lines) which will be much closer to the lines of perfect prediction (dashed lines).

As can be seen the Artificial Neural Network has produced models that have greatly increased the accuracy of the sand bar location estimates. R^2 correlation values for the outer and inner bars are 0.87 and 0.77 respectively. This is a significant increase in performance over the multiple regression models.

Figure 4.17 presents histograms of the residual errors for the outer and inner bars for both the raw video estimates and the Artificial Neural Network predictions. The onshore bias of the raw video estimates is particularly evident in this method of presentation, with typical residual magnitudes of up to 40m evident for both the outer and inner bars. As can be seen for the Artificial Neural Network predictions, the outer bar model performs better with most of the residuals being reduced to less than 5m. The residuals for the inner bar range are reduced to 10m or less.

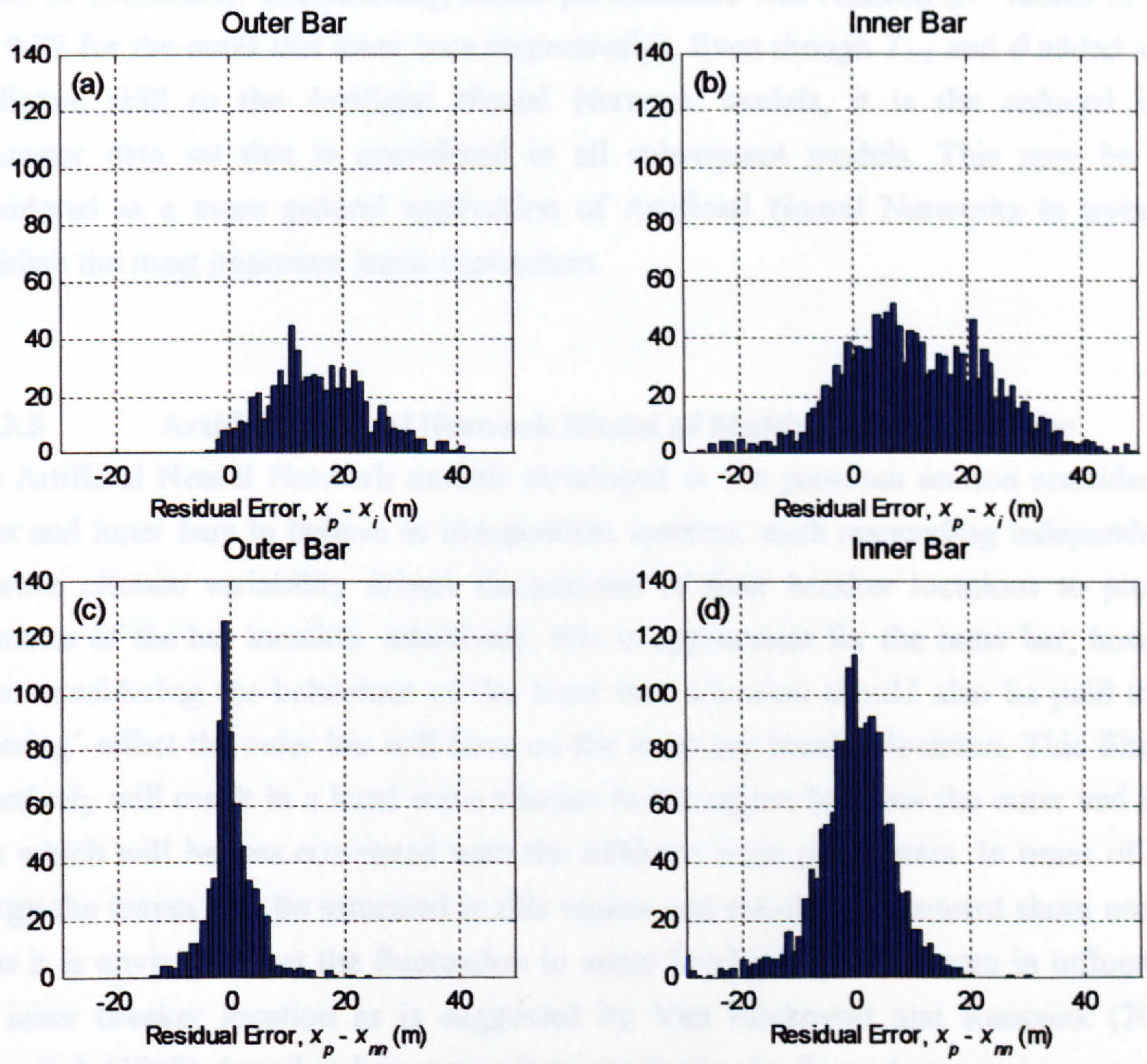


Figure 4.17 Histograms of residual errors $x_p - x_i$ (m) for (a) Outer bar (b) Inner bar. Histograms of residual errors $x_p - x_{nn}$ (m) for individual Artificial Neural Network bar models for (c) Outer bar (d) Inner bar

However it can be seen that the application of the Artificial Neural Network model to the testing data set is not perfect, with some points being generated where the model has not learned the appropriate correction (see for example figure 4.16d). This may be due to a lack of training examples in this region. A second reason for these errors may be a consequence of over-fitting of the model to the training data set resulting in poor generalisation.

A consideration when developing the Artificial Neural Network models was to keep the number of input parameters to a minimum. This allows a *'simpler'* Artificial Neural Network model to be developed, facilitating interrogation and interpretation of the resulting model due to the lower dimensionality. It would also facilitate generalising the technique to other sites where such a comprehensive data set may not be available.

A reduced input data set consisting of x_i, $H_{rms,0}$ and η was tested (for example with this model, data obtained from just one pressure sensor in addition to the video images would be sufficient). The resulting model performance was reduced (R^2 values of 0.84 and 0.72 for the outer and inner bars respectively). Even though $T_{1/3}$ and θ added some predictive skill to the Artificial Neural Network models, it is the reduced input parameter data set that is considered in all subsequent models. This may be also considered as a more general application of Artificial Neural Networks in trying to establish the most important input parameters.

4.4.3.3 Artificial Neural Network Model of Multiple Bar Behaviour

The Artificial Neural Network models developed in the previous section consider the outer and inner bars to behave as independent systems, each responding independently to wave climate variability driven fluctuations of their breaker locations to provide estimates of the bar location. Intuitively, this is appropriate for the outer bar, however when considering the behaviour of the inner bar, attention should also be paid to the 'filtering' effect the outer bar will have on the inner bar breaker location. This filtering effectively will result in a local wave climate in the region between the outer and inner bars which will be less correlated with the offshore wave parameters. In times of high energy the waves will be saturated in this region and should tend toward shore normal. Thus it is envisaged that the fluctuation in water level will predominate in influencing the inner breaker location as is suggested by Van Enckevort and Ruessink (2001). Masselink (1998) describes how secondary waves may be formed on passing over sand bars, thereby highlighting another means whereby the nature of the wave climate over the inner bar will be modified by the presence of the outer bar.

To build these influences into a better Artificial Neural Network model of the inner bar dynamics, the location of the outer breaker, x_i is taken as being representative of the *'filtering/modification'* of the offshore climate parameters. This extra information is then given to the Artificial Neural Network when training the inner bar model. In order to test the idea that a multiple bar model would provide better results for the inner bar, it is necessary to produce a data set with information available for both Argus estimates and WESP measurements of bar location simultaneously for both outer and inner bars. This greatly reduces the sample size of the data set to approximately 400 samples. Also significant is the fact that the parameter space which this reduced sample data set covers is also reduced. Table 4.4 presents the linear regression correlations for the reduced data set. The statistical characteristics of the inner bar data for the reduced data set are similar to that of the original data set.

Table 4.4 R^2 correlation matrix between Artificial Neural Network inputs and output variables (Combined Field Data) (all estimates are statistically significant at the 99% confidence level).

	$H_{rms,0}$	$T_{1/3,0}$	θ	η	x_i (Outer bar)	x_i (Inner bar)
$H_{rms,0}$	1.000	0.271	0.047	0.197	0.009	0.125
$T_{1/3,0}$	0.271	1.000	0.343	0.020	0.062	0.009
θ	0.047	0.343	1.000	0.348	0.324	0.063
η	0.197	0.020	0.348	1.000	0.116	0.286
x_i (Outer bar)	0.009	0.062	0.324	0.116	1.000	0.000
x_i (Inner bar)	0.125	0.009	0.063	0.286	0.000	1.000
x_p (Outer bar)	0.102	0.352	0.107	0.010	0.134	0.399
x_p (Inner bar)	0.066	0.092	0.031	0.000	0.094	0.451

Figure 4.18a presents the summary results of running the Artificial Neural Network model on the reduced input parameter data set for the outer bar. The model performance for the outer bar, as mentioned earlier, has been reduced to an R^2 value of 0.84. It is when the combined Artificial Neural Network inner bar model is considered, in figure 4.18b, that the merit of combined model approach is realised. The performance of the model increases significantly from an R^2 value of 0.72, obtained using the original inner bar model with a reduced parameter input data (x_i, $H_{rms,0}$ and η), to 0.93 surpassing that of the outer bar model. This increase in performance occurs even though the reduced input parameter data set has been used.

The increase in performance highlights the influence the outer bar has on the breaker location over the inner bar and justifies the approach when considering the inner bar behaviour. For larger energy events, the waves become saturated over the outer bar, resulting in a ceiling on the level of energy which arrives at the inner bar. The location of the breaking pattern over the inner bar is then primarily dependent on the water depth. This result is significant as it suggests that it is necessary that the sand bars are considered as a system and may not be treated individually. A summary of the model

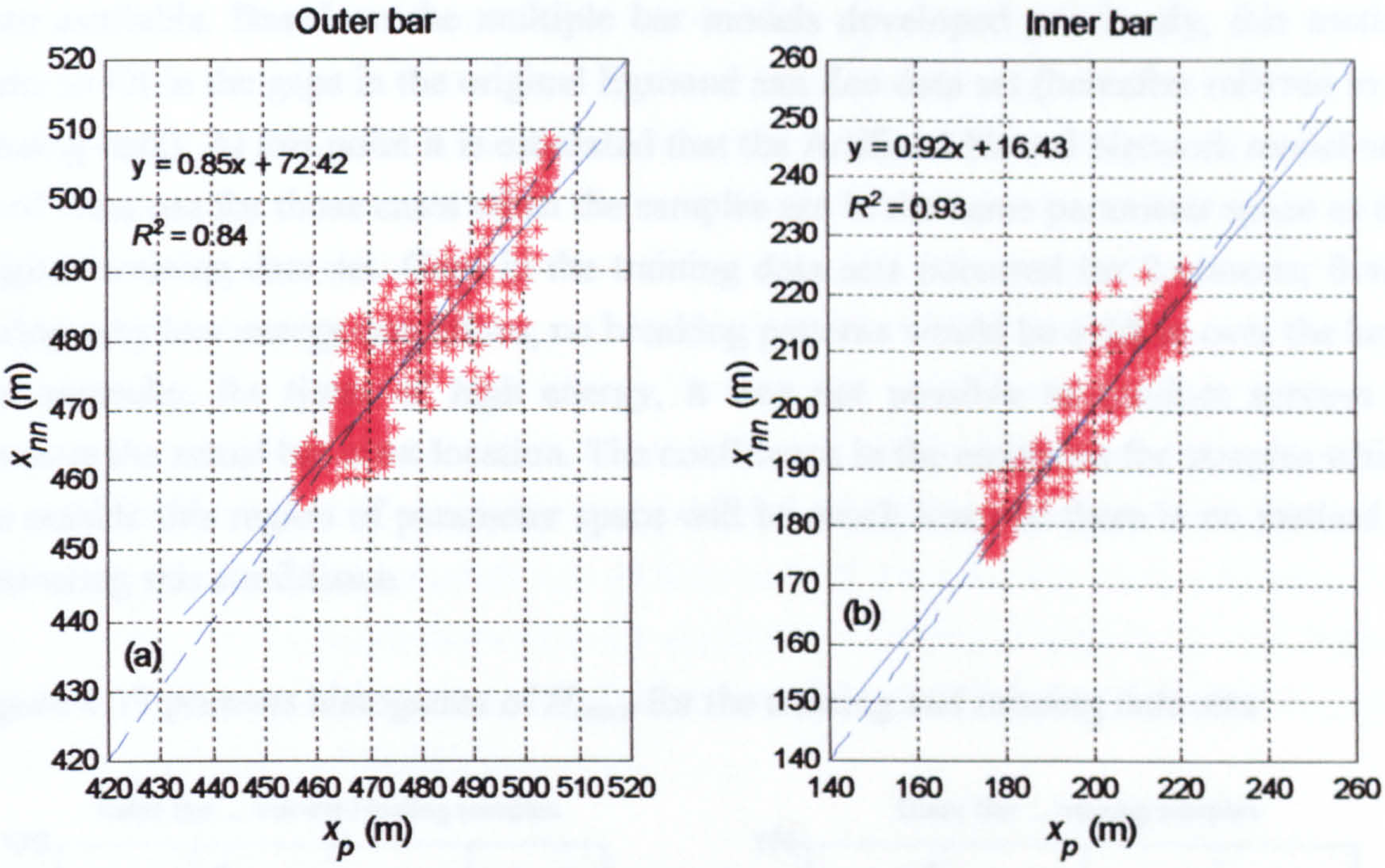


Figure 4.18 Regression plots for optimal Artificial Neural Network bar models.
(a) x_{nn} against x_p for outer bar (b) x_{nn} against x_p for inner bar

development is presented in table 4.5 highlighting that the Artificial Neural Network model has greater skill in providing more accurate estimates of bar location compared to a multiple regression model.

Table 4.5 R^2 correlations between Bar Location, x_p and both Multiple Regression Model output and Artificial Neural Network model output, x_{nn}
(all estimates are statistically significant at the 99% confidence level).

Outer Bar		Inner Bar	
Multiple Regression Model		**Multiple Regression Model**	
Input Parameters	R^2	**Input Parameters**	R^2
x_i(outer), $H_{rms,0}$, $T_{1/3,0}$, θ, η	0.59	x_i(inner), $H_{rms,0}$, $T_{1/3,0}$, θ, η	0.64
Artificial Neural Network Model		**Artificial Neural Network Model**	
Input Parameters	R^2	**Input Parameters**	R^2
x_i(outer), $H_{rms,0}$, $T_{1/3,0}$, θ, η	0.87	x_i(inner), $H_{rms,0}$, $T_{1/3,0}$, θ, η	0.77
x_i(outer), $H_{rms,0}$, η	0.84	x_i(inner), $H_{rms,0}$, η	0.72
		x_i(outer), x_i(inner), $H_{rms,0}$, η	0.93

4.4.4 Extending the Egmond aan Zee data set

One of the main objectives of this study was to investigate the extent to which an Artificial Neural Network model of sand bar behaviour at Egmond aan Zee could be used to fill in those times when no measurements of the actual cross-shore bar location were available. Based on the multiple bar models developed previously, this section seeks to fill in the gaps in the original Egmond aan Zee data set (hereafter referred to as missing data). At this point it is estimated that the Artificial Neural Network model will be of most use for those cases when the samples are in the same parameter space as the original training data set. Gaps in the training data sets occurred for 2 reasons; firstly during very low energy conditions, no breaking patterns would be evident over the bars, and secondly, for times of high energy, it was not possible to conduct surveys to measure the actual bar crest location. The confidence in the estimates for samples which are outside this region of parameter space will be much less and there is no method of estimating this confidence.

Figure 4.19 presents histograms of $H_{rms,0}$ for the training and missing data sets

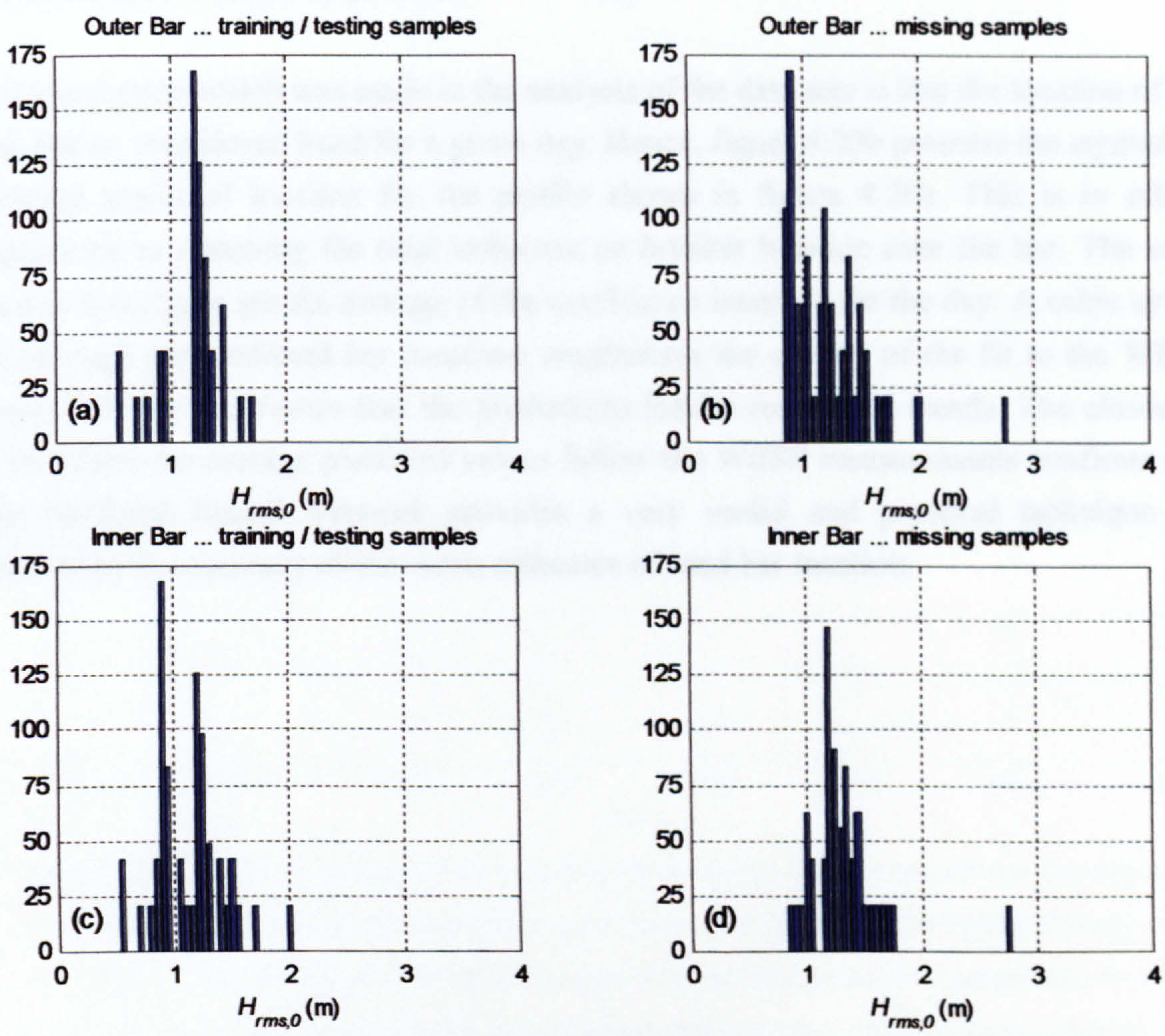


Figure 4.19 Histograms showing difference in distribution of training data and missing data based on $H_{rms,0}$ input parameter

respectively for both the outer and inner bars. It can be seen that the region of parameter space covered by the training data set is not the same as that required by the missing data to allow reliable estimates of bar location. This is especially true for the lower and higher wave conditions for the outer bar.

The results of applying the multiple bar model to the missing data are presented in figure 4.20. For clarity only the results of one cross-shore profile (-1600m) are presented (similar results are obtained for other profiles). Figure 4.20a presents the temporal variation in bar location of the Artificial Neural Network models for each available video estimate of bar location. The original WESP measurements used in the training data set are presented as circles, while the clusters of stars represent the Artificial Neural Network predictions. The WESP measurements are useful as a qualitative indication of Artificial Neural Network performance. It can be seen that these predictions closely match the location of the WESP measurements. The average range of the confidence intervals are ±8.83m and ±7.80m for the outer and inner bars respectively. Not all predictions have an associated confidence interval as this depends on whether the new input parameters lies in the region of influence of the training input parameters, as outlined in §4.2.1.2.

An assumption which was made in the analysis of the data sets is that the location of the bar can be considered fixed for a given day. Hence, figure 4.20b presents the equivalent average predicted location for the profile shown in figure 4.20a. This is in effect, equivalent to removing the tidal influence on breaker location over the bar. The error bars in this figure are the average of the confidence intervals for the day. A cubic spline fit through the predicted bar locations emphasises the quality of the fit to the WESP measurements and shows that the predictions follow reasonable trends. The closeness with which the average predicted values follow the WESP measurements confirms that the Artificial Neural Network provides a very useful and practical technique for increasing the accuracy of the video estimates of sand bar location.

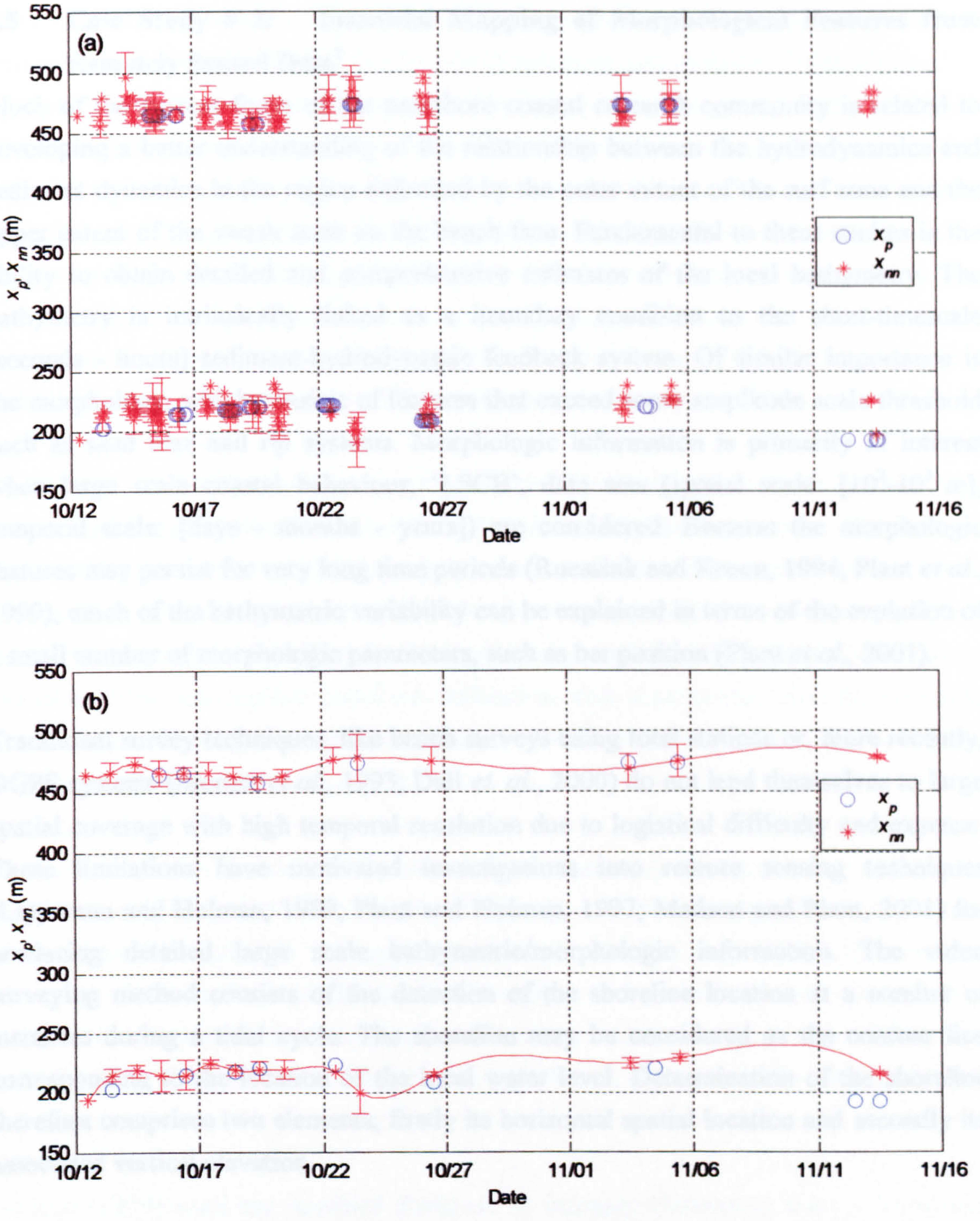


Figure 4.20 Application of multiple bar model to fill in missing data for Egmond aan Zee data set (profile = -1600m). The measured data, x_p are shown as circles. Artificial Neural Network predictions of missing data are shown as stars. Missing data for which is was possible to determine confidence intervals are shown as stars with error bars. Plot (a) shows all hourly estimates available for each day. Plot (b) shows the corresponding daily averages. The solid line is a cubic spline fit to the predicted bar locations.

4.5 Case Study # 2: Intertidal Mapping of Morphological Features from Remotely Sensed Data[2]

Much of the current focus of the nearshore coastal research community is related to developing a better understanding of the relationship between the hydrodynamics and sediment dynamics in the region delimited by the outer extent of the surf zone and the upper extent of the swash zone on the beach face. Fundamental to these studies is the ability to obtain detailed and comprehensive estimates of the local bathymetry. The bathymetry is intrinsically linked as a boundary condition to the short-timescale [seconds - hours] sediment-hydrodynamic feedback system. Of similar importance is the morphology, which consists of features that exceed some amplitude scale threshold such as sand bars and rip systems. Morphologic information is primarily of interest when large scale coastal behaviour, 'LSCB', data sets (spatial scale: [10^2-10^3 m], temporal scale: [days - months - years]) are considered. Because the morphologic features may persist for very long time periods (Ruessink and Kroon, 1994; Plant *et al.*, 1999), much of the bathymetric variability can be explained in terms of the evolution of a small number of morphologic parameters, such as bar position (Plant *et al.*, 2001).

Traditional survey techniques, like beach surveys using total stations or, more recently, DGPS systems (Morton *et al.*, 1993; Dail *et. al.*, 2000) do not lend themselves to large spatial coverage with high temporal resolution due to logistical difficulty and expense. These limitations have motivated investigations into remote sensing techniques (Lippmann and Holman, 1989; Plant and Holman, 1997; Madsen and Plant, 2001) for producing detailed large scale bathymetric/morphologic information. The video surveying method consists of the detection of the shoreline location at a number of instances during a tidal cycle. The shoreline may be considered as the contour line corresponding to the location of the local water level. Determination of the shoreline therefore comprises two elements; firstly its horizontal spatial location and secondly its associated vertical elevation.

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[2] A version of this section has been submitted to the Marine Geology as Kingston, K.S., Mallet, C., Plant, N.G. and Davidson, M.A., 'Intertidal Mapping of Morphological Features from Remotely Sensed Data'.

My contribution to this study was primarily in the development of the Artificial Neural Network model of shoreline discrimination. However I also participated heavily in all other aspects of the work. Cyril Mallet assisted in the organisation of data sets and the application of the developed techniques to the data sets. Nathaniel Plant contributed the section on an optimal approach to interpolating the shoreline estimates to produce the intertidal maps. Mark Davidson provided a valuable critical assessment at the paper preparation stage.

Plant and Holman (1997) mapped the Shoreline Intensity Maximum (or SLIM) as obtained from time-averaged video images (Lippmann and Holman, 1989; Holland *et al.*, 1997) of the nearshore region. This is the region of high image intensity associated with wave breaking at the shoreline. They related this feature to the mean sea level as recorded by a tide gauge with an adjustment for depth of water at the SLIM. The main limitation of this approach is the need for a clearly defined SLIM which is a function of the breaker type and shoreface gradient. Their technique worked well especially for the case of reflective planar beaches and waves of a magnitude such that they just break enough to be visibly observed. This resulted in a vertical error of 0.1 m when compared with survey data.

Davidson *et al.* (1997) also used spatial gradients in intensity in rectified time-exposure images to identify a shoreline. However they found, for their particular site, that the maximum in the intensity spatial gradient was correlated to the position of maximum run-up. The elevation of the shoreline feature was obtained from a tidal prediction model. To account for an offset due to wave setup, swash and atmospheric variations a constant offset was applied based on calibration with a particular, directly-surveyed, profile. Thus the remotely-sensed bathymetry obtained was specific to the conditions prevalent at the time of the survey.

A more detailed trinocular (three view) stereogrammetry approach was adopted by Holland and Holman (1997) to identify the foamy wave runup edge against the darker saturated sand background. This approach allowed a detailed map ($O(10^3)$ estimates per 10 m by 10 m region) of the foreshore region to be obtained with an accuracy comparable to that obtained by traditional survey techniques (1-3 cm). Whilst this resolution is comparable or better than traditional survey techniques, the spatial coverage is very limited.

Janssen (1997) used the standard deviation in intensity (estimated over a 10 minute period) video image as an alternative to the time averaged video images. These images highlight regions of high and low variance in images taken over the same time period as the time averaged images. Janssen showed that a spatial shift existed between the location of the standard deviation maximum and the time average maximum in a cross shore transect in the vicinity of wave activity at the shoreline. This shift changed sign just slightly shoreward of the intersection between the tidal water level and the bottom profile allowing the identification of the horizontal spatial location of a shoreline feature in the images. He found that this feature was situated seaward of surveyed shoreline locations. Also more than one cross-shore location of spatial jump were often observed leading to a certain ambiguity in the location of the correct shoreline feature.

Aarninkhof and Roelvink (1999) took a different approach to the problem of horizontal spatial shoreline identification by using the colour information content evident in the images to help distinguish between sand and water regions in the images. They transformed the colour content in RGB (red-green-blue) colour space to the HSV (hue-saturation-value) colour space and showed that regions of sand and water occupied different regions of the hue-saturation space. Thus by using a discriminator line between these two regions the location of the shoreline could be identified.

Ryan *et al.* (1991) investigated the possibility of determining shorelines from more remote sources as may be found in cartographic applications. They combined the versatility of Artificial Neural Networks with spectral measures of the characteristics of normalized grayscale maps of land/water regions to produce models capable of delineating shoreline pixels. These pixels were subsequently joined using edge detection algorithms. However they point out a shortcoming of the spectral approach in the case where there is a potential for large variability in the shading of land/water regions leading to misclassification of regions. Their algorithms were applied to images at 1:50,000 scale which resulted in water regions appearing reasonably homogeneous in the normalized images. This would not necessarily be the case for nearshore video images (near-field scale of ~ 1:5000) which provide much greater resolution of the shoreline region.

Although the identification of shoreline features from video imagery and other sources is not new, most of the existing techniques tend to be site specific and do not necessarily work well in all conditions. The aim of this case study is to present a robust technique for the identification of shoreline features using Artificial Neural Networks which subsequently allows the generation of maps of the inter-tidal topography.

4.5.1 Methodology

The primary data source for this study are time exposure images obtained from the Argus video programme (Lippmann and Holman, 1989; Holland *et al.*, 1997). These images average views of the nearshore region over a 10 minute period. The footprint of the individual pixels in an image is a function of distance from the camera. This is important as it means that the resolution with which the shoreline location may be defined will also be dependent on distance from the video cameras.

Intrinsic to the intertidal mapping procedure is the robust identification of a feature which may be interpreted as a shoreline. This identification process needs to be independent of beach type, incident wave energy and beach sand grain characteristics. For this study it was felt that the spectral information content, as used by Ryan *et al.*

(1991), of the Argus images would not be sufficient to differentiate the range of variability in shading of land and water regions. A stronger alternative would be to adopt the strength of Artificial Neural Networks to model the colour information content of the Argus images, as suggested by Aarninkhof and Roelvink (1999), which allows discrimination between regions in the image which are underwater or recently wet and those further up on the beach which are dry. The shoreline is subsequently identified as the boundary between these regions. A fundamental distinction between the two approaches is that the colour content information is obtained in RGB space for this study compared to HSV space as used in the Aarninkhof and Roelvink approach. The use of colour information may be justified if one considers the physical principles behind the visual observation of the shoreline region. A simplified interpretation of these principles is outlined as follows.

As light penetrates into water, its component wavelengths are absorbed at different rates. Wavelengths from the red end of the spectrum are attenuated more rapidly than those from the blue end of the spectrum. The rate of attenuation is greatly enhanced in water with a high suspended sediment content, the swash zone being an example of this. Hence the signal returned from a wet pixel of an image will consist of blue and green components which are reasonably unaffected in magnitude and a red component which has significant attenuation (i.e. much of its energy has been absorbed). For a corresponding dry pixel, in similar lighting conditions, the magnitude of the red component will be comparatively unaffected. This change in optical properties provides a technique to discriminate between wet and dry regions of the beach. For more detail on the optical properties of water see Kirk (1994).

The following sections outline the progression of considerations for intertidal mapping. Initially a treatment of the horizontal spatial location of an individual shoreline is presented. This is followed by an assessment of the appropriate vertical elevation to be assigned to the shoreline feature. The final step outlines a robust technique to interpolate these semi-ordered data to a regular grid. At all stages a consideration of sources and magnitude of errors is included.

4.5.1.1 Identification of horizontal spatial location of shoreline feature

Having established that there is potential for discriminating between land and water regions, the next step is to produce a model which adequately and robustly performs this discrimination. This may be considered as a input-output mapping problem, where the inputs are the red, green and blue channels of the image pixels and the output is a binary decision as with the identification of either land or water. This involves the classification of regions of the input parameter space. Various approaches may be adopted for this clustering problem. The one adopted by Aarninkhof and Roelvink (1999) mentioned previously was based on histograms. Even though histograms in themselves are not linear operators, the approach they took to partitioning the parameter space was intrinsically linear in nature. This presupposes the nature of the boundaries between the land and water regions. It would be useful to relax this linearity assumption as it is not suggested by the nature of the problem. The non-linear approach used in this study is that of an Artificial Neural Network model.

4.5.1.2 Horizontal spatial location of shoreline contours

For this study, the training data set required by the Artificial Neural Network consists of the red green and blue channels (RGB) values obtained from pixel samples as inputs and a manual binary classification of sand or water as the output, as shown graphically in figure 4.21. A 2-layer feed-forward artificial neural network model was used employing the Levenberg Marquardt training algorithm. Hyperbolic tangent activation functions were used in the hidden layer whilst a linear activation function was used in the output layer. 15 nodes were used in the hidden layer to provide sufficient processing power for the model. Training was carried out for a maximum of 40 epochs.

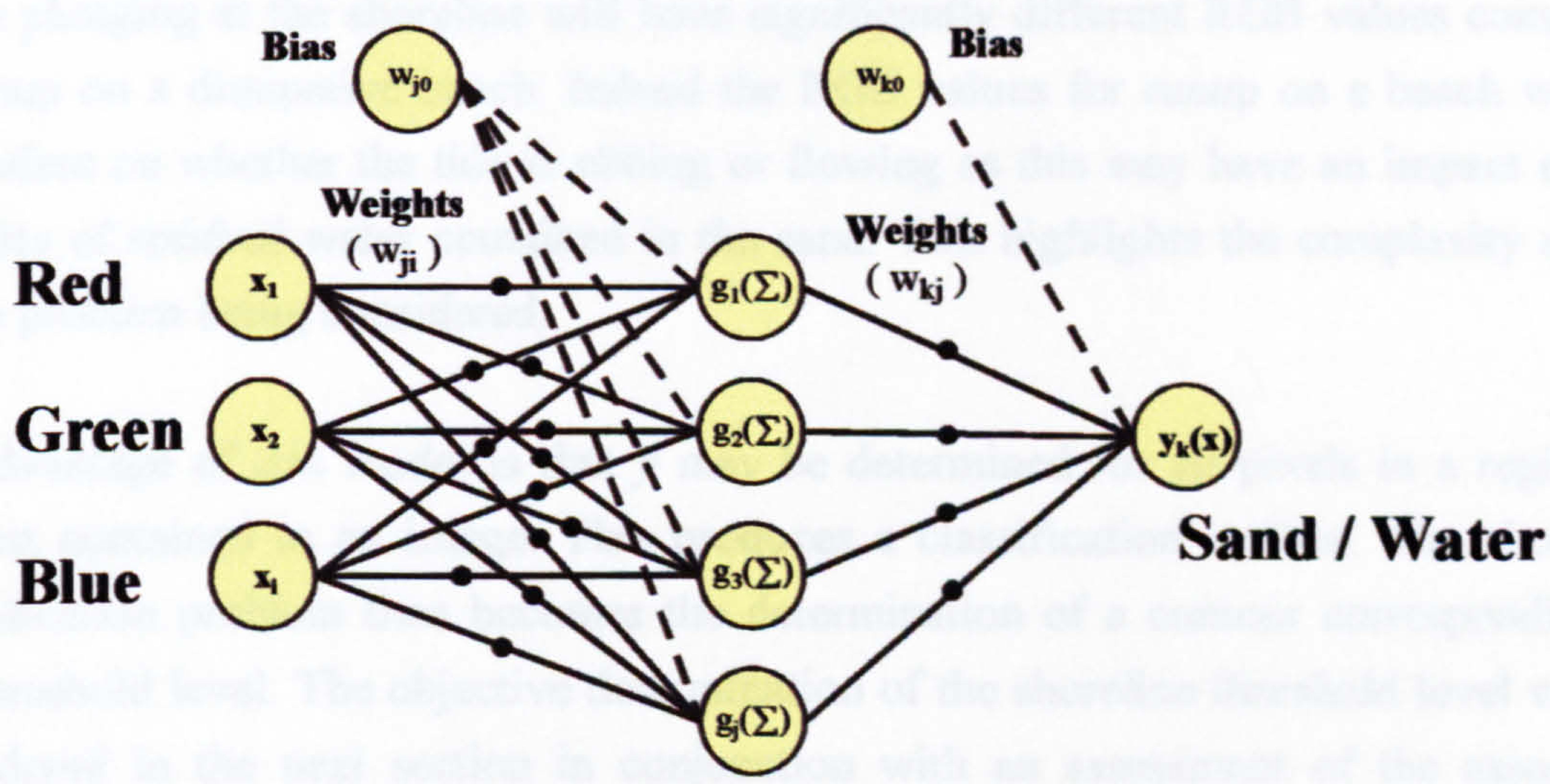


Figure 4.21 Artificial Neural Network model of shoreline classification

The training pixel samples are chosen to incorporate regions of an image near the shoreline which are definitely water and definitely sand. This is done for a range of images being considered to allow for the natural variability in lighting conditions. This ensures the Artificial Neural Network model establishes the extents of the occupied regions of the input parameter space. A separate model is established for each camera being considered for each day an intertidal morphology is required. The trained Artificial Neural Network model output, *y*, is no longer binary value but is a continuous variable, with water samples having a value close to 0 and land samples having a value close to 1 as shown for a sample cross-shore transect in figure 4.22.

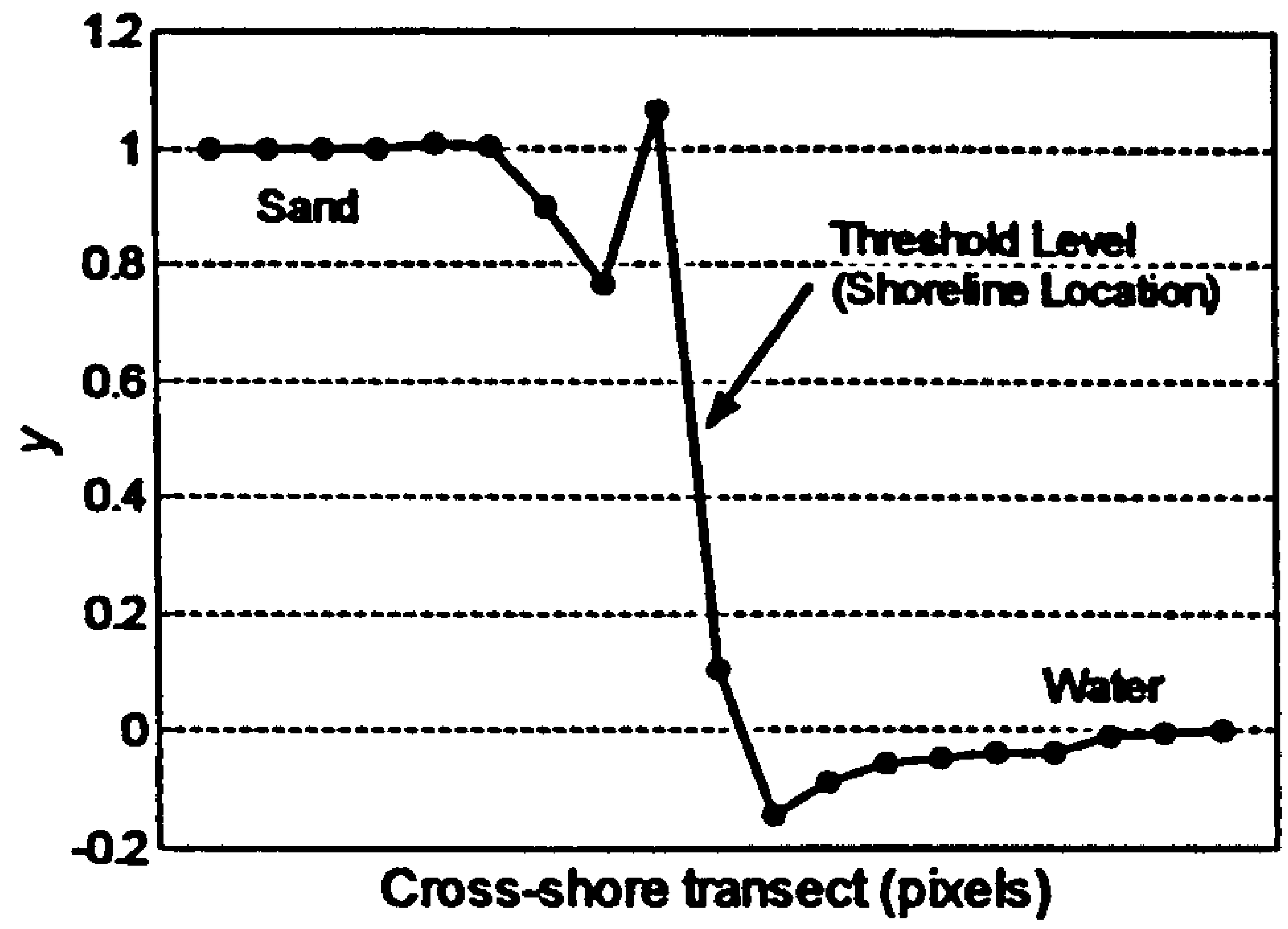


Figure 4.22 Artificial Neural Network classification of Sand / Water for a typical cross-shore transect

As the Artificial Neural Network model does not specifically determine the shoreline location, but regions which bound the shoreline, the aim when interpreting the Artificial Neural Network model output, y, is to objectively identify the threshold level which is associated with the shoreline location. This threshold level is not a constant as the behaviour of y is dependent on the visual nature (RGB values) of the shoreline itself. Wave plunging at the shoreline will have significantly different RGB values compared to runup on a dissipative beach. Indeed the RGB values for runup on a beach will be dependent on whether the tide is ebbing or flowing as this may have an impact on the quantity of residual water contained in the sand. This highlights the complexity aspect of the problem being considered.

An advantage of this model is that y may be determined for all pixels in a region of interest contained in an image. This produces a classification surface. The shoreline identification problem then becomes the determination of a contour corresponding to the threshold level. The objective determination of the shoreline threshold level will be considered in the next section in conjunction with an assessment of the associated confidence limits on the estimate of shoreline location.

4.5.1.2.1 Confidence interval estimates on horizontal spatial location of shoreline contours

Due to the uncertainty involved with the output, y, obtained from the Artificial Neural Network model it is necessary to try to establish confidence intervals on the threshold value chosen to be the shoreline location. The Artificial Neural Network model does not lend itself directly to this task. The procedure adopted in this study is as follows.

- A region of interest in an image is selected. This contains both land and water pixels bounding one or more shoreline features (figure 4.23a).
- A classification surface, y is produced for the region of interest (figure 4.23b).
- A histogram of values of y is generated. This allows the probability density function of the classified region to be inferred. The histogram will tend to be dominated by spikes around 0 and 1 corresponding to water and land values respectively. To cater for this the inherent variability in classification of land and water is identified, as is explained in figure 4.23c. This is then used to specify the extreme bounds of the region which statistically would not be classified as sand or water. This is the region taken into account when generating the histograms.
- 5% and 95% percentiles of the corresponding cumulative probability density function of y are calculated. These allow inference of the location of the shoreline threshold value and the corresponding 95% confidence intervals.
- These percentiles are then used to produce contours of y. The spread of the contours gives an indication of the confidence with which a shoreline has been identified spatially in image parameter space.
- Each point along the shoreline contour is considered and the corresponding points of the 5% and 95% confidence interval contours are identified as shown in figure 4.23d

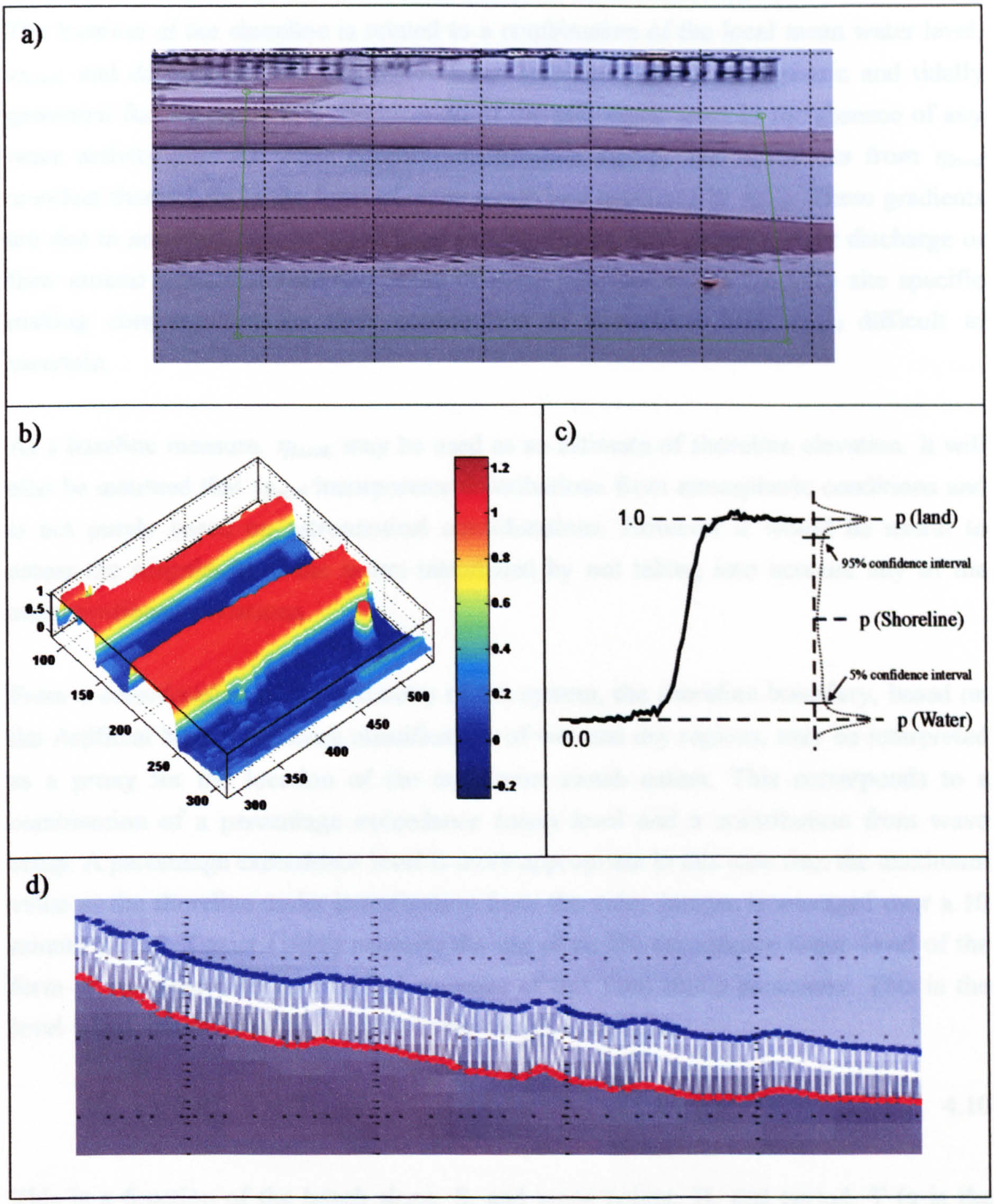


Figure 4.23 a) Region of interest bounding shoreline features. b) Classification surface, y, produced by Artificial Neural Network model of region of interest. c) Variability in classification of land/water regions. 3 separate regions are identified; water, shoreline and land and are separated by the 5 and 95% confidence intervals respectively. d) Identification of section of the shoreline feature and its associated confidence intervals in image parameter (uv) space. Shoreline denoted by white dots. The land/water bounds are denoted by the connected red/blue dots respectively.

4.5.1.3 Identification of vertical elevation of shoreline feature

The location of the shoreline is related to a combination of the local mean water level, η_{local}, and deviations from this mean water level caused by atmospheric and tidally generated forcing. η_{local} is a combination of the still water level in the absence of any wave activity plus the wave contribution towards set-up. The deviations from η_{local} manifest themselves in the form of wave runup and gradients in η_{local}. These gradients are due to non-uniformities in the local forcing due to tidal currents, river discharge or flow around sub-aerial features. Some of these later anomalies are very site specific making compensation for their contribution to deviations from η_{local} difficult to ascertain.

As a baseline measure, η_{local}, may be used as an estimate of shoreline elevation. It will also be assumed that η_{local} incorporates contributions from atmospheric conditions and is not purely based on astronomical considerations. However it would be useful to assess the magnitude of the errors introduced by not taking into account any of the aforementioned deviations.

From a consideration of the geometry of the system, the shoreline boundary, based on the Artificial Neural Network classification of wet and dry regions, may be interpreted as a proxy for the location of the maximum swash extent. This corresponds to a combination of a percentage exceedance runup level and a contribution from wave setup. A percentage exceedance level is more appropriate in this case than the maximum value as the shoreline under investigation from the video images is averaged over a 10 minute period. Komar (1998) suggests the use of an 2% exceedance runup level of the form of equation 4.10 as a typical estimate of this total runup parameter. This is the level which is exceeded by only 2% of the swash excursions.

$$R_{2\%}^{T} = \eta + R_{2\%} = \alpha ST\sqrt{gH} \qquad 4.10$$

This is a function of the beach slope, S, and wave height, H, and period, T (g is the acceleration due to gravity). He suggested a value of $\alpha = 0.36$, however it is likely that this will be site dependent. Increasingly reflective gradients typically have larger vertical runup levels for a given incident wave energy. It could be argued that the simplicity of this equation for the vertical component of the shoreline location is inadequate. Estimates of the vertical component may be improved by incorporating a modelling approach to establish the wave setup contribution as shown in Janssen (1997). However, the focus of this study is to establish the horizontal spatial location of the shoreline. Also as this is a rather simplistic expression for the vertical component of total runup it lends itself readily for the possibility of calibration of the constant term at different sites.

4.5.1.4 Generation of intertidal beach morphology

Having produced a data set of spatial co-ordinates and associated error intervals of the intertidal region it is then necessary to grid the data. This requires a robust interpolation technique which is capable of handling very large data sets of a semi-ordered nature (contour data).

The chosen interpolation technique is that outlined in Plant *et al.* (2002) and is summarised in appendix A.2. It locally fits a quadratic surface model to the data. The model allows the incorporation of any explicit information on confidence intervals of the data to be interpolated. Spatial scales may be specified which describe the typical wavelengths of the cross-shore and longshore features which are to be modelled. It is also possible to incorporate temporal scales for data which is taken at different times. The temporal scale allows data closer to the time of interest to be weighted more heavily. An assessment of the quality of fit of the model to the data is given in the form of an expected error at each of the grid locations.

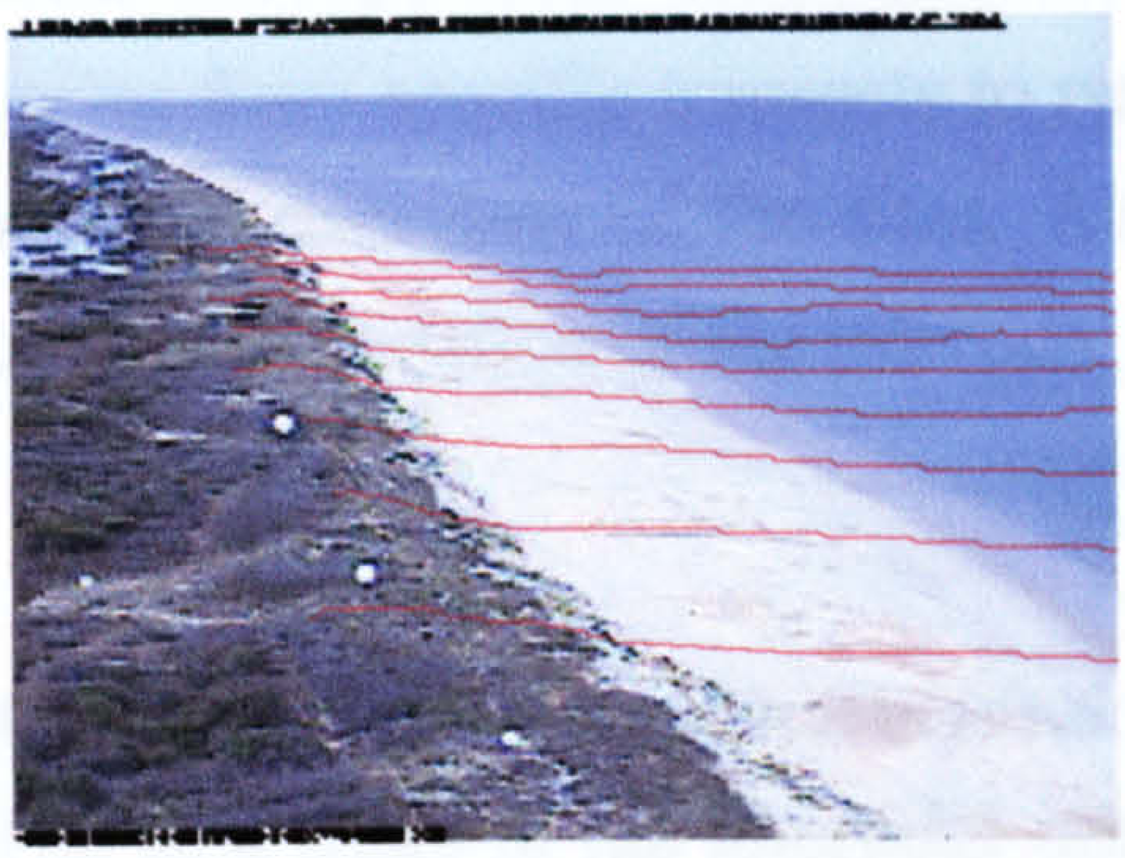
4.5.2 Comparison to directly surveyed bathymetry

A range of sites are considered in this study with beach and wave climate characteristics as shown in table 4.6. They fall into two broad categories; firstly quasi longshore uniform beaches; Duck, North Carolina, USA; Egmond aan Zee, the Netherlands and Perranporth, Cornwall, UK and secondly a highly 3-dimensional estuarine bar system at Teignmouth, Devon, UK. In total seven data sets are available, one each for the linear beaches and four for the estuarine bar system.

Table 4.6 Inter-site comparison of wave and beach characteristics for validation sites

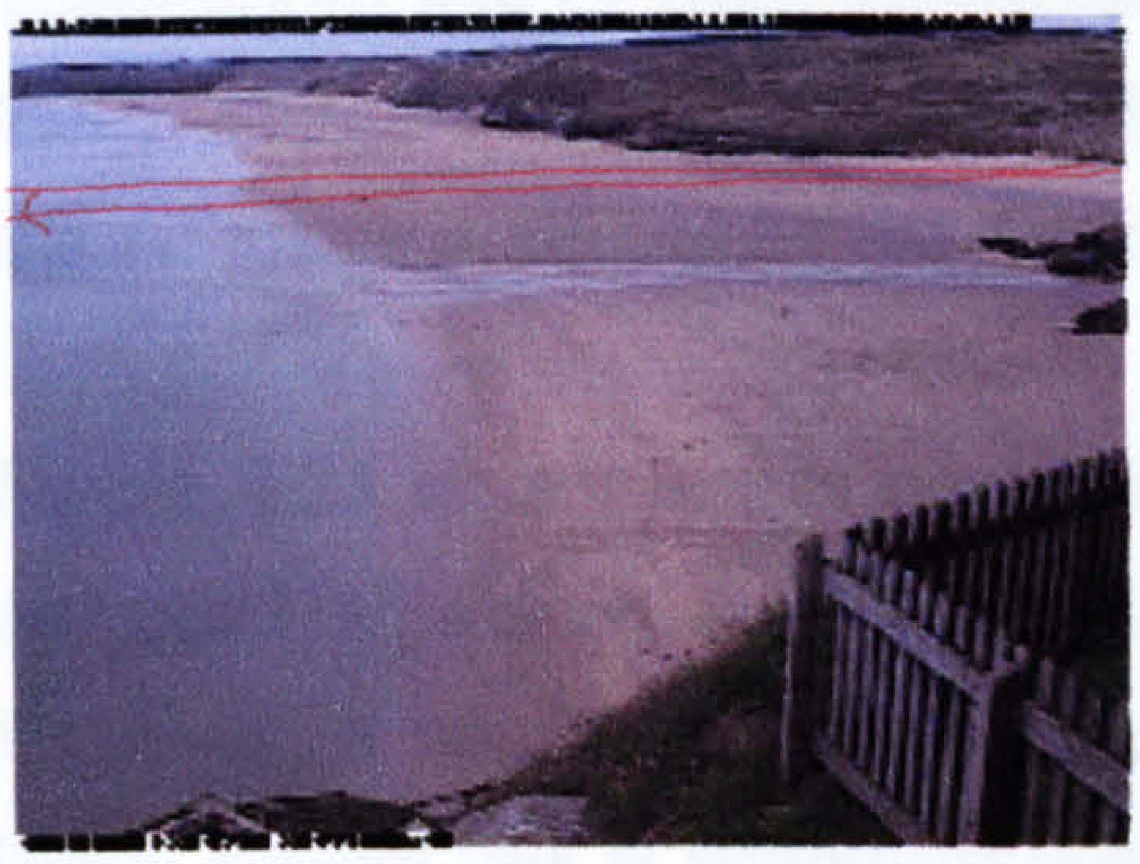
	Wave Climate Characteristics		Beach Characteristics			
Site	**Wave activity**	**Maximum Tidal Range**	**Beach Gradient - intertidal region**	**Beach Type**	**Beach Material**	**Beach Description**
Duck, N.C., USA	Medium mean H_S=1.4 m	Micro-meso tidal (1 m)	1:10	Reflective	Quartz sand, shell material diameter in range 0.2 to 5 mm	2d shore-parallel sandbar system
Egmond aan Zee, The Netherlands	Medium mean H_S=1.4 m	Micro-meso tidal (1.5 m)	1:70	Dissipative	Sorted sand; shell material 350 μm	2.5d shore-parallel double-sandbar system
Perranporth, UK	High mean H_S=1.4 m	Macro tidal (7.5 m)	1:85	Dissipative	Heterogeneous sand, medium sand to pebbles	3.5 km of beach bounded by headlands
Teignmouth, UK	Low mean H_S=0.5 m	Macro tidal (4.2 m)	1:12 (36) upper (lower) beach face	Reflective / Dissipative	Heterogeneous Red-Brown Sandstone	3-d system of sand bars at mouth of

estuary



Duck, NC, 19/04/1999

Egmond aan Zee, The Netherlands, 20/10/1998

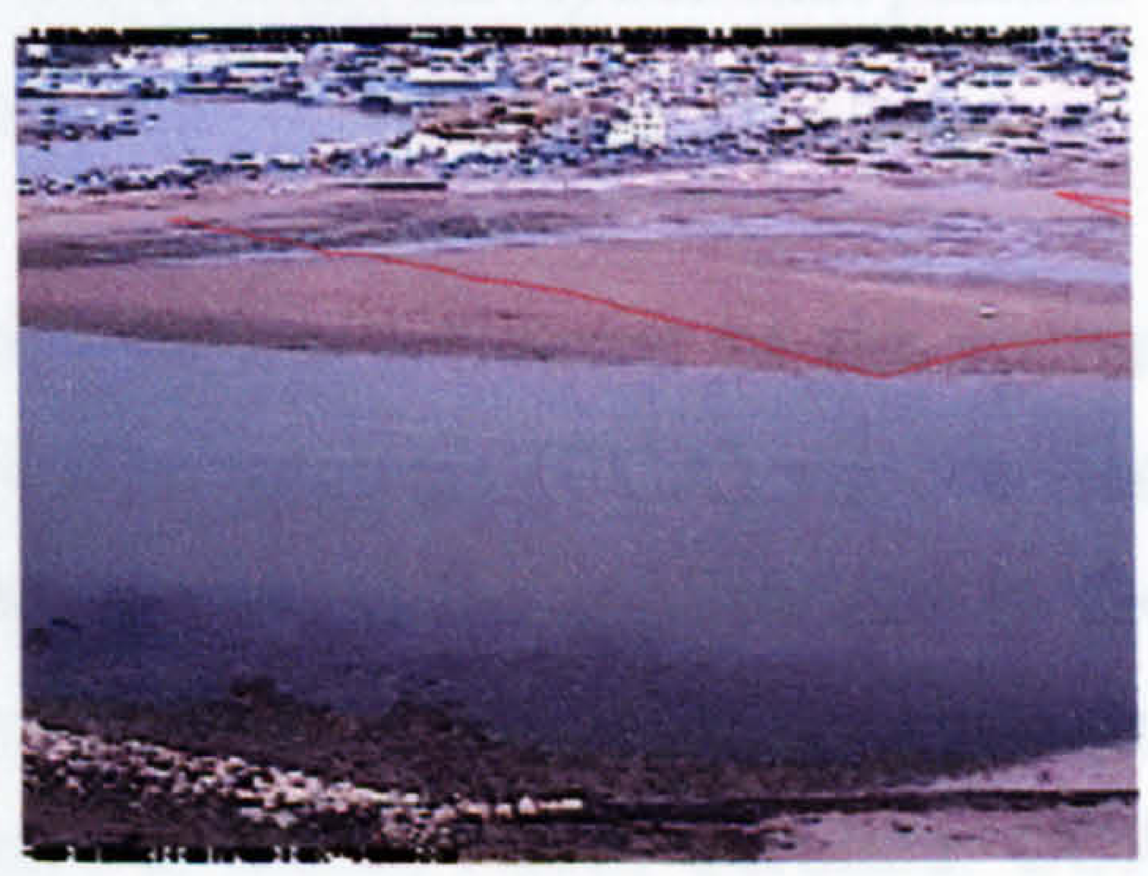


Perranporth, UK, 04/07/2000

Teignmouth, UK, 22/11/1999

Teignmouth, UK, 22/03/2000

Teignmouth, UK, 05/07/2000



Teignmouth, UK, 30/08/2000

Figure 4.24 Field sites used in the shoreline identification study. Survey data are presented as solid lines for transects and dots for individual spot heights.

For each site, data are available on wave climatology as well as bathymetric surveys. As these surveys were conducted for various purposes, the nature of the available data varies from specific transects to randomly scattered spot locations. Figure 4.24 presents a visual overview of the sites. Also shown in the images are transects which will be used for validation of the intertidal mapping technique.

4.5.2.1 Validation of horizontal spatial features

The first stage in the intertidal mapping procedure is the identification of the shoreline feature in terms of its horizontal spatial location. Nine shoreline surveys from the Teignmouth site (5 from 22/03/2000; 12:00, 13:00, 14:00, 15:00, 16:00 GMT, 4 from 05/07/2000; 13:00, 14:00, 15:00, 16:00 GMT) are available for direct comparison with the estimates produces by the Artificial Neural Network model.

Figure 4.25 demonstrates qualitatively the agreement in spatial location between the surveyed shoreline and that estimated by the Artificial Neural Network model. However, it would be useful to try to quantify this agreement. For the case of a linear beach system this is straightforward by quoting correlation statistics between estimated and observed cross-shore location as a function of alongshore distance. This approach is not possible for more 3-dimensional sites.

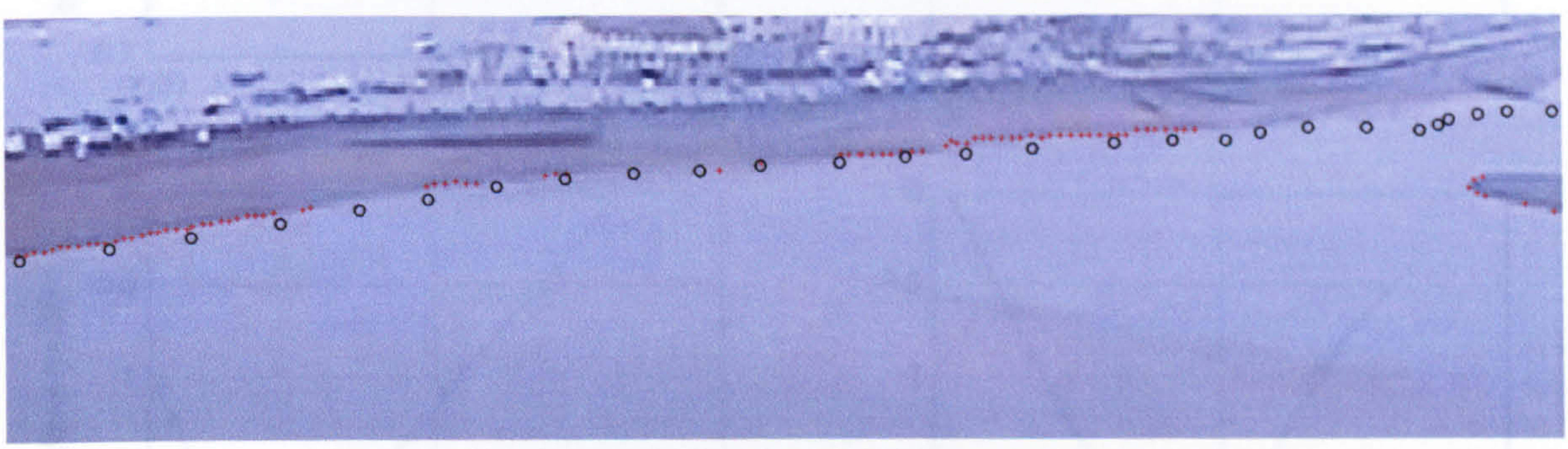


Figure 4.25 Sample shoreline comparisons (05/07/2000 Camera 2 13:00). Survey shoreline points in black, Artificial Neural Network shoreline estimates in red

To produce a quantitative assessment of the accuracy of the estimates of the spatial location of the shoreline features, a canonical correlation analysis (CCA) was carried out. This technique was initially developed by Hotelling (1936) for applications in the social sciences. Most recently it has been used by Larson *et al.* (2000) to investigate the relationships between beach profiles and wave climate at Duck, North Carolina. CCA considers functional relationships of the type ...

$$y_1, y_2, \ldots, y_n = f(x_1, x_2, \ldots x_n) \qquad 4.11$$

where, x_i and y_i are independent and dependent variables respectively. CCA is used to determine the dominant patterns of co-variability in two data sets. The idea behind CCA is to form two new sets of orthogonal variables from the original data sets. These are linear combinations of the original data sets such that the correlation between the new data sets is maximised. CCA provides an estimate, by means of squared canonical correlation values (eigenvalues), of the amount of shared variance between the two data sets.

In this case the two data sets are the surveyed shorelines and the Artificial Neural Network shoreline estimates respectively. As the Artificial Neural Network provides estimates in regions where surveyed shoreline points are not available, only locations in common are considered in this analysis. A summary of the canonical correlation coefficients are presented in graphical form in figure 4.26. The correlations are typically 0.9 or greater.

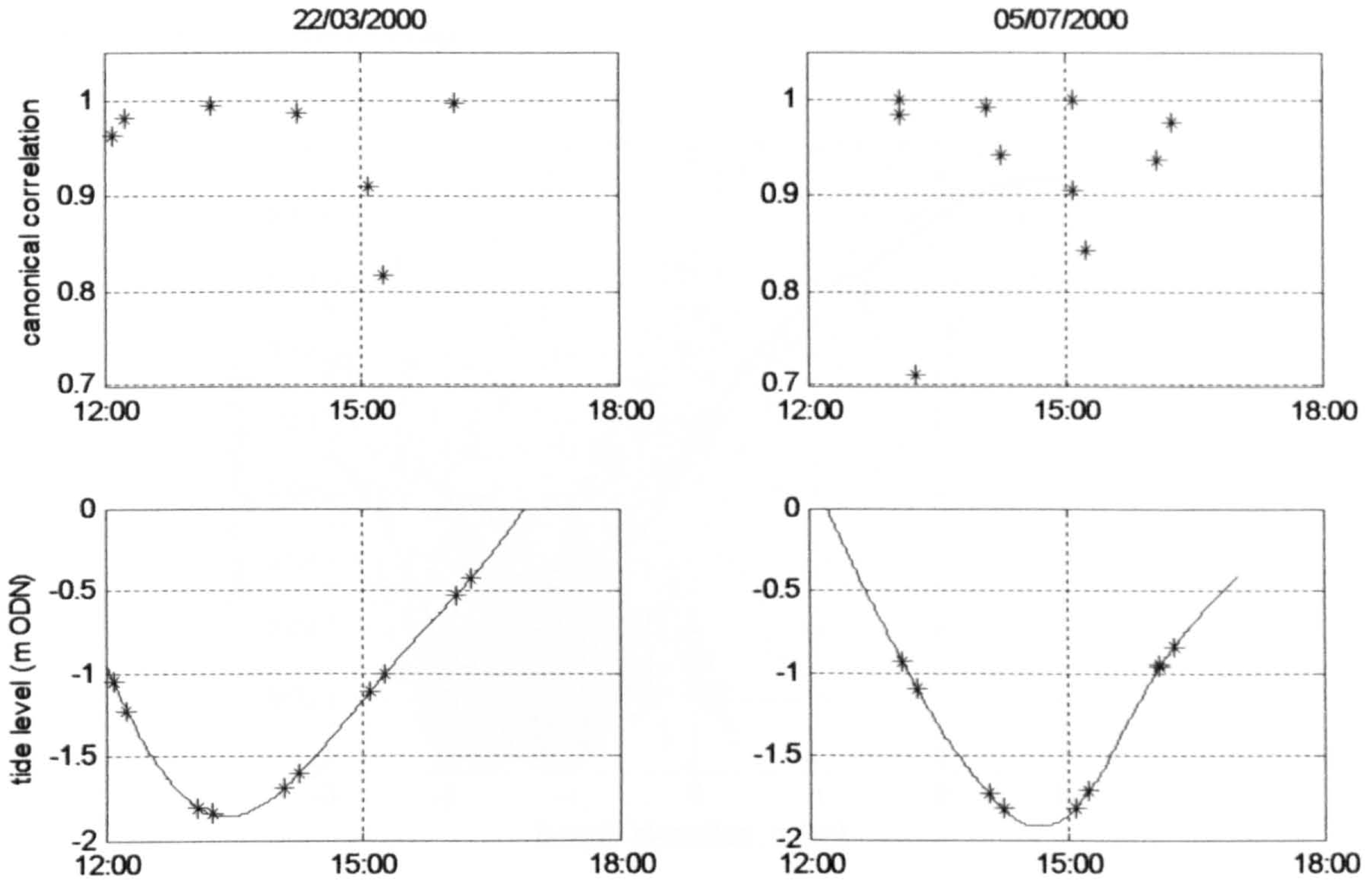


Figure 4.26 Canonical correlation analysis of surveyed and estimated shoreline location for Teignmouth. All correlations are significant at the 95% confidence level. The corresponding tidal elevations are shown in the lower tiles.

4.5.2.2 Validation of vertical spatial features

The base measurement for the vertical component of the shoreline features is the local tide level. In the absence of any wave activity this will be the only contribution to the vertical elevation of the shoreline. For the sites in this study the available tidal elevation information varied from a locally measured mean water level for Teignmouth and Duck, to a non-local measured tide level for Egmond aan Zee and a predicted tidal elevation for Perranporth.

The second contribution to the vertical component of the shoreline feature is the hydrodynamic contribution, $R_{T2\%}$, as given by equation 4.10. To calibrate this equation, it was possible to utilise the shoreline data available from the Teignmouth site allowing the direct determination of $R_{T2\%}$, the difference between the surveyed shoreline elevation and the tide elevation.

For this calibration equation 4.10 requires an estimate of the local beach gradient. Typically for longshore uniform beaches it is sufficient to adopt an average value of beach gradient from the intertidal region. However for the 3-dimensional site at Teignmouth this is not possible. In order to estimate the beach gradient it was established from all the available survey data that there was a relationship between the beach elevation and the beach gradient as shown in figure 4.27. The solid line is taken as a proxy for this relationship.

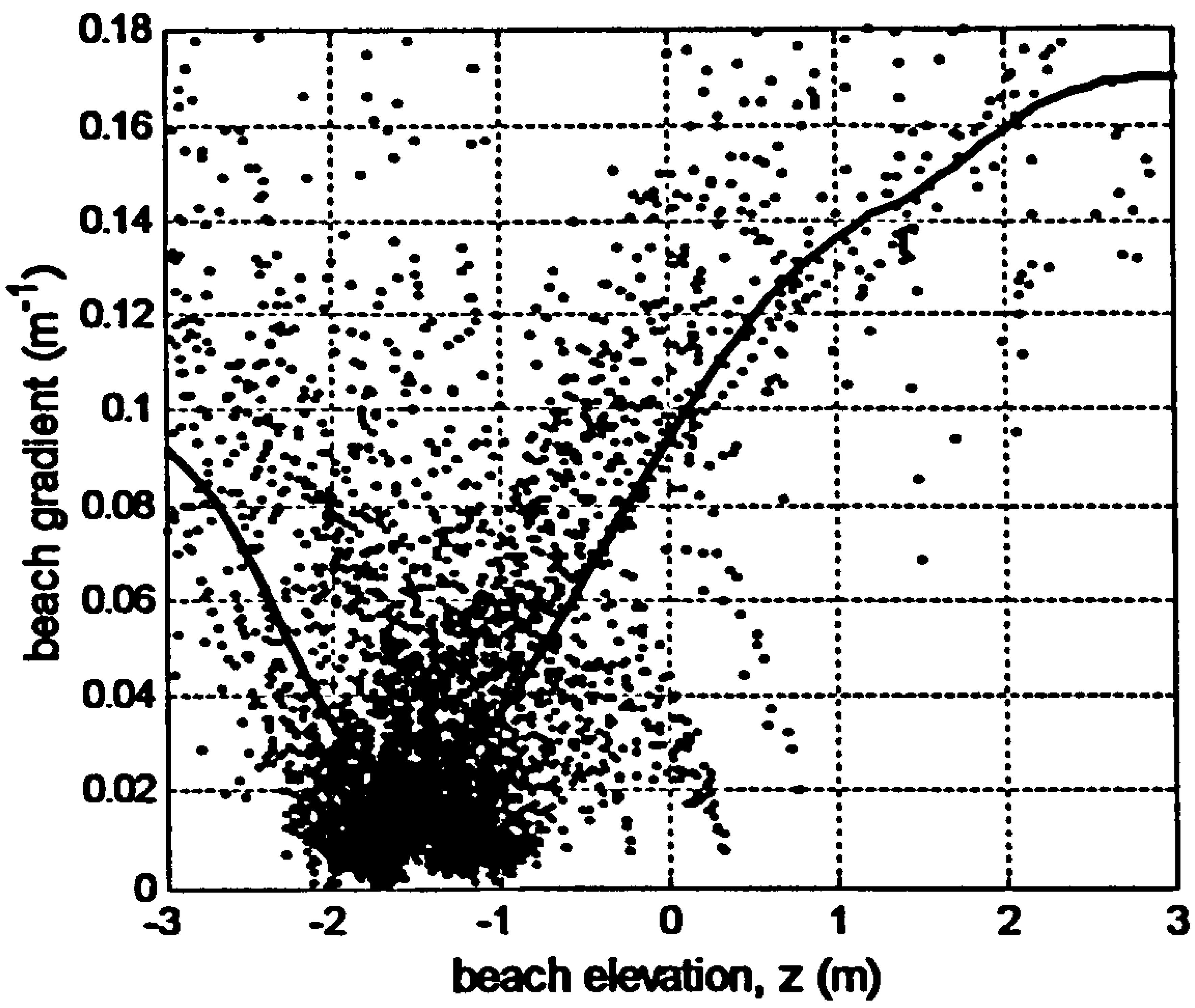


Figure 4.27 Beach gradient estimate for Teignmouth as a function of elevation

Table 4.7 presents the results of estimating α for the shoreline samples taken from the various tidal levels for 05/07/2000. A complicating factor for these estimates is that there was no wave climate information available for that day. Hence it is necessary to provide a reasonable estimate of the wave height and period parameters in equation 4.10. Visual observations of the wave climate on that day suggest low wave energy consistent with that of the 30/08/2000 for which wave climate information is available. Based on the wave climate of the that day a range of $T\sqrt{gH}$ of 5.78 - 8.35 m was

Table 4.7 Range of α for Teignmouth site, 5/7/2000

Image Date	Image time	Tide level (m ODN)	Shoreline elevation (m ODN)	$R_{2\%}$ (m)	S (m-1)	Range α
05/07/2000	13:05	-0.930	-0.843	0.087	0.0388	0.269 – 0.388
	13:15	-1.097	-1.001	0.096	0.0344	0.334 – 0.483
	14:05	-1.725	-1.697	0.028	0.0323	0.104 – 0.150
	14:15	-1.814	-1.751	0.063	0.0340	0.222 – 0.321
	15:05	-1.823	-1.784	0.039	0.0343	0.136 – 0.197
	16:05	-0.959	-0.920	0.039	0.0379	0.123 – 0.178
	16:15	-0.842	-0.652	0.190	0.0415	0.548 – 0.792
					Average	0.248 – 0.358

identified for low energy conditions. This leads to a average range of α of 0.248 - 0.358. This is consistent with the value of 0.36 as an upper bound as given by Komar. This is in line with the assumption of normal wave incidence to the shoreline for equation 4.10 which is not typically the case for 3-d site at Teignmouth. Unfortunately it was not possible to perform a similar calibration of α for the longshore uniform beaches as surveyed shoreline data was not available. For these sites a default value of 0.36 was taken for α.

4.5.2.3 Validation of intertidal maps

This section presents the results of applying the interpolation technique to the shoreline data derived in the previous sections to produce morphological maps of the intertidal region. The length scales adopted for the production of the intertidal maps are summarised in table 4.8. The magnitude of the length scales reflect the nature of the sites. Typically, the quasi 2-dimensional beaches have distinctly different cross-shore and longshore length scales with more variance expected in the cross-shore direction. The length scales for Perranporth are considerably larger than the other sites due to it being a highly dissipative shallow beach with little variation in its relief.

Table 4.8 Length scales used to produce morphological intertidal maps

Site	λ cross-shore (m)	λ longshore (m)
Duck	25	100
Egmond aan Zee	30	100
Perranporth	100	250
Teignmouth	40	40

Intrinsic to these length scales is the requirement of producing a morphology or smoothed version of the actual bathymetry. Were a sufficient density of data available for interpolation then it would be possible to identify the true bathymetric surface. However the shoreline data consists of densely sampled contours which do not satisfy the interpolation routine requirements for an highly detailed resolution of features as outlined in appendix A2. This necessitates the larger length scales, resulting in correspondingly smoother surfaces.

In order to validate the quality of the morphological maps produced, transects from the 7 days of intertidal shoreline data are presented in the figures 4.28 – 4.31.

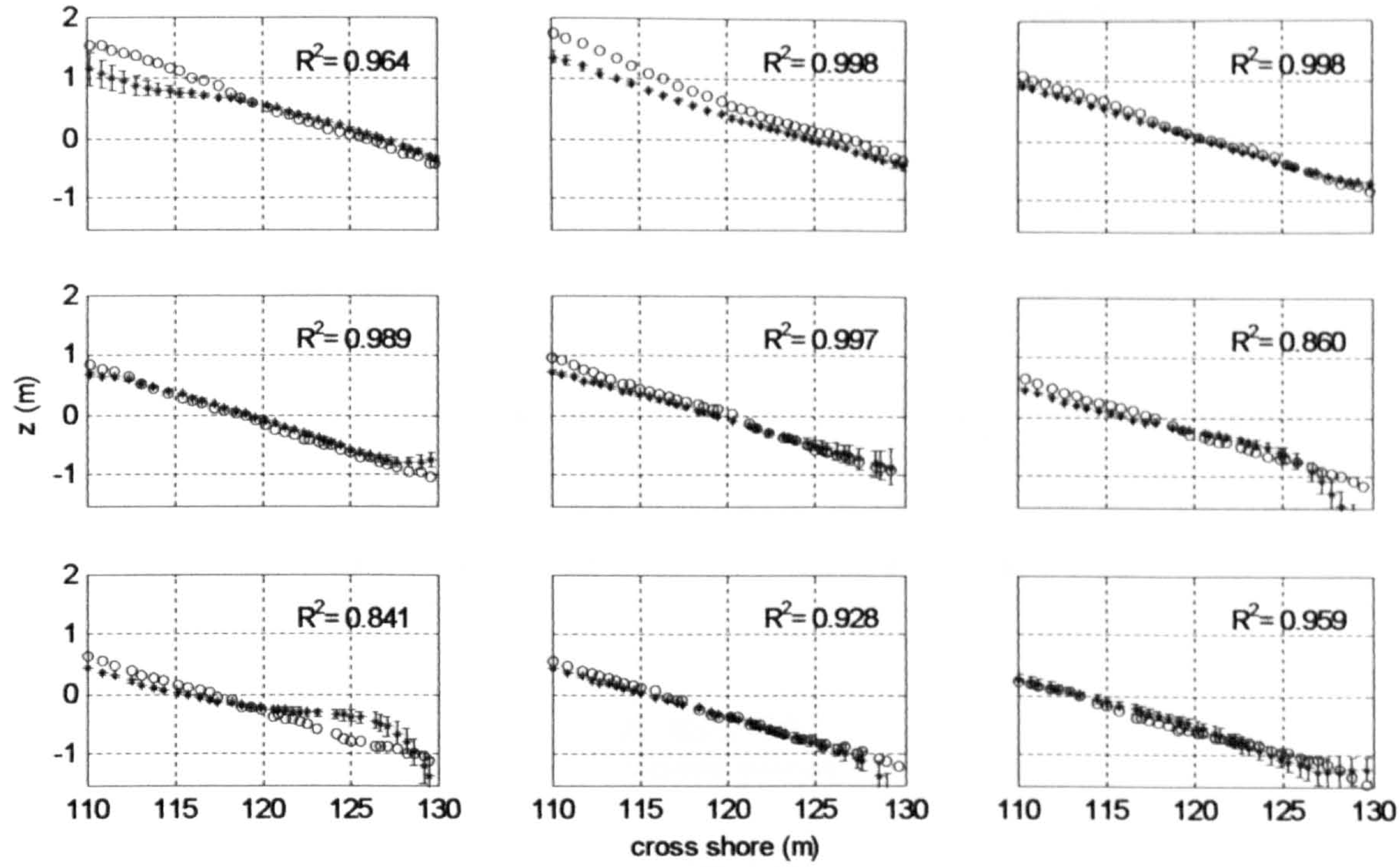


Figure 4.28 Surveyed (o) and estimated(*) transect profiles for Duck, NC, 19/04/1999. Expected error of estimated profile is given by error bars

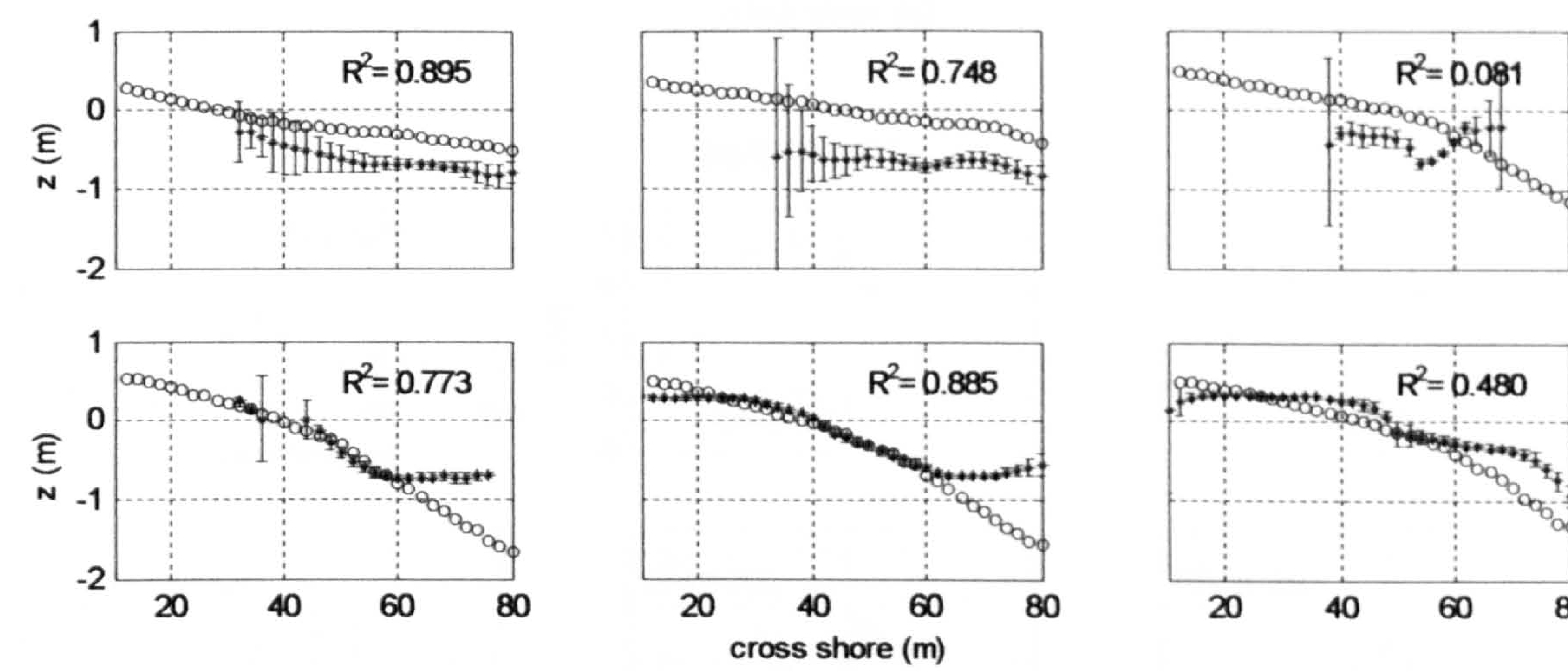


Figure 4.29 Surveyed (o) and estimated (*) transect profiles for Egmond aan Zee, The Netherlands, 20/10/1998. Expected error of estimated profile is given by error bars

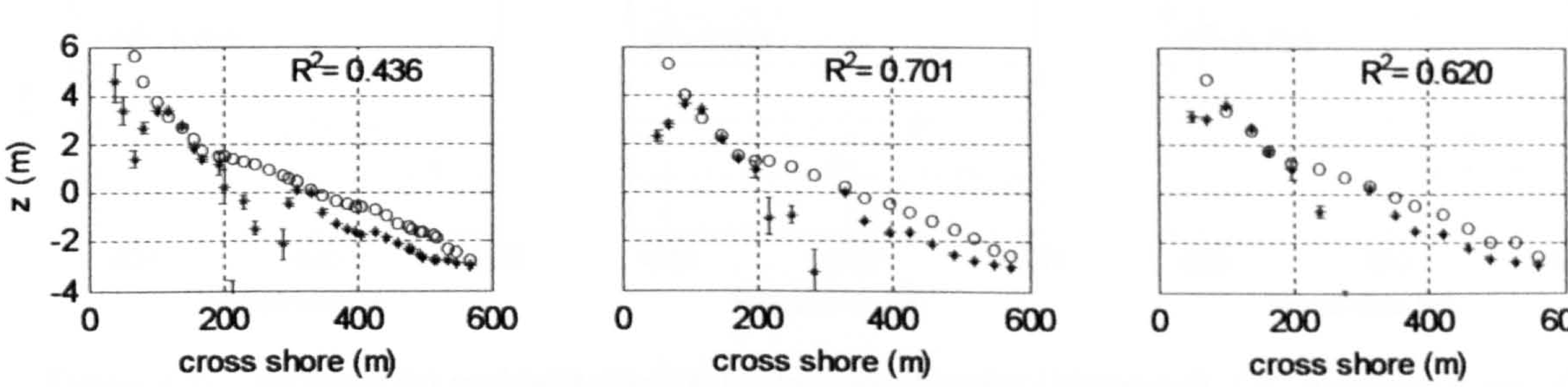


Figure 4.30 Surveyed (o) and estimated (*) transect profiles for Perranporth, UK, 04/07/2000. Expected error of estimated profile is given by error bars

22/11/1999

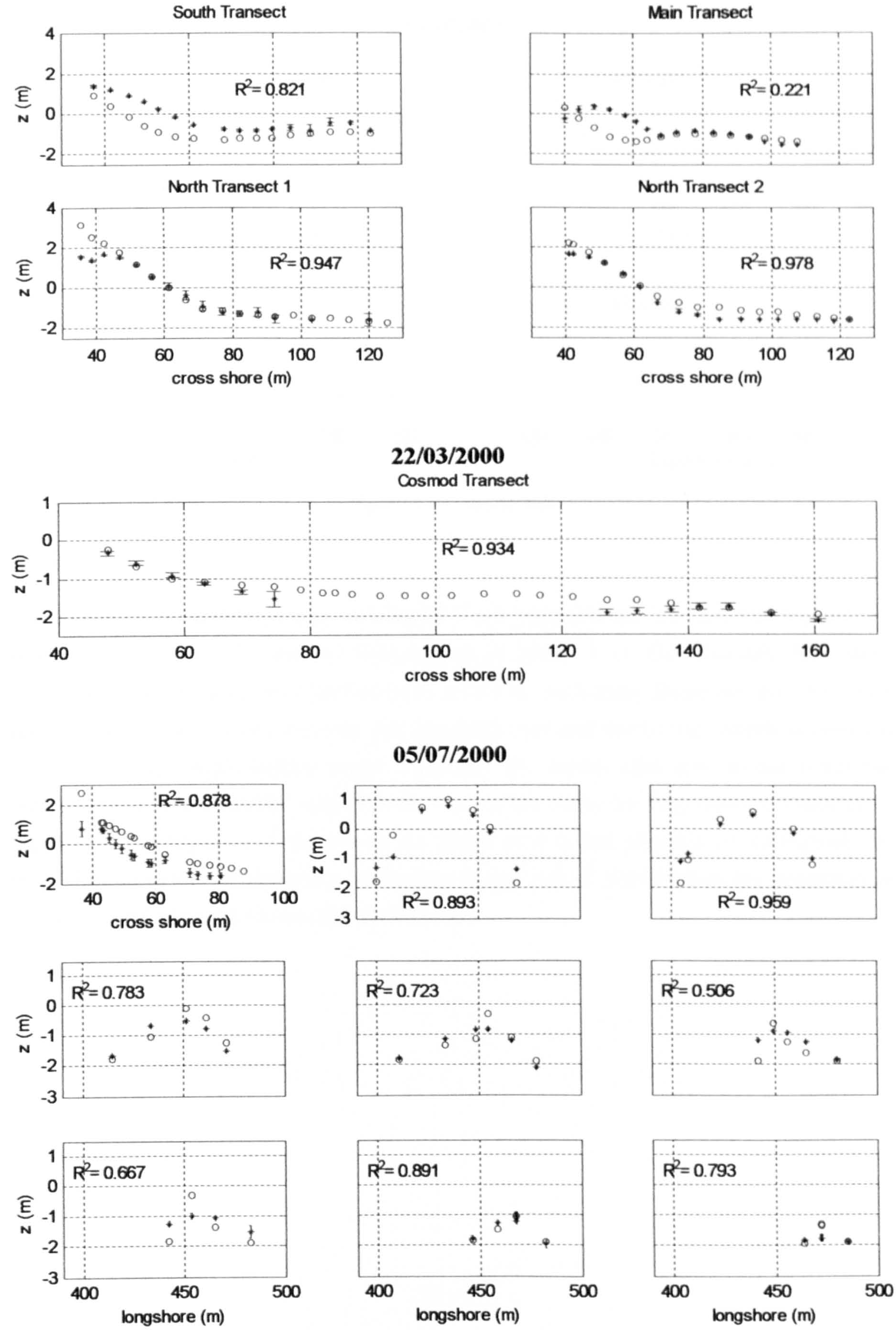


Figure 4.31 Surveyed (o) and estimated (*) transect profiles for Teignmouth, UK. Expected error of estimated profile is given by error bars

30/08/2000

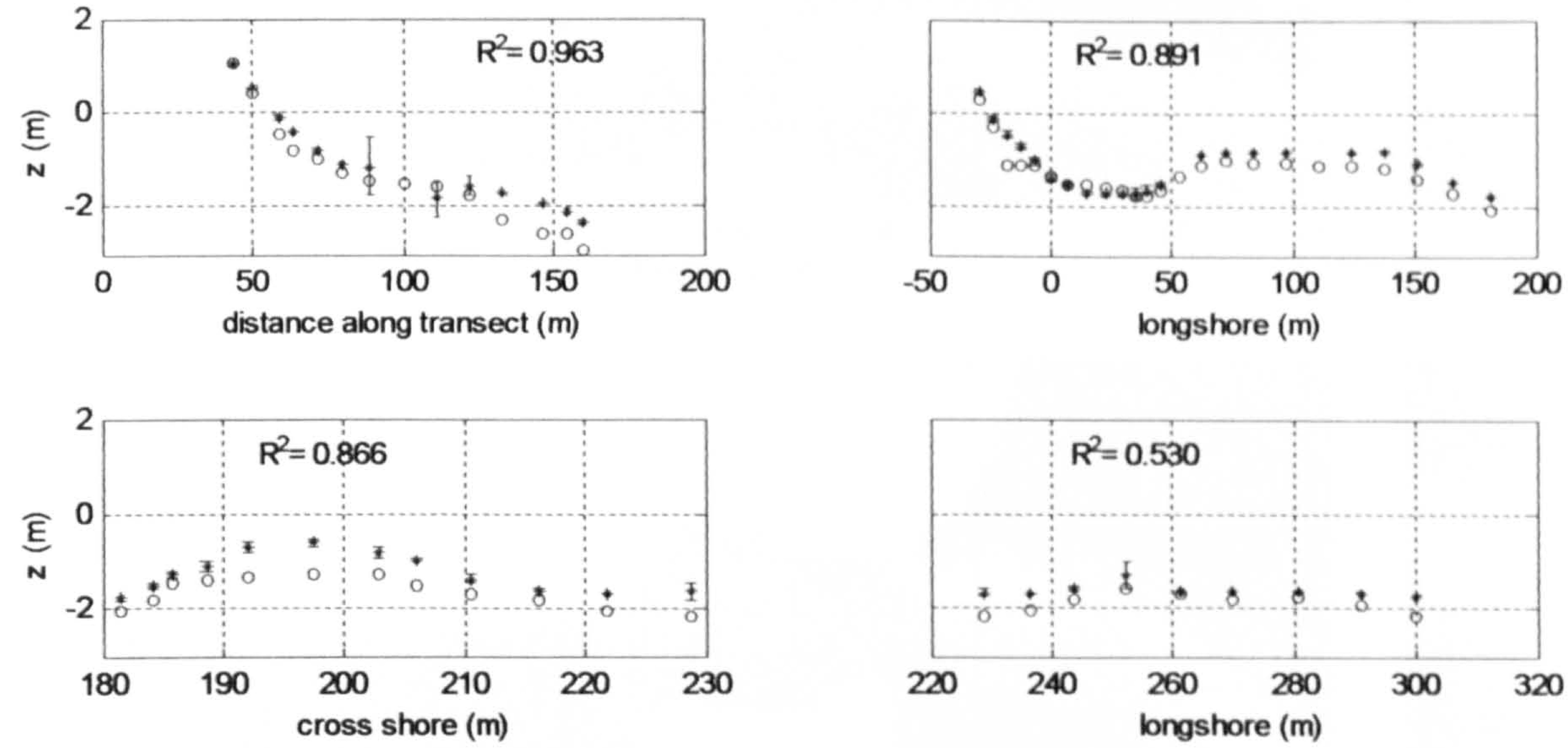


Figure 4.31 (continued)

The intertidal mapping technique results for Duck, Egmond aan Zee and Perranporth are presented in figure 4.32 and for Teignmouth in figure 4.33. Qualitatively they show good results as given by the distribution of errors for each map. These are indicated by a contour map of the errors between the intertidal map and the survey which is overlaid on each of the morphological maps. Typically the survey data sets do not cover the same extent as the intertidal map. For the case of the maps for Teignmouth presented in figure 4.33, histograms of the errors are given as it is not possible to distinguish the individual contours. A summary of the rms errors and R^2 correlations are presented in Table 4.9 and are discussed in the next section.

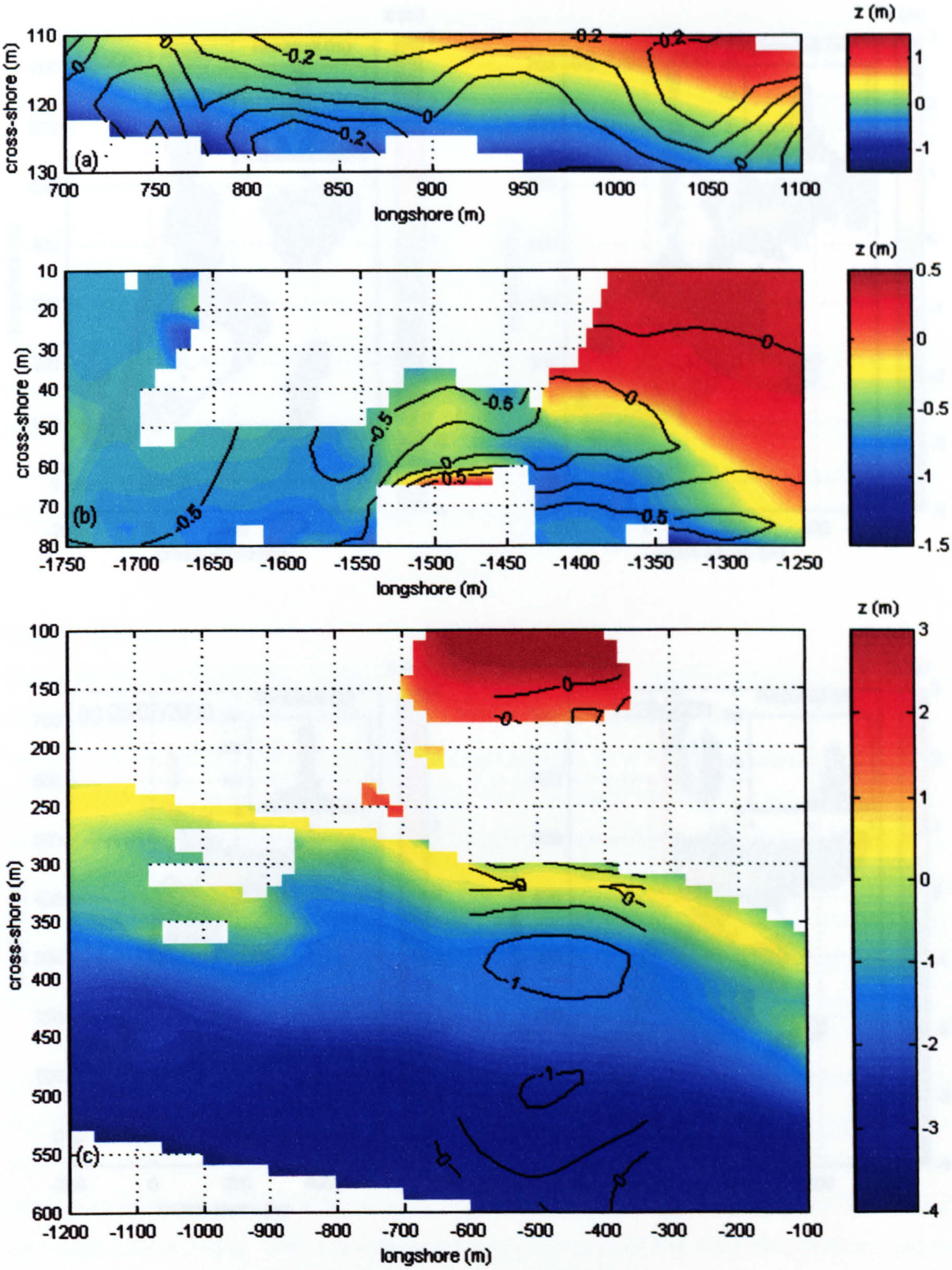


Figure 4.32 Remotely sensed inter-tidal morphological maps for a) Duck b) Egmond aan Zee c) Perranporth. Contours of error between surveyed and remotely sensed morphological maps are superimposed

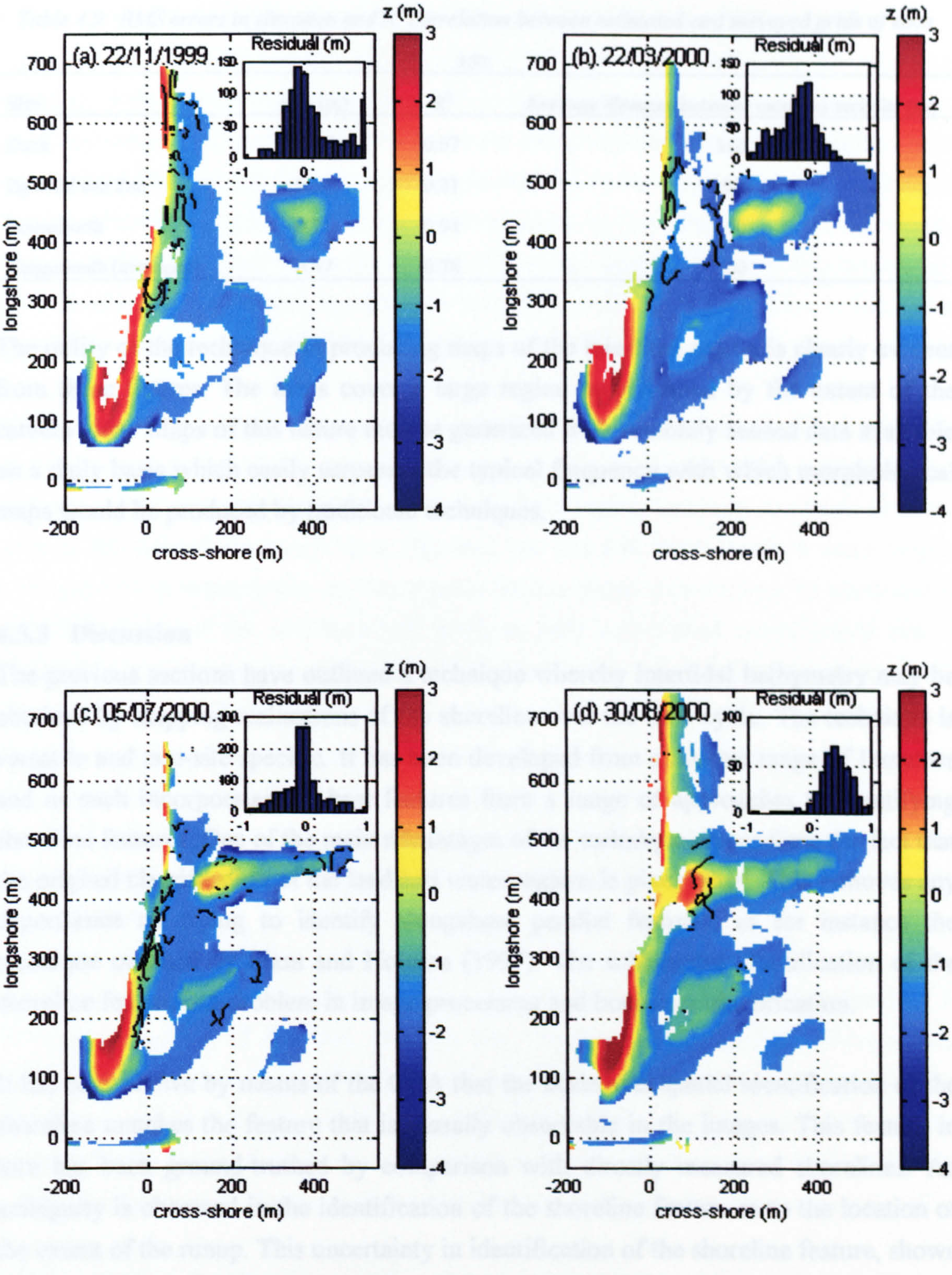


Figure 4.33 Remotely sensed inter-tidal morphological maps for Teignmouth. Contours of error between surveyed and remotely sensed morphological maps are superimposed. In addition histograms of the errors are presented

Table 4.9 RMS errors in elevation and R^2 correlation between estimated and surveyed grids of each site

Site	rms (m)	R^2	Average distance between cameras and site (m)
Duck	0.27	0.97	310
Egmond aan Zee	0.54	0.21	1500
Perranporth	0.71	0.94	650
Teignmouth (averaged)	0.47	0.78	500

The utility of the technique in producing maps of the intertidal region is clearly evident from these figures. The maps cover a large region only limited by the extent of the camera view. Maps of this nature may be generated from remotely sensed data available on a daily basis which easily surpasses the typical frequency with which morphological maps would be produced by traditional techniques.

4.5.3 Discussion

The previous sections have outlined a technique whereby intertidal bathymetry may be obtained by mapping realisations of the shoreline over the tidal cycle. The technique is versatile and non-site specific. It has been developed from a diverse range of literature and as such incorporates the best features from a range of approaches to identifying shoreline features. One of the main advantages of the technique comes from the fact that the original classification of the land and water regions is pixel based. This removes any dependence on trying to identify alongshore parallel features, as for instance the technique outlined by Plant and Holman (1997). The subsequent identification of the shoreline feature is a problem in image processing and boundary identification.

It has been shown by means of the CCA that the horizontal spatial identification of the shoreline matches the feature that is visually observable in the images. This feature in turn has been ground-truthed by comparison with directly measured shorelines. An ambiguity is observed in the identification of the shoreline feature as to the location of the extent of the runup. This uncertainty in identification of the shoreline feature, shown in figure 4.25, is significant for both the surveyed shoreline and shoreline identification in the images. The surveyed shoreline appears to be slightly seaward of the estimated shoreline, yet the estimated shoreline appears visually in the correct location. This may lead to a misleadingly low correlation between the spatial location of the two shorelines, shown in figures 4.26a,b. The uncertainty of identifying both of the shoreline features is especially prevalent on shallow sloping beaches and may be related to groundwater effects (Turner and Nielsen, 1997). Figure 4.26 suggests the discrepancy occurs at the lower tide levels and is most pronounced in the period just after low tide.

4.5.3.1 Intertidal maps

Figures 4.32 and 4.33 present the morphological maps obtained from the intertidal mapping technique for each of the data sets at the chosen sites. Qualitatively they show good agreement as given by the overlaid error maps obtained from a comparison with survey data. The general features are reproduced with lower residual errors occurring in regions where reasonable spatial coverage is given by the distribution of shorelines. This is evident for figure 4.32c for Perranporth where larger residual errors correspond to the mid-tide region which has a sparse covering of shoreline data. This is due to the larger rates of ebbing and flowing at this phase of the tidal cycle.

The best results of the intertidal mapping technique are obtained for the Duck site with an rms error at the grid locations of 0.27 m and an R^2 of 0.97 (table 4.9), indicating that both the spatial location and shape of the intertidal region has been resolved. The rms error at the other linear beach sites, Egmond aan Zee and Perranporth is much larger; 0.54 and 0.71 m respectively. At Perranporth the increased variance may be attributed to poor knowledge of the reference tide level, as only a predicted astronomical tide is available. This increased variance manifests itself as an offset as seen in figure 4.30. The overall shape of the morphological map is still represented well. At Egmond aan Zee the overriding factor in the degraded performance of the technique is attributable to the significantly larger distance between the remote sensing source and the location of the field site resulting in a poor resolution of both location and shape of the morphological map. This is to be expected considering the decrease in pixel resolution at this distance.

The morphological maps produced at Teignmouth display the complicated 3-dimensional nature of the site. Despite this, the intertidal mapping technique has succeeded in producing maps of both the shoreline and emergent sand bar regions, which was not logistically feasible by traditional techniques. Rms residuals between estimated and surveyed grids are approximately 0.5 m and the corresponding high R^2 value of 0.78 suggests that the 3-dimensional nature of the site has been captured well.

As mentioned in the previous section, correction determination of the constant term α in equation 4.10 is necessary and was calibrated for the Teignmouth site. To estimate the effect an incorrect value of α would have on the overall quality of the morphological map produced, the value of α used was varied from 0 – 0.36 for the Duck site. The results of this investigation are presented in figure 4.34. Two measures of quality of the resulting morphological maps sets are presented; firstly an R^2 value and an rms error calculated at the grid locations between interpolated maps of the surveyed data set and the intertidal shoreline data set, and secondly an R^2 and rms error between the two data sets at the survey locations.

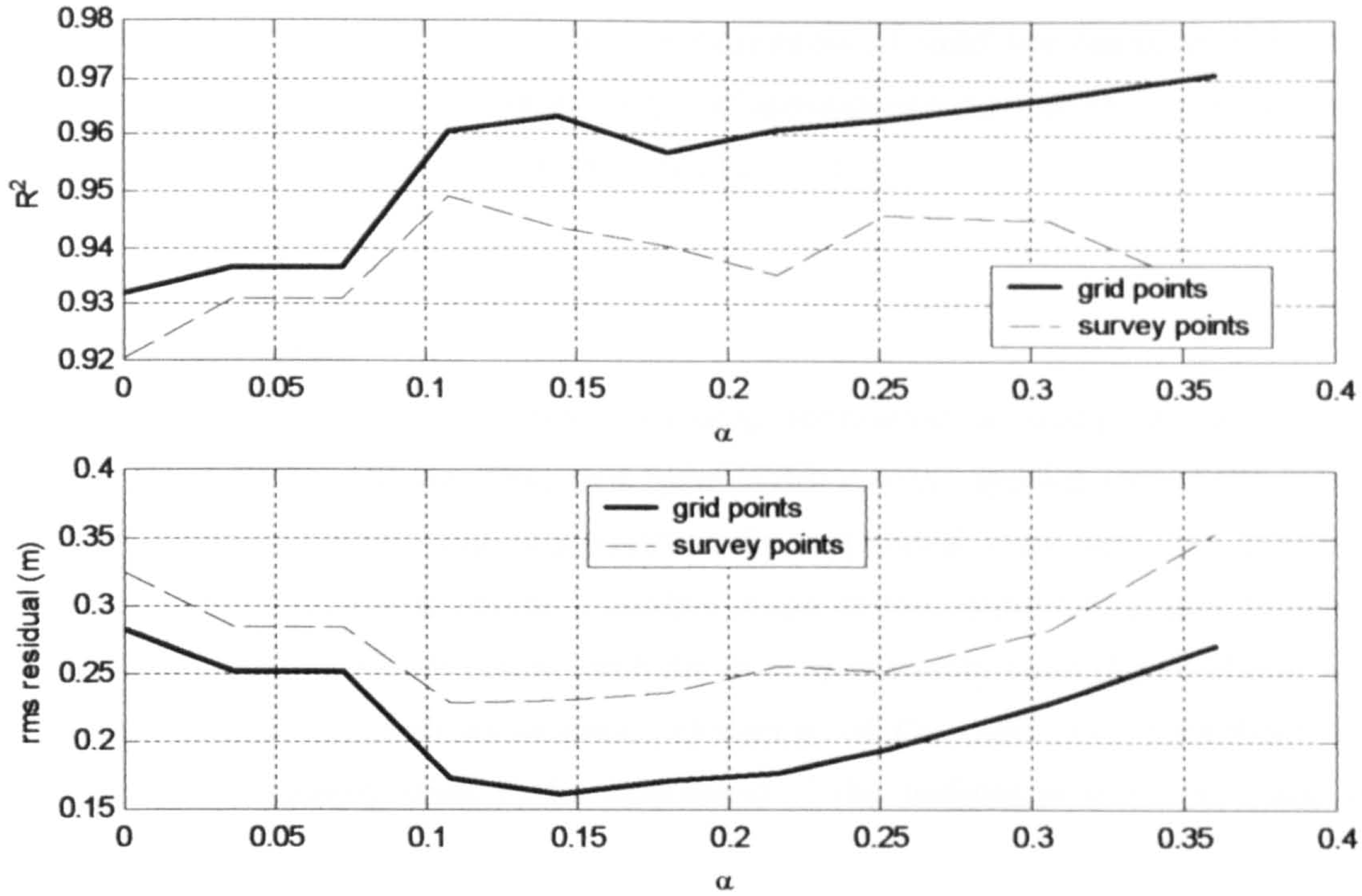


Figure 4.34 Calibration of the wave runup equation for the Duck site. Solid lines represent comparisons at grid point locations whereas broken lines are comparisons made at original survey locations

A better match is obtained where both the survey and the intertidal shoreline data sets are interpolated rather than the case of where comparison is made at the original survey locations. This would be expected as the interpolation would introduce consistent smoothness in both data sets for the former scenario. These plots suggest that a value of α of ~ 0.14 produces the best match to the original data. It results in a corresponding rms error of 0.16 m and an R^2 value of 0.96. This suggests that the transects presented in figure 4.28 are not optimal as a value of $\alpha = 0.36$ had been used. This calibration highlights the sensitivity of the intertidal mapping to the estimation of the vertical component of the shorelines. As an alternative to the calibration of a simple expression such as equation 4.10, it may be more appropriate to utilise a more detailed expression which provides an accurate estimate of the vertical elevation of the shorelines.

4.5.3.2 Bathymetry versus Morphology

Ideally we would like to be able to reproduce a detailed bathymetry from observations of the shoreline. However, as already shown, the unresolved variance is still larger than that would be obtained from traditional direct techniques for determining nearshore morphological maps. Typical residuals obtained are of the order >= 0.2 m compared to residuals from GPS surveys of 0.05 – 0.2 m). Hence this approach is ideally suited to the production of morphological maps of the nearshore region for incorporation into LSCB data sets where small scale variance in the data is not of a prime consideration. This is the case when it is the long term evolution of the larger features which are of primary interest, i.e. shoreline evolution or migration of sand bar features. With this in mind it should be possible to produce maps of appropriate resolution covering a region of approximately 1 km either side of the camera location.

4.5.3.3 Operationality

A key intended use of the intertidal mapping technique is study of the long term evolution of intertidal regions. This will require the routine application of the intertidal mapping technique to existing and continually appended data sets. At present the technique has been shown to produce quality maps of the intertidal region. However it still requires a significant interaction with the user to correctly train the Artificial Neural Network model and perform subsequent 'cleaning' of the individual shorelines where necessary. These aspects need to be addressed if the technique is to be made more operational.

To summarise, the following present a list of the main advantages and disadvantages of the intertidal mapping technique.

4.5.3.4 Advantages:

- Versatile, non-site specific technique developed from a diverse range of literature and as such incorporates the best features from a range of approaches to identifying shoreline features
- Capable of establishing a map of the entire intertidal region encompassed by the camera view. This includes emergent sand bar features which typically would be inaccessible to traditional survey techniques.
- Capable of analysing complex 3d sites as initial assessment of land/water regions is pixel based. Vectorisation of shoreline location is a subsequent operation.
- Does not have limitations as to the type of shoreline feature it tries to recognise ... works equally well for shore breaks as well as non-breaking runup bores.
- Production of bathymetric maps utilises information on the quality of the estimated data. It can therefore determine regions of the bathymetrical map in which it has high or low confidence.

- Modular approach to producing intertidal map (intermediate data available for analysis if required) ...
  - → Spatial location of shoreline
  - → Associated vertical elevation of shoreline
  - → Robust interpolation of shoreline data to produce intertidal map

- As the main data source is remotely sensed the technique is ideally suited to the production of long term data sets for the study of nearshore morphological evolution.

4.5.3.5 Disadvantages:

- Unresolved variance is still larger than that would be obtained from traditional direct techniques for determining nearshore morphological maps. Residuals of the order >= 0.2 m (GPS residuals 0.05 – 0.2 m).
- The magnitude of the unresolved variance becomes larger with increasing distance from the remote sensing source to the region of shoreline of interest
- Even though the generation of shoreline features is computationally inexpensive the corresponding determination of confidence intervals adds significantly to the runtime.
- At present considerable user input is required. This occurs at both the training of the Artificial Neural Network model stage and the later acceptance/rejection of shoreline points. The overall procedure needs to be made more operational

Chapter 5 Evolutionary Computation

5.1 Introduction

"If under changing conditions of life organic beings present individual differences in almost every part of their structure, and this cannot be disputed; if there be, owing to their geometrical rate of increase, a severe struggle for life at some age, season, or year, and this certainly cannot be disputed; then, considering the infinite complexity of the relations of all organic beings to each other and to their conditions of life, causing an infinite diversity of structure, constitution, and habits, to be advantageous to them, it would be a most extraordinary fact if no variations had ever occurred useful to each being's own welfare, in the same manner as so many variations have occurred useful to man. But if variations useful to any organic being do occur, assuredly individuals thus characterised will have the best chance of being preserved in the struggle for life; and from the strong principle of inheritance, these will tend to produce offspring similarly characterised. This principle of preservation, or the survival of the fittest, I have called Natural Selection. It leads to the improvement of each creature in relation to its organic and inorganic conditions of life; and consequently, in most cases, to what must be regarded as an advance in organisation." The Origin of Species, Charles Darwin

It is almost 150 years since this revolutionary publication by Charles Darwin originally appeared. He proposed that the state of development of any given species on this planet is a consequence of adaptation and competition to best survive in its surrounding environment with the overall aim of perpetuation of the species. The concepts of evolution that Darwin proposed are still as relevant and prevalent today having permeated throughout the scientific community and beyond to society in general (Dawkins, 1982).

Little did Darwin realise that the paradigm, which he skilfully assembled, would not only be applicable to species of an organic nature, as he had intended and is most easily seen in the field of genetics, but also to more abstract constructs.

"A grand and almost untrodden field of inquiry will be opened, on the causes and laws of variation, on correlation, on the effects of use and disuse, on the direct action of external conditions, and so forth." The Origin of Species, Charles Darwin

In the latter half of the 20th century that is exactly what happened. Scientists and engineers began to investigate the possibilities of the application of evolutionary theory to the more abstract study of numerical optimisation of a variety of problems. Many optimisation techniques are plagued by becoming trapped in regions of parameter space which produce local or sub-optimal solutions to a problem. This is especially prevalent when the problem at hand involves a high dimensional parameter space.

The classical approach to numerical optimisation has been the application of calculus. Solutions to the typically non-linear system of equations arising from setting the local gradients of the objective function to zero allow the inference of maxima or minima for problems where the solution space has the form of region (a) of the function shown in figure 5.1. An alternative to gradient based optimisation technique are the direct search techniques. These techniques move around on the objective function and in a direction related to the local gradient. This is the concept generally known as '*hill-climbing*'.

However if the search is started in region (b) or (c) of the solution space then it is obvious that either of these gradient based optimisation techniques may become trapped in local extrema. These approaches are good at exploiting local information but do not have any inherent capability to more fully explore the complete solution parameter space.

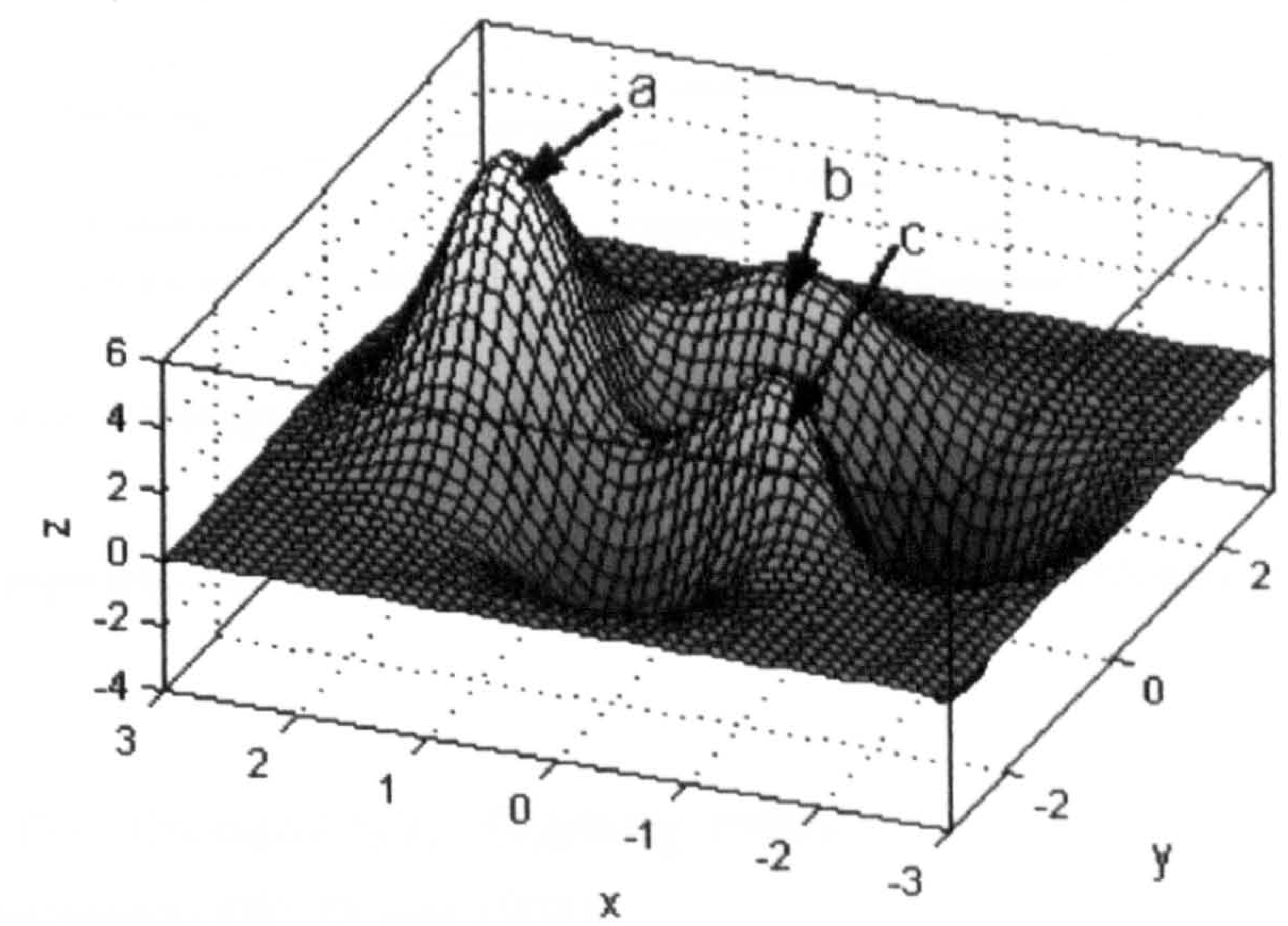


Figure 5.1 Sample solution space

An alternative to the calculus based approach are enumerative techniques (for example dynamic programming), which try to evaluate as completely as possible all regions of the parameter space, thereby identifying the global extrema. This approach tends to be highly inefficient as search spaces, for even relatively low dimensional problems tend to be exhaustive, and hence these techniques are seldom considered.

As the limitations of calculus based optimisation techniques became more apparent, interest in the development of random search algorithms grew. Simulated annealing is an example of such an approach, (Kirkpatrick *et al.*, 1983), using random processes to help guide its search for minimal energy states. However this particular technique in itself requires the production of an additional function (a temperature cooling schedule) which is not always that intuitive for a given problem.

It was this lack of robustness of traditional optimisation and search techniques which encouraged the investigation and development of evolutionary computation. Here, apparently, were concepts which had millions of years of success to justify their capability of being able to solve diverse multi-dimensional problems. The only requirement was the ability to find an appropriate methodology to apply the concepts of evolutionary theory. Figure 5.2 presents an overview of the relationship of the various approaches to search and optimisation. As can be seen, evolutionary computation is an example of a guided random search approach.

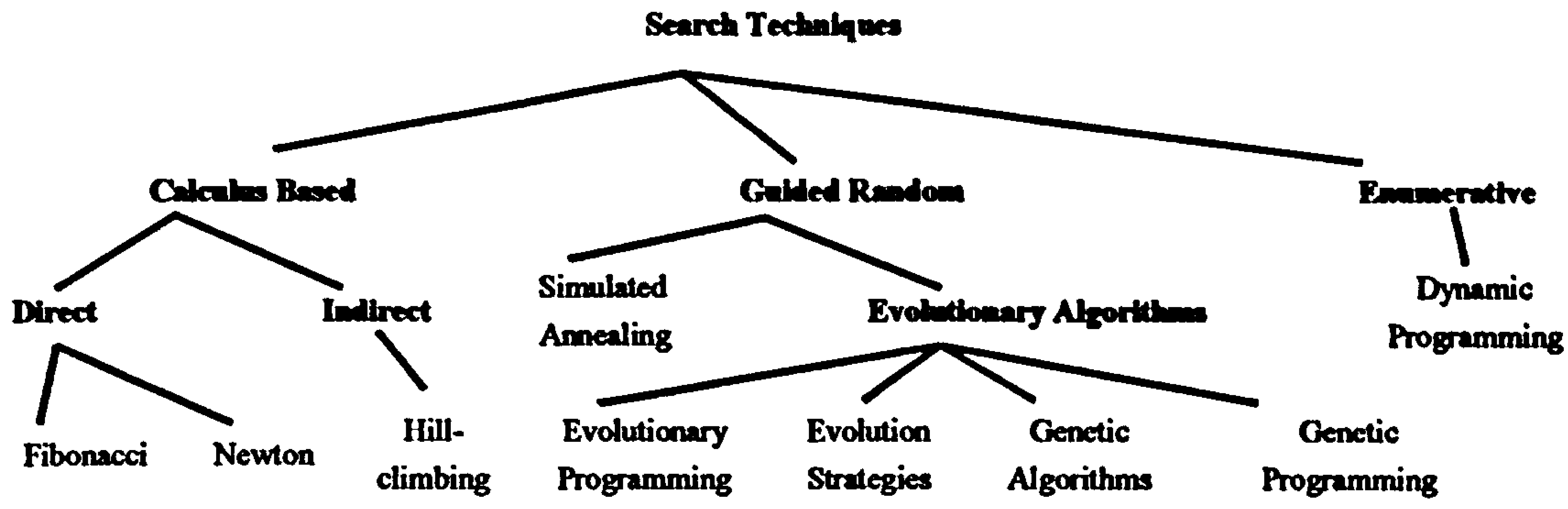


Figure 5.2 Overview of search and optimisation algorithms (after Babovic, 1996)

Four main streams of development have emerged in the evolution of evolutionary computation paradigms ...

Genetic Algorithms (GA) (Holland 1962, Goldberg 1989)
Evolutionary Programming (EP) (Fogel 1962).
Evolution Strategies (ES) (Rechenberg 1965)
Genetic Programming (GP) (Koza 1992)

These approaches have many elements in common and typically only differ in the details. This study will consider the operation and application of Genetic Algorithms and Genetic Programming in some detail. There are also many hybrid systems that potentially incorporate various features of the four main paradigms. The paradigms of evolutionary computation, as a whole, can solve a wide range of real-world problems, although each one may have its own merits for specific problems. When evolutionary computation is used for a specific application, the problem-specific knowledge is usually incorporated into the system.

The applications of evolutionary computation have in themselves been very diverse. From initial investigation of rules in game-playing programmes, evolutionary computation has been utilised in scientific applications, such as simulation of biological cells, pattern recognition and function optimisation. They also have been applied extensively in the fields of engineering and operational research in problems such as structural optimisation and scheduling. More recently it has been used directly in the development of control systems in robotics and in the development of evolvable hardware by means of Field Programmable Gate Arrays (FPGAs).

The typical applications of evolutionary computation are classed as being data rich. This is not a specific requirement for evolutionary computation techniques. The main requirement being that the data set is representative of the dynamics of the system. Their application to data rich problems is a result of their ability to effectively explore the parameter space. For problems with smaller data sets some of the other search and optimisation techniques may be equally appropriate.

The following sections present an outline of the typical elements required for the implementation of an evolutionary computation paradigm. They then proceed to give a detailed explanation of the typical implementation of the Genetic Algorithm and Genetic Programming paradigms. Explanations will be aided with the help of examples where appropriate.

5.2 Evolutionary Computation Theory

Evolutionary computation adopts the concepts which evolutionary theory encapsulates. Instead of the situation whereby organic species with their myriad of subtle variation in characteristics, interact and evolve, in evolutionary computation the individuals are mathematical equations which are models of, or solutions to, a particular problem. A typical evolutionary computation paradigm consists of the following components ...

1. **A representation or encoding scheme** ... this is the means whereby candidates for a particular problem may be coded to allow the application of the typical operations of the evolutionary computation paradigm.
2. **A measure of fitness** ... an essential part of evolutionary computation techniques is a measure of how well a particular individual succeeds in providing an optimal answer to the problem being considered. A point to note is that quite often we do not expect to achieve a perfect solution (for example due to uncertainty in measurements). Therefore it makes sense for the measure of fitness of a particular solution or individual to be normalised relative to fitness of the other solutions in the population.
3. **Control parameters** ... these parameters govern the amount of effort that we wish to expend in developing an optimal solution to a problem. Typical parameters are the number of individuals in a population, the type and probabilities of reproduction
4. **Termination criteria** ... at some point in the application of the evolutionary computation paradigm, we would like to say that we have obtained an optimal solution for the problem being investigated. Again this may be due to actually having achieved a near global optimum solution, or we have spent a designated amount of effort in trying to achieve the global optimum solution. This latter case is generally governed by specifying a parameter which identifies the maximum number of generations of populations of solutions to be considered. It is also possible that the evolutionary algorithm reaches a state where it fails to find an improved solution. This stagnation may also be used to identify a termination point.

Koza (1992) points out that, in nature, an evolutionary process occurs when the following conditions are satisfied ...

1. An entity has the ability to reproduce itself
2. There is a population of such self-reproducing entities
3. There is some variety among the self-reproducing entities
4. Some difference in ability to survive in the environment is associated with the variety

The following sections demonstrate how these components of evolutionary computation are implemented in both Genetic Algorithms and Genetic Programming. A sample application is then used to illustrate the concepts.

5.2.1 Genetic Algorithms

It is in the field of genetics that the mechanism and operation of evolution is most transparent. Hence it is not surprising that it is from this area that evolutionary computation borrows many concepts and terminology. In nature, the variety in a species is manifested in their chromosomes. A similar approach to representation of individuals is taken in Genetic Algorithms (Holland, 1975). Therefore for a particular problem being considered it is necessary to initially establish a representation (phenotype) or mapping capable of expressing each point (genotype) in the search space of the problem.

In Genetic Algorithms the representation takes the following general form even though the actual mapping between phenotype and genotype can vary considerably depending on the nature of the problem. Each individual consists of a fixed length character string, i.e. chromosome. Each character is taken from an alphabet of a given size (in Genetic Algorithms this is often binary, in natural systems it is base 4). Consider a problem where we want to maximise the function $f(x) = x^2$ over the domain $0 < x < 31$. An appropriate representation in this case might be a string consisting of binary unsigned integers and of length 5. This allows us to obtain integer values between 0 (00000) and 31(11111). If we need higher resolution we can either have a longer string or use a non-binary representation. The string (phenotype), 10011, for this problem has the corresponding genotype of 361 (10011 corresponds to 19 in base 10 and is subsequently squared to obtain $f(x)$).

A fitness measure is used to assign a value to a particular individual which ranks the quality of the solution. It is envisaged that individuals with a high fitness have some inherent characteristics or genetic material which give them an advantage for survival over other weaker individuals. The fitness measure tends to be quite problem specific, but typically may be related to the magnitude of residual errors determined from comparing evaluation of the individual at selected sample points of the problem, or phenotype, with the true values. It is seldom that perfect fitness is achieved by an individual. Consequently the measure of fitness of an individual is often normalised relative to that of the other individuals in the population.

Having established the relative merit of the individuals in a population, the next step is to generate a new population of individuals. The new individuals are generated by selecting parents from the parent population which have a high fitness, and using those to partake in reproduction. Parents are typically selected probabilistically. Those having a higher fitness are more likely to be chosen, but high fitness in itself does not guarantee that an individual and its genetic material will be chosen to survive into the next population. This helps to promote diversity in the population. If only the strongest solutions were chosen, the population would soon reach stagnation as there would not be any '*new*' genetic material available to generate new variants.

There are three possibilities for the generation of new individuals ...

- *Reproduction*: Individuals are selected on the bases of their fitness and copied into the next generation unchanged. This operation ensures that good quality genetic material, even if not optimal, is passed on to subsequent generations. This material may subsequently be used in later generations to produce individuals with a higher fitness.

- *Crossover*: Two individuals (parents) are selected on the basis of probability. A node is selected at random and both parents strings are cut at this location. The cut segments are then swapped over between the chosen individuals. This is illustrated in figure 5.3. Both the modified individuals are passed on to the next generation. This is the main technique used to produce new individuals that have a good probability of having a high fitness. The logic behind this is that parents with a high fitness inherently have some traits or genetic material in their composition that give them this fitness advantage, as already mentioned. The crossover operator isolates sub-strings or building blocks of genetic material. If the '***building blocks***' used to construct an offspring contain useful genetic material then there is a high probability that the new combination of material will also give the new offspring a high fitness. Thus this operator is the main means whereby the solution space of potential solutions may be explored.

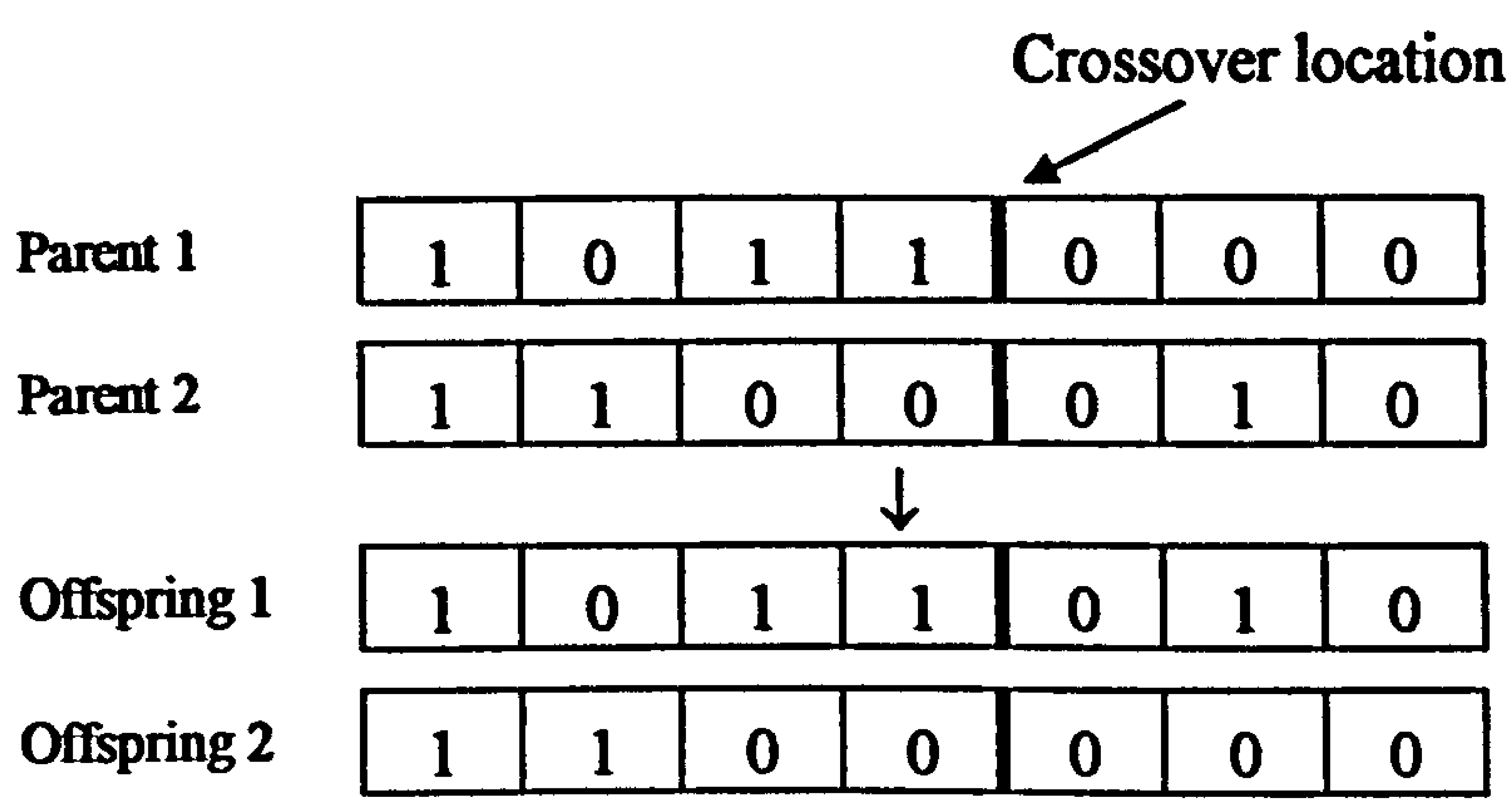


Figure 5.3 Crossover operation for Genetic Algorithms

- *Mutation*: This is a minor operation which involves selecting an individual on the basis of fitness then mutating (changing the value of) a randomly selected node as shown in figure 5.4. This method is used to promote diversity in the population and can help to prevent trapping on sub-optimal peaks of the fitness function.

Parent	1	0	1	1	0	0	0
Offspring	1	0	1	1	1	0	0

Figure 5.4 Mutation operation for Genetic Algorithms

Each of these operations are typically chosen probabilistically. Typical probabilities for the operators are 0.1 and 0.9 for reproduction and crossover respectively. Mutation being a secondary operation has a much lower probability of occurrence, typically less than 1%.

The individual with the highest fitness from a given population is designated as the result for that generation. Termination occurs when a specified number of generations of solutions have elapsed, unless a very high fitness individual causes premature termination. The control parameters for a typical run consist of the number of individuals in the population, M, the number of generations that will be run, G, as well as the probabilities of occurrence of the different forms of producing new individuals. Figure 5.5 presents the typical flow of operations in the Genetic Algorithms paradigm.

Genetic Algorithms are an example of a '*weak*' optimisation method in that they typically make little or no assumptions about the domain they are investigating. The operations carried out on individuals from a population are independent of the nature or formulation of the problem and also of the fitness evaluation. This results in a technique which is widely applicable to a range of problems. Their strength comes from their ability to isolate blocks of useful genetic material and then capitalise on this in the generation of fitter solutions in latter generations.

The outline of the Genetic Algorithms paradigm presented here is very general in nature. Usually problem specific knowledge is incorporated in the formulation of the exact implementation of the paradigm, thereby making it a '*stronger*', i.e. a more specific application, as will be shown later in this chapter.

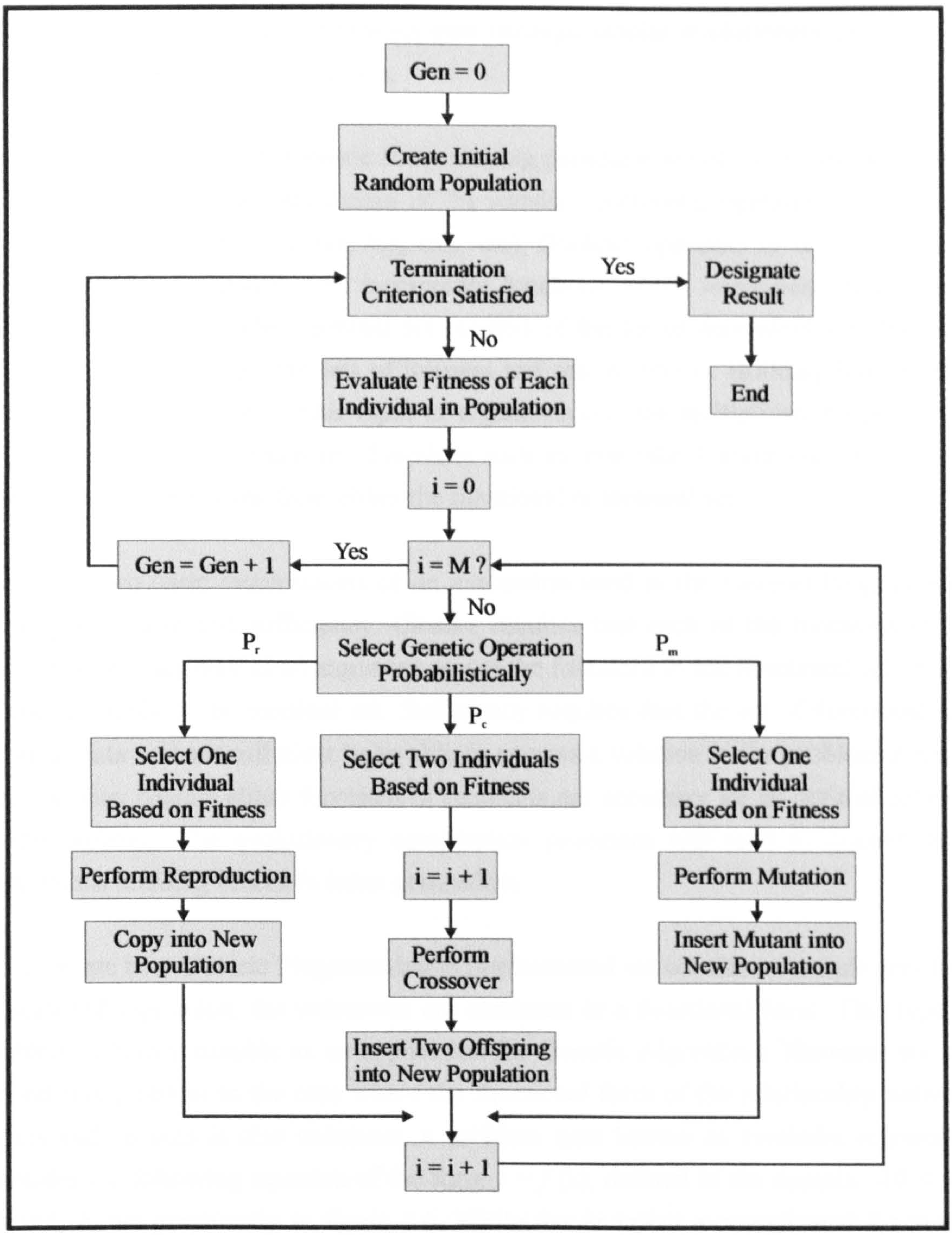


Figure 5.5 Flowchart of the conventional Genetic Algorithm paradigm

5.2.2 Genetic Programming

Genetic programming was developed by John Koza (Koza, 1992). He capitalised on the idea of utilising building blocks of genetic material. However the structures that he wanted to generate from these blocks were much more complicated in their nature than the character strings used in Genetic Algorithms. In essence, the structures he had in mind were computer programs or mathematical expressions. The process of solving problems therefore becomes the search for an optimal computer program from the search space of possible computer programs. In Genetic Programming the computer programs or mathematical expressions then undergo similar evolutionary processes to that occurring in Genetic Algorithms.

The building blocks of the Genetic Programming paradigm are of two types; functional and terminal. Functional sets consist of the standard arithmetic operators (+, -,*, etc), mathematical functions (sin, tan, log, exp, etc), Boolean operators or domain specific functions. It is also possible to incorporate functions which implement looping and conditional operators. The Terminal set consists of the set of dependent variables and constants (i.e. x, y, z, pi, the sets of integers and real numbers). Building blocks from the functional set require further input or arguments (i.e. the multiplication operator, *, takes 2 arguments, trigonometric functions such as sine take 1 argument, etc.). These arguments may be chosen from either the functional or terminal set.

There are two basic requirements of an expression used in the Genetic Programming paradigm; closure and sufficiency. Closure requires that each of the functions in the functional set may take as an argument any of the functions in the functional set, or any of the terminals in the terminal set. Sufficiency requires that the set of functional and terminal data sets are sufficient to be able to express a solution to the problem at hand. The sets may contain either functions or terminals not necessary for an optimal solution to the problem. The evolutionary computation processes will tend to discard these superfluous building blocks in latter generations.

To illustrate how Genetic Programming is implemented we consider a sample problem. In standard regression, the unknowns are constants in a functional form. This type of problem is highly suitable as an application for Genetic Algorithms. However we can extend this problem to the case where the functional form of the relationship between inputs and outputs is also unknown, a problem type known as symbolic regression. Consider the following equation of the form $y = f(x)$, defined in the domain $-10 < x < 10$ and shown graphically in figure 5.6. While this is rather a complicated functional form it is still a low dimensional problem.

$$y = \cos\left(4.978x^3 - 5.083\exp\left(x^2\right)\right) - \pi \qquad 5.1$$

The objective will be to determine both the functional form and the constants in the equation given a number of input/output samples of the function within the chosen domain. To satisfy the sufficiency condition the functional set should consist of at least the arithmetic and trigonometric functions. The terminal sets should contain the dependent variable, x, and $\Re$, the set of real numbers.

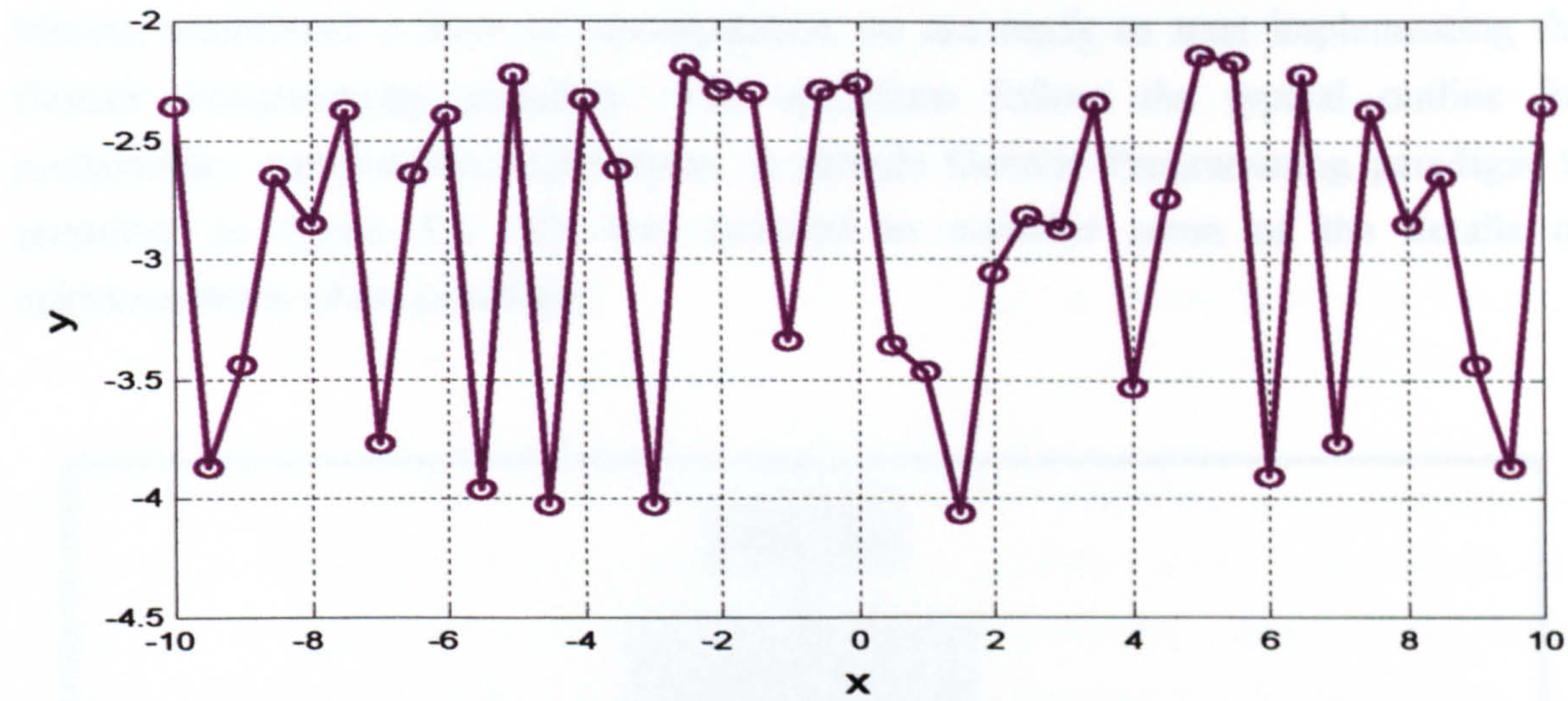
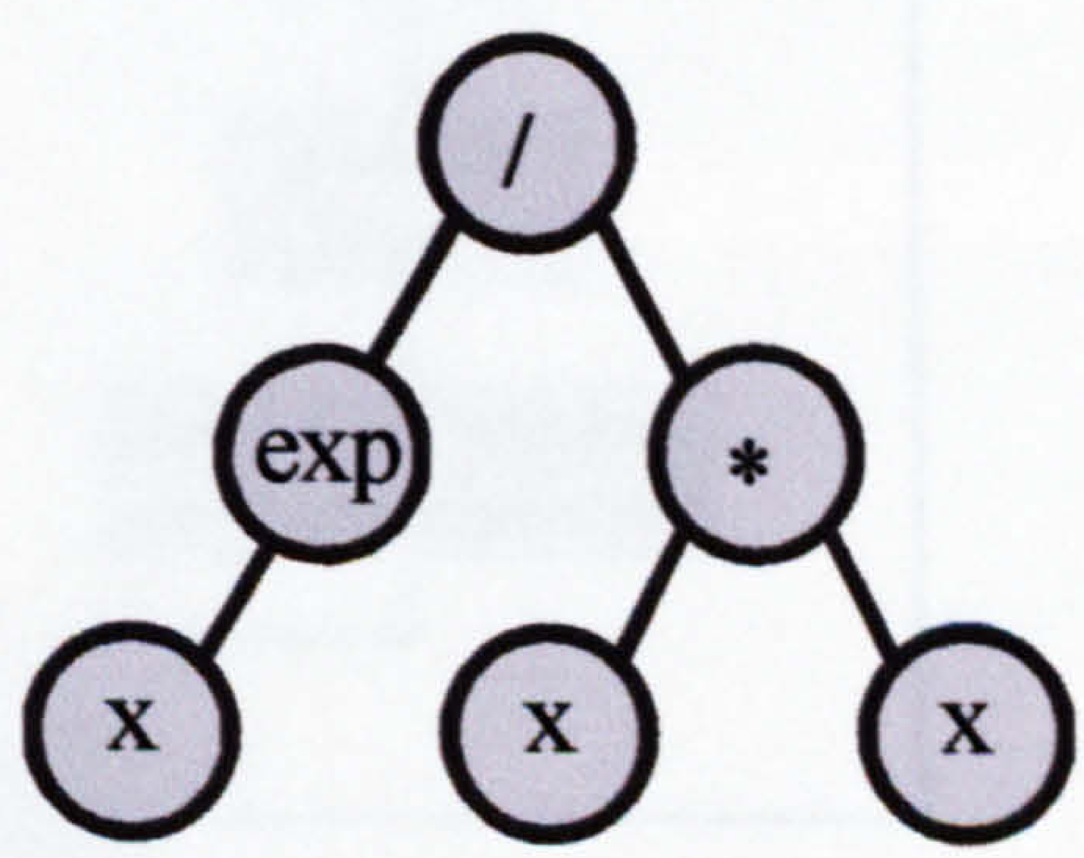


Figure 5.6 Sample function to illustrate Genetic Programming paradigm

In order to implement Genetic Programming it is necessary to establish a representation for individual expressions. Computer programming languages typically are very good at handling hierarchical structures. The chosen representation is best visualised as an hierarchical treelike structure. However for implementation in a general computer programming language this representation is not very useful. Polish Notation (sometimes known as "prefix notation"), on the other hand, is a particular form of hierarchical representation which is easily implemented. For the applications used in this thesis, the latter form of representation is implemented in the Matlab™ programming environment. However for discussion of individual expressions the tree structure will be used, as they are equivalent in nature. Figure 5.7 presents the three different manners of representation for a sample expression.

a) Standard Mathematical $$\frac{e^x}{x^2}$$

b) Hierarchical tree structure



c) Polish Notation / (exp (x) , * (x x))

Figure 5.7 Alternative representations of the same mathematical expression

Having established a form of representation we are ready to start implementing the Genetic Programming paradigm. The operations follow the typical outline for evolutionary computation applications. A sample Genetic Programming paradigm is presented in figure 5.8. We now proceed to consider some of the details of implementation of the paradigm.

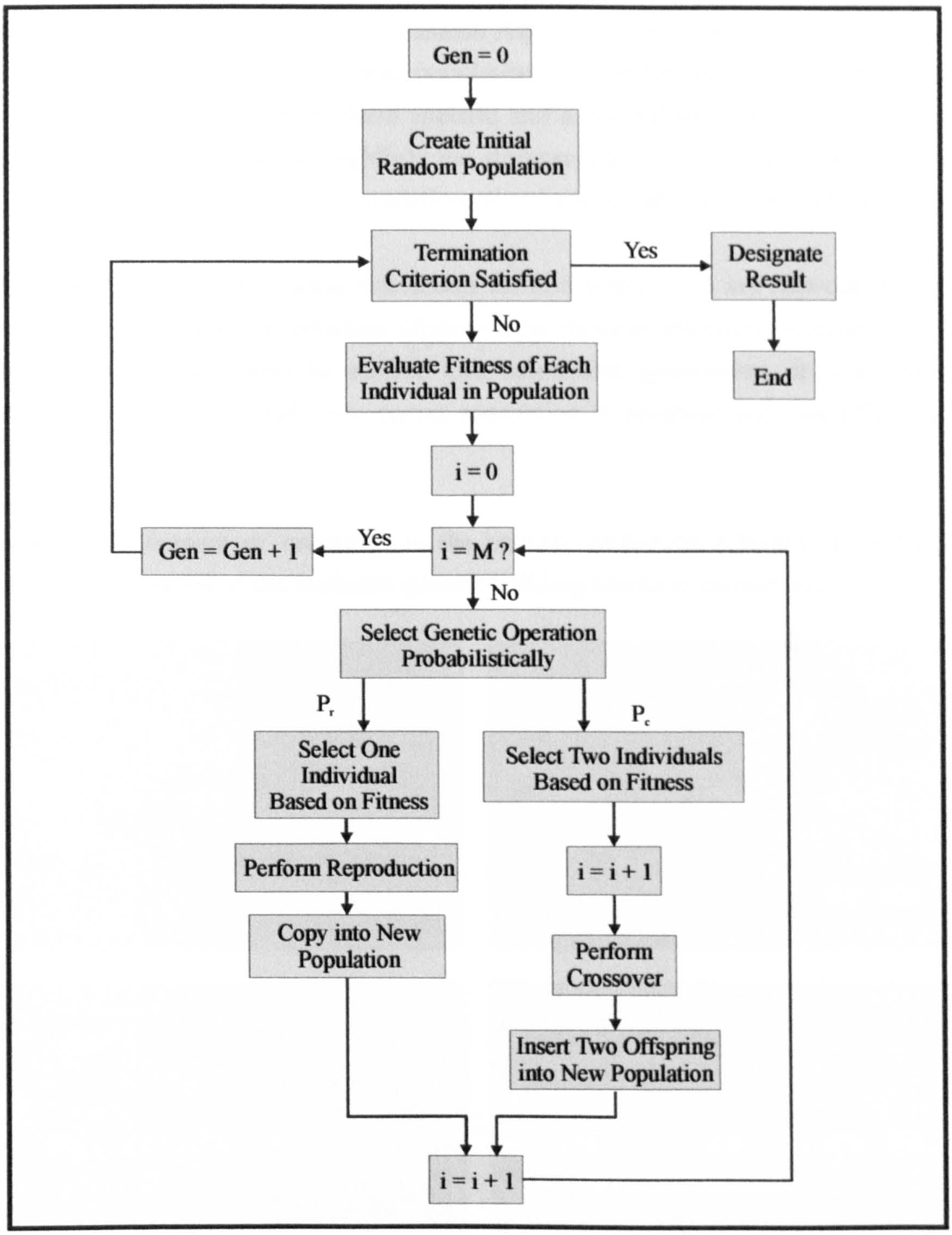


Figure 5.8 Flowchart of the conventional Genetic Programming Paradigm

The first step in the Genetic Programming paradigm is to create a population of randomly generated individual expressions. When creating these individuals, initially a function is chosen at random from the functional set. The arguments of this function are then filled with either functions or terminals chosen at random. This process continues recursively until the full tree has been '*filled*' out. For the initial population, a limit is usually placed on the number of layers, or depth, in the tree, otherwise the expressions tend to become rather unwieldy. To do this the functions at the depth – 1 layer are forced to take terminals for their arguments.

The next step, as was the case in the Genetic Algorithms paradigm, is the evaluation of each of the individuals in the initial population to establish their fitness. Again this fitness measure tends to be problem specific and a normalised version of the fitness measure tends to be useful to highlight the stronger individuals in the population. We are now ready to generate a new population of probabilistically fitter individuals.

The primary forms of producing individuals for new populations are *Reproduction* and *Crossover*. Darwinian reproduction (fitness-proportionate selection) ensures that the fitter individuals are likely to survive into subsequent generations. It is a form of asexual reproduction as only one parent expression is involved and one offspring is produced.

Sexual recombination or crossover is the primary technique whereby an extensive search and utilisation of the available genetic building blocks is carried out.

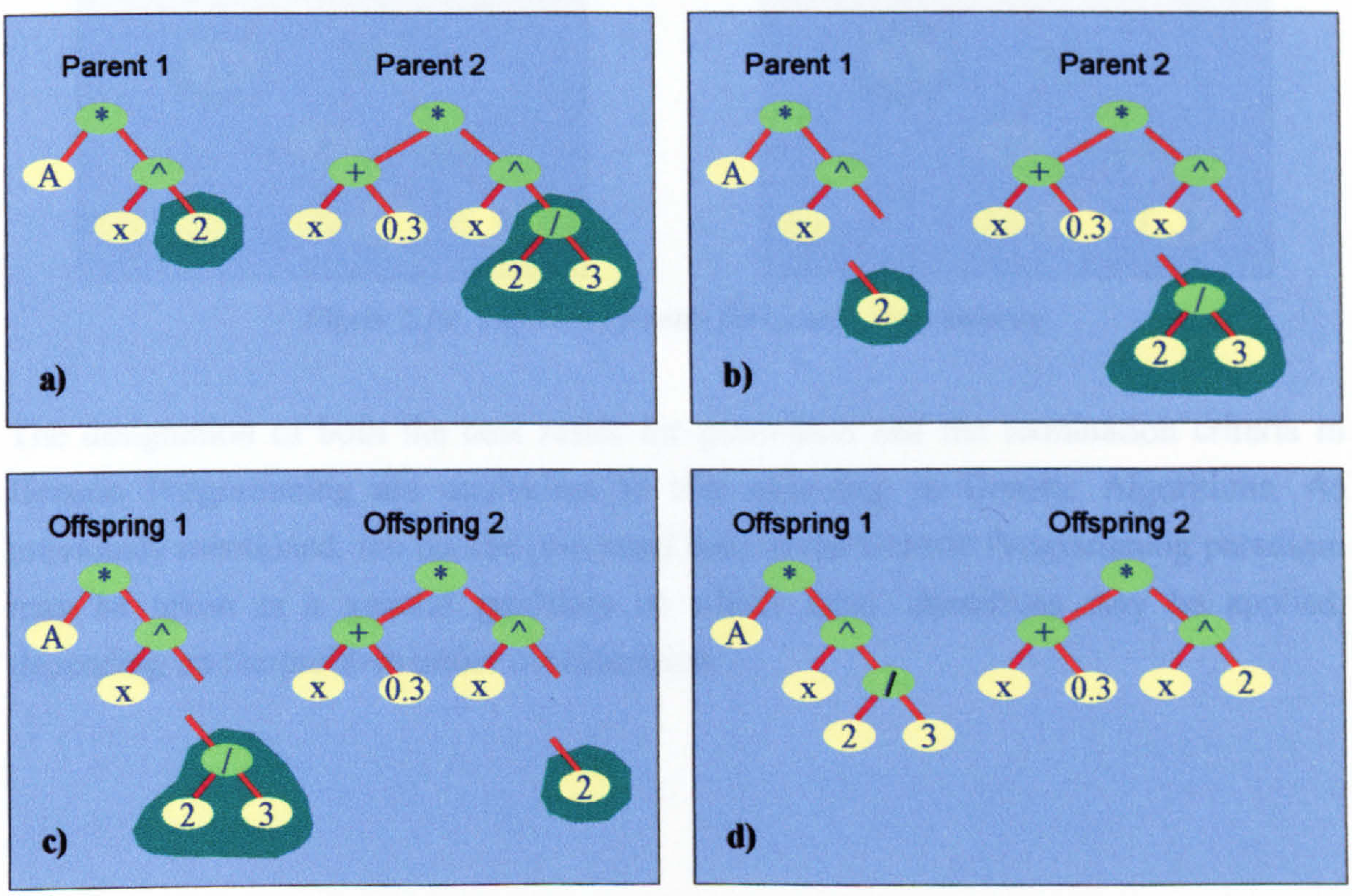


Figure 5.9 Crossover operator for Genetic Programming

Figure 5.9a-d show the crossover operation for the Genetic Programming paradigm. Two individual expressions are initially chosen probabilistically based on their normalised fitness. In each structure a node is chosen at random. The branch below this node is then removed. This '*subtree*' in itself becomes the building block of genetic material which has the potential to pass on its parents high fitness characteristics. The subtrees from both parent individuals are swapped and recombined with the other parent individual to produce two offspring for insertion into the new population. It is obvious that after several generations that quite complicated expressions may be generated by the crossover operator. This requires a limit on the maximum size to which a tree may be allowed to grow. As the crossover operation typically produces quite diverse offspring, there tends to be a lower likelihood of stagnation in the population than that which may occur in Genetic Algorithms.

The mutation operator as outlined in figure 5.10 tends to play only a minor role, if any, in the Genetic Programming paradigm. Its primary function in Genetic Algorithms was to produce diversification which is adequately catered for in most cases in Genetic Programming by the crossover operator. Hence it had been omitted from the flowchart presented earlier in figure 5.8.

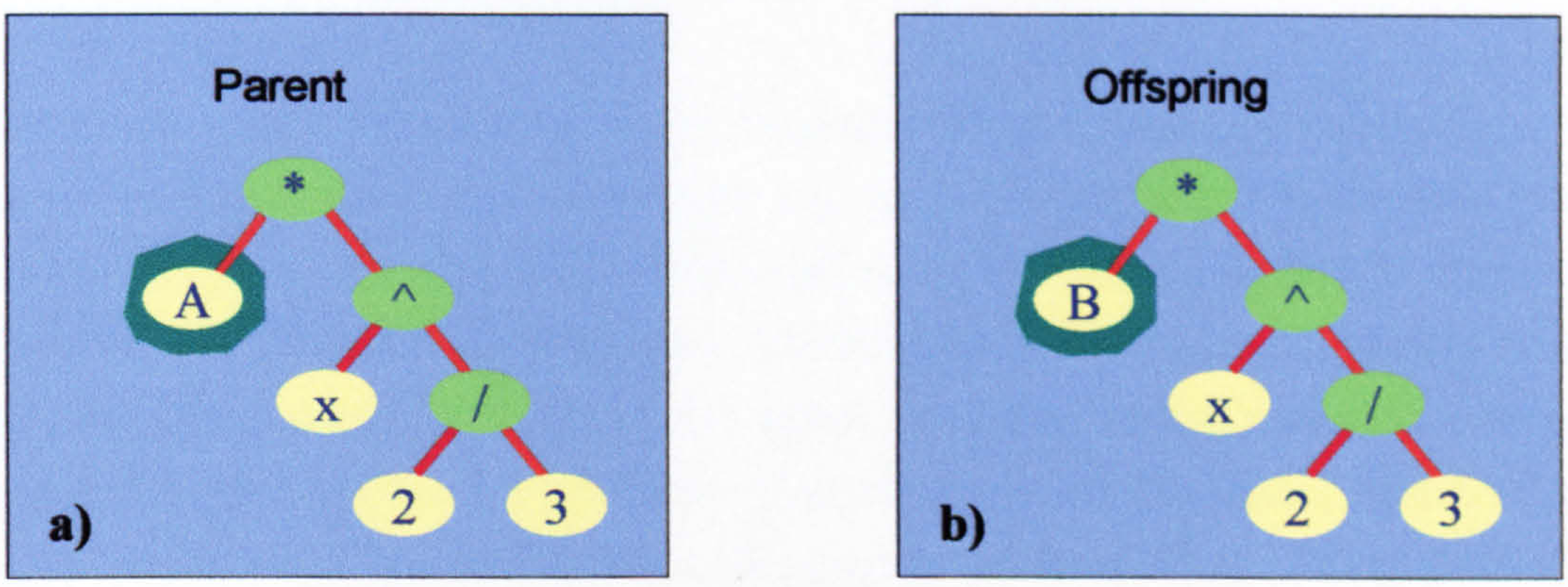


Figure 5.10 Mutation operator for Genetic Programming

The designation of both the best result for generation and the termination criteria in Genetic Programming are equivalent to that occurring in Genetic Algorithms. As previously mentioned, the outline presented here of the Genetic Programming paradigm may be taken as a general guideline to which many alterations may be applied, depending on the problem under consideration.

5.3 Application of Evolutionary Computation Techniques

The purpose of this section is to demonstrate how the evolutionary computation techniques proposed in the previous section may be applied to problems arising from coastal systems. In particular an attempt has been made to choose applications for which more established mathematical approaches have not yet been able to provide solutions.

Two problems are presented ...

- the first considers the determination of the directional distribution of wave fields in the vicinity of reflectors.
- The second is applied to the problem of data reduction for the description of nearshore morphological features.

5.4 Case Study # 3: Application of Evolutionary Computation Techniques to the Study of Directional Wave Analysis[3]

There are a large number of algorithms for the estimation of directional wave spectra reported in the literature. However, only a small subset of these deal with the problematic situation where strong phase-locked reflections are present. The motivation for this study stems from the need to evaluate accurately the directional wave spectrum in the close proximity to highly reflective coastal structures. In particular accurate measurements of reflection are required in order to ascertain the reflection performance of different structures in multidirectional random sea states.

Isobe & Kondo (1984) proposed the first solution (the modified maximum likelihood method, MMLM) that was able to accurately evaluate the directional wave spectrum in the presence of strong reflections. Later Hashimoto and Kobune (1988) developed the modified Bayesian method that is also capable of evaluating the directional spectrum of waves close to reflective structures after optimisation of an unknown hyper-parameter. However, the major problem with both of these methods is that they require the reflection line position as an input parameter. This parameter is notoriously difficult to determine and is not necessarily located at the shoreline. Additionally, phase-locked methods seem to be very sensitive to errors in the reflection line position.

Davidson *et al.* (1998) developed an extension of the MMLM that evaluated the unknown reflection line position through a process of iteration. The iterative process adjusts the reflection line distance until an optimum correlation is achieved between the measured and estimated cross-spectrum. In both field and data simulations this method proved very successful providing that the sensor array was located close to the reflector. However like the conventional MMLM, when the array was positioned further offshore spurious peaks were generated in the directional spectra, $S(f,\theta)$. These peaks were shown to be correlated with frequency-direction combinations that gave rise to predicted nodes at sensor locations. At these points any uncorrelated noise is interpreted as very large amplitude waves.

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[3] A version of this section has been published as Davidson, M.A., Kingston, K.S. and Huntley, D.A., 2000, 'A New Solution for Directional Wave Analysis in Reflective Wave Fields', *Journal of Waterway, Port, Coastal and Ocean Engineering*, Vol. 126, No. 4, pp 173-181

Mark Davidson originally recognised the need to produce a generalised parametric approach to directional wave distribution analysis as an alternative to non-parametric approaches which were known to have various limitation and restrictions on their respective regions of application.

My contribution to this study was primarily related to the development of the genetic algorithm approach to estimation of parameter values for the parameterised form of the directional distributions as well as being involved in the writing and reviewing stages of the manuscript. My contribution was later extended to the recognition of the value of the spectral fitness which could be used to conduct a comparison of directional spectral estimates produced from a variety of approaches.

Huntley and Davidson (1998) recognised that the effect of phase-locked reflections on the directional analysis technique is strongly dependent on the location of the reflection-line position relative to the sensor array. Clearly, there are distinct regimes where phase-locked and non phase-locked methods are exclusively appropriate, separated by an area where neither method is valid. It was also found that the effect of phase-locking on the directional analysis is sensitive to the bandwidth of the Fast Fourier Transform (FFT) used. Huntley and Davidson (1998) showed that increasing the bandwidth of the smoothed FFT by either frequency-averaging more points or ensemble-averaging shorter FFT segments can effectively smooth out the effect of phase-locking. If a complete node/anti-node cycle is encompassed in a single frequency bin then the effect of phase-locking is effectively smoothed over permitting the application of non phase-locked methods. This has the dual advantage of not requiring an input of the reflection line distance, and not suffering from spurious peaks at predicted nodal locations. However, there is an obvious upper-limit to the degree of smoothing that can be applied. Ultimately, the bandwidth of the FFT becomes too broad, limiting the frequency resolution and affecting the accuracy of the directional analysis technique.

Davidson *et al.* (1998) quantified the appropriate regions of application of phase-locked and non phase-locked reflection methods. These regions were expressed in terms of the dimensionless parameter L/S. Here L is the time lag between incident and reflected waves at the sensor location and S is the segment length used in the FFT analysis. For co-located velocity and surface elevation sensors the numerical tests showed that phase-locked methods are appropriate for L/S ratios of less than 0.2. Non phase-locked measurements were appropriate for $L/S > 0.5$. However, there is a broad zone ($0.2 < L/S < 0.5$) for which neither method performs well.

The motivation for this contribution comes from the need for a robust directional analysis technique that does not require an input of the reflection line position and is effective regardless of the distance to the reflection line. A new parametric solution for the directional wave spectrum is presented here which satisfies these criteria. The theory behind this simple parametric solution is discussed first, followed by a description of how the solution is optimised using a genetic algorithm (GA). Numerical tests are conducted including a sensitivity and stability analysis. Finally, the new method is applied to field data collected at various distances from the reflector (different L/S ratios) in order test the robustness of the new method.

5.4.1 Theory

In this section a mathematical expression for the theoretical cross-power spectrum $(\hat{\phi})$ for a predefined directional spreading function G is developed. The theoretical cross-power spectrum of this form can be expressed in terms of a finite number of parameters. These parameters are then simultaneously optimised using a genetic algorithm to minimise the differences between the amplitude and phase of the theoretical and measured cross-power spectra, yielding an estimate of the directional wave spectrum. In this contribution the term 'measured data' refers to either numerically simulated data or field data.

For a phase-locked reflected wave field the theoretical cross-power spectrum between spatially separated wave sensors at locations $\mathbf{x} = \mathbf{x}_n$ and $\mathbf{x} = \mathbf{x}_m$ is given by Isobe and Kondo (1984) as:

$$\hat{\phi}_{mn}(\sigma) = \int_{\mathbf{k}} [\exp(i\mathbf{k}\mathbf{x}_m) + K_r \exp(i\mathbf{k}\mathbf{x}_{mr})][\exp(-i\mathbf{k}\mathbf{x}_n) + K_r \exp(-i\mathbf{k}\mathbf{x}_{nr})] S(\mathbf{k},\sigma) d\mathbf{k} \qquad 5.2$$

Here $\mathbf{k}$ is the wave number vector defined for all <u>incident</u> wave angles, θ from $-\pi/2$ to $+\pi/2$ $(\mathbf{k} = (2\pi/\lambda)[\cos(\theta) + i\sin(\theta)])$, λ is the wavelength, σ is the angular frequency and S is the directional (or wave number–frequency) spectrum. K_r is the coefficient of wave reflection and $\mathbf{x}_{nr}$, $\mathbf{x}_{mr}$ are the position vectors to elements nr and mr in an image of the real array about the reflection line. The product of the first two terms in the two brackets in equation 5.2 represents the incident wave component and the product of the second two terms represents the reflected wave component. The remaining two products describe the interaction of the incident and reflected wave fields. For a full derivation of these equations the reader is referred to Isobe and Kondo (1984).

The directional wave spectrum is given by; $S(\mathbf{k},\sigma) = E(\sigma)G(\mathbf{k},\sigma)$, where E is the incident wave energy density at angular frequency σ and G is the directional distribution function. Notice that it is assumed in equation 5.2 that both the incident and reflective wave fields both conform to the same Mitsuyasu *et al.* (1974) spreading function of the form;

$$G(\mathbf{k},\sigma) \propto \cos^{2s(\sigma)}\left(\frac{|\theta - \theta_p(\sigma)|}{2}\right) \qquad 5.3$$

where, θ_p is the principal incident wave direction and s is a spreading parameter. Although a Mitsuyasu *et al.* (1974) spreading function has been adopted here, in principle, any spreading function may be applied in place of equation 5.3. Large values of s in equation 5.3 represent narrow directional distributions. The spreading function equation 5.3 is normalised such that:

$$\int_{\mathbf{k}} G(\mathbf{k},\sigma)\,d\mathbf{k} = 1 \qquad 5.4$$

Initially the cross-power spectrum is defined with unit incident wave energy density at each angular frequency ($E(\sigma)=1$ for all σ). Then the coefficient of proportionality, κ between the theoretical and measured cross-spectrum can be obtained from:

$$\kappa(f) = \frac{1}{nm}\sum_n \sum_m \frac{|\phi_{nm}(f)|}{|\hat{\phi}_{nm}(f)|} \qquad 5.5$$

The magnitude of the theoretical cross-power spectral estimate is then retrospectively adjusted on the basis of this estimate $(\hat{\phi}_{nm}(f) \Rightarrow \kappa(f)\hat{\phi}_{nm}(f))$. Therefore it is not necessary to predefine the incident wave energy density function, $E(f)$ before computation of the theoretical cross-power spectrum.

Thus, the theoretical cross-power spectrum maybe reduced to a simple parametric solution that is a function of only four variables, where:

$$\hat{\phi}_{mn}(\sigma) = f(K_r, \theta_p,\ s,\ rld) \qquad 5.6$$

Here *rld* refers to the reflection line distance relative to an arbitrary reference position, and is needed to compute the position vectors of the array (and image array) elements. Note that in the absence of reflection the problem is much simpler and reduces to just two unknown parameters $(\theta_p,\ s)$.

For given estimates of K_r, θ, s and rld, a theoretical cross-power spectrum can be computed using equations 5.1 – 5.4. The 'goodness of fit' of the theoretical cross-power spectrum to the measured cross-spectrum can then be assessed via a fitness function. Here a combined fitness function, r has been used that reflects the similarity between the amplitude, A and phases, P of the theoretical and measured cross-spectra.

$$r_a = \frac{1}{1+\sum_n \sum_m |A_{nm} - \hat{A}_{nm}|} \qquad \text{(amplitude-fitness)} \qquad 5.7$$

$$r_p = \frac{1}{1+\sum_n \sum_m |P_{nm} - \hat{P}_{nm}|} \qquad \text{(phase-fitness)} \qquad 5.8$$

$$r = \frac{r_a + r_p}{2} \qquad \text{(combined-fitness function)} \qquad 5.9$$

The combined-fitness function equals 1 for a perfect fit between the predicted and observed cross-spectrum, and tends towards zero, as the fit becomes increasingly poor. It should be noted that in order that the combined fitness function equally reflects the phase and amplitude, it is necessary to normalise the measured cross-power spectrum such that the maximum magnitude is equal to 2π. This means that the potential range in the phase and amplitude fitness will be approximately equal. The effect of this normalisation on the final estimate of the directional spectrum is reversed at the end of the analysis. Also note the importance of unwrapping the phase before calculating the phase fitness.

The aim is to maximise the fitness function Eqn 5.9 by simultaneously optimising the 4 dependent variables $(K_r, \theta_p,\ s,\ rld)$. The parameter space for this problem is very large. Thus, a decision was made to implement a genetic algorithm as this method can efficiently search a large parameter space and is fairly resistant to becoming trapped in sub-optima.

5.4.2 Application of a Genetic Algorithm

The purpose of this section is to outline the Genetic Algorithms paradigm used in this example. In particular it will highlight areas where the implementation tends to vary from the general form outlined in §5.2.1. It will also indicate the control parameters adopted in the implementation. The implementation of the GA paradigm to the directional analysis problem is outlined in figure 5.11.

An initial population of 600 individuals are used. For this application each individual or string is made up of 4 characters or *nodes*. These 4 nodes correspond to the variables that are to be optimised $(K_r, \theta_p,\ s,\ rld)$. Values are chosen for each node using a random number generator. Random numbers are generated between sensible limits for each of the given variables. For example for K_r a sensible range is 0 to 1. Thus the alphabet used in this study is in effect infinite (at least to the resolution of the random number generator).

The fitness of each of the individuals in the population is estimated by applying equations 5.2 - 5.9. Following Koza's (1992) recommendations the probabilities of reproduction, *Pr* and crossover, *Pc* are set to 0.1 and 0.9 respectively. Goldberg (1989) discusses mutation as a relatively unimportant secondary operation. Experimentation not shown here showed that mutation little improved the efficiency of this Genetic

Algorithm implementation and it was therefore left out in favour of an optimisation routine described later in this section.

The basic Genetic Algorithm paradigm described above provides an effective way of finding an approximately optimised solution to the directional wave spectrum. However, since the parameters in the search space are continuous variables, an infinitely large population would be required in order to achieve a perfect optimisation. This is clearly not practical. One solution to the problem is to randomly select a percentage of the population (on the basis of fitness) for optimisation. In this case a form of hill-climbing is adopted. For each of the selected individuals nodes are selected in a random

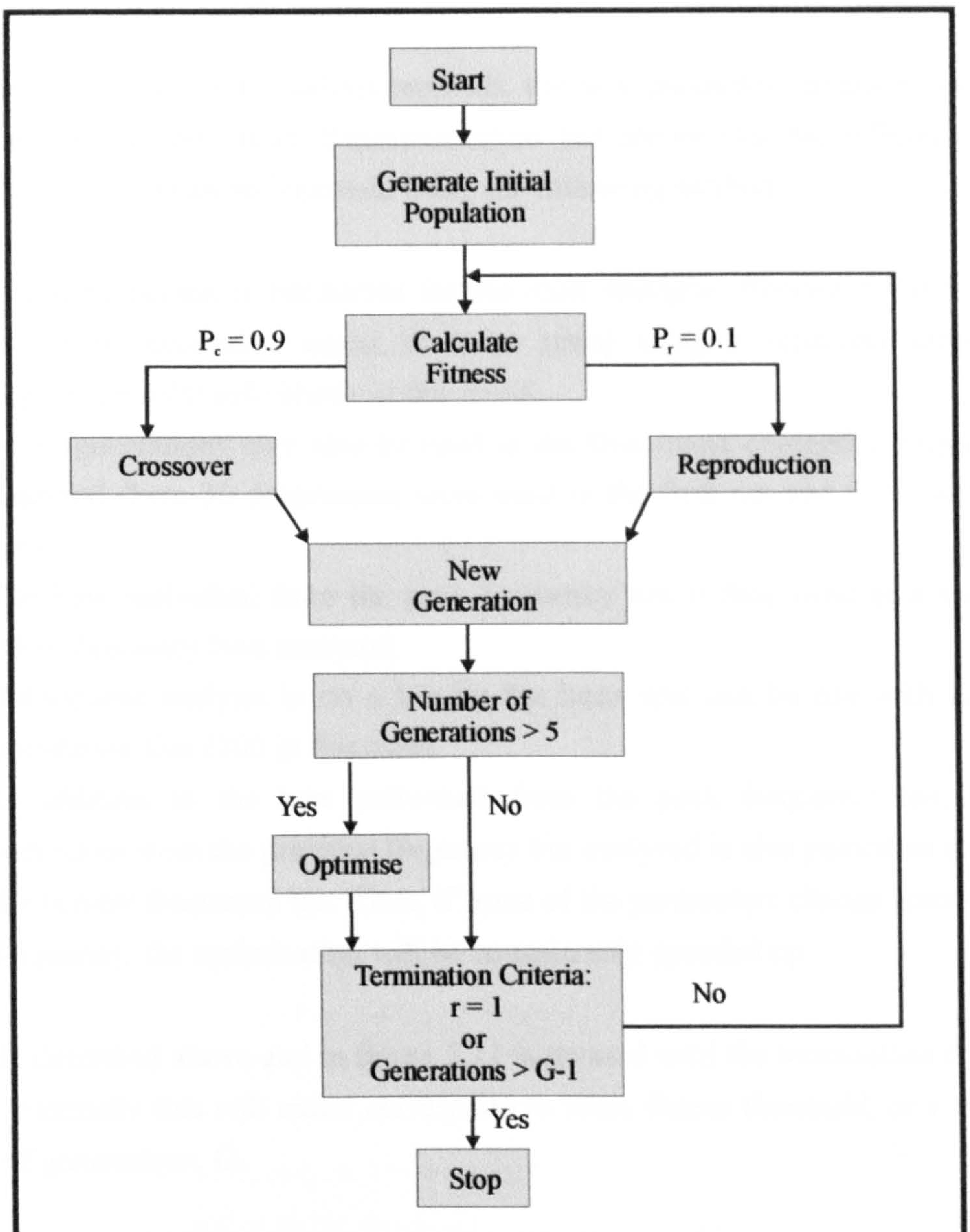

Figure 5.11 A flow chart describing the GA paradigm used to provide a parametric solution to the directional wave spectrum. Here r is the fitness of the best individual, G is the total number of generations and Pc and Pr are the probability of cross-over and reproduction respectively.

order and perturbed slightly. If the perturbation increases the fitness the optimisation is repeated with the same perturbation factor. If the perturbation decreases the fitness it is rejected, the original value is reinstated and a new perturbation factor is randomly selected. The above process is repeated five times.

Best results were obtained by using a combination of the GA with the optimisation technique described above. The GA is allowed to propagate for a set number of generations (typically 5) before the optimisation is introduced. The two optimisation-methods are then used concurrently. The idea is that the GA is utilised to effectively search a large parameter space and the second optimisation method is used for fine-tuning. Note that the optimisation routine allows the GA to find solutions that may be outside the original search space.

Much like other directional analysis methods, the new parametric solution operates on a frequency bin by bin basis. Experimentation has shown that the efficiency of the optimisation process can be improved using the following methods:

1. The optimisation is conducted for the most energetic frequency bin first (with the most favourable signal to noise ratio) using a relatively large initial population (600 individuals in this case).
2. More generations may also be used in the first (most energetic) frequency bin analysed (here 30 generations were used in the first run and 25 in subsequent runs).
3. The best individual from the peak frequency run is then used as a seed in all other frequency bins analysed.
4. Subsequent analysis is on a bin by bin basis and can be run with a reduced population size (100 in this case).
5. In addition to the best individual from the peak frequency bin, the best individual from the previous frequency bin analysed is also passed as a seed into the current frequency bin. Thus, if some of the parameters change smoothly with frequency, the optimisation will be considerably speeded up.

The cycle described above and in figure 5.11 is iterated until the termination criterion is reached. Normally this will either correspond to some fitness threshold, or a maximum number of generations, G.

Typical output from the GA can be seen in figure 5.12. Figure 5.12a shows the evolution of the combined fitness, equation 5.9, with each generation. The program has evolved through 10 of the 25 generations at this point. Notice the rapid increase in fitness over the first few generations. Numerically simulated data has been used in this example. The simulated case here is for K_r=0.5, ϑ_p=150°, s=100, and L/S=0.13. Figure 5.12b shows the directional distribution of variance for a given frequency bin. Note that even after 10 generations the incident and reflected peak are at the correct location and that the reflection coefficient is very close to the target value. The lower two panels in Figure 5.12 show the theoretical (equations 5.2 - 5.5) and measured cross-spectral amplitudes and phases.

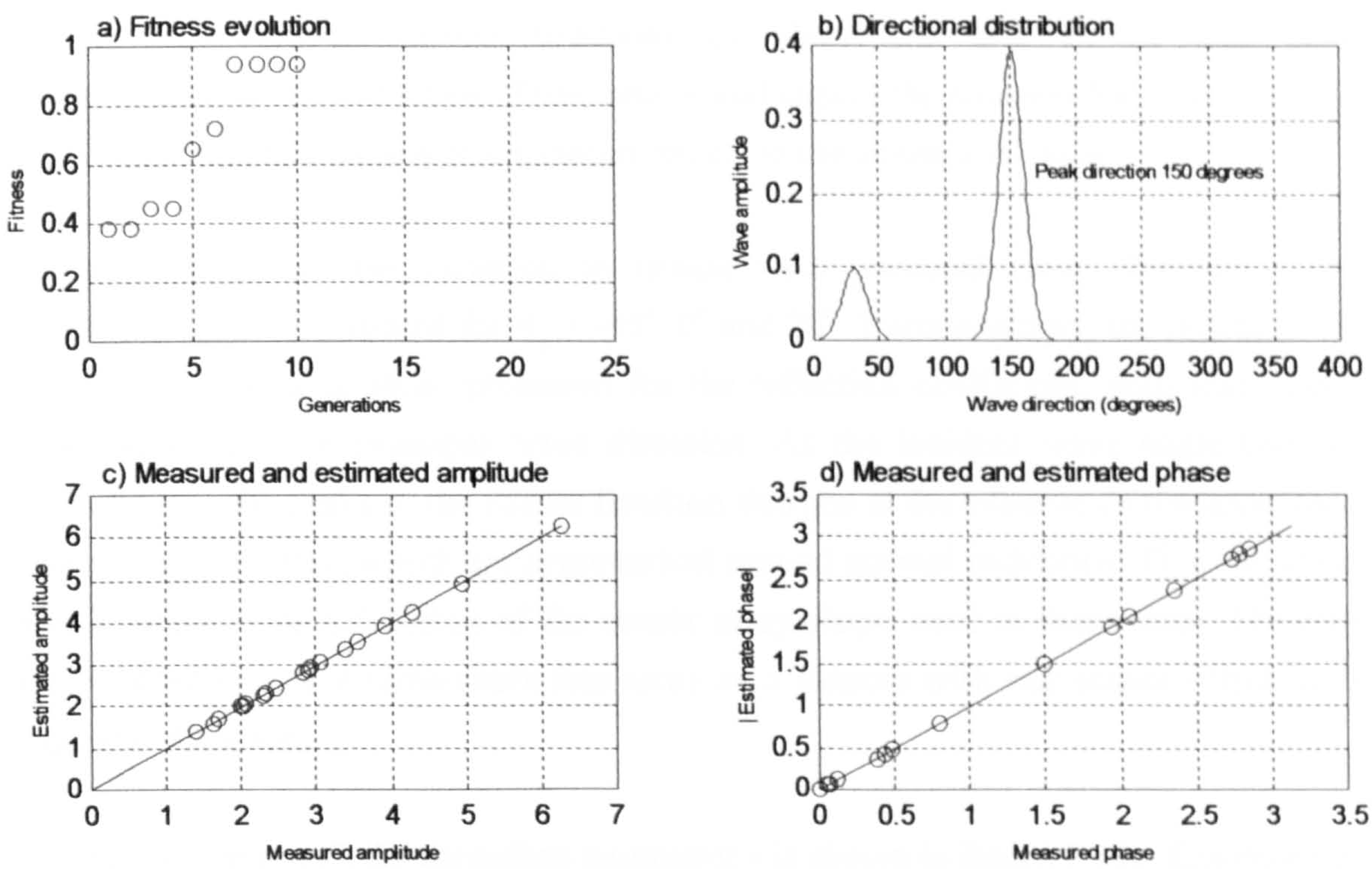

Figure 5.12 Typical output from the new directional wave analysis routine after 10 generations. a) A typical evolution of the fitness for the best individual. b) Directional distribution. c) Measured and estimated amplitude; d) Measured and estimated phase.

5.4.3 Numerical Tests

A series of numerical tests were carried out on the new parametric directional analysis method in order to examine the sensitivity of the fitness function to the various unknown parameters, the stability of the analysis technique and the effect of varying the reflection line distance. All numerical tests here were carried out using an array of 6 spatially separated surface elevation sensors. Here a sensor array design has been chosen to match that used later in the field tests. The x (cross-shore) and y (longshore) positions measured relative to the most shoreward sensor are [0, 3, 9, 9, 21, 45] and [0, 0, -12, 0, 0, 0] metres respectively. This is a right-handed co-ordinate system where x increases positively in an offshore direction. Random waves were generated with a Mitsuyasu *et al.* (1975) spreading function as given by equation 5.3. The precise method of wave simulation is given in Davidson *et al.* (1998).

5.4.3.1 Sensitivity Analysis

In this section we describe simulations conducted in order to ascertain the sensitivity of the fitness function (equation 5.9) to variations in the free parameters K_r, θ_p, s, and *rld*. The sharpness and form of these functions will dictate the efficiency with which the GA can recover a suitably 'fit' solution and highlight any possibilities of erroneous solutions.

Figure 5.13a illustrates the variation in the fitness function with the reflection coefficient. Three tests are shown here for actual reflection coefficients of 0, 0.5 and 1.0. In each case the fitness functions are sharp and symmetrical with peaks corresponding to the true value. Thus, one would expect the solution for K_r to converge efficiently with little chance of erroneous results in the absence of noise.

Figure 5.13b shows the variation in fitness with principal wave direction. Three different cases are illustrated for $\theta_p = -45°$, $0°$ and $20°$. Encouragingly, the results of this analysis are similar to those presented for the reflection coefficient, with sharp peaks occurring around the principal wave direction. As the incident wave angle becomes more oblique, the peaks in the fitness function sharpen at the expense of the appearance of subsidiary maxima, which are symmetrical around normal incidence. This subsidiary peak is likely to be a function of the sensor array shape used in these tests. The array implemented here is a cross-shore line array of 5 sensors with one sensor offset in the longshore direction.

The variation in r with the spreading parameter s is shown in figure 5.13c. Examples are given here for s = 100, 250 and 500. The reader should note that these values are high compared to real sea states, which are typically in the range of 1 to 100. These high values have been selected in order to set a more rigorous test for the algorithm. However, as the actual value of s increases, the peak around the true value becomes much less sharp, and the sensitivity of the fitness function to s is radically reduced. It would be reasonable to expect, therefore, that for narrow angular distributions in the incident wave field the fitness parameter will be relatively insensitive to the spreading function.

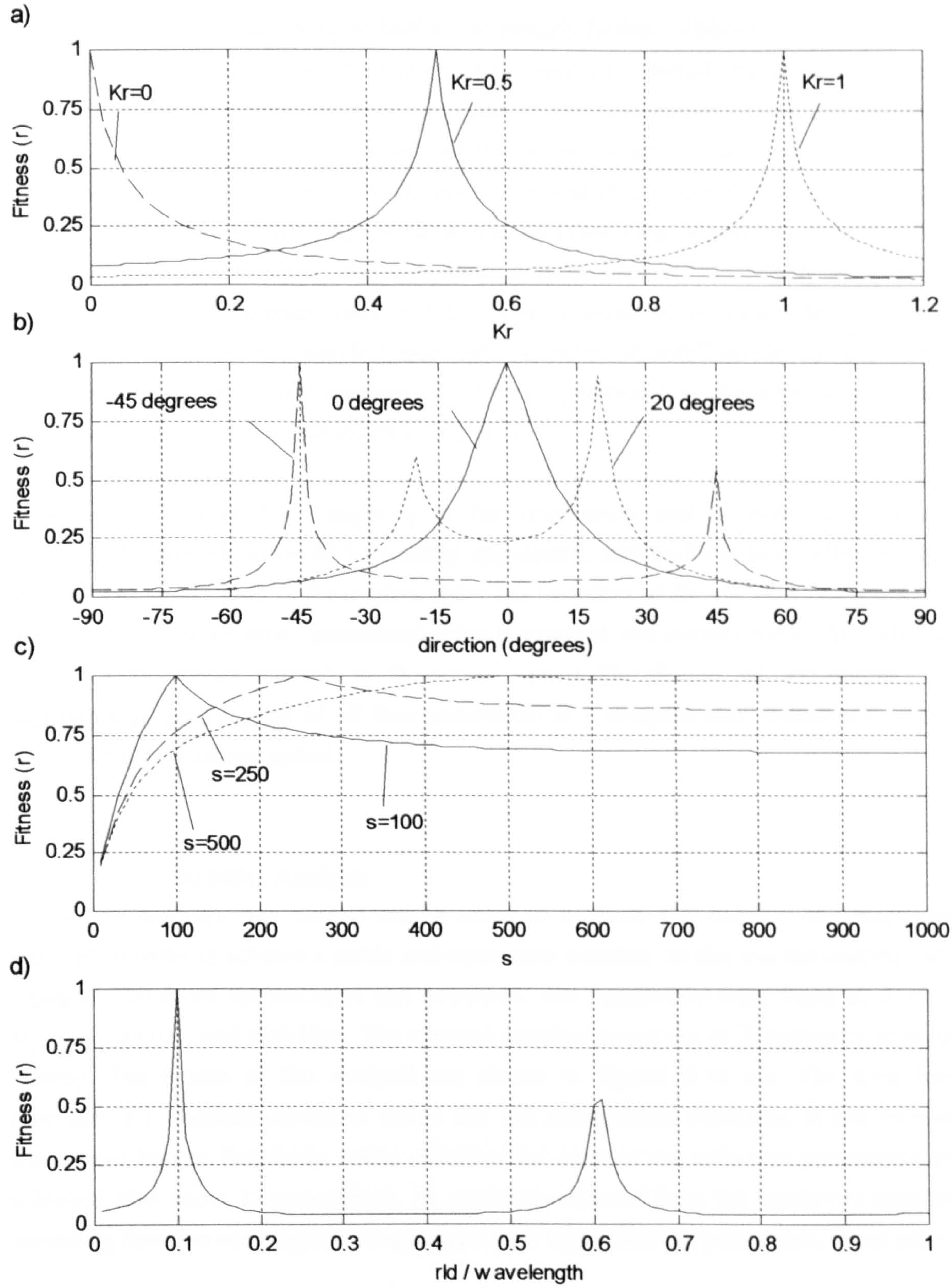

Figure 5.13 A sensitivity analysis showing the variation in fitness with a) reflection coefficient; b) principal wave direction; c) spreading parameter and d) reflection line position (λ=100m, rld*=10m).*

Finally, the sensitivity of r to variations in the reflection line distance is explored in figure 5.13d. Values of fitness have been plotted against the reflection line distance (*rld*=10m in his case) which has been non-dimensionalised by dividing by the wavelength (λ =100m). Here there is a sharp peak around the true value at (rld/λ=0.1) with a smaller subsidiary peak at half a wavelength further offshore (rld/λ =0.6). The subsidiary peak occurs when the trough of the spatially shifted (theoretical) standing wave (by $rld + \lambda/2$) coincides with the crest of the non-shifted (measured) standing wave (i.e. they are 180° out of phase). At this point the amplitude fitness = 1 and the phase fitness = 0 gives a combined fitness of 0.5, and thus a subsidiary peak. Although there is potentially a problem here with the routine optimising parameters corresponding to the subsidiary maximum, the GA method used here is particularly efficient at searching a large parameter space and therefore is expected to locate the true value. Additionally, the initial search space can be selected intelligently to avoid this possibility. For example if the estimated reflection position is x, the initial search space for the reflection line distance might be $x \pm \lambda/3$.

Inspection of figure 5.13 might give the impression that a more conventional optimisation procedure would be equally appropriate and perhaps more efficient than the GA. However, each of these plots show the variation of fitness with one particular parameter, whilst all other parameters have a constant and correct value. So although these curves appear smooth in form and reasonably devoid of sub-optima, the simultaneous optimisation of all four parameters is a complex task indeed and one to which the GA is ideally suited.

5.4.3.2 Stability Analysis

A stability analysis was carried out in order to evaluate the number of generations required in order to achieve a stable and repeatable solution. In this test the analysis was repeated 100 times for the same test condition. The parameters were fixed at, K_r=0.5; θ_p = 30°; s=100; and rld=10m. The spectral amplitude was set at 3, (arbitrary units of length). The results of this analysis are shown in figures 5.14 a-e. The error bars represent ± 1 standard deviation within the 100 independent estimates. It can be seen from these figures that fairly stable solutions for most of the unknown parameters are achieved after about 15 generations. As might be expected from the sensitivity tests the spreading function converges least quickly of the four unknown parameters. Even after

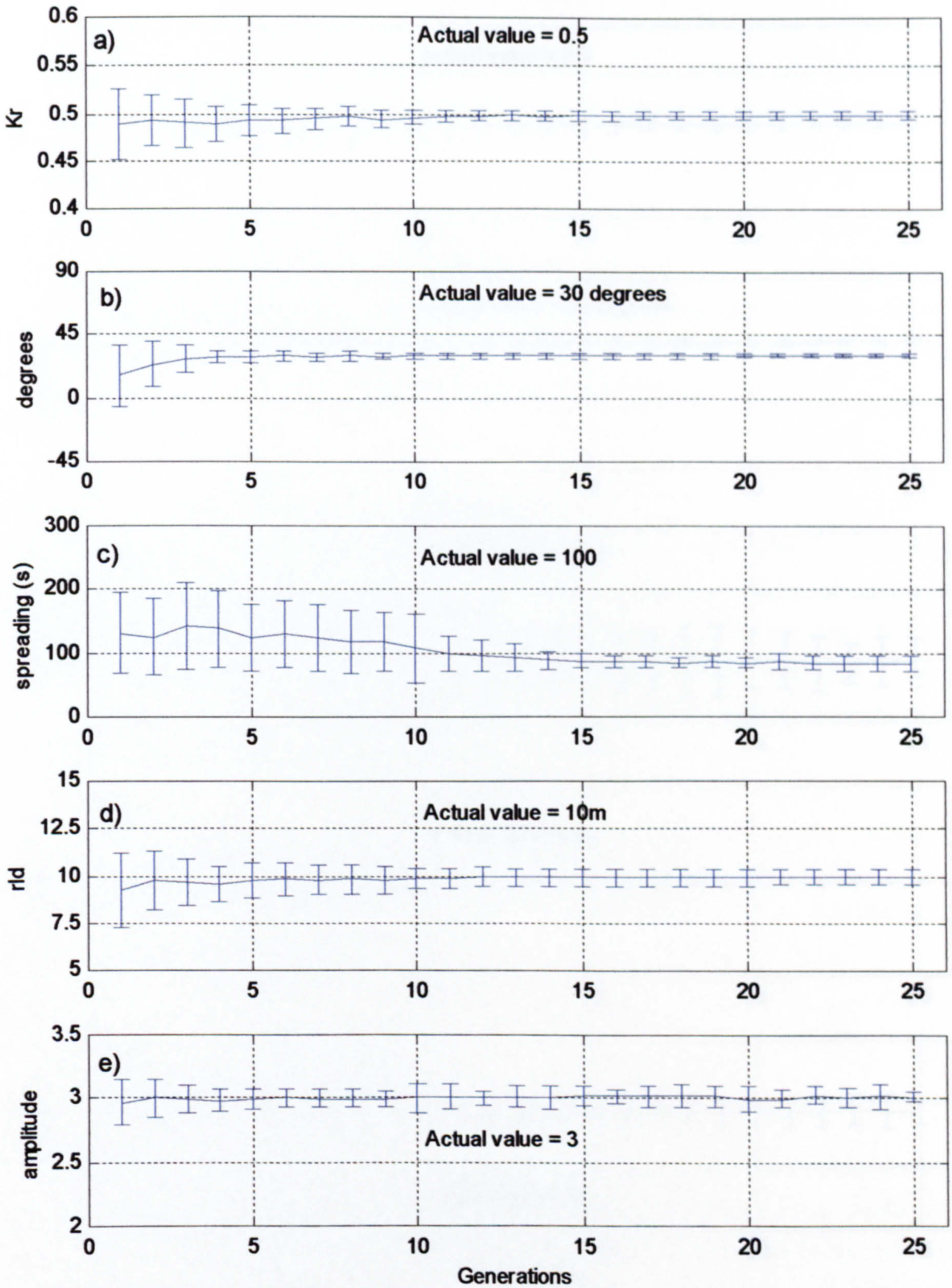

Figure 5.14 A stability / repeatability check for a) reflection coefficient; b) principal wave direction; c) spreading parameter; d) reflection line distance and e) wave amplitude.

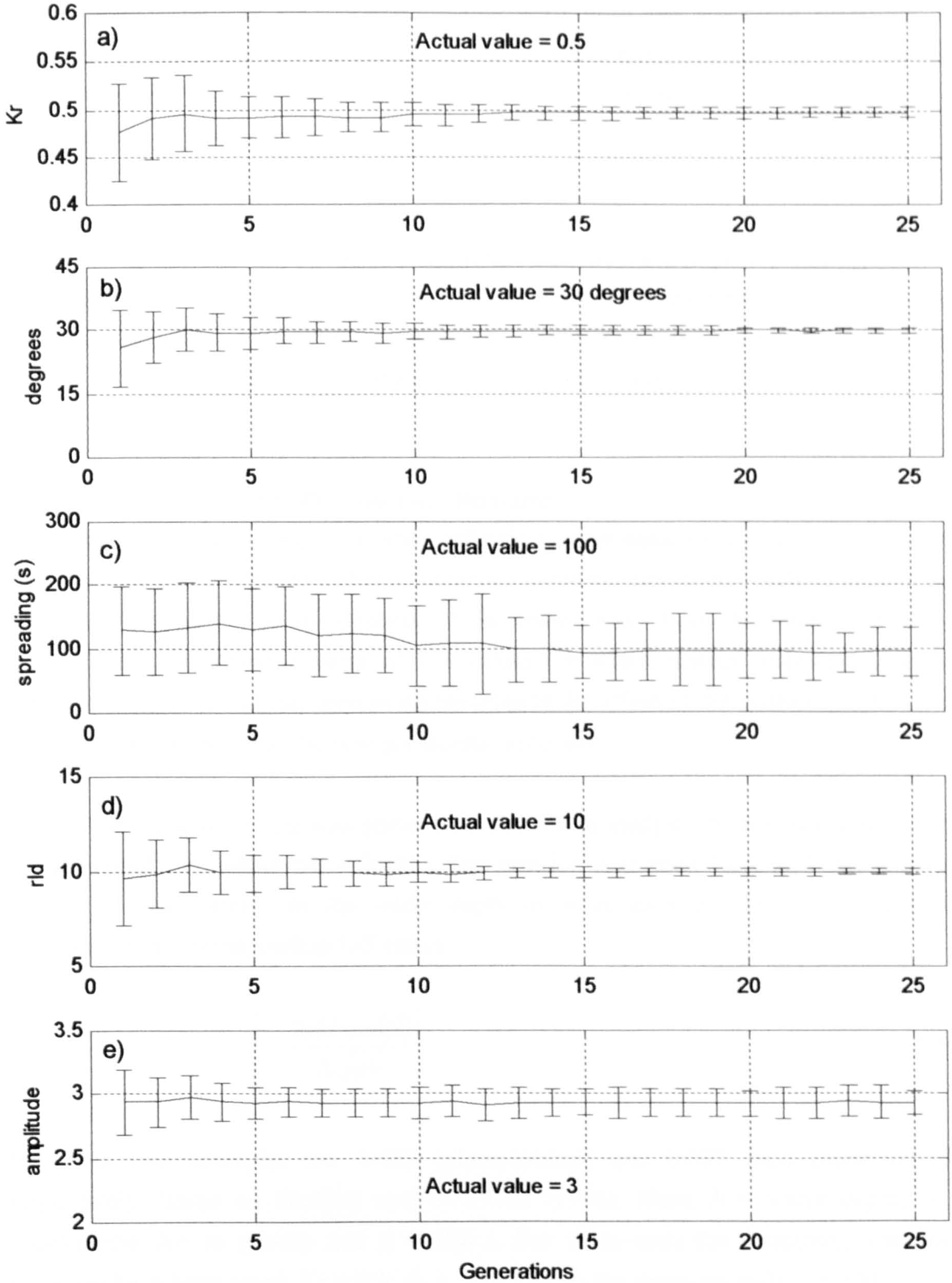

Figure 5.15 A stability / repeatability check for a) reflection coefficient; b) principal wave direction; c) spreading parameter; d) reflection line distance and e) wave amplitude. This example has 20% added noise.

25 generations the spreading function shows an 8% underestimate of the defined value of 100. This is almost certainly due to the low sensitivity of the combined fitness function to variations in the spreading parameter (see figure 5.13c). Other tests not

shown here show that the uncertainty associated with the spreading parameter is reduced if a broader directional spread is used in this analysis (smaller *s*). This result is to be expected given the sensitivity analysis on the spreading parameter presented previously.

The tests described above were conducted without any added noise. Figure 5.15 shows a repeat of this test with 20% added noise. Notice that the main impact of adding noise is to increase the uncertainty associated with the spreading parameter (Figure 5.15c). Encouragingly the estimates of the reflection coefficient remain unbiased unlike many other 2-D and 3-D methods for evaluating reflection coefficients.

5.4.3.3 Effect of Reflection Line Distance

As mentioned in the introduction, when reflections are present the applicability of either phase-locked and non phase-locked maximum likelihood directional analysis techniques is strongly dependent on the distance of the sensor array from the reflector (the *L/S* ratio). There also exists a range of *L/S* values for which neither technique yields a satisfactory solution. In this section we investigate the effect of the position of the array relative to the reflector on the new parametric solution.

To test the versatility of the new parametric directional analysis method two simulations are presented here where the reflection line position is located 14 m and 500 m away from the sensor array. In the water depth of 6 m used in these non-dispersive simulations the corresponding L/S ratios

$$\left(= \frac{2rld\cos(\theta)}{S\sqrt{gh}} \right) \qquad 5.10$$

for these two examples are 0.025 (phase-locked) and 0.882 (non phase-locked) respectively, based on Huntley and Davidson (1998). Here, h = water depth, g = acceleration due to gravity and S = 128 s. For these tests the remaining unknown variables have been set at, Kr = 0.5; θ_p = 150° (30° to the shore-normal); s = 100.

For comparison with the new parametric solution the MLM (non phase-locked) and MMLM (phase-locked) solutions were also computed (Isobe and Kondo, 1984). Here an iterative version of the MMLM has been used in order to evaluate the unspecified reflection line position (Davidson *et al.*, 1998). Figures 5.16 a-c show the phase-locked simulation for the MLM, MMLM and parametric solution respectively. In each case the target (solid lines) and actual frequency and directional distributions are projected onto the side panels of these plots. Both the target and estimated data have been normalised by the maximum value of the target, for ease of comparison on the same plot.

Notice that the MLM (Figure 5.16a) is severely effected by the presence of phase-locked reflections and shows very large errors in the directional distribution. Conversely, the MMLM (Figure 5.16b) accurately locates the reflection line position and produces an estimate that is close to the target values. The new solution (Figure 5.16c) provides a near perfect representation of the target directional spectrum.

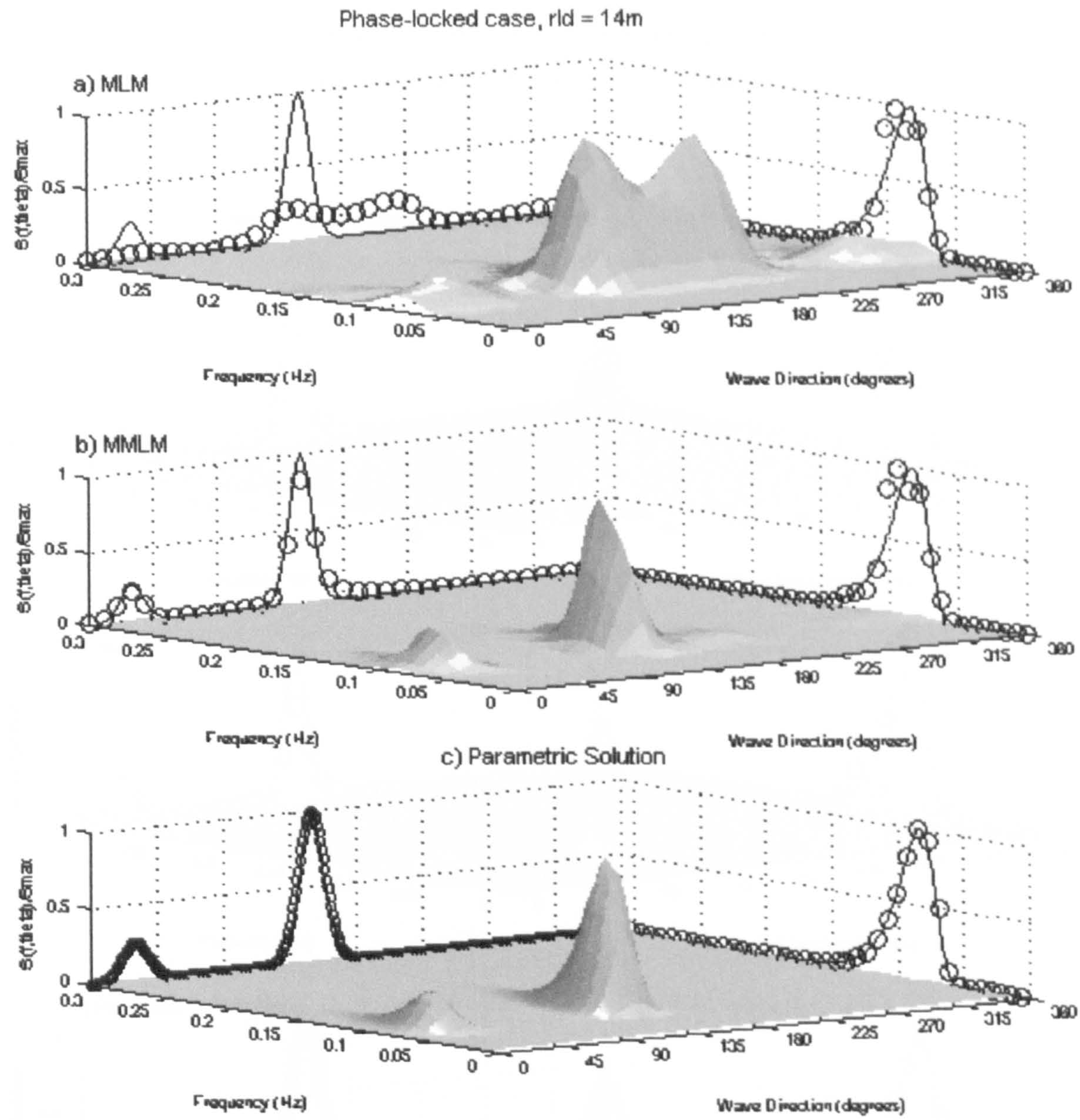

Figure 5.16 Directional analysis of simulated data (Kr = 0.5, $\vartheta_p = 150^o$, s = *100,* rld = *14 m,* L/S = *0.025) a) MLM; b) MMLM; c) New Parametric Solution.*

Further offshore (500 m) the performance of the MLM (Figure 5.17a) is now much improved, with the importance of the phase-locked components being effectively smoothed over by the spectral analysis procedure. The MMLM method however is starting to show the presence of some spurious peaks at predicted nodal locations in the directional spectrum (Figure 5.17b). As we will see later, in real data sets these spurious peaks are likely to be very large indeed due to the amplification of uncorrelated noise at the predicted nodal locations. The new parametric solution still gives excellent results (Figure 5.17c).

These simulations indicate that the new method may be accurately applied in the presence or absence of wave reflections, at any distance from the reflector and without prior knowledge of the reflection line position. Thus, the solution is potentially far more robust than existing phase-locked and non phase-locked techniques. The following section investigates the performance of the three directional analysis methods on field data.

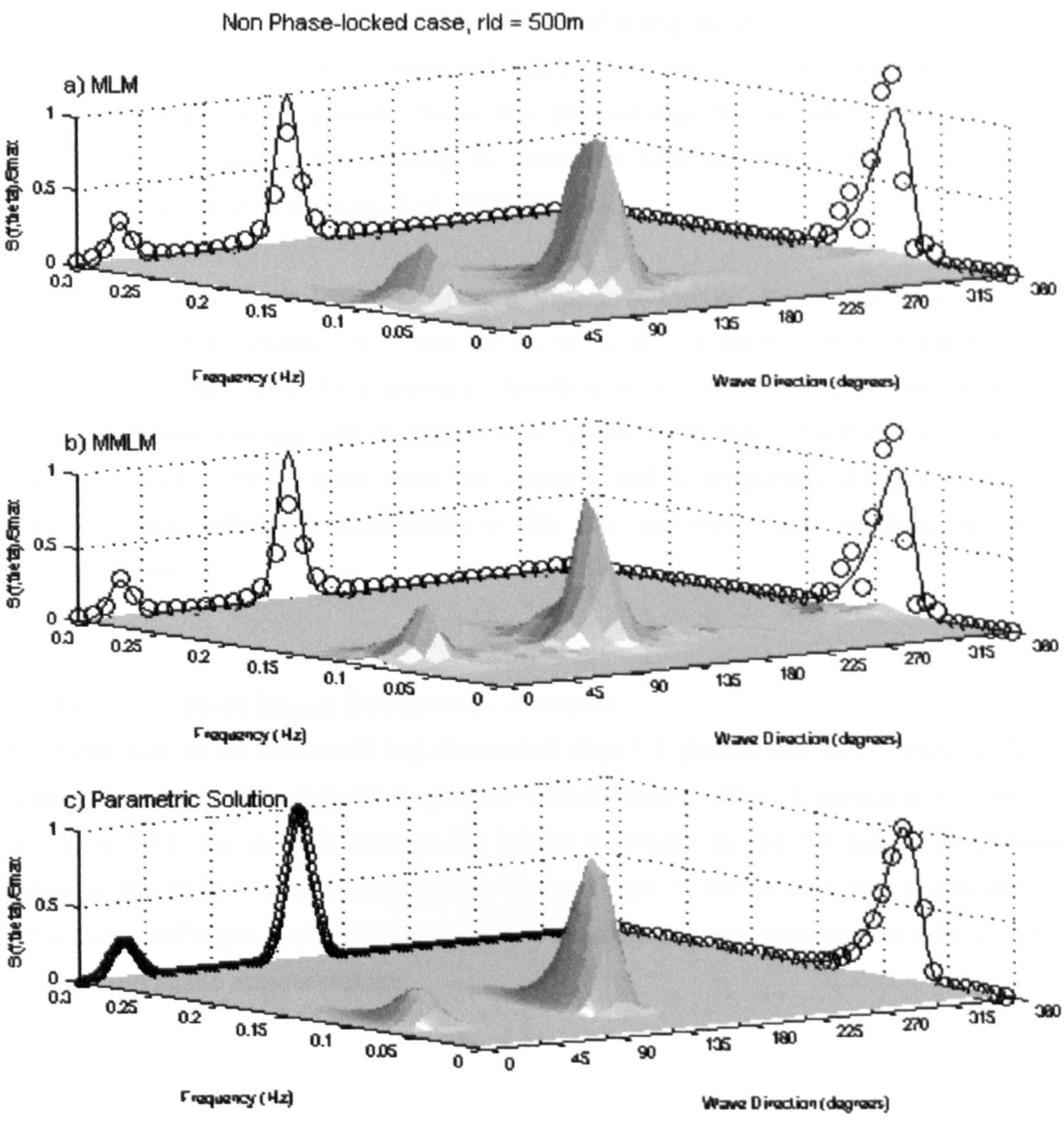

Figure 5.17 Directional analysis of simulated data (Kr = 0.5, $\vartheta_p = 150^o$, s = 100, rld=500m, L/S=0.882). a) MLM; b) MMLM; c) New Parametric Solution.

5.4.4 Field Tests

Data from two different localities are analysed here in order to determine the performance of the new parametric solution in both phase-locked and non phase-locked environments. Data were recorded from a purpose built wave recording system consisting of a series of 6 pressure transducers connected to a central signal conditioning and data storage unit via armoured cables. 12 minute data records were recorded at 2 Hz, every 3 hours, for the duration of several months at each site.

In the first phase-locked example the sensor array is positioned in less than 7 m of water, approximately 8 m seaward of a rubble-mound breakwater at Elmer, in West Sussex, UK. The structure is a low crested rubble mound breakwater of reef type. The original structure consisted of 4-8 tonne carboniferous limestone blocks. The stability of the provisional structure was later improved through the addition of 6-10 tonne syonite blocks to its seaward face. The gradient of the reflecting surface of the final structure is approximately 1:1.55. Nearly a thousand independent records were obtained using this system over a six-month period. These data showed that typical reflection coefficients were between 0.2 and 0.7 depending on wave and tidal conditions. Full details of the field site are given in Davidson *et al.*, (1994, 1996).

The second (non phase–locked) site is a highly reflective impermeable sea wall at Alderney, Channel Islands, UK. Here the sensor array is located in approximately 20 m of water 123 m seaward of the seawall (Davidson *et al.*, 1998). Alderney Breakwater is a 12 m high near vertical wall of granite with rubble in-fill built on a rubble mound. It is open to energetic swell wave from the Atlantic and is frequently damaged by wave attack. Typical reflection coefficients at this site are very high, attaining values of between 0.8 to 1.0.

5.4.4.1 Rock Island Breakwater Analysis

A typical plot of the measured and theoretical Eqn 5.1 phases and amplitudes of the 21 unique estimates in the 6x6 cross-spectral density matrix after 15 generations is shown in Figure 5.18. As the GA evolves the points converge on the 1:1 line. The absolute values of the phases have been plotted in Figure 5.18b. It can be seen that due to the low reflection coefficient (0.4) in this example progressive wave components lead to a full range in the phase measurements.

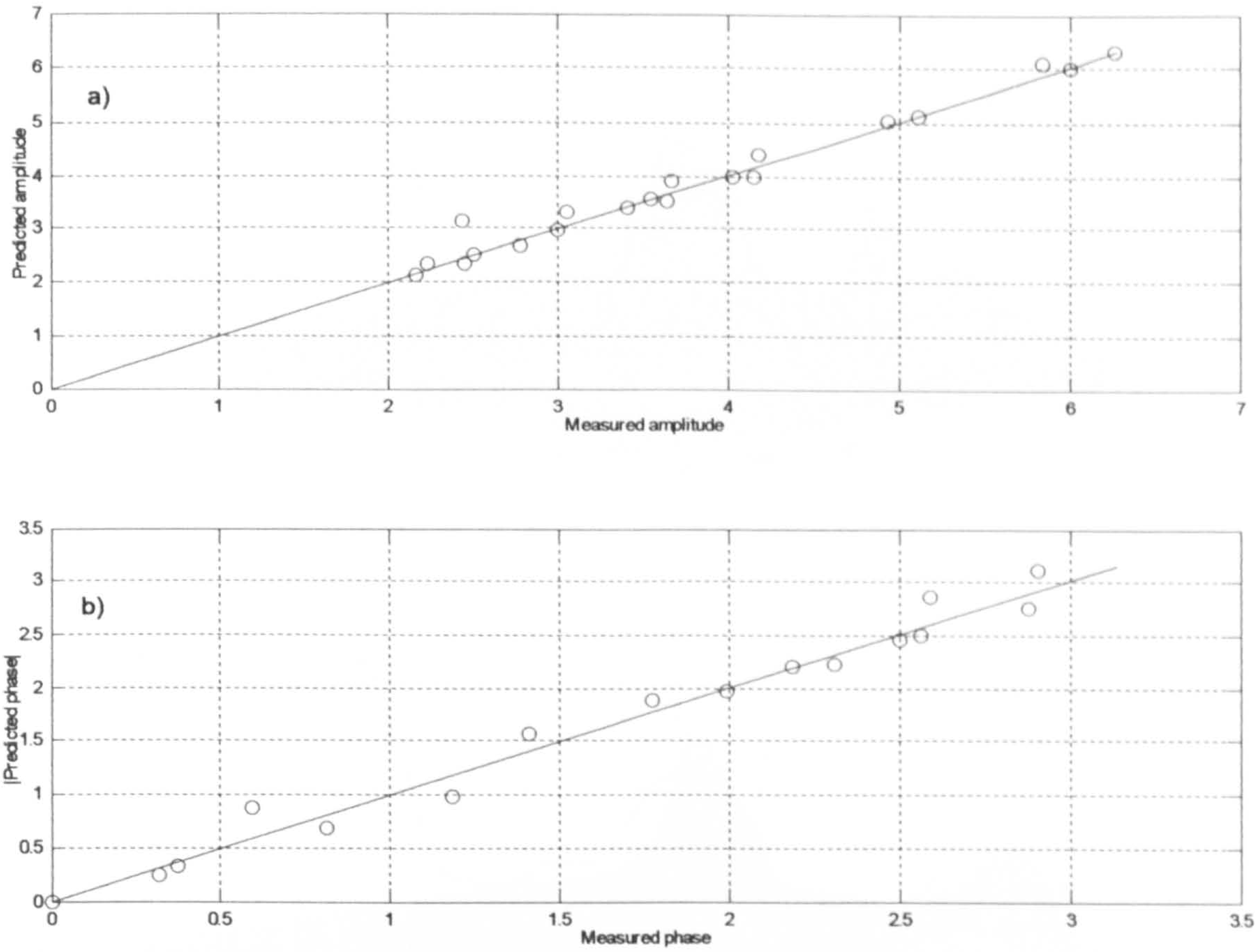

Figure 5.18 Measured versus estimated amplitude (a) and phase (b) from the new parametric solution after 10 generations. Field data collected from Elmer, West Sussex.

Directional analysis of data collected from the rock-island breakwater on the July 5 1992 can be seen in Figure 5.19. These data were collected in a phase-locked regime with an *L/S* value of 0.02. For comparison the MLM, MMLM and new parametric solution have all been applied to the same data set. Even though the target spectrum is not known for the field data it can be seen that the MLM gives a rather broad and irregular representation of the directional wave field. The MMLM provides a sharper solution although there appear to be some anomalous peaks propagating at right angles to the breakwater. The new parametric solution (Figure 5.19c) provides the clearest pattern of incident and reflected waves, more consistent with the expected narrow directional spread in this depth of water. Similar values for the reflection coefficient and peak direction are obtained from the MMLM (Figure 5.19b) and the new method (Figure 5.19c).

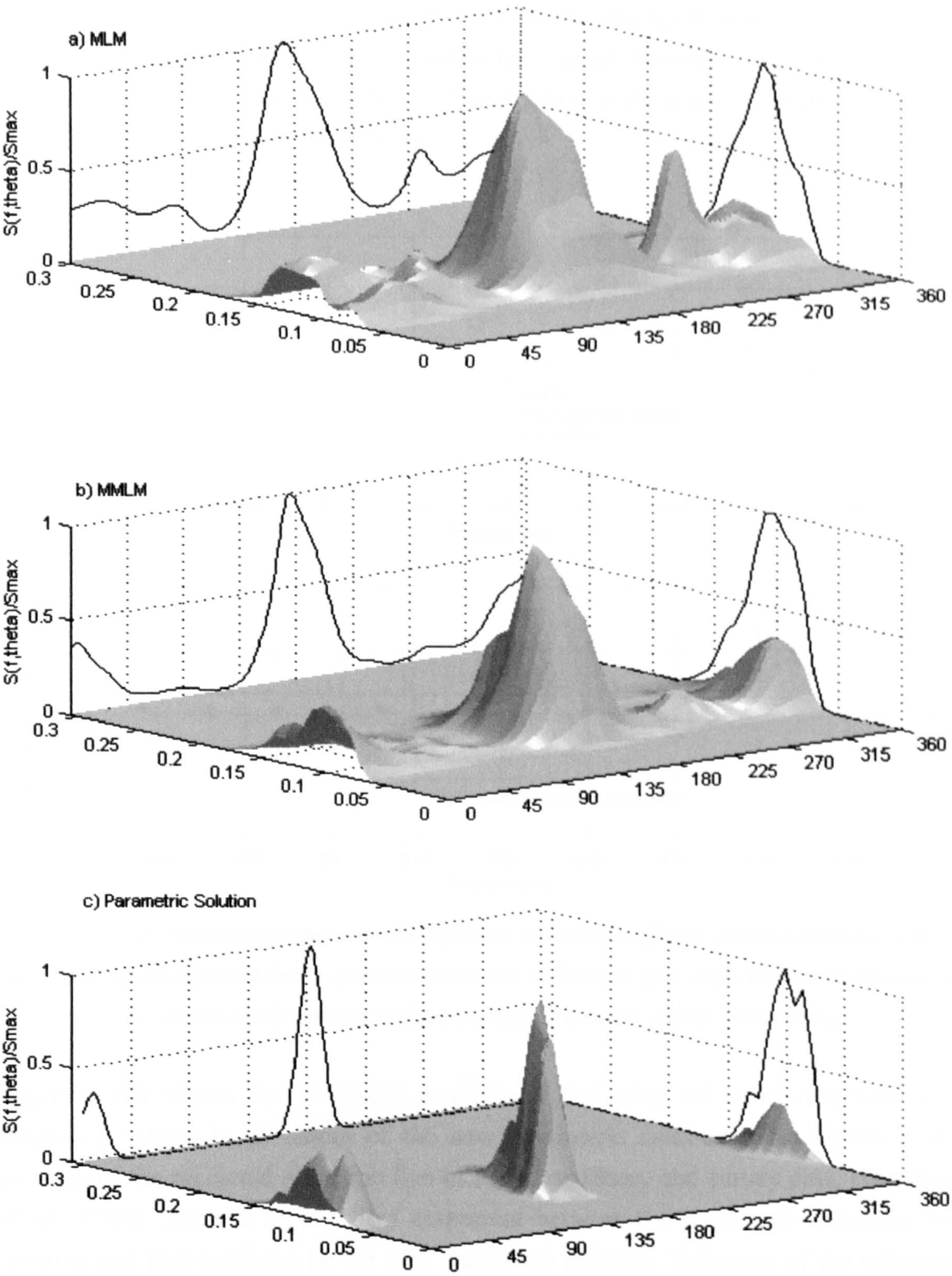

Figure 5.19 Directional analysis of field data collected from Elmer, West Sussex using a) the MLM; b) the MMLM and c) the new parametric solution. (phase-locked example).

Figure 5.20a shows the frequency dependent reflection function computed using the new parametric method, MMLM and the 2D reflection analysis of Gaillard *et al.*, (1980). Here, data is plotted in only the most energetic region of the spectrum, which is defined as those frequencies containing a variance of greater than 5% of the spectral-peak value. It can be seen that that there is a reasonable agreement between all three estimates of K_r. The agreement is particularly good between the new parametric solution and the 2D method. The MMLM seems to provide slightly higher estimates of the reflection coefficient in this example.

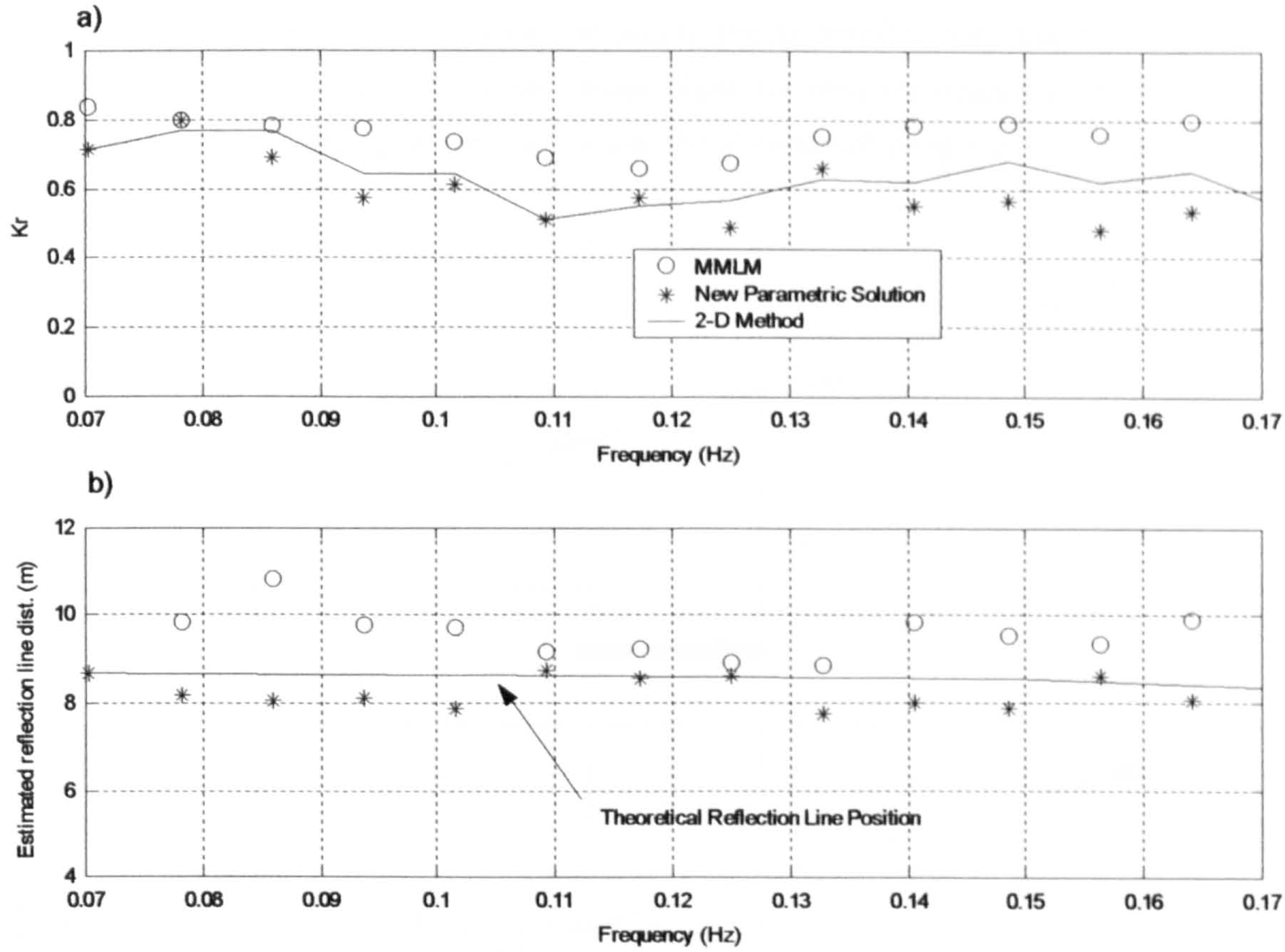

Figure 5.20 a) Comparison of the frequency dependent reflection coefficient obtained using the MMLM, 2-D reflection analysis and the new parametric solution. b) Estimate of the reflection line position using the iterative MMLM, theory and new parametric solution. (Elmer, West Sussex).

Figure 5.20b shows the estimated position of the point of wave reflection with frequency, which is an output of the new parametric solution. Also shown is the position of the predicted reflection line using linear theory and survey data, (Davidson *et al.*, 1998). There is an excellent agreement between the theoretical reflection line position and that predicted by the new parametric solution. Estimates of the reflection line position using the iterative MMLM are also shown in Figure 5.20b. Both estimates of the reflection line position appear similar to the theoretical value around the spectral peak frequency (0.1Hz), but the MMLM tends to predict larger values at other frequencies.

5.4.4.2 Sea Wall Analysis

Data from Alderney is collected in the non phase-locked regime with an L/S ratio that is approximately an order of magnitude higher than the Elmer example shown previously. Reflections are particularly high (> 0.8) from this near vertical impermeable sea wall. An example of the measured and predicted cross-spectral phases and amplitudes for this site are shown in Figure 5.21. Notice that due to the high reflection, phase estimates and prediction at this site typically have values close to zero (in-phase) or π (anti-phase) indicating a stable standing wave system and the absence of progressive components.

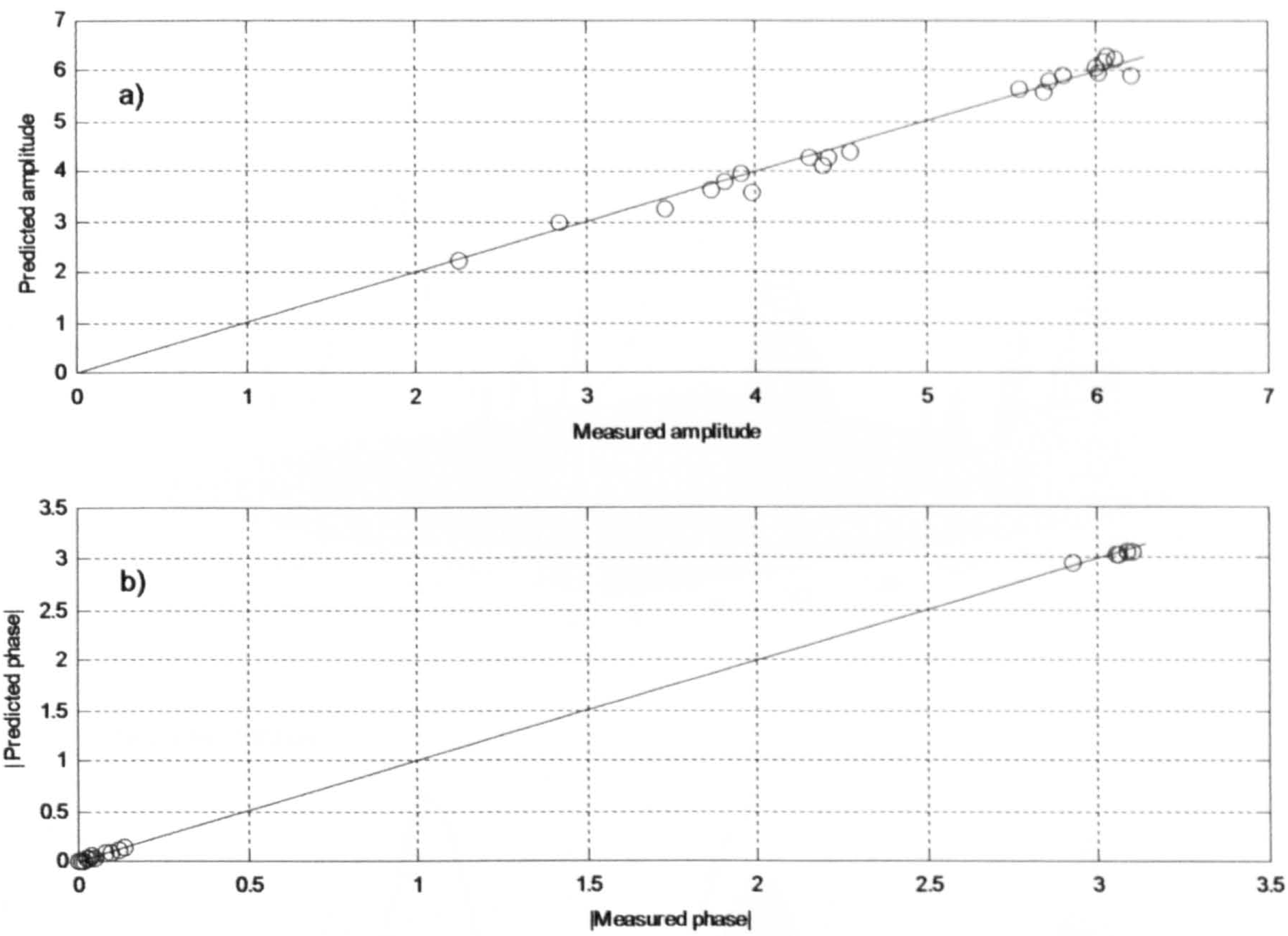

Figure 5.21 Measured versus estimated amplitude (a) and phase (b) from the new parametric solution after 10 generations. Field data collected from Alderney, Channel Islands, (non phase-locked example).

Directional analysis of data from Alderney can be seen in Figure 5.22. The MLM performs significantly better in this environment with a clearly defined incident and reflected wave peaks. The MMLM however, shows several spurious peaks at predicted locations for nodes at specific sensor locations. This is due to the sensitivity of the MMLM to large amplification of noise, at the location of predicted nodes. Huntley and Davidson (1998) showed that the position of these spurious peaks could be easily determined. However, the effect is so large in this example (Figure 5.22b) it is doubtful that these spurious peaks could be satisfactorily removed.

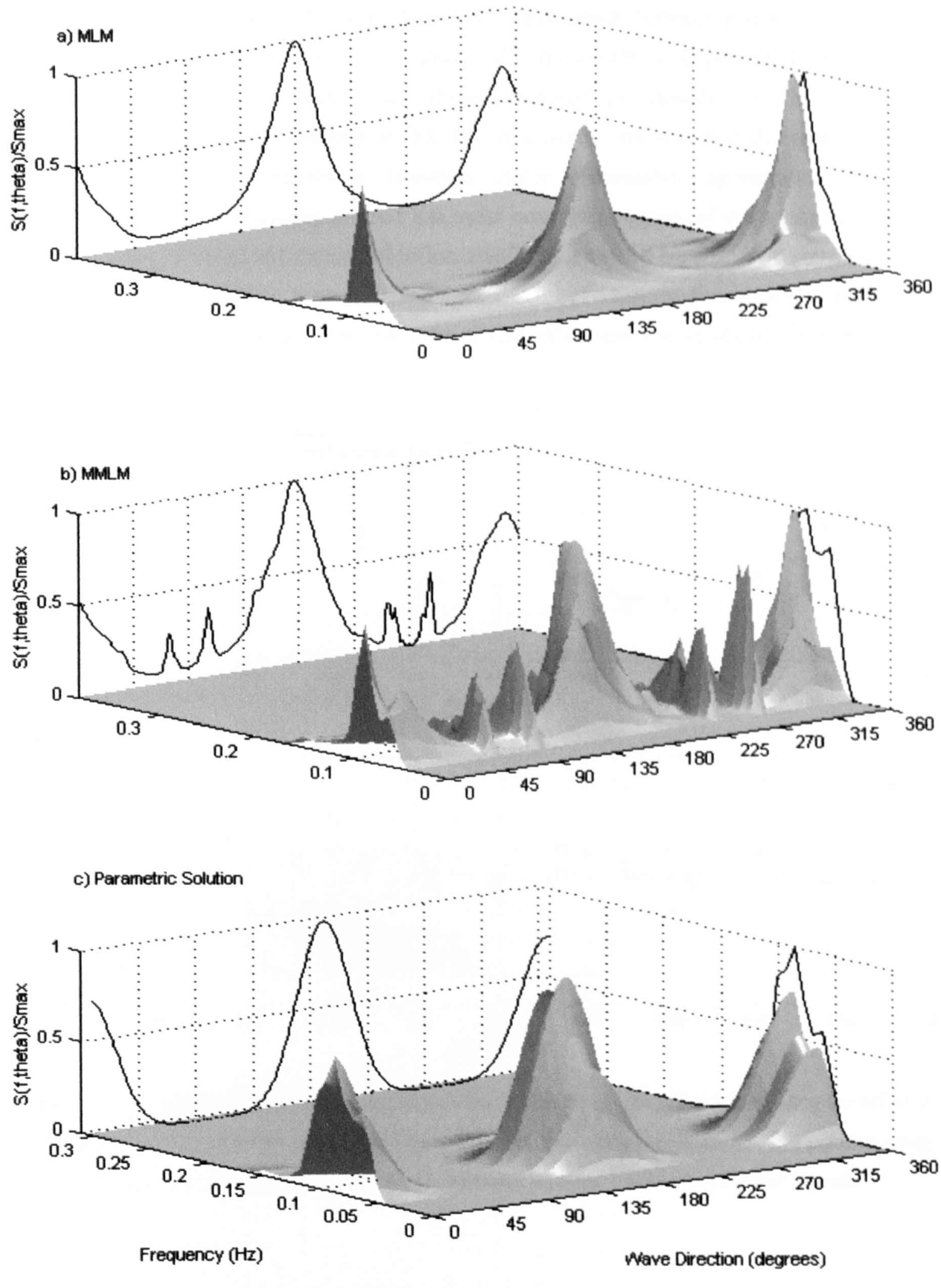

Figure 5.22 Directional analysis of field data collected from Alderney, Channel Islands using a) the MLM; b) the MMLM and c) the new parametric solution. (non phase-locked example).

The new parametric method also provides a realistic solution to the directional wave spectrum that compares quite closely to the MLM estimate, proving its versatility in both phase-locked and non phase-locked environments.

Figure 5.23a shows the estimated frequency dependent reflection coefficient for the directional wave spectrum shown in figure 5.22. As would be expected, these estimates of reflection are much higher than those obtained previously for the rock-island breakwater. Here all three estimates (MLM, parametric solution and 2D method) of the frequency dependent reflection function show reasonable agreement. All three reflection-estimates converge around the most energetic region of the spectrum (around 0.1 Hz). Thus, a weighted mean reflection coefficient would be similar regardless of the technique used. Similarly, there is good agreement between the theoretical, MMLM and new parametric solution as to the location of the reflection line position (Figure 5.23b).

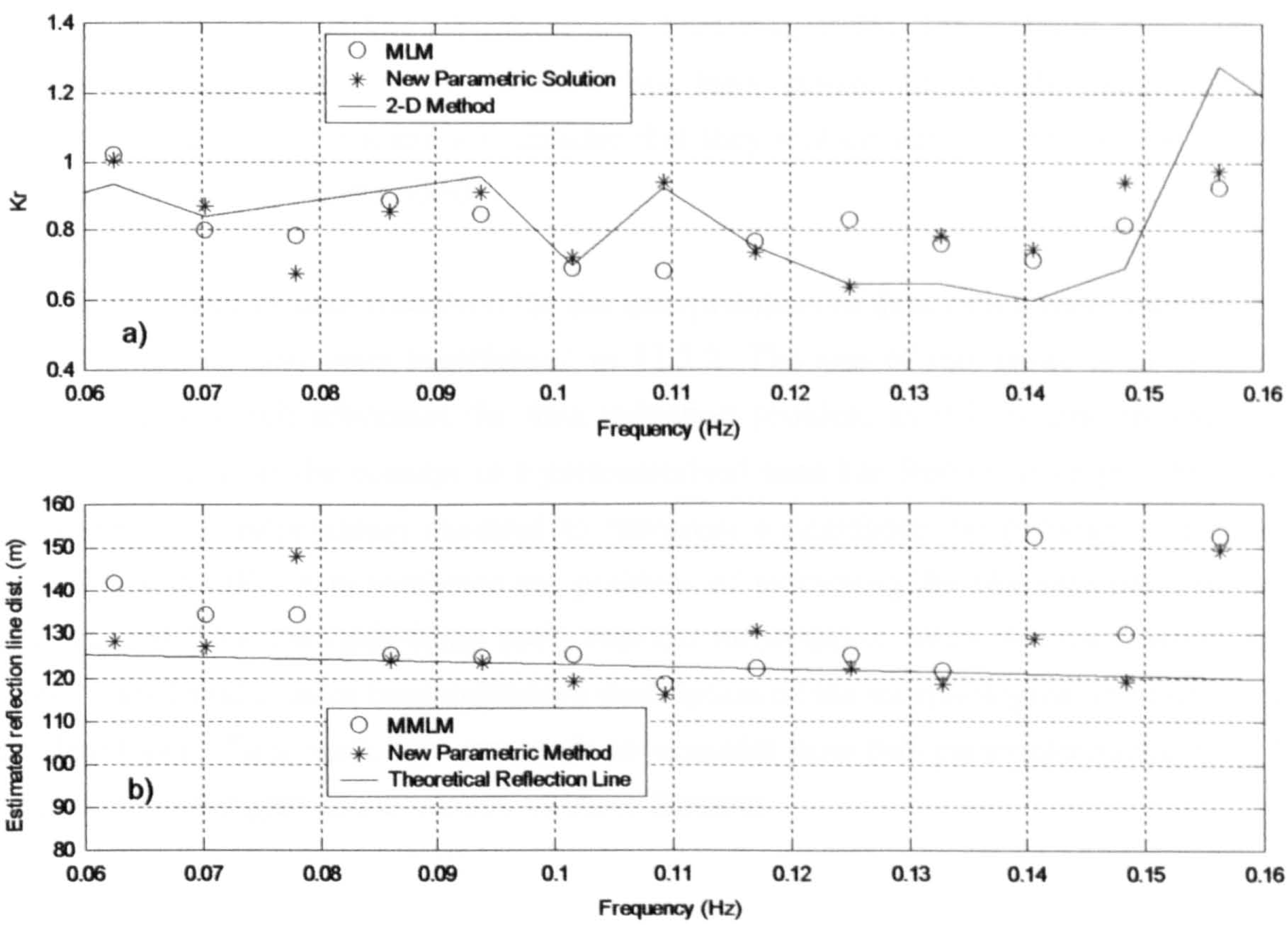

Figure 5.23 Comparison of the frequency dependent reflection coefficient obtained using the MLM, 2-D reflection analysis and the new parametric solution. b) Estimate of the reflection line position using the iterative MMLM, theory and new parametric solution. (Alderney, Channel Islands).

5.5 Case Study # 4: Application of Evolutionary Computation Techniques to the Development of a Morphologic Descriptor for Nearshore Sandbar Features[4]

Until recently, nearshore morphological research has focused predominantly on small scale (mm to m and seconds to hours) sediment dynamics and its relationship to the hydrodynamic regime. The provision of Large Scale Coastal Behaviour (LSCB, length scales of 1 km to 100 km and temporal scales of the order of months to decades) data sets has been highlighted as a priority activity for the nearshore research community (Thornton *et al.*, 2000). These data sets will provide a wealth of information on morphological processes occurring at large scales. At present only a few of these data sets are in existence; Jarkus (Wijnberg and Terwindt, 1995), Duck (Plant *et al.*, 1999), Argus (Holland *et al.*, 1997). Already they have started to provide much valuable information and it is reasonable to assume that they will continue to reveal new insights as these data sets are augmented.

The significance of data reduction for the interpretation of data rich coastal morphology data sets has already been highlighted in §2.3.2. The aim of this study is to present a methodology which addresses the data reduction problem as it is related to nearshore data sets. It utilises the concept of a parameterised sand bar feature descriptor to reduce the quantity of information required to represent a nearshore morphology in a spatial sense. Specifically, it investigates the problem of extracting the characteristics of sand bar features from the underlying bathymetrical information. With this data reduction it is envisaged that a more comprehensive description of the morphological evolution may be developed. This work then proceeds to consider how this parameterisation may be utilised to investigate the evolution of these features.

5.5.1 Methodology

When considering data reduction as it may be applied to nearshore topography it is necessary to sacrifice some information. The approach taken in this study is to simplify the nearshore topography to an underlying surface on which perturbations, as represented by sand bars, exist. This is consistent with the philosophy of observing the gross features or morphology of a system rather than the small-scale spatial variance.

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[4] A reduced version of this section has been presented at Coastal Dynamics '01, Lund, Sweden. as Kingston, K.S. and Davidson, M.A., 2001, 'A Parametric Morphologic Descriptor for Nearshore Sandbar Features'.

My contribution to this study was the recognition of the requirement of a data reduction approach for the interpretation and analysis of large scale morphological data sets. The use of a parametric approach seemed like, and subsequently proved to be, an ideal candidate. Mark Davidson contributed a critical review of the study and valued comments at the manuscript stage.

The sand bar features are represented in a parametric manner. This is done by extending to three dimensions the concept of fitting gaussian shapes to cross-shore profiles to identify sand bars (Plant *et al.*, 1999). The chosen representation, z_{bar} (equation 5.11) has a set of 10 parameters describing the location and magnitude of the bar feature.

$$z_{bar} = A.\exp\left(-\frac{\left(x - x_0 + a\cos\left(\frac{360\,(y_0 - y)}{\lambda} + \phi\right)\right)^2}{\left(\frac{\omega}{2}\right)^2}\right).\Psi\left(y, y_0, L, \kappa_1, \kappa_2\right) \qquad 5.11$$

where x_0, y_0 are the cross-shore and longshore locations of the bar shape respectively
- A is the maximum bar amplitude
- ω is the maximum bar width
- L is the maximum bar length
- κ_1 is the degree of attenuation of amplitude towards the ends of bar
- κ_2 is the degree of the asymmetric bias of the degree of attenuation of bar amplitude
- λ is the wavelength of the longshore bar rhythmicity
- a is the amplitude of longshore bar rhythmicity
- ϕ is the phase of longshore bar rhythmicity.

The degree of attenuation of the alongshore bar amplitude is calculated by a cosine taper function, Ψ. It divides the length of the bar into 3 regions each having a differing degree of attenuation of the maximum amplitude, A. Outside of these regions, $\Psi = 0$, thereby defining the longshore extent of the bar. The extent of the regions in the longshore direction and the corresponding magnitude of the attenuation are given by equations 5.12a,b,c.

$$y_0 - \frac{L}{2} \le y < y_0 - \frac{L}{2} + f_1 L \quad , \qquad \Psi = \sin\left(y\frac{\pi/4}{Lf_1}\right) - \left(y_0 - \frac{L}{2}\right)\frac{\pi/4}{Lf_1} \qquad 5.12a$$

$$y_0 - \frac{L}{2} + f_1 L \le y < y_0 + \frac{L}{2} - f_2 L \quad , \quad \Psi = 1 \qquad 5.12b$$

$$y_0 + \frac{L}{2} - f_2 L \le y < y_0 + \frac{L}{2} \; , \; \Psi = \sin\left(y\frac{\pi/4}{Lf_2}\right) - \left(y_0 + \frac{L - Lf_2}{2}\right)\frac{\pi/4}{Lf_2} - \frac{\pi}{4} \qquad 5.12c$$

where
$$f_1 = \kappa_1 \kappa_2$$
$$f_2 = \kappa_1 (1 - \kappa_2) \qquad 5.12d$$

It is capable of reducing a bathymetry of several thousand spot levels, such as the numerical example shown in figure 5.24 to a mean surface plus an appropriate number of bar features. In this simulation the underlying surface is given by a Bruun profile ($z = ax^{2/3}$) repeated in the longshore direction, with two bar features each described by 10 parameters. This results in a total of 21 parameters to describe the surface. This simplification represents a dramatic data reduction while still encapsulating the significant morphological features.

Due to the simplistic nature of the representation, it is only the gross features which are identifiable and it is not possible to resolve smaller scale features such as rip channels. This is acceptable as it is the larger scale features which will dominate in long term evolution.

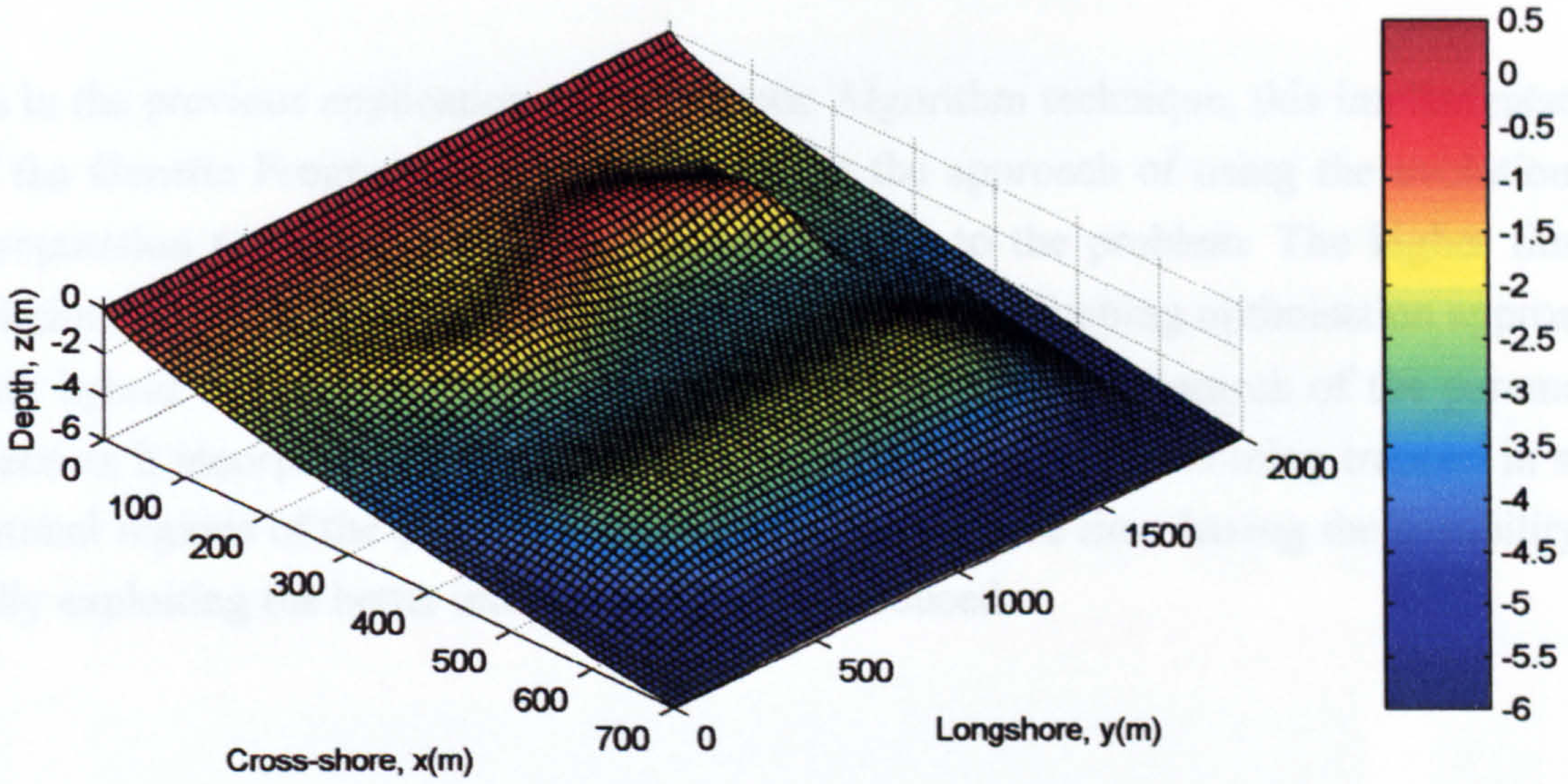

Figure 5.24 Example of a parametric bathymetry

Having established a model which may describe various morphological states, it is necessary to establish a methodology for fitting the model to a particular bathymetry. Numerically this is a problem in high dimensional optimisation. The values the parameters may take also need to be maintained within sensible ranges. The approach taken in this study is that of evolutionary computation.

In this study, a reduced version of the genetic programming paradigm originated by Koza (1992) is adopted. The functional set in this implementation consists of a function based on equations 5.11 and 5.12 and the addition operator. The purpose of the minimal functional set is to speed up the process of finding an appropriate solution to fitting the bathymetry. A more complete functional set of basic operators, without the user defined morphological operator, would also be able to provide a solution (this was confirmed during preliminary investigations), however the equivalent computational effort would be much greater.

The fitness function, ξ, for this study is the normalised residual between the original bathymetric surface, z and the estimated surface, z' as given by equation 5.13

$$\xi = \frac{1}{1 + \frac{\sum_{j=1}^{n}\sum_{i=1}^{m} z_{i,j} - z'_{i,j}}{mn}} \qquad 5.13$$

where m, n are the number of data points in the cross-shore and longshore directions respectively. A solution which has a perfect fit to the original bathymetric surface will have $\xi = 1$.

As in the previous application of the Genetic Algorithm technique, this implementation of the Genetic Programming paradigm adopts the approach of using the evolutionary computation processes to provide a good solution to the problem. The higher fitness solutions are then optimised using a variant on the hill-climbing optimisation approach. This hybrid technique is efficient in performing an extensive search of the parameter space as it incorporates characteristics which help prevent it becoming trapped in sub-optimal regions of the parameter space whilst at the same time having the capability of fully exploiting the better individuals that are produced.

5.5.2 Data Sets

To test the generality of the proposed technique, it is applied to data sets having different characteristics. These are bathymetries from a quasi 2-dimensional beach and a second data set consisting of video images of the wave breaking patterns observed at the quasi 2-dimensional site.

5.5.2.1 Egmond aan Zee, The Netherlands

Egmond aan Zee in the Netherlands is a quasi 2-dimensional beach characterised by a shore-parallel double sand bar system. The predominant forcing is by sea conditions from the North Sea. It is a micro-tidal beach with a semi-diurnal tide having a range of approximately 1.5m. During a six week period in Oct-Nov 1999, morphological data and wave climatology was acquired as part of the Coast3d field experiment. Direct bathymetric surveys were performed with the WESP. A sample of five of the surveys obtained are used in this study; namely those from 16/10/1998, 24/10/1998, 04/11/1998, 12/11/1998 and 19/11/1998, which are shown in figure 5.25.

These demonstrate an initial, essentially shore parallel double bar system which becomes more 3-dimensional in the longshore direction for the later surveys. Even though the increasing non-linearity of the bar features is not particularly visually apparent in the figures, the increase of non-linearity is especially true of the inner bar.

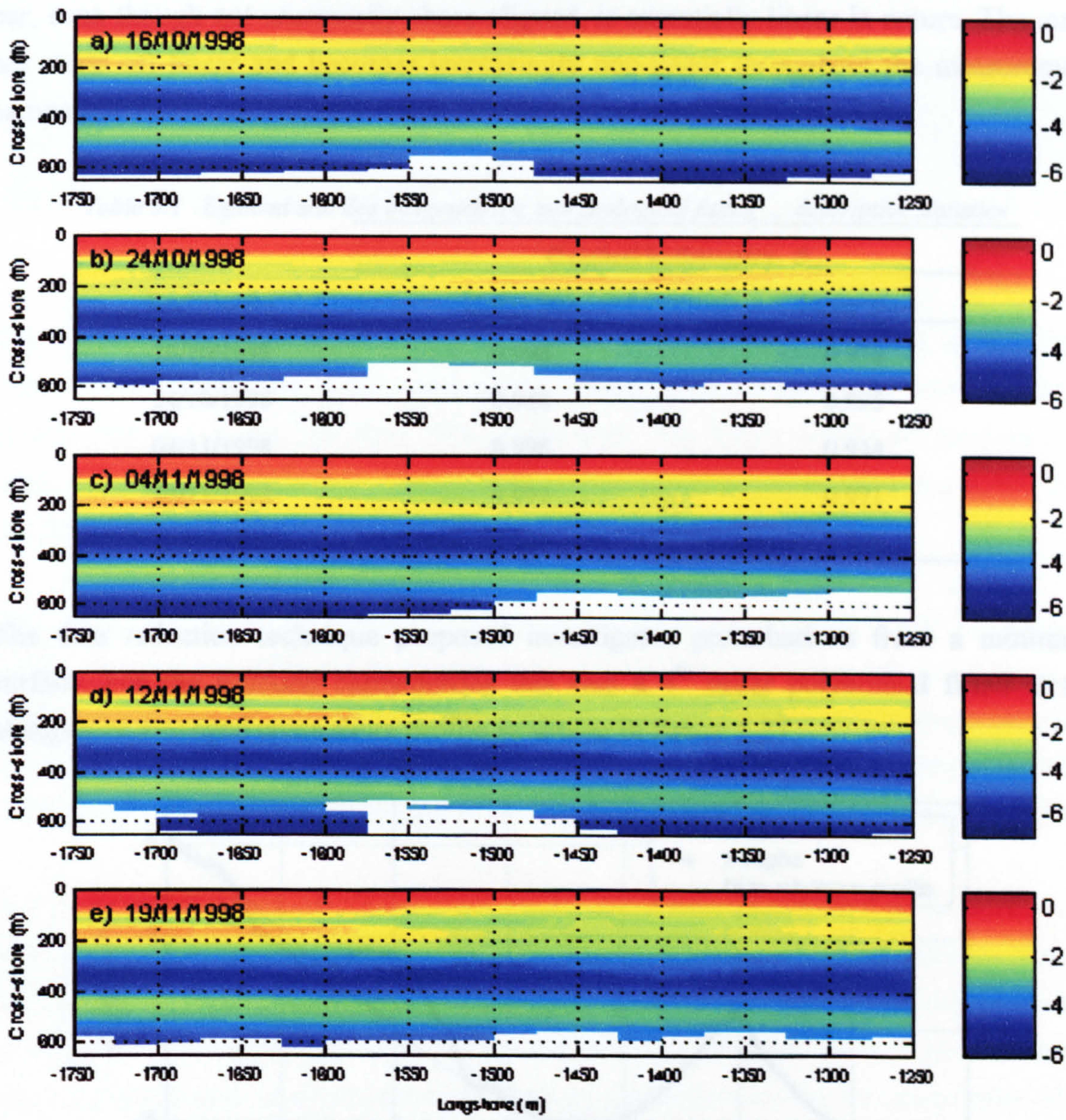

Figure 5.25 Egmond aan Zee bathymetries

To overcome this lack of clarity, a numerical technique for describing the non-linearity of the bar features is introduced. The longshore rhythmicity of a bar feature is given by ϑ, the curl. This parameter is most readily explained graphically as shown in figure 5.26. This is the ratio of the length measured along the spine of the feature to the shortest equivalent linear distance.

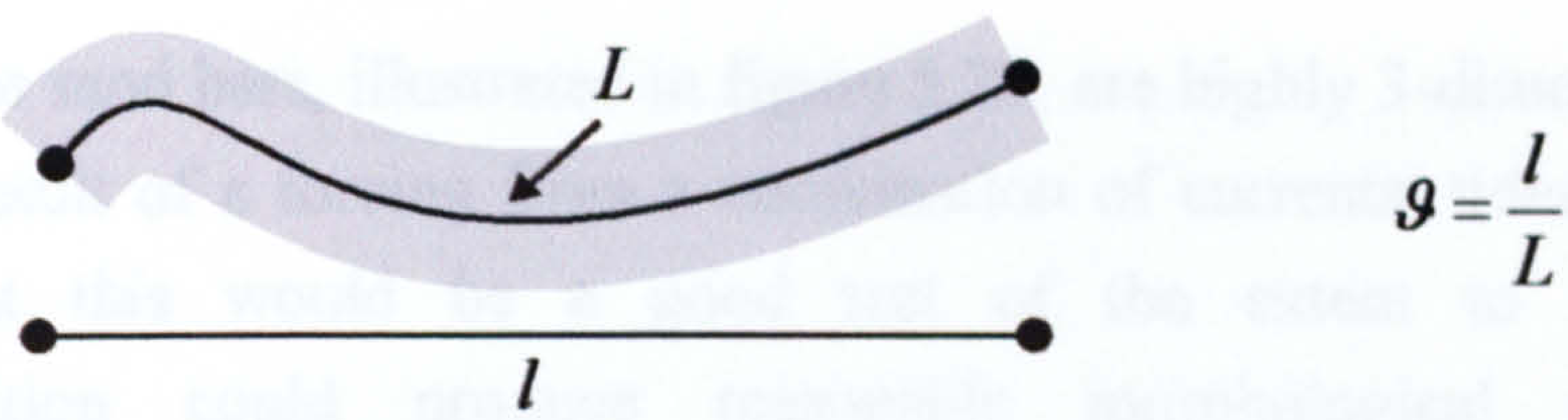

Figure 5.26 Non-linearity of a feature as represented by, ϑ, the curl of the feature

Linear features have ϑ =1, with this value decreasing with increasing non-linearity. Table 5.1 gives the values for the outer and inner bars shown in figure 5.25. The outer bar, even though not necessarily shore-aligned, is essentially linear in nature. The inner bar starts off linear and becomes increasingly non-linear throughout the measurement campaign.

Table 5.1 Egmond aan Zee bathymetries; morphological fitting ... descriptive statistics

	Original bathymetry, ϑ_{bar}	
Bathymetry	**Outer Bar**	**Inner Bar**
16/10/1998	0.998	0.978
24/10/1998	0.988	0.995
04/11/1998	0.998	0.914
12/11/1998	0.997	0.971
19/11/1998	0.997	0.929

The data reduction technique proposed investigates perturbations from a minimum surface. For the Egmond bathymetries this was a 4[th] order polynomial fitted to the alongshore averaged cross shore profile as shown in figure 5.27.

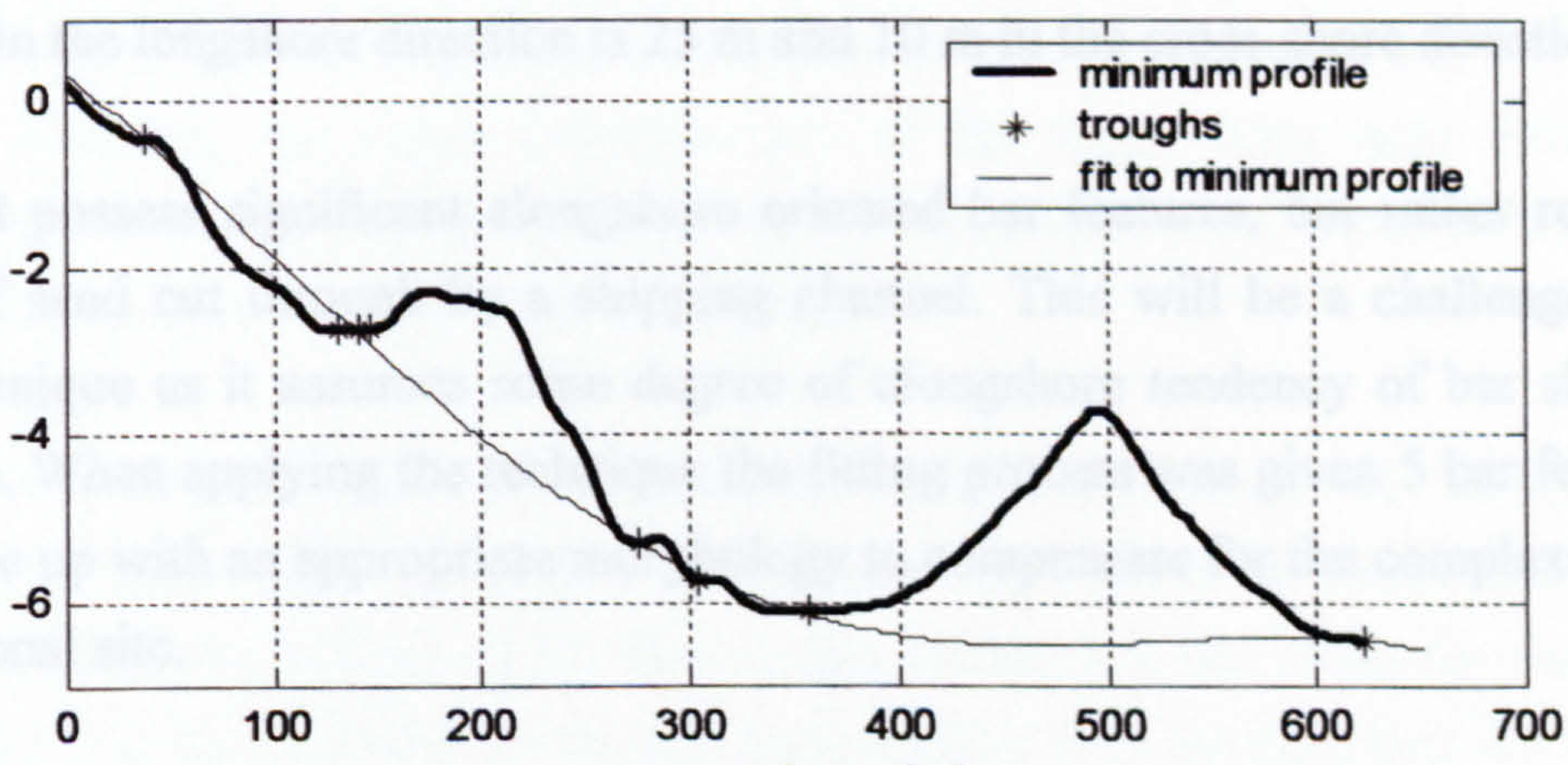

Figure 5.27 Cross-shore minimum profile for Egmond aan Zee

5.5.2.2 Teignmouth, UK

Teignmouth is located in the south-west of the UK. It is the estuary to the river Teign and is characterised by a system of sand bars (Robinson, 1975) which are formed at the mouth. These sand bars, illustrated in figure 5.28, are highly 3-dimensional in nature as they are a result of a forcing from a combination of currents, tides and waves. It was decided that this would be a good test of the extent to which the chosen parameterisation could produce reasonable morphological representations of bathymetric features.

Figure 5.28 Teignmouth Estuary, UK

The typical tidal range experienced are 1.7 m and 4.2 m for neap and springs tides respectively. Waves are short wind-driven waves, with a significant wave height of greater than 0.5 m for less than 10% of the year. The larger waves are generated by storms arriving from the east. The grain size distribution is mainly of coarse sand (d_{50} = 0.4 mm) with larger particles of 5-50 mm.

The application of the morphology fitting technique to the 3-dimensional Teignmouth site is significantly different to the previous 2.5-dimensional Egmond ann Zee site. A bathymetrical region from March 1999 covering an area of 950m longshore by 650m cross-shore at the mouth of the estuary was chosen as shown in figure 5.29. Grid resolution in the longshore direction is 25 m and 10 m in the cross-shore direction.

It does not possess significant alongshore oriented bar features, but rather regions or mounds of sand cut through by a shipping channel. This will be a challenge for the fitting technique as it assumes some degree of alongshore tendency of bar shape and orientation. When applying the technique the fitting process was given 5 bar features to use to come up with an appropriate morphology to compensate for the complexity of the 3-dimensional site.

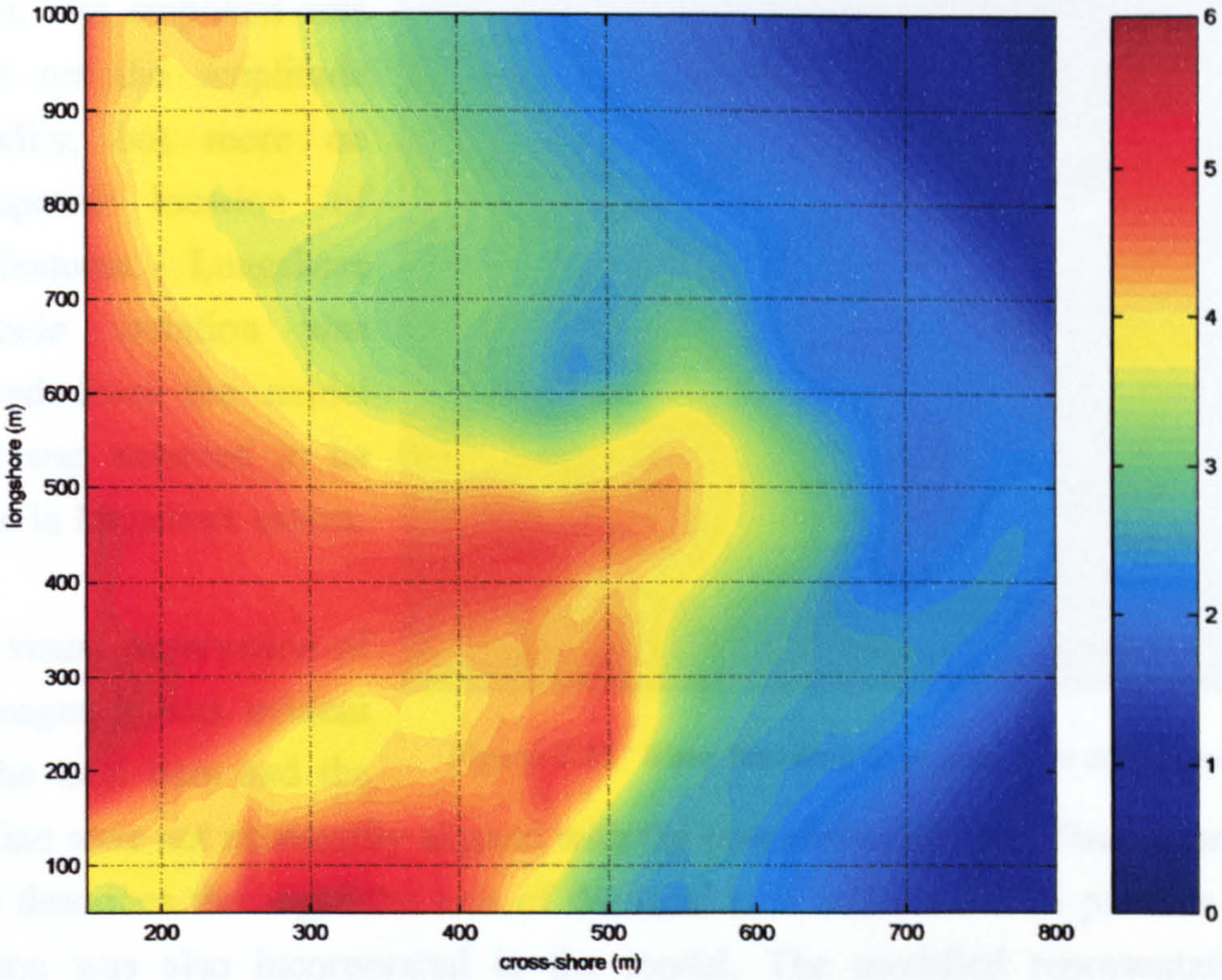

Figure 5.29 Teignmouth bathymetry, 10/03/1999

5.5.2.3 Egmond aan Zee Video Images

The sand bar system at Egmond aan Zee has been observed to migrate offshore in a cyclical manner over a period of 12-15 years. With this in mind it leads to the question of the utility of observing the evolution of the sand bars as represented by their parameterised form. In order to be able to track this evolution it is necessary to have a data set which will have sufficient temporal resolution of the spatial change. The Argus video monitoring system (Lippmann and Holman, 1989; Holland *et al.*, 1997) fulfils those requirements. As Argus provides one of the major long term data sets in existence, and is continually being updated, this technique could prove to be a useful approach to long term analysis of these data sets.

It has been shown (Lippmann and Holman, 1990; Kingston *et. al*, 2000) that the location of the wave breaking patterns may be used as a proxy for the underlying sand bar location as shown in figure 5.30. Thus in this section it is this proxy for the sand bar location that is to be identified by the parameterisation. It is assumed that the long term behaviour displayed by both the sand bars and the wave breaking patterns they generate will be identical. A selection of images, for which significant wave breaking was evident over the sand bars, were chosen from the period 03/08/1998 to 09/10/1999.

A modification of the parameterisation model was required for the video image analysis. As there is no direct measure of the amplitude of the sand bar features in the images, less emphasis was placed on the amplitude variability, but more on the spatial location of the features. Longshore amplitude variation was removed from the model and it was assumed to be infinite in longshore extent.

Figure 5.30 Wave Breaking over sand bars at Egmond aan Zee

From visual observation of the images it was evident that the sand bars and the shoreline were not necessarily aligned with the co-ordinate system. Thus a parameter, α, which describes the angle the axis of the sand bars make with the positive longshore direction was also incorporated in the model. The modified representation has 8 parameters as given by equation 5.14.

$$bar(x,y) = A.\exp\left(-\frac{\left(x - x_0 + (y_0 - y)\tan\alpha + a\cos\left(\frac{360(y_0 - y)}{\lambda} + \phi\right)\right)^2}{\left(\frac{\omega}{2}\right)^2}\right) \qquad 5.14$$

When fitting the model to each image, a similar approach was taken as for the case of bathymetries. Initially a planar surface was fitted to the image to remove any background trends. The remaining image was then re-scaled to maximise contrast. The chronological evolution of the parameters was considered to be important. Thus the fitting to each image was seeded with the parameter results from the previous image. This required the outer and inner bars to be treated in isolation.

5.5.3 Morphology Fitting To Data Sets

This section presents the results of applying the morphological fitting technique to the chosen data sets, accompanied by a discussion of its success. In this study, the resultant surface of the fitting technique will be referred to as the morphology as it will generally be a smoothed version of the original surface.

5.5.3.1 Egmond aan Zee Bathymetries

To assess the results of applying the morphology fitting procedure to the Egmond aan Zee bathymetries two criteria are considered; the magnitudes of the residuals between the surfaces and the quality of fit for specific profiles. In addition to these, the quantification may be broken down into two considerations; firstly quality of fit in the cross-shore direction in terms of number and location of features, and secondly the reproduction of longshore non-linearities.

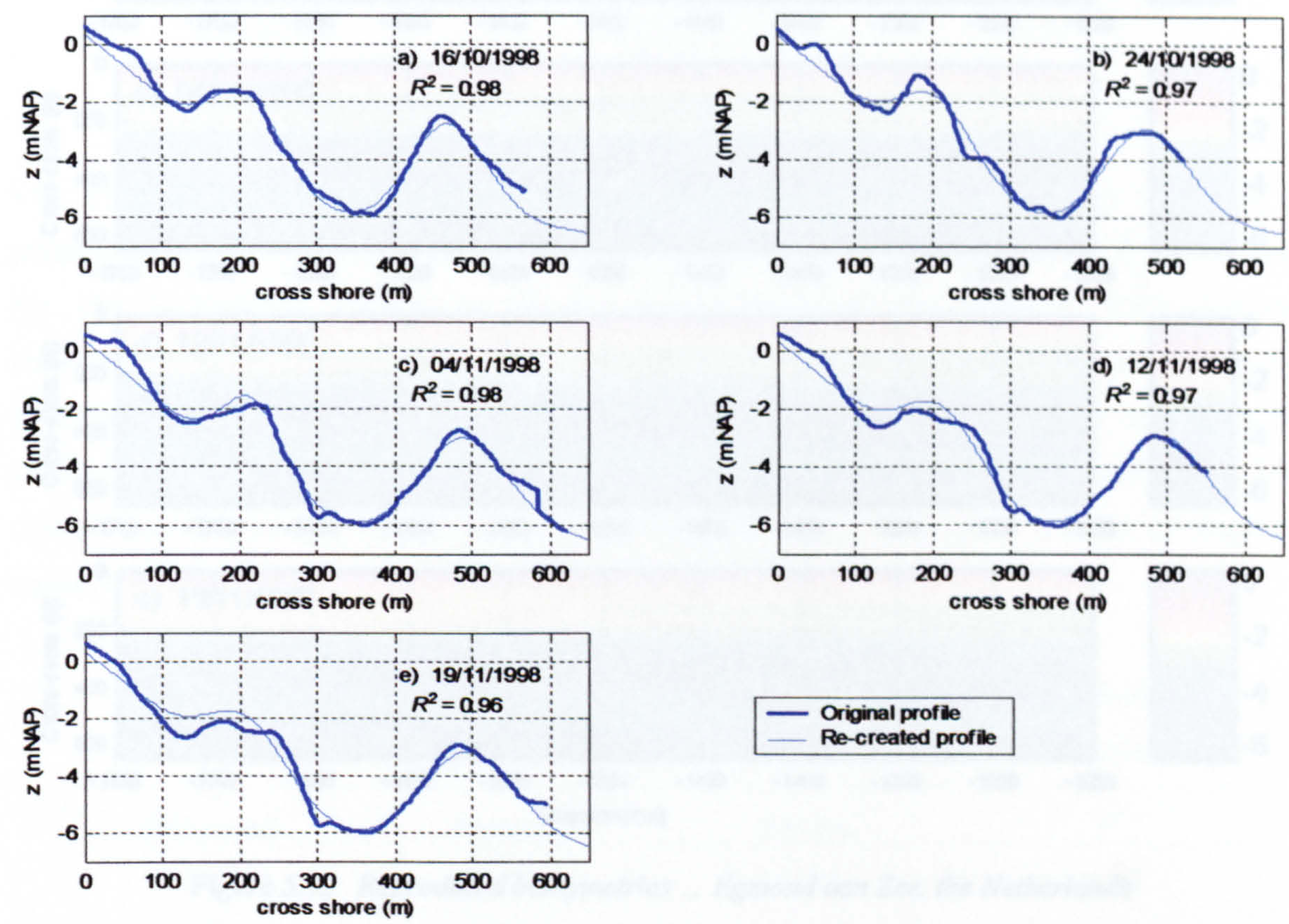

Figure 5.31 Cross shore profiles ... Egmond aan Zee, The Netherlands

To investigate the quality of fit in the cross-shore direction, a comparison of cross-shore profiles from the original bathymetry and recreated morphologies were considered. 5 sets of profiles (-1500 m longshore) for each of the survey dates are presented in figure 5.31. The relative location and magnitudes of the sand bars is reproduced remarkably well considering the simplicity of the model formulation, as indicated by the R^2 values of 0.96 or greater. Only when the inner bar starts to take a more 'platform' shape does the fit not correlate well with the original bathymetry. This is partly due to the constraint of having to concurrently produce a fit to the profile and simultaneously the longshore variability.

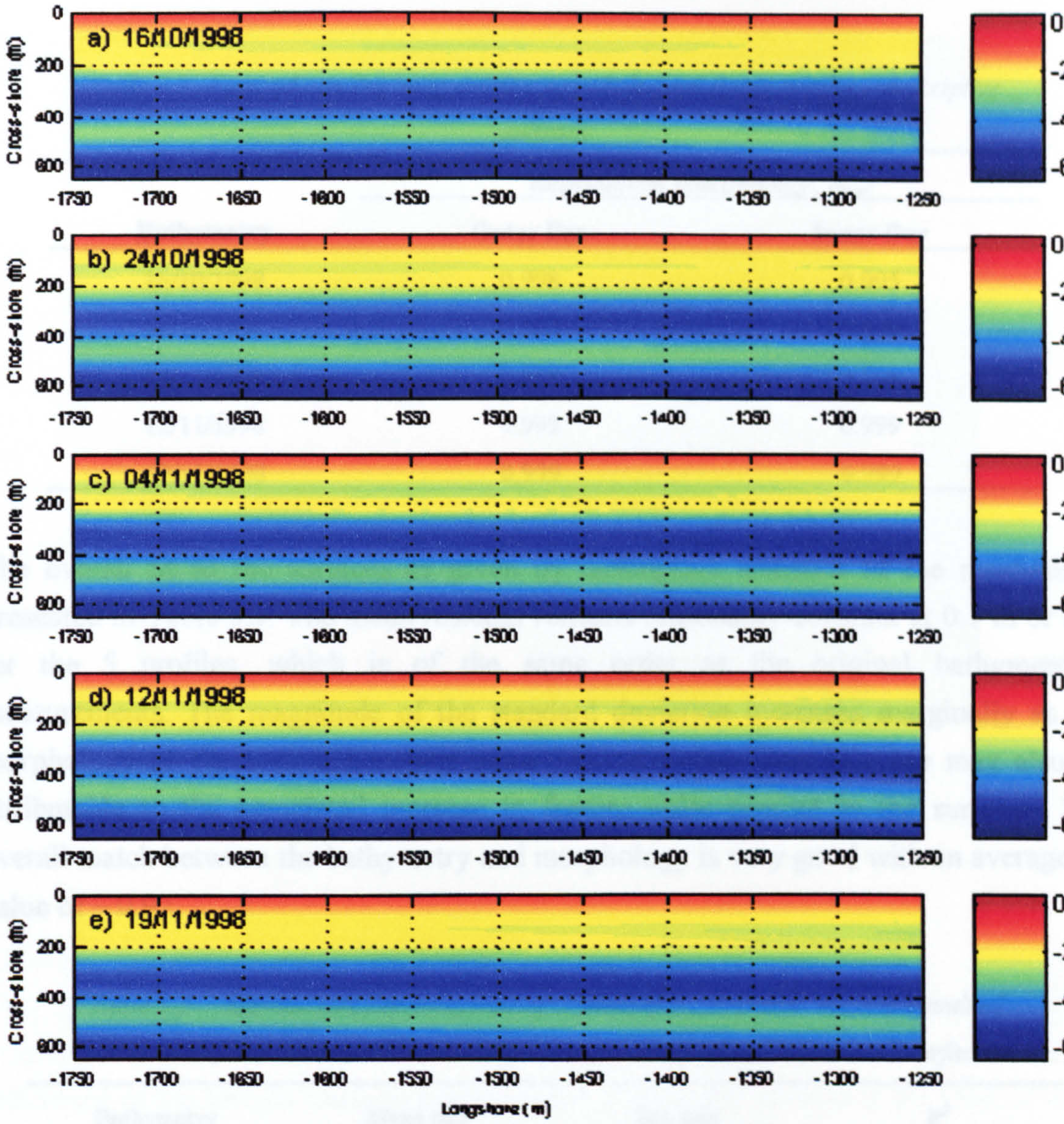

Figure 5.32 Reproduced bathymetries ... Egmond aan Zee, the Netherlands

An independent measure of quality of fit in the longshore direction is given by the curl as presented in Table 5.2. As essentially most of the longshore non-linearity in the original bathymetry exists as small scale noise superimposed on an underlying trend, it is not expected that the magnitudes of curl for the original bathymetry and the reproduced morphology will be identical. Those values of curl determined from the morphologic representation will be large as the adopted model formulation will only pick out the underlying trend. Thus unless the underlying trend is significantly rhythmic, the curl parameter will indicate a near linear feature.

Table 5.2 Egmond aan Zee bathymetries; morphological fitting results... descriptive statistics

Bathymetry	Reproduced morphology, ϑ_{bar}.	
	Outer Bar	**Inner Bar**
16/10/1998	0.998	0.995
24/10/1998	0.999	0.999
04/11/1998	0.998	0.998
12/11/1998	0.999	0.999
19/11/1998	0.999	0.999

The overall fit to the surfaces as given by descriptive statistics of the residuals is presented in Table 5.3. The mean residual remains reasonably constant at 0.1 m or less for the 5 profiles, which is of the same order as the original bathymetrical measurements. The magnitude of the standard deviation increases marginally as the morphology of the system becomes more 3-dimensional. This increase may also be attributable to the associated increase in feature noise present in the surfaces. The overall match between the bathymetry and morphology is very good with an average R^2 value of ~ 0.97.

Table 5.3 Egmond aan Zee bathymetries ... descriptive statistics: mean & standard deviation of residuals and R^2 correlation between original and reproduced surfaces

Bathymetry	Mean (m)	Std. (m)	R^2
16/10/1998	0.070	0.293	0.980
24/10/1998	0.080	0.289	0.979
04/11/1998	0.102	0.298	0.979
12/11/1998	0.053	0.343	0.973
19/11/1998	0.072	0.366	0.965

5.5.3.2 Teignmouth, UK

The morphology fitting procedure behaved as expected in not being able to reproduce the 3-dimensional bathymetry present at Teignmouth as shown in figure 5.33. It has managed to generate the main part of the upper beach region and a part of the channel, however, the overall tendency of the technique to produce alongshore oriented features is very evident. If this approach were to be adopted in the future a change in the model formulation would be required.

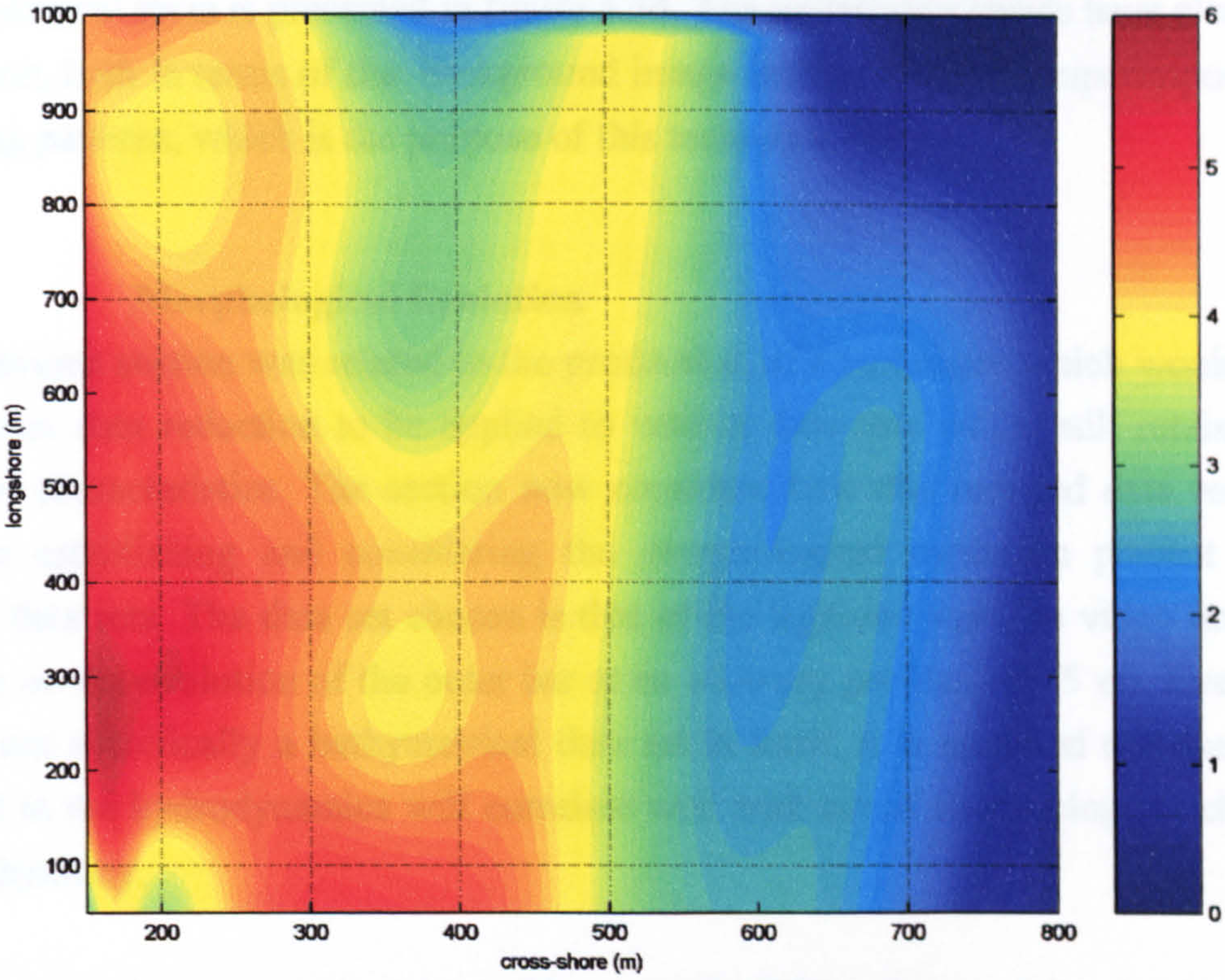

Figure 5.33 Reproduced bathymetry ... Teignmouth, UK

5.5.3.3 Egmond aan Zee images

This section considers the application of the fitting technique to patterns of wave breaking in the nearshore region as seen in time averaged video images. The main difference of the images when compared to the bathymetric surveys is the level of noise present. Due to the nature of wave breaking they are much more susceptible to local variations in wave hydrodynamics and light levels. In spite of this, the fitting procedure produced good results. A typical example of an original image and its reproduced

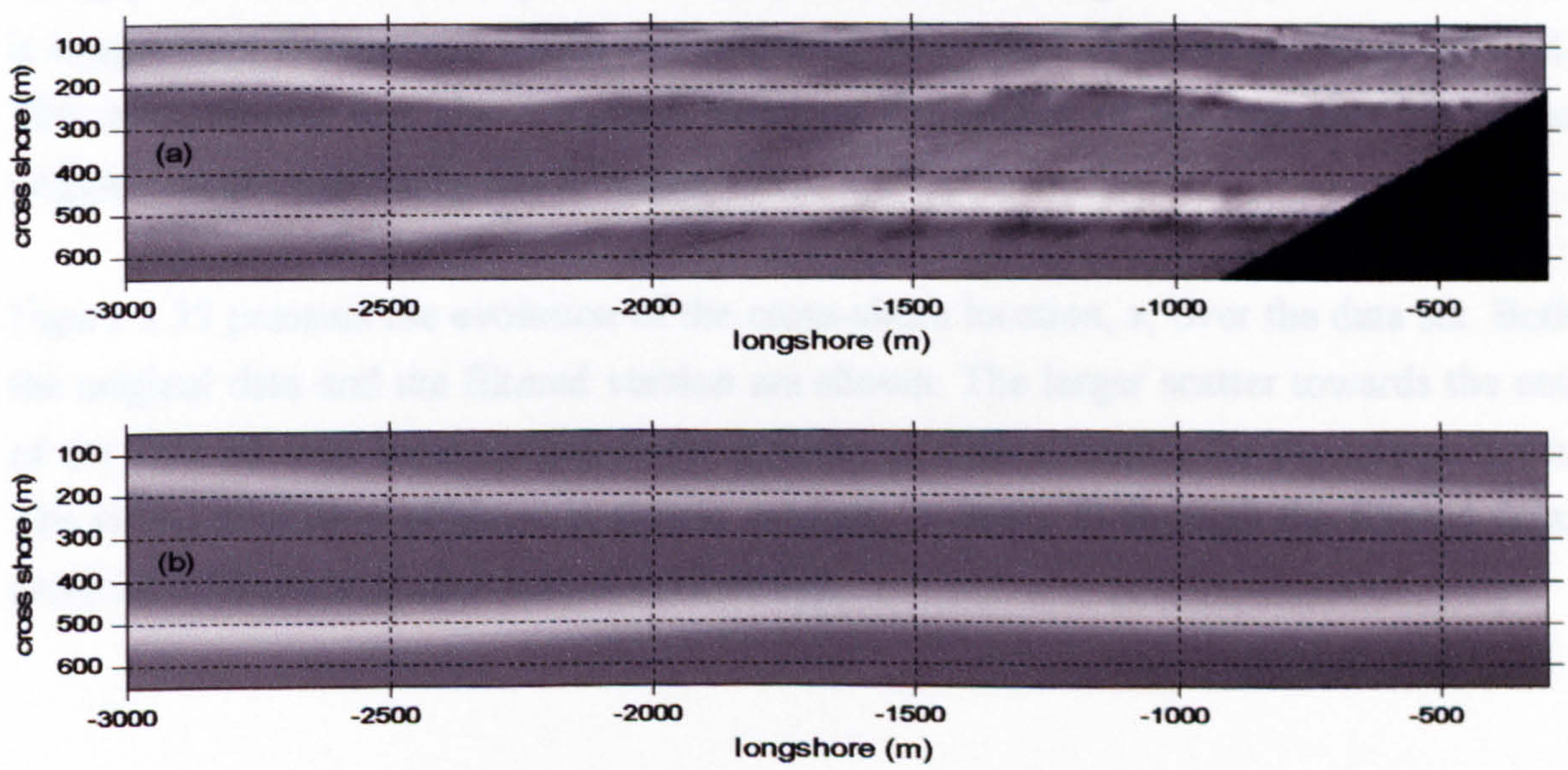

Figure 5.34 (a) Typical Argus image and (b) its morphological reproduction

morphological form is presented in figure 5.34. The underlying trends have clearly been identified, both in terms of the background image intensity and the superimposed wave breaking patterns, which is the purpose of this technique.

5.5.4 Morphological Evolution

The previous section was related to the production of a technique which would allow a significant data reduction to be applied to various data sets whilst still retaining their inherent characteristics. The section now considers how this reduced data set may be used in establishing and considering the morphological evolution present in these typical data sets. The data set chosen is that of the Egmond aan Zee video images and focuses on the evolution of the outer bar at an arbitrary profile (-1575 m). Even though this is not specifically a bathymetrical data set in itself, it is assumed that the changes evident in the hydrodynamics will correlate well with actual morphological changes of the bathymetry.

The fitting technique employed provides a methodology for spatial reduction of data, which makes the assessment of temporal variability more feasible. This is done in terms of change of the parameters describing the morphological shape descriptor. The Egmond aan Zee data set encompasses data interspersed over a 15 month period from Aug 1998 – Oct 1999. This is a relatively short time scale in terms of the expected fluctuations which are evident on an inter-annual timescale; i.e. such as the cyclic behaviour the sand bars off the Netherlands coast at Terschelling, as reported by Ruessink and Kroon (1994). Thus this section sets out to indicate a proposed methodology for the interpretation of longer term behaviour morphological data sets.

Due to the small signal to noise ratio present in the data set, the raw estimates of the fitting parameters were interpolated to daily increments using a 30 day filter. Hence, it is longer term fluctuations which will primarily be evident in the interpolated data set. This interpolation was also weighted based on the quality of the reproduction of the original image as given by the R^2 value.

Figure 5.35 presents the evolution of the cross-shore location, x, over the data set. Both the original data and the filtered version are shown. The larger scatter towards the end of the data set may be attributed to the sparsity of data available for the interpolation. The initial migration offshore is clearly evident. A linear fit through the filtered data, gives an offshore migration rate of 0.12 m/day.

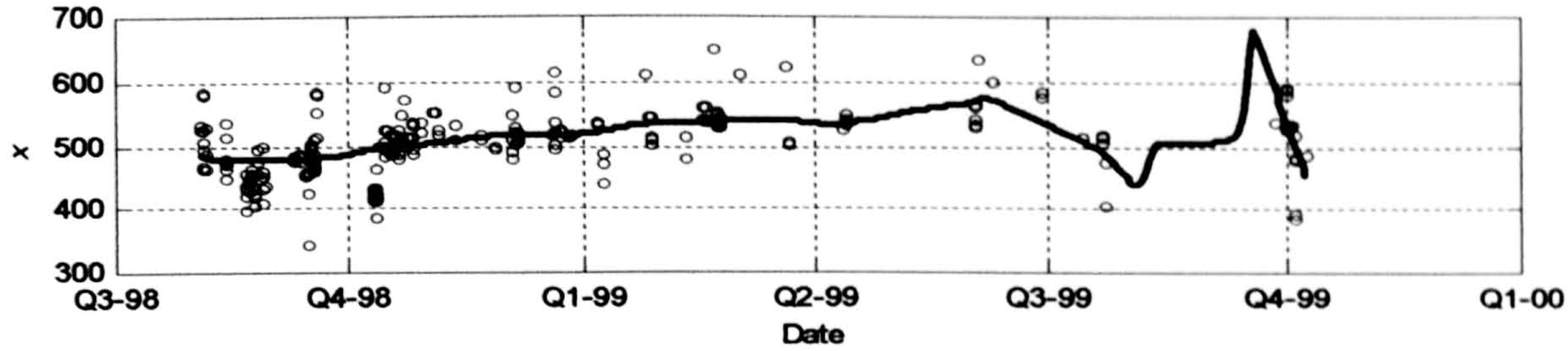

Figure 5.35 Evolution of cross-shore location of outer sand bar, o *raw data,* — *filtered data*

Chapter 6 Discussion

6.1 Introduction

"We shall not cease from exploration,
And the end of all our exploring
Will be to arrive where we started
And know the place for the first time"

TS Elliot - from '*Four Quartets*'

The primary purpose of this chapter is to address the philosophy of approach to the study of coastal systems. Considerable effort has been invested in the study of coastal systems with the aim of obtaining a better understanding of their dynamical behaviour. This goal has often been motivated by a desire to establish the impact anthropogenic influences may have on evolving coastal systems. As both technological and conceptual advances have been made, aspects of coastal systems have been repeatedly revisited with the hope that new insights would be obtained. It would be encouraging to think that having completed any one cycle of knowledge acquisition about such systems, as the above well known quotation suggests, a higher level of understanding would have been achieved. In general this has probably been proven to be the case, even if it is only to dismiss unfruitful avenues of enquiry.

The structure of this chapter mirrors, in reverse order, the material presented in the thesis to this point. In this chapter a discussion of the more detailed insights pertinent to the case studies is initially given in §6.2 and §6.3. This is followed by a more general discussion of Artificial Neural Networks and Evolutionary Computation respectively. In addition some suggestions as to the future directions each of these complex adaptive systems approaches may take is presented.

The remainder of the chapter is devoted to consideration of the role complex adaptive system approaches can play in studying coastal systems. Two main threads are followed; firstly the applicability of complex adaptive systems to the study of coastal systems and secondly the ability of these approaches to introduce new insight into the behaviour of coastal systems. Based on these threads an assessment of the future potential of applicability of complex adaptive systems to coastal systems is presented.

6.2 Artificial Neural Networks Applied to Coastal Systems

6.2.1 Case Study # 1: Artificial Neural Network Correction of Video Estimates of Sand Bar Location

Summary: The motivation for this study was to the establish a methodology for the acquisition of long term, large scale data sets for coastal evolution. In particular, the focus was the correct identification of the cross-shore location of nearshore sand bars. These were inferred from patterns of wave breaking observed in video imagery of the nearshore region. Observations had shown that these wave breaking patterns were strongly correlated to the underlying sand bar location. However, the observed breaking patterns were modulated by influences from tide and wave conditions. Therefore the aim of the study was to provide a technique which would account for the tide and wave climate modulations of the observed wave breaking location, allowing inference of the underlying sandbar crest location.

An Artificial Neural Network model of the double sandbar system at Egmond aan Zee, the Netherlands, was developed. Initially the outer and inner sand bars were modelled individually. Results showed a significant increase in correlation between actual bar crest location and the corrected estimate given by the Artificial Neural Network model compared to that of the raw estimate obtained from the wave breaking pattern [Outer bar ... R^2 increased from 0.51 – 0.87; Inner bar ... R^2 increased from 0.45 – 0.77].

The study then proceeded to treat the dual sand bars as a linked system, particularly for the inner bar i.e. behaviour of wave breaking at the inner bar needed to consider the impact of wave transformation over the outer sandbar. A further increase in correlation (0.93) was obtained for the inner bar. The study concluded by demonstrating the utility of the Artificial Neural Network models to help 'fill in the gaps' in a time series of bar location.

Discussion: This case study was an ideal opportunity to demonstrate the skill of Artificial Neural Network models in tackling the problem of input-output mapping. Having established the appropriate inputs for the system, it was not necessary to prescribe the form of the mapping used. This is a particular strength of Artificial Neural Networks. This case study also highlighted the importance of using existing system knowledge to produce a better overall model of the system. Hence, a reductionist approach to obtaining information about a system, whilst informative in itself, does not necessarily reveal the full story. The reasoning behind this may be considered in terms of the complex nature of coastal systems. Reductionist or deterministic systems approaches will not explore all possible ensemble states, as randomness plays an important role in the exploration of potential system states. This becomes even more prevalent as longer temporal scales are investigated.

Many of the existing morphological data sets have already been shown to be plagued by a lack of appropriate spatial and temporal resolutions which allow the potential of revealing the complete range of system behaviour (Southgate *et al.*, 2002). In many cases large gaps may exist in the data sets. This inhomogeneity in temporal coverage does not lend itself readily to the application of many of the existing analysis techniques (spectral analysis, empirical orthogonal functions, etc.) which tend to rely on uniformity of sampling. If full use of existing data sets is to be made it is necessary to find ways of getting around this issue. As shown in this case study Artificial Neural Networks have shown themselves to be one such approach. For example, Ruessink *et al.* (2000) investigated the level of 3-dimensionality of a nearshore bar system over a period of 6 weeks. Prior to conducting the study it was firstly necessary to use a combination of the Artificial Neural Network technique used in this case study, in addition to an empirical approach to fill in gaps in the data set of bar crest position.

6.2.2 Case Study # 2: Intertidal Mapping of Morphological Features from Remotely Sensed Data

Summary: The purpose of this study was to develop a robust technique which allowed the mapping of intertidal bathymetry from remotely sensed video data. The approach taken was to track the evolution of the shoreline as the tidal elevation changes. The shoreline mapping was broken into two elements; firstly, estimating the horizontal spatial location of the shoreline feature and secondly, assigning a vertical elevation to the shoreline.

An Artificial Neural Network model was utilised to classify regions of sand and water observable in the video images. The shoreline was subsequently derived from the boundary between the features. Classification was complicated by the variability observed in the nature of the shoreline feature, both in terms of wave breaker type and the sediment characteristics. This required an individual Artificial Neural Network model to be trained for each required day's bathymetry at a given site.

The technique was tested with data from a range of sites encompassing a variety of wave and beach characteristics. Typical rms elevation errors of morphological maps produced by the intertidal mapping technique compared to maps produced by traditional survey techniques were in the range of 0.15 – 0.50 m.

Discussion: Establishing methodologies for the production of geomorphological information of appropriate temporal and spatial resolution has been highlighted in this thesis, and elsewhere, as a high priority for investigation by the coastal community. This case study has demonstrated a methodology which is highly appropriate for just this task. The approach taken is innovative in that the method of discrimination of a shoreline feature is independent of those physical processes (water level, wave setup etc.) which generally would be considered to play a role in determining shoreline position. Instead a parallel system is examined which considers the manner in which the eye distinguishes the shoreline as seen in video images.

Perhaps it should be noted at this stage that the form of remote sensing considered in this case study (namely video remote sensing) fills an important niche in the range of measurements which are currently possible for the study of nearshore morphological behaviour. On one side are the traditional measurement techniques (land based surveying techniques, GPS etc) which have the capability of high resolution (5 – 10 cm in the vertical) but are not highly appropriate for large areas. On the other side are the airborne and satellite based forms of remote sensing (Ashenazai *et al.*, 2000). These have the spatial coverage capability but not necessarily the temporal coverage. These remote sensing techniques also fall down in terms of expense for the airborne techniques and resolution for the satellite based measurements. Therefore any research which shows promise for the helping to fill this niche is worthwhile. Video remote sensing combined with intertidal mapping has shown itself to be capable of producing such geomorphological information.

For any technique which is part of a methodology for long term monitoring of coastal systems, robustness is vital. This case study established the robustness of Artificial Neural Networks in estimating the shoreline location. This was done for a range of sites and wave conditions. Aarninkhof *et al.* (2002) extended the evaluation of robustness of shoreline mapping techniques. They evaluated four shoreline detection models (including the Artificial Neural Network approach presented here) for a range of sites and wave conditions. The Artificial Neural Network approach overall proved to provide the most robust estimates of shoreline location.

One current disadvantage of this particular technique is the level of user interaction required. This was also highlighted in Aarninkhof *et al.* (2002). Automation of this technique forms part of ongoing work which will greatly enhance the shoreline mapping technique. The main obstacle which this automation faces is the requirement for robustness. It is difficult to ensure that the empirical approach taken has catered for the range of variability which the system modelled presents. This would suggest that a better understanding of the physical processes underlying the model discriminating between sand and water regions would be advantageous. In spite of this, the use of Artificial Neural Networks to interpret shoreline location has shown great potential to provide robust and reliable measures of the intertidal region.

6.2.3 Pros and Cons of Artificial Neural Networks

The advantages and disadvantages of using Artificial Neural Networks for studying coastal systems are in general very similar to those that would apply in studying any other system. These have been expounded upon to a large extent in the Artificial Neural Network literature. The following is a brief summary of some of these put in the context of coastal systems.

Artificial Neural Networks are a general framework for mapping input output systems. The fact they are a general class of models is a strength which means the user of this model does not require intimate knowledge of all the physical processes governing the system. This is typically the case for coastal systems. Certain aspects of a problem will be well understood, whilst other aspects will have a large degree of uncertainty attached to them. For example, in case study #1 the physics governing the nature of the modulation of the wave breaking pattern, though qualitatively understandable, was not easily quantifiable. This was primarily due to the stochastic variability associated with the forcing. Thus, Artificial Neural Networks are useful for bridging gaps in knowledge. In this role they allow the researcher to bypass obstacles (unknown physics, computational expense, etc) which will allow the subsequent modelling/interpretation of more interesting phenomena, i.e. they are a mechanism which allow science to be uncovered.

Of those statistical models and analysis techniques that have been applied to coastal systems many have made assumptions as to the underlying model of the system. This is not the case for Artificial Neural Networks. The Artificial Neural Network model in itself will establish the form of model most appropriate for the problem being considered. This can also include transformation of variables (i.e. standardisation to a common mean and standard deviation). This latter point is not considered to be good practice, however, as inputs tend to have largely differing means and ranges. This has the possibility of biasing the strength of contribution a particular input may have. Artificial Neural Network models are applicable to multivariate non-linear problems, which are prevalent in coastal systems and sub-systems (as highlighted by both case studies). Again no assumptions are prescribed as to the nature of the non-linearity between the variates.

A general requirement for any model of a system is robustness. As with most models Artificial Neural Networks are often required to perform on regions of parameter space on which they had not been specifically trained. For example, in case study #1 this is specifically the requirement when trying to fill in the gaps in the data set of cross-shore sandbar locations. Similarly in case study #2, the sand/water discrimination models are trained on a limited set of samples of sand and water pixels. The resulting model is then expected to be able to generalise for all other discrimination cases. In order to ensure robustness it is vital to utilise training data sets which encompass the anticipated required parameter space.

Even though Artificial Neural Networks may not be able to extrapolate far into regions of parameter space not covered by the training data set, they still have been shown to have good generalisation capabilities using techniques such as those outlined in §4.2.2. Thus their interpolation capability is adequate. However, if the system itself is non-stationary then the model will be expected to have limited predictive capability. This is true irrespective of model type and is not a specific feature of Artificial Neural Network models. This was demonstrated in case study #2 by the fact that a new model needed to be trained for each day's worth of images. It was not valid to assume that sand or water pixels demonstrated exactly the same radiance characteristics at all times but were reliant on other subtleties which were non-stationary.

Another way of considering the issue of the generalisation / predictability capability of a model is how well the model can cope with noise. If a model is trained on a very noisy data set it is often ambiguous as to whether over-fitting has occurred. The resulting model may either be the required model of the system of interest, or a model of the data set which has characteristics of the system, but is contaminated with a large level of noise. In both cases the results of the training will lead the modeller to believe that an optimal model has been produced. This minimisation of over-fitting is not a trivial task and requires serious treatment. For Artificial Neural Networks the generalisation techniques outlined have been shown to help avoid the problem of over-fitting.

From an operational point of view Artificial Neural Network models typically have a very short development time and are relatively easy to set up. Given a particular data set of a system it is possible to establish an Artificial Neural Network model within a matter of hours. This is a large advantage for the user who is interested in obtaining results with a minimum of effort. Results obtained from Artificial Neural Network models are comparable to and quite often surpass those obtained from equivalent statistical model approaches. This was shown by the results of the Santa Fe time series prediction competition (Weigend and Gershenfeld, 1994) where a range of predictive modelling approaches were applied to the prediction of a variety of data sets. The other important outcome of this study was that Artificial Neural Networks also have the potential to provide the worst results in cases where they were used in an inappropriate or naïve manner.

However, Artificial Neural Networks definitely have certain limitations in the context of their application to coastal systems and especially morphodynamic systems. Perhaps the most critical of these is the requirements of sample size. In the Artificial Neural Network literature, data set size requirements in the order of thousands of data points are not uncommon. However, it should be remembered that the main requirement for these large data sets is the need to cover the range of variability of the parameter space rather than have numerous examples from a subset of the parameter space. This is where typical coastal system data sets may cause difficulty. Morphological data sets of such size are limited in number and it is difficult to ensure that those data sets available cover the range of behaviour inherent in their respective system.

The main criticism laid at the door of Artificial Neural Networks is that they are black-box systems which map input/output relationships very effectively but directly they reveal little about the actual mapping. This is true. However, it does not mean that it is impossible to reveal information on both the model and the system. In particular, it is possible to reveal a large amount of information on the relative significance of the input parameters for a particular model. In case study #1 it was shown that a reduced set of appropriate input parameters tend to only a minimal reduction in performance, thereby indicating the significant parameters governing the physical processes.

An extended example of this type of sensitivity analysis is presented in Woodd-Walker *et al.* (2000). In their study input parameters were dropped one at a time to indicate the least significant parameter for the model. An alternative to performing a sensitivity analysis on the input parameter set is to investigate directly the weights associated with particular inputs in the trained model (Aoki and Komatsu, 1997). Large weights will tend to be associated with the more significant inputs. This is definitely the case if linear activation functions have been used, but may not be the case if non-linear activation functions such as the sigmoid functions have been employed.

However, it is not so easy to interpret directly the numerical form of the model and is beyond the scope of this thesis. This is especially true for those Artificial Neural Network models which rely on non-linear activation functions as their main processing capability. The form of the activation function used and its embedding in the overall model (e.g. equations 4.2 - 4.3) do not readily lead to simplification (i.e. a reduced set of equations as may be obtained from a Taylor series expansion). Ideally it would be useful to reduce the Artificial Neural Network model to a set of reduced equations.

These would be available for comparison with those equations which are believed to be representative of the dynamics governing the system.

Perhaps the most successful treatment of this topic to date was presented by Dibike *et al.* (1999). They initially showed that for the case equations of advection, a trained Artificial Neural Network model was equivalent to the advection equations for the case of linear activation functions, and very closely approximated the advection equations when sigmoid activation functions were employed. They then extended the work to investigate the transformation of short-period waves. Their work showed that by analysing the weights obtained from linear Artificial Neural Networks it was possible to derive the governing one-dimensional form of the Boussinesq-like partial differential equation.

Establishing equivalence of model form/capability is important for two reasons. Firstly, it would help to confirm or otherwise our current understanding of coastal systems. Secondly and maybe more significantly, if Artificial Neural Network models were shown to be capable of producing comparable knowledge to existing techniques, it would be a strong incentive for the coastal community to accept these techniques as having an important contribution to play in the role of knowledge discovery. This is an opportune moment, as many members of the coastal community realise the shortcomings of many of the established techniques and are actively seeking alternatives to deal with the challenges presented by longer term understanding of the coastal system.

Even though it is relatively easy to establish an Artificial Neural Network model of a data set, the quality of the information it provides is, as already shown, dependent on a number of factors. Hence it would be a mistake to invest minimal effort in establishing an Artificial Neural Network model of a system. It should not only include establishing an initial model of the data set, but progress to conducting a sensitivity analysis on both the model architecture and the model inputs. This results in a more reliable model of the system. Inherent in this procedure is the assumption that the modeller invests prior system knowledge and judgement in establishing the optimal model. This latter point is probably the most significant contribution to the success or otherwise of the Artificial Neural Network modelling approach.

There is a certain ambiguity as to whether Artificial Neural Networks are analytical tools or models of a system. Quite often there is little distinction between the two roles. Perhaps the distinction is most clearly defined by the type of output required of the Artificial Neural Network. In the analytical role, the output is typically some measure of the system, whereas for the modelling role the output is another system variable. In that sense, case study #1 involved a modelling role for Artificial Neural Networks; the output is the cross-shore bar location, whereas case study #2 adopted a more analytical role in that the output was a descriptor of the state of a given pixel (sand/water). In either role the Artificial Neural Network, has proven to be both effective and efficient.

6.2.4 Future Directions for Artificial Neural Networks

Even though Artificial Neural Networks are effective complex adaptive systems approaches to studying coastal systems their application in this field, and others, is still in its infancy. From a system knowledge point of view the amount of information they reveal directly about the system is still minimal. Equally from a modelling point of view the models are completely dependent on training data sets.

One possible way forward for the application of Artificial Neural Networks to coastal systems and the development of techniques for understanding coastal systems in general is to attempt merging system knowledge with Artificial Neural Network models. System knowledge in this case may be taken to be such underlying principles as conservation of mass. This would result in models which have better generalisation behaviour in regions outside the parameter space of the training data.

Just such an approach has been taken by Oussar and Dreyfus (2001). An hybrid modelling approach, which they term dynamic semi-physical modelling, combines both an Artificial Neural Network and system knowledge. System knowledge is incorporated by means of a discretisation scheme which casts the appropriate governing equations (these may consist of coupled, possibly non-linear, differential / partial differential or algebraic equations) into a form which is.compatible with Artificial Neural Network schemata. They demonstrate successfully this approach for an industrial application. As yet this approach has not been applied to coastal systems, however it appears to be an exciting area for future research.

One problem which has been identified as being characteristic of large scale coastal system behaviour is that the dynamics of the system as represented by the traditionally adopted systems of equations is not well reproduced. Additional insight into the dynamics can be achieved by recasting coastal systems as systems with complex trajectories in phase space. As Artificial Neural Network models have considerable skill as black-box systems, one area of future research where they should prove to be very fruitful is in the development of hybrid models of coastal systems which have been cast into a non-linear dynamical representation.

6.3 Evolutionary Computation Applied to Coastal Systems

6.3.1 Case Study # 3 Application of Evolutionary Computation Techniques to the Study of Directional Wave Analysis

Summary: The motivation behind this case study was to develop a robust algorithm for the estimation of directional distributions in the presence of strong reflections. Both scenarios of phase-locked and non-phased-locked reflections needed to be catered for. Different regimes could be identified which were related to the distance of the measurement array location to the reflector (*L/S* ratio as defined in §4.5.4). Existing techniques had been shown to provide adequate solutions for either the phase-locked (modified maximum likelihood method; $L/S < 0.2$) or non-phase-locked (maximum likelihood method; $L/S > 0.5$) situation. However, there remained a large region of applicability ($0.2 < L/S < 0.5$) where phase locked or non-phased-locked approaches provided poor solutions.

The approach taken in this study utilised a genetic algorithm to determine the appropriate values of a parametric solution to estimate the directional distribution. Numerical tests indicated that this approach could be robustly applied in the presence or absence of wave reflections, at any distance from the reflector and, significantly, without prior knowledge of the location of the reflector.

The performance of the parametric approach was subsequently evaluated, along with those of the phase-locked and non-phase-locked approaches, for two field sites. The field sites fell into one of the two categories of phase-locked or non-phased-locked reflections. For the phase-locked case, the parametric solution provided the clearest pattern of incident and reflected waves which were consistent with the expected narrow directional spread for the given water depth. In the non-phased-locked case, the parametric solution provided a realistic solution comparable to that of the maximum likelihood method.

Discussion: In this case study, as presented in §5.4, a qualitative assessment was made of the relative performance of the three analysis approaches for estimating the directional distribution at the field sites. From this evaluation, the parametric solution developed in the study appeared to provide robust meaningful estimates of the directional distribution (this has already been confirmed for the numerical examples that were considered). A more quantitative evaluation was hampered by the fact that the true directional distribution was unknown for the field data sets. This is the typical scenario for field data. However, it would be extremely useful to obtain an independent measure of the quality of the resulting directional distributions from each of the techniques.

For directional analysis problems we are lucky enough to have such an independent measure of the quality of the directional spectrum that has been used already in the development of the parametric solution. The genetic algorithm approach to estimating the parametric directional distribution relies on evaluating a fitness function (equations 5.7 – 5.9). This evaluates how well the phases and amplitudes of the estimated and measured cross-spectra match. The measured cross-power spectrum is derived directly from the measured data and the estimated cross-spectrum is obtained from the estimated directional distribution.

Note that in this comparison (equations 6.1 – 6.3) the exact form of the equations was modified slightly. A normalisation factor is introduced which accounts for the number of available sensors. This allows the utilisation of the fitness function to compare results from arrays having different numbers of sensors as would be the case for example when comparing the results from an array of pressure transducers (typically 5-10 sensors) with those from a pressure velocity sensor (3 sensors). These calculations are conducted for each frequency band of the spectrum. The final fitness value is the spectrally weighted fitness (equation 6.4). Therefore those frequency bands which contain significant energy will contribute most strongly to the final fitness value.

$$r_a = \frac{1}{1+\frac{1}{nm}\sum_n \sum_m \left|A_{nm} - \hat{A}_{nm}\right|} \quad \text{(amplitude-fitness)} \qquad 6.1$$

$$r_p = \frac{1}{1+\frac{1}{nm}\sum_n \sum_m \left|P_{nm} - \hat{P}_{nm}\right|} \quad \text{(phase-fitness)} \qquad 6.2$$

$$r = \frac{r_a + r_p}{2} \quad \text{(combined-fitness function)} \qquad 6.3$$

$$fitness = \frac{\int r S(f) df}{\int S(f) df} \quad \text{(spectral weighted fitness)} \qquad 6.4$$

To assess the quality of the directional distribution obtained from each of the three techniques, the spectrally weighted fitness is calculated for each of the two field cases. The results are shown in figure 6.1. Immediately it can be seen that in terms of this assessment, the evolutionary computation approach produces the best results for both the phase-locked and non-phase-locked cases. Higher fitness values are obtained for the phase locked case irrespective of analysis approach. It is also encouraging to note that the fitness measure correctly reflects the appropriateness of the non-parametric techniques at each of the two sites giving added credibility to the measure.

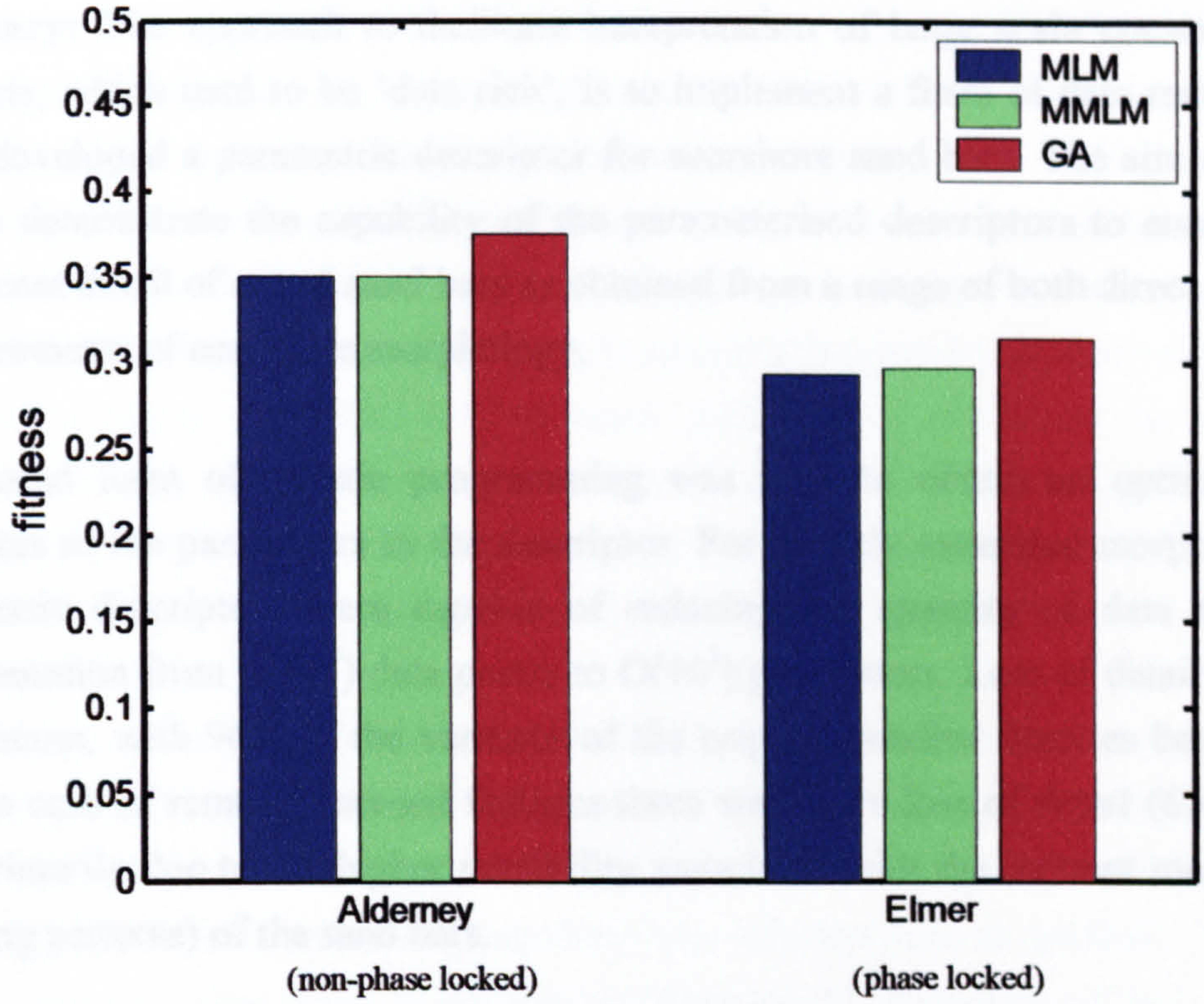

Figure 6.1 Relative performance of the analysis approaches to estimating the directional distribution for field data sets.

Adopting a parametric approach to establishing the spectral distribution helps to ensure the 'smoothness' of the resulting spectral shape. This was evident in figures 5.19 and 5.22. The level of smoothness raises the question as to the validity of the result, in the sense that variability of the energy distribution in terms of direction is to be expected. In other words, is there too much damping of noise (or minor energy signals which are considered as noise) in the parametric approach? Figure 6.1 suggests this is not so. If this were the case, with serious over-damping of minor contributions of energy to the spectral distribution estimate, it would be expected that the spectrally weighted fitness value of the non-parametric approaches would surpass that of the parametric approach.

The complexity evident in hydrodynamic systems is predominantly stochastic in nature. When trying to produce an estimate of the directional wave spectrum it can be surmised that there is not an identifiably unique solution but rather a range of similar solutions which would have practically identical fitness evaluations. This is unavoidable. Adopting a parametric approach to this problem results in a solution which has a large probability of being optimal without having to consider the minor variations in energy resulting from the stochastic contributions

6.3.2 Case Study # 4: Application of Evolutionary Computation Techniques to the Development of a Morphologic Descriptor for Nearshore Sandbar Features

Summary: One approach to facilitate interpretation of large scale coastal behaviour data sets, which tend to be 'data rich', is to implement a form of data reduction. This study developed a parametric descriptor for nearshore sand bars. The aim of the study was to demonstrate the capability of the parameterised descriptors to encapsulate the significant detail of actual sand bars as obtained from a range of both direct and indirect measurements of nearshore morphology.

A reduced form of genetic programming was used to obtain an optimised set of estimates of the parameters in the descriptor. For directly measured morphologies, the parametric descriptors were capable of reducing the quantity of data required for representation from $O(10^3)$ data points to $O(10^1)$ parameters. Loss of detail was kept to a minimum, with 96% of the variance of the original sandbar features being retained. For the case of remotely sensed features there was more loss of detail (65-90%). This was primarily due to the higher variability associated with the indirect measure (wave breaking patterns) of the sand bars.

The study then proceeded to demonstrate the utility of the data parameterisation for the characterisation of morphological evolution. It was shown that the assessment of temporal variability of the sand bar features was feasible by directly investigating the evolution of the parameter set of the morphological descriptor.

Discussion: As has been emphasised several times previously in this thesis, Large Scale Coastal Behaviour data sets are and will be a primary mechanism for revealing insight into the behaviour of coastal systems at those time scales which are of direct interest to coastal managers. The prospect of data mining these data sets, however, is daunting to say the least, due to the large volumes of data involved. Of the case studies considered in this thesis, this was the most ambitious in terms of both the spatial and temporal scales being considered. As already mentioned in §3.3, increased dimensionality greatly increases the likelihood of complex behaviour occurring, making interpretation more challenging.

Mining of these data sets is also complicated by the non-linear behaviour of the signals which need to be extracted from the data sets. The non-linearity makes the identification and isolation of the behavioural signals more difficult. In certain cases the isolation of the behaviour signals may not be possible, as they are intrinsically linked to the system as a whole and may not be interpreted independently of the system. From this point of view any approach which may help investigate such data sets is worthy of consideration. This was the purpose of this particular case study.

To date the main approaches that have been used to investigate large scale morphological data sets have come from the EOF family of techniques. The main criticism which may be raised of this particular approach is that any patterns of behaviour which are revealed by EOF's will by definition be characteristic of the entire data set in terms of temporal duration. The approach presented in this case study does not have this limitation. Each realisation is analysed independently, hence this approach has the potential to pick out transient patterns of behaviour in a data set. Computationally, the parametric approach presented has the advantage that the entire data set does not need to be processed at once. This point has the potential to become an issue as the size of the morphological data sets available becomes larger.

A limitation of the parameterisation method, highlighted in this case study, was the fact that several comparable 'optimal solutions' are possible for the same morphology given the number of parameters involved. This ultimately resulted in parameter time series which were noisy or tended to jump from one solution state to another. This required serious consideration when attempting to interpret the evolution of these series. The compromise adopted was to apply a filter to the time series to remove short term fluctuations. These fluctuations had two possible sources; firstly naturally occurring short term variability and secondly unwanted variability induced by the problem just mentioned. However, as it was the longer term trends which were of primary interest this smoothing of the parameter time series was considered valid.

One of the decisions which had to be made when establishing the parametric form to be used in the data reduction process was the level of simplicity which was required. An obvious trade off exists between having a very simplistic model which captures a limited amount of the naturally occurring longshore and cross-shore variability, yet which in a temporal sense produces 'well behaved' evolution, and a more complicated parameterisation which captures more of the instantaneous variability but leads to a noisy evolution signal as was highlighted above. This suggests further consideration is required to establish criteria to indicate the appropriate levels of parameterisation as was suggested by figure 2.2. At this stage it is surmised that an over-riding factor in the criteria will be the intended usage of the reduced data set with higher levels of parameterisation being appropriate for shorter temporal considerations.

6.3.3 Pros and Cons of Evolutionary Computation

In a learning paradigm the goal is to search some parameter space in an adaptive and intelligent way such that the information gained at one state of the search is used to influence the future direction of the search. The trajectory of the search is therefore dependent on the information gained along the way. Evolutionary computation provides effective tools for dealing with extremely large search spaces and noisy solution sets. Their ability to search simultaneously several solutions, and combine the best of these, allows convergence on progressively better solutions. Therefore evolutionary computation should not be seen as a means of modelling a system but rather an effective technique for optimising models of systems.

When studying coastal systems, the success (or otherwise) of the study, in terms of how much information is revealed about the system, is largely dependent on the model formulation rather that the chosen optimisation approach. The strength of evolutionary computation is that it is a particularly robust approach which simultaneously explores the parameter space and exploits the fitter regions of parameter space. This was evident in both case studies, where the parameter space being searched was large in both cases (5-dimensional for case study #3 and 10-dimensional for case study #4). Yet in both studies results achieved were satisfactory and in the former case were shown to surpass the results achieved by traditional techniques. For case study #4 there was no directly comparable traditional approach study available.

Operationally, evolutionary computation approaches tend to be time consuming to implement. This time factor comes from two sources. Firstly establishing the representation of the problem tends to be lengthy. This is especially true of genetic programming. This is compounded by the fact that each new problem being considered is slightly different. Hence, it will need careful treatment as how best to cast the evolutionary computation representation of the problem. This may not be such a serious disadvantage over traditional modelling approaches, especially when it may be considered that for any hydro-morphodynamic model a large percentage of time invested in conducting a study is invested in setting up the model. However in the case of evolutionary computation problems this will quite often entail modifications at the level of coding.

Secondly, the runtime required to obtain a reliable solution may be prohibitive. As one of the main premises of evolutionary computation is to exploit randomness, it is recommended that problem solutions should not be based on a single run of the paradigm. Instead a statistical treatment of multiple runs should be adopted where possible. Whilst this maximises the robustness of the modelling approach and the final outcome it greatly increases the overall time required to achieve an optimal solution.

6.3.4 Future Directions for Evolutionary Computation

Based on the preceding discussions it can be seen that evolutionary computation has numerous possibilities for application in the study of coastal systems. John Koza in the foreword to Banzhaf *et al.* (2001) summarises the eligibility criteria for suitable areas of application of Genetic Programming (equally applicable to evolutionary computation in general) as ...

- areas where the interrelationships among the relevant variables are poorly understood.
- areas where finding the shape and size of the ultimate shape to the problem is a major part of the task.
- areas where conventional mathematics does not or cannot provide analytical solutions.
- areas where there is a large amount of data that requires examination, classification and integration.

From these suggestions, coastal researchers should recognise many parallels for their particular system. Hence, coastal systems are an ideal candidate for future exploration utilising evolutionary computation. However, based on previous arguments it can be concluded that unless the solution space of the problem at hand is of high complexity, adopting an evolutionary computation approach may not be warranted. This is true irrespective of the system being considered. The main issue remaining therefore is the determination of the level of complexity of the system being considered. This issue will be addressed in §6.5.

6.4 The Utility of Complex Adaptive System Approaches for Studying Coastal Systems

Scientists and non-scientists alike are involved in the business of trying to make sense of the world. In doing so, both scientists and non-scientists make use of conceptual frameworks - habitual ways of thinking which influence both how one tries to make sense of the world and the new questions one asks (and doesn't ask). The conceptual frameworks themselves are products of the observations that have been made and can be made. The pitfall of this trait is the danger of becoming trapped in established frameworks.

This thesis has already shown the merit of complex adaptive approaches for specific coastal systems problems. The purpose of this section is to evaluate the appropriateness of complex adaptive system approaches in general for studying coastal systems. The methodology adopted addresses the following points.

- The question remains as to whether those successes achieved in the case studies in this thesis are indeed attributable to the framework of the general complex adaptive system approaches to studying systems. In performing this evaluation, the first question which needs to be asked is the appropriateness of the individual case studies for consideration as complex adaptive systems?
- Having established the validity of the case studies as complex adaptive systems, an assessment of the insights which have been gained is considered.
- The final assessment criteria considered will be based on arguments of generality of complex adaptive system approaches. This argument is driven by the fact that the utility of complex adaptive approaches to the coastal community approaches will be governed by a combination of generality of approach and ease of application.

6.4.1 Validity of Case Studies as Complex Adaptive Systems

The following paragraphs identify the systems which were considered in each of the case studies. Each system is evaluated in terms of the five characteristics of complex adaptive systems previously presented in table 3.2. These characteristics encapsulate the main characteristics of complex adaptive systems. The purpose of this evaluation is to establish the validity of the case studies as being representative of complex adaptive systems and hence the appropriateness of using complex adaptive systems approaches.

Case Study #1 ... the discrepancy between inferred and actual measure of cross-shore sub-tidal sandbar location.

The system under consideration here is the interaction between the wave breaking patterns and how this is being modulated by the stochastic forcing.

- This study considers hydro-morphodynamic interactions at the level of sandbar features. The hydrodynamic sub-system is characterised by many interacting waveforms superimposed on a long period tidal fluctuation.
- It is a typical realisation of a dissipative coastal system.
- Deterministic chaos is possible as sandbars display complex patterns of behaviour.
- The governing dynamics is highly non-linear, due to feedback processes
- Sandbar systems have been shown to have more than one attractor state. However these realisations occur over temporal scales much larger than the scale of interest required for correcting the estimates of sand bar location.

Case Study #2 ... a methodology for mapping the inter-tidal region from remotely sensed data.

Initially there is a little ambiguity as to what the system being considered consists of. There is the nature of the shoreline itself, with complex behaviour being derived from feedback resulting from the stochastic forcing and the corresponding morphological response. However these sub-systems in themselves are not the only ones being considered. On a higher level there is the system comprising the manner in which the shoreline is recognisable in an image and the physics which makes this feasible, thereby adding to the level of complexity of the problem.

- The study considers that multiple wave form component types are incident at the shoreline. Behaviour is complicated by interaction with sediment at the beach face.
- It is a typical realisation of a dissipative coastal system.
- Deterministic chaos possible.
- The governing dynamics for the shoreline system is non-linear. Unknown system dynamics govern the visual interpretation of the shoreline feature, with a high probability of being non-linear.
- There are multiple attractor states, depending on the nature of the shoreline feature which is being identified.

Case Study #3 ... a novel parametric approach for estimating directional wave spectra.

This is an optimisation problem where the system being modelled is the solution space of all possible combinations of the parameters which are required for the directional wave distribution.

- The hydrodynamic system is characterised by many interacting waveforms.
- Dissipative process are less significant, especially in reflective wave fields.
- Deterministic chaos is possible, however stochastic chaos is more probable.
- The dynamics are typically assumed to be linear in nature. This facilitates spectral analysis approaches for the decomposition of waveforms. This does not rule out the possibility of non-linear wave-wave interactions occurring even if they are typically ignored.

- There is no obvious evidence for multiple attractors or bifurcations.

Case Study #4 ... an approach for the data reduction of large scale coastal behaviour data sets as applied to nearshore sandbar systems.

The system modelled here is a large scale morphological data set. The goal is to find an optimal data reduction technique to encapsulate the essential dynamics of the system.

- It is a hydro-morphodynamic system comprising multiple interactions
- It is a typical realisation of a dissipative coastal system.
- Deterministic chaos is probable, due to the combination of large temporal and spatial scales
- Non-linear governing dynamics are likely, due to feedback processes, especially over the large temporal scales considered in the study.
- There is evidence for sandbar systems having multiple attractor states.

It is now necessary to give a qualitative assessment of the strength of argument for each case study being considered as a complex adaptive system. This gives a strong indication as to the nature of the system. In terms of the case studies having multiple interacting components, case studies #1 and #4 most closely fulfil this criterion. All case studies bar that of #3 (which relies on linear wave theory in a reflective wave field) may be considered as dissipative systems. Case study #3 also does not fulfil the criteria of non-linear governing equations and evidence of multiple attractors/ bifurcation points, whereas the other case studies do. The evidence for the case studies exemplifying deterministic chaos is marginal for most examples except for case study #4 where clear evidence of chaotic behaviour is evident in the evolving series of video images of the wave breaking over the nearshore bars.

Based on the above assessment, there is a strong argument to consider the hydro-morphodynamic case studies as examples of complex adaptive systems. This is most likely due to the large range of temporal and spatial scales which they incorporate, as this increases the likelihood of complex behaviour occurring. Hence, the use of novel systems approaches to gaining insight into hydro-morphodynamic systems is both appropriate and acceptable.

Case study #3 is the least likely candidate for the application of complex adaptive approaches, being primarily a hydrodynamic problem occurring over short time scales. This removes to a large extent the role of feedback. Therefore the complexity which may be displayed in the situation of reflective wave fields is stochastic, rather than being illustrative of deterministic chaotic. However, this does not detract from the success achieved by the complex adaptive system approach for the case study. An important point that may be derived from this classification, is that the application of complex adaptive techniques is not strictly limited to complex adaptive systems. Non-linear approaches applied to linear systems still have the capability to extract the underlying dynamics.

6.4.2 Ability to Introduce Insight into the Behaviour of Coastal Systems

One of the main criteria in conducting a particular study is the prior knowledge that the techniques to be used have the ability to give insight into the nature of the system being considered. In the following discussion, an overview of the insights obtained by complex adaptive techniques applied to coastal systems is presented. The nature of these insights is assessed in terms of the objectives outlined in Chapter 1. This is followed by an assessment of the generality and the ease of application of these approaches. This is an important consideration as it is a large factor in the choice of approach adopted for studying a system.

The following summarise some of the main insights which have been achieved for each of the case studies.

Case Study #1 ... the discrepancy between inferred and actual measure of cross-shore sub-tidal sandbar location.

- Local water depth and incident wave height are the primary factors influencing the modulation of the location of wave breaking patterns over submerged sand bars.
- The location of the intensity maximum is shoreward of the bar crest at the study site.
- When considering multiple sand bar systems it is important not to treat the modulation of wave breaking patterns over the inner bars in isolation from wave transformations which may have occurred over the outer bars.

Case Study #2 ... a methodology for mapping the inter-tidal region from remotely sensed data.

- The horizontal spatial mapping of shoreline location from video images requires not only an understanding of those processes which govern shoreline position but also the physics which underlie the visual interpretation of objects.
- Inter-tidal mapping shows most promise for sites which have a reflective beach face with corresponding small tidal excursions. This is due to a combination of higher density of shoreline estimates and a more readily definable shoreline feature.
- The inter-tidal mapping problem is complex with complications accruing from a variety of sources. An overall determining measure which is useful to gauge the likely quality of the result is distance from the site to the camera system. Confidence in the output is adequate for regions up to 1 kilometre from the camera with the current configuration.

Case Study #3 … a novel parametric approach for estimating directional wave spectra.

- Parametric methods for estimating directional wave spectra have the capability of resolving directional energy distributions for reflective wave fields. This is independent of the distance from the reflector to the wave measurement array.
- The solution space for the chosen parameterisation is of such dimensions that any optimisation procedure needs to explore all dimensions of the parameter space simultaneously.
- The fitness of a particular directional wave estimate is least dependent on the spectral spreading parameter. Hence this is the parameter which is least likely to be well resolved.
- Even though this case study does not fall strongly into the category of complex adaptive system problems, these approaches to studying such problems still provide a robust solution comparable, if not better than, that which may be achieved by other techniques.

Case Study #4 … an approach for the data reduction of large scale coastal behaviour data sets as applied to nearshore sandbar systems.

- A parametric representation of sand bar features enables a significant data reduction capability (~ 2 orders of magnitude), whilst still retaining greater than 90% of the variance of the original data set.
- Definition of submerged sand bar features by wave breaking patterns requires special attention as only a smaller percentage of the variability is recoverable by data reduction.
- Average offshore migration rates at the Netherlands coast at Egmond aan Zee are of the order of 0.12 m / day.
- Representation of longshore variability by a single sinusoidal component is only sufficient to capture the lowest-order spatial variability. Additional components would be required to enhance the level of longshore variability captured.

As can be seen from this summary of insights into coastal system behaviour, the insights range from being quite specific (migration rates) to more general (appropriateness of complex adaptive techniques for particular case studies). In this sense scientific understanding of the systems at a range of levels is being highlighted. Therefore complex adaptive system approaches are shown to have the ability to introduce insight for coastal systems.

It is now necessary to evaluate the degree to which the objectives and aims outlined in Chapter 1 have been achieved. One of the primary objectives was to identify techniques, initially developed in other fields, which would prove useful for the study of coastal systems. The term 'useful' was graded according to the following criteria:

a) to produce insight into coastal systems equivalent to those achieved by traditionally accepted analysis and modelling techniques.
b) to provide new insights into the behaviour of coastal systems, as a result of taking a new view of the system, even though it may be possible in hindsight to achieve similar information from traditional approaches.
c) to provide new insights into the behaviour of coastal systems, as a result of taking a new view of the system, which are unlikely to have been achieved by other means.

In all 4 case studies equivalent insight has been obtained. This confirmation of existing knowledge would be the minimum requirement of any study. However in addition to this, new insights have been gained for each case study. For case studies #1 and #2 it is possible for traditional approaches to have reached the same conclusions had the appropriate lines of investigation been followed.

However, it is suggested that in case studies #3 and #4 insights would not have been achievable by traditional approaches, and it can be claimed that novel research has been obtained through the application of complex adaptive techniques.

Based on the above assessment of insight achieved by each of the case studies, it would appear that Evolutionary Computation approaches offer a distinct advantage over Artificial Neural Network approaches in terms of potential insight to be gained. However, insight is not the only criterion by which an approach to studying systems may be assessed. The following are a few general points which should be considered when trying to establish the utility of a particular technique for studying coastal systems.

- Insight into the behaviour of a system can be achieved either directly or indirectly. In the former case, the particular analysis or model utilised allows direct inference of system behaviour, whereas in the latter and more typical case, subsequent analysis or interpretation is necessary.
- Along with ability to introduce insight also goes the ease of achieving a particular result. If a particular result is achievable by more than one approach, the approach which requires the least effort immediately becomes more appealing.
- The utility of a particular technique for coastal systems will be governed by its ability to cater for the particular system characteristics which are inherent in nearshore studies.

For case studies #1 and #2, the fundamental theory behind the complex adaptive techniques, i.e. Artificial Neural Networks, is readily understandable and its implementation is straightforward, thereby enhancing its utility for studying coastal systems. The form of Artificial Neural Network model presented in this thesis is characteristic of the type of model which is readily applicable to a range of other potential problems in coastal systems. In contrast, the theory behind case studies #3 and #4, representative of Evolutionary Computation, is a little more difficult to grasp and implement. This is compounded by the fact that each evolutionary computation application needs individual consideration for the manner in which it will be applied. In terms of computational expense, Artificial Neural Networks require much less effort than Evolutionary Computation. Typical model runs are of the order of tens of minutes rather than hours. Whilst these assessment criteria are by no means exhaustive, they give a good indication as to the general utility of the complex adaptive techniques. Based on this assessment, it is reasonable to come to the conclusion that Artificial Neural Networks show considerably more potential for utility in study of coastal systems.

6.4.3 Artificial Neural Networks versus Evolutionary Computation

To conclude this discussion on the utility of complex adaptive techniques for the study of coastal systems, it is appropriate to compare and contrast the two complex adaptive systems considered.

- Artificial Neural Networks have proved themselves highly adaptable and have the ability to provide robust models or analyses of coastal systems.
- Establishing the exact nature of these Artificial Neural Network models requires a considerable investment of effort.
- Evolutionary computation approaches require more care in implementation than Artificial Neural Networks.
- Evolutionary computation approaches provide a robust methodology to the optimisation of a large range of numerical models.
- Genetic programming has the additional appeal of 'automatically' generating numerical formulations of the processes which they are modelling ... thereby giving a direct link to providing insight on process behaviour.

In both complex adaptive system approaches the utility of the techniques is most strongly limited by the quality of the theoretical framework into which the application is placed. Based on the various criteria of utility presented at the end of the previous section, it can be concluded that an overall result is that Artificial Neural Networks show more promise than Evolutionary Computation for the study of coastal systems.

6.5 A 'Correct' Approach to Studying Coastal Systems ?

In trying to address the question of whether there is a correct approach to the studying coastal systems, it is necessary to start by considering a broad overview of the state of coastal system science as was presented in Chapter 2. The purpose of including this 'big picture' overview is that this consideration lends itself to identifying the types of problem which arise in undertaking a study of coastal systems. As outlined in Chapter 2, the major challenge currently facing the nearshore research community is related to the development of an understanding of the larger scale behaviour (in particular the larger temporal scales) of the coastal region.

As has already been pointed out, coastal systems problems are those which are inherently non-linear in nature and tend to display complex evolution over time. This explains to a large extent the comparative success that has been achieved in producing models of coastal systems for small scale behaviour considerations and the comparative failure at larger scales. In small scale behaviour scenarios the models required only had to be sufficiently robust to cater for snapshots of the evolving coastal system. Any apparent anomalies that arose would usually have been attributed to noise, whereas in fact it is likely that on at least some occasions these were traits of the actual variability in the evolving system behaviour. This is a strong argument in favour of the pursuit of alternative approaches which have the potential to unravel some of the non-linear complexities prevalent in coastal systems. It also highlights the need for long term data sets which encapsulate system evolution.

Much of the approach to studying coastal systems presented in this thesis revolves around the simple model presented in Figure 1.1. Whilst this model of acquiring system knowledge is highly simplistic in nature, its simplicity may also be viewed as a strength. Firstly, the cyclic nature and interconnectedness of the 3 stages of observation, interpretation and modelling, highlight the evolving nature of acquisition of system knowledge. It requires many iterations of the model to begin to achieve a reasonable level of overall knowledge of the system. Equally well it is unlikely that complete knowledge will ever be achieved.

Of the three stages of the model, perhaps the least ambiguous is the observation stage. Once the measurements have been made, they may be taken as absolutes in themselves to within the tolerances of the measurement equipment. Perhaps more significant than these systematic measurement errors, is the assessment of levels of noise in the system

It has been suggested that adopting a policy of long-term monitoring is a vital aspect of gaining insight into coastal system behaviour, especially as this is consistent with the time scales of interest to coastal managers. The immediate impact of this is twofold.

Firstly, it is necessary to find appropriate ways to manage and extract useful information from the large data sets which are generated. This was the purpose of case studies 2 and 4.

Secondly, the subsequent interpretation of both the original data sets (if possible) and the extracted information is complicated by the non-linear nature of the coastal system. One of the difficulties when faced with the analysis of a data set is determining that a non-linear form of analysis is required or whether a linear approach is sufficient. Southgate *et al.* (2002) outlined the following characteristics of a time series which suggest the use of a non-linear or systemic approach.

- The probability distribution of the data has a strong asymmetry
- The time series contains sudden occurrences of large values with irregular spacings in time
- The time series displays a change in variance over time
- The time series exhibits time irreversibility
- Background knowledge indicates the time series is generated by non-linear physical processes

Whilst these attributes give an indication of the level of linearity of a system, indicating whether a traditional approach (i.e. linear reductionist approaches) is adequate, they do not preclude the application of more comprehensive non-linear systemic approaches.

When dealing with processes incorporating shorter time scales it is sometimes possible to ignore the non-linearity of the system, i.e. we end up looking at snapshots of the system where the non-linear relationships between components are not fully developed or significant, thereby allowing a reduction to a linear interpretation. However, as longer and longer temporal scales are considered it becomes more prevalent to establish the fuller implications of the non-linearity of the system as the level of complexity exhibited by the system increases correspondingly. Hence, the importance of utilising approaches which can cater for the non-linearity of coastal systems becomes more and more significant as the demands with regards to long term system predictability become increasingly more onerous.

At the modelling stage, one particular characteristic of coastal systems, which is significant, is the range of temporal and spatial scales of behaviour evident. From foregoing arguments it is clear that a process based approach to modelling such a system leads to difficulties when trying to cater for larger scales. This raises the question as to whether a behaviour oriented modelling approach would be more fruitful, as typically one is immediately looking at the larger scales. However it is still difficult to ascertain the correct approach to linking the smaller scale observations (model validation) to larger scale behaviour (model predictive capability). Indeed the validity of linking of scales has been called into question by Werner (1999). He suggests that it is necessary to ensure that observations and modelling efforts should be conducted at similar scales and that extrapolation outside of these ranges is not appropriate or probably even valid.

It is the interpretation stage which this thesis primarily addresses. Traditionally, coastal research has tended to concentrate on studies which deal with limited temporal and spatial scales. Much system insight and understanding at these scales has been achieved. However as previously mentioned, societal pressure requires a predictive capability based on system knowledge at increasingly larger scales. This has only been met with limited success. In this thesis two complex adaptive systems approaches have been presented and compared by means of a number of case studies. From the case studies presented, and the subsequent assessment it is apparent that there is an advantage in using complex adaptive systems approaches for studying coastal systems. This is especially true when looking at larger scales of behaviour. This greatly complements the existing linear approaches which are routinely employed.

Having recommended the use of complex adaptive approaches for the study of coastal systems, it is useful to point out that the utility assessment carried out previously for Artificial Neural Networks and Evolutionary Computation may be used as a guide to choose the more appropriate approach for studying a particular system. The utility assessment highlights those properties of both the coastal system and the complex adaptive system approach which are prevalent when considering embarking on a new study. It is not possible to say that there are broad classes of coastal system problems for which either Artificial Neural Networks or Evolutionary Computation are most appropriate. Rather each problem needs to be considered on a case by case basis. Consideration of the discussion points should facilitate researchers to identify characteristics common to their particular problem and those problems considered in this thesis.

To conclude there is not any single approach which one can (or should) advocate exclusively for the study of coastal systems. Rather it is better to accept a range diverse approaches, and the outcomes associated with them, as each contribution helps cast light on a new facet of the coastal system.

Chapter 7 Conclusions

7.1 General Conclusions

Science exists only in people. Each scientific project has its creative inception, its process, and its tentative conclusion, in a person or persons. Knowledge – even scientific knowledge – is that which is subjectively acceptable. Scientific knowledge can be communicated only to those who are subjectively ready to receive its communication. The utilisation of science also occurs only through people who are in pursuit of values which have meaning for them.

Carl Rogers, 1961

This thesis has provided a synopsis of some aspects of the current state of understanding of the nearshore physical coastal system and highlights the main challenges facing the research community, namely, the development of a large scale morphological predictive capability. Intrinsically linked with this goal is the need to continue collecting large scale (temporal and spatial) morphological data sets. Traditional deterministic system approaches have shown to have limited applicability for the modelling and prediction of large scale coastal system behaviour.

This thesis has advocated the use of complex adaptive system approaches for the study of coastal systems. Morphological coastal systems have been shown to be ideal candidates for consideration as complex adaptive systems (hydrodynamic systems somewhat less so). The complex adaptive systems approaches considered in this thesis are Artificial Neural Networks and Evolutionary Computation.

Artificial Neural Networks are a general framework for the mapping of input/output systems and readily lend themselves to the study of Coastal Systems. They may be viewed as a robust approach to either the modelling or analysis of an aspect of a coastal system. The main advantage of using Artificial Neural Networks is that they make no apriori assumptions about the system under consideration and are straightforward to implement. A shortfall is their lack of transparency in directly revealing the nature of the system under consideration. Artificial Neural Networks show much promise for further implementation for Coastal Systems. This implementation may take the approach outlined in the case studies in this thesis, or potentially more exciting applications, where they will be utilised as part of a hybrid model approach.

Evolutionary Computation is as effective approach for the optimisation of models of systems. It is capable of exploring extremely large search spaces which may be contaminated with noise. There are characteristics which are highly prevalent for coastal system data sets. Either of these characteristics preclude or greatly reduce the versatility of other optimisation approaches. Operationally, however, they tend to be computationally expensive and require careful treatment in implementation.

Both these complex adaptive system approaches have shown themselves to be useful in studying coastal systems. It was shown that the morphological case studies could be considered validly as complex adaptive systems. The strength of argument for considering the hydrodynamic case as a complex adaptive system was much less, as it behaved in a much more deterministic fashion. Interestingly, this did not impact on the success of utilising a complex adaptive system approach for analysing the system.

Complex adaptive systems approaches showed themselves capable of introducing insight into the behaviour of coastal systems on a range of levels from being specific considerations (migration rates) to more general observations as to the nature of coastal systems. The level of insight obtained by complex adaptive systems was shown to equal that obtained by more traditional deterministic approaches for all case studies. In some cases it was possible to achieve results or insights which were not possible by using traditional approaches.

The utility of complex adaptive systems approaches for studying coastal systems is intrinsically linked not only to the expected level of success that these approaches offer, but also their ease of application. It was suggested that in this respect Artificial Neural Networks show more potential in terms of ease of application rather than Evolutionary Computation. However, it must be emphasized that the overall success of any study is most strongly limited by the theoretical framework into which the application is placed.

Whichever approach is taken to studying coastal systems the one thing that is assured is that coastal systems will prove to be a challenging area of study for quite a while to come before they reveal all their intricacies. A conclusion which emerges from the review of approaches taken to studying coastal systems is that each approach has its own merits and helps to build towards a unifying picture of the behaviour of the coastal system.

7.2 Case Study Specific Conclusions

The following sections highlight the conclusions pertinent to the specific complex adaptive system applications to coastal system case studies considered in this thesis.

7.2.1 Artificial Neural Network Correction of Video Estimates of Sand Bar Location

Video images provide estimates of sand bar location as may be inferred from the position of the breakers. However, it was found that these estimates may be in error by up to 30-40 m. Artificial Neural Network modelling provides a technique whereby the accuracy of these estimates may be increased by taking variations in wave climate and water level into account.

Initially the approach adopted in this study was shown to accurately reproduce the intrinsic processes incorporated in the Battjes and Janssen numerical model of wave breaking. The methodology was then extended to look at field data from Egmond aan Zee in the Netherlands. The Artificial Neural Network models of the outer and inner bar behaviour show that they can accurately correct the video estimates of bar location to take account of the fluctuations in wave climate and water level forcing conditions. Residual errors ($x_p - x_{nn}$) for the developed Artificial Neural Network models were 5m or less for the outer bar and 10 m or less for the inner bar, with R^2 correlation values between the Artificial Neural Network estimates, x_{nn} and the actual locations, x_p of 0.87 and 0.77 respectively.

An improved model of the multiple bar system at Egmond utilised the location of the outer bar breaker as a proxy to encapsulate the filtering effect the outer bar has on the wave forcing conditions arriving at the inner bar. This increased the R^2 correlations for the inner bar to 0.94, emphasising the importance the local beach profile has on breaker location. As the location of x_i is taken to be dependent not only on the local wave climate and water level but also the local profile, this would suggest that the developed Artificial Neural Network model is site specific. This would require a separate model to be trained at each location this technique is to be used. In fact, if the system behaviour changed significantly at a given site there would be reduction in the accuracy of the estimated sand bar locations, because to all intensive purposes the Artificial Neural Network would have been trained on essentially a different system.

The developed models were successfully used to fill in gaps in the data set for periods when no direct measurements were available. The magnitude of the associated confidence intervals was less than 10 m. An important consideration when developing Artificial Neural Network models of the sand bar systems is to ensure that the training data sets adequately cover the parameter space. The developed models are most effective when used for inputs within the training sample space. Performance deteriorates when the model is required to extrapolate outside this region. Thus the developed models are ideal for filling in gaps when measurements are limited by the impracticality of conducting surveys with a high frequency over extended periods. They are slightly less capable of accurately predicting bar locations during extreme conditions when physical measurements are impossible as the model would not have been trained on this section of parameter space.

7.2.2 Intertidal Mapping of Morphological Features from Remotely Sensed Data

This paper has outlined a technique for the production of morphological maps of the intertidal region. The modular approach taken here is appropriate to any source of data which allows interpretation of the spatial location of a shoreline feature which may be mapped over a tidal cycle. The utilization of an Artificial Neural Network produced a model which allowed discrimination of sand and water regions, emulating the visual interpretation as made by the eye. This allowed the inference of a shoreline feature and was capable of dealing with a wide range of both hydrodynamic conditions and site characteristics. As the approach is pixel based it makes no prior assumptions as to the shape of the intertidal region. This allows, for example, mapping of a shoreline on emergent sand bar features as readily as mapping at the beach face.

The technique was validated at a range of sites. The typical rms error obtained by comparing a grid generated from data obtained by the intertidal mapping technique to data obtained by traditional surveyed techniques is in the range 0.15 m to 0.5 m. The best results were obtained at Duck, with an rms error of 0.16 m after calibration of the expression for the vertical component of the shoreline. The accuracy of the technique depends on a combination of site complexity and distance to the remote sensing source. Reflective sites with a smaller tidal excursion tend to produce more accurate maps as they lend themselves to a higher density of shoreline estimates. Also plunging breakers often give a sharper shoreline feature, due to greater contrast, than breakers found on shallow sloping beaches. The morphological maps produced at Teignmouth display the complicated 3-dimensional nature of the site. The technique is most suited to the production of morphological maps for incorporation in large scale coastal behaviour data sets. In these data sets, small scale variation is not paramount, it is more important to have larger features resolved adequately over a large region.

7.2.3 Application of Evolutionary Computation Techniques to the Study of Directional Wave Analysis

A new robust method of evaluating the directional wave spectrum has been described here. The method utilises a genetic algorithm (GA) to optimise a parametric solution for the directional wave spectrum. The fitness function required by the GA is based on a comparison of the theoretical and measured cross-spectrum. In the presence of reflection the parametric solution contains four unknown parameters requiring optimisation. These include the reflection coefficient, the principal wave direction, a spreading parameter and the reflection line distance. Numerical tests have shown that the parametric solution is sensitive to, and therefore converges quickly, for three out of the four parameters. However, there is relatively low sensitivity to the spreading and this is particularly true for sharp directional distributions of wave energy. Thus, estimates of the spreading parameter are likely to be the least accurate of the four unknown variables.

The new method provides stable repeatable estimates for all of the unknown parameters after about 15 generations of the GA.

Both numerical and field trials indicate that whilst conventional phase-locked and non phase-locked techniques are restricted to regions in space which may be defined by the dimensionless *L/S* ratio, the new parametric method provides a robust solution which is independent of the distance of the array from the reflector. Additionally, the distance from the reflector is not a required input to the analysis.

However, there are some disadvantages of the new technique described here that should be made clear. Firstly, execution times are relatively long compared to existing methods (up to 15 minutes on a modern personal computer). Secondly, the directional distribution is predefined. The Mitsuyasu *et al.* (1974) directional distribution is used here. However, other directional distributions may be easily implemented. Indeed, it is even possible to design a GA that selects the most appropriate spreading function itself on the basis of fitness, from a pool of predefined functions.

At present there is no provision made for multiple incident wave components with the same frequency but different directions (except of course the reflected component). This is easily rectified for the non-reflective situation. However, where reflection is important it is likely that a multidirectional solution would have more free parameters to be optimised than the GA can easily handle (typically 5 parameters seems to be the maximum).

A further possibility and area of future research is the application of a genetic programming technique (GP) (Koza, 1992). The GP method is another evolutionary algorithm based on the evaluation of the fitness of individuals within a population. As with a GA, generations evolve through the same processes of reproduction, crossover and mutation. The difference is that the GP actually evolves mathematical expressions to describe a process. Thus, in theory a GP could be used to derive equations for the directional distribution based on the same fitness function used here. This would of course be a non-parametric solution to the directional wave spectrum, unlike the method described here. Certain appropriate base functions (e.g. equation 5.3) could be provided in order to speed up the evolutionary process. Work is in progress to assess the value of GP techniques.

7.2.4 Application of Evolutionary Computation Techniques to the Development of a Morphologic Descriptor for Nearshore Sandbar Features

If long term data sets, which have significant spatial and temporal resolution, are going to be analysed it is advantageous to work with a subset of the information they contain. This contribution showed that a parameterisation of sand bar features successfully captured a significant proportion of the information content of the original morphological data sets. This is especially true of LSCB data sets comprising of direct bathymetrical measurements and to a lesser extent when the measurements are indirect such as those obtained from the Argus data sets. The parametric data sets are capable of reproducing results obtained from an investigation of the original data sets.

Chapter 8 Appendices

A.1 Cross-shore wave transformation model

In the following, the cross-shore wave transformation model applied in §4.4.2, is outlined. It is based on the energy balance for wave energy, which reads as

$$\frac{d}{dx}E_w c_g \cos\theta = -D \qquad \text{a1}$$

in which E_w is the wave energy ($1/8\rho g H_{rms}^2$, ρ is the density of water, g is the gravitational acceleration and H_{rms} is the root-mean-square wave height), c_g is the group velocity, θ is the angle of incidence with respect to the shore normal, and D is the energy dissipation due to wave breaking. x is the cross-shore co-ordinate, positive in the onshore direction. The cross-shore variation in θ follows from Snell's Law. D is modelled according to Battjes and Janssen (1978) as

$$D = \frac{\rho g}{4T_p}\alpha H_{max}^2 Q_b \qquad \text{a2}$$

where T_p is the peak period of the incident waves and α is a constant set to 1. H_{max} is the maximum wave height given by

$$H_{max} = \frac{0.88}{k_p}\tanh\left(\frac{\gamma k_p h}{0.88}\right) \qquad \text{a3}$$

in which k_p is the wave number corresponding to T_p, h is the water depth and γ is a wave breaking parameter computed following Battjes and Stive (1985). Q_b represents the fraction of breaking waves and is computed from the relationship

$$\frac{1-Q_b}{\ln Q_b} = -\left(\frac{H_{rms}}{H_{max}}\right)^2 \qquad \text{a4}$$

Linear wave theory was applied to compute k_p, the wave celerity c and c_g.

For a given bottom profile $z(x)$ and offshore values of H_{rms}, T_p, θ and η, equation a1 can be numerically integrated in the onshore direction to obtain the theoretical cross-shore variation in D. As mentioned in §4.4.2, the location of maximum in D across the bar is assumed to behave similarly to the location of maximum image intensity. A simple forward stepping numerical scheme, which is of sufficient accuracy to solve equation a1, was applied here. The bottom profiles $z(x)$ used in §4.4.2 were modelled according to (Bakker and De Vroeg, 1987)

$$z(x) = z_{mean}(x) - A_b \exp\left[-\left(\frac{x - x_b}{R_b}\right)^2\right] \cos\left(2\pi \frac{x - x_b}{L_b} - \Phi_b(t)\right) \qquad \text{a5}$$

in which the first term on the right hand side is a mean smooth profile and the second term represents the variations ('bars') around it. A_b is the maximum bar amplitude, x_b is the location of maximum bar amplitude, R_b controls the width of the barred part of the profile, L_b is the bar spacing and $\Phi_b(t)$ is the time-varying phase of the bar system.

A double-barred beach, comparable to Egmond aan Zee, can be obtained by $z_{mean}(x) = -0.1117x^{2/3}$, $A_b = 2.5$ m, $x_b = 250$m, $L_b = 250$ m and $R_b = 200$ m. The mean profile was extended to a water depth of 15 m ($x = 1500$ m), being the depth where the offshore wave and water level information shown in figure 4.11 was measured. Bar migration can be simulated by varying Φ_b in time. Φ_b was deliberately chosen to vary as otherwise the artificial neural network would be trained and tested on a constant output. The resulting bar locations are shown with the thick line in figure 4.12a. It is finally noted that the positive x direction in the wave decay model is opposite to that used in equation a5 and in the Egmond data set (§4.4.2). For consistency, all results shown in the case study are based on x being positive in the offshore direction.

A.2 Interpolation method (local quadratic functions)

An interpolation method that locally fits a quadratic beach surface model to the survey data is used. The surface model is

$$\begin{aligned}\hat{Z}_i(x,y) &= \hat{b}_0(x_i,y_i)+\hat{b}_1(x_i,y_i)[x-x_i]+\hat{b}_2(x_i,y_i)[y-y_i] \\ &+\hat{b}_3(x_i,y_i)[x-x_i]^2+\hat{b}_4(x_i,y_i)[x-x_i][y-y_i]+\hat{b}_5(x_i,y_i)[y-y_i]^2\end{aligned} \qquad \text{a6}$$

where $\hat{b}_0$ is the elevation estimate at an arbitrary location (x_i, y_i). The parameters $\hat{b}_1..\hat{b}_5$ include the cross-shore and alongshore components of the local beach slope and quadratic dependencies. The beach surface model is fit to the observations by minimising a weighted mean square deviations between the model and data, in which the parameters solve the "generalised normal equations" (Priestley, 1981, page 315). The weighted mean square deviations are

$$Q_i^2 = \sum_{i'} \left[\left(\hat{z}_{i'} - z_{i'} \right) W_{i,i'} \right]^2 \qquad \text{a7}$$

where $W_{i,i'}$ is a weighting function that explicitly defines the meaning of "local". We used Loess weights, where

$$W_{i,i'} = \begin{cases} \left[1-\left(w_{i,i'}\right)^3\right]^3 & w_{i,i'}<1 \\ 0 & \text{otherwise} \end{cases} \qquad \text{a8}$$

and

$$w_{i,i'} = \left[\left(\frac{x_{i'}-x_i}{\lambda_x} \right)^2 + \left(\frac{y_{i'}-y_i}{\lambda_y} \right)^2 \right] \qquad \text{a9}$$

Here, λ_x and λ_y are spatial scales that determine the spatial smoothness of the interpolated values. The filtering characteristics of this interpolation method are described in detail by Schlax and Chelton (1992). Rules of thumb (based on a series of simulations) for setting the smoothing scales are that

- they must be at least 4-6 times the sample spacing in order to minimise errors due to unresolved variations.
- the smoothing scales must be less than about ½ the wavelength of any features whose structure we wish to resolve. For instance, beach cusps at Duck had a wave length of about 30 m. To resolve these feature adequately requires

smoothing scales that are shorter than about 15 m ($\lambda y = L_{cusp}/2$). Interpolating with this scale requires sample spacing no greater than 3 m ($\Delta x = \lambda y/5$).

The expected mean square interpolation errors are computed by assuming that the model-data deviations are due to uncorrelated noise. In this case, the model parameter estimates are Normally distributed random variables whose variance about the true parameter value as given by Priestley, (1981, page 368) is

$$\hat{\sigma}_m^2(x_i, y_i) = \frac{\Phi_{m,m}^{-1}(x_i, y_i) Q_i^2}{\sum_r W_{i,r} - M} \qquad \text{a10}$$

where m indicates the model parameter (m = 0 is the elevation estimate at the interpolation point and there are 3 parameters so M = 3) and Φ^{-1} is the inverse of the M by M data correlation matrix (i.e., Φ describes the correlation between the independent variables used in the linear regression). The summation of the weights yields the effective degrees of freedom if the model-data deviations are spatially uncorrelated. (See Schlax and Chelton (1992) for a description of the error estimates when the wave number spectrum of the observations is known.)

This interpolation method is efficient in our situation due to the large size of the data sets (i.e., $O(10^3)$ observations), since the computational effort increases proportionally to the number of samples: N. An alternative approach of using sub-optimal interpolation (Plant *et al.*, 1999) requires a computational effort that increases with N^2 (Schlax and Chelton, 1992). We found (through a series of simulations) that the sub-optimal interpolation scheme was more accurate and yielded more consistent error estimates only if the sample density and smoothing scales violated the rule of thumb guidelines mentioned above.

Chapter 9 References

Aarninkhof, S.G.J. and Roelvink, J.A., 1999, 'Argus-based Monitoring of Intertidal Beach Morphodynamics', *Proceedings of Coastal Sediments '99*, pp 2,429-2,444

Aarninkhof, S.G.J., Janssen, P.C. and Plant, N.G., 1997, 'Quantitative Estimations of Bar Dynamics from Video Images', *Proceedings of Coastal Dynamics '97*, Plymouth, UK, pp 365-374

Aarninkhof, S.G.J., Plant, N.G., Turner, I. and Kingston, K.S. 2002, 'Shoreline Identification From Video Imagery. Intercomparison and Ground Truthing of Four Detection Models', *Coastal Engineering*, (in review)

Abarbanel, H. 1996, '*Analysis of Observed Chaotic Data*', Springer-Verlag, New York

Anderson, R.S., 1990, 'Eolian Ripples as Examples of Self-Organisation in Geomorphological Systems', *Earth Science Reviews*, Vol. 29, pp 77-96

Aoki, I. and Komatsu, T. 1997, 'Analysis and Prediction of the Fluctuation of Sardine Abundance using a Neural Network', *Oceanologica Acta*, Vol. 20, No. 1, pp 81-88

Ashenazai, V., Dumville, M., Bingley, R. and Dodson, A., 2000, The Use of Remote Sensing in Climate Change', *Research and Development Technical Report E82*, Environment Agency, UK

Ashton, A, Murray, A.B. and Arnoult, O., 2001, 'Formation of Coastline Features by Large-Scale Instabilities Induced by High-Angle Waves', *Nature*, Vol. 414, pp 296-300

Atger, F., 1999, 'The Skill of Ensemble Prediction Systems', *Monthly Weather Review*, Vol.127, pp 1,941-1,953

Aubrey, D.G., 1979, 'Seasonal Patterns of Onshore/Offshore Sediment Movement', *Journal of Geophysical Research*, Vol. 84, No. C10, pp 6,347-6,354

Babovic, V. and Minns, A.W., 1994, 'Use of Computational Adaptive Methodologies in Hydroinformatics', *Proceedings of Hydroinformatics '94*, Balkema, Rotterdam, pp 201-210

Babovic, V., 1996, '*Emergence, Evolution, Intelligence; Hydrodynamics. A Study of Distributed and Decentralised Computing Using Intelligent Agents*', PhD thesis, IHE, Delft University of Technology, The Netherlands.

Bailard, J.A. 1981, 'An Energetics Total Load Sediment Transport Model for a Plane Sloping Beach', *Journal of Geophysical Research*, Vol. 86, No. C11, pp 10,938-10,954

Bailey, D.G. and Shand, R.D., 1997, 'Data Fusion Issues in Analysing Coastal Morphodynamic Systems', *Proceedings of the First Joint Australian and New Zealand Conference on Digital Image and Vision Computing: Techniques and Applications. Auckland*, New Zealand, pp 107-112.

Bak, P., 1997, '*How Nature Works: The Science of Self-Organised Criticality*', Springer-Verlag, New York

Bakker, W.T. and De Vroeg, J.H., 1987, 'Is de kust veilig? Analyse van het gedrag van de Hollanse kust in de laatste 20 jaar. (Is the coast safe? Analysis of the behaviour of the Dutch coast over the last 20 years; in Dutch)', Rijkswaterstaat, Tidal Waters Division, The Hague, Report GWAO 88.017

Banzhaf, W., Nordin, P. Keller, R. and Francone, F., 2001, '*Genetic Programming: An Introduction on the Automatic Evolution of Computer Programs and its Applications*', Morgan Kaufmann, San Francisco.

Barnett, T.P., 1983, 'Interaction of the Monsoon and Pacific Trade Wind System at Interannual Time Scale. Part 1: The Equatorial Zone', *Monthly Weather Review*, Vol. 111, pp 756-773

Battjes, J.A. and Janssen, J.P.F.M, 1978, 'Energy Loss and Set-up due to Breaking of Random Waves', *Proceedings of the 16th International Conference of Coastal Engineering*, New York, ASCE, pp 569-587

Battjes, J.A. and Stive, M.J.F., 1985, 'Calibration and Verification of a Dissipation Model for Random Breaking Waves', *Journal of Geophysical Research*, Vol. 90, pp 9,159-9,167

Bell, P.S., 1999, 'Shallow Water Bathymetry Derived from an Analysis of X-Band Marine Radar Images of Waves', *Coastal Engineering*, Vol. 37, pp 513-527

Bird, E.C.F., 1985, '*Coastal Changes: A Global Review*', Wiley, Chichester

Bishop, C.M., 1995, '*Neural Networks for Pattern Recognition*', Oxford University Press, Oxford

Bowen A.J. and Guza, R.T., 1978, 'Edge Waves and Surf Beat', *Journal of Geophysical Research*, Vol. 83, No. C4, pp 1,913-1,920

Bowen, A.J. and Huntley, D.A., 1984, ' Waves, Long Waves and Nearshore Morphology', *Marine Geology*, Vol. 60, pp 1-13

Bowen, A.J., 1980, 'Simple Models of Nearshore Sedimentation: Beach Profiles and Longshore Bars', In McCann (Ed.), *The Coastline of Canada*, Geological Survey of Canada Ottawa, pp 1-11

Capobianco, M., De Vriend, H.J., Nicholls, R.J. and Stive, M.J.F., 1999, 'Coastal Area Impact and Vulnerability Assessment: The Point of View of a Morphodynamic Modeller', *Journal of Coastal Research*, Vol. 15, No.3, pp 701-716

Coco, G., 'Mechanisms for the Formation of Rhythmic Topography in the Nearshore Region', PhD thesis, University of Plymouth, UK.

Corne, S., Kneale, P., Openshaw, S. and See, L., 1998, 'The Use and Evaluation of Artificial Neural Networks in Flood Forecasting', *Proceedings 33rd MAFF Conference of River and Coastal Engineers*, pp 6.4.1-6.4.10

Cote, S. and Tatnall, A.R.L., 1997, 'Estimation of Ocean Surface Currents from Satellite Imagery Using a Hopfield Neural Network', *MTS Journal*, Vol. 30, No. 4, pp 4-13

Cowell, P.J. and Thom, B.G., 1994, 'Morphodynamics of Coastal Evolution', In R.W.G. Carter and C.D. Woodruffe, *Coastal Evolution*, Cambridge University Press, pp 33-86

Cowell, P.J., Roy, P.S. and Jones, R.A., 1995, 'Simulation of Large-Scale Coastal Change using a Morphological Behaviour Model', *Marine Geology*, Vol. 126, pp 45-61

Crespo, J.L. and Mora, E., 1993, 'Drought Estimation with Neural Networks', *Advances in Engineering Software*, Vol. 18, pp 167-170

Dail, H.J., Merrifield, M.A. and Bevis, M., 2000, 'Steep Beach Morphology Changes Due to Energetic Wave Forcing', *Marine Geology*, Vol. 162, pp 443-458

Darwin, C., 1859, '*The Origin of Species by Means of Natural Selection*', Random House, New York.

Davidson, M.A., Bird, P.A.D., Bullock, G.N. and Huntley, D.A., 1994, 'Wave Reflection: Field Measurements, Analysis and Theoretical Developments', *Proceedings of Coastal Dynamics '94*, Barcelona, Spain, pp 642-655

Davidson, M.A., Bird, P.A.D., Huntley, D.A., and Bullock, G.N., 1996, 'Prediction of Wave Reflection from Rock Structures: An Integration of Field and Laboratory Data', *Proceedings of the 25th International Conference of Coastal Engineering*, Orlando, Florida, pp 2,077-2,086

Davidson, M.A., Huntley, D.A. and Bird, P.A.D., 1998, 'A Practical Method for the Estimation of Directional Wave Spectra in Reflective Wave Fields', *Coastal Engineering*, Vol. 33, pp 91-116

Davidson, M.A., Huntley, D.A., Holman, R.A. and George, K., 1997, 'The Evaluation of Large Scale (km) Intertidal Beach Morphology on a Macrotidal Beach using Video Images', *Proceedings of Coastal Dynamics '97*, Plymouth, England, pp 385-394

Davidson, M.A., Kingston, K.S. and Huntley, D.A., 2000, 'New Solution for Directional Wave Analysis in Reflective Wave Fields', *Journal of Waterway, Port, Coastal and Ocean Engineering*, Vol. 126, No. 4, pp 173-181

Dawkins, R., 1982, '*The Extended Phenotype*', Penguin Books, London.

De Hilster, N., 1998, 'Measuring Accuracy WESP', Internal Rijkswaterstaat Report, (unpublished), 3pp

De Vriend, H.J., 1991, 'Mathematical Modelling and Large-Scale Coastal Behaviour, Part 1: Physical Processes', *Journal of Hydraulic Research*, Vol.29, pp 727-740

De Vriend, H.J., 1997, 'Prediction of Aggregated-Scale Coastal Evolution', *Proceedings of Coastal Dynamics '97*, Plymouth, UK, pp 644-653

De Vriend, H.J., Zyserman, J., Nicholson, J., Roelvink, J.A., Péchon, P. and Southgate, H.N., 1993, 'Medium-term 2DH Coastal Area Modelling', *Coastal Engineering*, Vol. 21, pp 193-224

Dean, R.G. and Dalrymple, R.A., 1993, '*Water Wave Mechanics for Engineers and Scientists*', Advanced Series on Ocean Engineering, Vol. 2, World Scientific, Singapore.

Dean, R.G., 1991, 'Equilibrium Beach Profiles: Characteristics and Applications', *Journal of Coastal Research*, Vol. 7, No. 1, pp 53-84

Deigaard, R., Drønen, N., Fredsøe, J., Jensen, J.H. and Jørgensen, M.P., 1999, 'A Morphological Stability Analysis for a Long Straight Barred Coast', *Coastal Engineering*, Vol. 36, pp 171-195

Deo, M.C. and Sridar Naidu, C., 1999, 'Real Time Wave Forecasting using Neural Networks', *Ocean Engineering*, Vol. 26, pp 191-203

Deo, M.C. Gondane, D.S. and Samil Kumar, V., 2002, 'Analysis of Wave Directional Spreading Using Neural Networks', *Journal of Waterway, Port, Coastal and Ocean Engineering*, Vol. 128, No. 1, pp 30-37

Dibike, Y.B., Solomatine, D. and Abbott, M.B., 1999, 'On the Encapsulation of Numerical-Hydraulic Models in Artificial Neural Network', *Journal of Hydraulic Research*, Vol. 37, No. 2, pp147-161

Dong, P. and Chen, H., 2001, 'Wave Chronology Effects on Long-Term Shoreline Erosion Predictions', *Journal of Waterway, Port, Coastal and Ocean Engineering*, Vol. 127, No. 3, pp 186-189

Dyer, K.R. and Soulsby, R.L., 1988, 'Sand Transport on the Continental Shelf', *Annual Review of Fluid Mechanics*, Vol. 20, pp 295-324

Falques, A., Montoto, A. and Iranzo, V., 1996, 'Bed Flow Instability of the Longshore Current', *Continental Shelf Research*, Vol.16, No. 15, pp 1927-1964

Feigenbaum, M.J., 1980, 'Universal Behaviour in Nonlinear Systems', *Los Alamos Science*, Vol. 1, pp 4-27

Fogel, L.J., 1962, 'Autonomous Automata', *Industrial Research*, Vol. 4, pp 14-19

Fredsøe, J. and Deigaard, R., 1992, *'Mechanics of Coastal Sediment Transport'*, Advanced Series on Ocean Engineering, Vol. 3, World Scientific, Singapore.

French, M.N., Krajewski, W.F. and Cuykendall, R.R., 1992, 'Rainfall Forecasting in Time and Space Using a Neural Network', *Journal of Hydrology*, Vol. 137, pp1-29

Frison, T.W. and Abarbanel, H.D.I., 1997, 'Ocean Gravity Waves: A Non-linear Analysis of Observations', *Journal of Geophysical Research*, Vol. 102, No. C1, pp 1,051-1,059

Frison, T.W., Abarbanel, H.D.I., Earle, M.D., Schultz, J.R. and Scherer, W.D., 1999a, 'Chaos and Predictability in Ocean Water Levels', *Journal of Geophysical Research*, Vol. 104, No. C4, pp 7,935-7,951

Frison, T.W., Earle, M.D., Abarbanel, H.D.I. and Scherer, W.D., 1999b, 'Interstation Prediction of Ocean Water Levels Using Methods of Nonlinear Dynamics', *Journal of Geophysical Research*, Vol. 104, No. C6, pp 13,653-13,666

Gaillard, P., Gauthier, M. and Holly, F., 1980, 'Method of Analysis of Random Wave Experiments with Reflecting Coastal Structures', *Proceedings of 17th Conference on Coastal Engineering*, ASCE, New York, pp 204-220

Gallagher, E.L., Elgar, S. and Guza, R.T., 1998, 'Observations of Sand Bar Evolution on a Natural Beach', *Journal of Geophysical Research*, Vol. 103, No. C2, pp 3,203-3,215

Gell-Mann, M., 1994, '*The Quark and the Jaguar. Adventures in the Simple and the Complex*', Abacus, London

Gleick, J., 1987, '*Chaos: The Making of a New Science*', Viking, New York

Goldberg, D.E., 1989, '*Genetic Algorithms in Search Optimisation and Machine Learning*', Addison-Wesley, Reading MA.

Goldberg, D.E., 1994, '*Coastal Zone Space – Prelude to Conflict ?*', UNESCO, Paris

Guza, R.T. and Thornton, E.B, 1981, 'Wave Set-up on a Natural Beach', *Journal of Geophysical Research*, Vol. 86, No. C5, pp 4,133-4,137

Guza, R.T. and Thornton, E.B, 1985, 'Velocity Moments in the Nearshore', *Journal of Waterway, Port, Coastal and Ocean Engineering*, Vol. 111, No. 2, pp 235-256

Hagan, M.T. and Menhaj, M., 1994, 'Training Feedforward Networks with the Marquardt Algorithm', *IEEE Transactions on Neural Networks*, Vol. 5, No 6, pp. 989-993

Hallet, B., 1990, 'Spatial Self-Organisation in Geomorphology: From Periodic Bedforms and Patterned Ground to Scale-Invariant Topography', *Earth-Science Reviews*, Vol. 29, pp 57-75

Hanson, H. and Larson, M., 2000, 'Simulating Coastal Evolution Using a New Type of N-Line Model', *Proceedings of 27th Conference of Coastal Engineering*, Sydney, Australia, ASCE, pp 2,808-2,821

Hanson, H., 1989, 'Genesis – A Generalised Shoreline Change Numerical Model', Journal of Coastal Research, Vol. 5, No.1, pp 1-27

Hashimoto, N. and Kobune, K., 1988, 'Directional Spectrum Estimation from a Bayesian Approach', *Proceedings 21st Conference on Coastal Engineering*, ASCE, Malaga, pp 62-76

Hasselmann, K., 1988, 'PIPs and POPs: The Reduction of Complex Dynamical Systems Using Principal Interaction and Oscillation Patterns', *Journal of Geophysical Research*, Vol. 93, No. D9, pp 11,015-11,021

Hobbes, T., 1651, *Leviathan*, Revised Ed., Cambridge University Press

Holland, J.H., 1962, 'Outline for a Logical Theory of Adaptive Systems', *Journal of the Association for Computing Machinery*, Vol. 3, pp 293-314

Holland, J.H., 1975, '*Adaptation in Natural and Artificial Systems*', University of Michigan Press.

Holland, K.T. and Holman, R.A., 1997, 'Video Estimation of Foreshore Topography using Trinocular Stereo', *Journal of Coastal Research*, Vol. 13, No. 1. pp 81-87

Holland, K.T. and Holman, R.A., Lippmann, T.C. , Stanley, J. and Plant, N., 1997, 'Practical use of Video Imagery in Nearshore Oceanographic Field Studies', *Journal of Oceanic Engineering*, Vol. 22, No. 1, pp 81-92

Holland, K.T., Vincent, C.L. and Holman, R.A., 1999, 'Statistical Characterisation of Nearshore Morphodynamic Behaviour', *Proceedings of Coastal Sediments '99*, pp 2,176-2,189

Holman, R.A. and Sallenger Jr., A.H., 1986, 'High Energy Nearshore Processes', *EOS*, Vol. 67, No. 49 pp 1,369-1,371

Holman, R.A., and Bowen, A.J., 1982, 'Bars, Bumps and Holes: Models for the Generation of Complex Beach Topography', *Journal of Geophysical Research*, Vol. 87, No. C1, pp 457-468

Horel, J.D., 1984, 'Complex Principal Component Analysis: Theory and Examples', *Journal of Climate and Applied Meteorology*, Vol. 23, pp 1,660-1,673

Hotelling, H., 1936, 'Relations Between Two Sets of variates', *Biometrika*, Vol. 28, pp 321-377

Howd, P., Bowen, A.J. and Holman, R.A., 1992, 'Edge Waves in the Presence of Strong Longshore Currents', *Journal of Geophysical Research*, Vol.97, No. C7, pp 11,357-11,371

Huntley, D.A. and Davidson, M.A., 1998, 'Estimating the Directional Spectrum of Waves near a Reflector', *Journal of Waterway, Port, Coastal and Ocean Engineering*, Vol. 124, No. 6, pp 312-319

Huntley, D.A., Guza, R.T. and Thornton, E.B., 1981, 'Field Observations of Surf Beat! Progressive Edge Waves' *Journal of Geophysical Research*, Vol. 86, No. C7 pp 6,451-6,466

Isobe and K. Kondo, 1984, 'Methods for Estimating Directional Wave Spectrum in Incident and Reflected Wave Field', *Proceedings of 19^{th} Conference on Coastal Engineering*, ASCE, New York, pp 467-483

Janssen, P.C., 1997, '*Intertidal Beach Level Estimations from Video Images*', M.Sc. Thesis, Delft University of Technology

Jordan, M.I. and Bishop, C.M., 1996, 'Neural Networks', In A. Tucker, (Ed.) '*The Computer Science and Engineering Handbook*', CRC Press, Boca Raton, Florida.

Kaplan, D. and Glass, L., 1995, '*Understanding Non-Linear Dynamics*', Springer-Verlag, New York

Karunanithi, N. Grenney, W.J., Whitley, D. and Bovee, K., 1994, 'Neural Networks for River Flow Prediction', *ASCE Journal of Computing in Civil Engineering*, Vol. 8, No. 2, pp 279-284

Kingston, K.S. and Davidson, M.A., 1999, 'Artificial Neural Network Model of Sand Bar Location for a Macro-Tidal Beach, Perranporth, UK', *IAHR Symposium on River Coastal and Estuarine Modelling*, Genoa, Italy, pp 227-236

Kingston, K.S. and Davidson, M.A., 2001, 'A Parametric Morphologic Descriptor for Nearshore Sandbar Features', *Proceedings of 4^{th} Conference on Coastal Dynamics '01*, ASCE, Lund, June 11-15, pp 673-682

Kingston, K.S., Mallet, C., Plant, N.G. and Davidson, M.A., 2002, 'Intertidal Mapping of Morphological Features From Remotely Sensed Data', *Journal of Geophysical Research*, (in review)

Kingston, K.S., Ruessink, B.G., Van Enckevort, I.M.J. and Davidson, M.A., 2000, 'Artificial Neural Network Correction of Remotely Sensed Sandbar Location', *Marine Geology*, Vol. 169, No. 1-2, pp 137-160

Kirk, J. T., 1994, '*Light and Photosynthesis in Aquatic Ecosystems*', Cambridge University Press

Kirkpatrick, S., Gelatt, C.D. and Vecchi, M.P., 1983, 'Optimisation by Simulated Annealing', *Science*, Vol. 220, No. 4,598 pp 671-680

Kohonen, T., 1990, 'The Self-Organising Map', *Proceedings of IEEE*, Vol. 78, pp 1,464-1,480

Komar, P.D, 1998, '*Beach Processes and Sedimentation*', Prentice Hall Inc.

Koza, J., 1992, 'Genetic Programming: On the Programming of computers by means of natural selection', The MIT Press, Cambridge

Larson, M., Capobianco, Jansen, H., M., Różyński, G., Southgate, H.N., Stive, M.J.F., Wijnberg, K.M., and Hulscher, S.J.M.H., 2002, 'Analysis of Field Data of Coastal Morphological Evolution over Yearly and Decadal Timescales. Part 1: Background and Linear Techniques', *Journal of Coastal Research, PACE Special Issue*, (*in press*)

Larson, M., Capobianco, M. and Hanson, H., 2000, 'Relationship Between Beach Profiles and Waves at Duck, North Carolina, Determined by Canonical Correlation Analysis', *Marine Geology*, Vol. 163, pp 275-288

Larson, M., Hanson, H. Kraus, K.C. and Newe, J., 1999, 'Short- and Long-Term Responses of Beach Fills Determined by EOF Analysis', *Journal of Waterway, Port, Coastal and Ocean Engineering*, Vol. 125, No. 6, pp 285-293

Liang, G., White, T.E. and Seymour, R.J., 1992, 'Complex Principal Component Analysis of Seasonal Variation in Nearshore Bathymetry', *Proceedings of 23rd Conference of Coastal Engineering*, Venice, Italy, ASCE, pp 2,242-2,250

Lippmann, T.C. and Holman, R.A, 1989, 'Quantification of Sand bar Morphology: A Video Technique Based on Wave Dissipation', *Journal of Geophysical Research*, Vol. 94, No. C1, pp 995-1,011

Lippmann, T.C. and Holman, R.A, 1991, 'Phase Speed and Angle of Breaking Waves Measured with Video Techniques', *Proceedings of Coastal Sediments '91*, pp 489-497

Lippmann, T.C. and Holman, R.A., 1990, 'The Spatial and Temporal Variability of Sand Bar Morphology', *Journal of Geophysical Research*, Vol. 95, pp 11,575-11,590.

Lippmann, T.C., Holman, R.A. and Hathaway. K.K., 1993, 'Episodic, Nonstationary Behaviour of a Double Bar System at Duck, North Carolina, USA, 1986-1991', *Journal of Coastal Research*, Vol. S1, No. 15, pp 49-75

List, J.H. and Terwindt, J.H.J., 1995, 'Large Scale Coastal Behaviour, *Marine Geology*, Vol. 126, pp 1-3

Lorenz, E.N., 1963, 'Deterministic Non-Periodic Flow', *Journal of Atmospheric Science*, Vol. 20, pp130-141

Lovelock, J., 1995, '*Gaia. A New Look at Life on Earth*', Oxford University Press, Oxford.

MacKay, D.J.C., 1992, 'Bayesian Interpolation', *Neural Computation*, Vol.4, No.3, pp 415-447

Madsen, A.J., and N.G. Plant, 2001, 'Intertidal Beach Slope Predictions Compared to Field Data', *Marine Geology*, Vol. 173, No.1-4, pp121-139

Mase, H., Sakamoto, M. and Sakai, T., 1995, 'Neural Network for Stability Analysis of Rubble-Mound Breakwaters', *Journal of Waterway, Port, Coastal and Ocean Engineering*, Vol. 121, N. 26, pp 294-299

Masselink, G., 1998, 'Field Investigation of Wave Propagation Over a Bar and the Consequent Generation of Secondary Waves', *Coastal Engineering*, Vol. 33, No. 1, pp 1-9

McCulloch, W.S. and Pitts, W.H., 1943, 'A Logical Calculus of Ideas Immanent in Nervous Activity', *Bulletin of Mathematical Biophysics*, Vol. 5, pp 115-133

Mitsuyasu, H., Tasai, F., Subara, T., Mizuno, S., Okusu, M., Honda, T. and Rikiishi, K., 1975, 'Observations of the Directional Spectrum of Ocean Waves Using a Clover-Leaf Buoy', *Journal of Physical Oceanography*, Vol. 5, pp 750-760.

Morton, R.A., Leach, M.P., Paine, J.G., and Cardoza, M.A., 1993, 'Monitoring beach changes using GPS surveying techniques', *Journal of Coastal Research*, Vol. 9, 702-720, 1993.

Murray, A.B. and Paola, C., 1994, 'A Cellular Model of Braided Rivers', *Nature*, Vol. 371, pp 54-57

Murray, A.B. and Reydellet, G., 2001, 'A Rip Current Model Based on a Hypothesised Wave/Current Interaction', *Journal of Coastal Research*, Vol. 17, No. 3, pp 517-530

Nairn, R.B. and Southgate, H.N., 1993, 'Deterministic Profile Modelling of Nearshore Processes. Part 2. Sediment Transport and Beach Profile Evolution', *Coastal Engineering*, Vol. 19, pp 57-96

Nicholls, R.J., Birkemeier, W.A. and Lee, G-H, 1998, 'Evaluation of Depth of Closure using Data from Duck, NC, USA', *Marine Geology*, Vol. 148, pp 179-201.

Nicholson, J., Broker, I., Roelvink, J.A., Price, D., Tanguy, J.M. and Moreno, L., 1997, 'Intercomparison of Coastal Area Morphodynamic Models', *Coastal Engineering*, Vol. 31, pp 97-123

Oltman-Shay, J., Howd, P.A., and Birkemeier, W.A., 1989, 'Shear Instabilities of the Mean Longshore Current. 2. Field Observations', *Journal of Geophysical Research*, Vol. 94, No. C12, pp 18,031-18,042

Ouchi, N.B. and Nishimori, H., 1995, 'Modelling of Wind-Blown Sand Using Cellular Automata', *Physical Review E*, Vol. 52, No. 6, pp 5,877-5,879

Oussar, Y. and Drefus, G., 2001, 'How to be a Gray Box: Dynamic Semi-Physical Modelling', *Neural Networks*, Vol. 14, pp 1,161-1,172

Patil, D.A.S., Hunt, B.R. and Carton, J.A., 2001, 'Identifying Low-Dimensional Nonlinear Behaviour in Atmospheric Data', *Monthly Weather Review*, Vol. 129, pp 2,116-2,125

Peet, A.H., Sutherland, J. and Soulsby, R.L., 2002, 'Skill Assessment in Coastal Models', *Journal of Coastal Research* (in preparation)

Phillips, J.D., 1992, 'Nonlinear Dynamical Systems in Geomorphology: Revolution or Evolution', *Geomorphology*, Vol. 5, pp 219-229

Phillips, J.D., 1993, 'Spatial Domain Chaos in Landscapes', *Geographical Analysis*, Vol. 25, pp101-117

Phillips, J.D., 1999, '*Earth Surface Systems. Chaos Order and Scale*', Blackwell Publishers Ltd., Oxford, UK

Pilkey, O.H., Young, R.S., Riggs, S.R., Sam Smith, A.W., Wu, H. and Pilkey, W.D., 1993, 'The Concept of Shoreface Profile of Equilibrium: A Critical Review', *Journal of Coastal Research*, Vol. 9, No. 1, pp 255-278

Plant, N.G. and Holman, R.A., 1997, 'Intertidal Beach Profile Estimation using Video Images', *Marine Geology*, Vol.140, pp 1-24

Plant, N.G. and Holman, R.A., 1998, 'Extracting Morphologic Information From Field Data', *Proceedings of 26th Conference of Coastal Engineering*, Copenhagen, Denmark, ASCE, pp 2,773-2,784

Plant, N.G., Freilich, M.H. and Holman, R.A., 2001, 'Role of Morphologic Feedback in Surf Zone Sandbar Response', *Journal of Geophysical Research*, Vol.106, No. C1, pp 973-989

Plant, N.G., Holman, R.A. and Freilich, M.H., 1999, 'A Simple Model for Interannual Sandbar Behaviour', *Journal of Geophysical Research*, Vol.104, No. C7, pp 15,755-15,776

Plant, N.G., K.T. Holland, and J.A. Puleo, 2002, 'Analysis of the Scale of Errors in Nearshore Bathymetric Data', *Marine Geology*, Vol. 191, pp 71-86

Priestley, M.B., 1981, '*Spectral Analysis and Time Series*', Academic Press, New York.

Rechenberg, I., 1965, 'Cybernetic Solution Path of an Experimental Problem', Royal Aircraft Establishments, Library Translation 1112, Farnborough, UK.

Reeve, D.E. and Fleming, C.A., 1997, 'A Statistical-dynamical Method for Predicting Long Term Coastal Evolution', *Coastal Engineering*, Vol. 30 pp. 259-280

Richaume, P., Badran, F., Crepon, M., Mejia, C., Roquet, H. and Thiria, S., 2000, 'Neural Network Wind Retrieval from ERS-1 Scatterometer Data', *Journal of Geophysical Research*, Vol. 105, No. C4, pp 8,737-8,751

Robinson, A.H.W., 1975, 'Cyclical Changes in Shoreline development at the Entrance to Teignmouth Harbour, Devon, England, In: Hails, J. and Carr, A., Nearshore Sediment Dynamics and Sedimentation, John Wiley, London. pp 181-198

Roelvink, J.A. and Broker, I., 1993, 'Cross-shore Profile Models', *Coastal Engineering*, Vol. 21, pp 163-191

Roelvink, J.A. and Stive, M.J.F., 1989, 'Bar-Generating Cross-Shore Flow Mechanisms on a Beach', *Journal of Geophysical Research*, Vol. 94, No. C4, pp 4,785-4,800

Roelvink, J.A., Meijer, Th.J.G.P., Houwman, K. Bakker, R. and Spanhoff, R., 1995, 'Field validation and Application of a Coastal Profile Model', *Proceedings International Conference Coastal Dynamics*, Gdansk, Poland, ASCE, pp 818-828

Rogers, C.R., 1961, '*On Becoming a Person. A Therapist's View of Psychotherapy*', Constable, London

Rosenblatt, F., 1961, '*Principles of Neurodynamics*', Spartan Press, Washington D.C.

Ruelle, D, 1990, 'Deterministic Chaos: The Science and the Fiction', *Proceedings of the Royal Society London*, Vol. 427, pp 241-248

Ruessink, B.G. and Kroon, A., 1994, 'The Behaviour of a Multiple Bar System in the Nearshore Zone of Terschelling, The Netherlands', *Marine Geology*, Vol. 121, pp 187-197

Ruessink, B.G., 1998, '*Infragravity Waves in a Dissipative Multiple Bar System*', PhD Thesis, Utrecht University, The Netherlands.

Ruessink, B.G., Van Enckevort, I.M.J., Kingston, K.S., and Davidson, M.A., 2000, 'Analysis of Observed Two- and Three-Dimensional Nearshore Bar Behaviour', *Marine Geology*, Vol. 169, No. 1-2, pp 161-183

Rumelhart, D.E. and McClelland, J., (eds.), 1986, '*Parallel Distributed Processing: Explorations into the Microstructure of Cognition, Volume 1: Foundations*', The MIT Press, Cambridge, Mass.

Rumelhart, D.E., Hinton, G.E. and Williams, R.J., 1986, 'Learning Representation by Back-Propagating Errors', *Nature*, Vol. 323, pp 533-536

Russell, P.E. and Huntley, D.A., 1999, 'A Cross-Shore Transport "Shape Function" for High Energy Beaches', *Journal of Coastal Research*, Vol. 15, No. 1, pp198-205

Ryan, T.W., Sementilli, P.J., Yuen, P. and Hunt, B.R., 1991, 'Extraction of Shoreline Features by Neural Nets and Image Processing', *Journal of Photogrammetric Engineering & Remote Sensing*, Vol. 57, No. 7, pp 947-955

Sarle, W.S., 1994, 'Neural Networks and Statistical Models', *Proceedings of the 19th SAS Users Group International Conference*

Schlax, M.G. and Chelton, D.B., 1992, 'Frequency Domain Diagnostics for Linear Smoothers', *Journal of American Statistical Association*, Vol. 87, No. 420, pp 1,070-1,081

Schoones, J.S. and Theron, A.K., 1995, 'Evaluation of 10 Cross-Shore Sediment Transport Morphological Models', *Coastal Engineering*, Vol.25, No. 1-2, pp 1-41

Science, 1999, Insert on 'Complex Systems', *Science*, Vol. 284, pp 79-109

Shannon, C.E., 1948, 'A Mathematical Theory of Communication', *Bell System Technical Journal*, Vol. 27, pp 379-423, 623-656

Skyttner, L., 1996, '*General Systems Theory - An Introduction*', Macmillan Press, London

Southgate, H.N. and Beltran, L.M., 1996, 'Self-Organisational Processes in Beach Morphology, *Proceedings of the Conference on Physics of Estuarine and Coastal Seas*, September 1996, The Hague, The Netherlands

Southgate, H.N. and Möller, I., 2000, 'Fractal Properties of Coastal Profile Evolution at Duck, North Carolina', *Journal of Geophysical Research*, Vol. 105, No. C5, pp11,489-11,507

Southgate, H.N., 1995, 'The Effects of Wave Chronology on Medium and Long Term Coastal Morphology', *Coastal Engineering*, Vol. 26 pp 251-270

Southgate, H.N., Wijnberg, K.M., Larson, M., Capobianco, M. and Jansen, H., 2002, 'Analysis of Field Data of Coastal Morphological Evolution over Yearly and Decadal Timescales. Part 2: Non-Linear Techniques', *Journal of Coastal Research, PACE Special Issue, (in press)*

Stewart, W.K., Jiang, M. and Marra, M., 1994, 'A Neural Network Approach to Classification of Sidescan Sonar Imagery from a Midocean Ridge Area', *IEEE Journal of Oceanic Engineering*, Vol. 19, No. 2, pp 214-224

Stive, M.J.F. and De Vriend, H.J., 1995, 'Modelling Shoreface Profile Evolution', *Marine Geology*, Vol. 126, pp 235-248

Stockdon, H.F., and Holman, R.A., 2000, 'Estimation of Wave Phase Speed and Nearshore Bathymetry from Video imagery', *Journal of Geophysical Research*, Vol. 105, No. C9, pp 22,015-22,033

Takens, F., 1981, 'On the Numerical Determination of the Dimension of an Attractor', In D. Rand and L.S. Young; '*Dynamical Systems and Turbulence*', Warwick 1980 *Lecture Notes in Mathematics*, Vol. 898, 230pp, Springer-Verlag

Thiria, S., Mejia, C., Badran, F. and Crepon, M., 1993, 'A Neural Network Approach for Modelling Nonlinear Transfer Functions: Application for Wind Retrieval From Spaceborne Scatterometer Data', *Journal of Geophysical Research*, Vol. 98, No. C12, pp 22,827-22,841

Thornton, E.B., Dalrymple, R.A., Drake, T.G., Gallagher, E.L., Guza, R.T., Hay, A.E., Holman, R.A., Kaihatu, J.M., Lippmann, T.C. and Ozkan-Haller, H.T., 2000, 'Nearshore Process Research', Report based on the Nearshore Research Workshop, St. Petersburg, Florida, September, 14-16, 1998.

Tsai, C.-P. and Lee T.-L., 1999, 'Back-Propagation Neural Network in Tidal-Level Forecasting', *Journal of Waterway, Port, Coastal and Ocean Engineering*, Vol. 125, No. 4 pp 195-202

Turner, I.L. and Nielsen, P., 1997, 'Rapid Water Table Fluctuations within the Beach Face: Implications for Swash Zone Sediment Mobility?', *Coastal Engineering*, Vol. 32, pp 45-59

Van Enckevort, I.M.J. and Ruessink, B.G., 2001, 'Effects of Hydrodynamics and Bathymetry on Video Estimates of Nearshore Sandbar Position', *Journal of Geophysical Research*, Vol. 106, pp 16,969-16,980

Van Gent, M.R.A. and Van den Boogaard, H.F.P, 1998, 'Neural Network and Numerical Modelling of Forces on Vertical Structures', *Proceedings of the 26th International Conference on Coastal Engineering*, Copenhagen, Denmark, ASCE, pp 2,096-2,109

Van Rijn, L.C., 1993, '*Principles of Sediment Transport in Rivers, Estuaries and Coastal Seas*', Aqua Publications, Amsterdam, The Netherlands

Vittori, G. and Blondeaux, P., 1990, 'Sand Ripples under Sea Waves. Part 2. Finite-Amplitude Development', *Journal of Fluid Mechanics*, Vol. 381, pp 271-303

Von Bertalanffy, L., 1968, '*General Systems Theory*', Braziller, New York

Vrijling, J.K. and Meijer, G.J., 1992, 'Probabilistic Coastline Position Computations', *Coastal Engineering*, Vol. 17, No. 1-2, pp 1-23

Waldrop, M.M., 1992, '*Complexity: The Emerging Science at the Edge of Order and Chaos*', Simon and Schuster, New York

Weigend, A.S. and Gershenfeld, N.A., editors, 1994, '*Time Series Prediction: Forecasting The Future and Understanding the Past*', Addison Welsey, Reading, MA.

Werner, B.T. and Fink, T.M., 1993, 'Beach Cusps as Self-Organised Patterns', *Science*, Vol. 260 pp 968-970

Werner, B.T. and Kocurek, G., 1997, 'Bed-form Dynamics: Does the Tail Wag the Dog', *Geology*, Vol. 25., No. 9, pp 771-774

Werner, B.T., 1995, 'Eolian Dunes: Computer Simulations and Attractor Interpretations', *Geology*, Vol. 23, No. 12, pp 1,107-1,110

Werner, B.T., 1999, 'Complexity in Natural Landform Patterns', *Science*, Vol. 284, pp 102-104

Wijnberg, K.M. and Terwindt, J.H.J., 1995, 'Extracting Decadal Morphological Behaviour from High-Resolution, Long-Term Bathymetric Surveys along the Holland Coast using Eigenfunction Analysis', *Marine Geology*, Vol. 126, pp 301-330

Wijnberg, K.M., 1995, 'Morphologic Behaviour of a Barred Coast over a Period of Decades', PhD thesis, Utrecht University, The Netherlands.

Woodd-Walker, R.S., Kingston, K.S. and Gallienne, C.P., 2001, 'Using Neural Networks to Predict Surface Zooplankton Biomass Along a 50°N to 50°S Transect of the Atlantic, *Journal of Plankton Research*, Vol. 23, No. 8, pp 875-888

Wright, L.D. and Short, A.D., 1984, 'Morphodynamic Variability of Surf Zones and Beaches: A Synthesis', *Marine Geology*, Vol. 56, pp 93-118

Wright, L.D. and Thom, B.G., 1977, 'Coastal Depositional Landforms: A Morphodynamic Approach', *Progress in Physical Geography*', Vol. 1, pp 412-459