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Multi-fractal Analysis
of SAR
Ocean Wave Imagery

submitted by

Eric S. Storie B.Sc.

in partial fulfilment of the requirements for
the degree of Master of Arts

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The undersigned recommend to the Faculty of Graduate Studies
and Research acceptance of the thesis

Multi-fractal Analysis
of SAR
Ocean Wave Imagery

submitted by

Eric S. Storie B.Sc.

in partial fulfilment of the requirements for
the degree of Master of Arts

Thesis Supervisor

Chair, Department of Geography

Dedication

I would like to dedicate this work to my family and friends who have provided me with the inspiration to finish this work.

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Abstract

The exact relationship between fractal dimension and landscape patterns or development is not fully understood. The multi-fractal dimensionality of an ocean wave data set was investigated in an attempt to determine its relationship with fractal dimension. Airborne CV-580 SAR imagery from the Canada Centre for Remote Sensing (C.C.R.S) of an area of ocean over the Grand Banks, Newfoundland, was provided for this research. No radiometric or geometric corrections were applied to the data. Peleg's blanket method was used to calculate the fractal dimension of both the SAR imagery and a data set simulated to respond like ocean waves. The fractal dimension of actual waves was analyzed visually, graphically, and statistically by comparison to simulated wave data. Regression of SAR imagery digital values and fractal dimension imagery digital values indicated that a significant relationship existed between the variates. The results of the regression imply that a relationship exists between Bragg resonant scattering and fractal dimension, although most of the variance between the variates can be explained by speckle. Regressions indicate that relationships between the mean fractal dimension and geophysical parameters, such as significant wave height, mean zero-crossing period and wind speed, were less significant than the relationships with the change in mean fractal dimension. Correlations of change in mean fractal dimension with wave height and wave period appear to be in agreement with SAR ocean wave imaging models which use the variation in speckle intensity as a means of measuring ocean waves. Variation in mean fractal dimension with respect to scale change was attributed to artifacts of sampling. This research found that the fractal dimension is correlated with image texture in SAR ocean wave imagery and is fairly constant with mean values in a range of 2.08 to 2.20. A significant and strong correlation coefficient was found between variance of SAR digital values within the sample window used to calculate the fractal dimension and the fractal dimension. This result indicated that the fractal dimension is a measure of image texture.

Table of Contents

	<i>page</i>
Chapter 1	
Introduction	
1.1 Purpose.	1
1.2 Background of the investigation.	1
1.3 Scope of the research.	7
 Chapter 2	
Ocean Turbulence	
2.1 Overview.	9
2.2 Introduction.	9
2.3 Theory of ocean turbulence.	10
2.3.1 Wind stress.	10
2.3.2 Bottom friction.	12
2.3.3 Lateral stress from the coastline.	14
2.3.4 Shear in currents due to pressure stress.	14
2.3.5 Resultant surface waves and ocean turbulence.	14
2.4 Remote sensing techniques used to observe turbulence.	15
2.4.1 Infrared radiometry.	16
2.4.2 Synthetic aperture radar.	18
2.4.3 Altimetry.	23
2.5 Summary.	23
 Chapter 3	
Observation of Ocean Waves using SAR	
3.1 Overview.	25
3.2 Introduction.	25
3.3 Basic concepts of SAR.	25
3.4 Interaction of SAR and ocean waves.	28
3.5 Models of SAR ocean wave imaging.	32
3.6 Summary.	36

Chapter 4	Methodology	
4.1 Overview.		38
4.2 Data sources.		38
4.3 Image naming standard adopted.		38
4.4 Pre-processing of SAR imagery.		39
4.5 Calculation of fractal dimension.		45
4.6 Detailed analysis of one image data set		57
4.7 Comparison of fractal dimension to corresponding geophysical data.		61
 Chapter 5	 Results	
5.1 Introduction.		63
5.2 Processing of SAR and simulation data.		63
5.3 Analysis of the variation in Fd with image scale.		67
5.3.1 SAR data analysis.		67
5.3.2 Simulated data analysis.		75
5.3.3 Analysis of noise data.		76
5.3.4 Combined simulated plus noise data analysis.		76
5.3.5 Effects of image re-sampling on fractal analysis.		77
5.4 Statistical relationship between SAR and fractal dimension imagery.		82
5.5 Statistical relationship between geophysical parameters and fractal dimension.		95
5.6 Summary.		99
 Chapter 6	 Conclusions	
6.1 Conclusions of research.		100
6.2 Discussion.		103
6.3 Fractal definition for SAR ocean wave imagery.		105
6.4 Paths for future research and speculation based on research.		106

References

References.

108

Appendix-A

Prints of standardized SAR imagery and simulation imagery.

List of Tables

Table 2.1	Wave types based on spatial and time scales.
Table 4.1	CV-580 imaging parameters.
Table 4.2	SAR, simulation, and noise data image names and statistical data gathered
Table 4.3	Resampled SAR image output pixel sizes.
Table 4.4	The results of processing the 512 pixel by 512 line sample of the standardized SAR image li25603n with fractal analysis software using several different input parameters.
Table 4.5	The results of processing the 512 pixel by 512 line sample of the standardized SAR image li2575n with fractal analysis software using several different input parameters.
Table 4.6	The results of processing the 512 pixel by 512 line sample of the standardized SAR image li2586n with fractal analysis software using several different input parameters.
Table 4.7	Analysis of variance for the regression of thickness and mean fractal dimension using values from Tables 4.4 - 4.6.
Table 4.8	Analysis of variance for the regression of number of layers and mean fractal dimension using values from Tables 4.4 - 4.6.
Table 4.9	Analysis of variance for the regression of window size and mean fractal dimension using values from Tables 4.4 - 4.6.
Table 4.10	The results of processing the 512 pixel by 512 line samples of the standardized SAR images li2575n, li2580n, li2586n, li2591n, li2598, li2603n, and li2609n with fractal analysis software.
Table 4.11	SAR and geophysical parameters gathered near the CSS Hudson at the time of each SAR pass.
Table 5.1	Summary of descriptive statistics output during processing of simulation image data set images with fractal analysis software.
Table 5.2	Summary of descriptive statistics output during processing of standardized SAR images with fractal analysis software.
Table 5.3	Regression statistics and analysis of variance of input Dn values and output local fractal dimension imagery Dn values.
Table 5.4	Regression statistics and analysis of variance of input Dn values and output local fractal dimension imagery Dn values for well formed wave images Li2586, Li2598, and Li2603.

Table 5.5	Regression statistics and analysis of variance of input Dn values and output local fractal dimension imagery Dn values for SAR background noise data set.
Table 5.6	Summary statistics for samples of the variates used in the regression of SAR image 9li2586n and corresponding fractal image 9l2586nf.
Table 5.7	Regression statistics and analysis of variance for regression of SAR image 9li2586n and corresponding fractal image 9l2586nf.
Table 5.8	Summary statistics for samples used in the regression of fractal dimension image values extracted from li2586nf and local variance measured in standardized SAR image li2586n.
Table 5.9	Regression statistics and analysis of variance of measured variance in 9 by 9 sample window and local fractal dimension image digital values.
Table 5.10	Descriptive statistics of geophysical data.
Table 5.11	Correlation coefficients (r) for regressions of measured fractal dimension parameters and geophysical data.

List of Figures

- Figure 1.1 Histogram surface derived from fractal signatures.
- Figure 2.1 Motion of water induced by wind.
- Figure 2.2 Transport of water by wind near the coastline.
- Figure 2.3 Geometry of SAR imaging.
- Figure 2.4 Example of return signal sampling.
- Figure 3.1 Satellite borne SAR imaging geometry.
- Figure 3.2 Geometry of Bragg resonant scattering.
- Figure 3.3 Swell alteration of Bragg wave amplitudes.
- Figure 3.4 Modulation of SAR backscatter by tilt of the ocean surface.
- Figure 4.1 SAR image sample of the same spatial region at various resampling levels.
- Figure 4.2 Regression of mean fractal dimension and thickness parameter used for processing.
- Figure 4.3 Residuals for the regression of mean fractal dimension and thickness parameter used for processing.
- Figure 4.4 Regression of mean fractal dimension and number of layers parameter used for processing.
- Figure 4.5 Residuals for the regression of mean fractal dimension and the number of layers parameter used for processing.
- Figure 4.6 Regression of mean fractal dimension and window size parameter used for processing.
- Figure 4.7 Residuals for the regression of mean fractal dimension and the window size parameter used for processing.
- Figure 5.1 Mean fractal dimension vs. resolution Li2586.
- Figure 5.2 Mean fractal dimension vs. resolution Li2603.
- Figure 5.3 Mean fractal dimension vs. resolution Li2598.
- Figure 5.4 Mean fractal dimension vs. resolution Li2575.
- Figure 5.5 Mean fractal dimension vs. resolution Li2591.
- Figure 5.6 Mean fractal dimension vs. resolution Li2580.
- Figure 5.7 Mean fractal dimension vs. resolution Li2609.
- Figure 5.8 Mean, maximum, and minimum fractal dimension vs. resolution Li2575.

- Figure 5.9 Mean, maximum, and minimum fractal dimension vs. resolution Li2580.
- Figure 5.10 Mean, maximum, and minimum fractal dimension vs. resolution Li2586.
- Figure 5.11 Mean, maximum, and minimum fractal dimension vs. resolution Li2591.
- Figure 5.12 Mean, maximum, and minimum fractal dimension vs. resolution Li2598.
- Figure 5.13 Li2603 image data set maximum, minimum and mean fractal dimension values.
- Figure 5.14 Mean, maximum, and minimum fractal dimension vs. resolution Li2609.
- Figure 5.15 Comparison of simulated and real data.
- Figure 5.16 Frequency distribution of L2586n digital values.
Pixel spatial resolution = 1.
- Figure 5.17 Frequency distribution of 2L2586n digital values.
Pixel spatial resolution = 2.
- Figure 5.18 Frequency distribution of 3L2586n digital values.
Pixel spatial resolution = 3.
- Figure 5.19 Frequency distribution of 4L2586n digital values.
Pixel spatial resolution = 4.
- Figure 5.20 Transect of SAR images of different resolutions.
- Figure 5.21 Transect of fractal images of different resolutions.
- Figure 5.22 Transect of fractal [l2586nf] and SAR image [l2586n].
- Figure 5.23 Fractal dimension imagery Dn vs. standardized SAR imagery Dn.
- Figure 5.24 SAR standardized image Dn value residual plot.
- Figure 5.25 Fractal dimension imagery Dn vs. standardized SAR image Dn.
- Figure 5.26 Standardized SAR image Dn value residual plot.
- Figure 5.27 Comparison of standardized SAR image fractal image.
- Figure 5.28 Fractal dimension imagery Dn vs. SAR noise Dn.
- Figure 5.29 Fractal dimension imagery Dn vs. standardized SAR image Dn.
- Figure 5.30 Standardized SAR image Dn value residual plot.

Figure 5.31 Variance versus fractal dimension.

Figure 5.32 Residual plot for regression of 9x9 window variance and F_d .

Figure 5.33 Wave height vs. average change in mean F_d .

Figure 5.34 Wave period vs. average change in mean F_d .

Figure 5.35 Instantaneous wind speed vs. average change in mean F_d .

List of Notations

Symbols used for variables and parameters are displayed below, along with the appropriate units where applicable.

Symbol	Explanation [units]
D_T	Topological Dimension [no units]
F_d	Fractal Dimension [no units]
D_n	Image digital number [no units]
H_s	Significant wave height [m]
V	Aircraft velocity [m/s]
T_0	Mean zero-crossing period [s]
U	10 m equivalent height neutral stability wind speed [m/s]
θ	Incidence Angle [degrees]
λ_o	Wavelength used for sensing by the SAR sensor [cm]
λ_b	Wavelength of an ocean wave [cm]
R/V	Scene range to platform velocity ratio [s]

Chapter 1

Introduction

1.1 Purpose.

The objectives of this thesis were to investigate the multi-fractal dimensionality of a SAR image data set, to try to evaluate existing definitions and explanations of fractal dimension, and attempt to relate the fractal dimension to measured geophysical parameters. To do so required an investigation into the relationship between a surface and the fractal dimension of a surface. The exact relationship between fractal dimension and landscape patterns or development is not yet fully understood [de Jong and Burrough, 1995 p.1043]. It may be that the definition of a fractal requires some refinement, or at least a description of the limits within which the definition is applicable. This research will attempt to build upon the work of Broscoe [1993] which investigated the fractal nature of aerial photography of a city. In order to limit the variables involved in this research, it was deemed necessary to use a data set containing one type of phenomenon with measurable surface texture and be composed of a limited number of materials to simplify any analysis. The data set selected was synthetic aperture radar [SAR] imagery of ocean waves. SAR backscatter is determined by a feature's surface roughness and its dielectric constant. Using SAR imagery of ocean waves is an attempt to isolate one factor influencing the SAR backscatter, surface roughness, while other factors, typically present in land covers, can be assumed to be constant.

1.2 Background of the investigation.

Fractal analysis is a derivative of Chaos theory. Chaotic systems exist in nature. Chaos is the apparent unpredictable behaviour which can occur in deterministic systems [Shlesinger et al., 1993 p.31]. A deterministic system is one in which the future state of the system is determined through some dynamic law by its preceding state [Davies, 1990 p.51]. In general we incorrectly equate chaos and randomness. Random behaviour could be described as the chance occurrence of a behaviour within a system, where every type of behaviour has the equal probability of occurring. Chaos theory of non-linear dynamic systems provides a means of understanding processes which appear random because of our

ignorance of the fine details in a system with only a few degrees of freedom [Davies, 1990]. According to chaos theory, a very low number of degrees of freedom is adequate to create "deterministic chaos" [Leung and Haykin, 1990; Davies, 1990].

Meteorology is one of the geosciences which has made use of chaos theory. At present, scientists can only supply reliable local weather forecasts, for up to a few days in advance. Weather is perceived as a system containing both apparently random and predictable events. Events such as tornadoes are perceived as chaotic occurrences, while the occurrence of snow rather than rain in winter is perceived as normal and predictable. As early as 1963, Edward Lorenz successfully demonstrated the deterministic chaos present in models of weather. Lorenz [1963] modelled the climate of the Earth using only three non-linear equations, or three degrees of freedom. Initial conditions of the model defined by Lorenz [1963] demonstrated the sensitivity of the system. It was discovered that slightly different initial states can produce considerably different final states [Lorenz, 1963]. This effect is commonly described as the butterfly effect. A small input can over time result in a large output. Lorenz [1963] translated his results into a prediction problem, recognising that reliable, very long range weather prediction may be impossible beyond a set period of time because of the lack of knowledge of the initial conditions of the system. This is recognised by the meteorological community and directly affects the prediction of weather [Palmer, 1989 pp. 58-59]. Consequently, reliable local forecasts by meteorologists are rarely made beyond one week.

Fractal analysis relies upon the recognition that some chaotic systems are deterministic. Chaotic systems which are deterministic follow, or are attracted to, a set path. The path is referred to as a strange attractor or strange repeller. Repellers and attractors are self explanatory, repelling or attracting, and in Euclidean geometry could both be represented by a point. The path which a deterministic chaotic system follows tends to be more complex with the attractor or repeller being a fractal [Mandelbrot, 1983]. If this is the norm, then it can be said that chaotic systems which are deterministic can have their behaviour mapped and measured in the geometry of a fractal. Fractal analysis measures the geometry of a fractal. Fractals are

mathematical functions which can produce shapes or objects which have special properties [Pentland, 1986]. The properties of fractal objects will be presented in succeeding paragraphs. At present, geoscientists hope to make use of fractal analysis to predict precisely the behaviour of chaotic systems.

The geometry of a fractal has a dimension which can be measured. The simplest "normal" idea of dimension is the topological dimension. The topological dimension of a point is zero [0], the topological dimension of a line is one [1], and the topological dimension of a plane is two [2]. A topological dimension is always an integer. Fractals on the other hand can have dimensions which are real numbers, not integers.

Visually, our concept of surface roughness has been demonstrated [Pentland, 1986] to correspond with the fractal dimension of a surface or a line. Using ten subjects, the mean of the estimate of perceived roughness of several surfaces displayed a near perfect correlation ($r=0.98$; $p<0.001$) with fractal dimension [Pentland, 1986 p.2]. Pentland described the fractal dimension of a surface as being invariant with respect to linear transformations of the data and to transformations of scale [Pentland, 1986 p.2]. This implies that the measurement of fractal dimension of one type of surface at one spatial extent is sufficient to determine the fractal dimension within any spatial extent of that surface. Pentland qualifies the definition of a fractal as being stable over a wide range of scales, but it is unreasonable to expect a physical surface to be fractal over all scales. Physical surfaces have an overall size that places an upper limit on scale range, and a lower limit set by the size of the constituent particles [Pentland 1986]. It is therefore important to quantify the scale range over which measurements of fractal dimension take place, if a definition of a fractal is formulated for a surface. Ocean waves, as an example, are unlimited in wavelength at the lower limit. The upper limit of wavelength for ocean waves is more tangible depending on the force of energy input into the ocean system, the amount of dampening affecting that force from sources such as gravity, and the limit of the size of basin containing the water.

Margerum and Werkheiser [1988] summarised the definition of a fractal as a mathematical construct that gives a realistic representation of natural patterns and textures and that exhibits invariant properties under scale change. Here again the independence from changes in measurement scale is stressed by the authors.

Mandelbrot [1983] defined a fractal using pure mathematical terminology. Mandelbrot [1983] defined a fractal as a set of points for which the Hausdorff-Besicovitch dimension exceeds the topological dimension, where the topological dimension is as described in earlier paragraphs. The Hausdorff-Besicovitch dimension is a theoretical concept which is difficult to describe in non-mathematical terms. It is described here as a gross simplification of the mathematical concept. A space exists in which there is a set of points to be measured, and the measurement tool is a ball with a radius not exceeding the size of the set and not less than zero. To measure the length that the points describe in the space, the ball would have to be placed from beginning to end over the set of points. By considering all the possible coverings that could be carried out using the ball, the measurement of the dimension of the set of points is found to be proportional to the dimension of the ball. This measurement of dimension of the set of points is known as the Hausdorff measure and is not always an integer. For a non-fractal set of points, the dimension of the ball is an integer which corresponds to the topological dimension, which could be a length, area, or volume [Margerum and Werkheiser, 1988]. For fractal sets, the dimension of the ball may not be an integer, and there will be one value for the ball dimension for which the Hausdorff measure is positive and finite [Margerum and Werkheiser, 1988 p.3]. This one value of dimension is called the Hausdorff-Besicovitch dimension [Margerum and Werkheiser, 1988]. This implies that measurement of the points must be carried out several times, each time using a ball of different dimension for each complete measurement of the points. The mathematical definition described by Mandelbrot [1983] is simple to understand if you consider the measurement of a three dimensional object. The following example is derived from Crilly et. al. [1991]. The Rubics cube is topologically a three dimensional object which is divided up into 64 smaller cubes. If you allow a standard measurement scale to be equal to one side of the small cubes, then by this scale the length of each side of the Rubics

cube is 4. The change in scale at which we can view one entire small cube is one quarter the original scale. This gives the following relationship:

$$\text{number of copies } N = \left(\frac{\text{dimension } D_T}{1/\text{scale factor } f} \right) \quad (1)$$

The dimension of the object can be calculated by taking the logarithm of each side of the equation.

$$\text{dimension } D_T = \frac{\log(N)}{\log(1/f)} \quad (2)$$

For the case of the Rubics cube:

$$\text{dimension } D_T = \frac{\log(64)}{\log(1/4)} \quad (3)$$

$$\text{dimension } D_T = 3$$

The Hausdorff-Besicovitch dimension or fractal dimension is calculated as the limit of the quotient of the log change in object size and the log change in measurement scale, as the scale approaches zero [Shirriff, 1993 pp.17]. In mathematical terms:

$$\text{Fractal dimension} = \lim_{\text{scale} \rightarrow 0} \frac{\log [\text{change in object size}]}{\log [\text{change in measurement scale}]} \quad (4)$$

The relationship in equation 4 is again a quotient of two logarithms similar to equation 2. In general, the different methods used to calculate the fractal dimension vary in terms of what is defined as "object size" and "measurement scale" [Shirriff, 1993]. The limit on the function indicates that the fractal dimension approaches one value for the entire scale range. The definition of a fractal by Mandelbrot is a mathematical abstraction. Mathematical abstractions, or models, can only approximate real world processes.

Definitions described here are applicable to mono-fractal dimensional patterns and textures. It has been observed in previous work [Broscoe, 1993] that changes in spatial resolution of imagery may

Histogram Surface Derived from Fractal Surfaces

White lines indicate modal trend for each surface Col1, Col2, Col3, Pik1, Pik2, Fish, and Sor.

Figure 1.1. Fractal signatures of resolution degraded imagery. As the resolution of each image is degraded from 1 to 256 pixels, the modal fractal dimension appears to drift. This drift is indicated by the heavy lines. (Source: Broscoe [1993], p. 124.)

cause changes in the fractal dimension measured. This indicates that the fractal dimension changes as the scale at which a pattern or texture is measured changes, and if this does occur then the texture or pattern being analysed is not a fractal by mathematical definition. The results of Broscoe [1993] are similar in appearance to a spectral signature [Figure 1.1], and could probably be described as a fractal signature. Lovejoy and Schertzer [1991] also determined that natural phenomena may commonly display multi-fractal dimensionality. A system which displays multiple fractal dimensions is termed multi-fractal. The results of the work by Lovejoy and Schertzer [1991] and Broscoe [1993] indicate that the pure definitions of a fractal as described above, and in their earliest mathematical form by Mandelbrot [1983], are unsettling to geoscience at present because of such observed changes in fractal dimension with changes in scale. It may be that measured fractal dimension is only stable over a range of scales for geoscientific phenomena, as indicated by Pentland [1986], or that the observed changes in measured fractal dimension are artifacts of processing. If artifacts are the bases of changes in measured fractal dimension of geoscientific phenomena then identification of possible artifacts is critical in the analysis, since this would suggest that the fractal dimension is stable and follows the mathematical definition. Another possibility is that changes in observed fractal dimension could be caused by changes in the state of the system being observed. Systems can become unstable as they are driven further from equilibrium, at which point a bifurcation may occur leading to a new steady state [Coveney, 1990]. Bifurcation is a "branching" or "splitting". If the system being observed is already in a state of equilibrium, which involves a bifurcation between two states, for example one state in which the return signal is dominated by noise and another which is dominated by a return signal of backscatter from ocean waves, then it might be expected that a variation between two fractal dimensions should be observed.

1.3 Scope of the research.

Some limitation is present in any research. An attempt is made in this section to identify the major limitations present in this research.

Research was limited to the use of SAR imagery of the east coast of North America, which may not be representative of the entire oceanic

basin. It is possible that imagery selected of other areas of the world would produce different results. Another limitation was the selection of the range of ocean state information contained within the SAR imagery. An attempt was made to select imagery which contained SAR backscatter information on varying ocean states. It is possible that the imagery selected is not representative of all ocean states.

Chapter 2 *Ocean Turbulence*

2.1 Overview.

The purpose of this chapter is to describe the general characteristics of the test target, the ocean, used in the experiment. The similarity of ocean wave shape and the self-repeating nature of waves in the ocean lend credibility to the idea that the ocean may be fractal. Further credibility for the fractal nature of the ocean is provided by turbulence in the ocean which may produce non-linear interactions of ocean waves. Non-linearity is a basic mechanism of chaos. The theory of ocean turbulence and of ocean features caused by ocean turbulence, which includes ocean waves, is reviewed. This chapter also provides a description of how the ocean has historically been observed using remote sensing technology. General descriptions are provided of the various techniques which can be employed to observe the ocean. Finally, a justification for using synthetic aperture RADAR to measure the target is made.

2.2 Introduction.

To gain insight into the possible fractal nature of the oceanic process requires investigation of the process of ocean turbulence, which can operate on several observational scales. Ocean turbulence is primarily a random mixing process. Mixing of the ocean can occur in both the horizontal and vertical planes. The process of mixing generates visible features on the ocean surface which can be detected in remotely sensed imagery. Features generated include, at a large observational scale, ocean waves, and at a small observational scale, oceanic eddies and upwellings or downwellings. These features may visually appear to contain order in their structure similar to fractal objects. Visually, ocean waves are similar in shape and self-repeating at several scales, which partially by definition describes a fractal. Fractals, by one definition, are mathematical constructs that give realistic representation of natural patterns and textures and that exhibit invariant properties under scale change [Margerum and Werkheiser, 1988 p.3].

2.3 Theory of ocean turbulence.

Turbulent flow is a phenomenon which can be defined by several characteristics. Turbulent flow is random or irregular in both velocity and acceleration. It is diffusive causing rapid mixing, increased momentum, heat, and mass transfer, and is associated with large Reynolds numbers [Tennekes and Lumley, 1972]. Turbulence translates in three dimensions and can be rotational, causing dissipation of energy [Tennekes and Lumley, 1972]. Turbulence is a phenomenon which is governed by the equations of fluid mechanics [Tennekes and Lumley, 1972], or hydrodynamic equations. It should be noted that turbulence is not a property of a fluid, but a phenomenon of fluid flows. Unresolved theoretical problems exist regarding small scale ocean turbulence in that the motions are too complex and detailed to be described on all scales simultaneously [Apel, 1987].

Ocean turbulence is generated by the following four processes: wind stress, bottom friction, lateral stress from the coastline, and shear in currents due to pressure stress [Bowden, 1962]. Each of these processes will be discussed separately, and should be considered as variables in this research which can affect production of ocean surface waves.

2.3.1 Wind stress.

Ocean circulation is driven by the heating and cooling of the atmosphere, and by direct transfer of momentum from wind. Atmospheric pressure forcing and thermal forcing are inefficient forces when compared to wind stress forcing [Feron and De Ruijter, 1992]. Thermal forcing, is caused by the heating of the ocean by the sun, which can produce convection currents. Pressure forcing results from elevation changes of the ocean surface due to vertical forces exerted by high and low atmospheric pressure systems. A high pressure system will depress the ocean surface and a low pressure system will elevate it, causing water flow between the two systems [Apel, 1987]. Wind shearing stress on the ocean results from atmospheric pressure gradients causing the movement of air at the ocean-atmosphere boundary layer. The movement of air over the ocean surface is constantly turbulent [LeBlond and Mysak, 1978, p.475]. Wind shearing can produce water waves with variable height and frequency. The exact process by which wind generates waves is not completely understood [Ritter, 1978 and Pond and Pickard, 1983],

despite having been the subject of theoretical and experimental investigation for three decades [Shen et al., 1994]. These investigations have also produced a sometimes confusing descriptive terminology which describes wind-generated waves as capillary waves, wind waves, and gravity waves. It should be noted here that the intent of this thesis is not to attempt to resolve the differences in theories of the process of wind wave generation. The intent in this section is to point out that wind-generated waves can produce a turbulent ocean surface.

In general, the literature appears to support the contention that wind-generated waves are produced by friction between the wind and the sea surface [Stowe, 1983 and Pond and Pickard, 1983], with the force of gravity acting as a restoration force. The wind blowing across the ocean surface can form small ripples, usually less than 10 mm in height, with rounded crests and V-shaped troughs [Gross, 1980]. These ripples, or capillary waves as the literature commonly terms them, move with the wind direction for a short period of time [Gross, 1980]. In the region on the ocean surface where waves are produced, waves appear to propagate in an irregular or chaotic manner [Ritter, 1978]. Wave crests in the generating area are usually out of phase, causing interference and superposition of the waves.

Water waves vary in size from millimetres in wavelength, known as capillary waves, to ocean swells with wavelengths of hundreds of metres. Table 2.1 displays the length and time scales for various ocean waves. Wind-generated waves have wavelengths in the middle range of wavelengths, between centimetres and tens of metres [Robinson, 1985]. Wind speeds of 5 m/s or less have little effect on the ocean surface, causing small ripples, while wind speeds of 10 m/s are capable of producing rough seas [Robinson, 1985 p.82]. Although capillary waves have periods of less than one second [Table 2.1], they significantly roughen the ocean surface, having great influence on the transfer of momentum between the wind and the waves [Robinson, 1985]. Flow instabilities which lead to turbulence are often manifested as waves; however, pure wave motion never occurs during turbulent flow [Landahl and Mollo-Christensen, 1992].

Table 2.1 Wave types based on spatial and time scales.

Wave Type	Swell	Wind waves	Capillary waves
Wavelength	500-100m	0.05-100m	1-50 mm
Period	20-10s	10-1s	<1s

Source: (Robinson [1985] p.86.)

Ocean swell, often described as gravity waves, on the open sea has plenty of time and distance available for non-linear development and, therefore can be expected to have fully developed non-linear modulation characteristics [Landahl and Mollo-Christensen, 1992]. At small scales the ocean could be considered to be constantly in a state of turbulent flow [Fairbridge, 1966]. At all scales, it is logical to assume that, as waves of similar periods intercept a wave group(s) of different periods, both superposition and interference will produce an irregular or chaotic wave surface indicative of turbulent flow. It is probable that the dynamics of the ocean can be considered to be in a continuum of both turbulent and laminar flow.

2.3.2 Bottom friction.

Bottom friction on flows in the ocean environment cause drag forces which reduce the velocity of fluid flow. Drag forces on a body of water are due partially to pressure differences and partially to viscous shear stresses [Fairbridge, 1966 p. 292]. During laminar flow, the drag coefficient varies inversely in proportion to the Reynolds number [Fairbridge, 1966 p. 292], the Reynolds number being a non-dimensional value equal to the ratio of inertial force and frictional force. As the flow increases in velocity, the relationship between the drag coefficient, or coefficient of friction, and Reynolds number can become non-linear. In this way, the flow can become turbulent. The specific velocity at which a flow becomes turbulent depends on the shape of the container, fluid density and fluid viscosity.

Bottom friction aids the production of spirals in currents in both horizontal and vertical planes. The spiral, usually referred to as an Ekman spiral [Figure 2.1], is caused by the inability of the water to

Figure 2.1. Water is initially set in motion by wind. The direction of flow and the speed of the flow change with depth to form the Ekman Spiral, shown in black. (Source: Duxbury [1971] p. 216.)

Transport of water by wind near the coastline.

Figure 2.2. In this diagram T represents transport and W wind direction. In Case 1 transport of water is forced on shore by the wind causing a wedge of surface water along the beach. This produces downwelling. In Case 2 transport of water is off the beach causing a depression of water near the coastline, producing upwelling. (Source: Duxbury [1971] p. 216.)

transmit a driving force, such as wind shearing, downward through the water column due to frictional effects. Ekman flow near-shore can cause upwelling or downwelling, depending on the direction of fluid transport with respect to the shoreline [Figure 2.2]. Turbulence can arise in this type of flow when the inertial forces greatly exceed the frictional forces, causing instabilities in the flow. An Ekman spiral can, in fact, increase in vorticity because of deflection caused by the Coriolis effect [Duxbury, 1971], this being the acceleration of water particles in a perpendicular direction to the velocity of the particle, due to the spin of the Earth.

2.3.3 Lateral stress from the coastline.

Lateral stress along a coastline functions similarly to bottom friction, producing spirals or rings of ocean currents due to lateral friction forces caused by the coastline.

2.3.4 Shear in currents due to pressure stress.

Horizontal shear between currents or vertical shearing due to pressure stress acts to produce turbulence through viscous properties of the flow. Dampening due to molecular viscosity produces shear forces which act to transfer horizontal momentum into the vertical direction [Apel, 1987]. Shear forces transfer momentum perpendicular to the flow momentum. If shear forces or inertial forces exceed the frictional forces and produce high Reynolds numbers, the flow will become turbulent.

Analogous to molecular viscosity is anisotropic eddy viscosity [Apel, 1987]. The viscosity of the ocean is anisotropic, meaning the effective fluid viscosity varies spatially. To understand small scale effects of viscosity, oceanographers make use of hydrodynamic equations which describe ocean eddies, small scale spirals or rings in ocean currents, with respect to eddy viscosity. These equations are an attempt to simplify the motions which are complex, detailed, and difficult to describe on all scales at the same time [Apel, 1987].

2.3.5 Resultant surface waves and ocean turbulence.

It is important to state that the effects described in the preceding sections 2.21 to 2.24 are always coexisting in nature. The

net effect of the coexistence is a combination of energy from various sources and scales which can, as one by-product, produce waves on the ocean surface. In general, the resulting waves can then be considered as a manifestation on the ocean surface of the interaction of water molecules and energy at many different scales. If part of the energy supplied to a wave is produced by turbulent motions in the ocean, then it is possible to extrapolate that the wave motions may produce non-linear interactions at the ocean surface. The natural horizontal symmetric motion of a wave may become asymmetric because of the non-linear interactions. This is observed in work studying wind-generated waves by Shen et al. [1994] which states that the horizontal asymmetry of wave profiles may be a product of the non-linear interaction of wind waves and other water motions. More significantly, Shen et al. note that the non-linear interaction produces local significant enhancement of energy of short wind wave components. They pose the question as to whether or not this may be the basic mechanism which allows the observation of internal waves and fronts in SAR [Synthetic Aperture Radar] imagery. Non-linearity is a basic requirement of deterministic chaos, which was described in section 1.2 in discussion of early research by Lorenz [1963]. If ocean waves are in part a product of turbulent motions in the ocean, which could result from non-linear deterministic chaotic motions of water molecules, then the path of the deterministic chaotic system could be mapped using fractal analysis. Further, if the non-linear interactions of ocean waves are significant, it should be possible to observe these interactions with a fractal analysis of SAR ocean wave imagery, since the area of non-linear interaction should produce a local significant change in energy and surface roughness.

2.4 Remote sensing techniques used to observe turbulence.

Observation of turbulent flow in the oceans using satellite or airborne sensors has been restricted to visualization of the surface effects of turbulent flow. Surface features visible in remotely sensing imagery include, at a small spatial extent, ocean waves, and at a large spatial extent, eddies in ocean currents, upwellings or downwellings. These features combine to produce spiral patterns on imagery not unlike fractal diagrams, which are similar in shape and self repeating at several scales.

Observations of turbulent features in remotely sensed imagery of oceans have been carried out using passive remote sensing devices, radiometers capable of sensing in several wavelengths of the electromagnetic spectrum simultaneously. Radiometers are used most extensively to determine sea surface temperature allowing for the interpretation of the dynamics of ocean currents, which can reveal turbulent features. Research [Riou et al. 1988] indicates that surface roughness indirectly influences the relationship between daily evaporation and surface temperature. Surface roughness was demonstrated to modify a quasi-constant which influenced the relationship. If the fractal dimension is a measure of surface roughness it may be possible to derive information on daily evaporation on the basis of surface temperature and fractal dimension measurements of the ocean surface. The need to determine climate-related parameters, such as sea surface temperature and daily evaporation, has increased in the last decade due to the El Nino [Topliss, 1995]. El Nino refers to the periodic warming of the sea surface temperature along the Pacific coast of South America [Kasoy, 1996].

Satellite remote sensing of sea surface temperature can be carried out using three basic instruments: 1) infrared radiometers, 2) multifrequency atmospheric sounders, and 3) microwave radiometers. Infrared radiometers are the most common airborne or space-borne remote sensing instruments used by oceanographers, and for this reason the instrument will be discussed in detail. Microwave radiometers operate similarly to infrared radiometers but sense in a different range of wavelengths [7.5-1000 mm]. There have been few, if any, studies published which used microwave radiometers or sounding instruments to specifically monitor ocean turbulence. A description of the microwave radiometric technique, which can be used to monitor sea surface temperature, can be found in Lillesand and Kiefer [1979]. For a description of multifrequency atmospheric sounding see Burroughs [1991] and Wark and Flemming [1966].

2.4.1 Infrared radiometry.

In general, oceanographers require measurement of the absolute sea surface temperature with a precision of 0.1 to 0.5 degrees C and a temporal resolution of 24 hours for two dimensional measurements and 3

17
hours for boundary-layer measurements [Manson, 1991]. Uncertainty in measurements can be caused by surface foam, water vapour, and liquid precipitation in the path between the target and the sensor [Stewart, 1982].

Infrared radiometers sense sea surface temperature using information gathered in the 10-12 micrometer region of the electromagnetic spectrum [Maul, 1985]. Based on the number of published studies, research requiring infrared radiometry of the ocean has typically made use of satellite-borne thermal scanners. A thermal scanner is similar to a radiometer in that it contains a radiometer as an integral part of the sensing system. A thermal scanner employs a rotating mirror to collect data as a series of scan lines, gradually building up an image of the scanned area. The rotating mirror has, in recent years, been replaced by a sophisticated electronic sampling device which simulates data sampling produced with a rotating mirror. A scanning radiometer is made up of the following components:

- 1) Collecting-Optics - concentrates the source of thermal infrared radiation onto an area where the measurement is taken.
- 2) Filter - limits the spectral range of the instrument.
- 3) Detector - converts the radiation which passes through the optics and filter into electrical signals.
- 4) Electronics - a device which amplifies the signal from the detector, and transmits these signals to a receiving station.

Limitations of infrared radiometry include the inability of the sensor to see the ocean surface when clouds are present between the sensor and the sea surface [Kandel, 1991]. Atmospheric attenuation by scattering or absorption limits the amount of target radiance measured by radiometric techniques. In addition, emission of energy from particles or gases in the atmosphere can add to the amount of radiation measured by a thermal sensor. To overcome these limitations a calibration of the sensor is carried out to allow the detection of energy from the sea surface. Calibration is carried out by comparison

of measured emissions to a source of known temperature. Infrared radiometry of the sea surface can measure temperature with an accuracy of better than 0.5 degrees K using satellite-based sensors [Schlüssel and Meywerk, 1992].

As previously stated, infrared radiometric observation is the most prevalent method used for the extraction of sea surface temperatures. Instruments such as the CZCS [Coastal Zone Colour Scanner], AVHRR [Advanced Very High Resolution Radiometer], MOS-1 VTIR, Landsat MSS [Multi-Spectral Scanner], Landsat TM [Thematic Mapper] and the Along track Scanning Radiometer [ASTR] flown on the ERS-1 spacecraft have been used successfully to extract sea surface temperatures in an image format. Examples of research using radiometric observation are Stevenson [1977], Solomon and Ahlnas [1978], Toba et al. [1984], Rasool [1987], Lutjeharms [1989], and Schlüssel and Meywerk [1992].

Images of sea surface temperature are commonly contrast-stretched, single channel images which display sea surface temperature anomalies. A sea surface temperature anomaly is defined by Njoku and Brown [1993, p. 237] as a departure of absolute sea surface temperature from the long term climatological mean sea surface temperature. Single channel images can also be processed to reveal absolute sea surface temperatures if insitu temperature data is available. Research relating sea surface temperature to self-similar turbulent ocean structures, chains of vortices and anticyclonic eddies, has been carried out by Bunimovich et al. [1993]. The fractal dimension of isotherms derived from AVHRR infrared images, was found to be 1.27 ± 0.07 for space scales from 4 km to 120 km. Dynamic ocean structures could possibly, as a result of this research, be considered to be fractal in nature within the stated scale range.

2.4.2 Synthetic aperture radar.

Studies using SAR [Synthetic Aperture Radar] have not been carried out for the purpose of sensing turbulence. Instead, researchers have used SAR to sense ocean waves as a feature of the ocean surface. Chapter 3 of this thesis is devoted to a detailed discussion of the observation of ocean waves using synthetic aperture radar, since SAR imagery of the ocean surface is the basic data set used in this thesis. Synthetic

aperture radar is an active microwave remote sensing instrument which makes use of a synthesized antenna length to image a target. The antenna length is synthesized by combining several observations of the target as the antenna beam moves across the target. The synthesized antenna length is equal to the distance between the first and last observation of the target as the SAR antenna beam moves across the target. By synthesizing an antenna length, SAR sensors can provide higher along track, or azimuth, resolution than a real aperture radar system using the same physical antenna length.

The basic geometry of a SAR sensor emitting a microwave signal at the ocean surface is shown in Figure 2.3. The sensor emits microwave radiation at a target and measures the returning signal, discriminating signal positions by their Doppler frequency shifts. The difference in the frequency between the return signal and the emitted signal is the Doppler frequency shift. Doppler frequency shifts are a function of the relative velocities of the transmitter and reflecting target. The frequency shifts are due to the Doppler effect. Microwave radiation emitted by the SAR antenna can be represented as a wave, if wave theory of electromagnetic radiation is adopted. The frequency of the wave signal received by the SAR sensor can be used to determine the relative position of an object based on the frequency shift of the return signal. Objects receding from the SAR sensor will display lower frequencies in the measured return signal, compared to the frequency of the signal emitted by the SAR. Objects approaching the SAR sensor will display higher frequencies in the measured return signal, compared to the frequency of the signal emitted by the SAR.

Imaging is carried out by the emission of microwave radiation in the slant range direction. The oblique viewing angle produces a beam footprint with both a range and azimuth resolution. Range is the perpendicular direction with respect to the direction of travel of the SAR sensor. The path, or direction of travel, the SAR sensor follows is described as the azimuth. Parameters which determine the spatial resolution of SAR imagery include chirp length or pulse duration, band width, and sample spacing. Each of the parameters can equally influence the ability of the SAR sensor to distinguish objects as separate entities.

Pulse duration or chirp length is the amount of time which passes during the emission of the signal pulse. If the time delay in the return signals from separate targets is greater than the time duration of the pulse emitted by the SAR the two separate return signals are observed by the SAR [Kingsley, 1992]. Chirp length or pulse duration of the C.C.R.S CV-580 SAR is 7 μ s [Livingstone et al. 1995].

Geometry of SAR imaging.

Figure 2.3. The basic geometry of a SAR. The SAR sensor emits a pulse of microwave radiation at a target at a specific viewing angle. The return signal or backscatter measured by the SAR is used to construct an image of the target. Part of the signal is subject to specular reflectance and as such is not measured by the sensor.

Range pulse bandwidth of the SAR determines the ability of the SAR to accurately resolve the distance a feature is from the sensor. Bandwidth describes, in general terms, the shape of the emitted pulse. Pulse shape can be created by adding together several frequencies of

signal. Chirp systems use a pulse which is linear in shape and covers the entire frequency range which can be produced by the sensor [Kingsley, 1992]. The emitted pulse, by using a broad frequency range, produces distinct return signals.

Azimuth resolution of a SAR is dependent on antenna size. As described earlier the sensor's along track, or azimuth, resolution is dependent on the synthesized antenna length. The distance between the first and last observation of the target in the along track direction determines the length of the synthetic aperture. By sampling the return signal at specific frequencies the relative position of the targets with respect to the sensor can be determined. The bandwidth of the output signal will again determine how distinct are return signals.

Return signal strength can be altered by sample spacing. Sample spacing refers to the distance between sample measurements made of the returning signal. The larger the sample spacing is, with respect to the signal pulse shape, the less representative are the samples of the return signal pulse shape. A common sampling method used is based on the Nyquist sampling criterion. The Nyquist sampling criterion states that two samples are required per period of the highest spatial frequency [Anuta et al. 1983, pp.732]. Further, in order to avoid sampling bias the samples must be spaced close enough to measure both peak and valley locations in the signal being measured. The maximum information is obtained by spacing the samples at one half the full width at half the maximum height of the curve [Figure 2.4]. The main intent in using a specific sample spacing is to accurately depict the shape of the return signal while minimizing the total number of samples acquired. Sample spacing used in the CV-580 SAR data collected for this research is approximately 4 m in range and azimuth.

Sampling design used by the sensor can also determine the amount of image degradation resulting from speckle. Speckle is the variation in image intensity produced in SAR imagery due to constructive and destructive interference of samples. It is a result of the fluctuation of the return signal by the independent samples per resolution cell [Fung and Ulaby, 1983 p.136]. The fewer the independent samples per resolution cell the greater is the fluctuation of the return signal,

which results in speckle in the SAR imagery. As a result of speckle in the SAR imagery, any single pixel sampling of the SAR imagery will probably contain local extreme values which will result in large residuals if regressions are carried out against other variables such as measured fractal dimension.

Switching the antenna from send to receive is carried out, allowing the backscattered signal from the target to be measured. SAR processing involves the correlation of the backscattered signal with a suitable reference signal to produce an image. Several backscattered measurements of a target are combined to produce a high resolution image of the target. Analogous to sample spacing, the more "looks" at an area by a sensor that are combined to form an image the more representative of the actual target is the processed image.

Example Return Signal Sampling

Figure 2.4. Nyquist sampling criterion of a SAR return signal. The SAR sensor detects the emitted pulse shape by sampling the signal at regular intervals. Maximum information is obtained by spacing the samples at one half the full width at half the maximum height [FWHM] of the curve describing the return signal.

This technique of observing the ocean surface attempts to determine the dynamics of the ocean surface from variations in microwave backscatter, sent and received by the sensor. Surface roughness is the determining factor for the response of the sensor to the sea surface. As described earlier, the dependence of this technique on pulse

duration, band width, sample spacing, and number of looks, make the instrument capabilities as a sensor variable. Each of the dependencies can influence the ability of the SAR to resolve a target. If fractals are measurable at all scales and the ocean surface is fractal, then the detection of fractal information should be independent of the resolution of the sensor. However, if the fractal information is only measurable within a set scale range and the SAR sensor is incapable of measuring the required information then the ocean surface will appear not to be fractal when in fact it may be fractal. For a more extensive review of remote sensing of ocean waves with SAR, see Tomiyasu [1978] or Napolitano [1991]. A detailed discussion of the interaction of SAR and ocean waves will be provided in the following chapter.

2.4.3 Altimetry.

Altimetry is another method used to detect ocean turbulence through measurement of sea level variations. Microwave altimeters are similar to SAR in that both make use of active microwave sensing systems. Laser altimeters operate within the optical wavelength range $0.4\ \mu\text{m}$ to $0.7\ \mu\text{m}$ to provide data on sea surface height. Microwave altimeters measure the nadir distance from the satellite to the sea surface, recording a profile of the ocean surface [Zandbergen, 1990]. If the position of a satellite-borne altimeter is known, then the height of the satellite above the reference earth ellipsoid can be derived from the radius, the latitude, and parameters defining the ellipsoid [Zandbergen, 1990]. The height can then be compared to the height measured by the altimeter on board the satellite to determine the height of the sea surface above the reference ellipsoid, or sea level. Altimeters can also be carried by airborne platforms. Fernon and De Ruijter [1992] provide a good example of research using altimetry to monitor turbulence in the ocean. Using time series data from the Geosat altimeter they were able to detect a reoccurring pulse in sea level as the current formed anticyclonic rings.

2.5 Summary.

Ocean turbulence is primarily a random mixing process which can produce ocean waves. Wind stress, bottom friction, lateral stress from coastlines and shear in currents due to pressure stress are each seen to

have the potential to produce turbulence, which can result in the production of ocean waves or in general a roughening of the ocean surface. Ocean waves have not been researched as a turbulent phenomenon, but as a feature of the ocean surface. Studies of ocean waves using remote sensing methods have historically made use of radiometry or SAR [Synthetic Aperture Radar].

Radiometric methods used for remote sensing of turbulence have proven to be successful by authors such as Stevenson [1977], Solomon and Ahlnas [1978], Toba et al. [1984], and Lutjeharms [1989]. These methods, however, have limited application because cloud cover can reduce visibility of the ocean surface for the sensor. Cloud cover does not limit the use of SAR for remote sensing. Further work should be carried out to determine the applicability of multifrequency sounding methods and microwave radiometric methods.

The application of altimetric methods for monitoring turbulence appears to have potential for measurement of ocean turbulence from sea level variations, but further studies will be required to confirm the results of Feron and De Ruijter [1992].

Turbulence is probably the most important and least understood problem in classical physics [Mullin, 1989 p.52]. Turbulent motions of the ocean are, in general, thought to be too complex and detailed to be described on all scales at the same time. Fractal analysis, being independent of scale, has potential to allow the determination of properties at one scale to be validated or invalidated for all scales simultaneously. It was the supposition of this research that if ocean waves are in part a product of turbulent motions in the ocean, which could result from non-linear deterministic chaotic motions of water molecules, then the path of the deterministic chaotic system could be mapped using fractal analysis. Further, if the fractal dimension is related to surface roughness, as discussed in Section 1.2, which can be a result of ocean turbulence, then SAR is the remote sensor with the greatest potential for acquiring information on the fractal nature of the ocean surface.

Chapter 3

Observation of Ocean Waves using SAR

3.1 Overview.

This chapter describes in detail the use of SAR remote sensing technology to observe the ocean. SAR imagery of the ocean surface is the basic data set for this thesis. A literature review on the physics of SAR, and on the interaction of SAR and ocean waves, is provided to give a background against which the properties of the imagery data set can be discussed. The means by which SAR ocean wave imaging can take place is a subject of controversy. Models of SAR ocean wave imaging are presented here to describe the controversy that exists in the nature of SAR sensing of ocean waves. Further, the discussion of the various models provides insight into the interpretation of what parameters of the ocean surface are being measured when using a SAR.

3.2 Introduction.

Remote sensing of ocean waves using Synthetic Aperture Radar [SAR] has been a subject of controversy for several years. Controversy centred on what model should be used to describe the processes remotely sensed by a SAR. Ocean waves are dynamic phenomena which do not usually move uniformly. The interaction of SAR and dynamic targets is a complex problem involving both the properties of the target and the physics of SAR imaging. Part of the controversy stems from the imperfect nature of SAR as a remote sensing device, as described in chapter 2.0. This chapter will be restricted to cover only the investigation into the physics of SAR imaging and the interaction of SAR with the target, ocean waves. The properties of the target have been discussed in the previous chapter.

3.3 Basic concepts of SAR.

Synthetic aperture radar is an active microwave remote sensing instrument which makes use of a synthesized antenna length to image a target [Alpers, 1983]. The sensor emits microwave radiation at a target and measures the returning signal, discriminating signal positions by their Doppler frequency shifts.

The basic geometry of a SAR carried aloft by a satellite platform is illustrated in Figure 3.1. Imaging is carried out by the emission of microwave radiation in the slant-range direction. The oblique viewing angle produces a beam footprint with both a range and azimuth resolution. Switching of the antenna from send to receive is carried out, allowing the backscattered signal from the target to be measured. SAR processing involves the correlation

Satellite-borne SAR imaging geometry.

Figure 3.1. Basic geometry of a satellite-borne SAR. The incident beam of microwave radiation follows the slant range path covering the surface with a beam footprint. The length of the beam foot print in the ground range direction is termed swath. (Source: Robinson, I.S. [1985], p. 346.)

of the backscattered signal with a suitable reference signal to produce an image. Several backscattered measurements of a target are combined to produce a high resolution image of the target.

SAR can operate in several polarization modes. Polarization modes are described in terms of the polarization of the emitted signal and the polarization mode used to measure the returning signal. Microwave signals from the antenna can be emitted either horizontally [H] or vertically [V]. The antenna used by the SAR can receive signals in either horizontal [H] or vertical [V] modes. If single reflections occur for a target, polarization of the emitted signal is not changed. For multiple reflecting targets, the polarization of the emitted signal can be significantly altered. SAR sensors used for oceanographic applications are commonly HH or VV polarizations, since the ocean is presumed to act as a single reflecting type target [Robinson, 1985] and because of the availability of sensors.

Resolution of SAR imagery can be specified in both range and azimuth [Figure 3.1]. By maintaining constant range and azimuth resolutions the SAR system is said to be focused; constant resolution is produced by sampling the target with many cycles of the reference signal [Tomiyasu, 1978 p.315]. Without examining in detail digital SAR processing issues, it is enough to state that in digital SAR processing range and azimuth components of the return signals are processed separately. SAR focusing is carried out by adjusting the velocity setting of the azimuth component of the SAR return signal to the relative velocity between the surface and the platform to obtain an optimum contrast in the image. The adjustment of azimuth velocity is made to simulate a stationary target. In effect SAR focusing is a motion compensation adjustment. Work by Hayt et al. [1990] indicates that the optimum focus adjustment for SAR ocean wave imagery is one half the phase speed of the dominant wave.

Platform motions can affect SAR imagery as can motions of the target. Platform motions cause Doppler frequency shifts. Several types of target motion can be described, all of which cause amplitude reduction of the return signal. An object that moves while it is imaged will modify the frequency of the SAR signal energy bounced off it.

Frequency shifts in the SAR system modify the signal history of the object, and as a result the moving object may be reconstructed in an image position other than the location on the ground where it actually was located [Leberl, 1989 p.68]. The resulting effect is to shift the position of the target in the positive azimuth direction if the target is moving towards the sensor, and in the negative azimuth direction for targets moving away from the sensor [Robinson, 1985 p.360]. The effect on the SAR image is image smear or a blurred image. Amplitude reduction is the reduced return signal strength due to the motion of the target, thereby further degrading the imagery. Motion of the target in the azimuth direction produces what is known as "azimuth defocusing" [Robinson, 1985; Werle, 1988; Ouchi, 1990]. The resulting effect of azimuth defocusing in the imagery is again image smear.

3.4 Interaction of SAR and ocean waves.

The application of SAR for monitoring ocean waves is generally a research area of remote sensing technology in oceanography. The evidence that SAR can be used to detect ocean waves is undisputed, since ocean waves can be seen in SAR ocean images. It is the mechanism for SAR imaging of the ocean waves which has become quite controversial in the literature. Much of the controversy revolves around the modelling of ocean dynamics and the effects measured in the backscattered signal.

Most research to date is based on a two scale model of the interaction of SAR and the ocean surface. The very short ocean waves travel on the larger ocean waves, or swell, as a superposition. Radar backscatter at incidence angles of 20° to 70° is principally produced by Bragg resonance [Hasselmann et al., 1985 p.4663; Werle, 1988]. Bragg resonant scattering is the response of the radar wave to the short surface waves or wind waves. This type of scattering is considered to be the most important backscattering mechanism of SAR ocean imaging [Vachon, 1987 p.42]. Bragg resonant scattering occurs when the fields scattered by a periodic structure, ocean waves, coherently interact to reinforce the fields seen at the observation point [Napolitano, 1991 p.56]. Figure 3.2 illustrates Bragg resonant scattering. The wavelength of the ocean wave is λ_b and the SAR wavelength is λ_o . If the distance from the source of the SAR signal to each succeeding wave crest is an integer multiple of $\lambda_o/2$, the round trip phase difference between

signals returned from successive crests is 360 degrees, which allows the signals to add in phase. If the distance from the source of the SAR signal to each succeeding wave crest is any other distance, the signals fail to add in phase. The return signal from the addition of signals from scatters which are not in phase is proportional to their number, while the return signals from the scatters which add in phase are proportional to the square of their power [Leopold, 1989 p.293]. The resulting backscatter from very small scatters can then exceed that of larger scatters with nonresonant spacing but comparable numbers [Leopold, 1989 p.293]. The wavelength of the ocean wave λ_b that the incident electromagnetic radiation is resonant with can be defined as:

$$\lambda_b = \frac{n\lambda_o}{2\sin\theta} \quad (5)$$

where n is a positive integer, λ_o is the wavelength used by the SAR, and θ is the incidence angle of the sensor [Napolitano, 1991 p.56]. For a C-band SAR such as RADARSAT, operating at a frequency of 5.3 GHz making λ_o approximately 5.66 cm, the wavelength λ_b would be approximately 8.27 cm and 3.69 cm for incidence angles of 20 degrees and 50 degrees respectively when $n=1$. RADARSAT is designed to operate with user selected incidence angles in the range of 20 to 50 degrees. For a L-band SAR, similar to SEASAT, with λ_o approximately 23.5 cm, the wavelength λ_b would be approximately 34.35 cm and 15.34 cm for incidence angles of 20 degrees and 50 degrees respectively when $n=1$.

The Bragg resonant scattering of SAR by the ocean is dominated by the short capillary and wind waves, even when the underlying ocean swell is several metres in height [Ulabay et al., 1982 p.841]. Bragg scattering occurs in the tangential plane or facets of the swell, which move with the swell orbit velocity [Werle, 1988 p.c-76]. The two scale models are not capable of describing surface roughness at high sea states where wave amplitudes are high and interactions are non-linear [Robinson, 1985 p.366]. In high sea states, wind speeds are high causing breaking or almost breaking wind waves. In this state, sea spray and air bubbles in the water near the surface could cause Rayleigh scattering of the incident SAR signal. Rayleigh scattering is the

interaction of radiation with particles smaller in diameter than the wavelength of the incident radiation [Lillesand and Kiefer, 1987 p.10].

Hydrodynamic modulation of the Bragg waves is caused by the phase interaction with the swell. The effect is to increase amplitude of Bragg waves near the crest of the swell and decrease amplitude near swell troughs [Werle, 1988]. The alteration of Bragg wave amplitudes is attributed to the convergent and divergent velocity patterns caused by the swell orbital velocity pattern [Figure 3.3]. This interaction produces high backscatter near the crest of swells and low backscatter in the trough of swells.

Electromagnetic or tilt modulation is produced by slope variations of swell. The tilting of Bragg waves by swell produces a spatially variable local angle of incidence for the SAR [Vachon, 1987 p.43]. This modulation produces the strongest backscattered signal from the slope of the wave facing towards the SAR [Figure 3.4]. It has been demonstrated that HH polarization is more sensitive to slope variations than VV polarizations [Vachon, 1987 p.43].

Figure 3.2. Bragg coherent backscatter from the ocean surface. λ_b is the wavelength of the ocean surface that the incident microwave radiation is resonant with.

(Source: Napolitano, D.J. [1991], p. 55)

Swell Alteration of Bragg wave amplitudes.

Figure 3.3. Convergent and divergent motions of the swell alter Bragg wave amplitudes.
(Source: Robinson, I.S. [1985], p. 366.)

Modulation of SAR backscatter by tilt of the ocean surface.

Figure 3.4. Tilt modulation of SAR backscatter.
(Source: Robinson, I.S. [1985], p. 367.)

Image smearing in SAR ocean imagery is caused by motion of the wave surface during the integration time of the backscattered signals received by the SAR [Werle, 1988 p.c-77]. This problem has been outlined in previous sections on the basic concepts of SAR. Image smear can be diminished by refocusing the SAR or by decreasing the SAR integration time [Werle, 1988].

Azimuth image shift in SAR ocean imagery is the shifting of the apparent position of a wave crest or trough within a SAR image due to the motion of the target. The rising surface of the wave is shifted in the positive azimuth direction and the falling surface is shifted in the negative azimuth direction [Robinson, 1985 p.368]. If the swell propagates in the range direction, that is wave crests and troughs oriented perpendicular to the SAR look direction, azimuth image shift does not affect the SAR image [Werle, 1988 p.c-77]. Swell propagating in the azimuth direction, that is wave crests and troughs oriented parallel to the SAR look direction, can result in azimuth image shift which leads to the production of velocity bunching. Velocity bunching is the alternating concentration and spreading of the apparent position of the Bragg waves within the swell [Alpers, 1983 p.115]. Velocity bunching can produce a reversal of apparent brightness in SAR imagery for waves propagating in the positive azimuth direction; wave crests can appear darker than wave troughs [Robinson, 1985 p.368]. The reverse situation can occur for waves travelling in the negative azimuth direction. It should be noted that a reversal of brightness does not occur on every wave in every SAR image. Non-linearities of SAR ocean wave imaging are due mostly to the velocity bunching mechanism and image smear [Hasselmann et al., 1985 p.4679].

3.5 Models of SAR ocean wave imaging.

The models used to describe SAR imaging of ocean waves are controversial. Much of the research to date is based on a two scale model of the interaction of the SAR and the ocean surface. Very short ocean waves travel on the large ocean waves, or swell, as a superposition. Radar backscatter at incidence angles of 20° to 70° is principally produced by Bragg resonance. Bragg resonant scattering is the response of the radar wave to the short surface waves or wind waves. Bragg scattering of SAR by the ocean is dominated by short capillary

wind waves, even when the underlying ocean swell is several metres in height. Hydrodynamic modulation of Bragg waves is caused by the phase interaction with the swell. This interaction produces high backscatter near the crest of swells and low backscatter in the trough of the swells. Electromagnetic or tilt modulation is produced by slope variations of the swell. Since it has been demonstrated that HH polarization is more sensitive to slope variations than VV polarization, SAR imagery with VV polarization will be used for the experimental part of this research. This limits the variables involved with the modulation of Bragg waves, which can be observed in the SAR imagery, and allows for a more coherent measurement of the effects of surface roughness variation on fractal dimension, if any variation exists. Research, presented later in this chapter, indicates that SAR imaging theories are converging towards the consensus that velocity bunching provides a major contribution to the construction of SAR images of the ocean. Velocity bunching can in some cases produce a reversal of brightness in SAR imagery for waves propagating in the positive azimuth direction, causing wave crests to appear darker than wave troughs.

It is clear that a controversy exists in the nature of SAR sensing of ocean waves. The models of the process that allow SAR to be used to sense ocean waves have been a subject of debate by researchers. Early research by Banner et al. [1983] described the ocean as a set of facets which produced backscatter of varying intensity depending on their orientation and size. Evidence from Hasselmann et al. [1985] seems to point to an agreement that ocean waves can be modelled using a two scale model. This is supported by research of Ouchi [1982], Jain [1982], Alpers [1983], and Hasselmann et al. [1985]. The two scale model describes the backscattering process as signal returns from small amplitude and short wavelength Bragg waves which are modulated by large amplitude and long wavelength, ocean swell. There is less agreement on the determination of the dominant backscattering processes involved. The lack of agreement can be attributed to the lack of observational evidence. Velocity bunching and hydrodynamic modulation appear to be the dominant processes influencing the imaging of Bragg type scattering waves. Observational evidence for the velocity bunching effect is presented in research by Lyenga et al. [1985].

Raney [1980] describes the ocean surface as a duality of both random and deterministic dynamics. Orbital motions of wave facets may cause Doppler shifts resulting in image displacements, which produce wave-like features in SAR imagery if focus and coherence are maintained [Raney, 1980, p.243]. The fact that SAR imagery of the ocean has a wave-like appearance, and that the ocean wave parameters such as length and direction produced in the imagery have a direct relationship to the ocean waves, was the only concern.

Ouchi [1982] presents a two scale model which takes account of both the spatial and temporal dependence of small capillary waves and large scale waves or swell. Both hydrodynamic modulation and velocity bunching were considered to contribute to the backscattering process. Ouchi emphasizes that the major contribution to the construction of SAR images is velocity bunching; image contrast depends on the parameters of SAR and ocean waves, if the amplitude modulation is uniform. Further to this, if the amplitude modulation and velocity bunching are the major contributors to the SAR imaging process then the direction of wave propagation determines the image contrast. The best images are produced for waves travelling in the range direction towards the SAR, if the amplitude modulation is uniform [Ouchi, 1982 p.11]. Ouchi [1982a] considered the effects of random motions of capillary waves. It was concluded that the random motion tends to degrade the contrast of ocean wave SAR imagery through the production of speckle [Ouchi, 1982a p.274].

Jain [1982] proposes a model in which ocean wave heights are measured by determining the variation in speckle intensity with frequency and the angle of illumination. This model is based on earlier work by Jain [1977] which describes the principle as a determination of the change in the electric field scattered from ocean waves. The variation is attributed to the height difference between the wave crest and trough, and a measurement of the rate of variation is an indication of ocean wave height. Both tilt and hydrodynamic modulation are considered in this model. Velocity bunching is not considered.

Early research by Banner et al. [1983] described the ocean as a set of facets whose wavelength must be larger than the radar wavelength for specular backscatter to occur. Close to nadir, specular

backscattering is dominant, while Bragg scattering is dominant in the off-nadir look direction [Banner et al., 1983 p.118].

Alpers [1983] presents a two scale ocean model of Bragg scattering waves superpositioned on larger gravity waves or swell, and describes three processes which contribute to ocean wave imaging. Microwave backscatter is attributed predominantly to Bragg waves. Ocean swell is observable because of the modulation of signals produced by Bragg waves. The three processes which are proposed to modulate the return signal are hydrodynamic, electromagnetic modulations and temporal variations caused by azimuth shift and smear. The backscatter cross-section modulation due to the hydrodynamic and electromagnetic effects are assumed to be linearly dependent on the long-wave field or ocean swell. After the motion effects have been corrected, the SAR image can be represented as a product of a random and complex white noise process [Alpers, 1983 p.110]. The backscattering process is described as uniformly distributed Bragg waves whose backscatter is modulated by long gravity waves, or swell.

Hasselmann et al. [1985] note that it is not clear whether or not non-Bragg scattering processes can be neglected in scattering models. For small incidence angles, specular reflection is the primary scattering mechanism, while at large incidence angles cusping waves, white caps, along with specular reflection from the forward face of breaking waves probably influence the backscattering process. In general, the velocity bunching modulation dominates the SAR backscatter over the hydrodynamic and tilt modulation for waves not travelling in the range direction. Research indicates that the velocity bunching mechanism becomes non-linear during low wind speeds. These non-linearities are particularly degrading to SAR imagery for waves travelling in near-azimuthal directions. Orientation of ocean waves with respect to the imaging sensor appears to influence the backscattered signal, either by enhancement or degradation of the signal, as pointed out by Hasselmann et al. [1985] and Ouchi [1982].

Research by Alpers [1992] indicates that SAR imaging theories are converging towards the consensus that velocity bunching is a basic imaging mechanism. Alpers describes the theory as "generalized velocity

bunching theory". The theory proposed by Alpers states that the ocean wave field can be described as a two scale model, as in Alpers [1983], and stresses the need to include velocity bunching as a basic imaging mechanism. Alpers notes that past work has disputed the concept that velocity bunching affects the imaging of waves travelling in the azimuthal direction. Research, by Lyenga et al. [1985], Beal et al. [1986] and Alpers et al. [1986] documented such a phenomenon. Specifically, Lyenga et al. [1985] observe a periodic shift of the boundary between ice and water, in SAR imagery of waves in water and ice, which is attributed to Doppler shift effects caused by gravity wave orbital motions. Lyenga et al. [1985] interpret the observation as significant evidence for the velocity bunching effect.

3.6 Summary.

The application of SAR for monitoring ocean waves remains to date as a research application of remote sensing technology in oceanography. SAR sensors used for oceanographic applications are commonly HH or VV polarizations. Several image distortions are present in SAR imagery, which can be removed or minimized. The oblique viewing angle of a SAR produces a beam footprint with a resolution which must be specified in both range and azimuth. Maintaining a constant resolution in both the range and azimuth, by sampling the target with many cycles of the reference signal produces a focused SAR image. Platform motions can cause Doppler frequency shifts which can be mathematically modelled and removed provided they are measurable.

Effects due to motion of the ocean surface on the resulting SAR imagery have been discussed and presented here because these effects may be present in the imagery used for this thesis. Corrections for image smearing or focus adjustments will not be applied to the imagery data set, since averages of the full scene radiometric values are used for the analysis. Further, research by Raney [1988] demonstrates that focus adjustment could not be recommended for improvement of single or multi-look SAR imagery of ocean waves, as it is not optimal to degrade the true system focus since it will enhance erroneous looks.

It is important to note that the lack of mention of the dielectric property of the ocean by the various SAR ocean wave imaging models

indicates that this property has little or no effect on the resulting SAR imagery.

Research by Jain [1982] provides justification for measuring fractal dimension of the SAR images, the underlying assumption being that fractal dimension is a measure of image texture. Change in the speckle intensity from ocean waves is attributed to the height difference between wave peak and trough. Since imagery used in this research had no speckle removal, the fractal dimension should then vary within the SAR imagery because of the height differences.

In summation, the SAR ocean wave imaging models proposed by the various authors are in agreement that the return signal measured in a SAR over a target of ocean waves is affected by the ocean wave modulations. This being the case, measurement of the fractal dimension of the SAR imagery should provide useful information about the ocean surface modulations and allow a determination of the fractal nature of the ocean surface. In particular, if the research consensus is correct, that velocity bunching and hydrodynamic modulation are the major contributors to construction of SAR imagery, then the fractal dimension should provide information on the alternating concentration and spreading of the apparent position of the Bragg waves within the swell. This would require knowledge, not readily available for this research, of the direction of propagation of the ocean waves. Further, the fractal dimension should provide information about short capillary and wind ocean waves, the dominant process responsible for Bragg resonant scattering of SAR by the ocean.

Chapter 4

Methodology

4.1 Overview.

This chapter describes in detail the methodology used in this research. Information is provided on both pre-processing and processing of the SAR imagery provided by the Canada Centre for Remote Sensing [C.C.R.S.]. Included in this chapter is a description of the method used to calculate the local fractal dimension of surfaces.

4.2 Data sources.

The general location of the study area over which the CCRS CV-580 aerial SAR ocean wave imagery was acquired was the ocean area, known as the Grand Bank, east of the province of Nova Scotia and south-east of the province of Newfoundland, Canada. The location is between Latitude North $44^{\circ} 0'$ - North $49^{\circ} 0'$ and Longitude West $53^{\circ} 30'$ - West $50^{\circ} 30'$. SAR data were gathered in VV polarization mode. No corrections were applied, such as speckle reduction or geometric correction used to correct distortion of pixel size in the range direction, since averages of the full scene radiometric values were used in this analysis for regression with geophysical data. A summary of the CV-580 image product parameters is shown in table 4.1. Seven SAR images each created on unique dates are used in this study. Each SAR image provides distinct coverage within the study region, with a range resolution of 6.6 m and an azimuth resolution of 6.7 m. The seven SAR images are each representative of different ocean conditions. One image composed of background noise and one image of simulated sine wave data were also made use of in this study. The background noise and simulated sine wave data were used in a simulation described in a later section. Sample spacing for each of the seven SAR images and the background noise image is 4.0 m in the range direction and 3.89 m in the azimuth direction.

4.3 Image naming standard adopted.

Each of the seven original SAR images was given a unique base name to which a number or letter was prefixed to indicate the level of resampling. Simulated imagery was given a suffix to indicate the level of resampling. Letters "a", "b", "c", "d" corresponded to resolutions of 1.1, 1.25, 1.43, and 1.67 times the original spatial resolution.

Numbers 2 to 12 corresponded to spatial resolutions of 2 to 12 times the original spatial resolution. SAR images which have been standardized were given the suffix "n". For example, the original SAR image name prior to resampling might be "li2575". After standardization the image name would become "li2575n". After resampling to a spatial resolution of 12 times the original spatial resolution the image name would become "12li2575n". The letter "i" was dropped because of file name length restrictions. A simulated image "sine", which corresponds to the simulated wave data, after standardization was given the name "sinen". After resampling to a spatial resolution of 10 times the original spatial resolution the image name would become "sinen10". The only exception to the above convention was the wind rippled data set which used the base name "ripl", and was produced by a combination of the standardized noise data and simulated wave data. The letter "n" was not used, but the convention of using a suffix to represent the level of resampling was maintained. The base name for the noise data set was "notop".

4.4 Pre-processing of SAR imagery.

SAR imagery acquired from C.C.R.S. was provided as 512 pixel by 2048 line raster images, with no headers. All SAR imagery was imported into EPPL7© [1991] and converted to a run-length encoded file format. EPPL7© [1991] is a raster-based geographic information system.

Descriptive statistics, such as mean digital values and dispersion measures of all SAR imagery were calculated [Table 4.2]. All SAR data, including SAR background noise data, were standardized, similar to the research by Broscoe [1993]. Parameters for the standardization were determined based on the calculated values for maxima, minima, means, and standard deviations of the raw digital image values. Data were not standardized to a mean value of 127.5 since this would have caused saturation and a loss of data. Chaos theory requires that all data be considered in an analysis, since even the smallest measurable data may influence the outcome. This is consistent with the butterfly effect described in Gleick [1987]. Saturation of data was eliminated by standardizing all data to a mean digital value D_n of 40. The digital value of 40 was selected based on calculations using dispersion values

Table 4.1. CV-580 imaging parameters.

Property	Units	CV-580
SAR processor		RTP ^a
Image product		Nadir
Band		C
Wavelength	cm	5.62
Polarization		VV
Nominal incident angle	deg.	0-85
Range presentation		slant
Range sample spacing	m	4.0
Nominal range resolution	m	6.6
Azimuth sample spacing	m	3.89
Nominal azimuth resolution	m	6.7
Physical number of looks	looks	7
MSVR	looks	6.0
Look summation		voltage
Noise equivalent	dB	-27
Radiometric calibration		none

^a The Real Time SAR Processor on board the C.C.R.S. aircraft. Data is transcribed from high density digital tape [HDDT] to computer compatible tape [CCT] at C.C.R.S.

Source: Adapted from Vachon, P.W. et al 1994 p. 86.

Table 4.2. SAR, simulation, and noise data image names and statistical data gathered.

Image File Name	Description of Image	Minimum Digital Value [Dn]	Maximum Digital Value [Dn]	Mean Digital Value [Dn]	Standard Deviation [Dn]
Li2575	SAR ocean image	2.00	139.00	23.41	5.69
Li2586	SAR ocean image	3.00	137.00	36.24	12.11
Li2580	SAR ocean image	13.00	160.00	66.49	17.40
Li2591	SAR ocean image	15.00	217.00	82.51	21.48
Li2603	SAR ocean image	6.00	240.00	86.91	24.29
Li2609	SAR ocean image	8.00	218.00	67.56	23.53
Li2598	SAR ocean image	7.00	138.00	44.50	13.14
Sine	Simulated wave image	64.00	192.00	127.49	45.22
Notop	Background noise image	24.00	208.00	90.64	21.79

for each of the SAR images. Standardized image Dn values were calculated based on the following equation:

$$\text{Output Dn} = 10.55 * [(\text{Input Dn} - \text{Mean Dn}) / \text{Standard Deviation}] + 40 \quad (6)$$

The value of 10.55 used in equation 6 was determined by calculating a slope using the maximum and minimum Z scores for all of the imagery with equation 7. The basic requirement for equation 6 was to ensure that the output values would be between 1 and 255.

$$\text{Slope} = \frac{[\text{max. Dn value on 8 bit image}] - [\text{min. Dn value on 8 bit image}]}{[\text{max. Z score of all images}] - [\text{min. Z score of all images}]} \quad (7)$$

Standardization of the data provides a means of comparing and contrasting raw data collected in different conditions against each other. Data are transformed with respect to the average range of the raw values of all the data sets. The transformed values can then be compared and contrasted since they are representative of the original raw data but are on a common measurement scale.

Simulation data, which were provided by C.C.R.S. in a raw 8-bit format, consisted of a simulated wave image standardized to a mean digital value of 127.5. To allow comparison of the simulation data to the SAR data a value of 87.5 was subtracted from each Dn value. This produced a simulated wave image with a mean Dn of 40, a minimum Dn of 0 and a maximum Dn of 105. Crest to successive crest distance, or wavelength, of the simulated wave data was 38 pixels oriented at 45° with respect to the first line of data. Some saturation of data was observed for the simulated wave data, due to translation of the mean to a value of 40. Approximately 5% of the original simulated wave data was subjected to radiometric underflow. While this is noted to be an error in processing, the resulting effect on the simulated image was to produce areas of like digital values included with continuously varying digital values. The reflection of SAR signals from smooth water is concentrated about the specular angle with little energy returned in the backscatter direction [Simonett and Davis 1983, p.1159]. These areas will be representative of relatively smooth or specular reflecting material not unlike that which might occur in "real" imagery. Fractal dimension measurements of the simulated imagery should then be similar to that which would be measured in the real SAR images.

All SAR imagery was resampled to produce multi-resolution imagery. Using a sample image from the top 512 pixels by 512 lines of SAR image Li2603n, rescaling was carried out using both nearest-neighbour and bi-linear methods, to determine if the resampling method would affect the calculation of fractal dimension. Sample images used in the test were rescaled to twice the original pixel size. The standard deviation of image brightness of Li2603n was close to the median value of standard deviations for all SAR images, and this qualified as a reference image for the entire data set. No difference in the resulting fractal dimension was recorded in sample imagery resampled using either the bi-linear or nearest-neighbour method of re-sampling. Nearest-neighbour resampling is known to introduce pixel-level discontinuities which change the textural properties of the resampled imagery, making it appear blocky, and for that reason it is not recommended for applications in which textural properties of the image are important [Dikshit and Roy, 1996 p.1086]. Bi-linear resampling was used to simulate scale change in the data set. Bi-linear resampling uses a rook's case sampling of the four nearest pixels, and assumes that image brightness at smaller scales is linearly related through aggregation of neighbouring pixels at each point. This provides a smoothing of the image similar to a low-pass filter [Dikshit and Roy, 1996 p.1086], which reduces noise in the imagery. However, the use of bi-linear resampling will allow speckle to be aggregated into the newly formed pixels. Speckle, described in a previous chapter, is the local maxima which is produced in SAR imagery. Any single pixel sampling of the SAR imagery will probably contain local extreme values, as a result of speckle, which will result in large residuals if regressions are carried against other variables such as measured fractal dimension. Since scattering of the SAR signal by the ocean is dominated by Bragg resonant scattering, which operates below the size of a single pixel, the use of unfiltered imagery may be warranted. Further it may be possible to observe the effects of speckle on the resulting fractal dimension by not removing the signal noise. All images were then resampled using the bi-linear sampling method to the following resolutions: 1.1, 1.25, 1.43, 1.67, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, and 12 times the original pixel size. Arbitrary resampling resolutions were selected to provide information at near original pixel spatial resolution and at resolutions close to satellite-based spatial resolutions. Resolution was assumed to vary in

the same manner as number of pixels used in resampling. To provide a visual understanding of the effects of bi-linear resampling of the SAR imagery Figure 4.1 is included here, which displays a SAR image sample of the same spatial region at various resampling levels. Table 4.3 displays the corresponding output pixel sizes, base on number of pixels used to produce the resampled SAR imagery.

The scale range for this work can be described in terms of both nominal azimuth and range resolution ranges. The nominal azimuth resolution range for all of the images used in this thesis was 6.7 m - 80.4 m. The nominal range resolution range for all of the images used in this thesis was 6.6 m - 79.2 m. The bi-linear resampling provided 16 images with discrete resolution levels for each of the original seven SAR images, the original SAR background noise image, and the simulated wave image. In total 144 images were pre-processed for calculation of fractal dimension.

Same spatial region of SAR image

Figure 4.1. SAR image sample of the same spatial region at various resampling levels. As the constant used to determine the number of original pixels which will combine to create a new resampled pixel increases the number of pixels required to cover the same spatial region decreases. Information within the spatial region is generalized but still maintains the same structure.

Table 4.3. Resampled SAR image output pixel sizes.

Naming of SAR Image Example	Number of original Pixels used to create one Pixel in image. [Units]	Output Pixel length in Range [m]	Output Pixel Length in Azimuth [m]	Total Area of Output Pixel [m ²]
Li2586N	1	6.6	6.7	44.22
aL2586N	1.1	7.3	7.4	54.02
bL2586N	1.25	8.3	8.4	69.72
cL2586N	1.43	9.4	9.6	90.24
dL2586N	1.67	11.0	11.2	123.20
2L2586N	2	13.2	13.4	176.88
3L2586N	3	19.8	20.1	397.98
4L2586N	4	26.4	26.8	707.52
5L2586N	5	33.0	33.5	1105.50
6L2586N	6	39.6	40.2	1591.92
7L2586N	7	46.2	46.9	2166.78
8L2586N	8	52.8	53.6	2830.08
9L2586N	9	59.4	60.3	3581.82
10L2586N	10	66.0	67.0	4422.00
11L2586N	11	72.6	73.7	5350.62
12L2586N	12	79.2	80.4	6367.68

4.5 Calculation of fractal dimension.

The fractal dimension [Fd] can be calculated using one of several methods. Vernazza [1987] describes and investigates four methods for the calculation of Fd. Of these four methods analyzed, the blanket approach and the Pentland spatial approach were considered to give satisfactory results [Vernazza 1987]. Based on the research by Vernazza [1987] the method selected for calculation of the fractal dimension of

imagery is the blanket approach. The blanket approach, described in detail in Peleg [1984], mathematically lays a blanket above and below the image surface. Surface textures can be classified based on the change in their properties with changing resolutions, or blanket thickness [Peleg 1984]. A grey level image surface, g , is defined by $g_e(i,j)$ where $u_{e+1}(i,j)$ is the upper blanket surface and $b_{e-1}(i,j)$ is the bottom blanket surface, each of which has a thickness of ϵ . In this manner the raster matrix co-ordinates x, y , correspond to i, j . The upper blanket surface can be calculated in one of two ways. The first method uses the maximum value of the pixel $u_{e+1}(i,j)$, the pixel on the surface below the pixel value being calculated, plus the blanket thickness. The second method uses the maximum value of the four adjacent pixels which surround pixel $u_{e+1}(i,j)$. The lower blanket surface is calculated by subtraction of the blanket thickness ϵ . The volume of the blanket can then be calculated using:

$$V(\epsilon) = \sum_{i,j} [u_{e+1}(i,j) - b_{e-1}(i,j)] \quad (8)$$

which is the sum of the difference in grey levels between the top and the bottom of the blanket. As such, the surface area can then be calculated using:

$$A(\epsilon) = [V(\epsilon) - V(\epsilon-1)] / 2 \quad (9)$$

As the number of blanket layers increases the surface becomes smoother and the total surface area decreases. By computing the surface area for several number of blanket layers the fractal dimension of the surface can be calculated. The fractal dimension is computed by plotting the log of the surface areas against the log of the volumes and calculating the slope of the line. The fractal dimension of the surface is then:

$$Fd = 2 - \text{slope of line} \quad (10)$$

Software used to calculate the fractal dimension of each image is based on the method described in Peleg [1984] and was developed originally at Carleton University, and written in Turbo Pascal by David Broscoe [1993]. Three processing parameters must be selected using the software, the window size, the blanket thickness, and the number of

blanket layers. The factors determining the selection of the optimum processing parameters used in the software were as follows:

- 1) The maximum fractal dimension should not exceed 3. Should this occur the image is being modelled as a body with greater than 3 dimensions.
- 2) The minimum fractal dimension should not be less than 2. If this occurs the image is being modelled as a line with dimensions approaching a plane.
- 3) The correlation of log of surface areas and the log of the volumes should fall within the range of a minimum of 45% to a maximum 100% correlation, and the mean correlation should be at least 65% or greater.

The third factor is a subjective choice and is stated here to indicate that correlation of log of surface areas and the log of the volumes should fall within a range that demonstrates that an association exists between the variates. Using sample images from the standardized SAR imagery the optimum parameters for calculation of fractal dimension were determined to be 20 layers, with a thickness of 4, and a 9 pixel by 9 line window. The sample images included a sample of li2603n the reference image of the data set, a sample of li2575n which has the highest dynamic range of all images, and a sample of li2586n. The results of processing three of the standardized SAR image samples using several different parameters are shown Tables 4.4 - 4.6. All three of the SAR image samples produced acceptable results, meeting all requirements when using 20 layers, with a thickness of 4, and a 9 pixel by 9 line window. Similar results could be obtained by using 15 layers, with a thickness of 3, and a 7 pixel by 7 line window. The choice to use the 9 pixel by 9 line window, thickness of 4 and 20 layers is based on the mean r-squared values produced with these parameters and an analysis of the residuals of regressions of the mean fractal dimension and the processing parameters. The fractal dimension is calculated based on slope of the line of best fit through the log of surface areas and the log of the volumes. Lower mean r-squared values produced by the 9 pixel by 9 line window, in comparison to the mean r-squared values produced using the 7 pixel by 7 line window, indicate that the line of best fit calculated for the 9 pixel by 9 line window is accounting for

higher residuals than the 7 pixel by 7 line window and as such should provide a more realistic representation of the data set.

Table 4.4. The results of processing the 512 pixel by 512 line sample of the standardized SAR image li2603n with fractal analysis software using several different input parameters. Input parameters are window size, blanket thickness, and number of layers. Grey areas indicate acceptable results for input parameters.

Window Size	Thickness	Layers	Mean R Sq.	Min R Sq.	Max R Sq.	Max Fd	Min Fd	Mean Fd
5x5	3	10	0.80	0.00	0.97	3.13	2.00	2.31
5x5	3	15	0.69	0.00	0.90	2.85	2.00	2.22
5x5	3	20	0.61	0.00	0.83	2.69	2.00	2.18
5x5	4	10	0.79	0.00	0.97	2.84	2.00	2.18
5x5	4	15	0.68	0.00	0.91	2.65	2.00	2.13
5x5	4	20	0.60	0.00	0.84	2.53	2.00	2.11
5x5	5	10	0.76	0.00	0.98	2.65	2.00	2.11
5x5	5	15	0.65	0.00	0.91	2.51	2.00	2.08
5x5	5	20	0.58	0.00	0.85	2.42	2.00	2.07
7x7	3	10	0.89	0.41	1.00	2.96	2.02	2.36
7x7	3	15	0.80	0.51	0.99	2.81	2.02	2.28
7x7	3	20	0.72	0.44	0.96	2.01	2.70	2.22
7x7	4	10	0.87	0.35	1.00	2.70	2.00	2.22
7x7	4	15	0.77	0.54	0.99	2.59	2.00	2.16
7x7	4	20	0.70	0.47	0.96	2.52	2.00	2.13
7x7	5	10	0.85	0.00	1.00	2.54	2.00	2.13
7x7	5	15	0.75	0.00	0.98	2.45	2.00	2.10
7x7	5	20	0.67	0.00	0.96	2.40	2.00	2.08
9x9	3	10	0.93	0.06	1.00	2.88	2.03	2.38
9x9	3	15	0.85	0.50	1.00	2.75	2.04	2.30
9x9	3	20	0.78	0.44	0.99	2.64	2.03	2.24
9x9	4	10	0.91	0.14	1.00	2.63	2.02	2.23
9x9	4	15	0.82	0.52	1.00	2.54	2.01	2.18
9x9	4	20	0.74	0.47	0.99	2.47	2.01	2.14
9x9	5	10	0.88	0.22	1.00	2.47	2.00	2.14
9x9	5	15	0.79	0.54	0.99	2.41	2.00	2.11
9x9	5	20	0.71	0.50	0.97	2.35	2.00	2.08

Table 4.5 The results of processing the 512 pixel by 512 line sample of the standardized SAR image li2575n with fractal analysis software using several different input parameters. Input parameters are window size, blanket thickness, and number of layers. Grey areas indicate acceptable results for input parameters.

Window Size	Thickness	Layers	Mean R Sq.	Min R Sq.	Max R Sq.	Max Fd	Min Fd	Mean Fd
5x5	3	10	0.81	0.00	0.97	3.06	2.00	2.34
5x5	3	15	0.69	0.00	0.90	2.81	2.00	2.24
5x5	3	20	0.61	0.00	0.83	2.66	2.00	2.19
5x5	4	10	0.79	0.00	0.97	2.80	2.00	2.20
5x5	4	15	0.68	0.00	0.90	2.62	2.00	2.15
5x5	4	20	0.61	0.00	0.84	2.52	2.00	2.12
5x5	5	10	0.78	0.00	0.98	2.64	2.00	2.13
5x5	5	15	0.67	0.00	0.91	2.51	2.00	2.09
5x5	5	20	0.59	0.00	0.85	2.42	2.00	2.08
7x7	3	10	0.90	0.46	1.00	3.02	2.03	2.39
7x7	3	15	0.80	0.51	0.99	2.81	2.02	2.30
7x7	3	20	0.72	0.44	0.95	2.70	2.01	2.42
7x7	4	10	0.87	0.43	1.00	2.75	2.00	2.24
7x7	4	15	0.77	0.54	0.99	2.60	2.00	2.18
7x7	4	20	0.70	0.47	0.96	2.52	2.00	2.15
7x7	5	10	0.85	0.00	1.00	2.58	2.00	2.15
7x7	5	15	0.75	0.00	0.98	2.47	2.00	2.11
7x7	5	20	0.67	0.00	0.95	2.41	2.00	2.09
9x9	3	10	0.93	0.22	1.00	2.93	2.07	2.41
9x9	3	15	0.84	0.53	1.00	2.77	2.06	2.32
9x9	3	20	0.77	0.46	0.99	2.67	2.05	2.26
9x9	4	10	0.91	0.25	1.00	2.67	2.04	2.25
9x9	4	15	0.81	0.54	1.00	2.56	2.03	2.19
9x9	4	20	0.74	0.47	0.99	2.49	2.02	2.18
9x9	5	10	0.88	0.38	1.00	2.51	2.01	2.16
9x9	5	15	0.78	0.57	0.99	2.43	2.01	2.12
9x9	5	20	0.71	0.50	0.97	2.37	2.01	2.10

Table 4.6. The results of processing the 512 pixel by 512 line sample of the standardized SAR image li2586n with fractal analysis software using several different input parameters. Input parameters are window size, blanket thickness, and number of layers. Grey areas indicate acceptable results for input parameters.

Window Size	Thickness	Layers	Mean R Sq.	Min R Sq.	Max R Sq.	Max Fd	Min Fd	Mean Fd
5x5	3	10	0.79	0.00	0.97	3.23	2.00	2.27
5x5	3	15	0.68	0.00	0.90	2.93	2.00	2.19
5x5	3	20	0.60	0.00	0.83	2.76	2.00	2.15
5x5	4	10	0.76	0.00	0.97	2.93	2.00	2.15
5x5	4	15	0.65	0.00	0.90	2.72	2.00	2.11
5x5	4	20	0.58	0.00	0.84	2.59	2.00	2.09
5x5	5	10	0.72	0.00	0.98	2.73	2.00	2.09
5x5	5	15	0.62	0.00	0.91	2.57	2.00	2.07
5x5	5	20	0.55	0.00	0.85	2.47	2.00	2.06
7x7	3	10	0.88	0.34	1.00	3.08	2.00	2.32
7x7	3	15	0.79	0.51	0.99	2.91	2.00	2.25
7x7	3	20	0.72	0.44	0.96	2.78	2.00	2.20
7x7	4	10	0.86	0.00	1.00	2.80	2.00	2.18
7x7	4	15	0.76	0.00	0.99	2.68	2.00	2.14
7x7	4	20	0.69	0.00	0.96	2.58	2.00	2.12
7x7	5	10	0.83	0.00	1.00	2.62	2.00	2.11
7x7	5	15	0.73	0.00	0.99	2.52	2.00	2.09
7x7	5	20	0.66	0.00	0.96	2.45	2.00	2.07
9x9	3	10	0.92	0.00	1.00	3.03	2.00	2.33
9x9	3	15	0.85	0.42	1.00	2.86	2.01	2.26
9x9	3	20	0.78	0.44	0.99	2.80	2.01	2.22
9x9	4	10	0.90	0.00	1.00	2.76	1.98	2.19
9x9	4	15	0.81	0.37	1.00	2.64	2.00	2.15
9x9	4	20	0.74	0.47	0.99	2.58	2.00	2.13
9x9	5	10	0.88	0.00	1.00	2.59	1.98	2.12
9x9	5	15	0.78	0.00	0.99	2.50	2.00	2.09
9x9	5	20	0.71	0.00	0.98	2.44	2.00	2.08

A regression of mean fractal dimension versus thickness [Figure 4.2], using values from Tables 4.4 - 4.6, indicated that mean fractal dimension decreases with increasing thickness value. Analysis of variance Table 4.7 shows that this regression was very significant. The residuals for the regression [Figure 4.3] were shown to decrease with increasing thickness value. This being the case, the optimum parameter selected for thickness was probably a value of 4, given the choice of 3 or 4 based on requirements stated earlier.

Table 4.7. Analysis of variance for the regression of thickness and mean fractal dimension using values from Tables 4.4 - 4.6.

Regression Statistics	
R	0.81561
R Square	0.66521
Adjusted R Square	0.66098
Standard Error	0.05246
Observations	81

ANOVA					
	df	SS	MS	F	Significance F
Regression	1	0.432017	0.432017	156.9721	1.84454E-20
Residual	79	0.217423	0.002752		
Total	80	0.64944			

Mean Fractal Dimension versus Thickness Line Fit Plot

Figure 4.2. Regression of mean fractal dimension and thickness parameter used for processing.

Figure 4.3. Residuals for the regression of mean fractal dimension and thickness parameter used for processing. Residuals decrease for increasing thickness value.

A regression of mean fractal dimension versus number of layers [Figure 4.4], using values from Tables 4.4 - 4.6, indicated that mean fractal dimension decreases with increasing number of layers value. Analysis of variance Table 4.8 shows that this regression was also very significant. The residuals for the regression [Figure 4.5] were shown to decrease with increasing number of layers. One anomaly is evident in Figure 4.5. This anomaly is representative of processing parameters 20 layers, a thickness of 3, and a 7 pixel by 7 line window. Since the use of a thickness of 3 has already been discounted, it was possible to ignore this anomaly. This being the case, the optimum parameter selected for number of layers was probably a value of 20 which had the lowest residual values.

Table 4.8. Analysis of variance for the regression of number of layers and mean fractal dimension using values from Tables 4.4 - 4.6.

<i>Regression Statistics</i>	
R	0.3613662
R Square	0.1305855
Adjusted R Square	0.1195803
Standard Error	0.0845414
Observations	81

ANOVA					
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>
Regression	1	0.08480741	0.08480741	11.86575	0.000918046
Residual	79	0.5646321	0.00714724		
Total	80	0.64943951			

Mean Fractal Dimension versus Number of Layers Line Fit Plot

Figure 4.4. Regression of mean fractal dimension and number of layers parameter used for processing.

Figure 4.5. Residuals for the regression of mean fractal dimension and the number of layers parameter used for processing. Residuals decrease for increasing number of layers if anomaly removed.

A regression of mean fractal dimension with window size [Figure 4.6] showed little difference in residuals [Figure 4.7] for the window sizes selected. Analysis of variance of the regression [Table 4.9] showed that the correlation of the variates was not very significant. The significance of the regression and the low coefficient of determination indicated that the relationship between the variates is weak and did not account for much of the variance in mean fractal dimension. This being the case the window size was not selected based on this regression. The larger window size of the two choices, 9 by 9 or 7 by 7, was selected because it was thought that a larger window size might produce less sampling error.

Table 4.9. Analysis of variance for the regression of window size and mean fractal dimension using values from Tables 4.4 - 4.6.

Regression Statistics	
R	0.20939
R Square	0.043844
Adjusted R Square	0.031741
Standard Error	0.088658
Observations	81

ANOVA					
	df	SS	MS	F	Significance F
Regression	1	0.028474	0.028474	3.622507	0.0606454
Residual	79	0.620965	0.00786		
Total	80	0.64944

Figure 4.6. Regression of mean fractal dimension and window size parameter used for processing.

Figure 4.7. Residuals for the regression of mean fractal dimension and the window size parameter used for processing.

The parameters for processing were confirmed by calculating the fractal dimension of samples from the remaining standardized SAR images [Table 4.10]. Each sample image was a 512 line by 512 pixel sample from the original 512 pixel by 2048 line image. All samples when processed using 20 layers a thickness of 4 using a 9 pixel by 9 line window produced acceptable results.

Imagery processed using the fractal analysis software created local fractal dimension and correlation image data sets with a digital range of 100-200 Dn. The local fractal dimension, and correlation, images were classified according to grey level values to produce pseudo-colour imagery. All imagery was visually interpreted. Visual interpretation should reveal if an increase in local fractal dimension is associated with an increase in backscatter on the SAR imagery, which is thought to be associated with an increase in apparent surface roughness.

Table 4.10. The results of processing the 512 pixel by 512 line samples of the standardized SAR images li2575n, li2580n, li2586n, li2591n, li2598, li2603n, and li2609n with fractal analysis software. Input parameters are a 9 pixel by 9 line window size, a blanket thickness of 4, and 20 layers.

SAR Image sampled	Mean R Sq.	Min R Sq.	Max R Sq.	Max Fd	Min Fd
li2575n	0.74	0.47	0.99	2.49	2.02
li2580n	0.75	0.47	0.98	2.45	2.02
li2586n	0.74	0.47	0.99	2.58	2.00
li2591n	0.73	0.47	0.98	2.51	2.01
li2598n	0.73	0.47	0.99	2.49	2.00
li2603n	0.74	0.47	0.99	2.47	2.01
li2609n	0.73	0.47	0.99	2.45	2.00

Plots of mean fractal dimension versus spatial resolution were constructed to analyze the change in fractal dimension with change in scale, for each of the SAR image data sets. The plots would provide a visible record of the multiple fractal dimensionality of the SAR imagery, if such a property existed in the imagery.

4.6 Detailed analysis of one image data set.

A detailed analysis of one standardized SAR image, Li2586n, and its corresponding fractal image, L2586nf, was carried out to attempt to determine what the fractal dimension of an image represented. Using an image with a mean fractal dimension which varied with scale change similar to the simulation imagery, it should have been possible to derive, by comparison, what factors were responsible for changes in the fractal dimension of the SAR imagery. Further, the detailed analysis attempted to provide a means of determining if the image resampling method, used to produce imagery at several resolutions, had caused changes in the measured fractal dimension.

Image li2586n was similar in radiometric appearance to the simulation data with a minimum Dn of 11 and a maximum Dn of 128, and had a mean wavelength of 48 ± 10 pixels oriented at 45° with respect to the first line of data. The mean wavelength of image Li2586n was calculated based on 26 peak-to-peak measurements on the image. The mean fractal dimension of image Li2586n at varying resolutions was compared graphically to the mean fractal dimension of both the simulated wave data and noise data. A plot was made of the variability of the fractal dimension of simulated wave data, simulated wave data with noise added,

and simulated wave data with noise and wind rippling added. This graph allowed the interpretation of the variability within each of the data sets, and between each of the data sets, corresponding to the SAR image Li2586n. Visual interpretation of the original SAR imagery indicated that wind may have been causing variation of wave features on the ocean surface. Using Adulus Photostyler SE© 1994 Ripple procedure the combined simulated wave and noise SAR data were processed to add a simulated wind rippled visual appearance. In order to produce an appearance similar to that of the original SAR imagery, Li2586n, the Ripple procedure parameters were set to a pixel size of 1 and a magnitude of 15. It is unknown if the scale of the generated ripple was similar to that which is producing Bragg scattering. This was a subjective procedure which produced visually similar imagery. The variation of the fractal dimension of noise data alone at varying resolutions was also included on the graph.

Using histograms of the resampled standardized SAR image data for image Li2586n, an analysis was made of the possibility that resampling had caused variations in measured fractal dimensions. Resampled image data corresponding to Li2586n was selected since it had been used for comparison in the simulation study. Analysis was completed by visual inspection of the histogram shape.

To observe the relationship between fractal imagery digital values and standardized SAR imagery digital values, transects were constructed of both fractal and SAR image data sets corresponding to SAR image Li2586n. To compare changes in the standardized SAR image digital values, with respect to changes in image spatial resolution, digital values across a transect for several image spatial resolutions were graphically compared. This was carried out to determine if the resampling, which simulated scale change, had properly produced a generalization of the data with each change in scale. Similarly, to compare changes in the fractal image digital values across the transect, digital values across the transect for several image spatial resolutions were graphically compared. This was carried out to allow observations to be made, at a pixel-by-pixel level, of the changes in the fractal dimension with respect to scale change. To directly compare the fractal digital values to the SAR digital values a plot was made to compare the

transect of Li2586n, the standardized SAR image, and its corresponding fractal image at the same scale. This was an attempt to graphically portray the relationship between standardized SAR image digital values and the corresponding fractal image digital values. The spatially corresponding line numbers on which the transects were made for images with resolutions of 1 to 5 times the original pixel size, respectively, were lines 720, 360, 240, 180 and 144. The line number 720 on the original full scale image was arbitrarily selected. Only 5 levels of scale change were selected because of results from the plot of variation in fractal dimension of the simulated wave imagery, which will be discussed in the following chapter.

Further research into the relationship between measured fractal dimension and input standardized SAR digital values was carried out through a regression of D_n values of the standardized SAR and local fractal dimension imagery. SAR imagery is composed of variations in digital values due to apparent surface roughness and the dielectric properties of the target. However, the models of SAR imaging of ocean waves suggest that the dominant process in the production of SAR backscatter from the ocean surface is due to wind roughening the surface which causes Bragg scattering. This implies that the dielectric constant can be considered to be constant for the ocean, and as such this regression should be highly significant and account for much of the variance of fractal dimension image digital values. Thirty points per image were sampled for pixel D_n values on both the standardized SAR and local fractal dimension imagery. Using the sampling method described in Hammond and McCullagh [1980, pp. 157-158] the required sample size to provide an accuracy of ± 0.05 in the fractal dimension at the 95 percent confidence limit was calculated to be approximately 20 observations. The spatial resolution of the imagery used in the statistical analysis was equal to the original un-resampled spatial resolution.

Limiting the regression between measured fractal dimension and input standardized SAR digital values to only those images in which wave forms were clearly visible in the standardized SAR imagery allowed an investigation into the effect of noise on the measured fractal dimension. Image noise such as speckle or background microwave radiation could have been causing significant changes in the measured

fractal dimension. If this was the case then the regression using what will be described here as "the well formed wave SAR imagery" should account for significantly more of the variance than the regression which included less "well formed waves". Background microwave radiation sources may include sensor system noise, emission of microwave radiation from the ocean surface, or man-made sources of microwave radiation. Images used in the regression include standardized SAR imagery Li2586n, Li2598n, Li2603n and the corresponding fractal images li2586nf, Li2598nf, and Li2603nf.

A similar analysis was carried out using the sample noise data set supplied by C.C.R.S.. A regression between measured fractal dimension and input standardized SAR background noise digital values was produced. It was expected that the amount of variance explained by these data would be much less than the previous two regressions. This would provide a general measure of the influence of noise on the measured fractal dimension.

Since speckle in the SAR imagery is dependent on the sample spacing within the individual pixels, an analysis of the relationship between measured fractal dimension and input standardized SAR digital values within the 9 by 9 sampling window used in the measurement of fractal dimension was carried out. A 9 by 9 window would contain roughly 230 samples per pixel per look in the SAR imagery based on Nyquist sampling criteria. To simplify the analysis SAR image data were collected from the resampled imagery, 9L2586n, and regressed against fractal dimension values from the corresponding pixel positions of the corresponding fractal image 9L2586nf. The resulting regression line should be constructed with smaller residuals than the single pixel value regressions, and as such provide a better fitting line.

To further investigate the relationship between fractal dimension, image digital values, and standardized SAR image digital values, an analysis of the variance within the 9 pixel by 9 line sample area used to calculate the fractal image digital values was carried out. The variance of the pixels within the window can be used as a means of measuring image texture [Ryherd and Woodcock, 1996]. Twenty-five, 9 by 9 sample areas were selected in a grid pattern from the standardized SAR

image Li2586n. Using the centre pixel position of each of the 9 by 9 sample windows, the corresponding fractal image digital value at that location was recorded. Variance within each of the 9 by 9 sample windows was calculated by importing the digital values for each window into Microsoft Excel. A regression of the variance of SAR image digital values within the 9 by 9 sample windows versus the fractal image digital values was carried out. The result of the regression indicates how much of the variance within each window area can be attributed to image texture, and provides insight into what process recorded in the imagery is responsible for the measured fractal dimension.

4.7 Comparison of fractal dimension to corresponding geophysical data.

The statistical analysis of the geophysical data set included a correlation and regression of mean Dn values of fractal imagery with geophysical data gathered by Vachon et al. [1994, p. 92]. These data are summarized in Table 4.11. This analysis would provide a determination of which geophysical parameters were associated with measured variations in the fractal dimension. Regressions between mean

Table 4.11. SAR and geophysical parameters gathered near the CSS Hudson at the time of each SAR pass. Wind measurements are from the bow mast on the CSS Hudson, and wave measurements are from the Marine Environmental Data service [MEDS] "Wavec" buoy, unless indicated.

Image	Sensor Altitude [km]	Platform Velocity V [m/s]	Look θ [°]	R/V [s]	Hs [m]	To [s]	U [m/s]
li2575	1.8	94	63.5	43	1.0	5.8	4.7
li2580	1.7	133	65.3	31	3.7	6.9	12.0
li2586	2.5	117	58.4	41	3.5 ^a	7.8 ^a	4.1
li2591	1.7	100	70.3	50	2.4 ^a	6.8 ^a	3.5
li2598	3.1	130	55.0	41	3.4	7.4	9.7
li2603	2.4	98	58.4	47	2.7	5.6	12.0
li2609	2.1	117	62.6	38	3.7	6.9	8.3

^a Data from "Waverider" buoy

^b Calculated using equation [29] in Krogstad et al. [1994] with $\bar{a}_2=0$. Referenced in Vachon et al. [1994] pp 92.

^c The cut-off wavelength is derived using a fitting procedure described in Vachon et al. [1994] pp 93-94.

R/V Scene range to platform velocity ratio [s]

Hs Significant wave height [m].

To Mean zero-crossing period [s].

U 10 m equivalent height neutral stability wind speed [m/s].

(Source: Vachon et al. [1994] p.92.)

fractal dimension of each of the standardized SAR images and significant wave height H_s [m], mean zero-crossing period T_0 [s] and instantaneous wind speed U [m/s] were produced. Significant wave height is defined as the average of the highest one-third of the waves present in a sample [Gross, 1990, pp.202]. Mean zero-crossing period is the mean of the inverse of the number of up-crossings per second of a wave [Guymer, 1990]. Wind speed measurements were collected from the bow mast of the CSS Hudson as the 10 m equivalent height neutral stability wind speed.

Similar regressions were produced between the average change in mean fractal dimension and the following geophysical parameters: significant wave height H_s [m], mean zero-crossing period T_0 [s] and wind speed U [m/s]. This regression attempted to associate the variability of mean fractal dimension, due to changes in image scale, to geophysical parameters. The presence of such a relationship would also provide insight into the multi-fractal nature of the geophysical parameters.

Chapter 5

Results

5.1 Introduction.

Results were gathered based on the methodology described in chapter 4. The investigation proceeded to analyze the parameters of a surface, SAR imagery of ocean waves, and the fractal dimension of the surface. Analysis of the relationship proceeded in the following manner: 1) investigate the variation of fractal dimension with respect to changes in spatial resolution; 2) a detailed statistical and visual analysis of a SAR image data set and the corresponding fractal image data set for a single SAR image at variable spatial resolutions; and 3) regression of known geophysical parameters with mean fractal dimension.

5.2 Processing of SAR and simulation data.

Using the fractal analysis software, developed based on the blanket approach of Peleg [1984], each of the 144 images was processed to produce the local fractal dimension and correlation imagery. Using the input parameters of 20 layers, a thickness of 4 with a 9 by 9 sampling window, described in the methodology section 4.2, all images were processed. A summary of the statistics output during image processing with the fractal analysis software is shown in Table 5.1 for the simulation and noise data sets. Table 5.2 contains the statistics output during image processing using the fractal analysis software for the SAR imagery data set. Spatial resolution in Tables 5.1 and 5.2 is given in terms of the total number of original pixels, in length and width, used to create one pixel in an image during resampling. Mean fractal dimension in both tables can be observed to fall within an acceptable range of 2.06 - 2.64 units. Maximum fractal dimension never exceeds 3.00 and minimum fractal dimension never falls below 2.00. Examination of Mean r-squared values in both tables 5.1 and 5.2 shows that the variance in the log of the surface area which is explained ranges from 49% to 89%. The amount by which the log of the surface area is statistically explained by the log of the blanket thickness, which were the values used to determine the fractal dimension [eq. 11], is indicated by the r-squared values. The minimum r-squared value recorded for both the simulation and SAR data sets

Table 5.1 Summary of descriptive statistics output during processing of the simulation image data set images with fractal analysis software. Spatial resolution is shown in number of pixels.

Image File Name	Spatial Resolution [Pixels]	Mean Fractal Dimension [Units]	Mean r-squared	Maximum Fractal Dimension [Units]	Minimum Fractal Dimension [Units]	Minimum r-squared	Maximum r-squared
sinen	1.00	2.15	0.78	2.31	2.00	0.00	0.94
sinena	1.10	2.18	0.81	2.37	2.00	0.00	0.95
sinenb	1.25	2.22	0.85	2.40	2.00	0.00	0.95
sinenc	1.43	2.27	0.86	2.45	2.03	0.57	0.95
sinend	1.67	2.34	0.87	2.49	2.13	0.68	0.95
sinen2	2.00	2.41	0.88	2.54	2.28	0.68	0.96
sinen3	3.00	2.57	0.89	2.61	2.48	0.82	0.92
sinen4	4.00	2.63	0.86	2.68	2.57	0.81	0.91
sinen5	5.00	2.64	0.81	2.68	2.60	0.76	0.84
sinen6	6.00	2.61	0.75	2.63	2.59	0.72	0.81
sinen7	7.00	2.56	0.69	2.58	2.54	0.66	0.73
sinen8	8.00	2.51	0.64	2.52	2.49	0.61	0.66
sinen9	9.00	2.45	0.57	2.50	2.40	0.47	0.63
sinen10	10.00	2.40	0.52	2.42	2.38	0.47	0.58
sinen11	11.00	2.35	0.49	2.38	2.32	0.47	0.53
sinen12	12.00	2.31	0.51	2.34	2.29	0.47	0.59
ripl	1.00	2.30	0.74	2.48	2.01	0.47	0.98
ripla	1.10	2.27	0.73	2.45	2.01	0.47	0.98
riplb	1.25	2.26	0.71	2.43	2.08	0.47	0.97
riplc	1.43	2.24	0.68	2.41	2.09	0.48	0.97
ripld	1.67	2.23	0.66	2.41	2.09	0.47	0.95
ripl2	2.00	2.20	0.64	2.38	2.06	0.47	0.93
ripl3	3.00	2.18	0.59	2.40	2.05	0.47	0.93
ripl4	4.00	2.16	0.58	2.30	2.06	0.47	0.88
ripl5	5.00	2.18	0.58	2.29	2.06	0.47	0.82
ripl6	6.00	2.16	0.57	2.29	2.07	0.47	0.76
ripl7	7.00	2.18	0.58	2.30	2.06	0.47	0.82
ripl8	8.00	2.16	0.56	2.26	2.05	0.47	0.73
ripl9	9.00	2.17	0.56	2.29	2.07	0.47	0.77
ripl10	10.00	2.15	0.56	2.23	2.05	0.47	0.70
ripl11	11.00	2.17	0.57	2.27	2.08	0.47	0.73
ripl12	12.00	2.15	0.56	2.23	2.07	0.47	0.72
notopn	1.00	2.13	0.68	2.40	2.00	0.47	0.98
notopna	1.10	2.08	0.65	2.36	2.00	0.47	0.97
notopnb	1.25	2.08	0.64	2.35	2.00	0.00	0.97
notopnc	1.43	2.08	0.63	2.34	2.00	0.47	0.96
notopnd	1.67	2.09	0.64	2.36	2.00	0.47	0.97
notopn2	2.00	2.06	0.59	2.26	2.00	0.00	0.93
notopn3	3.00	2.12	0.65	2.37	2.02	0.47	0.94
notopn4	4.00	2.06	0.58	2.22	2.00	0.47	0.89
notopn5	5.00	2.12	0.66	2.37	2.03	0.47	0.93
notopn6	6.00	2.06	0.59	2.28	2.00	0.47	0.90
notopn7	7.00	2.12	0.65	2.29	2.03	0.47	0.90
notopn8	8.00	2.06	0.59	2.19	2.01	0.47	0.83
notopn9	9.00	2.12	0.65	2.30	2.03	0.47	0.93
ntopn10	10.00	2.07	0.60	2.17	2.01	0.47	0.83
ntopn11	11.00	2.13	0.67	2.27	2.02	0.47	0.90
ntopn12	12.00	2.06	0.57	2.15	2.01	0.47	0.90

Table 5.2 Summary of descriptive statistics output during processing of standardized SAR images with fractal analysis software. Spatial resolution is shown in number of pixels.

Image File Name	Spatial Resolution [Pixels]	Mean Fractal Dimension [Units]	Mean r-squared	Maximum Fractal Dimension [Units]	Minimum Fractal Dimension [Units]	Minimum r-squared	Maximum r-squared
Li2575N	1.00	2.16	0.73	2.97	2.01	0.47	0.99
aL2575N	1.10	2.11	0.71	2.82	2.00	0.00	0.98
bL2575N	1.25	2.12	0.71	2.85	2.00	0.45	0.98
cL2575N	1.43	2.12	0.71	2.87	2.01	0.47	0.98
dL2575N	1.67	2.13	0.71	2.80	2.01	0.47	0.98
2L2575N	2.00	2.11	0.69	2.84	2.01	0.42	0.97
3L2575N	3.00	2.18	0.72	2.70	2.03	0.47	0.97
4L2575N	4.00	2.11	0.66	2.55	2.01	0.47	0.96
5L2575N	5.00	2.17	0.71	2.81	2.04	0.47	0.97
6L2575N	6.00	2.11	0.66	2.40	2.01	0.47	0.97
7L2575N	7.00	2.18	0.71	2.55	2.05	0.48	0.98
8L2575N	8.00	2.12	0.67	2.32	2.02	0.47	0.95
9L2575N	9.00	2.18	0.71	2.68	2.04	0.47	0.97
102575N	10.00	2.12	0.67	2.37	2.02	0.47	0.95
112575N	11.00	2.18	0.71	2.42	2.04	0.48	0.96
122575N	12.00	2.12	0.66	2.38	2.03	0.47	0.96
Li2580N	1.00	2.16	0.75	2.48	2.01	0.47	0.98
aL2580N	1.10	2.12	0.73	2.39	2.00	0.47	0.97
bL2580N	1.25	2.13	0.72	2.42	2.00	0.47	0.97
cL2580N	1.43	2.13	0.72	2.41	2.01	0.47	0.97
dL2580N	1.67	2.14	0.71	2.45	2.02	0.47	0.97
2L2580N	2.00	2.12	0.68	2.34	2.01	0.47	0.95
3L2580N	3.00	2.17	0.71	2.41	2.03	0.47	0.97
4L2580N	4.00	2.11	0.65	2.33	2.02	0.47	0.94
5L2580N	5.00	2.17	0.69	2.43	2.03	0.47	0.95
6L2580N	6.00	2.11	0.64	2.28	2.02	0.47	0.92
7L2580N	7.00	2.17	0.70	2.41	2.04	0.47	0.96
8L2580N	8.00	2.11	0.64	2.27	2.03	0.47	0.95
9L2580N	9.00	2.17	0.70	2.40	2.04	0.47	0.95
102580N	10.00	2.12	0.65	2.29	2.02	0.47	0.92
112580N	11.00	2.16	0.69	2.37	2.05	0.47	0.94
122580N	12.00	2.11	0.62	2.42	2.03	0.47	0.86
Li2586N	1.00	2.13	0.75	2.58	2.00	0.00	0.99
aL2586N	1.10	2.10	0.73	2.52	2.00	0.00	0.99
bL2586N	1.25	2.11	0.73	2.56	2.00	0.00	0.99
cL2586N	1.43	2.12	0.74	2.56	2.00	0.47	0.99
dL2586N	1.67	2.13	0.75	2.52	2.00	0.47	0.99
2L2586N	2.00	2.12	0.74	2.55	2.00	0.45	0.98
3L2586N	3.00	2.18	0.77	2.59	2.01	0.47	0.98
4L2586N	4.00	2.15	0.74	2.46	2.01	0.47	0.98
5L2586N	5.00	2.20	0.77	2.52	2.04	0.47	0.98
6L2586N	6.00	2.16	0.74	2.41	2.03	0.47	0.98
7L2586N	7.00	2.20	0.75	2.55	2.03	0.47	0.98
8L2586N	8.00	2.16	0.72	2.45	2.03	0.47	0.98
9L2586N	9.00	2.20	0.75	2.50	2.03	0.48	0.97
102586N	10.00	2.16	0.71	2.37	2.02	0.47	0.98
112586N	11.00	2.20	0.74	2.48	2.05	0.47	0.97
122586N	12.00	2.16	0.71	2.36	2.03	0.47	0.95
Li2591N	1.00	2.14	0.73	2.51	2.00	0.00	0.99
aL2591N	1.10	2.10	0.71	2.43	2.00	0.47	0.98
bL2591N	1.25	2.11	0.71	2.41	2.00	0.47	0.99
cL2591N	1.43	2.11	0.72	2.39	2.00	0.47	0.98
dL2591N	1.67	2.13	0.72	2.42	2.01	0.47	0.98
2L2591N	2.00	2.11	0.71	2.40	2.01	0.47	0.98
3L2591N	3.00	2.18	0.74	2.45	2.03	0.47	0.98
4L2591N	4.00	2.13	0.69	2.35	2.01	0.47	0.96
5L2591N	5.00	2.17	0.72	2.44	2.02	0.47	0.97
6L2591N	6.00	2.12	0.67	2.33	2.02	0.47	0.95

Table 5.2 Continued Image File Name	Spatial Resolution [Pixels]	Mean Fractal Dimension [Units]	Mean r-squared	Maximum Fractal Dimension [Units]	Minimum Fractal Dimension [Units]	Minimum r-squared	Maximum r-squared
7L2591N	7.00	2.17	0.70	2.45	2.03	0.47	0.96
8L2591N	8.00	2.12	0.67	2.32	2.02	0.47	0.95
9L2591N	9.00	2.18	0.72	2.42	2.03	0.48	0.97
10L2591N	10.00	2.12	0.65	2.33	2.02	0.47	0.95
11L2591N	11.00	2.17	0.70	2.45	2.04	0.48	0.95
12L2591N	12.00	2.11	0.64	2.29	2.02	0.47	0.90
Li2598N	1.00	2.13	0.72	2.51	2.00	0.47	0.99
aL2598N	1.10	2.09	0.70	2.46	2.00	0.00	0.99
bL2598N	1.25	2.10	0.70	2.47	2.00	0.47	0.99
cL2598N	1.43	2.10	0.71	2.46	2.00	0.47	0.98
dL2598N	1.67	2.12	0.72	2.48	2.00	0.47	0.98
2L2598N	2.00	2.10	0.70	2.48	2.00	0.47	0.98
3L2598N	3.00	2.16	0.75	2.49	2.01	0.47	0.99
4L2598N	4.00	2.13	0.72	2.37	2.01	0.47	0.97
5L2598N	5.00	2.18	0.75	2.46	2.03	0.47	0.98
6L2598N	6.00	2.13	0.71	2.44	2.02	0.47	0.96
7L2598N	7.00	2.18	0.74	2.49	2.03	0.47	0.97
8L2598N	8.00	2.14	0.70	2.39	2.03	0.47	0.95
9L2598N	9.00	2.19	0.74	2.49	2.04	0.48	0.97
10L2598N	10.00	2.15	0.71	2.34	2.02	0.47	0.96
11L2598N	11.00	2.19	0.74	2.45	2.05	0.48	0.96
12L2598N	12.00	2.13	0.67	2.38	2.03	0.47	0.96
Li2603N	1.00	2.14	0.74	2.51	2.00	0.47	0.99
aL2603N	1.10	2.11	0.72	2.48	2.00	0.47	0.99
bL2603N	1.25	2.11	0.72	2.48	2.00	0.47	0.98
cL2603N	1.43	2.12	0.72	2.44	2.00	0.47	0.98
dL2603N	1.67	2.13	0.72	2.42	2.00	0.47	0.98
2L2603N	2.00	2.12	0.70	2.44	2.00	0.47	0.97
3L2603N	3.00	2.17	0.73	2.51	2.03	0.47	0.97
4L2603N	4.00	2.12	0.68	2.35	2.01	0.47	0.96
5L2603N	5.00	2.18	0.72	2.45	2.03	0.47	0.97
6L2603N	6.00	2.12	0.67	2.34	2.02	0.47	0.95
7L2603N	7.00	2.18	0.71	2.43	2.03	0.47	0.97
8L2603N	8.00	2.12	0.66	2.35	2.01	0.47	0.95
9L2603N	9.00	2.17	0.70	2.46	2.04	0.47	0.96
10L2603N	10.00	2.12	0.66	2.41	2.02	0.47	0.96
11L2603N	11.00	2.17	0.71	2.40	2.03	0.48	0.96
12L2603N	12.00	2.12	0.65	2.31	2.03	0.47	0.92
Li2609N	1.00	2.11	0.72	2.46	2.00	0.00	0.99
aL2609N	1.10	2.08	0.70	2.44	2.00	0.00	0.99
bL2609N	1.25	2.09	0.70	2.42	2.00	0.00	0.98
cL2609N	1.43	2.10	0.71	2.40	2.00	0.00	0.98
dL2609N	1.67	2.11	0.71	2.44	2.00	0.00	0.99
2L2609N	2.00	2.10	0.70	2.36	2.00	0.00	0.98
3L2609N	3.00	2.15	0.72	2.49	2.01	0.47	0.99
4L2609N	4.00	2.12	0.68	2.36	2.01	0.47	0.96
5L2609N	5.00	2.16	0.71	2.45	2.02	0.47	0.98
6L2609N	6.00	2.11	0.66	2.32	2.01	0.47	0.95
7L2609N	7.00	2.16	0.70	2.46	2.02	0.47	0.97
8L2609N	8.00	2.12	0.66	2.33	2.01	0.47	0.96
9L2609N	9.00	2.16	0.71	2.41	2.01	0.47	0.96
10L2609N	10.00	2.11	0.66	2.28	2.01	0.47	0.95
11L2609N	11.00	2.15	0.71	2.38	2.02	0.47	0.96
12L2609N	12.00	2.12	0.68	2.33	2.01	0.47	0.96

was 0.00. The number of pixels having a minimum r-squared value equal to 0.00 were estimated, by visual inspection, to account for less than 1% of the total number of pixels in an image. Areas on the imagery with low r-squared values were observed to be related to areas with low

fractal dimension, and small variation in surrounding pixel brightness compared to areas with high fractal dimension.

5.3 Analysis of the variation in Fd with image scale.

The following sub-sections deal with the analysis of the variation in measured fractal dimension with changes in simulated scale. Observations of the measured fractal dimension of the SAR imagery, simulated wave imagery, noise imagery and combined noise plus SAR imagery at each level of spatial resolution are discussed.

5.3.1 SAR data analysis.

Plotting the mean fractal dimension of each image versus its spatial resolution allowed analysis of the variation of fractal dimension with respect to changes in scale. According to definition, the fractal dimension should remain constant regardless of changes in scale. However, a variation of fractal dimension with respect to scale was observed for all standardized SAR imagery processed using the fractal analysis software. Variations occurred in the curvature of the general trend on each graph and in the amplitude of the sinusoidal shape of the mean fractal dimension versus resolution curves. Figures 5.1 to 5.7 display the variation in mean fractal dimension with respect to scale change for each of the seven SAR image data sets. Within the SAR data sets it can be observed that some of the images were possibly influenced more than others by background noise and wind effects. Images Li2586, Li2603 and Li2598 [Appendix-A] were observed visually to have well formed sinusoidal wave patterns dominating the ocean surface. The other SAR images in the data set were dominated more by background noise and wind effects, producing blotted patterns in the imagery which mask out the regular bright and dark bands produced by ocean waves.

It is possible that the variation of mean fractal dimension with respect to scale change is not large enough to be of concern. If this is the case then the SAR ocean wave imagery could be considered to be mono-fractal. Further analysis of the significance of the variation in fractal dimension will be presented in later sections. Plots of mean, maximum, and minimum fractal dimension with respect to resolution [Figures 5.8- 5.14] reveal that the mean fractal dimension varies only slightly with in a range of 2.08 to 2.2, in comparison to maximum and

minimum values which have a much broader range of variation, for all cases.

Figure 5.1. Li2586 image mean fractal dimension variations due to changes in scale. Scale change is represented here as the number of pixels used to produce one output pixel in the resampled imagery.

Figure 5.2. Li2603 image mean fractal dimension variations due to changes in scale. Scale change is represented here as the number of pixels used to produce one output pixel in the resampled imagery.

Mean Fractal Dimension vs Resolution Li2598

Figure 5.3. Li2598 image mean fractal dimension variations due to changes in scale. Scale change is represented here as the number of pixels used to produce one output pixel in the resampled imagery.

Mean Fractal Dimension vs Resolution Li2575

Figure 5.4. Li2575 image mean fractal dimension variations due to changes in scale. Scale change is represented here as the number of pixels used to produce one output pixel in the resampled imagery.

Mean Fractal Dimension vs Resolution Li2591

Figure 5.5. Li2591 image mean fractal dimension variations due to changes in scale. Scale change is represented here as the number of pixels used to produce one output pixel in the resampled imagery.

Mean Fractal Dimension vs Resolution Li2580

Figure 5.6. Li2580 image mean fractal dimension variations due to changes in scale. Scale change is represented here as the number of pixels used to produce one output pixel in the resampled imagery.

Mean Fractal Dimension vs Resolution Li2609

Figure 5.7. Li2609 image mean fractal dimension variations due to changes in scale. Scale change is represented here as the number of pixels used to produce one output pixel in the resampled imagery.

Mean, Maximum and Minimum Fractal Dimension vs Resolution Li2575

Figure 5.8. Li2575 image. Maximum, minimum, and mean fractal dimension variations with respect to changes in resolution. Minimum values never fall below 2.0 while maximum values vary greatly but do not exceed 3.0.

**Mean, Maximum and Minimum Fractal Dimension vs Resolution
Li2580**

Figure 5.9. Li2580 image. Maximum, minimum, and mean fractal dimension variations with respect to changes in resolution. Minimum values never fall below 2.0 while maximum values vary greatly but do not exceed 3.0.

**Mean, Maximum and Minimum Fractal Dimension vs Resolution
Li2586**

Figure 5.10. Li2586 image. Maximum, minimum, and mean fractal dimension variations with respect to changes in resolution. Minimum values never fall below 2.0 while maximum values vary greatly but do not exceed 3.0.

Mean, Maximum, and Minimum Fractal Dimension vs Resolution Li2591

Figure 5.11. Li2591 image. Maximum, minimum, and mean fractal dimension variations with respect to changes in resolution. Minimum values never fall below 2.0 while maximum values vary greatly but do not exceed 3.0.

Mean, Maximum and Minimum Fractal Dimension vs Resolution Li2598

Figure 5.12. Li2598 image. Maximum, minimum, and mean fractal dimension variations with respect to changes in resolution. Minimum values never fall below 2.0 while maximum values vary greatly but do not exceed 3.0.

Mean, Maximum, and Minimum Fractal Dimension vs Resolution
Li2603

Figure 5.13. Li2603 image. Maximum, minimum, and mean fractal dimension variations with respect to changes in resolution. Minimum values never fall below 2.0 while maximum values vary greatly but do not exceed 3.0.

Mean, Maximum and Minimum Fractal Dimension vs Resolution
Li2609

Figure 5.14. Li2609 image. Maximum, minimum, and mean fractal dimension variations with respect to changes in resolution. Minimum values never fall below 2.0 while maximum values vary greatly but do not exceed 3.0.

5.3.2 Simulated data analysis.

An example of the variation in fractal dimension with respect to scale change for simulation imagery is displayed in Figure 5.15. Simulated wave imagery exhibited a gradual but constant increase in mean fractal dimension as the pixel size increased to 5 times the original pixel size and then began a gradual decline in value. It is expected that the maximum fractal dimension should occur when the sampling window size is equal to the wavelength of the simulated wave. When the window size matches the wavelength the sampling window would measure the maximum variability in the sample window, a full peak and a full trough. If the fractal dimension is a measure of roughness then the maximum fractal dimension should correspond to the maximum variability in digital values. For a resolution equal to 5 times the original pixel size and a sampling window of 9 lines by 9 pixels, the wavelength required for maximum fractal dimension is equal to 45 pixels. However, the wave pattern of the simulated wave imagery is oriented at 45 degrees with respect to the first line of data; the wavelength required for maximum fractal dimension is equal to 31.81 pixels. The wavelength of the simulated wave data for a resolution of five times the original spatial

Figure 5.15. Comparison of simulated and SAR data mean fractal dimension variations with respect to scale change. Scale change is represented here as the number of pixels used to produce one output pixel in the resampled imagery.

resolution was measured at 7 ± 1 pixels, which corresponds to 35 ± 5 pixels at the original pixel size. The measured wavelength is then within range of the expected value. The decline in mean fractal dimension could probably be attributed to overall smoothing of the image digital values due to resampling and to the inequality of the sample window size to the simulated wave data wavelength. Simulated wave imagery data are displayed in Table 5.1 with images "sinen" to "sinen12". No background noise was present in the simulated wave data.

5.3.3 Analysis of noise data.

In contrast to the increase in mean fractal dimension of the simulated wave data [Figure 5.15] and subsequent decrease, the mean fractal dimension of the background noise data set exhibited a sinusoidal type variation. Background noise data are displayed in Table 5.1 with images "notopn" to "notopn12", and is represented in Figure 5.15 as the Mean Fd Noise data set. The sinusoidal type variation of the noise data set might have been due to re-sampling or rounding error. The subsequent overall decrease in the mean fractal dimension of the simulated wave data set not observed in the noise data set could be argued to be caused by the random variability in digital values of the noise data.

5.3.4 Combined simulated wave plus noise data analysis.

In order to explore the variation of fractal dimension with respect to scale change with data which would provide a more realistic simulation of the SAR imagery, the noise data set was combined with the simulated wave data set. True SAR imagery is known to contain background noise. The noise data and simulated wave data were added in an equal ratio to produce simulated wave imagery with noise added. The mean fractal dimension of the simulated wave data set plus the noise data imagery was observed to have similar variations in fractal dimension to the simulated wave data set. The main differences between the noise data set and the simulated wave data set with noise added were a higher overall fractal dimension in the data set than the noise data and the absence of the sinusoidal shape to the resulting curve. The lack of sinusoidal shape with this image suggests that the sinusoidal shape in the real data is caused by a factor other than the background noise, since the addition of noise alone did not produce the sinusoidal

variation present in the SAR imagery data set. It is also possible that the sinusoidal type variation was insignificant, since adding the noise data which contained the variation to the simulated wave data produced a curve without the sinusoidal type variation. Visual analysis of the original SAR imagery indicated that wind may have been causing variation of wave features on the ocean surface. Using Adulus Photostyler SE© 1994 Ripple procedure the combined simulated wave and noise data were processed to add a simulated wind rippled appearance. The resulting imagery had an appearance similar to that of the original SAR imagery. Simulated wave plus noise data and wind rippling imagery data are displayed in Table 5.1 with images "ripl" to "ripln12". The mean Fd of the simulated wave plus noise and wind ripples imagery produced similar mean fractal dimension variation to the SAR imagery [Figure 5.15]. Only SAR image Li2586 mean fractal dimension is shown in Figure 5.15 for comparison.

5.3.5 Effects of image re-sampling on fractal analysis.

The investigation to determine if image resampling, prior to processing with the fractal analysis software, had an effect on the SAR imagery was carried out by histogram analysis [Figures 5.16 - 5.19]. Histograms of the resampled standardized SAR imagery revealed that the variation in sample spatial resolution may be causing variations in roughness on the imagery. Saw tooth patterns on the histograms were created in both the simulated wave data and the SAR imagery during normalization. Standardized SAR imagery was resampled to produce images at varying spatial resolutions. As the spatial resolution of the imagery changed, the saw-tooth patterns which are visible on the histograms changed by increasing or decreasing in frequency of occurrence. The effect is more pronounced on the SAR imagery than the simulated wave imagery. During resampling, the data may be shifting from one histogram bin to another, causing a peak to form in the histogram as more data is added to a specific bin. In effect, during the resampling process the sampling window may cover more of an ocean wave peak area at one resolution, then less of a peak area at the next resolution. If this is occurring then the resampled imagery could appear relatively smooth at one spatial resolution and then relatively rough at the next level of spatial resolution, a situation which might account for the sinusoidal variation of the mean fractal dimension.

Transects of digital values, corresponding to image Li2586n at different spatial resolutions, were collected to investigate further the possibility that the resampling method used was causing the sinusoidal variation of the mean values of the fractal dimension as the spatial resolution changed. Transects were made on both the fractal and standardized SAR imagery data set. Digital values along the transects for the SAR image at variable spatial resolutions are shown in Figure 5.20. Smoothing is observed, which eventually removes some peaks and troughs in the transects, as expected with any resampling method. However, it should be noted that some peaks and troughs are accentuated. An example of the accentuation occurs at pixel position six, in Figure 5.20. At pixel position six the original resolution standardized SAR image L2586n is observed to have a digital value between 50 and 60. After re-sampling to produce a five times original spatial resolution standardized SAR image 5L2586n, the digital value for the same pixel position is increased to a value near 70.

Figure 5.16. Frequency distribution of digital values for standardized SAR image. Spatial resolution equals 1 times the original pixel spatial resolution.

Figure 5.17. Frequency distribution of digital values for standardized SAR image. Spatial resolution equals 2 times the original pixel spatial resolution.

Figure 5.18. Frequency distribution of digital values for standardized SAR image. Spatial resolution equals 3 times the original pixel spatial resolution.

Figure 5.19. Frequency distribution of digital values for standardized SAR image. Spatial resolution equals 4 times the original pixel spatial resolution.

Figure 5.20. Transect across the SAR image at variable spatial resolutions. Scale change is represented here as number of pixels used to produce one output pixel in the resampled imagery. The number of pixels used to produce one output pixel is prefixed on the image name starting with L2586n which is processed at the original spatial resolution and as such has no prefix.

The transect of the fractal imagery [Figure 5.21] displays a much larger variation in digital values than the transect of the SAR images for each spatial resolution [Figure 5.20]. This indicates that the fractal analysis software is measuring some property of the SAR imagery which varies with scale. Part of the difference between the SAR and fractal image transects could be attributed to the 9 pixel by 9 line sampling window used in the fractal analysis software. Fractal image transects appear much smoother than SAR image transects. This is investigated by comparing a standardized SAR image transect to the corresponding fractal image transect of the same scale.

Transect of Fractal Images of Different Resolutions

Figure 5.21. The transect of the fractal imagery. Scale change is represented here as number of pixels used to produce one output pixel in the resampled imagery. The number of pixels used to produce one output pixel is prefixed on the image name starting with L2586nf which is processed at the original spatial resolution and as such has no prefix. Digital values of 100 to 200 correspond to fractal dimension values of 2.00 to 3.00.

Comparison of transects of SAR image Dn values and fractal image Dn values [Figure 5.22] reveals that the fractal image appears to correspond to the average variation in peaks and troughs on the SAR imagery. The fractal transect [Figure 5.22] has a shape which could be described as a phase shifted smoothed rendition of the SAR Dn image transect. The general trend of the standardized SAR digital values is visible in the trend of the fractal dimension image transect. The indirect correspondence of the two transects indicates that the production of the fractal image made use of information from the surrounding pixels within the 9 by 9 sampling window, as well as the central pixel in the sample window.

Figure 5.22. Comparison of transects of SAR image Dn values L2586n and fractal image Dn values L2586nf. Digital values of 100 to 200 in fractal image L2586nf correspond to fractal dimension values of 2.00 to 3.00.

5.4 Statistical relationships between SAR and fractal dimension imagery.

A descriptive statistical analysis of the SAR imagery input Dn values and the resulting output Dn fractal dimension values of the imagery was carried out to determine if a relationship existed between the two. It is expected that some type of relationship exists between the fractal dimension Dn values and SAR imagery Dn values, since the fractal dimension values are derived from the SAR imagery. Using Aldus

Photostyler® [1994], thirty points per image were sampled for pixel Dn values on both the SAR and local fractal dimension imagery. The fractal dimension imagery used in this statistical analysis has a spatial resolution equal to the original spatial resolution of 6.6 m in range by 6.7 m in azimuth, for all 210 of the observation pairs. Table 5.3 displays the results of the regression analysis. A plot of the regression line for the data used in Table 5.3 is shown Figure 5.23.

Table 5.3 Regression statistics and analysis of variance of input Dn values and output local fractal dimension imagery Dn values.

<i>Regression Statistics</i>					
R		0.565624			
R Square		0.31993			
Adjusted R Square		0.316661			
Standard Error		9.316243			
Observations		210			

<i>ANOVA</i>					
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>
Regression	1	8492.714	8492.714	97.85091	3.72509E-19
Residual	208	18052.81	86.79238		
Total	209	26545.53			

The sample data set used in the regression [Figure 5.23] has standard deviations of 11.27 for the fractal dimension imagery digital values and 15.52 for standardized SAR imagery digital values. While the difference between the standard deviations could be considered small, this means that the requirements of the parametric test were not entirely fulfilled. It should also be noted that both the variates were positively skewed, and as such are not statistically normal. Fractal dimension imagery digital values had a skew of 1.081 and a standard error of 0.778. Standardized SAR imagery digital values had a skew of 1.785 and a standard error of 1.071. Residuals for the regression shown in Figure 5.23 are displayed in Figure 5.24. The relationship between the two variables produced a low *r*-squared value of approximately 0.32 which was highly significant. This indicates that the removal of a few points from the regression would probably not significantly alter the results.

Figure 5.23. Regression of Input SAR Dn and output fractal dimension image Dn values. Error bars represent standard error.

Figure 5.24. Residual plot for regression shown in Figure 5.23.

Correlation and r-squared values increased by limiting the statistical analysis to images with well formed sinusoidal waves visible in the SAR imagery data set. Table 5.4 displays the results of the regression analysis for well formed wave imagery, which is a partial sample of data from the previous regression. A plot of the regression for the data used in Table 5.4 is shown Figure 5.25. The correlation of the two variates increased to approximately 0.691 with an r-squared value of approximately 0.477, compared to the previous regression. Once more the requirements of the parametric test were not entirely fulfilled. The sample data set used in the regression [Figure 5.25] had standard deviations of 12.97 for the fractal dimension imagery digital values and 18.14 for standardized SAR imagery digital values. The standard error for the fractal dimension imagery digital values was 1.367 and 1.912 for standardized SAR imagery digital values. The samples used for both of the variates were positively skewed. Fractal dimension imagery digital values had a skew of 0.949 and standardized

Table 5.4 Regression statistics and analysis of variance of input Dn values and output local fractal dimension imagery Dn values for well formed wave images Li2586, Li2598, and Li2603.

<i>Regression Statistics</i>	
R	0.690671
R Square	0.477026
Adjusted R Square	0.471083
Standard Error	9.43211
Observations	90

<i>ANOVA</i>					
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>
Regression	1	7141.063	7141.063	80.2685	4.97926E-14
Residual	88	7828.893	88.96469		
Total	89	14969.96			

Fractal Dimension Imagery Dn vs Standardized SAR Image Dn

Figure 5.25. Regression of Input SAR Dn and output fractal dimension Dn values. Error bars represent standard error.

Standardized SAR Image Dn value Residual Plot

Figure 5.26. Residual plot for regression Figure 5.25.

SAR imagery digital values had a skew of 1.7774. Residuals for the regression shown Figure 5.25 are displayed in Figure 5.26. Residuals did not change in the manner of their distribution when compared with previous residuals [Figure 5.24]. Residuals remained distributed between +30 and -15. The lack of change in residual distribution was not expected. However, it does indicate that the fractal dimension digital values are not entirely constructed based upon single SAR image digital values as the regression cannot account for most of the variance in the dependent variable.

A visual comparison of both fractal and standardized SAR imagery confirmed a relationship between the two variates [Figure 5.27]. Brightness in fractal dimension imagery was observed to vary similarly to brightness in SAR imagery.

A similar regression analysis was carried out on the SAR background noise data set. Fractal dimension imagery digital values were regressed against SAR noise digital values, the purpose of which was to determine the amount of correlation which was due to noise. Regression statistics for the SAR background noise data set are shown in Table 5.5. Plotting the regression line [Figure 5.28] for noise data shown in Table 5.5 revealed little correlation and a low r-squared between input SAR noise Dn values and output fractal dimension Dn values. The low R-squared value indicated that the relationship between the two variates did not account for a large amount of the variance in fractal dimension digital values.

Covariance of the input Dn value and the output fractal dimension Dn value for the complete data set was observed to be 103.039, compared to 160.656 for the well formed wave data set. Covariance for the noise data set between input SAR noise Dn and output fractal image Dn values was calculated to be 5.867. This appears to indicate that although single input SAR digital values may not account for most of the variance in fractal digital values they do account for more of the variance when other processes such as noise are reduced. However, since noise is demonstrated to account for little of the explained variance it is likely that other processes are causing changes in fractal digital dimension values.

Comparison of standardized SAR image and Fractal image

Figure 5.27. Comparison of 512 pixel by 512 line sample for corresponding areas in standardized SAR image li2586n and fractal image li2586nf. Brightness values are observed to vary similarly.

Fractal Dimension Imagery Dn vs SAR Noise Dn

Figure 5.28. Regression between input SAR noise Dn and output fractal dimension Dn values. Error bars represent standard error.

Table 5.5 Regression statistics and analysis of variance of input Dn values and output local fractal dimension imagery Dn values for SAR background noise data set.

<i>Regression Statistics</i>					
R		0.376718			
R Square		0.141916			
Adjusted R Square		0.112327			
Standard Error		1.420488			
Observations		31			

<i>ANOVA</i>					
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>
Regression	1	9.677776	9.677776	4.796237	0.036713035
Residual	29	58.51577	2.017785		
Total	30	68.19355			

The relationship between fractal dimension image digital values and standardized SAR digital values, for images sampled at 9 times the original pixel size, was investigated by regression. Using images sampled at 9 times the original pixel size should remove some of the effects of speckle. Samples of SAR image 91i2586n and corresponding fractal image 912586nf were regressed to determine if a direct relationship existed between the two variates. Data from the two variates were much more normally distributed than any of the previous regressions. Summary statistics on the variates are provided in Table 5.6. Results of the regression are provided in Table 5.7. A plot of the regression for the data in Table 5.7 is shown in Figure 5.29 with the corresponding residual plot on Figure 5.30.

Table 5.6 Summary statistics for samples of the variates used in the regression of SAR image 91i2586n and corresponding fractal image 912586nf.

	Standardized SAR Image Dn [Units]	Fractal Dimension Image Dn [Units]
Mean	47.84375	122.625
Standard Error	2.333620584	1.192846622
Median	47.5	122
Mode	54	122
Standard Deviation	13.20095152	6.747759485
Sample Variance	174.265121	45.53225806
Kurtosis	-0.535078986	-0.543435824
Skewness	0.518738036	0.26806762
Range	48	27
Minimum	30	110
Maximum	78	137

Table 5.7 Regression statistics and analysis of variance for regression of SAR image 91i2586n and corresponding fractal image 912586nf.

<i>Regression Statistics</i>	
R	0.42374612
R Square	0.17956077
Adjusted R Square	0.1522128
Standard Error	6.21302387
Observations	32

ANOVA					
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>
Regression	1	253.4500321	253.45	6.56578	0.01565716
Residual	30	1158.049968	38.60167		
Total	31	1411.5			

Fractal Dimension Imagery Dn vs Standardized SAR Image Dn

Figure 5.29. Regression of Input SAR Dn and output fractal dimension Dn values. Error bars represent standard error.

Figure 5.30. Residual plot for regression Figure 5.29.

The relationship between fractal dimension image digital values and standardized SAR image digital values, within the 9 pixel by 9 line sample area used to calculate the fractal image digital values, was investigated by regression. As the variance of the pixels within the window can be used as a means of measuring image texture, this will provide a means of relating differences in image texture to fractal dimension. Fractal image li2586nf and its corresponding standardized SAR image were used since previous results are based on this image data set. Both the SAR and the fractal dimension imagery used are full spatial resolution equal to the original, not re-sampled, spatial resolution. Summary statistics for the two variates are provided in Table 5.8. Results of the regression are provided in Table 5.9.

Table 5.8 Summary statistics for samples used in the regression of fractal dimension image values extracted from li2586nf and local variance measured in standardized SAR image li2586n.

	Fractal Dimension FD [Units]	Variance of 9 pixel by 9 line Sample
Mean	2.227391304	151.6647826
Standard Error	0.032212348	22.11166042
Median	2.19	101.92
Standard Deviation	0.154484992	106.0437981
Sample Variance	0.023865613	11245.28711
Kurtosis	-1.34571591	-0.890200277
Skewness	0.462277703	0.62224132
Range	0.45	346.94
Minimum	2.05	33
Maximum	2.5	379.94
Sum	51.23	3488.29
Count	23	23
Confidence Level(95.000%)	0.063134948	43.33799388

Table 5.9 Regression statistics and analysis of variance of measured variance in 9 by 9 sample window and local fractal dimension image digital values.

<i>Regression Statistics</i>	
R	0.914153
R Square	0.835677
Adjusted R Square	0.827852
Standard Error	43.99839
Observations	23

ANOVA

	df	SS	MS	F	Significance F
Regression	1	206743.3	206743.3	106.7967	1.08604E-09
Residual	21	40653.02	1935.858		
Total	22	247396.3			

A plot of the regression for the data corresponding to Table 5.9 is shown in Figure 5.31. Fractal dimension is presented as the independent variable instead of the dependent variable, as in previous plots, since fractal dimension is the known value in this case. The regression demonstrates that much of the variance in the local fractal dimension can be explained by the variance within the 9 by 9 sampling window. Further this relationship is highly significant, and as such indicates that fractal dimension can be associated with image texture. Residuals for the regression are displayed in Figure 5.32. Residuals are observed

Figure 5.31. Regression between local fractal dimension digital values and variance of 9 by 9 sample window. Error bars indicate standard error.

Figure 5.32. Residual plot for regression Figure 5.31.

to spread from zero as the local fractal dimension increases. This could be argued to be the consequence of speckle noise. Speckle noise is multiplicative with the noise free signal [Wakabayashi and Arai, 1996], and could cause extreme variance of digital values to occur within the 9 by 9 sample window.

5.5 Statistical relationships between geophysical parameters and fractal dimension.

Descriptive statistics on the geophysical parameters [Table 4.11] were collected [Table 5.10] which would allow a regression between fractal dimension imagery and geophysical parameters. To determine which parameters [Table 4.11] were associated with the variation in the mean fractal dimension, regressions and correlations between the values in Table 4.11 and parameters extracted from fractal dimension imagery Figures 5.1 - 5.7 were carried out. Recall that figures 5.1 - 5.7 are plots of mean fractal dimension values. Results of the regressions are displayed in Table 5.11. Parameters extracted from Figures 5.1 - 5.7 included mean of the mean fractal Dn for each image data set, average amplitude, measured as the average amount of change between mean fractal Dn values for an entire image data set, and partial amplitude, measured as the change in mean fractal Dn values for the sinusoidal part of the variation in mean fractal Dn values in an image data set. Partial amplitude measurements excluded data in Figures 5.1 - 5.7 with pixel spacing less than 2 pixels. Measurements of change in mean fractal

Table 5.10 Descriptive statistics of geophysical data.

Variable	Wave Height Hs [m]	Wave Period To [s]	Wind Speed [m/s]
Sample Size	7	7	7
Average	2.914	6.743	7.757
Median	3.400	6.900	8.300
Mode	3.700	6.900	12.000
Variance	0.965	0.633	13.486
Standard deviation	0.982	0.796	3.672
Standard error	0.371	0.301	1.388
Minimum	1.000	5.600	3.500
Maximum	3.700	7.800	12.000
Range	2.700	2.200	8.500
Skewness	-1.447	-0.398	0.0264
Kurtosis	1.838	-0.817	-2.174

dimension were used to determine if the change in mean fractal dimension observed in Figures 5.1 - 5.7 was indeed an artifact. Correlation coefficients for regressions [Table 5.11] indicate that a direct relationship between the mean fractal dimension and the geophysical parameters is small when compared to the relationship between the change in mean fractal dimension, represented by the partial average ΔFd measurements, and the wave geophysical parameters. The good correlation of wave height and wave period with ΔFd measurements may possibly be attributed to variation in speckle intensity. As Jain [1982] pointed out, the measurement of the rate of variation in speckle intensity is an indicator of wave height. If speckle intensity is changed by the image resampling then this would provide some explanation of the high correlation values for wave height and wave period, in comparison to wind speed.

Table 5.11 Correlation coefficients (r) for regressions of measured fractal dimension parameters and geophysical data.

Geophysical variable	r for mean of mean Fd [correlation]	r for average ΔFd [correlation]	r for partial average ΔFd [correlation]
Wave height Hs[m]	-0.067	-0.804	-0.800
Wave period To[s]	0.311	-0.675	-0.748
Wind speed U[m/s]	-0.329	-0.056	0.003

The lowest correlation and r-squared values were observed for regressions of wind speed (U[m/s]) measurements and change in fractal dimension measurements. A plot of wave height versus average ΔFd is shown Figure 5.33. No regression line is provided for any of the geophysical parameter plots, Figure 5.33-5.35, since the sample size of seven is too small to plot a regression line. For the same reason, a test of significance of the relationships presented in table 5.11 cannot be carried out. Only one value for each geophysical variable could be obtained for each of the original seven SAR images. A plot of wave period versus average ΔFd is shown on Figure 5.34, and wind speed versus average ΔFd is shown on Figure 5.35. The distribution of the geophysical data is another valid reason for not plotting a regression

line through the data points. None of the geophysical data are normally distributed. Wave height measurements [Table 5.10] were peaked with a value of 1.838 for kurtosis and data were negatively skewed. Wave period [Table 5.10] data distribution was slightly flattened with a kurtosis of -0.817 and a skew close to a normal distribution, -0.398. Wind speed values were closest to a normal distribution with a positive skew of 0.264, however the data was flattened with a kurtosis of -2.174.

Figure 5.33. Wave height versus average change in mean fractal dimension ΔFd .

Wave Period vs Average change in Mean Fd

Figure 5.34. Wave period versus average change in mean fractal dimension ΔF_d .

Instantaneous Wind speed vs Average change in Mean Fd

Figure 5.35. Wind speed versus average change in mean fractal dimension ΔF_d .

The small sample size of these data sets combined with the non-normal distributions mean that the correlations [Table 5.11] can only be considered indicators of possible causal relationships.

5.6 Summary.

This research investigated the multi-fractal dimensionality of a geoscientifically derived data set. To do so required an investigation into the relationship between the parameters of a surface, SAR imagery of ocean waves, and the fractal dimension of the surface. Analysis of this relationship was first pursued through examination of the way in which the fractal dimension varied with respect to changes in spatial resolution. This was followed by a more detailed, statistical, and visual analysis of an image data set which corresponded to a single SAR image. The relationship between fractal dimension image digital values and standardized SAR image digital values, within a 9 pixel by 9 line sample area used to calculate the fractal image digital values was investigated. Regression of the variance of the digital values within the 9 pixel by 9 line sample area with fractal dimension indicated that fractal dimension can be associated with image texture. The final step in the analysis was a statistical regression of known geophysical parameters with mean fractal dimension of standardized SAR images. This regression provided an indication that fractal analysis of SAR ocean wave imagery may have the potential to provide information on wave height, and wave period. However, the high degree of correlation of these parameters with the change in mean fractal dimension, compared to correlation with mean of the mean fractal dimension, makes this type of analysis questionable. The analysis indicates that the method is susceptible to artifacts of resampling. The significance of any of the relationships is weak given the small sample size that this is based upon.

Chapter 6

Conclusions

6.1 Conclusions of research.

Several conclusions can be drawn from this work. The simulation study [Figure 5.15] reveals that simulated sinusoidal type wave images of different simulated scales, with no noise or other processes present, have mean fractal dimensions which increase in value over a set scale range and then begin to decrease in value. The decrease in mean fractal dimension value, which begins just after a pixel size of five times the original pixel size, could be attributed to a smoothing or averaging of the image to a specific value, and to the inequality of the fractal sampling window with the wavelength of the data. If the dimension of the sampling window is large enough to contain a complete wavelength of the simulated wave then the window would see the maximum variability of the data, a full peak and a full trough. For the data evaluated in this research, it can be concluded then that the size of the sampling window selected and wavelength of the data will predetermine the re-sampling level, or scale, at which the maximum fractal dimension will occur.

The simulation study also provides information on the content of the SAR imagery provided by C.C.R.S. Processing the simulated sinusoidal imagery to add background noise and wind effects confirms the presence of multiple processes affecting the fractal dimension of the imagery. Background noise alone produced a sinusoidal shaped curve, but the mean fractal dimension values overall were too low to account for all the variation in the SAR data set. It was demonstrated, through similarity in curve shape, that the SAR imagery contained both background noise and wind rippling. The shape of the curve for SAR data of the test image nearly matched the simulation data with background noise and wind ripples added. This provided conclusive evidence that the shape of the graph of the mean fractal dimension versus level of re-sampling is in part influenced by background noise and wind rippling.

This research presents empirical evidence that the fractal dimension, as calculated using the blanket method, varies with simulated scale change. Graphic evidence of mean fractal dimension variation with simulated scale change was presented. However, histogram and transect

analysis demonstrated that variations in mean fractal dimension [ΔF_d] with respect to simulated scale change were most likely due to positioning of the sampling window during production of the rescaled SAR images, relative to the periodic structure of the data. If this is occurring then the resampled imagery could appear relatively smooth at one spatial resolution and then relatively rough at the next level of spatial resolution. The positioning of the sampling window during production of the simulated scale-changed SAR images is therefore the probable cause of the sinusoidal variation of the mean fractal dimension. In addition, the use of bi-linear interpolation on the SAR imagery combined to produce the variation of results observed. If this is the case, the variation in fractal dimension when considered with respect to the maximum and minimum values could be concluded to be fairly stable within a range of 2.08 - 2.20. This conclusion would support the definition of a fractal as being independent of scale change as described in section 1.2. Given that the results apply to different oceanic states it is possible to conclude that the dynamics of ocean registered in the SAR imagery, due to Bragg scattering, were probably fractal. The fractal dimension was similar for all of the SAR images since Bragg scattering is dominated by short capillary wind waves regardless of the ocean state.

Sampling digital values of the individual fractal images allows direct comparison of fractal dimension and SAR image values. Correlation of fractal dimension and SAR image values for a sample of the entire data set were found to show that a significant positive correlation of approximately $r = 0.6$ exists. This correlation demonstrates that high input digital values are associated with high fractal dimension values, and that low input digital values are associated with low fractal dimension values. This is confirmed further when a limited data set of images with well formed waves produced a positive correlation of approximately $r = 0.7$. The resulting positive correlations indicate that the fractal dimension represents a measure of brightness of the SAR imagery, which, in turn, is a function of surface roughness. Using SAR imagery resampled 9 times the original pixel spacing in a regression with corresponding fractal dimension values removed some of the effects of speckle. The regression resulted in a positive correlation of $r = 0.4$. The positive correlation of $r = 0.4$ is

much lower than the $r = 0.7$ for the previous regression. It is concluded that speckle accounts for a large part of the variance of the fractal dimension in SAR imagery which has not been resampled. This conclusion is supported by the analysis of the variance of the 9 by 9 sample window used to construct the fractal imagery. The regression of measured variance of SAR image digital values in the 9 by 9 sample window and local fractal dimension image digital values accounted for much of the explained variance with $r = 0.9$, which was highly significant. Variance of digital values can be used as a measure of image roughness.

Correlation of SAR image digital values and fractal dimension digital values for the noise data set produced a positive correlation of approximately 0.377. This correlation indicates that image noise may cause changes in the fractal dimension. Support for required noise reduction was provided by the regression of the variance of the 9 by 9 sample window against fractal dimension where speckle was determined to alter variance. It is probable then that noise causes variance that is measured in the fractal dimension. Alteration of fractal dimension from noise was further demonstrated in the simulation study. It is concluded that, if possible, future studies should attempt to minimize noise present in the SAR imagery.

The coefficient of determination, r-squared, value for the regression of SAR image values with fractal dimension image values for a sample of the entire data set [Table 5.3] was found to show that the amount of explained variance is approximately 32.0%. The amount of explained variance of fractal dimension image digital values increased to approximately 48.0% when the data set was limited to well formed wave images. The difference between the r-squared values for the two data sets indicates that approximately 16.0% of the variance in the full data set is due to background noise and unidentified processes. The difference between the r-squared values, while it may be coincidental, is important because it is close to the r-squared value calculated for the regression of the noise data set. The background noise data set was found to statistically explain 14.0% of the variance in fractal dimension digital image values. Using the 9 times original pixel resolution imagery in a regression between fractal and SAR digital

values, to allow for a greater number of samples per pixel than the full resolution imagery, the amount of explained variance was found to be 18.0%. This is much less than the 48.0% explained variance found with the well formed wave full resolution data set, which was subject to more variation in SAR digital values because of the lower number of samples per pixel. It is concluded then, because of the large difference in explained variance, that the characteristic which may account for much of the unexplained variance is most likely speckle.

The simulation study indicates that wind rippling is a process affecting the data set. Correlation statistics for wind speed with measured change in mean fractal dimension [ΔFd] indicate that it accounts for only 10.8% of the variance for the mean of the mean fractal dimension for each of the different spatial resolutions. Wind speed was the least correlated with ΔFd in comparison with other geophysical parameters. While wind is identified in ocean wave models as the dominant process responsible for the production of Bragg type waves, it can be concluded that the change in mean fractal dimension is not directly influenced by the presence of wind. This is consistent with discussions of SAR ocean wave imaging models (section 3.5) which indicate that Bragg resonant scattering of SAR by the ocean is dominated by short capillary and wind waves. The higher correlation of ΔFd with wave height and wave period appear to support the model by Jain [1982], which uses the variation in speckle intensity to determine ocean wave height.

6.2 Discussion.

Several items require discussion based on the conclusions. The positive correlation of fractal dimension and SAR image values, found for both the single pixel and 9 by 9 sampling, indicated a relationship between Bragg resonant scattering and the fractal dimension. Since Bragg resonant scattering produces high backscatter near the crest of swells and low backscatter in the trough of swells, high fractal dimension values should correspond to wave crests and relatively low fractal dimension values should correspond to wave troughs. If hydrodynamic modulation is influencing the Bragg type scattering waves, then the increase in backscatter near the crests of the swell due to this modulation should act to enhance the variation in fractal dimension

between wave crest and trough. Velocity bunching, which can cause a decrease in brightness towards the crest and an increase in brightness towards the wave trough if waves are travelling in the positive azimuth direction, probably did not greatly reduce or enhance brightness values. All waves in the imagery were oriented at approximately 45 degrees with respect to the azimuthal direction of the flight path of the SAR. Since the direction of wave propagation is unknown it cannot be determined if velocity bunching acted as an additive or subtractive process to the fractal dimension. However, the effect of velocity bunching will be reduced because of the orientation of the SAR with respect to the ocean waves.

Research by Bourissou et al. [1993] demonstrates that a possible relationship between the fractal dimension of SAR imagery and varying SAR polarizations exists. It was not possible to examine that aspect of the data since the entire data set used in this work was collected with VV [vertical send, vertical receive] polarization.

The result of work by Klinkenberg [1994], using optical imagery, indicates that the fractal dimension of a surface can be influenced by the amount of sunlight or shadow on the surface. It is possible, then, to extrapolate that the incidence angle of SAR imagery, which can influence the amount of RADAR shadow produced, and may change the signal-to-noise ratio, may also influence the fractal dimension of SAR imagery. The exact nature of this influence in SAR imagery is unknown. This was not investigated in this research because of the similarity of the incidence angles in SAR imagery made available by C.C.R.S. [Canada Centre for Remote Sensing].

Software limitations restricted the choices for resampling to produce SAR images at various simulated spatial scales to nearest neighbour or bi-linear resampling. This being the case the resulting resampled imagery was subject to the effects of speckle. SAR imagery is known to contain speckle noise. Speckle noise is multiplicative with the SAR signal; however both signal and noise are considered to be independent [Wakabayashi, 1996]. In principle speckle noise can only be reduced in SAR imagery, not removed. Scattering of the SAR signal returned by the ocean is dominated by Bragg resonant scattering, which

operates below the size of a single pixel. Observation of the effects of speckle on the fractal analysis were made possible by not filtering speckle noise. The effects of speckle or other noise present in the SAR imagery was examined through comparison of the results of correlations using samples obtained for both a 1 by 1 and 9 by 9 window. Single pixel sampling of the SAR imagery was marginally justifiable because there had already been some spatial averaging to produce the speckle-reduced seven look SAR imagery. Observation of the effects of speckle were not expected to be comprehensive since it would entail research far beyond the scope of this work.

Digital values in the SAR imagery represent roughness and changes in the dielectric properties of the ocean. As argued in chapter 1, the use of one target type should ensure fairly constant dielectric properties. Further, as indicated by the lack of consideration by the models of SAR ocean wave imaging, the dielectric constant should not affect the backscatter signature. Processes which may account for the unexplained variance of SAR digital values and have not been identified may include wind gusts rippling the ocean surface, and errors in sampling.

6.3 Fractal definition for SAR ocean wave imagery.

This research made observations for the simulated pixel spacings of 6.6 m to 79.2 m. In that scale range, it can be stated that the fractal dimension, as measured by the method described in Peleg et al. [1984], is a measure of local variance of digital numbers in SAR imagery. Variation in digital values in the SAR imagery of the ocean is produced by variations in surface roughness and speckle. While the fractal dimension can be influenced by roughness, or image texture, a significant amount of the variance in fractal dimension can be caused by noise and sampling methods. In this scale range the fractal dimension of SAR ocean wave imagery is fairly stable with mean values in a range of 2.08 to 2.20. The stability of the graphic figures charting mean fractal dimension versus change in pixel spacing would seem to indicate that the ocean surface may in fact be fractal.

6.4 Paths for future research and speculation based on research.

Geographic application of fractal analysis can be speculated to include nearly all research requiring a measurement of texture. In geomorphology, one application could be the determination of surface materials present in an image sample area. Landscape texture is an indicator of the composition of the material present. Materials which compose the Earth's surface have variable hardness, which significantly influences the drainage patterns present on the Earth's surface, and cause variable surface texture. At small scales using a SAR and fractal analysis of the SAR imagery, it should be possible to make inferences on the materials present and their spatial distribution in an area. The difficulty in this application will be caused by the differences in the dielectric constant with material type. As soil moisture increases, so does the dielectric constant (or conductivity), which in turn increases the reflectivity of the surface increasing SAR backscatter [Kasischke and Bourgeau-Chavez, 1997, p.282]. The resulting increase in SAR backscatter could significantly alter the fractal dimension. In-situ measurement of the dielectric constant could provide a correction for the measurement of fractal dimension on the Earth's surface.

From a biological perspective, fractal analysis could be applied to map spatial distribution of forest types. Using fractal analysis of SAR imagery of a forest stand, it may be possible to differentiate between tree crowns of different species. The problem with this method, as with the previous, is the change in dielectric constant due to changes in ground material types, and in this case the amount of water stored on the tree leaves after precipitation has occurred. The presence of dew or moisture from rainfall acts to increase the dielectric constant of vegetation surfaces [Kasischke and Bourgeau-Chavez, 1997, p.282]. The hindrance to the previous application could provide a benefit for mapping clearcuts in forest stands. Research by Yatabe and Leckie [1996] found that in most cases clearcuts visible in SAR images exhibited low backscatter in comparison to the surrounding forest stand. The mean SAR backscatter of sites used in the research generally increased with increased vegetation density. Local fractal dimension has been positively correlated with SAR backscatter, and as such should provide positive correlation with vegetation density.

As a measure of surface roughness, the fractal dimension combined with information on daily evaporation from the ocean surface may provide a means to derive sea surface temperature. Riou et al. [1988] carried out research which indicates that surface roughness influences the relationship between daily evaporation and surface temperature. Changes in temperature fields in El Nino areas have been linked to changes in fish catch in the Pacific ocean [Toplis, 1995, pp. 493]. In 1972 the El Nino significantly disturbed the cycle of up-welling along the coast of Peru and Chile producing a flow of warm nutrient poor water which reduced the ability of the ecological system to support existing marine life [Kasoy, 1996]. Up-welling and down-welling are known to be catalysts in the formation of turbulence in the ocean, which in some instances can be due to bottom friction and lateral stress from the coastline.

From a human perspective, application of fractal analysis for monitoring variation in agricultural practices, or urban development, could provide a socio-economic indicator. This has been demonstrated in research by Broscoe [1993] which carried out a fractal analysis of black and white visible wave-length imagery of an urban area.

It should be stressed that the type of imagery selected will determine the variables involved in any fractal analysis. SAR provides an ideal image type for fractal analysis because of its dependence on apparent surface roughness.

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Appendix - A

Prints of Standardized SAR imagery and Simulation Imagery

Standardized SAR image Li2575n 512 pixels by 2048 lines

Standardized SAR image Li2580n 512 pixels by 2048 lines

Standardized SAR image Li2586n 512 pixels by 2048 lines

Standardized SAR image Li2591n 512 pixels by 2048 lines

Standardized SAR image Li2598n 512 pixels by 2048 lines

Standardized SAR image Li2603n 512 pixels by 2048 lines

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Azimuth

<----- Range

Standardized SAR image Li2609n 512 pixels by 2048 lines

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Azimuth

<----- Range

Simulated wave image 512 pixels by 2048 lines

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Azimuth

<----- Range

IMAGE EVALUATION TEST TARGET (QA-3)

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