2005

Oceanic Rain Identification Using Multifractal Analysis Of Quikscat Sigma-0

Vasud Ganesh Torsekar
University of Central Florida

Part of the [Electrical and Electronics Commons](#)

Find similar works at: <https://stars.library.ucf.edu/etd>

University of Central Florida Libraries <http://library.ucf.edu>

This Masters Thesis (Open Access) is brought to you for free and open access by STARS. It has been accepted for inclusion in Electronic Theses and Dissertations, 2004-2019 by an authorized administrator of STARS. For more information, please contact STARS@ucf.edu.

STARS Citation

Torsekar, Vasud Ganesh, "Oceanic Rain Identification Using Multifractal Analysis Of Quikscat Sigma-0" (2005). *Electronic Theses and Dissertations, 2004-2019*. 510.
<https://stars.library.ucf.edu/etd/510>

OCEANIC RAIN IDENTIFICATION USING MULTIFRACTAL ANALYSIS OF QUIKSCAT
SIGMA-0

by

VASUD G. TORSEKAR
B.E. Bombay University, 2003

A thesis submitted in partial fulfillment of the requirements
for the degree of Master of Science
in the Department of Electrical Engineering
in the College of Engineering and Computer Sciences
at the University of Central Florida
Orlando, Florida

Summer Term
2005

© 2005 Vasud Torsekar

ABSTRACT

The presence of rain over oceans interferes with the measurement of sea surface wind speed and direction from the Sea Winds scatterometer and as a result wind measurements contain biases in rain regions. In past research at the Central Florida Remote Sensing Lab, it has been observed that rain has multi-fractal behavior. In this report we present an algorithm to detect the presence of rain so that rain regions are flagged. The forward and aft views of the horizontal polarization σ_0 are used for the extraction of textural information with the help of multi-fractals. A single negated multi-fractal exponent is computed to discriminate between wind and rain. Pixels with exponent value above a threshold are classified as rain pixels and those that do not meet the threshold are further examined with the help of correlation of the multi-fractal exponent within a predefined neighborhood of individual pixels. It was observed that the rain has less correlation within a neighborhood compared to wind. This property is utilized for reactivation of the pixels that fall below a certain threshold of correlation. An advantage of the algorithm is that it requires no training, that is, once a threshold is set, it does not need any further adjustments. Validation results are presented through comparison with the Tropical Rainfall Measurement Mission Microwave Imager (TMI) 2A12 rain retrieval product for one whole day. The results show that the algorithm is efficient in suppressing non-rain (wind) pixels. Also algorithm deficiencies are discussed, for high wind speed regions. Comparisons with other proposed approaches will also be presented.

ACKNOWLEDGMENTS

I wish to express my appreciation to my advisor Dr. Takis Kasparis for his advice and guidance. I would like to thank my co-advisor Dr. Linwood Jones for his guidance and encouragement. I would also like to thank my committee member Dr. Stephen Watson for his co-operation and help. I would like to thank Dr. Dimitrios Charalampidis for providing me with some of the programs used in his projects.

I wish to thank my mother, my father, and my best friends for their continuous support and encouragement throughout the years of my education.

TABLE OF CONTENTS

LIST OF FIGURES.....	vii
LIST OF TABLES.....	viii
LIST OF ABBREVIATIONS.....	ix
CHAPTER 1 INTRODUCTION.....	1
CHAPTER 2 QUIKSCAT GEOMETRY AND HIGH RESOLUTION SIR DATA.....	7
2.1 QUIKSCAT VIEWING GEOMETRY.....	9
2.2 SIR ALGORITHM.....	11
CHAPTER 3 FRACTALS & MULTIFRACTALS.....	16
3.1 FRACTALS.....	16
3.1.1 DEFINITIONS OF FRACTAL DIMENSION.....	17
3.1.1.1 BOX DIMENSION.....	17
3.1.1.2 MINKOWSKI-BOULIGAND DIMENSION.....	18
3.1.2 FRACTAL DIMENSION COMPUTATION.....	20
3.1.2.1 DIFFERENTIAL BOX COUNTING.....	20
3.1.2.2 VARIATION METHOD.....	21
3.2 MULTIFRACTALS.....	24
3.2.1 MOTIVATION.....	24
3.2.1 MULTIFRACTAL BASICS.....	25
3.3 MULTIFRACTAL ANALYSIS.....	27
CHAPTER 4 RAIN FLAGGING TECHNIQUES.....	29
4.1 TECHNIQUES USING EMPIRICAL FITS.....	30
4.2 INDEPENDENT RAIN DETECTION AND ESTIMATION TECHNIQUES.....	35

CHAPTER 5 RAIN DETECTION ALGORITHM.....	37
5.1 PRE-PROCESSING.....	38
5.2 STEP 1 USE OF MULTIFRACTAL EXPONENT FOR THE DESCRIPTION OF TEXTURE.....	41
5.3 STEP 2 THRESHOLD THE MUTLIFRACTAL EXPONENT.....	45
5.4 STEP 3 COMPUTATION OF THE CORRELATION OF THE MULTI-FRACTAL EXPONENT WITHIN A PRE-DEFINED NEIGHBORHOOD.....	46
5.4 STEP 4 APPLICATION OF NOISE THRESHOLD.....	48
5.5 POST-PROCESSING.....	48
CHAPTER 6 RESULTS AND COMMENTS.....	49
6.1 COMPARISON WITH TRMM VALIDATION DATA.....	50
6.2 ALGORITHM DEFICIENCIES.....	55
6.3 COMPARISON WITH DIFFERENTIAL POLARIZATION RAIN FLAG.....	59
CHAPTER 7 CONCLUSIONS & FUTURE WORK.....	63
LIST OF REFERENCES.....	64

LIST OF FIGURES

1.1	Additional backscatter due to precipitation.....	3
1.2	QuikSCAT H-pol σ_0	5
1.3	Negated Multifractal Exponent of fig. 1.2.....	5
1.4	Thresholded Multifractal Exponent.....	5
1.5	Rain-Flag.....	5
2.1	QuikSCAT picture.....	7
2.2	QuikSCAT viewing geometry.....	8
3.1	Box counting method.....	18
3.2	The Minkowski sausage.....	19
5.1	Scatterometer NRCS before application of Rain-detection Algorithm.....	37
5.2	Pre-Processing : Breaking down each pass into sub-images.....	39
5.3	Flow-chart of Rain Detection Algorithm.....	40
5.4	Computation of Measures.....	43
5.5	Multifractal Exponent computed from Fig. 5.1.....	44
5.6	Thresholded Multifractal Exponent.....	45
5.7	Rain-flag.....	47
5.8	Output after application of noise threshold.....	48
6.1- 6.16	Comparison of Rain-Flag with TRMM Rain-Rate.....	50-54
6.17-6.24	Algorithm Deficiencies.....	56-57
6.25-6.28	Comparison with Differential Polarization Rain-Flag.....	60-61

LIST OF TABLES

2.1	QuikSCAT Facts.....	8
4.1	Differences Between Empirical fit and Independent Rain-Flagging Techniques.....	29
5.1	Average Intensity Regimes, thresholds and exponents.....	44

LIST OF ABBREVIATIONS

H-POL	Horizontal Polarization
NRCS	Normalized Radar Cross-section
V-POL	Vertical Polarization
GMF	Geophysical Model Function
TRMM	Tropical Rainfall Measuring Mission
SIR	Scatterometer Image Reconstruction
SIRF	Scatterometer Image Reconstruction with Filtering

CHAPTER 1

INTRODUCTION

A scatterometer is a Microwave RADAR specifically designed to make high-precision measurements of the normalized radar cross-section (σ_0) of the ocean surface. The SeaWinds scatterometer on board the QuikSCAT satellite measures the ocean winds on a global scale via the relationship between σ_0 of the ocean and the wind vector. This relationship has been empirically determined and is known as the **Geophysical Model Function (GMF)** [2], [3]. The **GMF** is a function of wind speed, wind direction with respect to the antenna azimuth angle, azimuth angle, incidence angle, polarization, and frequency. The inversion of this GMF given several σ_0 measurements from different azimuth angles, gives the wind estimates.

SeaWinds on QuikSCAT data has been found to be highly accurate in non-raining and moderate wind-speed areas ($<10\text{m/s}$) [4]. However the quality of SeaWinds on QuikSCAT retrieved winds is degraded by rain contamination, especially in storm regions. If the wind retrieval methods do not incorporate effects of rain, the rain attenuation and backscatter are interpreted as wind induced features. In a rain-free environment, scatterometer wind retrieval is possible due to scattering from wind-generated gravity capillary waves. The main scattering mechanism at scatterometer incidence angles is “Bragg Resonance” from waves on the order of electromagnetic wavelength of the incident beam. The amplitudes of the centimeter scale capillary waves are in large part driven by wind stress on the surface of the water. The normalized backscattering cross-section (σ_0) is a function of the size and orientation of the waves and thus a function of vector wind stress.

As mentioned before, wind is inferred by inverting **Geophysical Model Function (GMF)**, the relationship between σ_0 and wind), given several σ_0 measurements at different azimuth angles. Rain corrupts this process by altering the wind-induced radar backscatter signature. Rain striking the water creates rings, stalks and crowns from which the signal scatters. Rain also alters the wind induced capillary wave field, suppressing the wind/backscatter directional dependence, which may limit wind estimation in cases of wide-spread rain. The scatterometer signal is additionally scattered and attenuated by falling hydrometeors. In summary, rain has 3 effects on the scatterometer radar measurements, namely,

1. it attenuates the radar signal
2. it introduces volume scattering by raindrops
3. it perturbs the water surfaces and, consequently, influences the radar backscatter from surface.

Because the GMF does not account for rain effects, the additional scattering from rain causes the estimated wind speeds to appear higher than expected. This is called the **over-estimation** of wind velocity. Also the directions of rain corrupted wind vectors generally point cross swath, regardless of the true wind directions. [5] QuikSCAT in particular is more susceptible to rain corruption than previous scatterometers, due to its relatively large incidence angles. Higher incidence angles lead to greater scattering and attenuation from the rain column. To prevent the meaningless values and over-estimation of wind velocity it is very important to flag the rain-affected regions in the σ_0 . Fig 1 depicts the additional scattering due to precipitation.

Fig. 1.1 Additional Backscatter due to precipitation

Many approaches in the past have been devised to tackle this problem. Stiles et al tried to model the impact of Rain of Ku-Band wind scatterometer data by employing collocated QuikSCAT σ_0 , SSM/I rain rate measurements and NCEP wind fields to empirically fit a simple theoretical model in [4]. In [6] and [7] Long et al used a simple wind/rain backscatter model with collocated Precipitation Radar data from TRMM satellite to evaluate the effect of rain on the collocated data to find the optimum parameters for their empirical fit. In [5] Weissman et al have utilized a basic property of the σ_0 in the rain-affected regions. The H-pol σ_0 exceeds the V-pol σ_0 in the rain-affected regions. Authors used this differential σ_0 along with the R-Z relationship to retrieve rain-rates from σ_0 .

We have used an image processing approach to tackle the problem of rain-flagging. In past research at the Central Florida Remote Sensing Lab (CFRSL), it has been observed that rain

has multi-fractal behavior [10]. The forward and aft views of the horizontal polarization σ_0 are used for the extraction of textural information with the help of multi-fractals. A single negated multi-fractal exponent is computed to discriminate between wind and rain. Pixels with exponent value above a threshold are classified as rain pixels and those that do not meet the threshold are further examined with the help of correlation of the multi-fractal exponent within a predefined neighborhood of individual pixels. It was observed that the rain has less correlation within a neighborhood compared to wind [1]. This property is utilized for reactivation of the pixels that fall below a certain threshold of correlation. The algorithm uses an adaptive multifractal exponent. The reason for using an adaptive multifractal exponent was that the latitudes we dealt with in this analysis extended from -40° to $+40^\circ$. In this entire range of latitudes the climate undergoes tremendous changes and thus there occur a variety of rain and non-rain events. There are some rain and non-rain events, which are worth a mention regarding the adaptive multifractal exponent and threshold.

1. Events with very high wind and no rain.
2. Events with very high wind and rain
3. Events with very weak rain.

The first type of events requires a very high multifractal exponent to suppress the wind pixels, which may not give very good results for the third type of events. The reason being the average intensity is very high in the first type and very low in the last type. The second type of events needs a moderate multifractal exponent and threshold. Through observation we have fixed the multifractal exponents for the different average intensity regimes.

Validation results are presented through comparison with the Tropical Rainfall Measurement Mission Microwave Imager (TMI) 2A12 rain retrieval product for one whole day,

Julian Day 315, 2004. The results show that the algorithm is efficient in suppressing non-rain (wind) pixels. Algorithm has shown deficiencies in high wind speed regions, where false alarms are generated [13]. We have also made comparison of the results with the results obtained from the differential polarization σ_0 [5].

Figure 1 below presents a preview of the algorithm for a selected region where we found prominent rain events.

Fig.1.2 QuikSCAT H-pol σ_0

Fig.1.3 Negated Multifractal Exponent of Fig. 1.2

Fig.1.4 Thresholded Multifractal Exponent

Fig.1.5 Rain Flag

Chapter 2 gives a brief description of QuikSCAT satellite geometry and elaborates on the high-resolution SIR data used in this project. Chapter 3 discusses the motivation for using multifractals and also the mathematical theory behind multifractals. Chapter 4 discusses different rain-flagging techniques developed so far. Chapter 5 describes the rain-detection algorithm step-wise and the results and comparison with other approaches are discussed in chapter 6. Chapter 7 discusses the conclusions.

CHAPTER 2

QUIKSCAT GEOMETRY & THE HIGH RESOLUTION SIR DATA

Fig. 2.1 QuikSCAT Picture

A scatterometer is incoherent surface-based radar that measures reflectivity over a set of different incident angles. Scatterometers average the detected returns from a sequence of pulses, a process known as post-detection integration. Averaging ensures more accurate measurements of the backscattering coefficient, since single return pulses are typically noisy. Because pulses from multiple ground targets interfere with one another, the return signal is distorted: a process referred to as fading, often achieving ± 0.10 to 0.15 dB accuracy. The downside to averaging together multiple return pulses is a significant reduction in spatial resolution: 25 to 50 km, compared to 1 to 10 km with SAR. The intensity of the backscattered signal depends on the roughness and dielectric properties of the target. Changes in wind velocity cause changes in ocean surface roughness, modifying the radar cross-section of the ocean and the magnitude of

the backscatter power. Multiple collated measurements acquired from several directions can be used to solve wind speed and direction simultaneously. For ice and snow, the backscatter is influenced by surface roughness (including orientation of the surface scatters), liquid water content, snow grain size, brine concentration in sea ice and density. Scatterometers can be calibrated to less than a few tenths of a decibel (dB); thus seasonal and interannual differences of only 1 to 2 dB can be accurately monitored using scatterometry data [4], [5], [6]

Fig. 2.2 QuikSCAT viewing Geometry

2.1 QuikSCAT Viewing Geometry

The SeaWinds on QuikSCAT scatterometer launched in 1999 by NASA provides wide coverage of instantaneous ocean vector winds. [2] The SeaWinds instrument on QuikSCAT is a pencil-beam scanning scatterometer collecting σ_0 measurements at 13.4 GHz. The QuikSCAT satellite revolves in a near polar orbit and covers over 90% of the earth daily. It differs from previous fan-beam scatterometer designs in that instead of multiple wide-beam stationary antennas, it has a conical scanning parabolic antenna illuminated by 2 antenna feeds. The two feeds are used to transmit 2 beams of differing incidence angles and polarizations, producing 2 helices of measurements upon the ground as the spacecraft moves along its ground track. The inner beam is horizontal polarization (H-pol) incidence at 46.1° and has a 3dB footprint of 34 x 44 km. The outer is vertical polarization (V-pol) at 54° and has a 3dB footprint of 34 x 52 km. Each 25km X 25km ground cell is sampled 8-15 times. However these samples are not distributed uniformly in azimuth, but rather correspond to four disjoint narrow ranges of azimuth angles from the forward and aft half of the antenna rotation and from each beam. These four look sets (also known as 4 flavors) are relevant for wind-direction discrimination. As seen in the later chapters we have used 2 of these 4 flavors for the purpose of rain detection. Fig 2.2 shows the QuikSCAT viewing geometry. For simplicity circles are used to depict each scan. A circle is a good approximation for a single rotation of the antenna, as the 'gap' in the beam ground track which results from movement of the spacecraft is only 22km as compared 700 km for the radius of the inner beam scan. Table 2.1 gives all the general information about QuikSCAT.

Table 2.1 QuikSCAT Facts	
Instrument Name:	SeaWinds Scatterometer
Platform:	QuikSCAT
Mass:	220 kg
Power:	220 W
Duty cycle:	100%
Data rate:	40 kbps
Thermal control:	By radiators
Thermal operating range:	5-40° C
FOV:	Rotating (at 18 rpm) pencil beam antenna with dual feeds pointing 40° and 46° from nadir
IFOV:	±51° from nadir
Swath:	1800 km (± 51°) from 705 km altitude

2.2 Scatterometer Image Reconstruction Algorithm

Space-borne scatterometers are satellite instruments that were originally designed to map wind speed and direction over oceans, but they also measure various land and ocean variables. Scatterometer actively transmit electromagnetic pulses to the earth's surface and measure the backscatter response, or the power of the returned pulse scattered back to the antenna. While originally designed for wind observation, scatterometers have proven useful in a variety of land and ice studies. To further improve the utility of the data, resolution enhancement algorithms have been developed by the Microwave Earth Remote Sensing (MERS) Laboratory at Brigham Young University [11], [12]. These algorithms produce images of the surface σ_0 at enhanced resolution (to better than 10km). Both conventional and enhanced resolution products are included in the SIR product suite. The enhanced resolution products are produced with the aid of Scatterometer Image Reconstruction (SIR) algorithm. This chapter elaborates on the QuikSCAT SeaWinds viewing geometry and the Scatterometer Image Reconstruction algorithm used to produce high resolution σ_0 images.

First we will go through the version of the SIR algorithm that was used with NSCAT data, and then look at its variation that applies to the QuikSCAT data. NSCAT is a real aperture dual-polarization Ku-band radar scatterometer designed to measure the σ_0 of the earth's surface. The NSCAT made dual-polarization σ_0 measurements over an incidence angle range of 17° - 55° . Over the limited incidence angle range $\theta \in [20^\circ-55^\circ]$ σ_0 (in dB) is approximately a linear function θ ,

$$\sigma^0(\theta) = A + B(\theta - 40^\circ) \quad (2.1)$$

Where A and B are functions of surface characteristics, azimuth angle and polarization. A is the incidence-angle normalized σ_0 value at 40° incidence angle while B describes the dependence of σ_0 on theta.

NSCAT produces nominally 25km resolution σ_0 measurements on a 25km sampling grid. Not originally designed as an imaging sensor, the measurements are disjoint in the along-track dimension and vary somewhat in shape over the swath. Combining multiple passes and using Scatterometer Image Reconstruction (SIR) with Filtering (SIRF) algorithm enhanced resolution images of the surface backscatter can be produced.

Combining multiple passes and using Scatterometer Image Reconstruction (SIR) with filtering (SIRF) algorithm enhanced resolution images of the surface backscatter can be produced. The SIR algorithm was originally developed to enhance the Seasat Scatterometer data. It has also been used with SSM/I radiometer, ERS scatterometer. A number of improvements to the original SIR algorithm have been developed to optimize its performance for NSCAT. The SIRF algorithm applied to NSCAT data produces both A and B images from the NSCAT σ_0 measurements.

The SIR algorithm is based on a multivariate form of a block multiplicative algebraic reconstruction. Combining multiple overlapping passes and robust performance in the presence of noise, it provides enhanced resolution measurements of the surface characteristics. Following is an intuitive explanation of the idea behind the SIR algorithm.

Let $f(x, y)$ be a function that gives σ_0 at a point (x, y) . The scatterometer measurement system can be modeled by,

$$Z = Hf + noise \tag{2.2}$$

Where, H is an operator that models the measurement system (sample spacing and aperture filtering) and z represents the measurements of σ_0 made by the instrument sensor. The set of measurements z are a discrete sampling of the function convolved with the aperture function (which may be different for each measurement). A particular measurement z_i can be written as,

$$z_i = \iint h_i(x, y) dx dy + noise \quad (2.3)$$

Where $h_i(x, y)$ is a measurement response (due, for example to antenna pattern and the Doppler filter response) of the i^{th} measurement. For resolution enhancement, we are interested in the inverse problem.

$$\hat{f} = \hat{H}^{-1} z \quad (2.4)$$

Where $\hat{f}$ is an estimate of f from the measurements z . The inverse of the operator H , H^{-1} , is exact only if H is invertible and the measurements are noise free, in which case $\hat{f} = f$. This represents a form of resolution enhancement since information in the sidelobes of the measurement response or aperture function is recovered in the inversion. In effect, this is what the iterative SIR algorithm does, producing images at a finer resolution than the original measurements. It should be noted that SIR is a true resolution enhancement algorithm which extracts information from sidelobes of the measurement response function to generate the final image product, in effect it is an Inverse Reconstruction Filter optimized to minimize noise in the

reconstructed image. This is how SIR algorithm works with NSCAT data. There are some alterations that need to be applied to it to be applicable to QuikSCAT data.

Unlike NSCAT which made σ_0 measurements over a broad range of incidence angles, QuikSCAT makes σ_0 measurements at only 2 nominal incidence angles, 46° and 54.1° , corresponding to the inner and outer beams. The inner beam measurement is horizontal-polarization while the outer beam is vertical-polarization. Since it is undesirable to combine measurements from different polarizations, it is not possible to infer B from QuikSCAT σ_0 measurements. Instead a single-variate form of SIR similar to the type developed for radiometer applications is used to generate enhanced resolution images of σ_0 at each of the 2 polarizations and nominal incidence angles of the antenna beams.

QuikSCAT σ_0 measurements are reported in 2 forms: termed “eggs” and “slices”. These differ in their spatial sizes and shapes. The nominal instantaneous QuikSCAT antenna footprint is an ellipse. However, the on-board range-doppler processing incorporated within the instrument improves the processing. Using the on-board processor, twelve individual σ_0 measurements are obtained for each footprint, though only 8 are reported in the L1B data product. These individual measurements are termed as slices. The slices are particularly 4-6 km long (depending on the instrument mode and antenna beam) by 20 km wide. The summed measurements of the 8 center slices are known as ‘egg’ measurements and are reported as standard product. The effective resolution and shape of the egg measurement nearly matches the elliptical 3 dB antenna footprint (approximately 15 km by 25 km depending upon the antenna beam and instrument mode). Although lower resolution the egg measurements have less noise and are less sensitive to calibration errors. The nominal pixel resolution of the slice-based SIR images is 2.225 km with an estimated effective resolution of approx(use sign) 4 km. Egg based SIR images have a

nominal pixel resolution of 4.45 km with an estimated effective resolution of approximately 8-10 km.

The SIR data that we used in this project consisted of the four flavors, namely, forward H-pol, aft H-pol, forward V-pol, and aft V-pol. The data consisted of individual passes for one whole day, Julian day 315, 2004 (Nov 10th 2004). The passes were not earth-gridded. Once the data was processed we earth-gridded the data, for the purpose of comparison with the validation data.

CHAPTER 3

FRACTALS & MULTIFRACTALS

3.1 Fractals

The word “fractal” was invented by Mandelbrot in recognition of his fundamental insight in the idea of self-similarity, requiring that a true fractal “fractures” or breaks apart into smaller pieces that resemble the whole. To get an intuitive explanation of the concept of fractals we will consider a real life incident, which might have occurred years ago. The British mapmakers discovered problem with measuring the length of the coast of Britain. On a zoomed out map, the coastline was measured to be 5,000 units. Measuring the coast on more zoomed in maps, the length turned out to be longer, 8000 units. By looking at really detailed maps, the coastline was over double the original. The closer they looked the more detailed the coastline got. This was because of the fractal nature of the coastline.

One of the unique things about fractals is that they have non-integer dimensions [14], [15]. In traditional geometry, Euclidean geometry, dimension signifies the number of independent parameters of an object, a point has zero dimensions, a line has one dimension and a plane has two dimensions. There are many definitions of the fractal dimension of an object, including box dimension, intersection dimension and Bouligand-Minkowski dimension. Fractal dimension has been characterized as a measure of an object. Any curve is an object with one topological dimension that occupies some part of a surface. Fractal dimension defined how much area of this surface is occupied by the curve. For instance, a highly irregular curve will have a larger fractal dimension than a straight line. The fractal dimension of a curve can be between 1, which is equal to its topological dimension and 2, which is equal to the topological dimension of

the surface that it can occupy. The concept of fractal dimension of a surface can be between 2, which is its topological dimension and 3, which is the topological dimension of the “box” that the surface can occupy. There are many methods for fractal dimension computation, but not all methods work for all objects. Nevertheless, all methods are complement of one another and provide the same answer for the same object. In addition, they give the correct dimension for traditional Euclidean object, consistent with Euclidean dimension. Following are some definitions and methods of computation of a fractal dimension of an object.

3.1.1 Definitions of Fractal Dimension

Two of the most popular definitions of fractal dimension are box dimension and Bouligand-Minkowski dimension.

3.1.1.1 Box Dimension

This definition is based on a quantization of the space in which the curve or the surface is embedded. Define a decreasing sequence ε_n tending to zero slowly, such as a geometric sequence. The set E can then be covered by a grid (two dimensional in the case if a curve and three dimensional in the case of a surface) with pixel length ε_n , and the number of pixels W_n that intersect E can be counted. An example for the case of a curve is shown in Figure 3.1 below. Fig. 3.1 shows the case for a curve. An estimate of the box dimension is give by the slope of the line passing through the points $(\log(1/\varepsilon_n), \log W_n)$.

The box dimension is given by,

$$\Delta_B(E) = \lim_{n \rightarrow \infty} \frac{\log W_n}{\log(1/\varepsilon_n)} \quad (3.1)$$

Fig.3.1 Box counting method. The curve is placed in a unit square which is subdivided into 144 small boxes of side $1/12$. The shaded boxes are counted and the number is equal to 34.

3.1.1.2 Minkowski-Bouligand Dimension

The Minkowski sausage of a set E is the set of all points $E(\varepsilon)$ defined as follows:

$$E(\varepsilon) = \{y : y \in B_\varepsilon(x), x \in E\} \quad (3.2)$$

Where $B_\varepsilon(x)$ is an n -dimensional ball (disk for the case of curves and sphere for the case of surfaces) of radius ε centered on x . $E(\varepsilon)$ consists in the union of all disks centered on E , with radius ε .

Fig. 3.2 the Minkowski sausage

Let $|S|_n$ denote the area of a region S in $\mathbb{R}^n$. The volume of the Minkowski sausage (area for the two-dimensional case) is then $|E(\varepsilon)|_n$ and the Minkowski–Bouligand dimension is as follows:

$$\Delta_{M-B}(E) = \lim_{\varepsilon \rightarrow 0} \left(n - \frac{\log |E(\varepsilon)|_n}{\log \varepsilon} \right) \quad (3.3)$$

The Minkowski-Bouligand dimension $\Delta_{M-B}(E)$ can be estimated by the slope of the log-log plot $(\log (1/\varepsilon), \log \{ (1/\varepsilon)^n |E(\varepsilon)|_n \})$. An example for the two-dimensional case of the curve is shown in Figure 3.2.

3.1.2 Fractal Dimension Computation

There are many methods for fractal dimension computation, but not all methods work for all objects. Nevertheless, all methods are complement of one another and provide same answer for the same object. In addition, they give the correct dimension for traditional Euclidean object, consistent with Euclidean dimension. Following are some methods of computation of a fractal dimension of an object.

3.1.2.1 Differential Box Counting

Differential box counting is one of the approaches for calculating fractal dimension of a surface. A bounded set A in Euclidean n -space is self-similar, if A is the union of N_r distinct (non-overlapping) copies of itself, scaled up or down by a factor r . Using this definition fractal dimension is defined by $1 = N_r r^D$ or

$$FD = \log N_r / \log(1/r) \quad (3.4)$$

In this method an image of size $M \times M$ pixels is scaled down to $s \times s$, where $M/2 \geq s > 1$, where s is an integer. Then $r = s / M$. The image is considered as a 3D space, where two dimensions defined the coordinates (x, y) of the pixels and the third (z) defines the grayscale values of the pixels. The (x, y) is partitioned into grid of size $s \times s$. On each grid there is a

column of boxes of size $s \times s \times s$. If the minimum and maximum grayscale levels in the $(i, j)^{\text{th}}$ grid fall into the k^{th} and l^{th} box respectively, then the contribution of N_r in the $(i, j)^{\text{th}}$ grid is defined as $n_r(i, j) = l - k + 1$. For this method N_r is defined as the summation of the contributions from all grids that are located in a window of the image:

$$N_r = \sum_{i,j} n_r(i, j) \quad (3.5)$$

If N_r is computed for different values of r , then fractal dimension can be estimated as the slope of the line that best fits the points $(\log(1/r), \log N_r)$.

3.1.2.2 Variation Method

Dubuc et al (1987) extended the variation method to two-dimension. The variation method uses the notion of ε -variation to measure the amplitude of the one-dimensional function in a ε -neighborhood. It has been shown that the variation method gives accurate and robust estimation of the fractal dimension of a surface. An image $Z(x, y)$ of size $R \times R$ can be considered as a surface of size $R \times R$, where its value at position (x_0, y_0) is $Z(x_0, y_0)$. If $P(x, y, x', y')$ is the slope of the line connecting points $(x, y, Z(x, y))$ and $(x', y', Z(x', y'))$, then this $|P(x, y, x', y')|$ goes to infinity as the point (x', y') tends toward (x, y) . Fractal dimension is defined as the rate in which $|P(x, y, x', y')|$ goes to infinity. The ε^{th} variation of Z at a region centered at the point with coordinates (x, y) can be defined as:

$$V_\varepsilon(x, y) = \max_{\text{dist}((x,y),(s,t)) \leq \varepsilon} Z(s, t) - \min_{\text{dist}((x,y),(s,t)) \leq \varepsilon} Z(s, t) \quad (3.6)$$

Where $\text{dist}((x, y), (s, t)) = \max(|x - s|, |y - t|)$ and $\varepsilon > 0$. The integral of $V_\varepsilon(x, y)$ tends to zero as ε tends to 0. The rate of growth of this integral is directly related to the fractal dimension of Z . The fractal dimension of the surface Z is given by:

$$FD_z = \Delta_v(Z) = \lim_{\varepsilon \rightarrow 0} \left(\varepsilon - \frac{\log \int_0^1 \int_0^1 V_\varepsilon(x, y) dx dy}{\log \varepsilon} \right) = \lim_{\varepsilon \rightarrow 0} \left(\frac{\log \int_0^1 \int_0^1 [V_\varepsilon(x, y) / \varepsilon^3] dx dy}{\log(1/\varepsilon)} \right) \quad (3.7)$$

The slope of the log-log plot of the line that is defined by:

$$\log \int_0^1 \int_0^1 [V_\varepsilon(x, y) / \varepsilon^3] dx dy, \log(1/\varepsilon)$$

gives the fractal dimension of the surface. The computation of the fractal dimension of a discretized surface involves substitution of the integrals with summations.

The fractal dimension of an image can be computed locally in all different regions of size $R \times R$ of the image, so that a fractal dimension space can be created. This fractal dimension space will be mapped one-to-one to the pixels of the image. The algorithm for computing the fractal dimension space of an image is implemented as follows. The difference $V_{\varepsilon/R}$ between the maximum and the minimum grayscale values is computed in a small window of size $T \times T$, where $T = 2\varepsilon + 1$. This window is centered at the pixel with coordinates (x, y) . The computation of $V_{\varepsilon/R}$ is repeated for $\varepsilon = 1, 2, 3, \dots, \varepsilon_{\max}$. The fractal dimension located at the window W is the slope of the line that best fits the points $(\log(R/\varepsilon), \log[(R/\varepsilon)^3 E_{\varepsilon/R}])$, where $\varepsilon = 1, 2, 3, \dots, \varepsilon_{\max}$ and $E_{\varepsilon/R}$ is the average of $V_{\varepsilon/R}(x, y)$ over a window of size $R \times R$. The slope of the line that best fits the points can be found using the least mean square approach given by:

$$slope = \frac{n \sum x_i y_i - \sum x_i \sum y_i}{n \sum x_i^2 - (\sum x_i)^2} \quad (3.8)$$

Where n is the total number of points with coordinates (x_i, y_i). This fractal dimension is mapped to the central pixel of the window W. The next step is to shift the window W and map its fractal dimension to the central pixel of the new window. The previous steps are repeated for all pixels of the image and the fractal dimension space is created.

The advantage of fractal dimension is that it is insensitive to differences of local intensity of the image and to local scaling of the grayscale levels (Charalampidis, 1998). However, a major problem with fractal dimension is that it alone is not sufficient for texture analysis and characterization. Mandelbrot (1983) showed that different textures may have the same fractal dimension.

3.2 Multifractals

3.2.1 Motivation

In the previous research at Central Florida Remote Sensing Laboratory at UCF Dr.Dimitrios Charalampidis used Multi-fractals to separate rain from no-rain regions in ground-based radar data [10]. Weather radars are designed to detect precipitation in the atmosphere. The echoes resulting from other sources are usually undesired. Examples of such sources are man-made structures, radar-chaff ejected by military aircrafts, birds, insects and even the earth's surface. Scattering resulting from antenna sidelobes striking the earth close-in to the radar are referred to as ground-clutter. Objectionable ground-clutter may result in cases of strong vertical gradient of atmospheric temperature and humidity. Here, the radar beam undergoes unusual refraction and strikes the earth repeatedly for distances of hundreds of kilometers producing anomalous propagation (AP) ground clutter, while it travels. Since non-precipitation echo intensities can far exceed those from precipitation, this creates serious problems for geophysical algorithms, such as estimation of instantaneous rain-rate or rainfall accumulation. Therefore it is necessary to identify the AP echoes from the rain echoes so that they can be suppressed. The suppression process is often referred to as Quality Control. Rain and AP echoes have significantly overlapping reflectivity values; therefore they could not be separated using only reflectivity thresholds. Thus, some other property had to be employed to discriminate between rain and AP echoes. Fortunately, the AP echoes possessed different variability that rainfall and thus their textural properties differed from that of rain. The AP echoes possess higher spatial variability in either horizontal, or vertical or both in horizontal and vertical extents. Therefore, the multifractal exponent computed in the 3-dimensional blocks tends to be more negative for

non-precipitation. Similarly intensity information was used because rain echoes exhibit higher correlation with neighboring pixels than non-rain echoes do.

Although we had a similar goal in the present project – rain identification, there were some basic differences in the data that was to be processed. We did not have 2 elevations of the data available, as in the case of radar data. This prevented us from using the vertical gradient property possessed by the AP echoes. Second difference was that in radar data the background of the echoes was black and had no texture. But in QuikSCAT σ_0 the background was wind and it had texture. The third difference was that in radar reflectivity the non-rain echoes were not from other geophysical processes, but with satellite data the non-rain echoes were from wind, which is just another geophysical parameter like rain.

3.2.2 Multifractal Basics

Multifractals have been found to be very useful in the analysis of complex geophysical systems. They are based on the principle of scale-invariance. Scale invariance analysis is a framework for developing statistical tools that account for all available scales at once. Scale invariance is a property that is respected by systems whose large and small scales are related by a scale changing operation involving the scale ratio. This leads to the fact that these systems do not have a characteristic scale. In multifractal analysis a power law behavior is sought for, of a partition function that is constructed from a measure, with respect to the scale parameter under consideration. If a single power-law exponent is sufficient to characterize all the statistics within a whole family, then we refer to the model as monofractal. If more than one exponent is needed to characterize the statistical behavior of the signal, then we refer to the model as multifractal. Multifractals are generated by a variety of different physical processes such as multiplicative-

cascading and turbulence. Self-similarity (and hence isotropy) is often assumed in scale-invariant models.

3.3 Multifractal Analysis

As we mentioned in the last subsection, the scaling behavior of signals can be expressed by different scale-independent relationships. Scale s can be defined as a parameter that specifies the size of the area under consideration (in the case of circular areas, scale can be the radius of the circle). Assume that the random process studied is an N -dimensional signal $f(x_1, x_2, \dots, x_N)$. The Goal in multifractal analysis is the examination of the different statistical characteristics of the signal f . For that purpose, a statistical measure μ_q is extracted from the function f . The measure $\mu_q(s, x_1, x_2, \dots, x_N)$ at scale s at the location $(x_1, x_2, \dots, x_N)$ of the N -dimensional signal is defined as,

$$\mu_q(s, x_1, x_2, \dots, x_N) = \mathcal{E}_s^q(x_1, x_2, \dots, x_N) \quad (3.9)$$

Where,

$$\mathcal{E}_s(s, x_1, x_2, \dots, x_N) = \sum_{x'_1=x_1-s/2}^{x_1+s/2} \dots \sum_{x'_N=x_N-s/2}^{x_N+s/2} f(x'_1, x'_2, \dots, x'_N) \quad (3.10)$$

is the sum of the function f inside a “box” of size $s \times s \times \dots \times s$. The scale-dependent q^{th} moment ensemble average of the measure $\mu_q(s, x_1, x_2, \dots, x_N) = \mathcal{E}_s^q(x_1, x_2, \dots, x_N)$ is called the partition function $\langle \mathcal{E}_s^q \rangle$. Basically, the partition function at the point with co-ordinates $(x_1, x_2, \dots, x_N)$ is the q^{th} moment of the function f , around point $(x_1, x_2, \dots, x_N)$, at scale s .

The scale-independent statistical behavior of the function f at point $(x_1, x_2, \dots, x_N)$ can be examined by the change of the statistical moments, computed around $(x_1, x_2, \dots, x_N)$, from one

scale to another. Then, one looks for a power-law relation between the partition functions (scale-dependent moments) and the scale parameter under consideration that describes the variation of the statistical moments with scale s . In our analysis the function f is defined on a discrete domain, since it is a sampled version of the continuous function. Then the power law relation is defined as

$$\left\langle \mathcal{E}_s^q \right\rangle \sim s^{K(q)} \quad (3.11)$$

The function $\mathbf{K}(q)$ is the so called *moment scaling function* and characterizes the multifractal behavior of the signal f . If the function, $\mathbf{K}(q)$ is a straight line then a single power-law exponent [for instance $K(2)$] is sufficient to characterize all statistics within a whole family and then we talk about monofractality. If the function $\mathbf{K}(q)$ is not a straight line then more than one exponent is needed to characterize the statistical behavior of the signal and we talk about multifractality.

Practically the ensemble average $\langle \mathcal{E}_s^q \rangle$ is approximated by the spatial average of $\mathcal{E}_s^q$ under the assumption of temporal stationarity of the function f . If we consider applying the log at both sides of (3.3), then the function $K(q)$ is estimated from the slope of the line that best fits the points $(\log s, \log \langle \mathcal{E}_s^q \rangle)$ $s = s_1, s_2, \dots, s_L$ where s_1 is the smallest available scale and s_L is the largest available scale.

CHAPTER 4

RAIN-FLAGGING TECHNIQUES

As mentioned in Chapter 1, it is very essential that we flag the rain-affected regions in the satellite σ_0 maps, to produce faithful wind velocity (speed and direction) estimates. There are several techniques in the literature that have tackled the problem of rain-flagging. Following sections describe a few of these techniques and elaborates on differential reflectivity technique with which we compare the results of our rain-detection algorithm. Basically 2 types of techniques have been used in the past for the purpose of rain-flagging. The first category of techniques applies empirical fit to the Geophysical Model Function (GMF) to incorporate the effects of rain. The second type of techniques works somewhat independently. Following Table discusses the basic differences between the 2 categories of rain-flagging techniques.

Table 4.1 Differences Between Empirical fit and Independent Rain-Flagging Techniques		
	Empirical Fit	Independent
1.	Use GMF	Do not use GMF
2.	Training	No need to train
3.	Needs rain-rate and wind-velocity estimates from other sources	Uses on NRCS
4.	Complex	Simple
5.	Examples: MUDH rain-flag	Examples: Differential Polarization Rain-flag

4.1 Techniques Using Empirical Fits

Many attempts have been made in this category of techniques to rain-flag the σ_0 . We will talk about 3 of such techniques in this section to give a general idea to the reader. The basic property of these techniques is that they do not make independent estimates of rain from radar backscatter cross-section. They depend on the collocated data from other sources such as TRMM and NWP to incorporate the effects of rain in the existing Geophysical Model Function (GMF). The empirical fit is done by training the Geophysical Model Function (GMF) with the collocated QuikSCAT backscatter cross-section σ and TRMM or SSM/I rain-rates and the wind estimated from NWP.

The first Rain-flag we consider under this category is the one which is officially used for the QuikSCAT σ_0 data. This flag is called as the Multidimensional Histogram (MUDH) rain flag. The basic premise of the (MUDH) algorithm is simple. It identifies the parameters that are sensitive to rain, estimates the probability of rain as a function of those parameters using a training set of data, and then use that rain probability estimate to flag for rain in new data. The data used for training the algorithm was SSM/I. A wind-vector cell was defined as rain-contaminated if the integrated rain rate for that wind vector cell was greater than 2.0 mm/hr. The probability of rain was estimated by accumulating two four-dimensional histograms in which each of the four rain-sensitive parameters was a histogram dimension. The first histogram was used to accumulate the total number of wind vector cells in each bin of parameter space. The second histogram was used to accumulate the number of wind vector cells that were considered to be rain-contaminated in each bin of parameter space. Dividing the second histogram by first gives an estimate of the probability of rain as a function of rain-sensitive parameters. The level processor calculates the values of the rain-sensitive parameters, converts them into table indices,

and looks up the estimated probability of rain from a provided table. A threshold is applied to obtain an initial rain-flag. Spatial filtering is then performed in an attempt to remove isolated rain flags. The rain sensitive parameters used in this technique were, Normalized Beam Difference, Retrieved Wind Speed, Retrieved Wind direction Relative to Along Track, Normalized Maximum Likelihood Estimator value, Brightness temperature. Normalized beam difference is a measure of the beam-to-beam bias exhibited in a wind vector cell. Normalized maximum likelihood estimator value is the maximum likelihood estimator value normalized by the number of σ_0 measurements. Due to the noisy nature of the rain-sensitive parameters and the probabilistic nature of the MUDH technique, there are times when the MUDH rain flag erroneously indicates rain. Often these spurious rain flags are isolated. To prevent this spatial filtering is introduced in the processor. First the probability of rain is estimated for each wind vector cell using MUDH technique. If the probability of rain is above a threshold value, the wind vector cell is initially flagged for rain. Then spatial filtering is applied. For each wind vector cell, the number of rain contaminated cell within a centered $N \times N$ window is counted. If the number of rain contaminated cells is less than $N_{\text{neighbors}}$, it is concluded that there is insufficient spatial evidence for rain. In such a case, the estimated probability of rain for that wind vector cell is then compared to a higher, more stringent threshold. If the probability of rain is higher than this new stringent threshold, the rain flag is maintained. Otherwise the rain flag is cleared.

In [2] Stiles et al try to achieve a direct assessment of rain effects on Ku-band space borne scatterometers. The authors collocated the QuikSCAT radar data with the rain-rate produced by SSM/I and the wind-speed from the NCEP. Similar to other techniques used to estimate the wind velocity, the Geophysical Model Function (GMF) was used, but they introduced SSM/I rain-rate as an additional parameter in the Geophysical Model Function

(GMF) to examine the effects of rain. As we saw earlier, the rain affects σ_0 in 3 different ways. First, the rain column attenuates both the transmitted radar signal and the wind-driven radar echo from the surface. Second, the rain-column produces its own backscatter. Third, rain impacting the ocean roughens the ocean surface, imposing some (possibly highly non-linear) modulation on the surface backscatter cross section. Rather than attempting to develop a detailed theoretical model based on the three effects stiles et al make three simplifying assumptions to derive a simple functional form for their model and then empirically fit that model to the data. The three assumptions are,

- All three of the effects are purely functions of polarization, incidence angle and columnar rain-rate
- Atmospheric scattering and surface roughening are additive on a physical scale
- In the absence of rain or wind, the ocean backscatter cross-section is negligible

The three assumptions yield the following model,

$$\sigma_0(u, b, \chi, r) = \sigma_{0rain}(r, b) + \alpha(r, b)\sigma_{0s}(u, b, \chi) \quad (4.1)$$

Where, b is antenna beam, r is columnar rain-rate, u is wind speed and χ is the relative azimuth. The collocated data is acquired and regressed to fit (1). The process is divided into 3 steps. First for each rain-rate bin and each beam, the best constant values are determined for $\sigma_{0rain}(r, b)$ and $\alpha(r, b)$. Second a parametric form is chosen for each of the two terms as a function of columnar rain-rate r for each beam. Finally, a last regression is performed to fit these parametric forms.

In [4] Long et al develop a simple phenomenological backscatter model to characterize effects of rain on SeaWinds on QuikSCAT backscatter. The model incorporates wind-induced surface scattering, surface rain-perturbation, and atmospheric rain attenuation and scattering. PR collocations are used for direct computation of SeaWinds-scale averaged rain rate, atmospheric rain-attenuation and scattering. An estimate of the wind-induced surface backscatter is computed via numerical weather prediction (NWP) winds. The SeaWinds, NWP, and PR data are synergistically combined to estimate surface rain perturbation and combined surface/atmospheric scattering are made as a function of PR-derived rain-rate. Using this model Long et al determine the conditions for which it is possible to estimate rain from scatterometer measurements and where wind retrieval is not possible. According to the previously mentioned effects of rain on backscatter cross-section, following model was developed by the authors,

$$\sigma_m = (\sigma_w + \sigma_{sr})\alpha_r + \sigma_r \quad (4.2)$$

Where, σ_m is the measured SeaWinds backscatter, σ_w is wind-induced radar backscatter, σ_{sr} is the surface backscatter perturbation due to rain striking the water, α_r is the two-way atmospheric rain attenuation, and σ_r is volume scattering due to falling hydro-meteors. Equation (2) combines all the surface rain-effects into once additive perturbation parameter σ_{sr} . Since the goal of the final analysis is to estimate the bulk augmentation of the scatterometer signal due to rain, the model in equation (2) is further simplified to,

$$\sigma_m = \sigma_w\alpha_r + \sigma_e \quad (4.3)$$

The parameters in equation (3) are estimated by synergistically combining collocated data from TRMM PR and NWP fields.

4.2 Independent Rain-detection/Estimation Techniques

These techniques use only the radar backscatter cross-section for the rain-detection purpose. They do not employ the Geophysical Model Function (GMF). There is no need for training, as Geophysical Model Function (GMF) is not involved. Since only radar backscatter cross-section is used, we termed them as independent techniques. Here we describe one such technique found in the literature. This technique is based on the Differential Polarization rain-flags.

Coherent dual-polarization backscatter measurements can be used discriminate between the smaller spherical raindrops and larger oblate drops, the distributions of which are functions of rain-rate. The difference of horizontal polarization backscatter cross-section and vertical polarization backscatter cross-section due to this effect is called “differential reflectivity”. This differential polarization response of the SeaWinds scatterometer to moderate and large rain-rates can be exploited for quantitative precipitation detection and measurement on many time and spatial scales. They have used the fact that the differential reflectivity (Z_{DR}) has a very similar dependence on drop-size and rain-rate at 16 GHz (Ku-band) as it does at 3 GHz, which is the frequency of the NEXRAD validation data used. A careful comparison of the data for rain-rates larger than 1 mm/h showed that Horizontal polarization NRCS tends to exceed the vertical polarization NRCS.

This effect is called as the differential reflectivity as mentioned before. The Z_{DR} is used to determine that the scatterometer is receiving backscatter from rain volume. The purpose it serves is a rain-flag. Once the rain-flags are estimated the authors have used the Z - R relationship between reflectivity and rain-rate to estimate the actual rain-rate from Normalized Radar Cross-section. Thus, the technique can be employed to detect rain of certain magnitudes from

SeaWinds scatterometer data. An observation was that for rain-rates above 3 mm/hr, majority of Z_{DR} points exceed zero, and a significant number of these points exceed 2 dB. Another observation mentioned in [3] is that in regions with no rain (where it can be conveniently assumed that the backscatter cross-section is due to the wind only) nearly 80% of the comparisons showed that Vertical polarization NRCS exceeds or is equal to Horizontal polarization NRCS. This facts reinforces the interpretation that positive differential reflectivity in the unique geometry of QuikSCAT, is a result of rainfall.

CHAPTER 5

RAIN DETECTION ALGORITHM

The rain-detection algorithm uses the forward and aft views of the H-pol σ_0 . We had 4 flavors of the high-resolution QuikSCAT data available. We chose the horizontal polarization σ_0 since horizontal polarization has better contrast than the vertical polarization. The algorithm utilizes 2 properties of wind and rain echoes for the purpose of separation. The first property is that the rain echoes in the presence of moderate wind have higher multifractal exponents than the wind echoes. The second property is that wind echoes have higher correlation in a comparatively larger neighborhood than rain echoes. Fig 5.1 represents the scatterometer NRCS before the Rain-Detection algorithm is applied. The algorithm is described in detail the following sections.

Fig. 5.1 Scatterometer NRCS before application of Rain-Detection algorithm

5.1 Pre-Processing

Before we actually analyze the data with multifractals and correlations, we bring it into desired format. The high-resolution data we deal with has 15 passes of QuikSCAT σ_0 for one whole day (Julian day 315, 2004). Each pass consists of 760×16231 data points, with 16231 corresponding to the latitudes and 760 corresponding to the longitudes. The data was not earth-gridded. Due to the polar orbit of QuikSCAT, each pass covers almost entire range of latitudes, from -90° to $+90^\circ$. We have considered only the tropical regions extending from latitudes -40° to $+40^\circ$, as in TRMM validation data, for the purpose of comparison. Even though this reduces the latitude range, it is still considerably wide and the weather undergoes tremendous changes along this range. Thus, it is not reasonable to use one single global exponent and threshold. We have used an adaptive exponent and threshold to take into consideration the wide latitude range. The two variables, exponent and threshold are adapted depending on the average intensities in a predefined neighborhood to 500 pixels along the latitudes. The value, 500 pixels, was empirically determined by comparing the results at many different neighborhood sizes ranging from 300 to 700 along the latitudes. Thus, we divided each pass into 33, 760×500 pixel images and then process them one by one. Fig. 5.2 shows the break-down of one pass into 33 sub-images. Fig 5.3 shows the flow-chart of the rain-detection algorithm.

Fig.5.2 Pre-Processing: Breaking down each pass into 33, 760×500 sub-images.

Fig. 5.3 Flow-Chart of Rain-Detection algorithm

5.2 Step 1. Use of Multifractal Exponent for the Description of Texture

As mentioned before, the rain-detection algorithm uses forward and aft views of high resolution SIR data. With the two images we consider the signal to be a 3-dimensional signal. We assume that the scale 's' (equation 2, chapter 3) takes 2 values, namely, s_1, s_2 . The measure at scale s_1 is defined as,

$$\mu_q(s_1, x, y, z) = [f(x, y, z)]^q \quad (5.1)$$

The measure at scale s_2 is defined as,

$$\mu_q(s_2, x, y) = \left[\sum_{x'=x-1}^{x+1} \sum_{y'=y-1}^{y+1} \sum_{z'=1}^2 f(x', y', z') \right]^q \quad (5.2)$$

The coordinated (x, y, z) correspond to the pixel that exists in the (x, y) position of the forward or the aft view of the horizontal polarization σ_0 . The power-law is the same as in equation (3.3) chapter 3. The function $K(q)$ is estimated from the slope of the line that best fits the points $(\log s, \log \langle \varepsilon_s^q \rangle)$ at $s = s_1, s_2$. The function $K(q)$ is then equal to,

$$\frac{\log \langle \varepsilon_{s_2}^q \rangle - \log \langle \varepsilon_{s_1}^q \rangle}{\log(s_2) - \log(s_1)} \quad (5.3)$$

The ensemble average in (3) is approximated with the spatial average of the measures in small 3-D windows, as given in equation (5.4) below.

$$\left\langle \mathcal{E}_{s_2}^q \right\rangle_{x,y}^w = (1/2w^2) \sum_{x'=x-w/2}^{x+w/2} \sum_{y'=y-w/2}^{y+w/2} \sum_{z'=1}^2 \mu_q(s_1, x', y', z') \quad (5.4)$$

$$\left\langle \mathcal{E}_{s_1}^q \right\rangle_{x,y}^w = (1/w^2) \sum_{x'=x-w/2}^{x+w/2} \sum_{y'=y-w/2}^{y+w/2} \mu_q(s_1, x', y') \quad (5.5)$$

From (5.3), (5.4) and (5.5) $K_{x,y}^w(q)$ are calculated. $K_{x,y}^w(q)$ is called the multifractal exponent. The superscript w denotes that the averages in (4) and (5) are taken in windows of size $w \times w$. Fig 4.2 illustrates how this step is implemented. A 5×5 portion of the forward view of the horizontal σ_0 and the corresponding 5×5 portion of aft view of the horizontal σ_0 centered at location $(x, y, 1)$ and $(x, y, 2)$ are shown. The measures $\mu_q(s_1, x', y', z')$ are computed as the reflectivity values corresponding to the pixels with coordinates (x', y', z') raised to the q^{th} power. Then, the approximate ensemble average at location (x, y) is the average of the measure $\mu_q(s_1, x', y', z')$ over all pixels for both portions. The measure $\mu_q(s_2, x', y')$ is computed as the reflectivity averaged in a box located at (x', y') , which is then raised to the q^{th} power. Then, the approximate ensemble average at location (x', y') is the average of the measure $\mu_q(s_2, x', y')$ over all (x', y') . We can thus compute different $K_{x,y}^w(q)$ at different exponents 'q' and also the local window-size 'w'. The exponent and the window-size that can be used in a particular region depend on the average intensity in that particular region. The reasons for this were mentioned in chapter 1. We restate these reasons here, for the purpose of reference.

Fig. 5.4 Computation of the measures and the approximate ensemble average using the corresponding portions of the reflectivity images obtained from the two flavors. One such box located at $(x+1, y+1, 1)$ and $(x+1, y+1, 2)$ respectively. The group of dark gray squares (including the white squares) defines a box at scale 2 and location $(x+1, y+1)$.

The latitudes we dealt with in this analysis extended from -40^0 to $+40^0$. In this entire range of latitudes the climate undergoes tremendous changes and thus there occur a variety of rain and non-rain events. There are some rain and non-rain events, which are worth a mention regarding the adaptive multifractal exponent and threshold.

4. Events with very high wind and no rain.
5. Events with very high wind and rain
6. Events with very weak rain.

The first type of events requires a very high multifractal exponent to suppress the wind pixels, which may not give very good results for the third type of events. The reason being the average intensity is very high in the first type and very low in the last type. The second type of

events needs a moderate multifractal exponent and threshold. Through observation we have fixed the multifractal exponents for the different average intensity regimes. Table 5.1 below summarizes the different average intensity regimes and the multifractal exponents used in our algorithm. Consider a small region selected from the data shown in fig.5.3. The region is not earth-gridded. Fig 5.4 shows the multifractal exponent computed from Fig.5.3. It can be easily seen that strong rain echoes have multifractal exponent value higher than wind echoes.

Fig. 5.5 Multifractal Exponent computed from Fig. 5.1

Table 5.1 Average intensity regimes and corresponding exponents and thresholds.		
Average Intensity Regime (m)	Exponent (q)	Exponent (q)
$m \leq 70$	5.5	61
$70 < m \leq 90$	6.0	61
$90 < m \leq 105$	6.5	65
$105 < m \leq 135$	7.0	65
$m \geq 135$	7.5	75

5.3 Step 2. Threshold the Multifractal Exponent

After the multifractal exponent $K_{x,y}^w(q)$ is computed, we threshold it to retain only those pixels, which are strong rain-events and consequently have a very high value of multifractal exponents. The threshold value used is also made adaptive for the same reasons as the multifractal exponent. The different threshold values used are tabulated in table 5.1 above. Fig. 5.6 shows the thresholded multifractal exponent.

Fig. 5.6 Thresholded Multifractal Exponent

5.4 Step 3. Computation of Correlation of the Multifractal Exponent within a Pre-defined Neighborhood.

After the multifractal exponent is thresholded we are left with only those pixels that represent obvious rain events. The basic function of the second step of the algorithm is to deal with those pixels, which may not be very obviously rain or wind events and need a further consideration before we reach a conclusion. Thus, the objective at this step is to re-activate all the pixels that were removed in the first step because of the strict thresholds. There are 2 types of such pixels,

1. The pixels that lie at the boundaries of the prominent rain events. These pixels have intensities lower than the central part of the event and get erased.
2. The pixels that correspond to very weak rain events, which are removed due to the strict thresholds in the first step.

These 2 effects of strict thresholding can be observed in fig. 5.6.

The thresholding has removed the boundaries of the rain events as well as the weak rain events. The re-activation of these pixels is achieved in the following manner. We compute the correlation of the multifractal exponent image in the predefined neighborhood. We have used a fixed window-size of 25×25 for this purpose. We basically compute 2 types of correlations. The first correlation excludes all the pixels that were removed in the first step in the process of thresholding. The second type of correlation includes all the pixels irrespective of the thresholding process in the first step. It can be easily inferred that for the pixels at the boundary of the rain event, which have been suppressed in the first step will have different values for the correlations. First correlation that excludes all the pixels removed in the first step; hence it is higher than the second correlation. The first type of pixels that were removed because of the

strict thresholds is re-activated by comparing the 2 correlations. In the first type of pixels the two correlations have different values. Such pixels are reactivated. The second type of pixels is reactivated by thresholding the second correlation. At this step we utilize the property of the rain events that rain has lower correlation than that of wind pixels in a relatively larger neighborhood. This neighborhood was fixed at 25×25 as mentioned before. This particular value of the neighborhood was empirically fixed by comparing the results at many different neighborhood sizes. The pixels that have correlation below a threshold of 5100 are reactivated assuming that they represent very weak rain events. The results of step 2 are illustrated in fig. 5.7. The boundary regions and the weak rain events are shown with an arrow in the figure for the sake of convenience.

Fig. 5.7 Rain- flag

5.4 Step 4. Application of a Noise Threshold

The algorithm has used thresholding at many stages of the algorithm. This thresholding produces many artifacts in the results. To get rid of these artifacts we try to threshold the final results again with a very nominal noise threshold of intensity 20.

Fig. 5.8 Output after application of noise threshold

5.5 Post-Processing

After all the passes of the QuikSCAT data were processed, they were earth-gridded and combined to form 2 images, the daytime passes and evening passes, to compare it to TRMM validation data.

CHAPTER 6

RESULTS & COMMENTS

As mentioned in previous chapters we used high resolution QuikSCAT data for processing. Enhanced resolution data for one day, Julian day 315, 2004 (Nov 10th, 2004) was available. The data was in form of multiple passes of the QuikSCAT satellite covering approximately 90% of earth. Each pass consists of ascending section and descending section within itself. Because of the enhanced resolution, each pass was 16231 pixels along latitudes and 760 pixels along longitudes. Combining all the passes would give a very large image of size nearly 16231 pixels $\times$ 35000 pixels, making the processing a tedious and time-consuming task. Instead we processed each pass separately and then combined them. Each pass, as mentioned earlier, spanned entire range of latitudes from $+90^0$ to -90^0 . We considered only the tropical regions from latitudes $+40^0$ to -40^0 . Each pass was divided into sub-images at the time of pre-processing in the algorithm. Each sub-image was processed separately with parameters dependent on the average intensity of the sub-image. After all the sub-images and passes were processed they were brought into a form, where they could be compared with the validation data. For a direct comparison we needed both the validation data as well as the results at same resolution. Apart from this the QuikSCAT passes of the enhanced resolution data were not earth-gridded. Thus, the data was earth-gridded and averaged to achieve a resolution of 0.25^0 along the latitudes and longitudes.

We have three sections in the results to be discussed in details; comparison of the results with the validation data (TRMM rain-rate), deficiencies of the algorithm in strong wind regions, comparison with the results obtained with differential polarization technique.

6.1 Comparison with TRMM validation data

We validated our results with TRMM TMI rain-rates. It should be noted that the comparison with TRMM TMI rain-rates is intended only to validate the presence of rain and not the comparison of the actual rain-rates. Thus, the individual pixels values may not match. We present eight events of the data we had, for the purpose of comparison. Figures 6.1 to 6.16 show the comparison of multifractal rain-flag and TRMM rain-rate at various precipitation events. The comparisons are not necessarily at collocations. This is so, because we did not find many collocations with precipitation. Both QuikSCAT and TRMM images are at 0.25° resolutions along the latitudes as well as the longitudes. The images as mentioned before are not collocated, the maximum time difference between the QuikSCAT image and its TRMM equivalent is sometimes 3 hours. Some of the rain events in the images can also be seen to be displaced relative to one another, when compared spatially, because of the time difference.

Fig 6.1 QuikSCAT Rain-flag

Fig 6.2 TRMM rain-rate

Fig 6.3 QuikSCAT Rain-flag

Fig 6.4 TRMM rain-rate

Fig 6.5 QuikSCAT Rain-flag

Fig 6.6 TRMM rain-rate

Fig 6.7 QuikSCAT Rain-flag

Fig 6.8 TRMM rain-rate

Fig 6.9 QuikSCAT Rain-flag

Fig 6.10 TRMM rain-rate

Fig 6.11 QuikSCAT Rain-flag

Fig 6.12 TRMM rain-rate

Fig 6.13 QuikSCAT Rain-flag

Fig 6.14 TRMM rain-rate

Fig 6.15 QuikSCAT Rain-flag

Fig 6.16 TRMM rain-rate

Comments

- Rain-affected pixels have been clearly identified in the QuikSCAT images.
- The intensities of the individual pixels do not match, thus the algorithm only identifies and does not estimate rain-rate.
- Due to the time-differences between some images the rain events appear to have a spatial displacement with respect to each-other, when compared.

6.2 Algorithms Deficiencies

The only deficiency of the rain-detection algorithm is it produces false alarms in the regions with strong wind echoes. The objective of the algorithm was to identify the rain-affected pixels. But data has a wide variety of events with combination of rain and wind events at different intensities and spatial characteristics. We used an adaptive Multifractal exponent as well as threshold. This adaptive threshold, although very helpful in bringing out the very weak rain events, sometimes gives confusing results with some particular combination of simultaneous and wind events. In events, where wind is very high, the Multifractal exponent exceeds the threshold we set for non-rain events. While selecting a particular Multifractal exponent and threshold, we look at the average intensity in a predefined neighborhood around a pixel. Although average intensity is a satisfactorily good measure to select these parameters it is not completely flawless. The reason for this is some confusing wind events or simultaneous rain-wind events. In these particular events the wind is very high in some region but simultaneously it reaches a very low value in the remaining image. The result of this is that the average intensity in the overall image is not high but still the image has some high wind events. These particular type of false alarms is shown in figures 6.19 to 6.22. Some times rain events buried in very high wind regions. In these regions wind pixels get reactivated along with boundary rain pixels mistaken as boundary rain pixels. This second type of false alarms is shown figures 6.23 to 6.24.

The false alarms are seen in the regions, where wind speed is 20-25 m/s or above. Figures 6.17 to 6. 21 show the false alarms and the QuikSCAT wind retrieval images obtained from Remote Sensing Systems' web pages.

Fig. 6.17 QuikSCAT False alarms

Fig. 6.18 Strong Wind Regions

Fig. 6.19 QuikSCAT False alarms

Fig.6.20 Strong Wind Regions

Fig. 6.21 QuikSCAT False Alarms

Fig.6.22 Strong Wind Regions

Fig. 6.23 QuikSCAT False Alarms

Fig.6.24 Strong Wind Regions

Comments

- Algorithm produces false alarms in strong wind regions, wind speed above 20-25 m/s
- Average intensity does not work very well in the regions with a combination of very low and very high wind-speeds
- Strong wind speed events surrounding rain events are reactivated in step 5 of the algorithm

6.3 Comparison with Differential Polarization Rain-Flag

In this section we compare the results obtained with multifractals analysis based rain-flagging algorithm with the rain-flags obtained with differential polarization technique [5] [D. E. Weissman, M. A. Bourassa, J. J. O' Brien, J. S. Tongue, "Calibrating the QuikSCAT/SeaWinds Radar for Measuring Rainrate Over the Oceans", *IEEE Trans Geosc and Rem. Sens.*, vol. 41, No.12, pp. 2814-2820, Dec. 2003].

Differential polarization technique uses the property that in presence of rain events of rain-rates above 1mm/hr the horizontal polarization tends to exceed the vertical polarization NRCS. Thus, the positive difference between H-pol NRCS and V-pol NRCS can be employed as a rain flag. We processed the same data using differential polarization rain-flag for the purpose of comparison. Similar to the multifractal results, the differential polarization rain-flag was earth-gridded and averaged. The resolution was brought to 0.25^0 along latitudes and longitudes for comparison.

The comparisons are shown in figures 6.23 to 6.26. The images represent the entire day of data, earth-gridded and averaged to 0.25^0 resolutions along latitude and longitude. First comparison represents the morning passes of the QuikSCAT satellite and the second comparison represents the evening passes. From comparisons it can be seen that Differential Polarization produces somewhat noisy results compared to the multi-fractal rain-flags.

Fig. 6.25 QuikSCAT Rain-Flag using Multi-fractals (Morning Pass)

Fig. 6.26 QuikSCAT Rain-Flag using Differential Polarization (Morning Pass)

Fig. 6.27 QuikSCAT Rain-Flag using Multi-fractals (Evening Pass)

Fig. 6.28 QuikSCAT Rain-Flag using Differential Polarization (Evening Pass)

Comments

- Differential Polarization produces noisier rain-flags than Multifractal based rain-flags
- Differential Polarization rain-flags contain false alarms in the regions, which do not necessarily have strong wind speeds unlike Multifractal based rain-flags.
- Differential polarization in some events fails to identify rain-affected pixels.

CHAPTER 7

CONCLUSIONS & FUTURE WORK

Rain-flagging is very important in oceanic remote sensing of wind velocity. In this thesis, a multifractal based segmentation algorithm to identify rain-contaminated pixels from scatterometer NRCS utilizing correlation properties was developed. An advantage of this technique is computational simplicity because it does not require any training. Excellent results are obtained with fixed parameters.

To validate the algorithm, results were compared with the TRMM TMI 2A12 rain rate products, and it was found that the multi-fractal based rain detection algorithm is very effective. We have also compared our results with that of another technique, the differential polarization, and our proposed method performed better in terms of noise, false alarms and in missing rain events.

A deficiency of the proposed algorithm is it produces false alarms under strong wind conditions and high rain rates. Since the precipitation does not affect the wind velocity estimation at strong wind speeds, these false alarms do not pose a very serious problem.

Future work involves estimating rain-rates from the scatterometer NRCS using multifractal analysis. To date TRMM is the only space borne meteorological radar intended for global coverage of rain. Because of its wide swath, it would be a great advantage to be able to estimate rain rates from SeaWinds. Therefore, the estimation of rain-rate independently from scatterometer data can be a development of tremendous value.

LIST OF REFERENCES

1. V. Torsekar, T. Kasparis, W. L. Jones, K. Ahmad, D. G. Long, "Oceanic Rain Identification of QuikSCAT sigma_0 using Multifractal Analysis," *OCEANS 2005*
2. C. Y. Chi, F. K. Li, "A comparative study of several wind estimation algorithms of spaceborne scatterometers," *IEEE Trans Geosc and Rem. Sens.*, vol. 26, No. 2, pp. 115-121, Mar. 1988.
3. M. H. Frielich, R. S. Dunbar, "Derivation of Satellite Wind Model Functions Using Operational Surface Wind Analyses: An Altimeter Example," *J. of Geophys. Res.*, vol. 98, No.V8, pp. 1463-14649, Aug.1993
4. B. W. Stiles, S. Yueh, "Impact of Rain on Spaceborne Ku-Band Wind Scatterometer Data", *IEEE Trans Geosc and Rem. Sens.*, vol. 40, No.9, pp. 1973-1983, Sept. 2002.
5. D. E. Weissman, M. A. Bourassa, J. J. O' Brien, J. S. Tongue, "Calibrating the QuikSCAT/SeaWinds Radar for Measuring Rainrate Over the Oceans", *IEEE Trans Geosc and Rem. Sens.*, vol. 41, No.12, pp. 2814-2820, Dec. 2003.
6. D. W. Draper, D. G. Long, "Evaluating the effect of rain on SeaWindsscatterometer measurements," *J. of Geophys. Res.*, vol. 109, No.C02005, Feb. 2004.
7. D. W. Draper, D. G. Long, " Simultaneous Wind and Rain Retrieval Using SeaWinds Data," *IEEE Trans Geosc and Rem. Sens.*, vol. 42, No.7, pp. 1411-1423, 2004.
8. M. Alber, J. Peinke, "Improved multifractal box-counting algorithm, virtual phase transitions, and negative dimensions", *Phys. Rev. Let. E*, vol. 57, No. 5, pp. 5489-5493, May 1998
9. M. I. P. de Lima, J. Grasman, "Multifractal Analysis of 15-min and daily rainfall from semi-arid region in portugal," *J. of Hydrology*, vol. 220, , Accepted April 1999

10. D. Charalampidis, T. Kasparis, W.L. Jones, "Removal of Non-precipitation Echoes in Weather Radar Using Multi-fractals and Intenensity," *IEEE Trans Geosc and Rem. Sens.*, vol. 40, No.5, pp. 1121-1131, May 2002.
11. D. G. Long, "Standard BYU QuikSCAT/SeaWinds Land/Ice Products," *Microwave Earth Remote Sensing Laboratory, BYU, Provo, Utah 84602*, <http://www.scp.byu.edu/>
12. D. S. Early and D. G. Long, " Image Reconstruction and Enhanced Resolution Imaging from irregular samples," *IEEE Trans Geosc and Rem. Sens.*, vol. 39, No.2, pp. 291-302, May 2001.
13. Web-Source, Remote Sensing Systems Website, QuikSCAT wind-retrieval.,
<http://www.remss.com/>
14. "Texture Segmentation Using Fractal Features", Masters Thesis, Nattorn Pongratananukul, UCF,
15. "Texture Segmentation Using Feature Combinations", Masters Thesis, Dimitrios Charalampidis, UCF