AN ANALYSIS OF IN SITU OBSERVATIONS OF SPECTRAL REFLECTANCE CHARACTERISTICS OF CORAL REEF FEATURES IN FIJI AND INDONESIA

By

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ABSTRACT

Increased awareness of the vulnerability of coral reef ecosystems to the synergistic effects of natural and anthropogenic environmental changes has lead to subjective reporting of observed changes, but there has been a significant lack of objective monitoring of coral reef ecosystems on a repetitive basis. Only consistent, repetitive monitoring over time will increase our understanding of the dynamic and complex nature of coral reef ecosystems and the ways in which changes in the ecosystem are related to environmental changes. One limiting factor to remote detection of coral reef well-being is the lack of a quantitative means of identifying optically similar features such as healthy coral and macroalgae.

In this study, a field program was designed to explore the differences in spectral reflectance characteristics of various coral reef features. High spectral resolution *in situ* data were collected with a hand-held hyperspectral radiometer. In 1996, *in situ* spectral reflectance data of submerged coral reefs were collected in Beqa Lagoon, Fiji; in 1997, *in situ* spectral reflectance measurements of exposed coral reef features were collected in Manado, Indonesia. Finally, *in situ* data of submerged coral reefs were collected in 1998 in Savusavu Bay, Fiji.

The spectra collected were divided into populations of healthy coral, unhealthy coral, algae-covered surfaces and rubble surfaces based on feature type according to field notes and photographic records. These data sets were compared and analyzed to test the following hypotheses. First, the within-population variability is low such that spectra of similar coral reef features display similar spectral reflectance characteristics, and

conversely, there are discernable spectral reflectance differences between populations. Secondly, the geographic location of measurement does not affect the spectral reflectance characteristics. The final hypothesis tested is that the slopes and changes in slopes of the spectral reflectance curves will allow differentiation of populations and subsequent classification.

Cluster and correlation analyses indicate that both the within- and between-population variability is low. Therefore, while spectra of similar features are comparable, there are predictable inaccuracies in classification due to spectral similarities between populations. Nevertheless, principal components analysis was used successfully as a data reduction tool to reduce the large data set of 334 spectra to 6 spectra representative of the pre-defined populations. A classification scheme was devised based on these representative spectra such that the slope, change in slope and magnitude of reflectance of the spectral curves enabled identification. This classification procedure was applied to the remainder of the data set and an error analysis was performed to investigate accuracy of identification. The overall accuracy was 80.1% and an investigation of the errors of omission and commission indicate that the majority of the errors are a result of an inability to characterize bleached coral correctly. The results of this study indicate that hyperspectral remote sensing may be a feasible means of accurate identification and subsequent monitoring of changes in coral health and overall well-being.

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CHAPTER 1

RESEARCH PROBLEM, OBJECTIVES AND THESIS ORGANIZATION

1.1 INTRODUCTION TO CORAL REEF ECOSYSTEMS

Coral reefs around the world are being damaged and destroyed at a seemingly increasing rate. The serious global decline of coral reefs is of urgent concern, for a coral community is but one component of a collection of highly integrated and interrelated biological communities, such as seagrass, mangroves and mudflats. Furthermore, coral reef communities represent one of the most diverse ecosystems in the world, and appear to be sensitive indicators of water quality and ecological integrity of the entire ecosystem.

Coral reefs are important for a number of reasons. There is great biodiversity preserved in a coral reef ecosystem. In fact, there are approximately 4000 species of fish and 800 species of reef-building corals that have been described, and experts have only just begun to catalogue the total number of species (Brown, 1997). Furthermore, coral reefs are an important source of seafood and thus protein for coastal communities, especially in developing regions. Unfortunately, fishers are depleting this resource through overexploitation and destructive fishing practices.

Coral reefs are now recognized as an important source of medicine, as coral reef species offer a promising array of chemicals produced for self-protection. Many coral reef organisms are already used for bone grafts, treating viruses, leukemia and skin cancer (Bryant et al., 1998). Coral reefs are also important sources for other products and economic goods such as jewelry and curios, aquarium fish, as well as sand and limestone used in the construction industry.

Recreational value is difficult to quantify, but the tourism industry commonly relies upon coral reefs to provide exceptional snorkeling, scuba diving, fishing and beaches. Another reason that coral reefs are important is their role in protecting the coast. Reefs buffer adjacent shorelines from wave action and the impact of storms, maintain highly productive mangrove fisheries and wetlands as well as support the local economy built around ports and harbours.

There are a number of threats to coral reef ecosystems. For instance, global climate change may be detrimental to coral reefs, as models predict increasing sea surface temperatures, increasing sea levels, as well as increasing frequency and intensity of storms (Jokiel and Coles, 1990). The physical damage to coral reefs due to damage from storms or the stress placed upon them due to increased water temperatures will increase "natural" stress levels and may leave them more vulnerable to human-induced disturbances (Mumby et al., 1995). While reefs often recover from short-term natural catastrophic events, such as hurricanes, and usually recover to normal community structure, they are reportedly not well adapted to survive exposure to long-term stress, such as agricultural and industrial run-off and toxic discharges (Bryant et al., 1998).

Coastal development is another threat to coral reefs, as dredging of harbours and shipping channels, hot water discharge from power plants, mine runoff and industrial toxic waste effluents are known to be detrimental to coral reefs (Goreau, 1964). Nutrient-rich runoff promotes growth of bottom-dwelling algal competitors and interferes with coral reproduction, while sediment resulting from construction and dredging settles on the reef and effectively starves it of light (Bryant et al., 1998). Furthermore, over fishing results in a shift in fish size, abundance and species composition, while removal of key herbivore and predator species causes large-scale ecosystem changes, and blast fishing, using cyanide and other poisons and non-selective trawling are common destructive fishing techniques that fishers use (McClanahan, 1996).

Unfortunately, there are no precise appraisals regarding the extent and location of coral reef degradation due to the special difficulties in monitoring underwater ecosystems (Mumby et al, 1998). Consequently, there is an immediate need to assess how, where and why coral reef damage is occurring, and determine the best methods for prevention. In order to aid management and sustainable conservation of coral reefs, it is essential to assess the status and trends in coral reef well-being through observation of appropriate indicators of stress. This objective can be met through effective use of remote sensing technology.

Monitoring coral reef ecosystems will help document the scale, extent and duration of ecosystem degradation related to natural changes as well as those related to human influence. Before such relationships can be established, coral reef stress must be (1) monitored on site or remotely, (2) quantitatively investigated and reported and (3) coupled with precise data regarding prevailing environmental conditions (Hayes and Goreau, 1992). The quantitative means of remotely identifying coral reef features presented in this thesis satisfies the first two requirements, and makes it possible for correlations to be made with prevailing environmental conditions.

1.2 OVERVIEW OF RESEARCH PROBLEM

Conceptually, using remote sensing as a tool to monitor coral reef and related ecosystems is ideal. A satellite image covers large geographic areas and repetitive images can be captured consistently over time. Furthermore, the information recorded on a satellite image allows for objective, quantitative analysis. Operationally, however, there are numerous restrictions. The operational impediment investigated herein is the optical similarity of spectral reflectance characteristics of features within a coral reef environment. For example, a similar optically dark signal is expected for deep water, healthy coral substrate and dark sand, so confusion can arise in identification. Broad-band signals have proven to be insufficient for detecting the subtle differences in spectral response expected for seemingly identical features (Mumby et al., 1998). High spectral resolution sensors are required to perceive these subtle differences; this is demonstrated through analysis of *in situ* measurements in this study.

Unfortunately, the images available from current satellite sensors are generally inappropriate for accurate monitoring of coral reef ecosystems. As mentioned above, the spatial and spectral resolution is too coarse to detect subtle differences in spectral reflectance and to accurately identify substrate types. Nevertheless, within the next few years, satellite sensors will be capable of generating imagery with spatial resolution of 4m in multispectral mode (Alpin et al., 1997) and hyperspectral satellite sensors are currently planned for launch in the United States and Australia by 2000. Additionally, currently available airborne spectroradiometers, such as the *casi* (Compact Airborne

Spectrographic Imager) system, offer acceptable spatial and spectral resolution for mapping submerged coral reef geographic extent (Mumby et al., 1998). At the present time, however, the finest spatial resolution available in a global mapping instrument is the French satellite, SPOT HRV, which offers coarse spectral resolution imagery (3 broad wavelength bands) at spatial resolutions of 20m.

Consequently, in preparation for future utilization of high spectral and spatial resolution airborne or satellite imagery, a feasibility study is necessary using high spectral resolution *in situ* reflectance measurements. For this study, spectral measurements using an identical radiometer were collected in Beqa Lagoon, Fiji in August 1996; in Manado, Indonesia in July 1997; and in Savusavu Bay, Fiji in July and August of 1998. A large spectral reflectance data set now exists for the first time consisting of measurements of typical coral reef features including healthy coral, unhealthy coral, algae-covered surfaces, and sand substrates.

The ultimate goal of this research is to establish a replicable and objective method of remotely monitoring changes in coral reef degradation and recovery. Toward this end, the objective of this study is to create an operational high spectral resolution classification procedure with which to identify both the geographic extent of coral reefs and the well-being of the reef with respect to the proportion of bleached and algae-covered coral versus healthy coral present. To meet this objective, measurements of spectral reflectivity are compared to determine if there is a wavelength-specific distinction between various coral reef components based on spectral reflectivity. It appears from the literature that coral stress is a direct indicator of the overall well-being of the coral reef ecosystem. Therefore, once baseline information can be reliably archived relating to the well-being of a coral reef over time, then correlations to environmental changes can be determined.

1.3 OBJECTIVES

The objective of this thesis is to determine the specific wavelength ranges that allow discrimination of specific coral reef ecosystem characteristics. To attain this objective, a field program was designed incorporating a hyperspectral radiometer, an underwater optical cable and cosine receptor and scuba diving technology.

In this study, a series of analyses is performed on the field data collected in three consecutive years in different geographic locations. The first stage of analysis involves separately comparing the spectral data collected in the three geographically distinct locations. Intuitively, the reflectance response of a coral reef feature should display similar spectral characteristics regardless of the geographic location. This type of comparison has not been conducted with respect to spectral reflectance, so the datasets collected in Beqa Lagoon, Manado and Savusavu Bay with the same radiometer are compared to test the hypothesis that there is no spectral reflectance difference between measurements taken in these three locations. In other words, it is hypothesized that similar features possess similar spectral characteristics regardless of geographic location. If geographic location has no effect on the spectral characteristics of corals, quantitative comparisons of coral spectral reflectance may be possible globally.

The morphology of coral is also investigated as a possible factor in the spectral reflectance response. There are two broad categories of coral morphology: branching and solid massive corals. Theoretically, the shape of a coral should affect the spectral response due to varying slope, shape, size, texture and shadow. Furthermore, the substrate underlying a branching coral will contribute to the overall reflectance of a coral if it is visible though branches. It is therefore hypothesized that the spectral reflectance of branching coral will differ from that of solid massive coral thus allowing broad categories of coral morphology to be distinguished.

Subsequent analysis is focused on discriminating between the populations of healthy coral, non-healthy coral, algae-covered dead coral, and sand. The hypothesis that these broad populations commonly found in a coral reef environment are spectrally distinct is tested using a number of techniques. Cluster analysis is used to examine the between- and within-population variability, and correlation coefficients are calculated to further examine the similarities and differences. Principal components analysis is used as a data reduction tool to identify one spectral reflectance curve for each of the broadly defined populations. These representative spectra are used as the basis for devising a classification scheme that will allow identification of the populations.

The slope of the spectral reflectance curves in specific wavelength regions is examined in an effort to distinguish between populations and develop a classification scheme for identification. A procedure is created to accurately discriminate between the populations based on the representative spectra identified using principal components analysis. This procedure is based on a 4-step classification scheme whereby first and second derivatives and magnitude of reflectance are used to identify populations.

The final stage of analysis is to apply the developed classification procedure to the remainder of the data set in an attempt to classify the spectra into populations based on feature type. The 4-step procedure is performed on the entire spectral data set, and the accuracy examined. An error matrix allows interpretation of errors of omission (exclusion) and commission (inclusion), which provides insight into the classification accuracies within each population.

1.4 THESIS ORGANIZATION

A brief introduction to the topic of coral ecosystems and their relationship to environmental change as well as a statement of the specific research objectives were provided in this chapter. The concept of coral bleaching and its relationship with global climate change, anthropogenic influences and natural variability are discussed in Chapter 2. In addition, a discussion of the management of coral reef resources, and the issues involved in discriminating healthy and bleached corals is included. The purpose of Chapter 2 is to provide background information revealing the importance of monitoring coral reef ecosystems for reasons beyond preservation of global biodiversity.

The research context is provided in Chapter 3 with respect to both active and passive marine remote sensing and coral reef monitoring using remote sensing. The purpose of Chapter 3 is to reveal the complexity of marine remote sensing due to the variable conditions of the overlying water column and the difficulties in establishing a confident methodology for submerged coral reef monitoring. Various case studies are discussed as an indication of the broad range of approaches to the problem of submerged feature detection.

In Chapter 4, I describe the study areas and present the sampling strategies used in the field data collection in 1996, 1997 and 1998. The various steps in data processing are also discussed. Additionally, potential sources of error are discussed in Chapter 4 relating to the use of remotely sensed imagery as a tool and the collection of spectral reflectance field data. Objectives as well as data analysis methodology and processing steps are presented and justified in Chapter 4.

The spectral reflectance data collected in the field in 1996, 1997 and 1998 are investigated in Chapter 5. For each separate year, the data available are presented, and average and standard deviation spectra compared. Second, cluster analysis is performed in an effort to determine the similarity among spectra of a given population, as well as determine the differences between spectra of different populations. Correlation coefficients are then calculated to further examine the between- and within-population variability. The goal of Chapter 5 is to present the data available and investigate the spectral characteristics of the coral reef features.

The spectra collected in 1996, 1997 and 1998 are amalgamated and compared in Chapter 6. Broadly defined populations are used to categorize the three years of spectra. Eight populations are examined for the within- and between-population variability. Cluster analysis is performed and correlation coefficients calculated to quantify the similarities and difference among and between spectra collected in geographically diverse areas. The goal of this chapter is to demonstrate that the between-population variability is high and the within-population variability is low, regardless of the geographic location of data collection.

Principal components analysis is used in Chapter 7 to reduce the data set to representative spectra for each population. These representative spectra comprise the training set on which a classification procedure is based. Spectral derivative analysis is the basis of this classification procedure. First and second derivatives are calculated in narrow wavelength regions in an effort to differentiate between populations. The final classification scheme devised is a 4-step procedure whereby first and second derivatives and magnitude of reflectance are used to identify populations defined by feature type. Finally, this classification procedure is applied to the remainder of the data set and an error matrix is used to examine the accuracy of the classification. The error matrix allows for an examination of errors of omission and commission. A summary of the work contained in this thesis as well as future work to be performed is discussed in Chapter 8.

CHAPTER 2

MONITORING CORAL REEF ECOSYSTEMS

2.1 INTRODUCTION

The purpose of this chapter is to provide background information on corals and coral reef ecosystems, the threats to corals, both natural and anthropogenic, as well as how corals typically respond to stress. Information is also provided on efforts that have been made to monitor and manage coral reef ecosystems and the approaches that have been taken. In addition, remote sensing is discussed in the context of monitoring coral reef ecosystems.

2.2 CORAL REEFS

Coral reefs were first formed more than 500 million years ago in warm tropical climates, and since that time they have successfully developed and supported a tremendous array of plant and animal life (Goreau, 1964). Amazingly, an entire coral reef ecosystem is built upon tiny animals that are typically less than 0.5cm in diameter and are called polyps. Coral reefs are formed by calcium carbonate produced by these tiny coral polyps and are important land builders in tropical areas, forming islands and altering continental shorelines. A coral colony may consist of thousands of polyps, which are typically carnivorous, feeding on small organic particles floating in the water (Sumich, 1992).

Corals are invertebrates that can be one of two types: hermatypic (hard corals that build reefs), or ahermatypic (soft corals that do not). Reef building hermatypic hard corals, which are of interest for this study, are of the order Scleractinia in the class anthozoa of the phylum cnidaria. In hard corals, many microscopic plant cells called endosymbionts, or zooxanthella, live in symbiotic relationships with the coral animal, and occur in concentrations of up to one million cells per cm^2 of coral surface (Sumich, 1992). The algae provide the polyp with food through the process of photosynthesis in which the plant cells use sunlight to convert carbon dioxide into oxygen and carbohydrates. The polyp uses oxygen for respiration and the carbohydrates are used to build the limestone skeleton. The polyp thus provides the endosymbionts with nutrients, protection and carbon dioxide.

The colour of the coral comes from the photosynthetic pigments with the symbiotic zooxanthellae living in the polyp's tissue. This colour can vary from white, yellow, brown and olive, to red, green, blue and purple, but without the symbiotic zooxanthellae, the coral is white. Furthermore, it is the nutrients provided by these symbionts that make it possible for the corals to grow and reproduce quickly enough to create reefs. In fact, the naturally high productivity of a coral reef is often attributed to an individual coral's mutualistic relationship with its symbiotic zooxanthellae. This mutualism, however, is especially sensitive to numerous environmental stresses, and appears to be experiencing disruption at an increasing rate.

When environmental conditions are altered, the stress placed upon the coral causes it to either expel its symbiotic zooxanthellae or experience a decrease in photosynthetic pigment concentration within the zooxanthellae. In a process popularly known as bleaching, they may lose 60-90% of their zooxanthellae, and/or the zooxanthellae may lose 50-80% of their photosynthetic pigment (Glynn, 1996). The result of both reactions is a loss of colour, as the coral tissue becomes translucent without its pigment, and the coral appears bleached. Bleaching greatly affects the coral host because those photosynthetic symbionts supply approximately 63% of the coral's nutrients, and also because zooxanthellae facilitate calcification (Glynn, 1991).

Fortunately, bleached corals are not necessarily dead, but bleaching can cause varying degrees of coral mortality depending on past exposure to stress, length of time the coral was under stress, and magnitude of the stress relative to the normal environment. In some cases, bleached corals recover when environmental conditions return to normal, and in others, zooxanthellae is regained through direct contact with healthy corals (Jokiel and Coles, 1990). Rates of mortality can vary considerably within and between species depending on the degree and duration of stress. Glynn (1991) states that if corals do not regain their zooxanthellae, they usually die, but if the bleaching is not severe, the corals will often recover. Unfortunately, the extent of zooxanthellae loss and tissue damage that can be tolerated is unknown.

Not all corals, even of the same species, will have identical responses to the same environmental stress: some coral heads of a given species may remain normally pigmented while adjacent colonies may bleach (Wells, 1995). Furthermore, closely related coral species might contain dissimilar strains or species of zooxanthellae, which may also show different physiological tolerances (Brown, 1997). Intra- and inter-specific variation in bleaching may result from (1) differential stress responses in the coral host (Gates et al., 1992); (2) varying susceptibilities of different genetic strains of zooxanthellae (Rowan and Knowlton, 1995); or (3) micro-scale environmental processes that could produce varying spatial effects (Glynn, 1996).

2.3 THREATS TO CORAL REEF ECOSYSTEMS

Coral reef degradation is the result of both natural and anthropogenic causes. Although natural disturbances may cause severe changes in coral communities, anthropogenic disturbances have been linked to the vast majority of decreases in coral cover and colony health in recent decades.

2.3.1 Natural Causes of Coral Reef Degradation

In addition to natural phenomena such as hurricanes, disease and bioeroders, bleaching is also induced as a result of increased water temperature due to the El Niño-Southern Oscillation (ENSO) and decreased salinity resulting from increased storminess. Furthermore, high natural light intensity accelerates bleaching at high temperatures, increases mortality rate, reduces carbon fixation and lowers the growth rate (Jokiel and Coles, 1990). Of the many documented stresses that are known to cause coral bleaching, elevated temperature has been suggested as the primary cause (Glynn, 1991). Several physical factors have been proposed to cause bleaching (Table 2.1), although a lack of long-term *in situ* data and systematic monitoring of coral health limit efforts to correlate mass bleaching events with extreme environmental anomalies (Glynn, 1996).

Table 2.1: Ecological causes of coral bleaching.

FACTOR	CASE STUDY CONCLUSIONS
Temperature	• anomalously low and high sea temperatures (Lesser, 1996) • ENSO-induced sea warming (Brown, B. and Suharsono, 1990) • sudden temperature drops due to upwelling episodes (Glynn and D'Croz, 1990)
Solar Radiation	• large range of wavelengths responsible for bleaching varies with circumstance (Glynn, 1996) • photosynthetically active radiation (PAR, 400-700 nm) (Brown et al., 1994) • ultraviolet radiation (UVR, 280-400 nm) (Gleason and Wellington, 1993; Shick et al., 1996) • reduced light levels (Glynn, 1996)
Subaerial Exposure	• sudden exposure during extreme low tides, ENSO-related sea level drops or tectonic uplift (Glynn, 1984)
Sedimentation	• sediment loading associated with river runoff contributes to coral reef degradation (Grigg and Dollar, 1990)
Fresh Water Dilution	• rapid dilution from storm-generated precipitation and runoff (Goreau, 1964)
Climate-related factors	• regional scale bleaching may result from synergistic changes in air temperature, solar irradiance, sea level, carbon dioxide and marine and atmospheric circulation patterns (Smith and Buddemeier, 1992)

Another common threat to coral populations is the crown-of-thorns starfish, *Acanthaster planci*, which feeds on corals by extruding its stomach out onto the coral to digest the living tissue layer (Birkland, 1989). Coral reefs can usually recover from these natural attacks if anthropogenic stresses do not impede the recuperation process.

2.3.2 Anthropogenic Causes of Coral Reef Degradation

As human population and influence on the coastal zone increases, so does the need to generate wider awareness of the social, technical, political and ecological problems facing coral reefs (Table 2.2). Tropical coastal zones, within which coral reefs can be found, are subject to a number of potentially damaging activities (Mumby et al., 1995). Corals are extremely sensitive, and slight changes in the reef environment may have detrimental effects on the health of entire coral colonies.

Table 2.2. Coral reefs provide many resources, yet they are under constant human induced stress.

Human Benefits of Coral Reefs	Human Threats to Coral Reefs
• Provide shorelines with protection	• Pollution from sewage and toxins
• Serve as nurseries for growing fish	• Destructive fishing habits
• Supply protein source for healthy diet	• Mining explosives
• Provide jobs through fishing and tourism	• Runoff and sedimentation from logging and coastal development
• Provide sources of medicine	• Boat damage from grounding and careless anchoring
• Provide food, shelter and protection for variety of marine species	• Recreational damage from reef walking, careless diving, souvenir collecting

Coral reefs throughout the world are being degraded through resource use beyond sustainable levels. Coral reef flats, for example, often suffer from nutrient stress from sewage discharge, sedimentation from terrestrial runoff, and water level change due to engineering works (Ahmad and Neil, 1994). Additionally, many coral reefs are becoming unproductive through over fishing, as they are colonized by undesirable grazers such as sea urchins (McClanahan, 1996).

One of the greatest threats to coral reefs is human expansion and development. As development continues to alter the landscape, the amount of freshwater runoff increases, which may include large amounts of sediment from land-clearing, high levels of nutrients from agricultural areas or septic systems, as well as many pollutants such as petroleum products or insecticides. Whether it is direct sedimentation onto the reef or an increase in the turbidity of the water due to eutrophication, a decrease in the amount of light reaching the corals may cause bleaching (Brown 1997).

In addition, increases in the amount of nutrients enhance the growth of other reef organisms such as sponges, which may out-compete the corals for space on crowded reefs. Outflows from water treatment plants and large power plants are the cause of much damage to coral reefs, as sewage treatment facilities greatly increase the nutrient levels surrounding outflow pipes, while large power plants alter water temperatures by discharging hot water into the coastal waters.

Harmful fishing practices and techniques, such as over fishing, cyanide poison fishing and dynamite fishing, have replaced traditional fishing methods in many situations. In some areas, people use fish traps with small mesh diameters, which catch even the small juvenile fish, and in others, the use of explosives or poisons has become quite common (Bryant et al., 1998). These practices kill all fish in the affected areas and severely damage the corals. Due to over fishing, reef fish populations have been greatly reduced in some areas of the world, and the removal of these fish has caused the coral reef ecosystem to become unbalanced (Glynn, 1996). Another significant result is that more competitive organisms, such as alga, which were once controlled by large fish populations, have become dominant on reefs in many regions (Green et al., 1996).

Coral reefs also sustain much damage from both commercial and private vessels. The leakage of fuels into the water and the occurrences of spills by large tankers are extremely damaging to local corals (Bryant et al., 1998). Boat anchors are also detrimental to reefs, as they break and destroy entire colonies, while the grounding of large sea-going vessels also results in large sections of coral reefs being destroyed. Furthermore, it has been found that the anti-fouling bottom paints used by many boats contribute to the formation of toxic concentrations of chemical compounds, which may be harmful to coral reef ecosystems (Bryant et al., 1998). Since most corals mass spawn and produce floating gametes, pollutants and toxins on the surface can affect coral reproduction and development for a large area.

There are thus a great number of threats to coral reefs, and many of the threats can be attributed either directly or indirectly to humans. Work must be done quickly to protect our threatened resources. The list of solutions to the many coral reef problems is extensive, ranging from better methods of coastal development in order to decrease runoff, to the installation of permanent moorings at heavily used anchorage sites depending on the nature of the problem.

2.3.3 Coral Reef Response to Stress

It is unknown how the reefs will respond to changes in the long term, and there is little evidence regarding reef recovery after repetitive bleaching events. There are, however, suggestions that corals may be able to acclimate by regulating physiological processes. Community composition would likely change with more tolerant genera such as massive Porites replacing more vulnerable ones such as branching Acropora (Glynn, 1991; Hoegh-Guldberg, 1994). Furthermore, parasitic and mutualistic species that require healthy corals for shelter and sustenance suffer when their hosts are stressed, and mortality of protective branching corals results in predation by corallivores such as the Crown-of-Thorns starfish (*Acanthaster planci*).

The response of corals to a given ecological factor varies with changes in other environmental parameters, and these synergistic interactions are most important near the limits of tolerance for a given parameter. Departure of light, salinity, or other factors from optimal conditions narrows the range of tolerable temperatures and interferes with vital temperature-related physiological mechanisms in reef corals.

Alternatively, it is possible that coral bleaching actually has a natural role in reef ecology and evolution, rather than simply being a reaction to environmental change. In other words, bleaching may not be pathological, but rather a normal regulatory process that maintains remarkably stable populations of symbiotic algae. While Buddemeier and Smith (1988) believe that bleaching is a generalized stress response resulting from a variety of environmental conditions outside the normal local range, they argue that bleaching allows the host to be re-populated with a different symbiotic partner. Therefore, bleaching may provide an opportunity for reshuffling: a potent adaptive mechanism that instantly creates a host-symbiont combination with features that may prove more robust under altered conditions. This hypothesis could account for local and regional variations in sensitivity to stress of identical host species. Although bleaching may represent instability in the short term, it may promote long term stability by enhancing the survival chances of zooxanthellae and hosts.

2.4 MONITORING AND MANAGING CHANGES IN CORAL REEFS

2.4.1 Introduction

While geologic history shows that coral reefs have survived times of major climatic change, corals still appear to be sensitive to the combined and synergistic effects of natural and anthropogenic environmental changes on a short time scale. Coral reefs are not stable communities living in a benign environment lacking seasonal fluctuations, but are ecosystems subjected to frequent disturbances on various time scales (Brown, 1997). In fact, corals may be the first organisms to react to such natural and anthropogenic environmental changes as increased ultraviolet radiation, extreme sea surface temperatures (SST), and sedimentation.

Glynn (1996) surveyed global coral bleaching events that were reported during a 17-year period, and found that 51 events were recorded between 1979 and 1990, and 55 events between 1991 and 1995, which suggests an increasing trend over this time scale. It is unclear if there has been an increase in frequency and intensity of coral bleaching, or an increase in awareness resulting from greater frequency and intensity of observations and the increasing popularity of SCUBA diving as a recreational sport. It has become very common to hear reports of changes in coral reef ecosystems, but it remains to be shown that change has actually occurred. Monitoring coral reef ecosystems systematically and repetitively will help document the scale, extent and duration of ecosystem changes.

A thematic map delineating areas where the corals are under stress and appear bleached would enable change detection studies to determine the extent and rate of coral health decline or recovery. This information could be correlated with climatic variables to gain insight on ozone depletion, incoming ultraviolet radiation, thermal pollution or the El Niño-Southern Oscillation (ENSO), for instance. Furthermore, a time series of thematic maps revealing areas of coral bleaching or stress would also be a useful tool in resource management and planning applications. For example, the user could identify areas that appear to be under stress or recognize the periods of time that may be related to stress. Such a thematic map would be an ideal component of a GIS, which contains information regarding local industrial and mining activity, sewage depositories, river discharge and protected areas.

2.4.2 Attempts at Monitoring Coral Reefs

Over the past decade, there have been increasing efforts to establish better management and conservation measures to protect the diversity of the biologically rich areas of coral reefs (Table 2.3). Management practices have historically focused on the coral reef proper and have not considered associated communities, such as seagrass, mangroves, mudflats or watersheds, in a meaningful manner. This approach did little more than manage the reef in isolation. Current management efforts recognize the importance of including reefs as part of a larger system, where integrated coastal zone management tools can be used in the development of comprehensive management and conservation plans.

Table 2.3. A summary is provided of current organizations with the common goal of monitoring and managing coral reef and related ecosystems.

Monitoring Program	**Since**	**Goals**	**Approach**	**Comments**
International Center for Living Aquatic Resources Management (ICLARM)	1973	Resolve technical and socioeconomic constraints to increased production, improved management and equitable distribution of benefits in economically developing countries	Develop a central repository of coral reef information to provide global and regional estimates of the status and utility of coral reefs such that management priorities and actions can be initiated; such a global database facilitates geographic comparison of reefs	The degree to which such a database is able to facilitate geographic comparisons of the status of coral reefs worldwide is limited by the nature of the observation. For example, qualitative observations are not reliable means of comparison.
Coral Cay Conservation	1986	Train volunteers to conduct detailed surveys of marine resources in preparation for sound management initiatives	Use a volunteer workforce of over 900 specially trained divers to collect detailed topographic, bathymetric and biological data for the establishment of management plans	Extremely people-intensive and therefore time consuming; although specially trained, subjective and potentially inconsistent data are collected
Great Barrier Reef Marine Park Authority (GBRMPA)	1988	Sustainable management, protection and wise use of the Great Barrier Reef (GBR), Australia	Community involvement in the protection, use, care and development of the GBR; provide for economic development; achieve integrated management	Quantitative techniques of monitoring coral reef resources would be a valuable component to an effective

				management program
Coastal Zone Management Unit (CZMU)	1990	Develop management initiatives for the protection and sustainable use of the country's coastal resources	Use satellite imagery to direct a volunteer field survey program by crudely identifying geomorphologic zones	Satellite imagery is not corrected for effects of the water column and classification is based solely on colour, which limits reliability. More efficient use could be made of the satellite imagery to provide a thematic map of the area.
Planetary Coral Reef Foundation (PCRF)	1991	Further knowledge regarding global coral reefs, global climatology and provide new ideas for ecological management	Develop technique to monitor coral reef health worldwide using satellite imagery; establish a global database of coral reefs; track the health of corals worldwide; provide the technology for restoration of coral reef ecosystems	This research has not yet begun, but requires an appropriate algorithm to account for the contributions of the water column and also an index to discriminate between spectrally similar substrates
International Coral Reef Initiative (ICRI)	1994	Ecosystem and community based management; implement sustainable management practices for the benefit of coral reefs and related ecosystems	Sponsor international workshops on coral reefs to define regional needs and priorities and initiate the development of national coral reef awareness programs	
Global Coral Reef Monitoring Network (GCRMN)	1995	Improve management and sustainable conservation of coral reefs with emphasis on the	Strengthen existing capabilities to examine reefs by providing a consistent monitoring program to identify trends in coral reefs; facilitate networks of	Networks of people provide good observations on a local scale, but the objective nature of the database limits the reliability and

		involvement of local communities	people trained to look closely at coral reefs and monitor their progress over time	consistency.
Florida Keys Coral Reef Monitoring Project	1995	Assess the status and trend of Florida's offshore reefs, patch reefs and hardbottom communities to evaluate progress towards protecting and restoring living marine resources	Reefs are sampled with underwater video units using transects to provide large-area coverage; video images are analyzed for percent cover of corals and other organisms using random dot overlay procedure	Extremely labour-intensive and therefore expensive and time consuming. The spatial resolution is perhaps too fine for the purpose of managing a large coastal area.

The concept of adaptive management provides a good framework in which scientists and managers can work together, as management measures are established to enable objective testing and evaluation so that approaches and goals can be revised according to new information (Wells, 1995). Adaptive management partnerships built between scientists and managers may lead to more rapid progress in managing reefs. Clearly, dependable scientific data are crucial in convincing policy makers, funding agencies and society in general that management is necessary. Furthermore, adaptive management decisions may benefit from reliable scientific data providing information to address questions such as what requires management in what geographic area and for what purpose, as well as what is the most appropriate technology for management.

2.4.3 Remote Sensing as a Coral Reef Monitoring Tool

Since coral reefs appear to be sensitive indicators of regional climate change, it is of immediate importance to improve our ability to detect and monitor changes in coral reef ecosystems using remote sensing techniques. Although not necessarily an indicator of the absolute health of the coral reef, coral bleaching or macroalgae overgrowth is a readily observable measure of change in a coral reef environment. Under environmental stress, coral polyps expel their photosynthetic algae (zooxanthellae), lose their colour and are referred to as bleached. Loss of zooxanthellae will be used as a remotely detectable measure of coral health, as it results in a distinct loss of colour and change in spectral reflectance. Remote sensing of the spectral reflectance of corals may provide a quantitative observational technique for identifying changes in a coral reef ecosystem consistently and accurately. Furthermore, a database of the spectral reflectivity of various coral reef components could be used as an objective index to remotely identify areas of coral reef bleaching.

Remote sensing is the only means of repeatedly and nonintrusively obtaining such integrated spatial data for large coastal areas uniformly in both space and time, but the use of remote sensing in tropical marine environments is limited by the selection of appropriate technology and data availability (Green et. al, 1996). When proposing the use of a mapping and monitoring technology for a given application, it is important to recognize varying agendas, purposes and goals, including scientific advancement, accuracy, cost effectiveness, technique comparison and turnover time. For instance, it would be inappropriate to attempt to map small patch reefs using Landsat TM with 30-

meter pixels, as the spatial resolution is inadequate; in this case, an airborne multispectral scanner might be more appropriate.

Remote sensing and geographic information system (GIS) technologies are becoming less expensive, more user-friendly, more versatile, and it is widely accepted that such technologies have extensive potential for environmental monitoring and management. The extent to which this type of approach can work on a regional scale or at the community level needs to be evaluated on an individual case basis to determine the appropriate technology. The issue of cost versus accuracy must be assessed on an individual case basis as well. For example, global positioning systems (GPS) provide an inexpensive means of geocoding to accuracies of 30-50m while the improved differential GPS increases that accuracy to less than 1m, but with a substantial increase in cost. A GIS is an excellent way to integrate several types of information, such as locations of coral bleaching, coastal land use and climate data. The cost of maintaining the adequate computer hardware and software, however, may be beyond the budget limits of many interested groups. The application must therefore dictate the type of technology, as suggested in Table 2.4 (after Poole, 1995).

Table 2.4: Various applications demand different data and mapping technologies based on need, cost and purpose.

APPLICATION	DATA NEEDED	MAPPING TECHNOLOGY
Land use	Spatial data based on local knowledge	Sketch maps, GPS
Ecological status	High resolution imagery, ground truth measures	Airborne or satellite imagery corrected to various degrees based on amount of ground truth
Resource mapping	Local field data imposed on base map	Remotely sensed data compatible with ground truth measures
Change detection	Remotely sensed imagery, periodic field measures	Consistent techniques and data required for on-going monitoring

Remote sensing cannot totally replace traditional means of exploration, but it has been shown by Apinan (1986) in Thailand to shorten the time and financial requirements of a coastal zone survey. Remote sensing of coral reefs could be a valuable tool for informed coastal zone management because it can provide a synoptic view of the earth consistently and repeatedly. According to Kuchler et al. (1988), however, progress in transferring high technology remote sensing tools into mapping and monitoring practical application has been slow. For modern remote sensing technologies, such as multispectral scanners, to be widely accepted and utilized, the recording, interpretation and use of the information must be more cost-effective than traditional practices of aerial photography and ground surveys. Additionally, potential users of coral reef remote sensing technology require the product to be appropriate to their needs.

This slow progress may be the result of the historical dichotomy between academic and applied research in many sectors, where scientists might demand higher confidence levels than managers. There is thus a need to compromise and balance scientific uncertainties and management needs. Coral reef scientists rarely undertake research with the objective of making intentional value judgements or risk assessments (Done, 1995), which places the onus upon coral reef managers to evaluate the scientific results. For a rigorous decision making process, managers need to specifically communicate their objectives and precise requirements in order for scientists to develop an appropriate method, use the most suitable technology, and assess the accuracy of their results. Clearly, these scientific tasks are beyond the scope and ability of one individual researcher, which emphasizes the need for long-term interdisciplinary collaboration.

2.5 SUMMARY

A large proportion of the coral reef resources in the world is in danger of destruction due to overexploitation and degradation of habitat. Several initiatives are underway to monitor the status of and threats to reefs at global, national and regional scales, but little progress has been made in developing database systems that will ensure broad dissemination of data and consistent, reliable quantitative interpretation and comparison of results.

Global awareness of coral reef ecosystem degradation has increased recently, which has encouraged monitoring and sustainable conservation endeavours. The majority of the monitoring programs use trained observers to document changes in the ecosystem over a relatively small area. While this technique is potentially thorough and accurate, it is inefficient with respect to time, money and space.

Alternatively, remote sensing can provide quantitative information quickly and relatively inexpensively compared to the cost of employing researchers to observe an equivalent area. The spatial coverage of a satellite image would provide managers with valuable geographic information regarding coral reef ecosystems, and allow informed decisions to be made on a regional basis. While managers do not demand 99% accuracy, sound management decisions rely partially upon reliable scientific techniques and results. A quantitative means of mapping and monitoring the well-being of coral reef environments will provide decision makers with the baseline information with which to develop management programs.

CHAPTER 3

MARINE REMOTE SENSING

3.1 INTRODUCTION

The purpose of this chapter is to provide an overview of the problems and advantages associated with remote sensing in a marine or coastal environment. Future planned satellite missions are discussed with reference to their applicability to monitoring the coral reef environment and previous attempts to applied remote sensing technology to the marine or coastal environment are outlined. Furthermore, the potential sources of error associated with remote sensing in general and remote sensing in the coastal zone in particular are presented.

3.2 MARINE REMOTE SENSING

Historically, aerial photography and navigational charts have been the basis of our knowledge of the regional-scale geographic extent of coral reefs. Navigational charts are restricted to deep areas accessible by ship-borne depth sounders, and photographic coverage of tropical coral reefs is often out of date due to the expenses involved in acquiring such information. Furthermore, although qualitative information on bottom composition of shallow water zones can be provided by aerial photographs, interpretation is complicated by the fact that water depth variations are difficult to distinguish from bottom colour variations.

Multispectral sensors on board satellite or airborne platforms are superior in quality to aerial cameras with respect to spectral resolution. This is primarily because multispectral sensors have distinct wavelengths in which radiance is sensed rather than the panchromatic feature of a traditional camera. Specific wavelengths in the visible region of the electromagnetic spectrum can be selected with multispectral sensors to maximize the penetration of energy through the water column, thus providing the most information regarding subsurface features.

The availability of accurate base maps is a prerequisite for the ecological assessment of marine resources, but the current inventory of maps is inadequate (Mumby et al., 1995). One of the greatest limiting factors in assessing the effects of stress on coral reefs is the general lack of quantitative data, both spatial and temporal (Grigg and Dollar, 1990). Although remote sensing technologies have potential for overcoming this quantitative void, there are many complications associated with extracting valuable information from imagery with confidence. One problem with remotely sensed measurements is that the atmospheric path between object and sensor will modify characteristics of the received radiation. The air-sea interface introduces to a second complicating factor since the amount of energy transmitted into the sea versus that reflected off the surface depends on sea surface state, wind speed and sun angle (Figure 3.1). A third problem with remote sensing of shallow water substrates is the difficulty in separating the water column signal from the substrate signal.

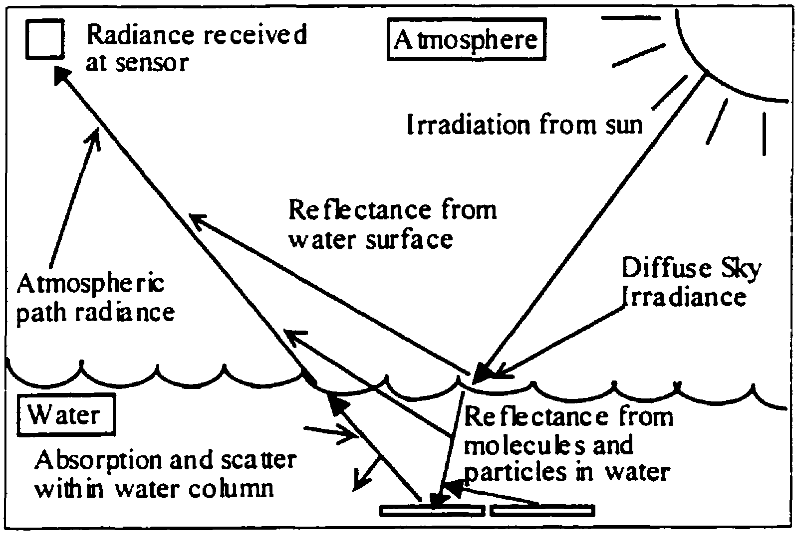

Figure 3.1. This schematic of the interactions between electromagnetic energy and the atmosphere and water reveals the complexity of the problem of radiative transfer in a marine environment.

3.3 FUTURE SATELLITE SENSORS

The next generation of satellites promises to host high-resolution sensors capable of generating imagery with spatial resolutions of 4m in multispectral mode (Alpin et al., 1997). Both the United States and Australia are planning launches of hyperspectral sensors onboard satellite platforms in the year 2000. The availability of many narrow spectral bands will greatly improve the ability to identify submerged coral reef features. The expected spatial resolution will be coarse (approximately 30m), which will limit high detail mapping of the coastal zone, but will enable regional scale inventories to be accomplished.

The poor spatial resolution of most future satellite sensors will limit their use for coral reef ecosystem mapping. Pixel size limits the amount of detail that can be extracted from the satellite image, but for regional-scale mapping, larger pixel sizes are preferable in order to minimize costs. The limiting factor for accurate identification is the spectral resolution of the sensor: the bandwidth and number of bands. There appears to be a technology-limited trade-off between spatial and spectral resolution (Alpin et al., 1997) such that as the pixel size decreases, typically the width of the spectral bands increases. Broad wavelength bands do not allow detection of subtle spectral characteristics, which decreases feature identification accuracy. In short, high spectral resolution allows identification of features in a scene, while high spatial resolution allows location of features in a scene (Gross and Schott, 1998).

The most important characteristic to consider when selecting a passive marine remote sensor is its ability to penetrate the water to the depths of interest. Therefore, only sensors with wavebands in the visible portion of the electromagnetic spectrum are useful for submerged feature detection. This requirement eliminates passive sensors using synthetic aperture radar (SAR), for example.

Furthermore, remote detection of submerged corals is complicated by the fact that large, discrete patches of bleached coral are rare, and the spectral signatures of individual coral heads are strongly influenced by surrounding coral and substrate, as well as the overlying water column within the sensor's field of view (FOV). Therefore, a sufficiently small pixel size is required to detect individual coral head bleaching. Additionally, a sufficiently high spectral resolution is required to enable spectral distinction of coral reef substrate types, which may have only very subtle spectral differences.

Table 3.1 briefly lists some characteristics of available satellites and sensors, which have capabilities of investigating marine features, and a table explaining abbreviations and acronyms is provided in Table 3.2. A more complete discussion of the satellite sensors available at present and in the near future is provided following the summary tables.

Table 3.1. Visible wavelength/multispectral sensors and their satellite platforms of use in marine remote sensing listed in chronological order.

Satellite	Sensor	Launch	Spectral Resolution	Spatial Resolution	Country
LANDSAT	TM, MSS	yes	7 visible, IR and thermal bands with 60-140nm resolution	30 -80 m	USA
SPOT	HRV	yes	3 visible and IR bands with 70-100nm resolution	10 - 20 m	France
IRS-P3	MOS-IRS	yes	18 multispectral bands	500	India, Germany
IRS-1C, RESURS	PAN, LISS, WIFS, MSU	yes	panchromatic	5 - 188 m	India, Russia
ADEOS	OCTS	Failed, 1997	8 visible and NIR; 4 thermal IR	700 m	Japan
ORBVIEW2	SeaWiFS	yes	8 multispectral bands	1100 - 4000 m	USA
EarlyBird	hi-res optical	Failed, 1997	3 visible and IR bands with 50-110nm resolution	1 - 15 m	USA
ORBVIEW3 & IKONOS1	hi-res optical	1999	4 visible and IR bands with with 70-140nm resolution	1-8	USA
LANDSAT-7	ETM	1999	8 visible, IR and thermal bands with 60-140nm resolution	15 -60 m	USA
EOS-AM	MODIS	1999	36 bands	250 - 1000m	USA
NEMO	COIS	June, 2000	210 bands with 10nm bandwidth	30-60m	USA
ARIES	ARIES	2000	105 bands with 16nm bandwidths	30m	Australia
SPOT-5	HRG	2002	4 visible and IR bands with 70-290nm resolution	10 and 20m	France
AVNIR-2	ALOS	2002	4 visible and IR bands with 80-100nm resolution	2.5m	Japan

Table 3.2. An explanation of acronyms used in the table above, listed in alphabetical order.

Acronym	Explanation
ADEOS	Advanced Earth Observing Satellite
ARIES	Australian Resource Information and Environment Satellite
ASAR	Advanced Synthetic Aperture Radar
AVNIR	Advanced Visible and Near Infra-red Radiometer
COIS	Coastal Ocean Imaging Spectrometer
ENVISAT	Environmental Satellite
EOS	Earth Observing System
ETM	Enhanced Thematic Mapper Plus
HRG	High Resolution Geometry
HRV	High Resolution Visible
IRS	India Remote Sensing Satellite System
LANDSAT	Land Remote Sensing Satellite
MERIS	Medium Resolution Imaging Spectrometer
MODIS	Moderate Resolution Imaging Spectrometer
MSS	Multispectral Scanner
NEMO	Naval Earth Map Operation
OCTS	Ocean Colour and Temperature Scanner
SeaWiFS	Sea-Viewing Wide Field of View Sensor
SPOT	Satellite pour l'Observation de la Terre
TM	Thematic Mapper

3.3.1 Satellite Sensors

The "hi-res optical" onboard the EarlyBird/ Space Imaging/ Orbview satellite, was launched in December 1997, but the mission failed. The pixel size of the "hi-res optical" was to be 1m for panchromatic images and 4m for multispectral images, which would have been a substantial improvement over the spatial resolution available at the present time.

The Indian Space Research Organization (ISRO) successfully launched the IRS-1D Earth Imaging satellite on September 29, 1997. This satellite and its identical twin, IRS-1C launched in December 1995, will not commence full operation until on-orbit testing is complete early in 1999. The dual use of these twin satellites allows 5.8m spatial resolution to be available to customers twice as often as with just IRS-1C. Additionally, users of IRS-1C and D will be able to take advantage of frequent updates of as little as three days, which is crucial for monitoring events that are changing quickly over time. Unfortunately, this 5.8m resolution imagery is only available in panchromatic (black and white) mode, which has limited applicability when attempting to identify spectrally similar submerged features such as distinguishing between bleached and healthy coral. Panchromatic images are especially limiting in a coral reef environment if the objective is to map submerged features, as only visible wavelengths penetrate the water column to appreciable depths. These satellites are also equipped with LISS-3 multispectral sensors that provide 23.5m spatial resolution, which may be adequate for certain large-scale monitoring applications. More information can be obtained at the Web Site: http://www.spaceimage.com.

The usefulness of ocean colour remote sensing is well recognized, largely as a result of the successful launch of the Coastal Zone Colour Scanner (CZCS) on Nimbus-7 in 1978. No spaceborne ocean colour sensor replaced the CZCS when it ceased to operate in early 1986 until August 17, 1996 when the Advanced Earth Observing Satellite (ADEOS) was launched successfully by the National Space Development Agency of Japan (NASDA) (Ishizaka et al., 1997). The OCTS sensor onboard the ADEOS satellite is no longer available, as it failed after only 7 months. While OCTS had 8 bands in the visible and near-infrared, a spatial resolution of 700m at nadir made its use for mapping coral reef ecosystems marginal. For further information, see http://mentor.eorc.nasda.go.jp/ADEOS/DataAdeos.html.

The OrbView-2 spacecraft (formerly SeaStar) was launched on August 1, 1997 carrying the SeaWiFS instrument, and data from the satellite can be acquired from ORBIMAGE and NASA. The objective of this project is to obtain broad-area multispectral remotely sensed imagery, and it is the first privately owned remote sensing satellite to be launched and operated. While SeaWiFS will provide valuable information for global change research and large scale environmental monitoring, the spatial resolution of greater than 1000m limits its use for coral reef remote sensing. Further information can be obtained at http://www.orbimage.com.

The Moderate resolution Imaging Spectroradiometer (MODIS) has an unscheduled launch date in 1999 on the EOS-AM satellite platform. MODIS will enable a comprehensive daily evaluation of the earth's surface with 36 spectral bands with a spatial resolution of 250-1000m.

Also scheduled for launch in 1999 is Landsat-7, which will carry the Enhanced Thematic Mapper Plus (ETM) sensor. The ETM is based on the design of the Thematic Mapper TM instruments flown aboard Landsat 4/5 and it will provide 8 spectral bands in the visible, near IR, short-wave IR and thermal IR regions at spatial resolution of 15m, 30m and 60m. ETM scenes will provide affordable (<USD600/image) moderate spatial and spectral resolutions, which may be of use for coastal mapping for many regional-scale applications.

The Medium Resolution Imaging Spectrometer (MERIS) will be launched by the European Space Agency in 1999, and will provide the first spaceborne European remote sensing capability for observing oceanic biology through observations of water colour (Bezy et al., 1996). MERIS is a 15 band programmable imaging spectrometer with a spectral range restricted to the visible near-infrared portion of the spectrum between 390 and 1040nm and a spectral bandwidth of between 1.25 and 30nm. Although MERIS will have a high spectral and radiometric resolution, the best spatial resolution possible will be 300m, which is a limiting factor for accurate and confident coral reef remote sensing.

In partnership with Space Technology Development Corp., the US Navy is planning to launch NEMO (Naval Earth Map Operation) in June 2000. A hyperspectral sensor, COIS (Coastal Ocean Imaging Spectrometer), will be onboard NEMO, which will provide 30-60m spatial resolution imagery in 210 bands with 10nm bandwidths. The spectral range will be from 400-2500nm and the swath width will be 30km. The data provided from this sensor will be highly appropriate for mapping submerged features in the coastal zone on a regional scale. The large pixel size will provide relatively low detail mapping for a large area, thus allowing cost-effective regional analysis. The high spectral resolution will enable identification of subsurface features with higher accuracy than possible with presently available satellite sensors. The cost of one image is not yet known, as of October 1998 at the Fifth International Conference on Remote Sensing for Marine and Coastal Environments, San Diego.

Competing with the USA to be the first to launch a satellite with a hyperspectral sensor onboard are the Australians with their ARIES (Australian Resource Information and Environment) satellite. This satellite has a planned launch in 2000, although a specific launch date has not been set. The hyperspectral sensor onboard ARIES will have 30m spatial resolution and a spectral coverage from 400-2500nm with 16nm wavelength bands. The swath width will be 15km with a revisit time of 7 days. The cost of each image is unknown although they will be making the satellite imagery as well as simulation airborne imagery available to a limited number of successful applicants competing for access.

3.3.2 Airborne Sensors

Presently available airborne spectroradiometers offer acceptable spatial and spectral resolution for mapping submerged coral reef geographic extent. The price of acquiring such airborne imagery is often quite high due to the fact that reefs of interest are often isolated and located in developing countries. Airports do not commonly serve these areas, and it is difficult to rent appropriate aircraft. In addition, a smaller geographic area is covered on one image, so it takes longer to acquire coverage of an area equivalent to a satellite image.

The Airborne Visible/Infrared Imaging Spectrometer (AVIRIS), designed by the Jet Propulsion Laboratory in 1983, has been used to collect high-resolution imagery since 1987. AVIRIS was the first imaging spectrometer to measure from 400 to 2500nm in 224 contiguous spectral channels at 10nm intervals. AVIRIS images are 11 km in width and up to 800km in length with 20m spatial resolution. Use of AVIRIS imagery in the visible wavelengths able to penetrate the water would be an excellent option for mapping and monitoring submerged coral reef ecosystems.

Airborne *casi* (Compact Airborne Spectrographic Imager) imagery has been used recently by George (1997) to map bathymetric data of a lake with the assumption that the bright pixels on the image were areas of shallow water. George (1997) tested a variety of water depth algorithms for bathymetric charting in marine and freshwater environments. George (1997) reported that the quality of the *casi* instrument produces low-noise, high-resolution images of very low reflectance targets, which allows for operation over land and water without saturating the sensor.

Clark et al. (1997) acquired *casi* data at 1m spatial resolution of a tropical coastal environment, and attempted to map a reef habitat without performing ground-based reference measurements. This study was done to provide a high resolution best-case assessment of coastal mapping to test the accuracy of coarser spatial and spectral resolution satellite imagery. While the authors acknowledge that some of the variations in colour on the image result from bathymetric changes, they concluded that the dominant control is the nature of the marine habitat. Therefore, no correction was applied to account for attenuation and multiple scattering, which contributes to the remotely sensed signal of a submerged habitat.

Other high-resolution airborne spectrometers are available such as the Daedalus Airborne Thematic Mapper, which has been recently used to survey phytoplankton chlorophyll in lakes (George, 1997). With ground truth verification available, algorithms were tested in this study to determine the optimal procedure for estimating chlorophyll concentrations.

The Advanced Airborne Hyperspectral Imaging System (AAHIS) is a compact, lightweight, portable hyperspectral imaging spectrometer developed by a US company called Science and Technology International. AAHIS is optimized for coastal environments with an operational range between 433 and 832nm at 5.5nm resolution.

The spatial resolution of AAHIS is dictated by height at which it is flown. For example, when flown at 6000 feet, AAHIS images have 2-meter pixels with 72 spectral channels. This would be an ideal instrument for high-detail mapping of coral reef ecosystems and related coastal ecosystems due to its high spatial and spectral resolution. The cost of operating this instrument, especially for coverage of large areas, is prohibitive to all but major government agencies.

An alternative to the passive techniques discussed above is an active airborne system, such as an airborne laser system, which is a proven tool for shallow water bathymetric surveying. An airborne laser sounder transmits green and infrared laser pulses to measure water depth. The infrared beam is reflected from the water surface and the green beam penetrates the surface into the water and is reflected from the bottom, objects in the water, and the water itself. The water depth is determined from the time difference between surface and bottom "echoes" (Steinvall et al., 1997). The use of airborne laser technology is presently being investigated for its usefulness in mapping bottom topography and substrate type (Steinvall et al., 1997).

3.4 MARINE REMOTE SENSING RESEARCH

Recently, remote sensing technologies have been used successfully in marine environments to gain valuable information on the extent and state of various submerged features (Table 3.3). Much of the work in Table 3.3 is based on classification of spectral response (e.g. Bina et al., 1979; Bour et al., 1986; and Mumby et al., 1994), yet few attempts have been made to account for effects attributable to variable water depth and turbidity. In some cases, to remove water depth and turbidity variation, images have been assumed horizontally and vertically homogeneous, and corrections have been applied to the entire image by subtracting a constant digital value or computing ratio values (e.g. Lyzenga, 1978; Vel and Bour, 1990; Estep 1991b). The assumption that both the vertical water column and the horizontal water surface are homogeneous may be unrealistic in many coral reef environments.

Table 3.3. A summary of work published to date on remote sensing of subsurface features, listed in alphabetical order.

AUTHOR	FEATURE	SENSOR	TECHNIQUE
Ackleson and Klemas, 1987	Submerged vegetation	Landsat MSS and TM	Comparison of ability to detect submerged vegetation using classified MSS and TM images
Ahmad and Neil, 1994	Coral reef zones	Landsat TM	Canonical variate analysis
Bierwirth et. al., 1993	Shallow bottom reflectance	Landsat TM	Mathematical constraint used to create residual representative of substrate reflectance
Bina et al., 1979	Coral reefs	Landsat TM	Supervised and unsupervised classification
Borstad et. al, 1994	Coastal Areas	Airborne *casi*	Integration with GIS
Bour et. al. 1986	Trochus shells	SPOT Simulation images	Comparison with ground truthing and aerial photography, polar coordinate transformation, classification
Bour, 1988	Living Corals	SPOT HRV	Classification based on bidimentional histogram
Clark et al., 1997	Tropical coasts	Airborne *casi*	Initial visual interpretation
Estep, 1991a	Bottom reflectance	Analytical	Inverted single scatter irradiance model
Estep, 1991b	Bottom sediments	Scanning spectro-radiometer	Eigenanalysis of in situ data to estimate bottom reflectance spectra to understand radiative transfer processes
Gordon and Brown, 1974	Water column constituents	Analytical	Monte Carlo
Hardy et. al.	Coral	Laser-	Laboratory study of use of remotely

1992	Bleaching	induced fluorosensor	sensed laser induced fluorescence to monitor coral pigmentation
Holden and LeDrew, 1998	Coral reef features	in situ radiometer	Principal components analysis, cluster analysis, derivative spectroscopy
Holden and LeDrew, 1998	Coral reef features	in situ radiometer	Principal components analysis, cluster analysis, derivative spectroscopy
Jupp et al., 1985	Coral reefs	Landsat	BRIAN System: Barrier Reef Image Analysis; band ratios used to separate depth and substrate type
Khan et. al., 1992	Subtidal coastal habitats	Landsat TM	Eigenvector rotation of TM 1 and 2 to enhance bottom type variation and reduce the effect of water depth variation
LeDrew et. al, 1995, 1996	Coral reefs	SPOT HRV	Optical correction of water column with published algorithm
Lubersac et. al., 1991	Geomorphology of bottom	SPOT HRV	Numerical transformation method for decorrelating XS1 and 2
Luczkovich et. al., 1993	Coral reefs, sea grass and sand	Landsat TM	Multivariate analysis of variance
Lyzenga 1978	Bottom features and water depth	Multispectral scanner data	Ratio processing algorithms, principal components analysis
Lyzenga 1981	Bottom reflectance	Landsat MSS	Linear transformation algorithm
Maritorena, 1994	Shallow water reflectance	Analytical	Analytical formulae
Michalek et al., 1993	Submerged features	Landsat TM	Change vector analysis
Mobley, 1993	Underwater light fields	Analytical	Invariant imbedding
Morel, 1996	Coral reef lagoon	SPOT HRV	Published algorithms and coefficients
Mumby et. al., 1994	Coral reefs	SPOT PAN	Supervised training classification
Peddle et. al, 1995, 1996a & b	Coral reefs	SPOT HRV	Spectral mixture analysis to separate end member spectra at sub-pixel scales
Philpot, 1987	Ocean colour	Analytical	Single scattering irradiance model
Spitzer and Dirks, 1987	Bottom depth and composition	Analytical	Two-flow radiative transfer
Vel and Bour, 1990	Shallow coral reefs	SPOT HRV	Non-linear polar coordinate transformation, created texture pseudo-channel for feature detection,

			supervised classification
Zainal et al., 1993	Submerged features	Landsat TM	Principal components analysis
Zainal, 1993	Submerged features	Landsat TM	Analysis of GIS of digital elevation model (DEM) and digital numbers (DN)
Zwick et al., 1981	Distribution and concentration of suspended material and chlorophyll	Analytical	Mathematical models for atmosphere, water-air interface, and water optics

Mazel (1997) has developed a new spectrofluorometer to measure *in situ* fluorescence emission over the full spectrum. This instrument has been used successfully at several field locations for investigating the optical properties of coral reef organisms and for collecting baseline data in support of remote sensing systems. This active sensor is proving to be a valuable tool for collecting spectral fluorescence and reflectance signatures of submerged organisms thus enabling the beginnings of a library of spectral signatures. This information will be used to interpret remotely sensed data and as a tool in understanding the nature and variability of the optical properties of benthic organisms and substrates. Mazel has not published any quantitative analysis of the spectra collected to date.

Hardy et al. (1992) examined the potential of using actively sensed laser-induced fluorescence to monitor coral pigmentation. Bleached coral samples, containing fewer photosynthetic pigments than healthy samples, were irradiated at 532 and 337nm with pulsed laser light, and spectral scans of fluorescence were collected at 1nm intervals. Clear and dramatic changes in active fluorescence spectra of corals using laser-induced spectroscopy were found: distinct reflectance peaks were found at 685 and 740nm corresponding to fluorescence in all five species. Moreover, under the influence of artificial temperature-induced stress, changes in the fluorescence spectra were detected prior to visible bleaching.

The NASA airborne laser can penetrate 30 meters in clear oceanic water (Hoge et al., 1986a & b), which lends encouragement to future studies of submerged coral fluorescence. Airborne laser-induced fluorescence (LIF) sensors can cover large areas rapidly, but pose problems of scale and resolution. For example, at a flight speed of 100 meters per second and 20 pulses per second, one fluorescence measurement would be collected every 5 meters, so several over-flights would be necessary to characterize the pigment of a reef (Hardy et al., 1992). Furthermore, the maximum depth from which a useful return signal can be processed and distinguished is dictated by the attenuation of a projected laser light source through the water (Cianciotto, 1995). An attenuation coefficient, described in a simple equation for light intensity as a function of distance from the light source in water, can be calculated to account for loss of light (Cianciotto, 1996).

A LIDAR (Light Detection and Ranging) system uses a pulsed laser to measure the fluorescence emitted by aquatic and terrestrial chlorophyll pigments (Hardy et al., 1992). With high directionality and intensity of laser radiation, LIDAR is able to observe large volumes of the ocean at high spatial and temporal resolutions while operating in narrow frequency bandwidths, which permits high signal-to-noise ratios (Cianciotto, 1995). The major advantage of gated LIDAR is that backscatter from layers of water above the coral substrate is eliminated, so the sensor only receives a return signal from the underlying substrate.

Since an imaging LIDAR system can be optimized by customizing the wavelength of the laser to specific atmospheric and water conditions, and multiple LIDAR systems can image simultaneously, chlorophyll fluorescence may more easily be detected than it would with a passive sensor. Phytoplankton pigments in the water column, which display similar fluorescence spectra to the pigments in the coral polyp, are potential sources of interference. Hardy et al. (1992) believe that the high pigment densities of corals would produce a stronger fluorescence signal than the overlying phytoplankton, especially for surface water less than 10 meters. Regardless, a nanosecond pulsed LIDAR system will detect two signals: one from the water surface, and one from the bottom, so the instrument can be time or depth gated to detect fluorescence only from the coral substrate, and to ignore the water column's phytoplankton response. Without the necessity of considering pigment fluorescence from phytoplankton in the water column, LIDAR offers a potentially useful method of determining the chlorophyll fluorescence of the coral alone. Therefore, it is beneficial to study the laser-induced chlorophyll fluorescence characteristics of individual coral heads for future application of LIDAR remote sensing of coral reefs.

3.5 SOURCES OF ERROR AND LIMITATIONS OF REMOTE SENSING

The capability of marine remote sensing technology may have been oversold in the past, so potential users have suffered disillusionment (Green et al., 1996). This phenomenon may result from failure to understand and communicate the fundamental limitations of remote sensing such as wavelength-specific penetration of light through water, spectral mixing within a pixel, and atmospheric attenuation.

Of course, the importance of each source of error or limitation depends on the objective of the remote sensing application, and varies from sensor to sensor. In fact, some limitations may be viewed as desirable in some applications. For example, data from sun-synchronous orbital satellites, such as SPOT, are collected at the same time each day. If the objective of the study is to document diurnal changes, then this type of orbit is a limitation, but if the objective is to monitor changes over a period of time, then this type of orbital consistency might be desirable.

Two broad categories of sources of error within marine remote sensing are (1) technical and (2) user limitations. Technological limitations are expected to be overcome with the development of new sensors, while user and management problems could be minimized by clearly defined objectives and requirements on the part of the manager, and full communication of possible errors and limitations from the scientist. Potential constraints to the technical and practical use of remote sensing for applications in the tropical coastal zone are presented in Table 3.4 with some possible solutions to the problems.

Table 3.4. Technical and practical constraints to marine remote sensing.

LIMITATION	EFFECT	SOLUTION
Coarse spatial resolution	Unable to detect spatial features within pixel; mixels	Spectral unmixing
Coarse spectral resolution	Unable to detect small spectral characteristics	Analytic techniques
Inappropriate spectral band location	Spectral characteristics lost within broad-band	Hyperspectral sensors
Infrequent temporal resolution	Difficult to perform temporal change analysis	Airborne imagery
Variable water attenuation	Confusion between deep water and dark substrate	Radiative transfer correction
Variable atmospheric conditions	Restricts comparison of multi-temporal images	Radiometric correction
Cloud cover	Obscures area of interest	Airborne imagery
Ground control unavailable	Poor geopositional accuracy	Differential GPS
High cost of imagery, hardware, software and expertise	Remote sensing not used to potential, change analysis not common	International cooperation
Inadequate user training	Inaccurate analysis, incorrect techniques	Communication between expert and user

The most problematic technical limitation of remote sensing in the tropics is likely cloud cover, as it significantly reduces the number of suitable images available. The problem of cloud cover depends on both the season and the location of interest. Other major technological limitations include atmospheric attenuation, as well as spectral and spatial resolution of available sensors. Although atmospheric attenuation can never be eliminated, radiative transfer algorithms are available to remove these effects if the required atmospheric variables are known.

The spectral resolution is important due to the limited penetration of light in water of some wavelengths. Since visible light penetrates to greatest depths in the clear waters of coral reefs, these wavelengths are ideal. Additionally, the width of the wavelength bands contributes to the overall accuracy of submerged feature detection. A waveband might be so wide that it obscures a spectral response that would have been detectable had the waveband been narrower. The spatial resolution of the sensor controls the amount of mixing within a pixel. Every pixel is actually a mixel since areas of heterogeneous substrate within a pixel are given an average brightness value. The smaller the pixel, the better the sensor for coral reef remote sensing, as there is great variability of bottom cover.

User limitations complicate the practical use of remote sensing to manage a coral reef ecosystem. The largest source of error in the use of remote sensing as a management tool, for example, is the failure to clearly define project objectives. Also included in the user limitations category are: the high cost of obtaining digitally recorded remotely sensed imagery; the problems involved in standardizing multiple images to account for different atmospheric, sea surface and water column conditions; and the difficulty in making rigorous accuracy assessments. Few studies have made comparisons of the capabilities of different sensors for particular objectives (Green et al., 1996). A study comparing the technical capabilities of various sensors based on cost effectiveness would allow scientists, planners and policy makers to produce an informed decision regarding the appropriate sensor and approach for their particular research objective. Additionally, the inclusion of an accuracy assessment of inventory and mapping projects using remotely sensed data would aid in the management decision making process.

3.6 SUMMARY

The complexities of remote detection of coral reef features have not been solved, although it is clear that progress has been made in the fields of water optics and algorithm development. Both empirical and analytical approaches are contributing to the understanding of how visible light interacts with the water surface, the water column and the shallow sea bottom.

The optical similarities of coral reef components present significant challenges for remote identification. Optically bright subsurface features, such as sand and bleached coral, are easily confused, while optically dark features such as seagrass, healthy coral, deep water and macro-algae are also inextricable. Experimental laboratory results involving active sensors have reported promising findings regarding spectral separation of bleached and healthy corals (Hardy et al., 1992). Furthermore, *in situ* experiments using passive technology to discriminate subsurface features have provided encouraging results (Holden and LeDrew, 1998a&c). Readily available images using passive remote sensing may therefore be an adequate tool for identifying subsurface features.

CHAPTER 4

STUDY AREAS, DATA AVAILABLE AND ANALYSIS TOOLS

4.1 INTRODUCTION

Data collection was performed in three consecutive years (1996, 1997 and 1998) in distinct geographic locations. In August 1996, spectral data were collected in Beqa Lagoon, Fiji; in July and August 1997, data collection took place in Manado, Indonesia; and in July and August 1998, fieldwork was carried out in Savusavu Bay, Fiji. Because this is the first known data set of *in situ* underwater spectra, and due to the complex nature of the sampling environment, it will be necessary to explain the challenges of field data collection and to describe the methods used to measure underwater spectra. The first purpose of this chapter is to describe the three study sites used for data collection. Further objectives of this chapter are to summarize the data available; to outline the data processing steps: to define the data analysis techniques employed; and, finally, to present some errors associated with spectral data measurements.

First, the sampling methodology designed to overcome the specific problems of underwater spectral measurements will be described. Next, the data collection techniques, instruments, and processing steps common to the three study sites are presented. Each study site is described separately with a complete presentation of data available at each site. Following the description of study sites and data available for each year, a summary of objectives and data analysis techniques are presented. Possible sources of error in collection of spectral reflectance in the field are also discussed.

4.2 DESCRIPTION OF UNDERWATER SAMPLING METHODS

The minimum number of assistants required for the sampling methods designed for *in situ* spectral measurement is four. One person remains on the boat as the spectrometer computer operator, while three scuba divers are underwater. One scuba diver holds the sensor and coils the unused optical cable, one takes a photograph of the measured feature and the third diver takes notes on an underwater template. Extra field assistants can dole out the cable from the boat to provide the optimum amount of cable, or an extra scuba diver can coil cable underwater to avoid tangles with branching corals and other features.

The computer operator on the boat is responsible for setting up the instrument; taking an above water reference measurement; setting the integration time of the instrument before each reference and target (coral, sand, etc.) measurement; and taking notes on sky and water surface conditions. The computer operator must be able to communicate with the underwater instrument operator. To accomplish this, a communication system is used whereby the scuba diver can talk with and hear the above water computer operator. An acoustic system designed for the US Navy is now commercially available which allows divers to talk to and hear an above-water person. The below water apparatus is attached to the diver's breathing regulator with a mouthand earpiece. A push-to-talk system is located on the mouthpiece of the underwater apparatus. The above water apparatus consists of a headset with a push-to-talk mechanism to allow two-way communication through a sensor that is dropped over the side of the boat to transmit the remote signals.

All three scuba divers descend at the same time. The scuba diver holding the instrument finds an appropriate target (coral, sand, etc.), orients the sun away from the body, and holds the sensor ready for a downwelling irradiance reference measurement. The reference measurement is taken by inverting the cosine receptor to measure the downwelling irradiance. The underwater operator indicates to the above water operator that a reference measurement can be taken. Once a downwelling reference measurement has been taken, an upwelling measurement is immediately captured of the target of interest.

A downwelling reference measurement is taken prior to each target measurement. Furthermore, multiple measurements are taken at each site to examine the variability within a given feature. The sensor is then inverted to take a target measurement. When the sensor is level and in place, the underwater operator communicates with the above water computer operator, who captures the upwelling radiance scan of the target. Once the measurement procedure is complete for one site, the underwater sensor operator signals to the other 2 scuba divers, swims aside and waits.

The underwater photographer takes a nadir shot of the target of interest at multiple levels to document the surface type as well as the surrounding substrate. The note taker records information regarding the target type, size, morphology, surrounding substrate, water depth, water quality, percent cover of branches, percent cover of algae, and any other pertinent information. When the notes and photographs are complete, the team moves together to the next sample site and repeats the procedure.

4.3 DATA COLLECTION AND PROCESSING COMMON TO THE THREE YEARS

The purpose of collecting three years of data was to create the first spectral database of the passive reflectance characteristics of coral reef features *in situ*. This database is important, as it allows for the fundamental study of the optical properties of features in a coral reef environment. This fundamental stage of spectral characterization allows for more accurate remote identification of coral reef features in the future. The common objective of taking spectral measurements of the reef substrate in all three years was to characterize spectral features of various reef components such as healthy coral, macro algae, bleached coral, sand and debris.

Essentially, the same instrumentation and sampling design were used and followed each year, with only minor differences as a result of external funding available. Each year a hyperspectral handheld radiometer (Analytical Spectral Devices, Personal Spectrometer II) was used to measure *in situ* reflectance of as many coral reef features as possible. This portable spectrometer can detect radiation in the range of 350 to 1050nm at a spectral resolution of 1.423nm. Only the visible wavelengths are of interest in this study, for only they are able to penetrate the water column with minimal attenuation and therefore prove useful for future passive remote sensing applications. Each year, a cosine receptor, which has a hemispherical field of view (FOV), was used to collect spectral data with the radiometer. The cosine receptor was held at a nadir angle approximately 5cm above each feature of interest. Although the cosine receptor has a hemispherical field of view, the primary response from the cosine receptor is expected from a field of view of approximately 60 degrees, so an area of $26cm^2$ is the expected area of measurement. A global positioning system (GPS) was available each year, as well as a camera for documenting the feature that was measured with the radiometer.

The sampling strategies in 1996, 1997 and 1998 were the same: collect the greatest amount of spectra possible with the highest degree of quality control. For the most precise spectral reflectance measurements, sampling should occur when the sun is highest in the sky, so data collection was limited to between 10am and 2pm local time. The level of generality in the sampling methodology was chosen to suit the use to be made of the data. For example, broad groupings of corals were used based on similarity of form and health (branching vs. massive corals and healthy vs. bleached corals).

The determination of reflectance is based on two measurements taken sequentially from the same instrument. First, a reference downwelling irradiance measurement is collected with the cosine receptor by leveling the sensor facing the sky. Immediately following the irradiance reference is an upwelling radiance measurement of the feature of interest. The time lapse between the reference and target measurements was considered negligible, as effort was made to minimize the interval. Furthermore, there was little chance that environmental conditions changed during the interval between the reference and feature measurement since data were collected under clear skies and calm surface water conditions.

The spectrometer automatically references the upwelling radiance to the total downwelling irradiance, giving a measure of spectral reflectance for the feature of interest. The spectrometer was programmed to average three measurements of both downwelling irradiance and upwelling radiance, so the spectra used in this study are actually three averaged spectra of the same target.

No radiometric calibration of the spectral data was necessary, as the values used in the analysis are reflectance values and not radiance measures. However, a dark current measurement was collected for each spectral measurement. This dark current is subtracted from all subsequent spectral measurements to correct for the light signal when the detector array is closed to light. Since the dark signal varies over time, a dark current measurement accompanied each target measurement.

4.4 STUDY SITE DESCRIPTION AND DATA AVAILABLE

4.4.1 August 1996 Study Site, Beqa Lagoon, Fiji

The 1996 field data were collected in Beqa Lagoon, Fiji under clear skies between 10:30 AM and 1:15 PM local time on August 8-10, 1996. Using a high spectral resolution hand held spectrometer, *in situ* spectral data of various submerged coral reef features were collected at close range. This was possible by using a ten-meter fibre optic cable, which enabled a scuba diving operator to measure substrate reflectance just above the target. Measurements are therefore representative of the feature without the attenuating effects of the water column.

A hand-held sonar echo-sounding device recorded water depths for each spectral measurement that ranged between 2.7 and 2.9m. This is a small depth range (0.2m), so no correction was performed to account for differences in water attenuation between spectral measurements. The water column between the sensor and the target is assumed negligible since the remote cosine receptor was held at approximately 5cm above the target, so no correction for attenuation was performed.

A Global Positioning System provided geographic coordinates of 18° 19.45S, 178° 06.48E for the vicinity of the study site, and an underwater photographer identified and took a picture of each target measured for future reference. The dataset includes 40 spectra representing bleached corals (n=9), healthy corals (n=21) and algae-covered surfaces (n=10). For visual examination, the spectra were separated into these three broad categories and plotted separately below in Figure 4.1, 4.2 and 4.3.

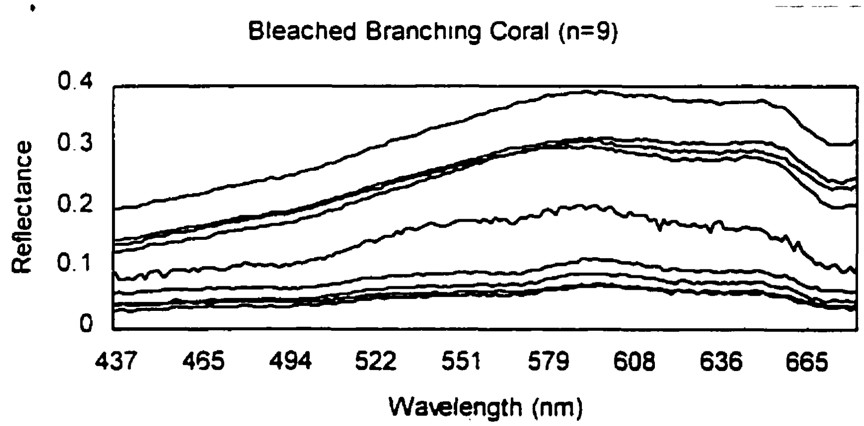

Figure 4.1. Nine bleached coral spectra were measured in 1996.

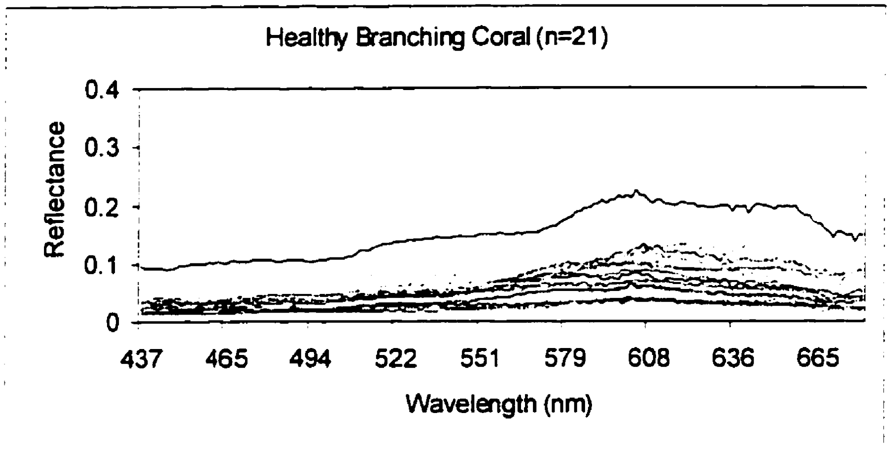

Figure 4.2. Twenty-one healthy branching coral spectra were collected in 1996.

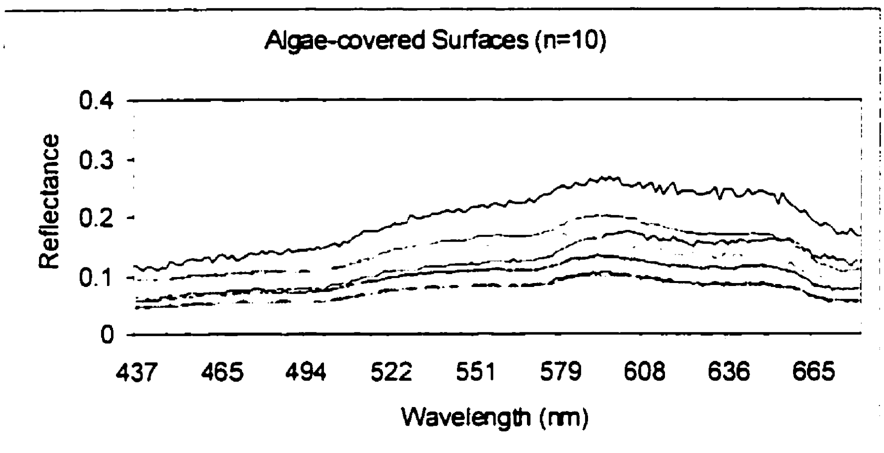

Figure 4.3. Ten algae-covered surface spectra were measured in 1996.

4.4.2 July and August 1997 Study Site, Manado, Indonesia

The second field season of this study took place outside the city of Manado on the island of Sulawesi in Indonesia. A suitable healthy coral reef flat 20-km south of the city of Manado was chosen as the study site with exposed reef features at low tide to allow sampling. The particular reef flat was chosen based on accessibility from land, variety of coral reef components, the presence of macro algae and bleached coral, and degree of exposure at low tide. There was a fairly sparse distribution of small coral heads, which allowed easy sampling on foot between coral heads separated by light coloured sand.

No underwater optical cable or underwater cosine receptor was available in 1997, so all sampling was performed with an above water cosine receptor attached to the radiometer. The nature of the non-water proof instrumentation demanded a sampling procedure whereby coral reef flats were sampled at low tide when features were exposed or nearly exposed (under less than one meter of water).

The geographic location of the coral reef flat on which measurements were taken in Indonesia was recorded with a GPS as 1° 24.82 north and 124° 42.44 east. A photograph was taken of each feature measured for compilation of a corresponding photographic and spectral database. In total, 80 spectra were measured on the coral reef flat in Manado, Indonesia in 1997. These spectra were separated into broad categories based on inspection of the photographs and notes accompanying each measurement. Five categories of spectra were created: healthy massive coral (n=6); healthy branching coral (n=19); sand surfaces (n=34); bleached unhealthy coral (16); and algae-covered surfaces (n=5). These categories of spectra were plotted separately in Figures 4.4 – 4.8.

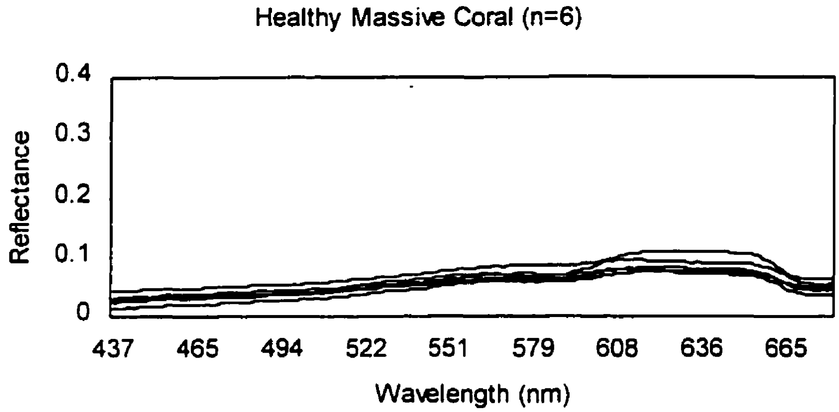

Figure 4.4. Six healthy massive coral spectra were measured in 1997.

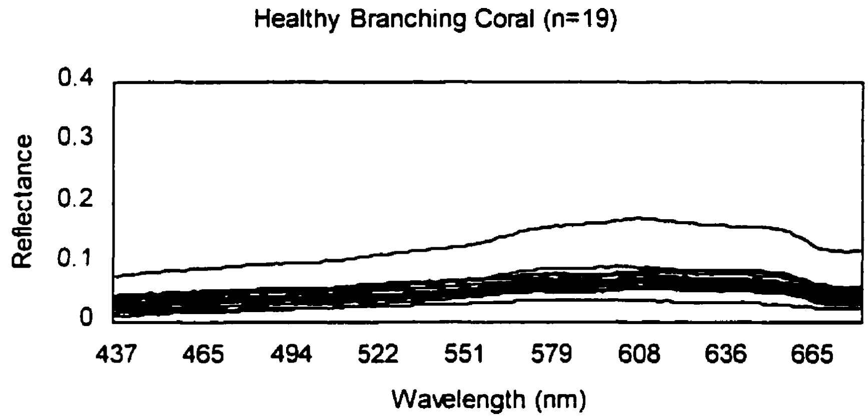

Figure 4.5. Nineteen healthy branching coral spectra were collected in 1997.

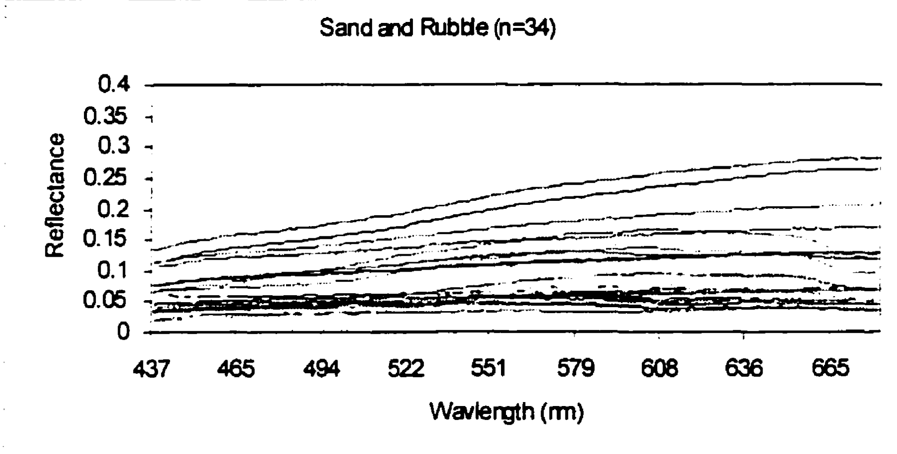

Figure 4.6. Thirty-four sand and rubble spectra were collected in 1997.

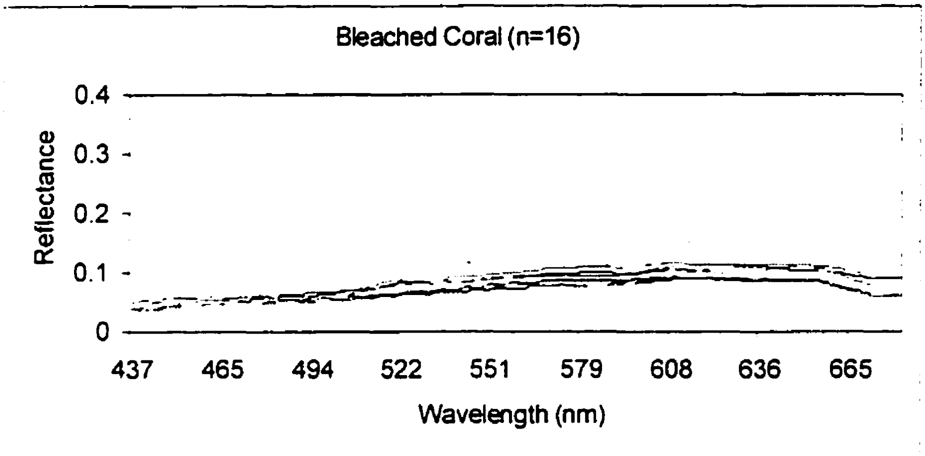

Figure 4.7. Sixteen bleached coral spectra were collected in 1997.

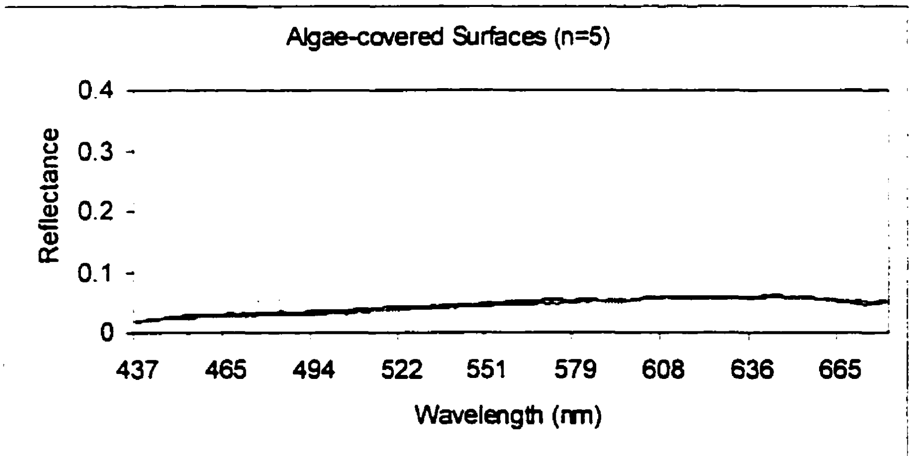

Figure 4.8. Five algae-covered surface spectra were measured in 1997.

4.4.3 July and August 1998 Study Site, Savusavu Bay, Fiji

Field data were collected in July 16 and August 20, 1998 in Savusavu Bay, Fiji. The same radiometer was used for the 1998 field season as for the 1996 and 1997 seasons. A 20-meter underwater optical cable and an underwater cosine receptor was purchased for the 1998 season, which allowed measurements to be collected underwater while the operator was scuba diving. The same sampling procedure was used as in the previous two years such that the maximum number and variety of coral reef features were sampled with the greatest degree of control possible.

In total 215 spectra were collected with the cosine receptor at three different locations within Savusavu Bay. The GPS coordinates of the first site are 16° 49.05 179° 16.76: of the second site are 16° 46.38 179° 19.72; and of the third site are 16° 50.01 179° 16.84. Algae-covered surfaces, bleached coral, healthy coral (both branching and massive), soft coral, and rubble surfaces were measured in Savusavu Bay.

A sonar depth sounder was used along with a standard scuba diving computer depth gauge to record the depth of each measurement. The depth range was from 4.2- 4.5 meters. An underwater photographer took at least two pictures of each target measured. The first picture was a close-up view of the surface and the second was one from a greater distance to record the surrounding substrate. A scuba diver recorded information on an underwater note-taking slate regarding the feature type, size, and depth, state-of-health, surrounding substrate, water quality and other pertinent information.

The 214 measured spectra were categorized into broad groups as in 1996 and 1997. Six categories were created based on inspection of the underwater photographs and the notes accompanying each measurement. Nineteen healthy branching corals; twenty-seven healthy massive corals; forty-six healthy soft corals; fifteen bleached corals; twenty-eight rubble surfaces; and seventy-nine algae-covered surfaces are included in the 1998 dataset. The broad categories of spectra are plotted for comparison in Figures 4.9 —4.14.

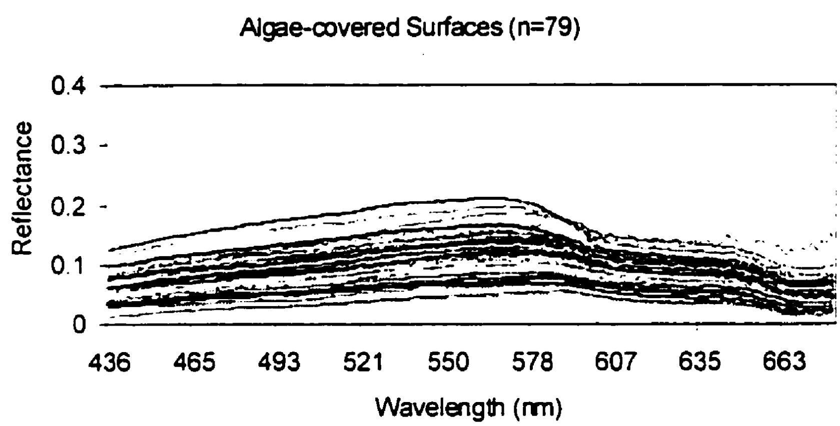

Figure 4.9. Seventy-nine algae-covered surface spectra were collected.

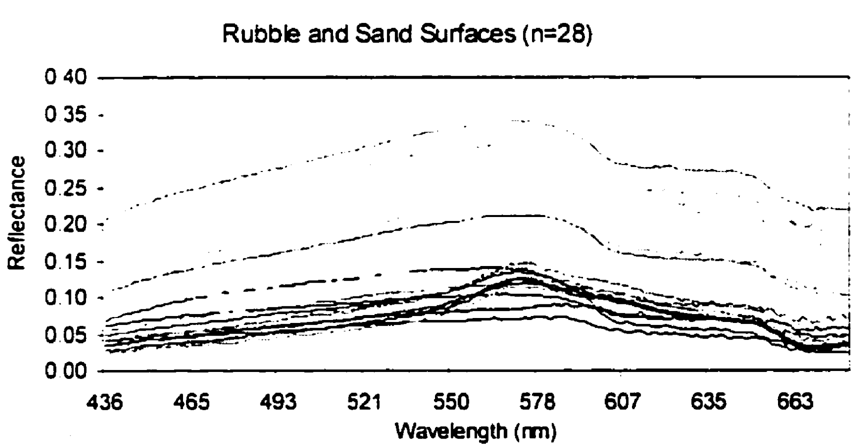

Figure 4.10. Twenty-eight rubble and sand surface spectra were collected.

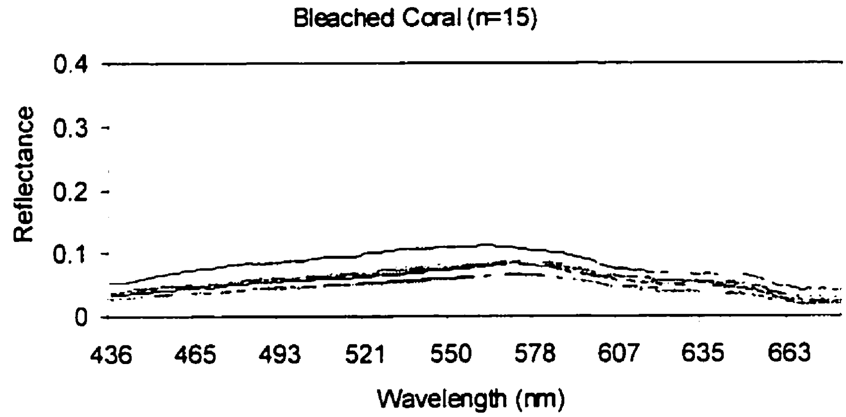

Figure 4.11. Fifteen bleached coral spectra were collected.

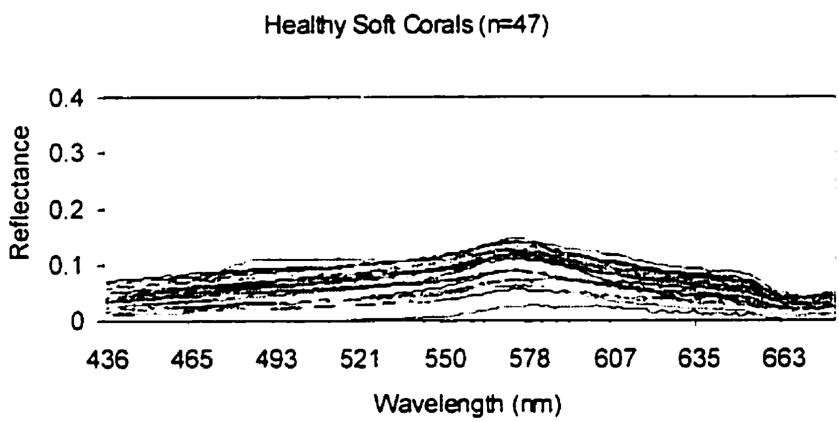

Figure 4.12. Forty-seven healthy soft coral spectra were collected.

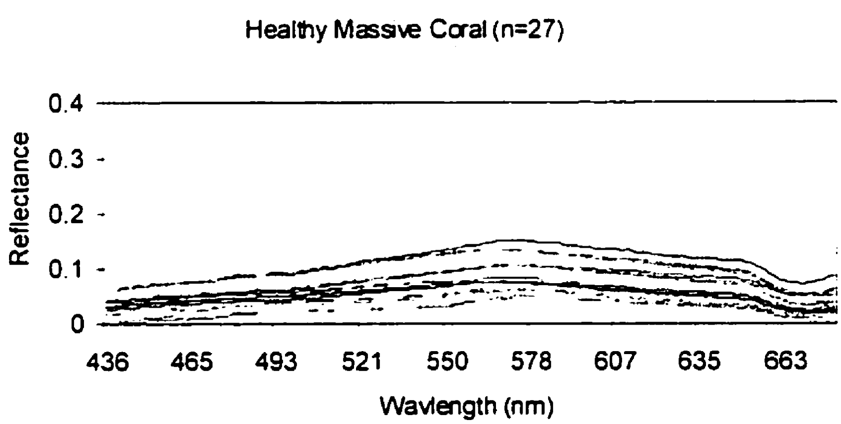

Figure 4.13. Twenty-seven healthy massive corals were sampled.

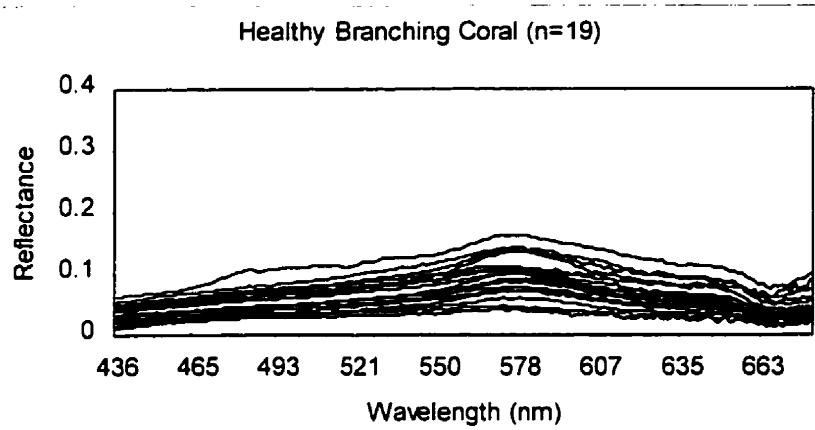

Figure 4.14. Nineteen healthy branching corals were sampled.

4.5 POTENTIAL ERRORS IN SPECTRAL REFLECTANCE MEASUREMENTS

There are several potential sources of error in the collection of spectral reflectance information with the cosine receptor attached to the ASD spectrometer (Table 4.1). Since reflectance is a relative measurement of reflected radiance to incident irradiance, stable solar irradiance conditions are extremely important. It is possible that the irradiance conditions could change between the reference measurement of downwelling irradiance and the target upwelling radiance measurement. However, great care was taken in all field seasons to collect measurements under clear and stable sky conditions and to minimize the time interval between the reference and the target measurements. Depending on the direction of change, an underestimation or overestimation of reflectance could result.

Table 4.1. The precision and accuracy in spectroscopy can be affected by numerous factors in a complicated manner (modified from Sommer, 1989).

Arising from the Operator	Arising from the Instrument	Arising from the Target
Failure to hold the sensor level	Incorrect signal amplification and processing	Geomorphologic variation between substrates
Failure to hold the reference card level	Fluctuations in electrical circuitry within system	Deviation from optimal conditions of purity
Measurement during unstable irradiance conditions	Low signal to noise ratio; high electronic noise level	Presence of interfering species (imperceptible algae) or substrates (debris)
Failure to minimize shadow	Incorrect or inaccurate calibration by manufacturer	Multiple scattering, inelastic scattering
	Stray sight generation causing false signals	

If two radiometers were available and perfectly calibrated to one another, the reference and target measurements could be measured simultaneously. In this study, one downwelling irradiance reference measurement was taken immediately prior to the upwelling radiance target measurement, and effort was made to minimize the time lag between measurements. Furthermore, reflectance measurements were restricted to solar noon and to times when the sky conditions were stable. Since the radiometer provides real time displays of spectra, changing irradiance conditions are readily viewed during downwelling irradiance collection, so measurements can be delayed until the response appears stable. In addition, care was taken to ensure that the sensor head was normal to the target surface since the radiometer is sensitive to leveling errors under clear sky conditions.

Another potential source of error during spectral reflectance measurement with the remote cosine receptor is contamination of the incoming and reflected radiation due to nearby objects such as the operator (Kimes et al., 1983). This interference can enhance the measured signal through reflection or reduce the signal through shadowing (De Abreu, 1996). Instrument and operator position was therefore kept constant throughout data collection. For example, the remote cosine receptor was held overhead to collect the downwelling irradiance reference signal and held at a constant height above the feature for all measurements. Reflectance is calculated by inverting the cosine receptor facing and level to the sky for a measure of incoming irradiance. The target measurement is compared to a reference measurement of incoming irradiance to calculate a relative value of reflectance. If the cosine receptor is not held perfectly level when inverted, then there may be errors associated with the reference measurement. Similarly, if the cosine receptor is not held level to the feature of interest, then the target measurement may contain errors.

Another source of error when taking measurements in the field relates to the specific morphology of the feature of interest. For example, the surface texture of features in a coral reef environment varies, which will affect the relative reflectance of illumination. A branching coral's spectral reflectance will be affected by multiple scattering from its branches, as well as by the contribution of the underlying substrate. Conversely, a hard, massive coral's smooth, solid surface will not allow contribution from the substrate below. However, the slope and geometry of a massive coral's rounded surface results in a complex mixture of directly and multiply-reflected light returned to the sensor.

4.6 DATA ANALYSIS

The use of a high spectral resolution radiometer allows for detection of subtle optical characteristics of coral reef feature reflectance, which in turn may permit more precise and accurate identification. For example, the spectral reflectance characteristics of a healthy coral are expected to be optically different than that of a non-healthy coral based on the difference in colour resulting from the loss of pigmentation. It would also be expected that a bleached coral would have not only a much higher reflectance in general, but also lack some spectral characteristics of a healthy coral.

4.6.1 Comparison of Spectra Collected Separately by Field Season

The analysis for this study begins with separate investigations of the spectral measurements by field season. In chronological order, the spectral datasets are investigated for the degree of within and between population variability, where a population is defined as a particular feature type, such as healthy branching coral. It is hypothesized that the within population spectral variability will be low, and the between population spectral variability will be high such that broad categories of coral reef features will be separable based on spectral reflectance.

After initial investigation of the spectra within categories, cluster analysis is used to examine spectral similarities. Following the cluster analysis, Pearson correlation coefficients are calculated to determine the degree of similarity between measured spectra within a given population or category. Cluster analysis and correlation analysis are discussed further later in this chapter.

4.6.2 Comparison of Three Years of Spectral Data

The next stage of analysis involves comparing the spectra collected in 1996 through 1998 to determine the degree of variability resulting from geographic location. It is hypothesized that measured spectra of similar features will be similar regardless of geographic location.

After visually comparing the spectra collected in geographically distinct areas, cluster analysis is used to explore the within-population variability. Correlation coefficients are then calculated to examine the relationships between and within populations.

4.6.3 Determination of Representative Spectra

The dataset consisting of 334 spectra can be reduced to representative spectra using principal components analysis. The purpose of determining representative spectra is to enable the general spectral reflectance characteristics of the populations considered in this study. Reducing the dataset to representative spectra allows for easier interpretation of differences in spectral reflectance than if the entire data set was considered.

4.6.4 Establish a Means of Discrimination

Inspection of the representative spectra suggests that the slope of the reflectance curves in specific wavelength regions may enable discrimination between populations. Therefore, spectral derivative analysis is used to determine the ideal wavelengths in the visible region to allow for accurate discrimination of coral reef features. First derivatives, or slopes, are determined by calculating the change in reflectance with respect to wavelength. The representative spectra identified by principal components analysis are used in this stage of analysis to identify specific wavelength regions for discrimination.

4.6.5 Accuracy Assessment

The accuracy of the procedure established in the previous step using spectral derivative analysis is assessed in this final analysis step. The first derivatives calculated for the representative spectra are also calculated for the remainder of the dataset. A classification of spectra into populations is performed and the errors analyzed by counting the correctly identified spectra versus the incorrectly identified spectra. An error matrix is used to display the errors of commission and omission as a means of assessing the accuracy of the classification procedure.

4.7 STATISTICAL TECHNIQUES USED FOR DISCRIMINATION

4.7.1 Cluster Analysis

Cluster analysis is the generic name for a multivariate procedure of clumping similar objects into categories enabling identification of (1) outliers, and (2) the basic structure of the dataset (Wilkinson et al., 1996). No training or prior knowledge of the distribution of the data is required, so clustering can be used as a subjective, exploratory procedure. Despite the obvious benefits of cluster analysis with respect to identifying structure and outliers, there are two related problems: (1) deciding on the number of clusters, and (2) deciding whether a solution is significant. The cluster analysis in this study is performed in Systat, version 7, for Windows.

No satisfactory general method has been developed for deciding how many clusters exist in a dataset of unknown structure (Wilkinson et al., 1996). Nor is there a goodness-of-fit index to determine the optimal number of clusters. Therefore, the number of clusters is a subjective decision based on knowledge of the dataset characteristics. With respect to the significance of a solution, Wilkinson et al. (1996) believe that there is no universally acceptable test statistic. According to Wilkinson et al. (1996) the main indicator of randomness in clustering is the length of the branches, where long branches indicate random clustering.

The objective of cluster analysis is to determine which objects are similar and dissimilar and categorize them accordingly. The method of achieving the categorization in this study is the hierarchical method which produces families of clusters which themselves contain other clusters. The purpose of the cluster analysis in this study is to determine if there is a spectral distinction between and within populations based on spectral response over the observed wavelengths.

Hierarchical cluster analysis produces families of clusters, which contain other clusters, which contain other clusters, and so forth. Objects, spectra in the case of this study, are joined sequentially according to similarity. The first step is to join the two most similar spectra and call this a cluster. Then the next two closest spectra are joined to that first cluster. The tree diagram generated from hierarchical cluster analysis has a unique ordering in which every branch is lined up so that the most similar objects are closest to each other.

4.7.2 Correlation Analysis

In an effort to describe the similarity of reflectance spectra within a population, correlation analysis is used. A correlation coefficient, r, is calculated from the data, which measures the degree to which the relationship between two measured spectra is linear. When r=0, there is no degree of linear relationship, but where r=1 or r=-1, a perfect linear relationship exists. The correlation analysis in this study is performed in Systat, version 7, for Windows.

The Pearson Correlation coefficient is used in this study to compare the strength of association between reflectance at a given wavelength of features within one population. For example, the similarity of measured reflectance spectra for all healthy corals measured in Fiji in 1996 can be examined by calculating correlation coefficients.

Since large volumes of data are explored in the correlation analyses, entire matrices are not included in the results. Instead, a sample of correlations is displayed in a matrix and graphically with a matrix of scatterplots with one plot for each entry in the correlation matrix. The graphical display shows histograms for each variable on the diagonal and scatterplots of each variable against the other. To characterize the relationship within each scatterplot, a 75% ellipse is used such that the center of the ellipse is the sample mean of the x and y variables in the plot and the axes are determined by the standard deviations of x and y.

4.7.3 Principal Components Analysis

Principal components analysis (PCA) has been used effectively in many studies as a data reduction technique, as it preserves the total variance while minimizing the mean square approximate errors, and is also used as a method to identify dominant modes of data (Fung and LeDrew, 1987). Furthermore, PCA is a technique that transforms the original dataset into a substantially smaller and easier to interpret set of uncorrelated variables that represents most of the information in the original dataset (Dunteman, 1984). Principal components are derived from the original data such that the first principal component accounts for the maximum proportion of the variance of the original dataset, and subsequent orthogonal components account for the maximum proportion of the remaining variance, and so forth (Fung and LeDrew, 1987, SAS Institute Inc., 1990).

The purpose of the PCA, performed in SAS, a statistical analysis package (SAS Institute Inc., 1990), is to reduce the amount of data to representative spectra. A loading is calculated in PCA to describe how closely a particular spectrum resembles or loads to the principal component spectra. Therefore, a separate PCA is performed for each population to reduce the data set to one representative spectral reflectance curve with the highest loading to the principal component reflectance curve. The result of the series of PCAs is a set of spectra, which are representative of each population. This provides a smaller and more manageable data set on which spectral derivative analysis can performed to determine the optimal wavelengths for discrimination based upon the representative spectra.

4.7.4 Spectral Derivative Analysis

Derivative spectroscopy uses changes in spectral reflectance or radiance with respect to wavelength to isolate or identify spectral features. Derivatives allow components of the spectrum to be more clearly separated. Furthermore, the use of derivatives solves many problems of quantitative analysis in a more effective way than ratios and differences (Demetriades-Shah et al., 1990). It is assumed in derivative spectroscopy that the variations are spectrally independent (Chen et al., 1992).

The simplest method of finding derivatives is by dividing the difference between successive spectral values by the wavelength interval separating them (Demetriades-Shah et al., 1990). This method gives the approximation of the first derivative at the midpoint between the spectral values used, which provides information on the rate of change in reflectance, which is the slope, with respect to wavelength. This technique is used to test the hypothesis that differences in the slope of the reflectance curve in specific wavelength regions will allow discrimination of population types.

4.8 SUMMARY

The data available were collected in three geographic locations in three successive years. The first dataset was collected in Beqa Lagoon, Fiji in August 1996; the second in Manado, Indonesia in July and August 1997; and the third in Savusavu Bay, Fiji in July and August 1998. The spectral data were measured with the same radiometer with a cosine receptor and with the same sampling strategy. In total, 334 spectra in 172 wavebands are available for this study.

In Beqa Lagoon, Fiji in 1996, an underwater remote cosine receptor and 10 meter optical cable made underwater measurements possible. However, in Manado, Indonesia in 1997, only above water instrumentation was available, so measurements were limited to exposed coral reef flats. A 20-meter underwater optical cable and underwater cosine receptor was available in 1998, so underwater measurements were possible in Savusavu Bay, Fiji. A summary of the data used in this thesis can be found in Table 4.2 and maps of the study areas are provided in Figures 4.15 and 4.16.

Table 4.2. A summary of the data used in the present study.

	1996, Beqa Lagoon, Fiji	1997, Manado, Indonesia	1998, Savusavu Bay, Fiji
GPS Location	18° 19.45 S 178° 06.48 E	1° 24.82 N 124° 42.44 E	a) 16° 49.05 S 179° 16.76 E b) 16° 46.38 S 179° 19.72 E c) 16° 50.01 S 179° 16.84 E
Number of Spectra	40	80	214
Number of Categories of Spectra	3	5	6
Measurement Technique	Underwater	Above water	Underwater
Depth Range	2.7-2.9m	All exposed	4.2- 4.5m

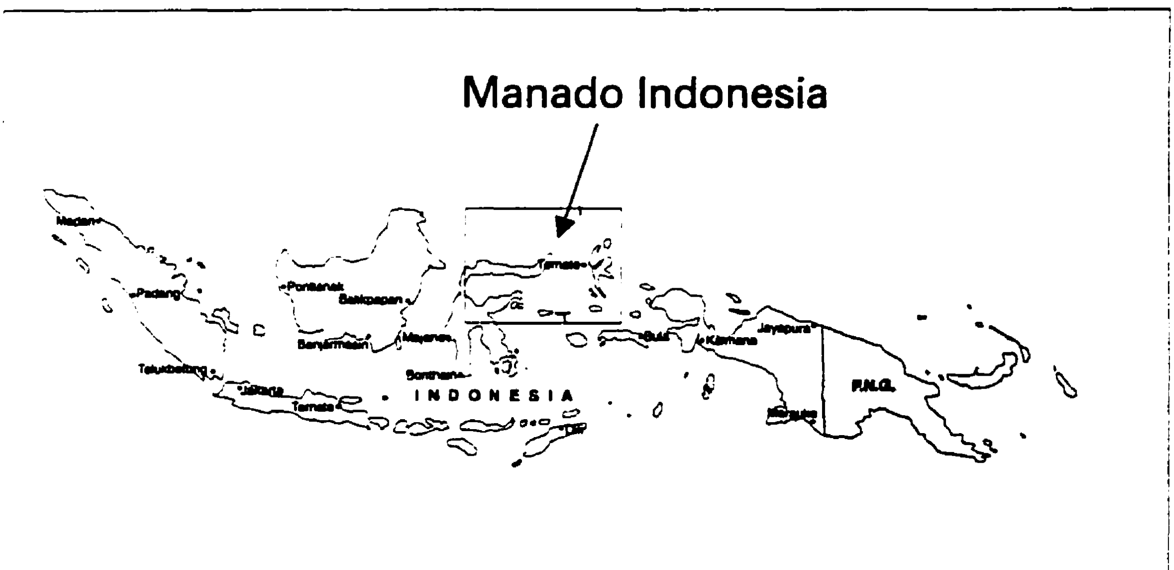

Figure 4.15. Data collection took place in Manado, Indonesia in 1997.

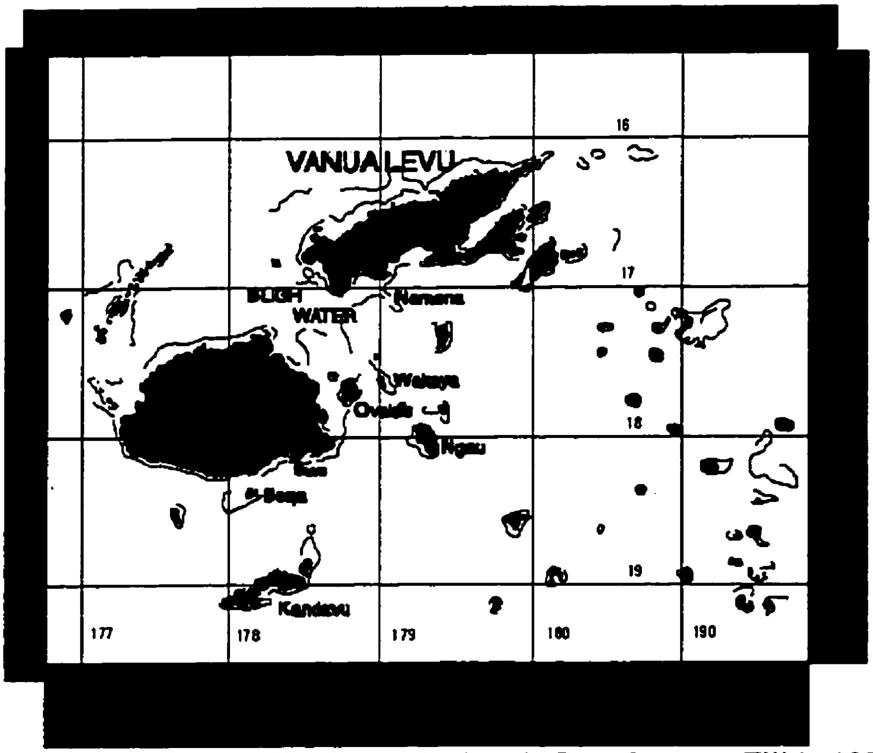

Figure 4.16. Data collection took place in Beqa Lagoon, Fiji in 1996 and Savusavu Bay, Fiji in 1998.

The main objective of this study is to determine a means of remotely identifying features in a coral reef environment. The purpose of the spectral reflectance measurements collected in the 3 field seasons was to allow geographic comparisons of the variation in response. Cluster analysis, correlation analysis, and principal components analysis are techniques to be used to determine the spectral separability of various broad categories of coral reef features. Representative spectra are determined based on the full dataset consisting of three years of field data, and spectral derivative analysis is used in an attempt to determine the specific spectral regions that would enable accurate identification. Finally, an accuracy assessment is conducted by performing the procedure based on spectral derivative analysis on the entire dataset and examining the proportion of correctly identified to incorrectly identified spectra.

CHAPTER 5

WITHIN AND BETWEEN POPULATION VARIATION OF SPECTRAL MEASUREMENTS COLLECTED IN 1996, 1997 AND 1998

5.1 INTRODUCTION

The purpose of this chapter is to separately examine the field data collected in Beqa Lagoon, Fiji in 1996, Manado, Indonesia in 1997 and Savusavu Bay, Fiji in 1998. An additional purpose is to describe the degree of variation within- and between-populations. The populations are defined broadly based on examination of photographs and field notes. There are three populations defined for the 1996 field data: bleached massive coral, healthy massive coral and algae-covered surfaces. Five populations were defined for the 1997 field season: healthy massive coral, healthy branching coral, bleached massive coral, sand surfaces and finally, algae-covered surfaces. Finally, six populations were defined for the 1998 field season: healthy branching coral, healthy massive coral, healthy soft coral, bleached branching coral, rubble surfaces and finally, algae-covered surfaces.

The spectra collected at the three study areas are considered separately for this stage of analysis. Initially the average and standard deviation spectra are calculated for each of the predefined populations. The average spectra for each population are compared to one another and the degree of separability examined. Following this initial comparison, cluster analysis is used as a tool to visualize the degree to which each field season's data set can be clustered into groups according to population. Cluster analysis is then used to examine the variation within populations by analyzing each population on its own. Finally, correlations are examined within the populations to determine the degree of similarity.

5.2 EXAMINATION OF 1996 SPECTRAL DATA SET

The 1996 field data collected in Beqa Lagoon, Fiji consist of 40 reflectance spectra in 172 wavebands measured underwater. The hyperspectral radiometer used allowed for a remote cosine receptor to be attached to the end of an underwater optical cable to facilitate underwater measurements. The features measured include bleached massive corals, healthy massive corals, and algae-covered surfaces. In the following sections, these 40 spectra are analyzed to determine the degree to which the features measured in the same geographic location are separable based on reflectance.

5.2.1 Initial Examination of 1996 Spectra

As a first step in examining the variability within populations in the 1996 data set, average and standard deviation spectra were found, as illustrated in Figure 5.2.1 (average bleached coral, n=9), Figure 5.2.2 (average healthy coral, n=21); and Figure 5.2.3 (average algae-covered surfaces, n=10).

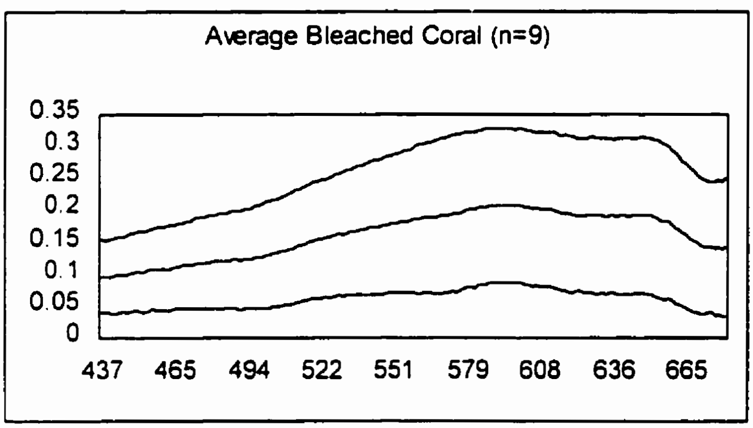

Figure 5.2.1. The average spectral reflectance was calculated based on 9 measurements of bleached corals collected in 1996 (gray lines represent plus and minus one standard deviation).

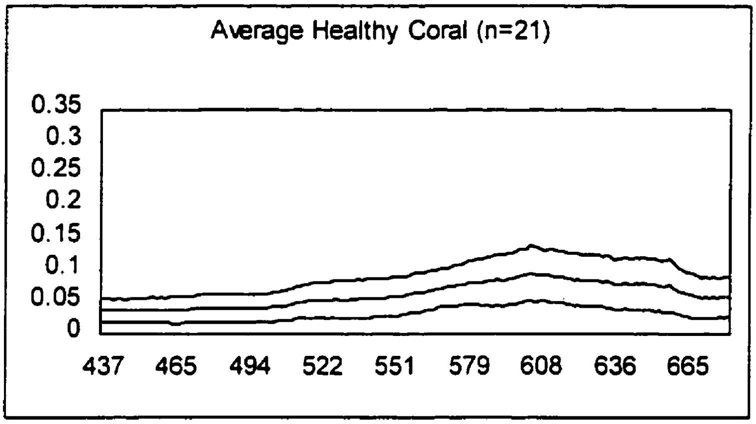

Figure 5.2.2. The average spectrum was calculated based on 21 measurements of healthy corals collected in 1996 (gray lines represent plus and minus one standard deviation).

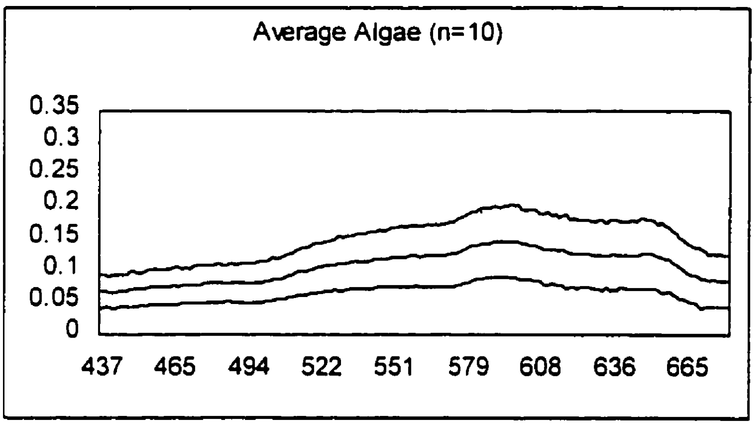

Figure 5.2.3. The average spectrum was calculated based on 10 measurements of algae-covered surfaces in 1996 (gray lines represent plus and minus one standard deviation).

Upon initial inspection, there appear to be spectral differences in terms of the magnitude and shape of the reflectance curves of the three populations. The reflectance curve of average bleached massive coral has the highest overall magnitude, with a maximum reflectance of 0.21 at 590.6nm. The average algae reflectance curve reveals slightly lower overall reflectance than bleached massive coral, with a maximum of 0.15 at 596nm. Average healthy massive coral has the lowest overall reflectance of the three curves, with a maximum of 0.10 at 603.4nm. The average reflectance curves for the three categories in the 1996 data set are compared in one plot in Figure 5.2.4.

The differences in magnitude are expected, as bleached massive corals have either lost their zooxanthellae or lost pigments within their zooxanthellae. In either case, the resultant effect is the same: the coral turns white in its stressed state. This change in colour is apparent in the reflectance spectra. Algae are known to colonize bleached massive coral in its vulnerable state. Therefore, it is not surprising that algae-covered surfaces have greater magnitude of reflectance than healthy massive coral since the algae is spread out over bleached massive coral, which has high average spectral reflectance.

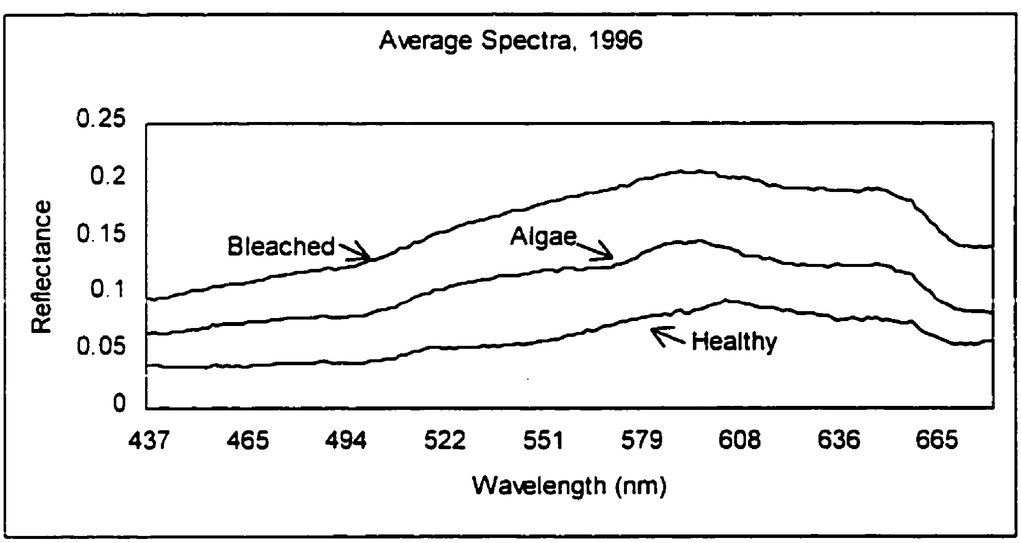

Figure 5.2.4. The average reflectance curves for the three broad categories are compared.

The differences in spectral shape between these three broad classes of coral reef features are subtle. For example, there is a gradual shift in the location of the reflectance maxima toward shorter wavelengths as the coral becomes stressed. The healthy massive coral reflectance maximum is at 603nm, while that of bleached and algae-covered coral is at less than 596nm. Additionally, the algae-covered surface average reflectance curve reveals a slight dip in reflectance at 570nm, which may indicate absorption by an accessory pigment not present in healthy massive coral.

Finally, and perhaps most importantly for discrimination, the slope of the reflectance curves between 555 and 575nm differs slightly between the three average spectra. The slope of the curve in this spectral region is steeper for the bleached massive coral spectra than the healthy massive coral, and the algae-covered surface spectra lies between the two. This spectral difference will be further investigated later in this thesis as a means of discrimination.

5.2.2 Cluster Analysis of 1996 Spectra

The objective of using hierarchical cluster analysis is to determine if the measured spectra can be grouped into classes based on reflectance characteristics. This technique was chosen because of its relative simplicity in terms of visualization of data analysis results. Output from hierarchical methods can be represented as a tree, or dendrogram. The linkage of each object, or spectra in this case, is shown as a joining of branches in a tree. The "root" of the tree is the linkage of all clusters into one group, and the ends of each branch lead to individual spectra. The cluster tree diagrams generated provide a means of visualizing the degree to which the spectra can be placed into similar classes.

The cluster analysis begins with a data matrix of columns (40 reflectance spectra) and rows (172 wavelengths). The separability of the measured spectra is based on both magnitude of reflectance and shape of the spectral response. Included in the cluster analysis are spectral measurements of healthy massive coral, bleached massive coral and macro algae. The cluster tree diagram in Figure 5.2.5 shows the order in which spectra were joined from left to right.

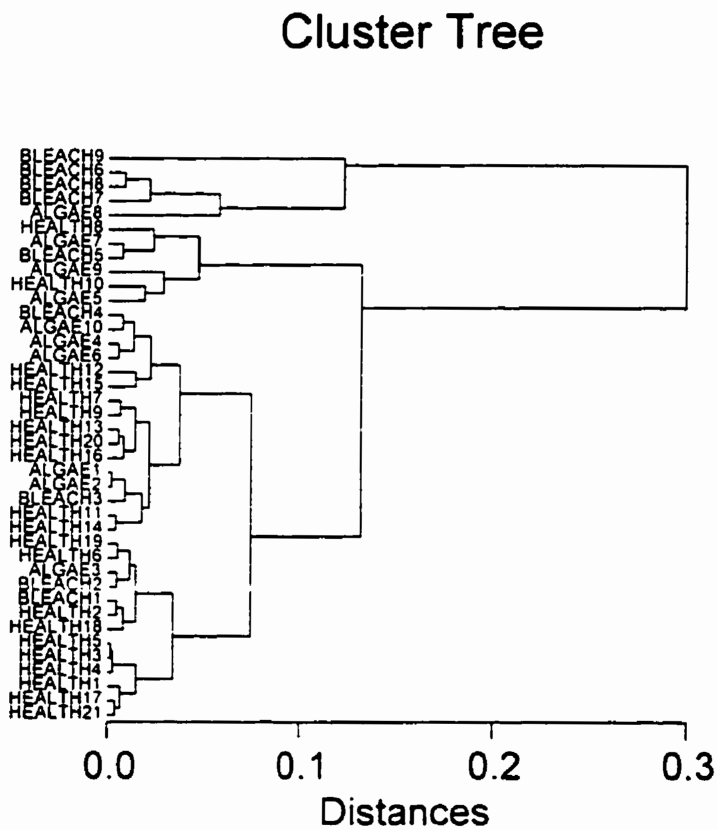

Figure 5.2.5. At a Euclidean distance of approximately 0.075, this cluster analysis tree diagram reveals four groups of spectra separable on the basis of spectral shape and magnitude of reflectance.

The distance scale at the bottom of the tree diagram is a normalized Euclidean distance that is the root mean square discrepancy between objects (spectra) across attributes (reflectance). On the left there are as many clusters as spectra, while on the right there is only one cluster. Therefore, moving from left to right represents an increasing degree of difference between spectra where a small Euclidean distance suggests that the spectra are most similar. Arbitrarily, a vertical line is drawn through the clusters at a specific Euclidean distance to determine the number of clusters present at that point.

The process of finding clusters is therefore somewhat subjective, but at a Euclidean distance of 0.075, there are four distinct clusters present, which can be related to substrate type. Cluster one, at the top, contains 5 spectra; 4 of these spectra are identified as bleached massive coral measurements. This result indicates that these 4 spectra are similar with respect to magnitude and shape. Five other bleached massive coral spectra were also included in this cluster analysis, but they are found scattered among the other spectra in the cluster tree. This indicates that within the dataset collected in 1996, there appears to be a certain degree of variability in spectral response within the population of bleached massive corals.

Cluster two, which is second from the top, contains 6 spectra. Spectra identified as 3 algae-covered surfaces, 2 healthy massive corals and 1 bleached massive coral are found within this cluster, which suggests that there is a high degree of similarity between the three populations of coral reef features. This cluster therefore cannot be identified with any of the three populations defined for this field season.

The third cluster contains 16 spectra. Nine of these are identified as healthy massive coral spectra, 5 as algae-covered surfaces and 2 as bleached massive corals. While 56% of this third cluster are healthy massive coral spectra, there is still a high degree of confusion between populations of coral reef features in the 1996 data set.

Finally, the fourth cluster, at the bottom of the cluster tree, contains 13 spectra in total. Ten of these spectra are healthy massive coral spectra, 2 are bleached massive coral spectra and 1 is an algae-covered surface measurement. Therefore, 73% of the bottom cluster is accounted for by healthy massive coral measurements. This indicates that there is a relatively high degree of similarity in the shape and magnitudes of the spectral curves of these healthy massive corals.

The percent cover of algae on the surface measured was not quantified during the field season. The relative abundance of algae compared to the underlying substrate is therefore not known. This limitation is addressed in future years, but may contribute to the spectral confusion in classification of the 1996 field data.

To examine the degree to which spectra within a population are considered similar according to hierarchical cluster analysis, three separate analyses were performed for each category. First, the nine bleached massive coral spectra were subjected to cluster analysis, as seen in the cluster tree in Figure 5.2.6. At a Euclidean distance of 0.1, there are 2 clusters present indicating two sub-populations of bleached massive coral spectra within the category. The spectral differences could be due to differing stages of bleaching, where some bleached samples may only have been partially bleached, while others completely bleached and possibly even partially colonized by algae.

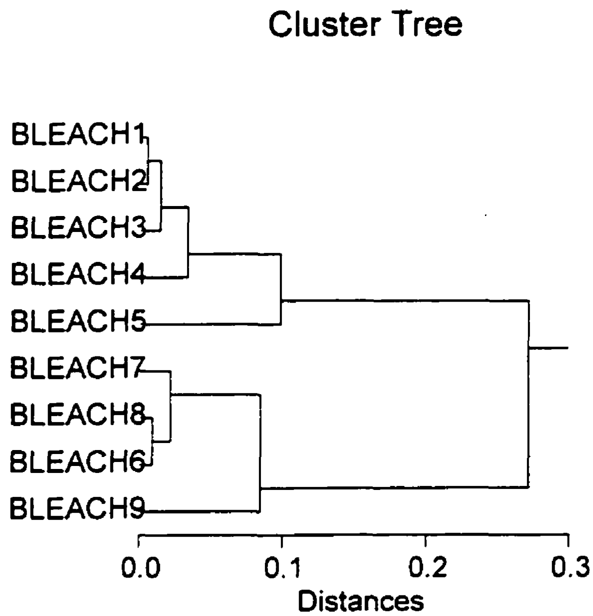

Figure 5.2.6. The category of bleached massive corals (n=9) was subjected to cluster analysis to determine the within population variation.

Secondly, the healthy massive coral spectra were clustered to determine the degree of similarity within the category. The cluster tree in Figure 5.2.7 reveals that at a Euclidean distance of 0.07, there are three clusters. All healthy massive coral spectra join together as one cluster at a Euclidean distance of equaling less than 0.15, which indicates that the spectra can be considered the same at this point. Comparing this to the bleached massive coral cluster tree diagram in Figure 5.2.6 indicates that there is less variability within the healthy massive coral population than the bleached massive coral population. In fact, the bleached massive coral do not join together as one cluster until a Euclidean distance of 0.3. This may be a result of fewer spectral measurements of bleached massive coral than healthy massive coral.

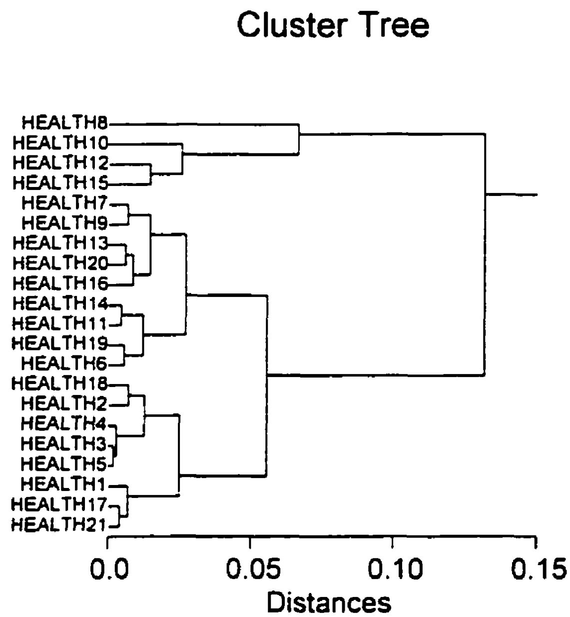

Figure 5.2.7. The population of 21 healthy massive coral spectral measurements was subjected to cluster analysis to examine the within population variability.

Finally, the ten spectra corresponding to algae-covered surfaces were included in a cluster analysis, as illustrated in Figure 5.2.8. At a Euclidean distance of 0.05, there are two clusters present. These clusters may be present due to varying degrees of algal cover on the surface. Varying amounts of algal cover will result in different spectral reflectance responses depending on the nature of the underlying surface. It should also be noted that, like the healthy massive coral spectra, the algae-covered surface spectra join into one cluster at a Euclidean distance of 0.15. This indicates that the algae-covered surface spectra, while they can be broken up into two clusters, contain less within population variability than the bleached massive coral spectra.

Cluster Tree

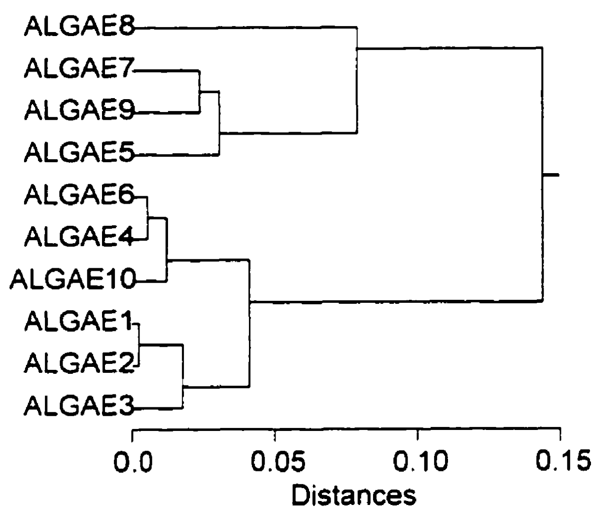

Figure 5.2.8. A cluster tree diagram illustrates the degree of within-population variability for ten algae spectral measurements.

5.2.3 Correlation Analysis of 1996 Spectra

A correlation analysis can be used to examine the relationship between variables. In this case, correlation analysis is used to examine the relationship between each of the measured spectra within a given category of features. The wavelength-specific reflectance values of one sample are therefore compared to the wavelength-specific reflectance values of another sample. The degree of spectral variability within a given population and between populations is of interest. Pearson correlation coefficients were calculated in Systat within each category to examine the similarity of spectra within the population.

All 9 bleached massive corals have a high degree of similarity to each other, as seen in the correlation coefficient matrix in Table 5.2.1. A strong positive linear relationship exists between all bleached massive coral spectral reflectance measurements. The minimum value of the correlation coefficients calculated for the matrix of bleached massive coral spectra was 0.83, which is still considered a strong correlation. Of the 36 correlation coefficients calculated, 88.8% were greater than 0.90, which suggests spectral similarity within the bleached massive coral population.

Table 5.2.1. Correlation coefficients for bleached massive coral spectra.

	Bleach1	Bleach2	Bleach3	Bleach4	Bleach5	Bleach6	Bleach7	Bleach8	Bleach9
Bleach1	1								
Bleach2	0.948	1							
Bleach3	0.990	0.972	1						
Bleach4	0.987	0.978	0.995	1					
Bleach5	0.957	0.968	0.973	0.972	1				
Bleach6	0.940	0.831	0.916	0.900	0.906	1			
Bleach7	0.957	0.890	0.947	0.935	0.952	0.989	1		
Bleach8	0.949	0.856	0.930	0.916	0.926	0.998	0.995	1	
Bleach9	0.947	0.848	0.927	0.912	0.920	0.999	0.993	0.999	1

Secondly, the 21 healthy massive coral spectral measurements collected in 1996 were compared to determine the degree of spectral similarity. As can be seen in the correlation coefficient matrix in Table 5.2.2, there is a positive linear relationship. Only the first 10 spectra were included in this matrix, although the entire data set of 21 spectra was included in the correlation analysis. The linear relationship is not as strong within the category of healthy massive corals as it is within the category of bleached massive corals. The minimum correlation coefficient calculated was 0.78, which is still considered indicative of a strong positive relationship. Additionally, 95.2% of the correlation coefficients were greater than 0.80. Therefore, it can be concluded that the within-population variability of the healthy massive coral population is relatively small.

Table 5.2.2. There is a positive linear relationship between healthy massive coral measurements, as seen in the correlation coefficient matrix.

	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10
H1	1									
H2	0.891	1								
H3	0.877	0.981	1							
H4	0.894	0.986	0.989	1						
H5	0.874	0.982	0.995	0.991	1					
H6	0.852	0.972	0.978	0.978	0.982	1				
H7	0.776	0.899	0.940	0.907	0.936	0.914	1			
H8	0.805	0.906	0.923	0.902	0.921	0.918	0.966	1		
H9	0.790	0.923	0.960	0.932	0.959	0.945	0.989	0.963	1	
H10	0.885	0.953	0.930	0.939	0.931	0.940	0.876	0.944	0.893	1

Finally, all 10 spectra measured in 1996 over algae-covered surfaces are examined for the degree of similarity within the population. There is a positive linear relationship between all spectral measurements of algae-covered surfaces. The strength of the linear relationship is displayed in matrix form in Table 5.2.3. The minimum correlation coefficient calculated in the matrix for algae-covered surfaces was 0.65. Only 2 correlation coefficients are less than 0.80 thus 94.4% are considered strong correlations. This is considered a relatively moderate correlation, which indicates that the spectra measured within this population are spectrally variable. This is consistent with previous investigations within this study, which have suggested that the algae-covered spectra measured in Fiji in 1996 are variable, possibly due to different amounts of algal cover on the surfaces.

Table 5.2.3. There is a positive linear relationship between the spectra measured over algae-covered surfaces, as seen in the correlation coefficient matrix.

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
A1	1									
A2	0.995	1								
A3	0.986	0.980	1							
A4	0.979	0.974	0.984	1						
A5	0.882	0.893	0.822	0.825	1					
A6	0.994	0.994	0.979	0.975	0.906	1				
A7	0.994	0.995	0.982	0.978	0.894	0.995	1			
A8	0.966	0.969	0.931	0.930	0.952	0.979	0.972	1		
A9	0.912	0.902	0.940	0.933	0.645	0.898	0.908	0.826	1	
A10	0.926	0.920	0.937	0.930	0.702	0.915	0.923	0.860	0.976	1

In an attempt to examine the between-population variability of spectral reflectance, correlation coefficients were calculated based on the average spectra for each population. Therefore, 3 average spectra were included in the following correlation analysis: average bleached massive coral, average healthy massive coral and algae-covered surfaces. The results of the correlation analysis can be found in the Pearson correlation matrix in Table 5.2.4. The correlation coefficients in all cases are strongly positive, which indicates that the average spectra for the 3 populations are all very similar. This result has significant implications for attempting to discriminate between these populations remotely. Since the populations are highly correlated, or spectrally similar, it will be very difficult to develop an accurate means of differentiation based upon the reflectance spectra across the entire visible spectrum.

Table 5.2.4. The Pearson correlation matrix reveals strong positive relationships between the three average spectra.

	Bleached	Healthy	Algae
Bleached	1		
Healthy	0.946	1	
Algae	0.987	0.928	1

5.2.4 Summary of 1996 Spectral Comparison

The spectral data set collected in Beqa Lagoon, Fiji in 1996 consists of 40 measurements of bleached massive coral, healthy massive coral and algae-covered surfaces. These spectra were measured underwater while scuba diving with a 10m optical cable and a remote cosine receptor. It was hypothesized that the within-population variability will be small such that all bleached massive coral spectra will be similar. Additionally, it was hypothesized that the between-population variability will be large as a result of wavelength-specific differences in reflectance.

Initial inspection revealed that there are subtle differences in the shape and magnitude of the reflectance curves, which may enable discrimination between broad classes or populations. The cluster analysis performed to investigate the difference between populations produced variable results. Cluster analysis was able to discriminate between different spectra although there was a certain degree of misclassification. The primary source of variability is most likely the differing amounts of algae present on the sample as well as the small sample set. The main value of the cluster analysis in this study may be its ability to reveal low variability within populations.

The correlation coefficients were calculated to examine the within-population variability of spectral reflectance measurements. This analysis revealed that, in all cases, a positive linear relationship exists between spectra within a given population. The relationship was strongest for the bleached massive coral group and weakest for the algae-covered coral group.

While the visual examination of the measured spectra revealed subtle differences in spectral reflectance characteristics, the correlation coefficients calculated for the average spectra for each of the 3 populations reveal strong positive relationships. The strong positive correlations indicate that it will be difficult to differentiate these populations spectrally.

5.3 EXAMINATION OF 1997 SPECTRAL DATA SET

Field data were collected in 1997 in Manado, Indonesia to augment the relatively small database initiated by the 1996 data set collected in Beqa Lagoon, Fiji. The 1997 dataset consists of 80 spectra measured with the remote cosine receptor. The features measured were exposed, so there was no contribution of the water column to spectral reflectance. The features measured were grouped into 5 broad categories: healthy massive coral (n=6); healthy branching coral (n=19); sand surfaces (n=34); bleached massive coral (n=16) and algae-covered surfaces (n=5).

5.3.1 Initial Examination of 1997 Spectra

The average and standard deviation spectra were computed and compared separately by category in Figures 5.3.1 through 5.3.5. There appears to be little variation in the spectral shape and magnitude between the categories defined above according to feature type. The spectral curve with the greatest maximum reflectance is sand. This is not surprising, as the sand surfaces in this coastal area were very bright white. As a summery, Table 5.3.1 provides the spectral locations of the peaks in the reflectance curves as well as the actual magnitude of those peaks.

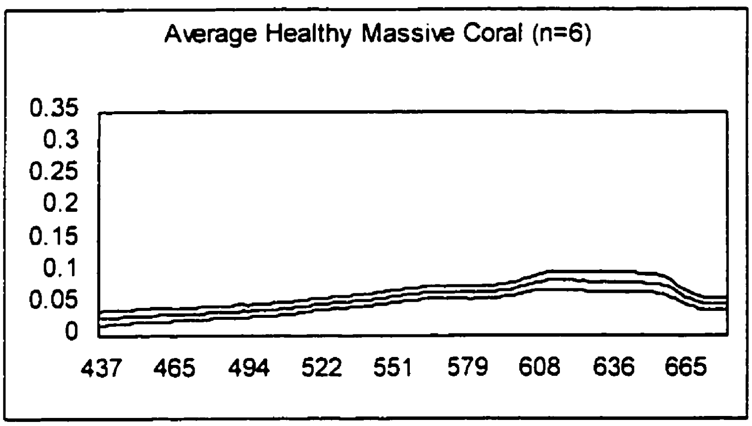

Figure 5.3.1. The average spectrum for healthy massive coral collected in Manado, Indonesia in 1997 (gray lines represent plus and minus one standard deviation).

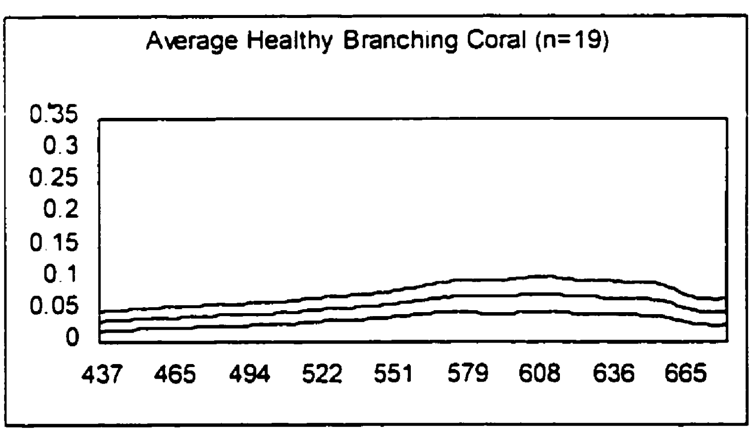

Figure 5.3.2. The average spectrum of healthy branching coral measured in Manado, Indonesia in 1997 (gray lines represent plus and minus one standard deviation).

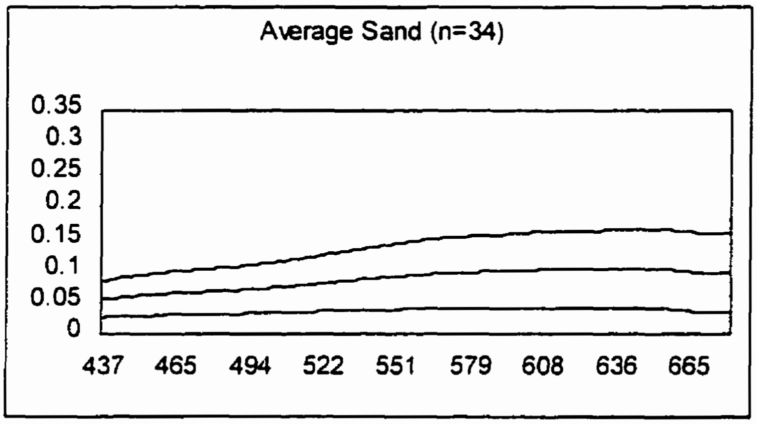

Figure 5.3.3. The average spectrum of sand surface spectra measured in Manado, Indonesia in 1997 (gray lines represent plus and minus one standard deviation).

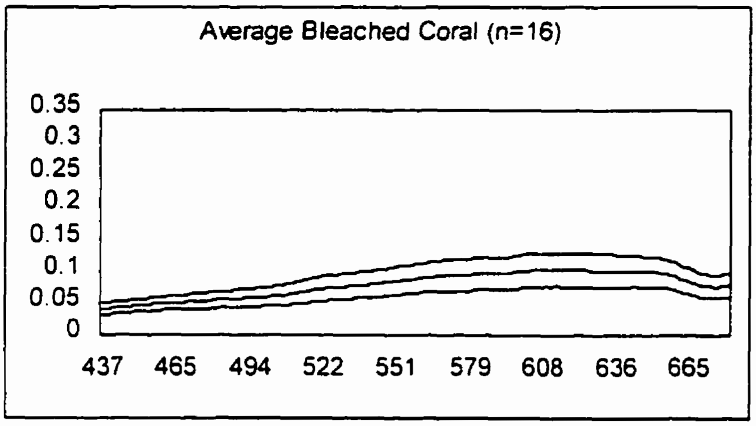

Figure 5.3.4. The average spectrum for bleached massive coral spectra measured in Manado, Indonesia in 1997 (gray lines represent plus and minus one standard deviation).

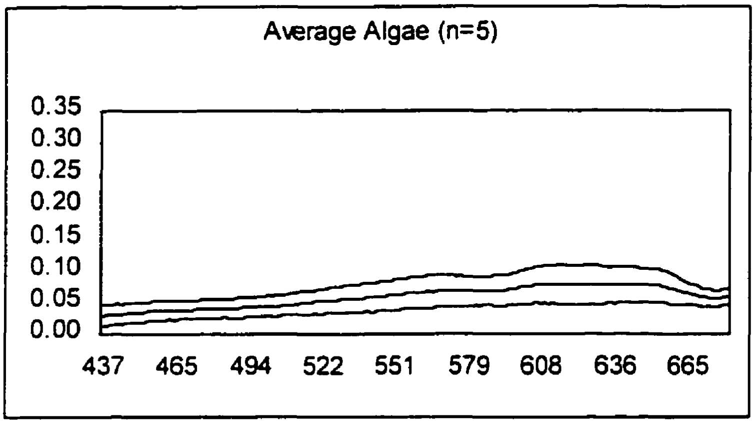

Figure 5.3.5. The average spectrum of algae-covered surface spectra measured in Manado, Indonesia in 1997 (gray lines represent plus and minus one standard deviation).

Table 5.3.1. The magnitude and spectral location of the peak in reflectance is compared.

	Sand Surfaces	Bleached Massive Coral	Healthy Massive Coral	Algae-covered Surfaces	Healthy Branching Coral
Magnitude of Reflectance Maximum	0.103	0.102	0.086	0.078	0.075
Spectral Location of Reflectance Maximum	644.6nm	609.1nm	614nm	611.9nm	609.1nm

The order of columns in Table 5.3.1 from left to right is according to decreasing magnitude of reflectance. Sand surfaces and bleached corals have very similar magnitudes of maximum reflectance, which will cause confusion in classification based on magnitude alone. The spectral locations of the reflectance maxima are different: 645nm versus 609nm, which result in a slightly different slope of the spectral curve in this wavelength region. This issue will be examined later in this thesis. Healthy massive coral, healthy branching coral and algae-covered surfaces display similar magnitudes and similar spectral locations of maximum reflectance, which is a limiting factor for discrimination of these populations in the 1997 data set.

For comparison, the average spectra are plotted in Figure 5.3.6. There appear to be 2 distinct populations based on spectral magnitude and shape. Bleached coral and sand have high overall reflectance and do not display a dip in the reflectance curve at approximately 595nm. Alternatively, healthy massive and branching corals as well as algae-covered surfaces have lower overall reflectance and display a dip in reflectance at 595nm. This dip in the reflectance curve could be a result of pigments present in the zooxanthellae of healthy coral and the algae that are not present in the bleached coral and sand surfaces. The slope of the spectral curve between approximately 590-615nm is therefore different for these two groups.

The algae-covered surface average spectral curve has characteristics that are quite similar to healthy massive and branching corals. The small number of spectra measured in the 1997 data set (n=5) may limit the degree to which algae-covered surfaces can be characterized. This weakness was recognized after the 1997 field season and addressed in the 1998 field season, as will be discussed later.

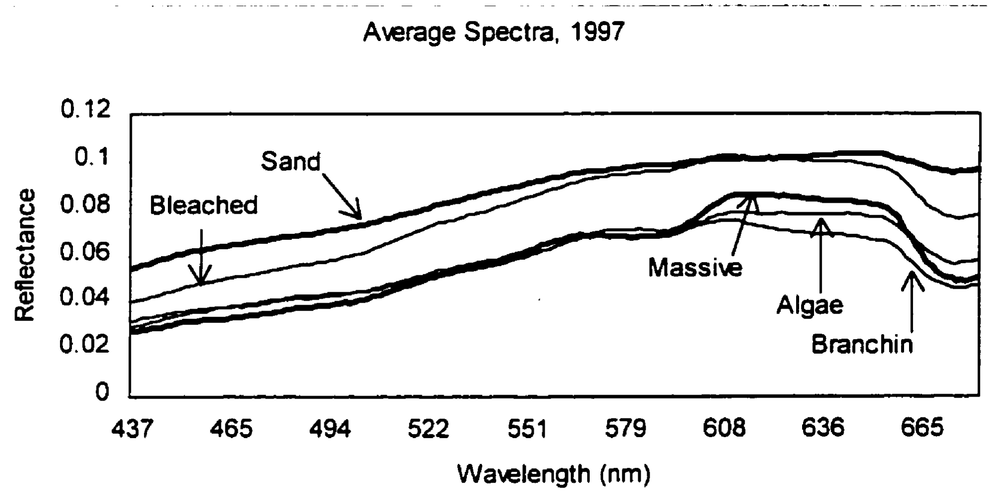

Figure 5.3.6. The average spectra for the 5 populations defined for the 1997 dataset are compared in one plot.

5.3.2 Cluster Analysis of 1997 Spectra

As in the earlier analysis of the 1996 spectral data set, the objective of using cluster analysis is to determine if the measured spectra can be grouped into classes based on reflectance characteristics. First, the full data set of 80 spectra measured in Manado, Indonesia was analyzed using cluster analysis. The cluster tree diagram in Figure 5.3.7 illustrates the results of the cluster analysis.

If a vertical line is drawn at a Euclidean distance of 0.0025, there are 5 clusters present. Starting at the bottom, there is a cluster of 21 spectra, of which 48% are healthy branching corals; 29% are sand surfaces; 14% are algae-covered surfaces; and less than 5% each are massive corals and bleached corals. Healthy branching corals account for the largest number of spectra present in this cluster. It is interesting that healthy massive corals are not similar enough to healthy branching corals to be placed in the same cluster.

This indicates that morphology influences the spectral measurements, which would be expected due to shadows, underlying substrate and texture.

Moving from the bottom towards the top, the next cluster contains 25 spectra. The majority of the spectra in this cluster are measurements of sand surfaces (52%), while branching corals (24%), massive corals (12%) and bleached corals (12%) are also present. The spectral similarity between these different features is enough that they can be placed in the same cluster, which emphasizes the complexity in differentiating between populations. The next cluster up from the bottom contains 19 spectra in total, with no population claiming the majority. As with the first cluster, all 5 populations are represented in this cluster, which emphasizes the degree of spectral similarity between populations.

Finally, the cluster closest to the top of the tree does not actually form a complete cluster until a Euclidean distance of 0.13. This large Euclidean distance indicates that the spectra are relatively dissimilar. Sand surfaces (73%); bleached coral (20%); and branching coral (7%) are included in this cluster. Since this cluster did not join until late in the process, the component spectra are considered unlike each other, but since most (73%) of the spectra are sand surface measurements, these spectra are also considered dissimilar to the other spectra in the 1997 data set.

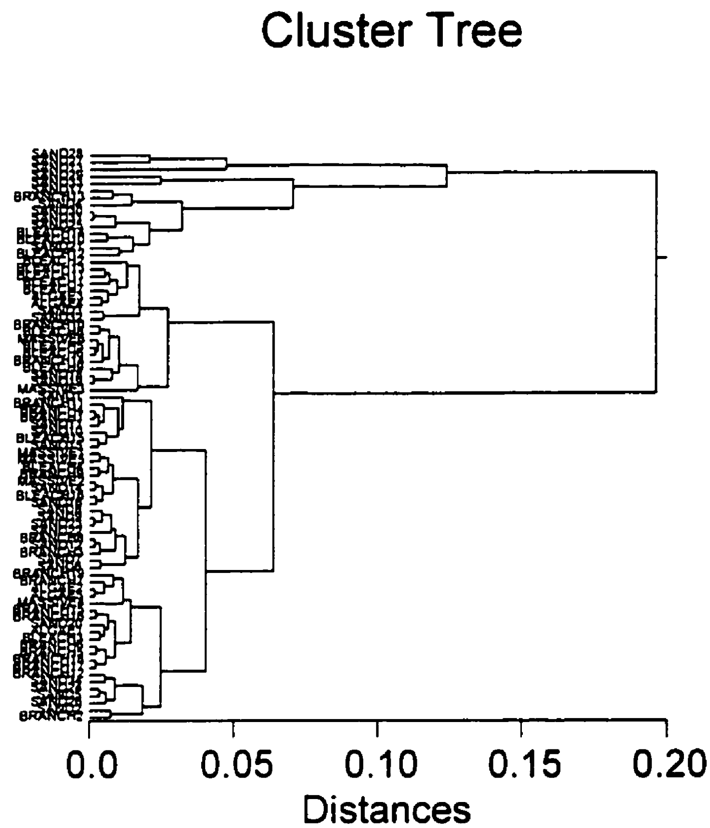

Figure 5.3.7. The entire data set collected in 1997 in Manado, Indonesia was subjected to cluster analysis in an effort to separate populations on the basis of spectral reflectance.

The results of five more cluster analyses are now presented. Each of the five cluster analyses considers only one population at a time in an effort to explore the variability within each population. The first cluster analysis is performed on the category containing 6 massive coral spectra, as in Figure 5.3.8. At a Euclidean distance of 0.015, two clusters are present, but this is a very small a Euclidean distance of indicating the spectra are actually all quite similar.

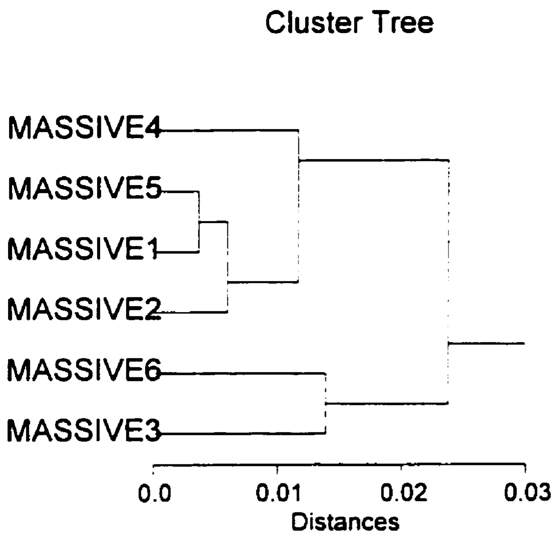

Figure 5.3.8. A separate cluster analysis reveals little within-population variability for the population of massive healthy corals.

The second of 5 cluster analyses focuses on the healthy branching coral population, as displayed in Figure 5.3.9. The spectra identified as Branch13 may be considered an outlier, for it does not join the remainder of the spectra until a Euclidean distance of 0.1. The other 18 spectra in this population join into one cluster at a Euclidean distance of 0.04, which is a relatively small distance indicating that the spectra are quite similar.

If a vertical line is drawn at a Euclidean distance of 0.02, three clusters are present. The similarity of spectra within these three clusters may be related to the density of the branches of the coral target. A branching coral allows the underlying substrate to be seen through the branches in some cases. If this is the situation, then the underlying substrate will contribute to the measured reflectance to varying degrees depending on the density of branching. Alternatively, a coral with very dense branching structure may have a spectral reflectance curve similar to that of a massive coral, as little or no contribution to the reflectance characteristics is a result of the underlying substrate.

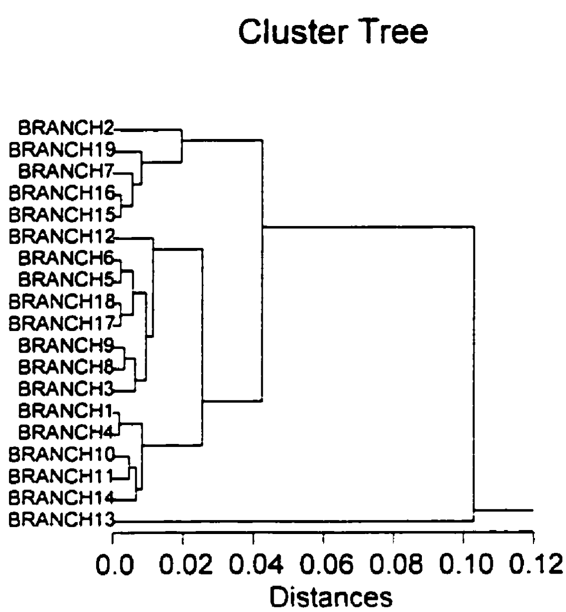

Figure 5.3.9. A cluster analysis of the population of branching corals indicates that there is little within-population variability.

The population consisting of 34 sand surface spectra was considered in the third cluster analysis. The cluster tree is illustrated in Figure 5.3.10. At a Euclidean distance of 0.06, three clusters are present, and the entire data set is joined into one cluster at a distance of less than 0.2. Within each of the clusters joined at 0.06, the spectra can be considered quite similar. Each of these three clusters may be similar based on the relative wetness of the sand sampled. Since the measurements were taken at low tide, the sand surfaces had varying states of wetness depending on the amount of time exposed to sunlight.

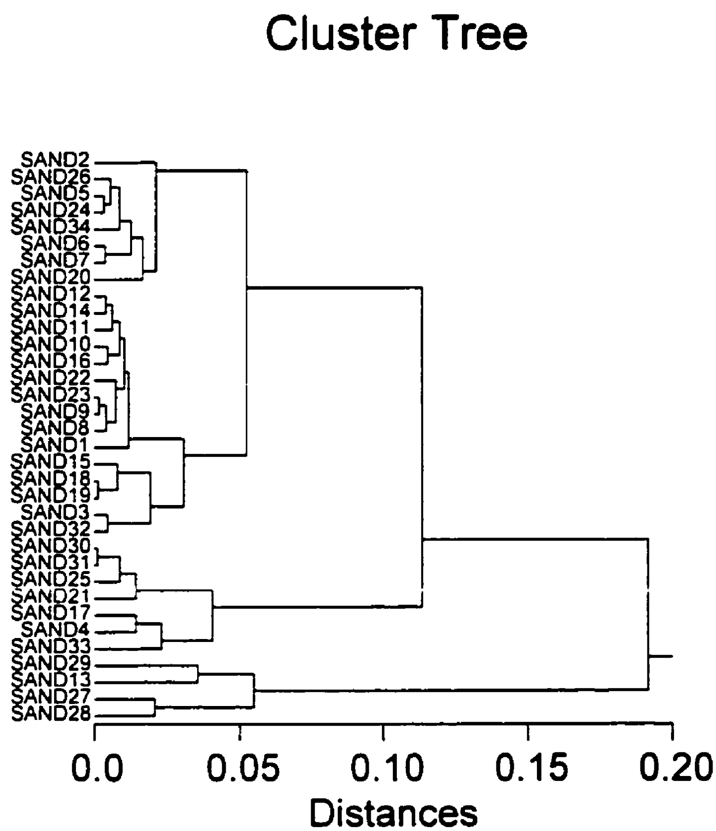

Figure 5.3.10. Thirty-four sand surface spectra were included in the above cluster analysis.

In the forth cluster analysis, 16 bleached massive coral spectra were included in order to examine the spectral similarity within this population. The results of the cluster analysis can be viewed in the cluster tree in Figure 5.3.11. At a Euclidean distance of 0.03, two clusters are present, and at a Euclidean distance of 0.7, all spectra join into one cluster. This indicates that there is little within population variability and the bleached massive coral spectra can be considered similar. The differences in spectral reflectance that are seen within these measurements may be a result of varying states of bleaching. For example, if a coral has been bleached for a week, it will have a greater number of zooxanthellae present than a coral that has been bleached for 3 weeks. The spectral reflectance curves for corals in different stages of bleaching may therefore show spectral differences. Overall, however, there is little within-population variability indicated by the cluster analysis of 16 bleached massive coral spectra.

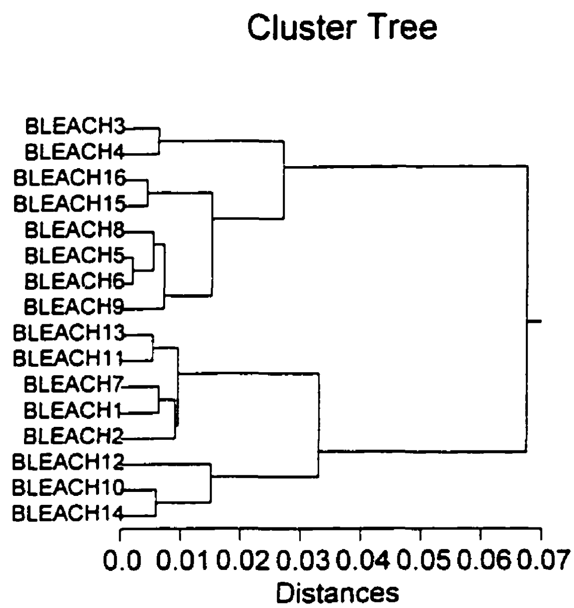

Figure 5.3.11. Sixteen bleached coral spectra were included in the cluster analysis above.

Finally, five algae-covered surface spectra were analyzed for within population variability using cluster analysis. The results are presented in the cluster tree in Figure 5.3.12. At a Euclidean distance of less than 0.025, there are two clusters present, and at 0.04, all five spectra join together as one cluster. The low values of the Euclidean distances indicate low variability within the population, such that the five spectra can be considered similar.

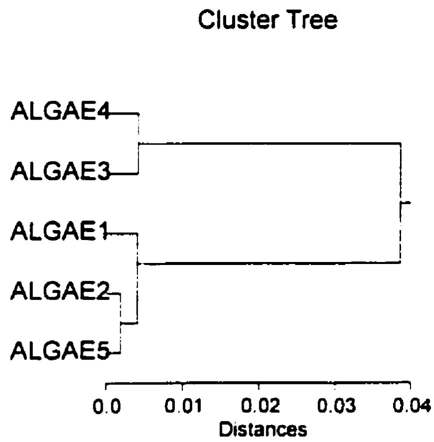

Figure 5.3.12. Five algae-covered surface spectra were included in the above cluster analysis.

The Euclidean distance at which the spectra in a population join to form one cluster is indicative of the similarity of the spectra within that population, where a small Euclidean distance suggests similar spectra and a large Euclidean distance suggests dissimilar spectra. As a summary, the Euclidean distances at which spectra within a given population joined to create one cluster is provided in Table 5.3.2.

Table 5.3.2. A summary of the unitless Euclidean distances at which the spectra within a population were considered similar in order of increasing distance.

Population	Euclidean distance
Healthy Massive Coral	0.023
Healthy Branching Coral	0.04
Algae-covered Surfaces	0.04
Bleached Coral	0.07
Sand Surfaces	0.20

The population with the lowest Euclidean distance has the least variability in spectral reflectance among its component spectra, while the population with the greatest Euclidean distance has the most variability in spectral reflectance among its component spectra. Healthy massive corals display the least variability within its population, followed by healthy branching coral and algae-covered surfaces. Sand surfaces have the greatest within-population variability, possibly due to varying degrees of water content (these measurements were taken on exposed reef flats) or sand crystal size.

5.3.3 Correlation Analysis of 1997 Spectra

In the following, correlation analysis is used to examine the relationship among each of the measured spectra within a given category of features. It is hypothesized here that the spectra within a given population will display strong positive linear relationships to each other, suggesting that the spectra within the population are similar. A separate correlation analysis is performed on each of the five populations defined for the 1997 data set. The five populations include healthy massive corals (n= 6); healthy branching corals (n= 19); sand surfaces (n= 34); and algae-covered surfaces (n= 5). A correlation analysis can be easily interpreted by viewing the correlation coefficient matrix, as with the 1996 data analysis.

The data set containing 6 healthy massive corals is included in the correlation analysis illustrated in the matrix in Table 5.3.3. As can be seen in the matrix, there is a high correlation among the healthy massive coral spectra. The correlations among healthy massive spectra are all greater than 0.94, which indicates low variability within the population. This reinforces the results of the cluster analysis of the healthy massive coral population.

Table 5.3.3. A correlation coefficient matrix illustrates the correlation between spectra within the population of healthy massive corals.

	Massive1	Massive2	Massive3	Massive4	Massive5	Massive6
Massive1	1					
Massive2	0.979	1				
Massive3	0.989	0.942	1			
Massive4	0.986	0.999	0.953	1		
Massive5	0.995	0.968	0.994	0.975	1	
Massive6	0.981	0.999	0.944	0.999	0.970	1

The second correlation analysis was performed on 19 healthy branching corals, but only the first 10 spectra are included in the matrix below. The results of the correlations of ten spectra are illustrated in the correlation matrix in Table 5.3.4. The correlations among the healthy branching coral spectra are strongly positive, and the lowest correlation coefficient calculated was 0.84. Furthermore, 97.1% of the correlation coefficients are greater than 0.90. As with the healthy massive coral spectra, the results of the correlation analysis reinforce the results of the cluster analysis.

Table 5.3.4. Nineteen healthy branching coral spectra are included in the above correlation analysis.

	Br1	Br2	Br3	Br4	Br5	Br6	Br7	Br8	Br9	Br10
Br1	1									
Br2	0.993	1								
Br3	0.994	0.989	1							
Br4	0.995	0.990	0.987	1						
Br5	0.996	0.991	0.989	0.998	1					
Br6	0.974	0.980	0.955	0.979	0.976	1				
Br7	0.968	0.972	0.952	0.975	0.972	0.990	1			
Br8	0.978	0.983	0.964	0.982	0.980	0.994	0.992	1		
Br9	0.963	0.974	0.953	0.963	0.961	0.984	0.982	0.991	1	
Br10	0.867	0.888	0.842	0.875	0.868	0.946	0.937	0.942	0.951	1

The third correlation analysis was performed on 34 sand surface spectra. While all spectra were included in the analysis, the correlation coefficients of the first 10 spectra can be viewed in Table 5.3.5. Some of the correlations among the spectra in the sand surface population are weak, suggesting that the spectra are dissimilar. The lowest calculated correlation coefficient is 0.32, however, 87.5% of the coefficients are greater than 0.6. The within-population variability may be a result of the varying degrees of wetness of the sand, as discussed previously. The high variability also indicates that it would be difficult to identify one representative spectral reflectance curve that would allow remote identification of sand surfaces. Even though there is great within-population variability, there is a chance that the spectral reflectance response of sand surfaces is so different than other features that accurate remote identification may be possible.

Table 5.3.5. Thirty-four sand surface spectra were included in this correlation analysis.

	Sand1	Sand2	Sand3	Sand4	Sand5	Sand6	Sand7	Sand8	Sand9	Sand10
Sand1	1									
Sand2	0.619	1								
Sand3	0.879	0.867	1							
Sand4	0.889	0.896	0.976	1						
Sand5	0.364	0.714	0.639	0.594	1					
Sand6	0.505	0.588	0.674	0.601	0.889	1				
Sand7	0.336	0.318	0.456	0.356	0.793	0.905	1			
Sand8	0.858	0.920	0.972	0.995	0.616	0.603	0.353	1		
Sand9	0.871	0.911	0.975	0.998	0.615	0.615	0.366	0.997	1	
Sand10	0.896	0.885	0.981	0.995	0.637	0.659	0.431	0.990	0.994	1

The within-population variability of the bleached massive coral population was also examined using correlation analysis, as seen in the correlation matrix in Table 5.3.6. The correlations among bleached massive spectra were very strong, which indicates small within-population variability. In fact, all correlation coefficients are greater than 0.90. It would appear that, due to the low variability within this data set, a reliable representative spectral curve could be identified to characterize the expected response of bleached massive corals.

Table 5.3.6. Correlations among sixteen bleached massive coral spectra were examined for the within-population variability.

	BI1	BI2	BI3	BI4	BI5	BI6	BI7	BI8	BI9	BI10
BI1	1									
BI2	0.999	1								
BI3	0.975	0.982	1							
BI4	0.983	0.988	0.991	1						
BI5	0.944	0.956	0.982	0.978	1					
BI6	0.951	0.962	0.989	0.982	0.997	1				
BI7	0.963	0.968	0.965	0.979	0.976	0.965	1			
BI8	0.968	0.974	0.975	0.987	0.984	0.976	0.998	1		
BI9	0.962	0.967	0.965	0.979	0.979	0.968	0.999	0.999	1	
BI10	0.977	0.984	0.992	0.985	0.979	0.986	0.961	0.972	0.962	1

Finally, all five algae-covered corals are examined for the within-population variability, as illustrated in the correlation matrix and scatterplots in Table 5.3.7. Correlation coefficients calculated for the algae-covered spectra were strongly positive indicating low variability within the population. This reinforces the cluster analysis results, and suggests that, even with a small number of spectra, a reliable data set appears to exist from which a representative spectrum could be selected.

Table 5.3.7. Five algae-covered surfaces were examined for the correlations among spectra.

	Algae1	Algae2	Algae3	Algae4	Algae5
Algae1	1				
Algae2	1.000	1			
Algae3	0.950	0.954	1		
Algae4	0.964	0.967	0.998	1	
Algae5	0.989	0.989	0.955	0.968	1

In an effort to examine the variability between spectral populations, a correlation analysis was performed comparing the average spectra from each population. Therefore, 5 spectra were included in this correlation analysis: average massive healthy coral, average healthy branching coral, average sand surface, average massive bleached coral and average algae-covered surface spectra.

The results of the correlation analysis can be seen in the Pearson correlation matrix in Table 5.3.8. The average spectra all display very strong positive correlations with each other, which suggests that the spectra are very similar. The results of this correlation analysis reveal that discriminating between spectral populations is complex, even if it is assumed that the within-population variability is low.

Table 5.3.8. A Pearson correlation matrix compares the correlation coefficients for the five average spectra included in the analysis.

	Healthy Massive	Healthy Branching	Sand	Bleached Massive	Algae-covered
Healthy Massive	1				
Healthy Branching	0.962	1			
Sand	0.942	0.916	1		
Bleached Massive	0.979	0.977	0.978	1	
Algae-covered	0.991	0.961	0.977	0.994	1

5.3.4 Summary of 1997 Spectral Comparison

Average and standard deviation spectra were examined at the beginning of this chapter to visualize the within-population variability of the 5 populations defined for the 1997 data set. Furthermore, the average spectra for each of the populations were compared to visually examine and compare the spectral reflectance characteristics of the different populations. Cluster and correlation analyses were then performed to examine the within- and between-population variability. Spectra were separated into populations for separate analysis to examine within-population variability. With the exception of the high variability among sand surface spectra, there was little within-population variability found. Correlation coefficients of average spectra were then examined to explore the between-population variability. The correlation coefficients were very strongly positive for all spectral comparisons, which suggests that the average spectra are all similar. These results emphasize difficulty in remotely identifying these spectrally similar features.

5.4 EXAMINATION OF 1998 SPECTRAL DATA SET

The 1998 field data collected in Savusavu Bay, Fiji consist of 214 reflectance spectra in 172 wavebands measured underwater. The spectra were separated into broad categories defined according to feature type, as was done in the 1996 and 1997 field seasons. Underwater photographs and a detailed description of each feature measured enabled separation into 6 categories, or populations.

5.4.1 Initial Examination of 1998 Spectra

As in the initial examinations of the field data collected in 1996 and 1997, average and standard deviation spectra were found for each of the 6 categories defined. These spectra are plotted separately in Figure 5.4.1 (healthy branching coral, n=19); Figure 5.4.2 (healthy massive coral, n=27); Figure 5.4.3 (healthy soft coral, n=47); Figure 5.4.4 (bleached branching coral, n=15); Figure 5.4.5 (rubble surfaces, n=28); and Figure 5.4.6 (algae-covered surfaces, n=79). Additionally, the average spectra for each of these 6 populations are compared in one plot in Figure 5.4.7.

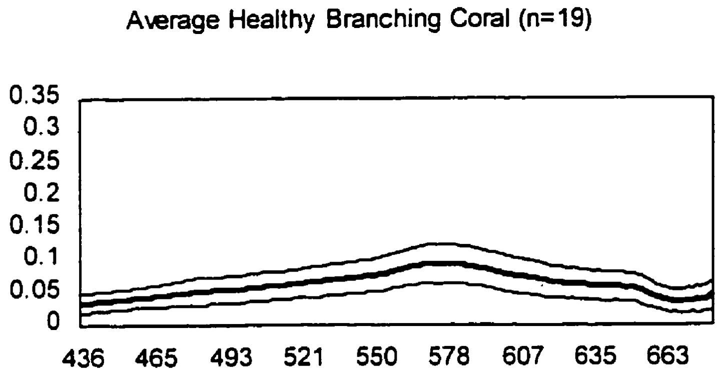

Figure 5.4.1. Average and standard deviation (gray lines) healthy branching corals.

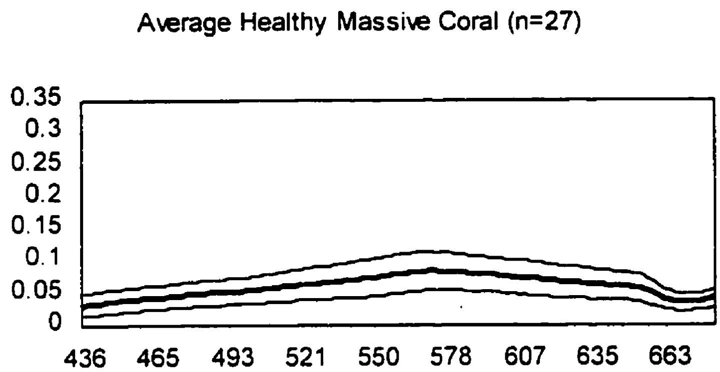

Figure 5.4.2. Average and standard deviation (gray lines) healthy massive corals.

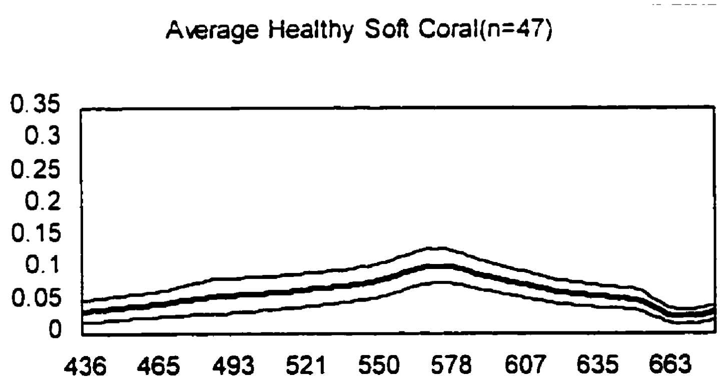

Figure 5.4.3. Average and standard deviation (gray lines) healthy soft corals.

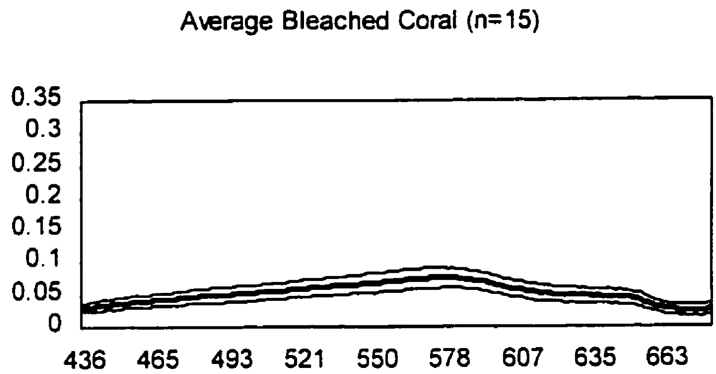

Figure 5.4.4. Average and standard deviation (gray lines) spectra for bleached corals.

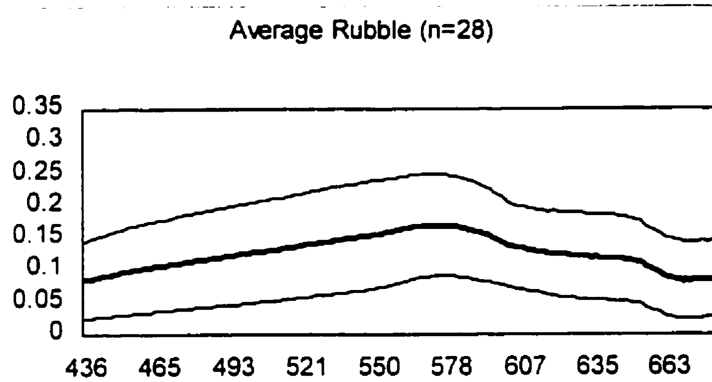

Figure 5.4.5. Average and standard deviation (gray lines) spectra for rubble surfaces.

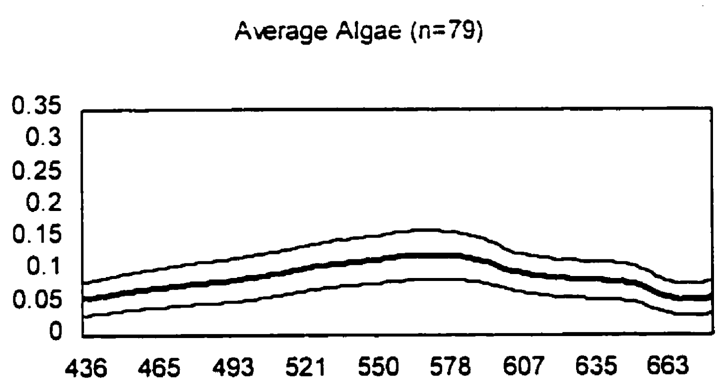

Figure 5.4.6. Average and standard deviation (gray lines) spectra for algae-covered surfaces.

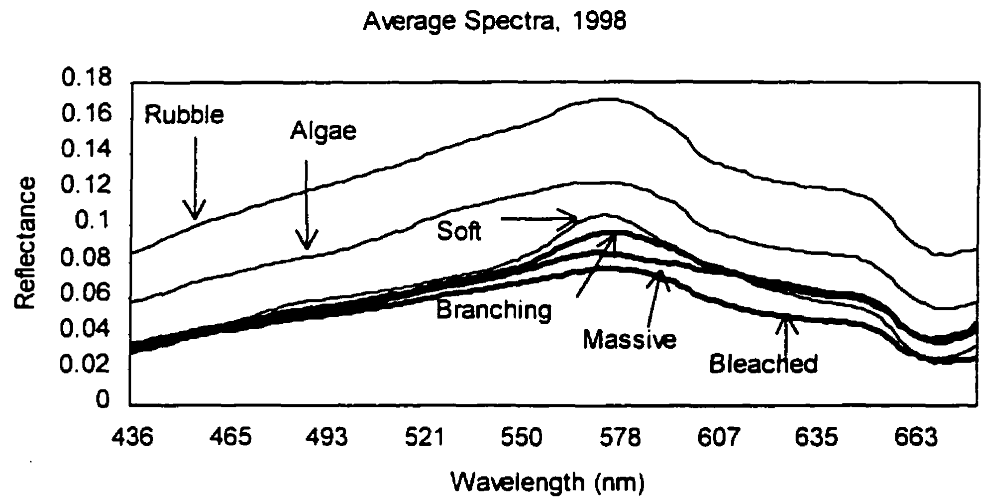

Figure 5.4.7. A plot of average spectra of the 6 populations allows comparison.

Inspection of Figure 5.4.7 reveals that rubble surfaces have the highest average reflectance. Coral sand and dead coral debris dominate rubble surfaces, which are typically bright white. It is therefore not surprising that the overall magnitude of reflectance is high. The spectral shape of the reflectance curve may be influenced by variable amounts of macroalgae that is commonly present on a rubble surface. The variable presence of macroalgae will contribute to within-population variability in spectral reflectance.

Inspection of Figure 5.4.7 also reveals that algae-covered surfaces display relatively high spectral reflectance as well. The high magnitude of reflectance may be a result of the particular pigment present in the colonizing algae as a function of the species of algae, which is unidentified. Additionally, algae will colonize dead corals, so the white calcium carbonate surface of a dead coral may contribute to the magnitude of reflectance measured. In other words, if the alga has colonized a dead coral, the white calcium carbonate of the dead coral (which has lost its photosynthetic zooxanthellae) will show through and result in a high magnitude of reflectance.

The three populations of healthy corals identified in the 1998 data set (branching, massive and soft healthy coral) have very similar average spectra. Both the spectral magnitude and shape of the reflectance curves are similar. This is intuitive since all healthy corals contain photosynthetic zooxanthellae in their polyps, which would result in similar spectral characteristics. The spectral similarity of these average reflectance curves is encouraging with respect to identifying spectral characteristics common to healthy corals.

Surprisingly, the average spectral reflectance curve for the bleached branching coral population has the lowest overall magnitude of reflectance. Although it is expected that a bleached white coral will have high reflectance, there may be an explanation for the low reflectance in this case. The bleached corals sampled were all branching corals with fairly sparsely located branches. If the branches are sparse then the underlying substrate may contribute to the measured reflectance in proportion to the percent cover. The estimated percent cover of branches ranged from 40% to 85%, and in all cases a dark surface was the underlying substrate. In the case where the bleached branching coral contributed only 40% to the overall reflectance, the underlying dark substrate contributed 60%, which would have the net effect of a low overall reflectance.

The spectral confusion within the bleached coral population may not be a major issue. This is because, while it is important to identify areas of bleached coral, it may be even more important to identify areas of dead coral that has already been colonized by algae. Since a bleached coral can recover, identification of a bleached coral serves to alert us to a vulnerable region. Algae will quickly colonize a bleached coral in a vulnerable state, and this may be a more important ecological change to identify.

There appears to be some variation in the average spectral reflectance curves measured for the 6 different populations. One feature that may enable differentiation between populations is the spectral peak at approximately 575nm. For comparison, the magnitude and location of the spectral peak of each of the 6 average reflectance curves is provided in Table 5.4.1. The populations are listed from left to right in order of decreasing magnitude of reflectance.

Table 5.4.1. A comparison of the magnitude and spectral location of peak reflectance, sorted according to decreasing magnitude of reflectance.

	Rubble Surfaces	Algae Surfaces	Healthy Soft Coral	Healthy Branching Coral	Healthy Massive Coral	Bleached Branching Coral
Magnitude of Reflectance Maximum	0.170	0.124	0.106	0.096	0.085	0.076
Spectral Location of Reflectance Maximum	572.4	569.6	572.4	576.7	572.4	576.7

5.4.2 Cluster Analysis of 1998 Spectra

The entire data set of 215 reflectance spectra were compared using cluster analysis to determine the degree of dissimilarity among and between populations. Due to the large number of spectra included in the analysis, a cluster tree diagram is not useful for visual interpretation. At a Euclidean distance of 0.05, there are 5 clusters present. The first cluster contains 100% rubble, but only 6 spectra are included in this cluster. The second cluster (n=45) contains 58% algae, but 24% rubble, 11% massive healthy coral and 7% branching coral, suggesting great spectral confusion between these populations. The third cluster (n=44) contains 43% algae, 30% soft coral, 14% rubble, 11% branching coral and 2% massive coral, which indicates spectral confusion within this cluster. Furthermore, this indicates spectral confusion between clusters since algae-covered surfaces are present in large proportion in both cluster 2 and cluster 3. Of the 97 spectra placed in cluster 4, 36% are algae spectra, 26% are soft coral spectra, 15% massive coral spectra, 12% bleached coral spectra, 6% branching coral spectra and 5% rubble spectra. There is no clear dominance of any one population in cluster 4. Finally, cluster 5 contains 23 spectra, 39% of which are soft corals, 26% are massive corals, 22% are branching corals and 13% are bleached corals, which suggests that there is great spectral confusion between these populations.

In conclusion, it is not possible to differentiate populations based on the entire spectrum of visible reflectance using cluster analysis. This emphasizes the complex and confusing issues surrounding identification of visually similar coral reef features. These results indicate that spectral classification based on traditional end-member selection whereby the entire visible reflectance spectrum is used since this will likely lead to significant misclassification and misidentification. Cluster analysis will be used further as a tool to investigate within-population variability of each of the 6 populations defined for the 1998 data set.

The cluster analyses performed in this section begin with an inspection of the algae-covered surfaces (n=79). The cluster analysis results can be viewed in the cluster tree diagram in Figure 5.4.8. At a Euclidean distance of approximately 0.05, there are 4 clusters present, and at 0.15, all spectra join as one cluster. Inspection of the photographs indicates no apparent differences in algae-covered surfaces that could account for the spectral differences. One explanation is that the clusters represent surfaces with varying percent cover of algae or varying densities of pigments within the algae. Alternatively, different species or strands of algae may have been sampled that we were unable to identify. Since there was high spectral confusion within the algae-covered surface populations collected in 1996 and 1997, attempts were made to create a much larger database in an effort to identify characteristic spectral features of algae. Even with 79 spectra in the 1998 data set, there still appears to be a certain degree of variability within the algae-covered surface population.

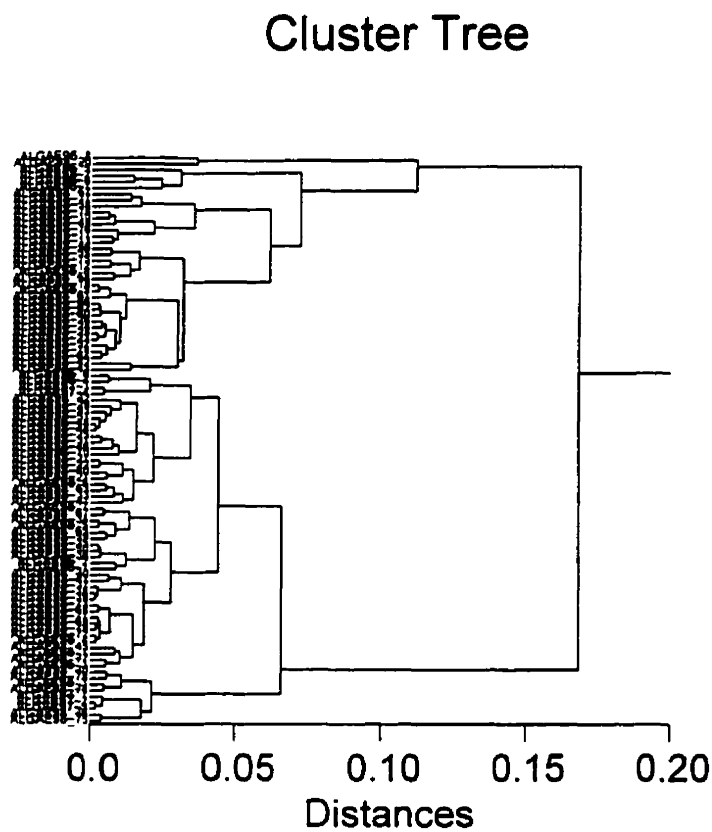

Figure 5.4.8. A cluster analysis was performed on all algae-covered surfaces (n=79).

The second cluster analysis was performed on the rubble surface spectral population, as seen in figure 5.4.9. At a Euclidean distance of 0.05, there are 6 clusters present in the rubble population, while the spectra do not join as one cluster until a Euclidean distance of 0.23. The cluster results indicate that the spectra of the rubble surface population are not particularly similar. The variability within the rubble surface population may be a result of varying proportions of dead coral debris to sand present in the sample. Inspection of the photographs indicates that there are no obvious differences in composition of the rubble surfaces. Alternatively, there may have been variable amounts of algae that had colonized the dead coral debris on the rubble surface, which was not readily observable. Varying amounts of algae would contribute to different spectral reflectance characteristics within the rubble surface data set.

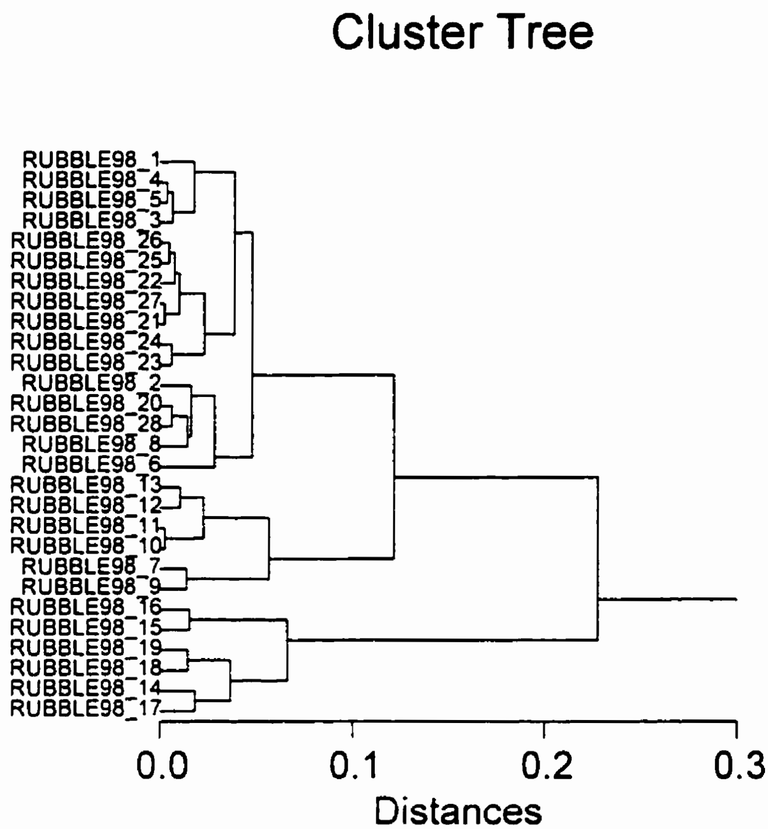

Figure 5.4.9. A cluster analysis was performed on rubble surface spectra (n=28).

A third cluster analysis examined the within-population variability of bleached branching corals (n=15), as in Figure 5.4.10. At a Euclidean distance of just greater than 0.05, the spectra within this population of bleached branching corals join as one cluster, indicating strong similarity. Therefore, at a relatively small Euclidean distance, all 15 of the bleached branching coral spectra in the 1998 data set are considered similar in spectral magnitude and shape. This is a promising result with respect to identifying one spectral reflectance curve characteristic of bleached branching corals with confidence since the within-population variability appears to be low.

In the inspection of the average spectra in the previous section, attention was brought to the bleached branching coral spectra due to its curiously low spectral reflectance. Although it would be expected that bleached coral would have high spectral reflectance magnitude since it has lost its photosynthetic zooxanthellae, the indication that the within-population variability is low lends confidence to the possibility of identifying a characteristic spectral reflectance curve based on this bleached branching coral population.

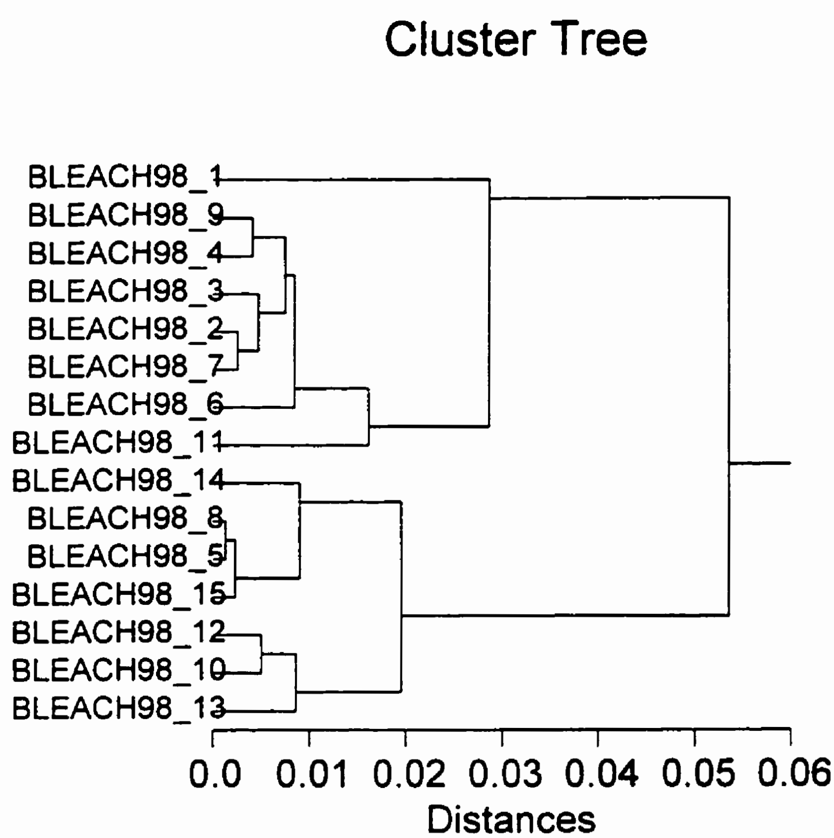

Figure 5.4.10. The bleached branching corals were analyzed with cluster analysis.

The following is based on a cluster analysis performed on the population of healthy soft corals (n=47), as in Figure 5.4.11. At a Euclidean distance of 0.05, there are only 2 clusters present, and all spectra join as one cluster at a Euclidean distance of less than 0.09. It can therefore be interpreted that the within-population variability of the healthy soft corals sampled is relatively low. Differences in measured spectral reflectance curves within the healthy soft coral population may be a result of differing morphologies of soft corals. Soft corals are continuous structures such that there is no contribution to the measured reflectance from the underlying substrate. The small branches or "fingers" that protrude from the surface of a soft coral are of varying shape, size and density. These differing features of soft corals may contribute to variable spectral reflectance curves. Therefore, the within-population variability that does exist within the healthy soft coral population is explainable.

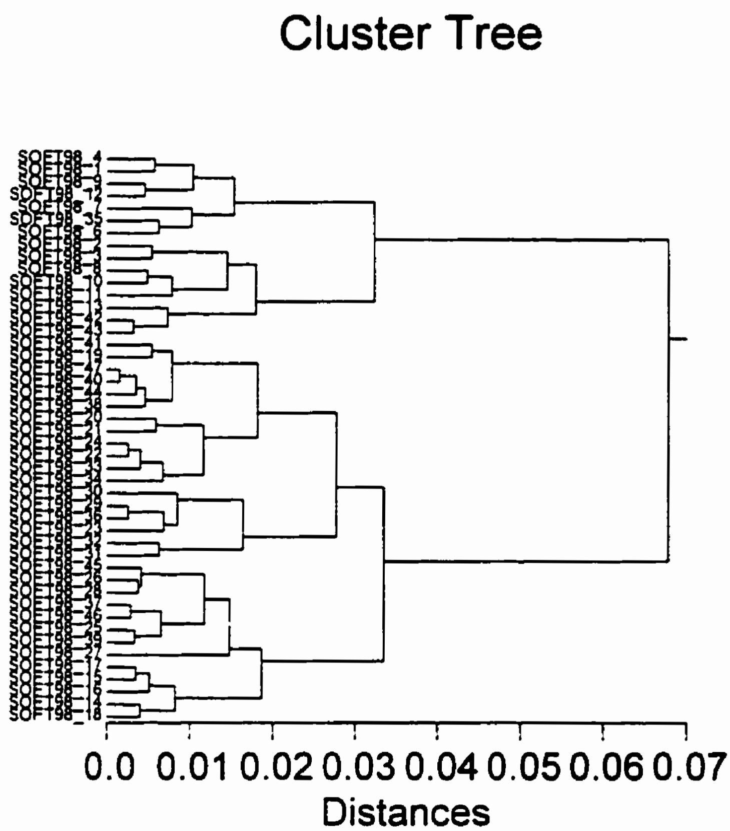

Figure 5.4.11. The healthy soft coral population was examined for within-population variability using cluster analysis.

The following interpretation is based on the cluster analysis performed on the healthy massive coral population (n=27), as in Figure 5.4.12. At a Euclidean distance of 0.05, there are 3 clusters present, but at a Euclidean distance of less than 0.09, all spectra join together as one cluster. The majority of the clusters are created at small Euclidean distances, which indicates that the spectra within the healthy massive coral population are similar to each other.

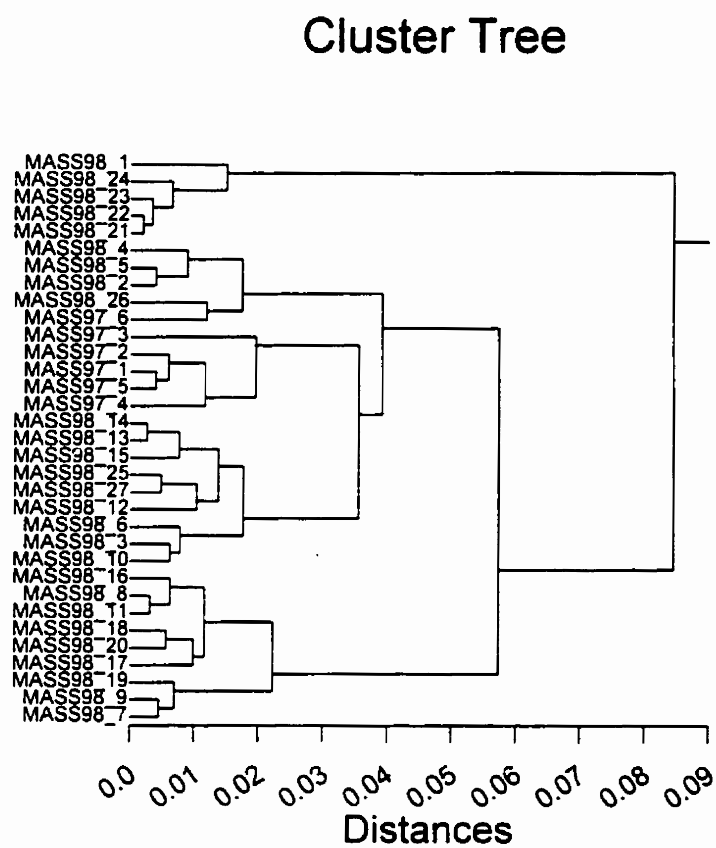

Figure 5.4.12. The within-population variability of healthy massive corals was examined using cluster analysis.

Finally, a cluster analysis was performed on the population of healthy branching corals (n=19) to examine within-population variability, as in Figure 5.4.13. There are 2 clusters present at a Euclidean distance of 0.05, and all spectra join as one cluster at a Euclidean distance of 0.09. Variability within this population of healthy branching corals could be related to the relative proportion of branches to underlying substrate in the sensor's field-of-view. In other words, the density of the branches may be related to the measured reflectance in terms of the relative contribution of coral to underlying substrate. If the underlying substrate is bright, the sensed reflectance spectra may display a higher magnitude, but if the underlying substrate is dark, the magnitude of reflectance may be low. Regardless, the within-population variability is no greater for healthy branching corals than for healthy massive corals, lending confidence to representative spectral characteristics defined by these populations.

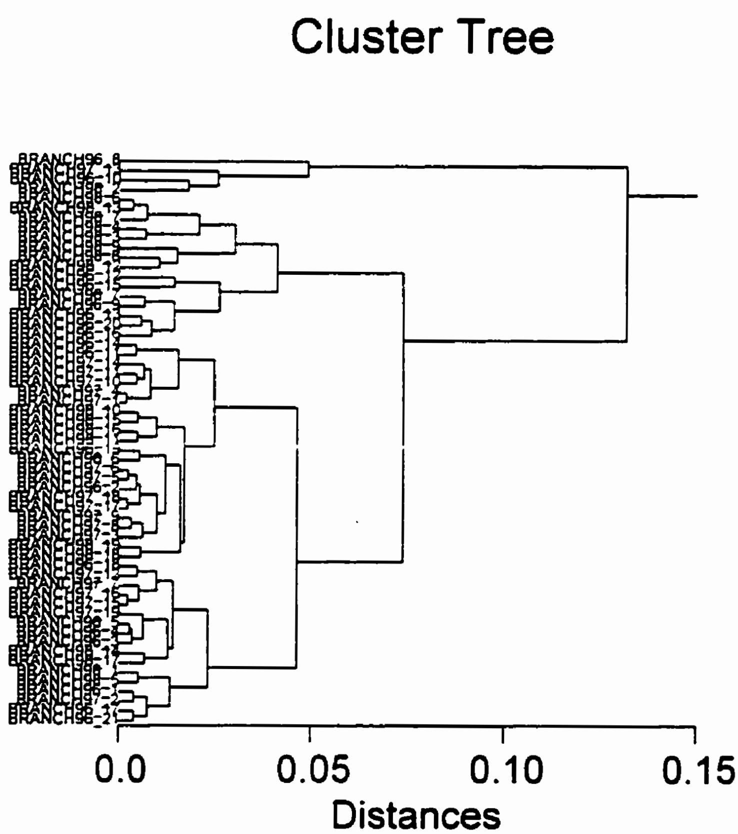

Figure 5.4.13. Cluster analysis is used to examine the within-population variability of healthy branching corals.

As a comparison, Table 5.4.2 contains the Euclidean distance at which the spectra of a given population were joined as one cluster. The populations are listed in order of increasing Euclidean distance. The bleached branching coral population is listed first with a joining Euclidean distance of 0.054, indicating that the within-population variability is lowest for this population. The spectra of the rubble surface population do not join as one cluster until a Euclidean distance of 0.23, indicating that the within-population variability is highest for this population. A comparison of the Euclidean distances at which all spectra of a population are joined as one cluster is a revealing means of comparing the within-population variability of the 6 populations included in the 1998 data set.

Table 5.4.2. A summary of the unitless Euclidean distances at which the spectra within a population were joined as one cluster compares within-population variability, in order of increasing distance.

Population	Euclidean Distance
Bleached Branching Corals	0.054
Healthy Massive Corals	0.085
Healthy Soft Corals	0.085
Healthy Branching Corals	0.09
Algae-covered Surfaces	0.14
Rubble Surfaces	0.23

5.4.3 Correlation Analysis of 1998 Spectra

Pearson correlation coefficients were calculated for each spectral pair within each population, but for clarity of illustration, only the first 5 coefficients and scatterplots are shown in the following results. Secondly, correlation coefficients are calculated for the average spectra of each population. The purpose of this analysis is to examine the between population variability, with the hypothesis that there will be weak correlations between populations. From the initial inspection of the average spectra for each population, it is expected that there will be a relatively strong correlation between the average spectra because of the overall spectral similarity of reflectance curves.

The correlation analysis begins with an examination of the algae-covered surface population. The Pearson correlation matrix in Table 5.4.3 reveals the relationship among ten spectra in the algae-covered surface population, although the entire data set of 79 spectra was included in the analysis. With a few exceptions, the 79 spectra included in the algae-covered surface population are highly correlated to each other, which reinforces the results of the cluster analysis and allows for a confidant statement that there is relatively little within-population variability among the algae-covered surfaces. The lowest correlation coefficient calculated is 0.35, but 96.6% of the coefficients are greater than 0.70, which suggests the spectra within the algae-covered surface population are relatively similar.

Table 5.4.3. The Pearson correlation coefficient matrix indicates the relationship among the algae-covered surface spectra.

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
A1	1									
A2	0.900	1								
A3	0.985	0.849	1							
A4	0.908	0.666	0.949	1						
A5	0.894	0.644	0.935	0.993	1					
A6	0.925	0.703	0.958	0.990	0.993	1				
A7	0.681	0.345	0.758	0.914	0.924	0.882	1			
A8	0.841	0.571	0.894	0.984	0.983	0.964	0.961	1		
A9	0.893	0.643	0.936	0.996	0.996	0.990	0.922	0.988	1	
A10	0.920	0.694	0.955	0.995	0.993	0.995	0.893	0.977	0.997	1

The next correlation analysis is performed on the rubble surface population consisting of 28 spectra, as can be seen the reduced matrix in Table 5.4.4. The correlation coefficients calculated for the spectra within the data set all show positive relationships among spectra, but there is a high degree of variability among the strengths of the relationships. The lowest correlation coefficient is 0.46 (not shown in matrix), but 94% of the correlation coefficients are greater than 0.70, which suggests that the majority of the spectra are highly correlated. The results of the correlation analysis are consistent with the results of the cluster analysis, indicating some degree of variability among rubble surface spectra, but an overall strong positive linear relationship.

Table 5.4.4. The correlation coefficient matrix reveals the relationships among rubble surface spectra.

	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10
R1	1									
R2	0.943	1								
R3	0.944	0.996	1							
R4	0.733	0.906	0.908	1						
R5	0.829	0.957	0.960	0.976	1					
R6	0.847	0.645	0.642	0.878	0.621	1				
R7	0.991	0.955	0.955	0.758	0.848	0.830	1			
R8	0.960	0.835	0.835	0.543	0.666	0.951	0.957	1		
R9	0.987	0.908	0.908	0.662	0.770	0.899	0.989	0.988	1	
R10	0.941	0.993	0.993	0.903	0.957	0.646	0.960	0.843	0.913	1

The correlation coefficient matrix in Table 5.4.5 reveals a strong positive relationship among bleached branching coral spectra. The fifteen bleached branching coral spectra included in this correlation analysis are strongly correlated to one another indicating low variability within the population. Although the lowest correlation coefficient is 0.54, the large majority (87.6%) of coefficients are greater than 0.80. This is consistent with the conclusions of the cluster analysis above.

Table 5.4.5. The correlation coefficient matrix indicates the relationships among bleached branching coral spectra.

	BI1	BI2	BI3	BI4	BI5	BI6	BI7	BI8	BI9	BI10
BI1	1									
BI2	0.937	1								
BI3	0.919	0.994	1							
BI4	0.968	0.988	0.979	1						
BI5	0.973	0.980	0.963	0.995	1					
BI6	0.959	0.989	0.980	0.998	0.993	1				
BI7	0.941	0.989	0.980	0.993	0.987	0.997	1			
BI8	0.962	0.984	0.971	0.997	0.995	0.997	0.995	1		
BI9	0.988	0.958	0.937	0.985	0.993	0.981	0.970	0.986	1	
BI10	0.942	0.990	0.980	0.990	0.987	0.992	0.991	0.990	0.971	1

Forty-seven healthy soft corals were compared and correlation coefficients calculated as seen in the reduced matrix in Table 5.4.6. The results of the correlation analysis reveal relatively strong positive relationships among the soft healthy corals. While the lowest calculated correlation coefficient is 0.44 (not shown in the reduced matrix). 87.5% of the coefficients are greater than 0.70. The within-population variability, as concluded in the cluster analysis, can therefore be considered low. Low within-population variability lends confidence to representative spectra selected from the population to characterize the spectral reflectance curves of healthy soft corals.

Table 5.4.6. The correlation coefficient matrix reveals the relationships among the healthy soft coral spectra.

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
S1	1									
S2	0.959	1								
S3	0.990	0.969	1							
S4	0.967	0.988	0.972	1						
S5	0.894	0.961	0.899	0.955	1					
S6	0.969	0.892	0.967	0.910	0.792	1				
S7	0.805	0.631	0.782	0.670	0.519	0.892	1			
S8	0.960	0.873	0.949	0.894	0.805	0.977	0.917	1		
S9	0.971	0.890	0.963	0.910	0.815	0.984	0.908	0.998	1	
S10	0.958	0.868	0.948	0.888	0.794	0.979	0.922	0.999	0.997	1

The measured reflectance spectra of 27 healthy massive corals were examined for the within-population variability by calculating correlation coefficients, as in the reduced matrix in Table 5.4.7. Strong positive correlations were found to exist among the healthy massive coral spectra indicating low within-population variability. The lowest correlation coefficient calculated is 0.63, but 75.8% of the coefficients are greater than 0.90, which suggests a strong correlation among healthy massive coral spectra. The results of the correlation analysis reinforce the results of the cluster analysis, and suggest that a confident representative reflectance curve could be selected from this population.

Table 5.4.7. The correlation coefficient matrix reveals the relationship among the healthy massive coral spectra.

	HM1	HM2	HM3	HM4	HM5	HM6	HM7	HM8	HM9	HM10
HM1	1									
HM2	0.995	1								
HM3	0.996	0.996	1							
HM4	0.989	0.974	0.981	1						
HM5	0.993	0.981	0.987	0.998	1					
HM6	0.860	0.898	0.878	0.782	0.803	1				
HM7	0.979	0.967	0.972	0.980	0.982	0.802	1			
HM8	0.986	0.981	0.984	0.974	0.980	0.853	0.991	1		
HM9	0.966	0.947	0.957	0.980	0.980	0.741	0.990	0.979	1	
HM10	0.977	0.984	0.980	0.947	0.957	0.916	0.968	0.987	0.943	1

Finally, a correlation analysis was performed for the population of 19 healthy branching corals in an effort to examine the within-population variability. A reduced matrix of the correlation coefficients for 10 of the healthy branching coral spectra can be found in Table 5.4.8. The results indicate positive relationships among the healthy branching corals. The correlation coefficients range from 0.478 to 0.998, with 93.0% greater than 0.70 and 79.5% greater than 0.80. The within-population variability that exists among the branching corals may be a result of varying densities of branches, as discussed previously.

Table 5.4.8. The correlation coefficient matrix indicates the relationships among the healthy branching coral spectra.

	HB1	HB2	HB3	HB4	HB5	HB6	HB7	HB8	HB9	HB10
HB1	1									
HB2	0.866	1								
HB3	0.820	0.954	1							
HB4	0.710	0.925	0.974	1						
HB5	0.927	0.863	0.841	0.748	1					
HB6	0.855	0.749	0.587	0.478	0.777	1				
HB7	0.905	0.871	0.744	0.658	0.848	0.975	1			
HB8	0.867	0.957	0.881	0.842	0.845	0.852	0.943	1		
HB9	0.721	0.943	0.946	0.964	0.744	0.585	0.746	0.920	1	
HB10	0.758	0.954	0.938	0.944	0.774	0.651	0.798	0.951	0.994	1

The second objective of using correlation analysis is to explore the between-population variability of the 1998 data set. Average spectra were determined for each population and correlation coefficients were calculated. The results of the correlation analysis can be found in Table 5.4.9. There is a strong positive correlation between each of the average spectra compared in this analysis, which indicates low variability between the populations. This result reveals that the spectral differences between populations commonly found in a coral reef ecosystem are subtle and therefore difficult to identify.

Table 5.4.9. A Pearson correlation matrix compares the correlation coefficients for the six average spectra included in the analysis.

	Branching	Massive	Soft	Bleached	Rubble	Algae
Branching	1					
Massive	0.985	1				
Soft	0.981	0.955	1			
Bleached	0.949	0.928	0.982	1		
Rubble	0.963	0.945	0.983	0.995	1	
Algae	0.951	0.937	0.972	0.993	0.997	1

5.4.4 Summary of 1998 Data Comparison

The spectral data set collected in Savusavu Bay, Fiji in 1998 consisted of 214 reflectance curves separated into 6 populations: healthy branching corals, healthy massive corals, healthy soft corals, bleached branching corals, rubble surfaces and algae-covered surfaces. Initially, the average and standard deviation spectra were determined and examined in an effort to identify spectral differences in reflectance that might enable remote discrimination. Subtle differences in spectral shape and magnitude were identified.

Cluster analysis was used to explore the within-population variability among spectra of a given population. Therefore, six separate cluster analyses were performed and summarized. In general, it was concluded that there is low within-population variability among spectra of the same population. Pearson correlation coefficients were also calculated to examine the relationships among spectra within a population. Overall, the relationships among spectra of a given population were strongly correlated, which reinforced the results of the cluster analysis.

Finally, the average spectra determined for each of the 6 populations were compared. Pearson correlation coefficients were calculated to explore the relationships between average spectra. The results indicate that there is a strong positive correlation between all of the average spectra, which reveals that there is low variability between spectra of different populations. This result suggests that it will be difficult to distinguish between populations of a coral reef ecosystem. Visual analysis of the measured reflectance spectra, however, indicates that subtle spectral differences do in fact exist between populations, which is encouraging for further analysis.

CHAPTER 6

COMPARISON OF SPECTRAL REFLECTANCE DATA SETS COLLECTED IN 1996, 1997 AND 1998

6.1 INTRODUCTION

The objective of this chapter is to compare the spectral data sets collected in 1996, 1997 and 1998. Spectra were collected in three consecutive years in three different geographic locations, although the broad populations defined for the spectra were similar for each of the three data sets. The hypotheses tested are that within-population variability will be low regardless of the geographic location of data collection, and that between-population variability is high, which will allow discrimination of broad populations of coral reef ecosystem features.

Several techniques are used to investigate the within-population variation of spectra measured in different years and in different geographic locations. First, average spectra are compared and spectral differences interpreted. Secondly, cluster analysis is used to examine the within-population variation of spectra measured in 1996, 1997 and 1998. And finally, Pearson correlation coefficients are calculated to explore the similarity among spectra within a given population.

6.2 INITIAL COMPARISON OF 1996, 1997 AND 1998 SPECTRA

In summary, the data set used in this study consists of *in situ* spectral measurements collected with an identical radiometer in Beqa Lagoon, Fiji in August 1996, Manado, Indonesia in July and August 1997 and Savusavu Bay, Fiji in July and August 1998. A large spectral reflectance data set now exists for the first time consisting of 334 high spectral resolution measurements of typical coral reef features including healthy branching coral, healthy massive coral, bleached branching coral, bleached massive coral, algae-covered surfaces, rubble and sand substrates. The objective is to demonstrate that there is a detectable spectral difference between these populations, regardless of the geographic location in which the spectra were collected.

The sampling strategies in all three years of data collection were essentially the same: measure the spectral reflectivity of as many features as possible given the restrictions of air availability while scuba diving and the narrow window of opportunity surrounding solar noon when spectral reflectance sampling is ideal. The objective of taking spectral measurements of the reef substrate was to characterize spectral features of various reef components such as healthy coral, macro algae, bleached coral, sand and debris. Therefore, transects were not necessary since the goal was not to map a predefined area, but to determine representative spectral characteristics of coral reef features. The data collected in 1996, 1997 and 1998 are summarized below in Table 6.1. The spectra were divided into populations defined by the measured feature. Initially, and for visual interpretation only, average spectra are compared, as in Figure 6.1 through 6.5.

Table 6.1. A summary of the data collected in Fiji in 1996, in Indonesia in 1997 and in Fiji in 1998.

Location	Time	GPS	Environment	Strategy	Sensor	#
Beqa Lagoon, Fiji, South Pacific	8 & 9 August, 1996, 10:30-1:15 local time	18° 19.45 South 178° 06.48 East	Underwater while SCUBA diving at an average depth of 2.9 meters, calm water, clear skies	Measure large number of coral reef features to create data base	ASD radiometer with underwater remote cosine receptor attached to 10 meter underwater optical cable	40
Manado Beach, Sulawesi, Indonesia	19–22 July, 1997, 10:00-2:00	1° 24.82 North 124° 42.44 East	Above water while walking on reef flat at low tide, clear skies	Measure large number of coral reef features to add to data base	ASD radiometer with above water remote cosine receptor	80
Savusavu Bay, Fiji	16 July – 20 August, 1998, 10:00-2:00	16° 46.38 South 179° 19.72 East	Underwater while SCUBA diving at an average depth of 4.3 meters, calm water, clear skies	Measure large number of coral reef features to create data base	ASD radiometer with underwater remote cosine receptor attached to 20 meter underwater optical cable	215

Beginning with Figure 6.1, average spectra of sand surfaces (1997) and of rubble surfaces (1998) are compared. The reflectance curve corresponding to average rubble surface reveals more spectral variation than the sand surface, which is a relatively straight curve gradually increasing toward larger wavelengths. The differences in spectral reflectance are most likely because rubble surfaces contain organic matter in the form of algae-covered dead coral debris. This discrepancy leads to the conclusion that sand and rubble surfaces could be considered two separate populations.

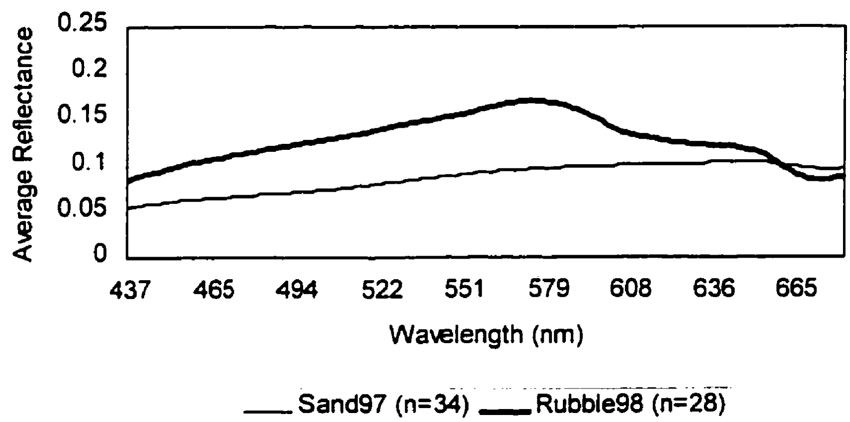

Figure 6.1. Average spectra of sand (1997) and rubble (1998) surfaces are compared.

Algae-covered surfaces measured in 1996, 1997 and 1998 are compared in Figure 6.2. There are differences in spectral shape between the three average reflectance curves. This difference may be a result of varying amounts of algal cover on the surfaces measured. The average spectral curve for algae-covered surfaces measured in 1997 reveals less spectral variation than the average spectra measured underwater in 1996 and 1998. This difference may be due to the possibility that algal growth on reef flats that are periodically exposed to the air is different than algal growth on surfaces continuously underwater. These differences will be further examined.

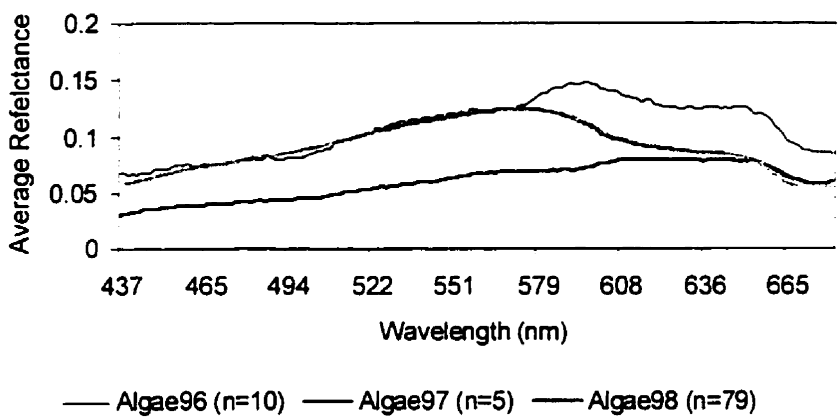

Figure 6.2. Average algae-covered surface spectra are compared.

Average bleached coral spectra are compared in Figure 6.3. Massive bleached corals were measured to determine the average spectral reflectance curves in 1996 and 1997. but branching bleached corals were measured in 1998. The differences in spectral reflectance between massive bleached coral and branching bleached coral will be further investigated to determine if there are 2 populations present based on morphology.

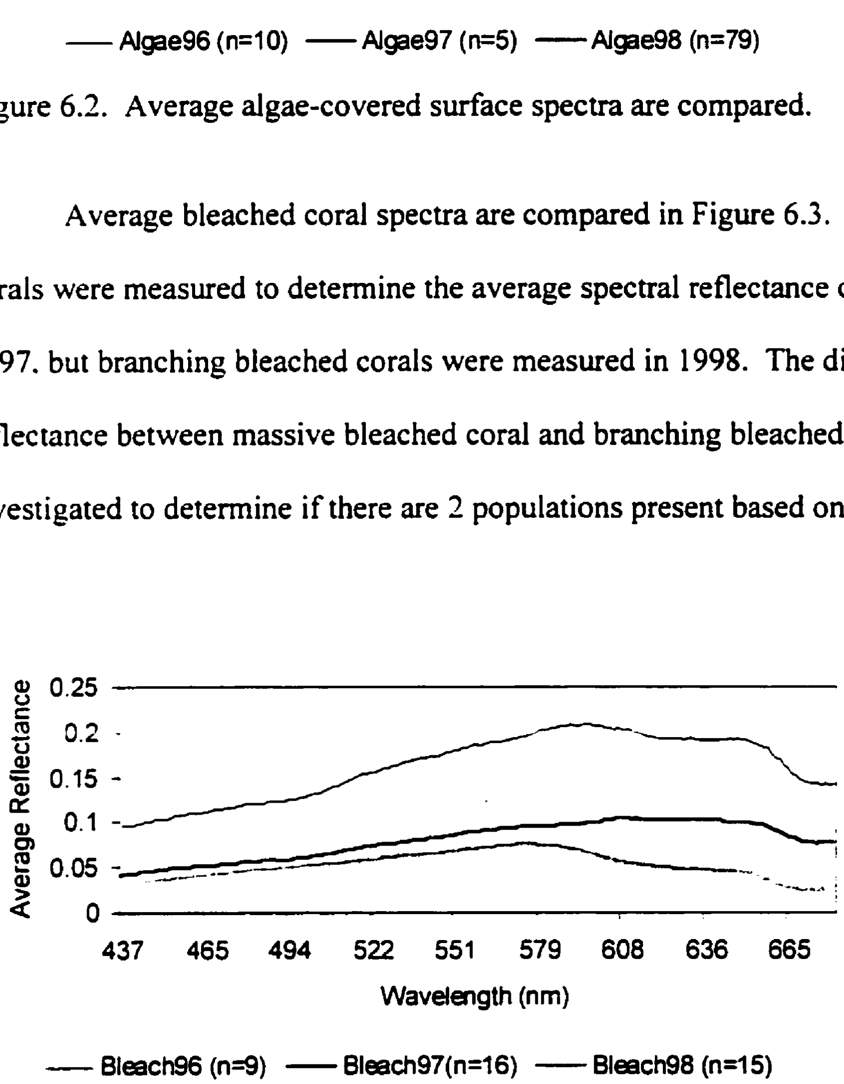

Figure 6.3. Average bleached coral spectra are compared.

Healthy coral spectra are divided into two distinct populations based on morphology. Figure 6.4 compares the average healthy branching coral spectra measured in 1996, 1997 and 1998. The three average spectra display similar spectral shapes with slight variation in the location of the peak reflectance. The average spectral reflectance curve for 1998 has a spectral reflectance peak in a shorter wavelength range than the other 2 average spectra. This difference will be further investigated.

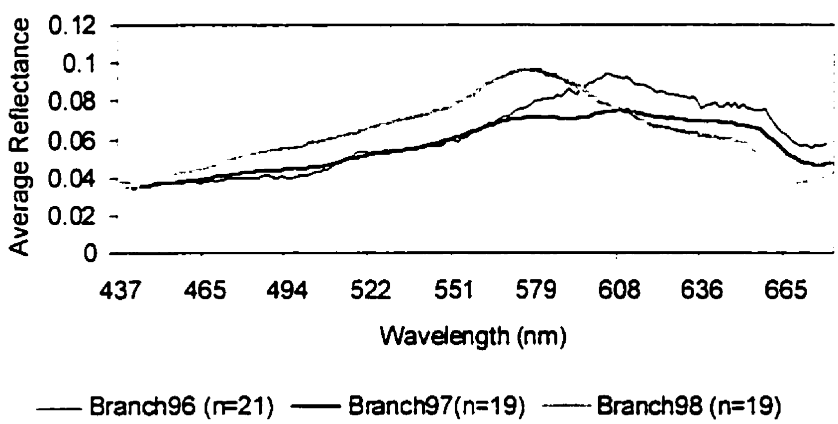

Figure 6.4. Average branching coral spectra are compared.

Finally, healthy massive corals are compared in Figure 6.5. The average soft healthy coral reflectance curve measured in 1998 is included in this comparison because although soft corals have finger-like extensions, they have a consistent surface such that the underlying substrate does not contribute to the reflectance characteristics. It is therefore assumed that soft corals will be most similar to massive corals in terms of spectral reflectance.

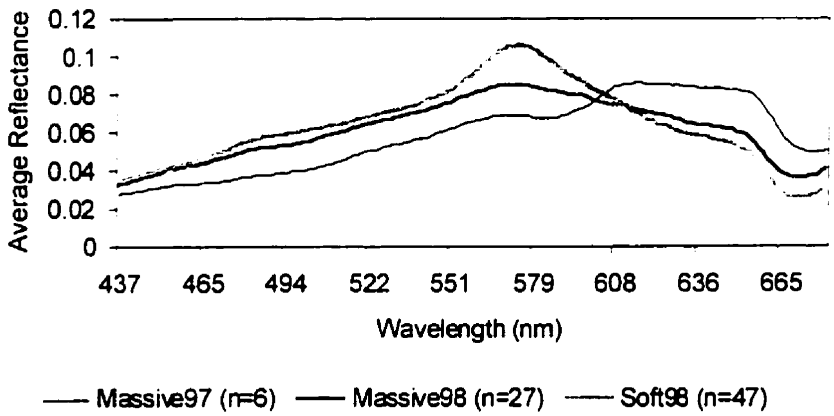

Figure 6.5. Average massive coral spectra are compared.

The comparisons of similar populations of coral reef features reveal that there is spectral similarity within populations regardless of geographic location. This will be further investigated using cluster analysis in the following section.

6.3 CLUSTER ANALYSIS

Cluster analysis is used in an effort to compare the spectra measured in 1996, 1997 and 1998. After combining the spectra collected in the three field seasons, and examining them in the previous section, 8 populations were defined. These populations were considered separately in the following cluster analyses to determine the within-population variability when spectra are from different geographic locations. Therefore, 8 separate cluster analyses are performed and interpreted in Figures 6.6 through 6.13.

The first cluster analysis is performed on the data set consisting of bleached branching corals, as in the cluster tree diagram in Figure 6.6. The spectra within the bleached branching coral population are all very similar according to the cluster analysis since the spectra are joined into one cluster at a Euclidean distance of 0.051. Furthermore, at Euclidean distance 0.03, there are only 2 clusters present, which is probably indicative of either varying degrees of bleaching or varying densities of branches.

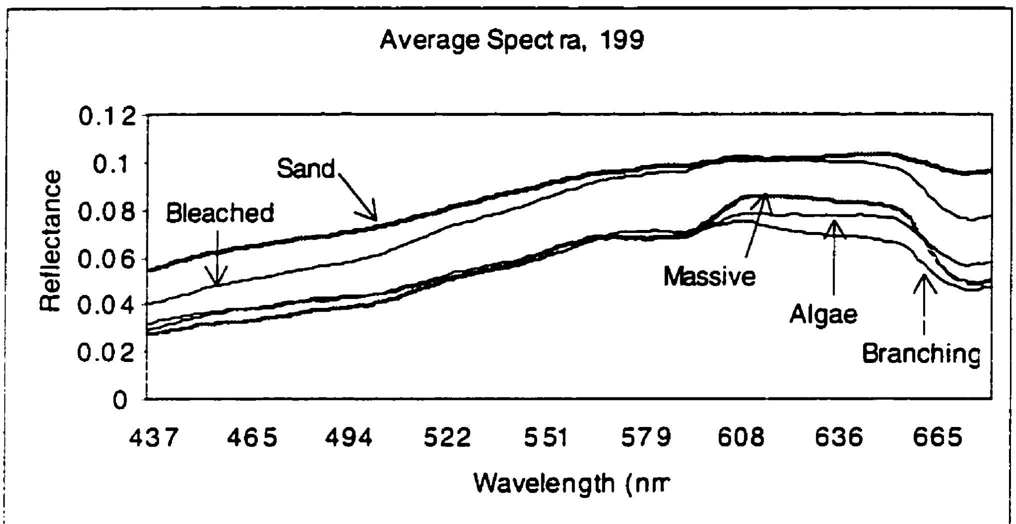

Figure 6.6. A cluster analysis was performed on all bleached branching corals.

The second cluster analysis was performed on all bleached massive corals, as seen in the cluster tree diagram in Figure 6.7. All but four of the bleached massive corals join into one cluster at Euclidean distance 0.1, which indicates moderate spectral similarity within the population. At Euclidean distance 0.05, there are 4 clusters present, which appear to be related to the field season of data collection. These discrepancies may be a result of the fact that the 1997 data set was collected on a coral reef flat without water cover, and the 1998 data set was collected while scuba diving underwater. These differences will be further examined using correlation analysis in the next section.

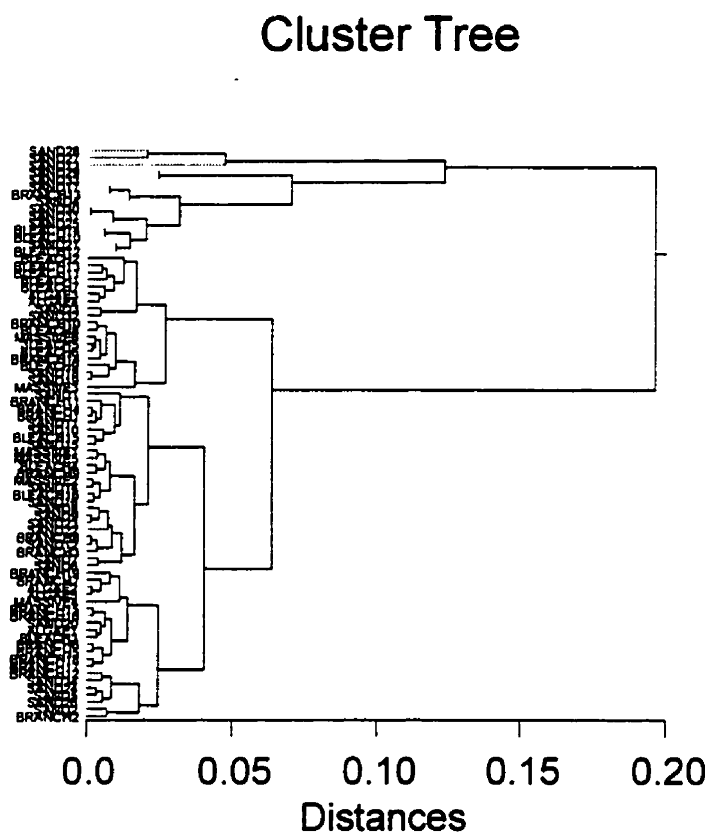

Figure 6.7. A cluster analysis was performed on all bleached massive corals.

To examine the difference between spectra measured of bleached massive coral and bleached branching coral. the 2 data sets were merged and considered in one cluster analysis. Forty bleached coral spectra are included in the cluster analysis described in the cluster tree diagram in Figure 6.8. The cluster tree reveals distinct clustering apparently based on the morphology of the bleached coral. Except for 4 bleached massive corals, the spectral data set joins as one similar cluster at Euclidean distance 0.11. This variability is greater than when the bleached massive corals are considered on their own, but similar to when the bleached branching corals are considered on their own.

Cluster Tree

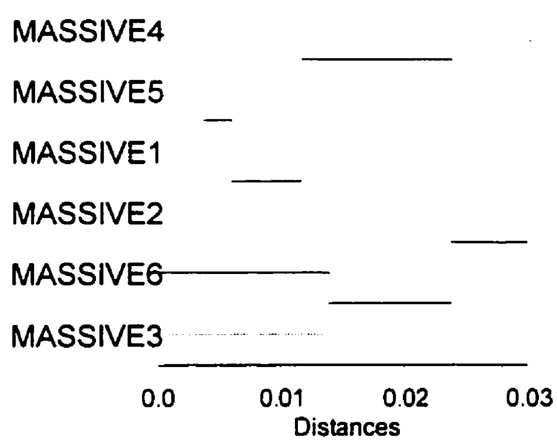

Figure 6.8. All bleached coral spectra, both massive and branching, are included in this cluster analysis.

All healthy massive corals collected in the 3 field seasons were compared in the cluster analysis shown in Figure 6.9. At Euclidean distance 0.05, there are 3 clusters present. There are only 6 spectra included in this population that were not collected in 1998, and these spectra are joined as one cluster at Euclidean distance 0.03. These 6 spectra, however, are considered similar enough to the 1998 spectra to be joined by Euclidean distance of less than 0.03, which suggests that there is no significant difference between healthy massive corals measured in 1997 and those measured in 1998. Of the 33 spectra included in this population, all but 5 join as one cluster by Euclidean distance of less than 0.06, which indicates spectral similarity within the population.

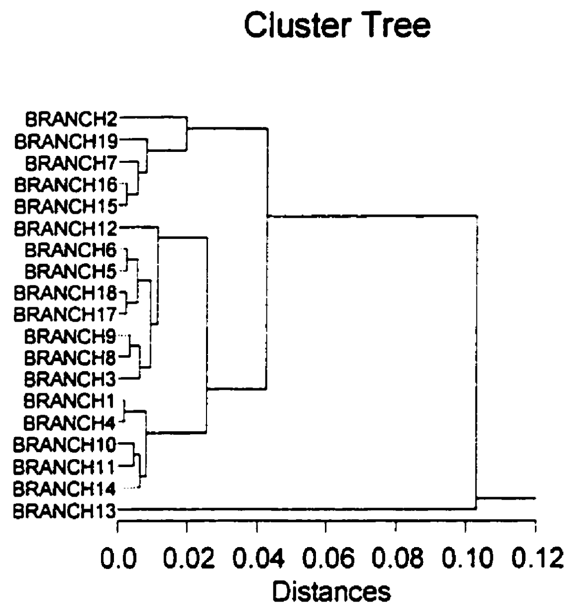

Figure 6.9. A cluster analysis was performed on all healthy massive corals.

All healthy branching corals were compared in a cluster analysis presented in Figure 6.10. At Euclidean distance 0.05, there are 3 clusters identified, and by Euclidean distance 0.07, all but 4 spectra have joined to create one cluster. The four spectra at the top of the cluster tree, which do not join the remainder of the spectra until Euclidean distance 0.13, were measured in both 1996 and 1997. This suggests that the spectral differences are not a function of the year/location of measurement.

All healthy branching corals were compared in a cluster analysis presented in Figure 6.10. At Euclidean distance 0.05, there are 3 clusters identified, and by Euclidean distance 0.07, all but 4 spectra have joined to create one cluster. The four spectra at the top of the cluster tree, which do not join the remainder of the spectra until Euclidean distance 0.13, were measured in both 1996 and 1997. This suggests that the spectral differences are not a function of the year/location of measurement.

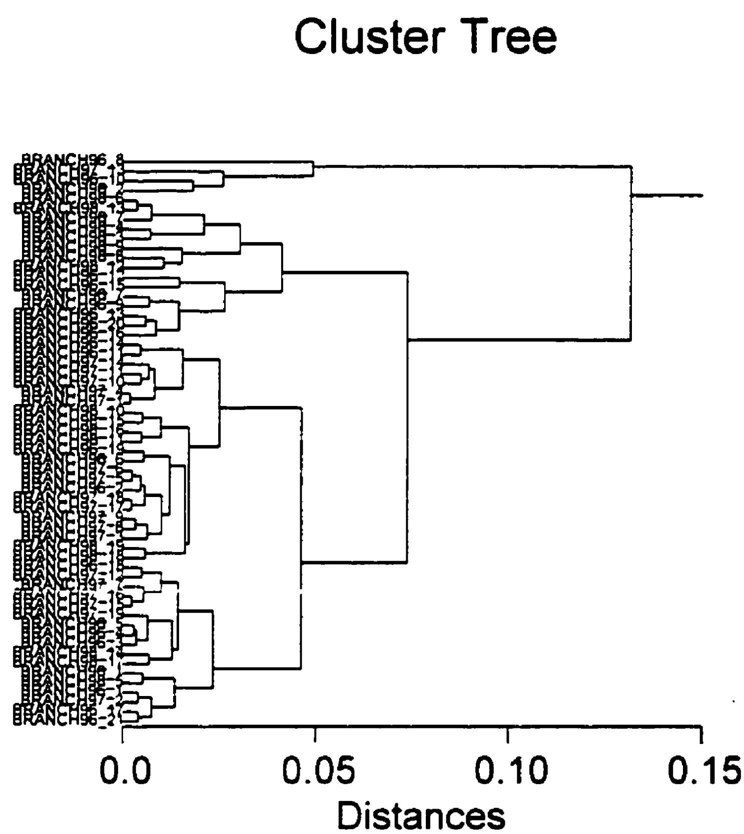

Figure 6.10. A cluster analysis was performed on all healthy branching corals.

A cluster analysis was performed on all healthy soft corals, as in Figure 6.11. At a small Euclidean distance of 0.035, there are only 2 clusters present, and the spectra are all joined together as one cluster by 0.07. This indicates a high degree of similarity within the healthy soft coral population consisting of 46 spectra. The variation in spectral reflectance that does exist within this population could be a function of the variable surfaces found on a soft coral. Differences in density, shape and length of the protrusions, or "fingers", could result in self-shading, which would affect the spectral reflectance characteristics.

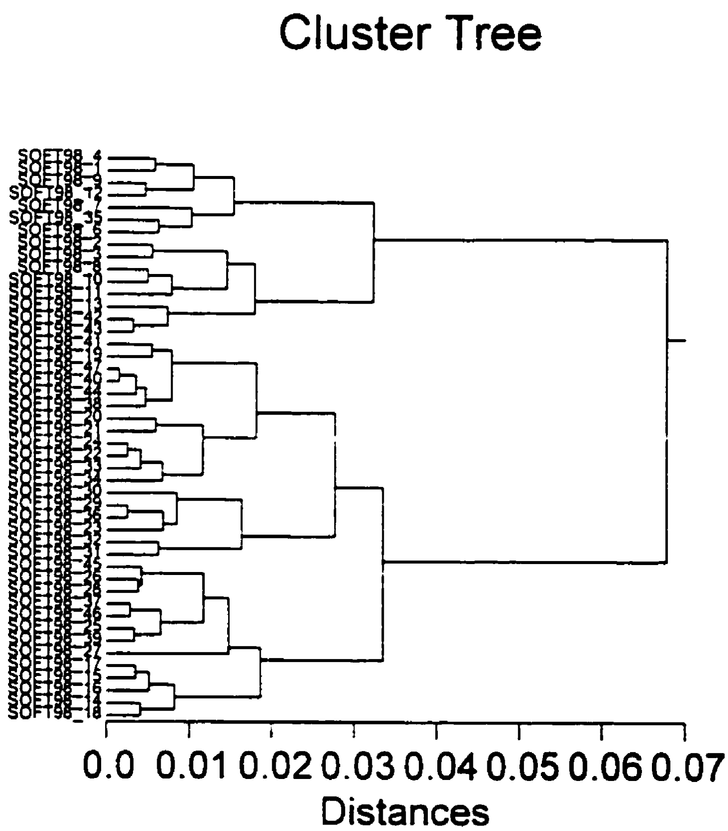

Figure 6.11. All healthy soft corals were compared in the cluster analysis above.

All healthy corals were amalgamated to form one population of healthy coral spectra. A cluster analysis is performed on this merged data set to examine the within-population variability if no distinction is made based on morphology. The results of the cluster analysis of all healthy corals are illustrated in Figure 6.12. In total, 139 healthy coral spectra are included in the new amalgamated population. The large number of spectra makes the cluster analysis tree difficult to read, but it is clear that 2 distinct populations exist, which do not join as one similar population until Euclidean distance 0.15. At Euclidean distance 0.05, two large clusters can be identified and 3 small clusters. While some clustering is apparent for spectra of the same morphology, the 3 sub-populations are irregularly dispersed amongst the clusters. The variability among healthy corals is greater when all morphologies are considered than if the 3 sub-populations are considered separately.

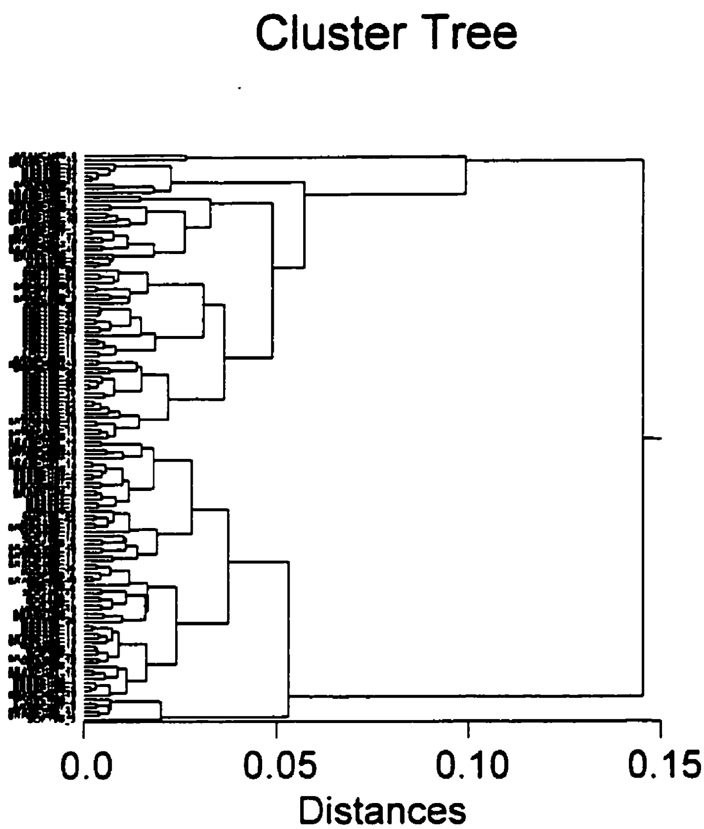

Figure 6.12. All healthy corals (massive, branching and soft) are amalgamated and considered in one cluster analysis.

The next cluster analysis is based on all algae-covered surface spectra collected in the 3 field seasons, as in Figure 6.13. The spectral reflectance measurements of algae-covered surfaces appear to contain a moderate degree of within-population variability. The 94 spectra do not join as one cluster until Euclidean distance 0.17. In comparison to the cluster analyses of the other populations in this study, the variability within this population is great. At Euclidean distance 0.05, there are 6 clusters present. There are only 2 spectra contained in the cluster at the very top of the cluster tree, and these were measured in different years (1996 and 1998). These 2 spectra are last to join the other spectra in the final cluster at Euclidean distance 0.017. This suggests that the variability within this population may be less a function of geographic location than differences in sample surfaces. For example, there may have been different amounts or densities of algae covering the surfaces measured, which would result in variable spectral reflectance characteristics within the population.

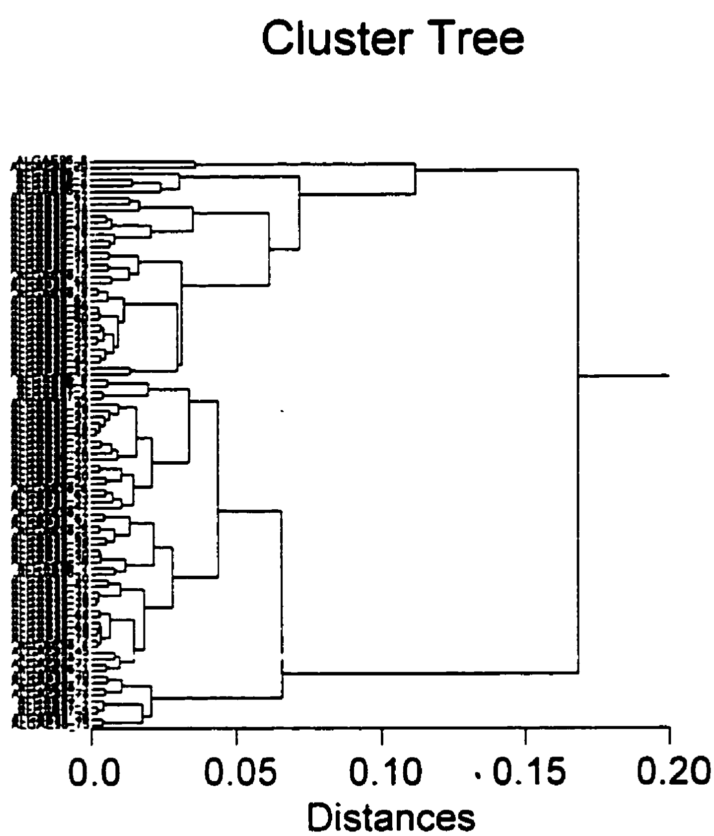

Figure 6.13. All algae-covered surfaces were compared using cluster analysis.

All sand surface spectra were compared in the following cluster analysis as shown in the cluster tree diagram in Figure 6.14. At Euclidean distance 0.05, there are 5 clusters present, and furthermore, the spectra do not join as one cluster until Euclidean distance 0.19. This suggests significant variability within the population. Fine sand measurements were only possible in Manado in 1997, so these measurements were taken on the exposed reef flat. As discussed earlier, the sand displayed varying degrees of wetness depending on the tidal cycle, whereby sand measured closer to shore that had had more time exposed to the sun was drier. The varying degree of sand wetness was not quantified in this study, and is cited as a possible source of spectral variability.

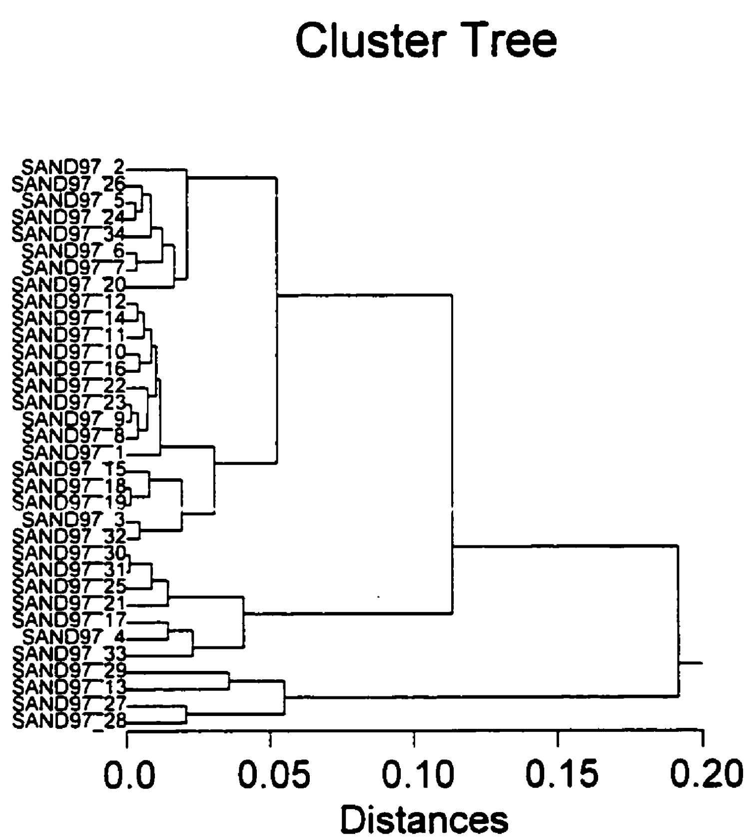

Figure 6.14. A cluster analysis was performed on all sand surface spectra.

Finally, a cluster analysis was performed on all rubble surface spectra, as in Figure 6.15. The 28 spectra in the rubble data set form 3 clusters at Euclidean distance 0.1, but do not join as one cluster until Euclidean distance 0.22. This high within-population variability may be a result of differing amounts of organic debris present in on the rubble surface. A rubble surface typically consists of broken branches of dead coral mixed with other fine coral debris, so the variable proportions of these components will result in a variable spectral reflectance response.

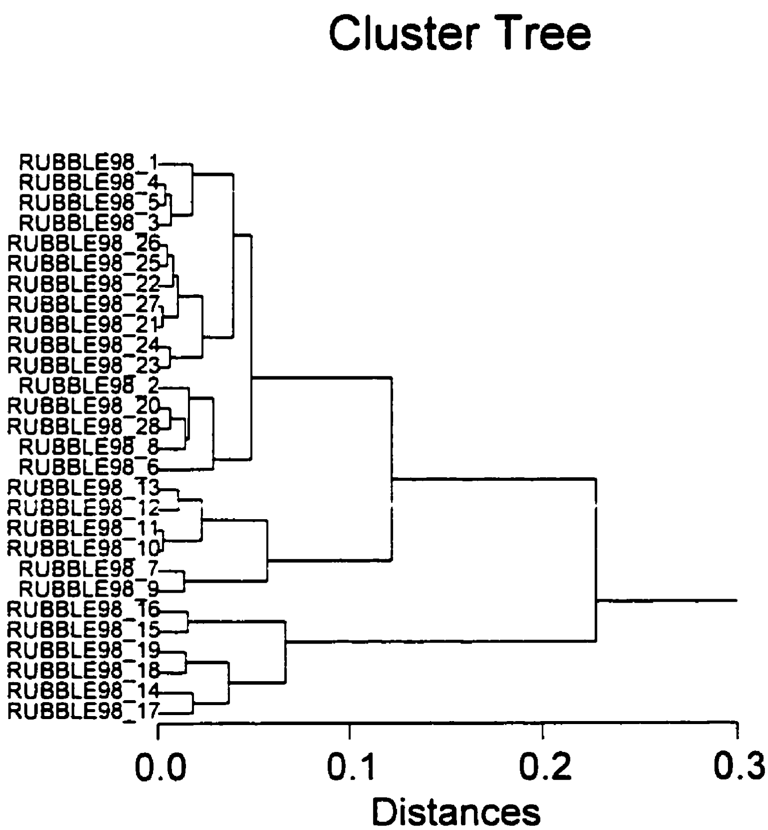

Figure 6.15. A cluster analysis was performed on all rubble surface spectra.

In summary, the within-population variability is low for the 5 healthy and bleached coral populations, but higher for rubble, sand and algae-covered surfaces. The differences in spectral reflectance identified by the cluster analysis can be explained by differences in features and are not assumed to be a function of geographic location. The differences in spectral reflectance are further investigated in the correlation analysis in the following section.

6.4 CORRELATION ANALYSIS

Pearson correlation matrices were calculated to further examine the spectral differences of the 8 populations defined for this study. The objective here is to determine the degree to which spectra of a given population are similar, even if measured in different geographic locations. The populations include bleached branching corals, bleached massive corals, healthy branching corals, healthy massive corals, as well as sand, rubble and algae-covered surfaces.

The first Pearson correlation matrix compares algae-covered surfaces measured in 1996, 1997 and 1998 (Table 6.2). There is a strong correlation between spectra measured in 1996 and 1997; a moderate correlation between those measured in 1996 and 1998; and a weak correlation between those measured in 1997 and 1998. The average algae-covered surface spectra vary as a result of differing amounts of algae present and differing surfaces underneath the algae. Another explanation for the low correlation among algae-covered surfaces could be that the spectra measured in 1997 were exposed while the spectra measured in 1996 and 1998 were submerged. Perhaps the macroalgae that colonizes surfaces on a coral reef flat that is frequently exposed is of a different strain than the macroalgae that colonizes consistently submerged coral reefs thus resulting in different spectral reflectance characteristics. These results agree with the high within- and between population variability results of the cluster analysis considering all 94 algae-covered surface spectra available from 1996-1998. Since both the cluster and correlation analyses conclude that there is high within-and between-population variability. confidence in the ability to identify spectral reflectance characteristics specific to algae will be limited.

Table 6.2. The average correlation coefficients are compared for algae-covered surfaces.

	Algae96	Algae97	Algae98
Algae96	1		
Algae97	0.905	1	
Algae98	0.688	0.391	1

The Pearson correlation matrix for the bleached massive coral data sets for 1996 and 1997 reveals a very strong positive correlation between the 2 years (Table 6.3). There were no bleached massive corals to be measured in the 1998 field season. Furthermore. there were no bleached branching corals available for measurement in the 1996 and 1997 field seasons. so the data set consists entirely of spectra measured in 1998.

Table 6.3. There is a strong correlation between the bleached massive coral data sets for 1996 and 1997.

	Bleached Massive96	Bleached Massive97
Bleached Massive96	1	
Bleached Massive97	0.977	1

Healthy massive corals measured in 1997 are compared to those measured in 1998 in Table 6.4. There were no healthy massive corals available for measurement in 1996. The healthy branching corals measured in 1996, 1997 and 1998 are compared in Table 6.5. There is a strong correlation between healthy branching corals measured in 1996 and 1997; a moderate correlation between those measured in 1997 and 1998; and a moderate correlation between those measured in 1996 and 1998. Rubble surface spectra were only collected in the 1998 field season; sand surface spectra were only collected in 1997; and soft coral spectra were only collected in 1998. Therefore, it is not possible to compare spectral measurements from different geographic locations for these populations.

Table 6.4. There is a moderately strong relationship between healthy massive corals measured in 1997 and 1998.

	Healthy Massive97	Healthy Massive98
Healthy Massive97	1	
Healthy Massive98	0.665	1

Table 6.5. Healthy branching corals measured in 1996, 1997 and 1998 are compared.

	Healthy Branching Coral96	Healthy Branching Coral97	Healthy Branching Coral98
Healthy Branching Coral96	1		
Healthy Branching Coral97	0.969	1	
Healthy Branching Coral98	0.637	0.765	1

The following Pearson correlation coefficients describe the relationship between the populations defined for this study. A correlation coefficient matrix is provided in Table 6.6. The spectra contained in these populations were collected in 1996, 1997 and 1998. There is a range of strong to weak correlations between the populations considered in this correlation analysis, as discussed below.

Table 6.6. The correlation coefficients describe the relationship between populations.

	Algae	Bleach-branch	Bleach-massive	Healthy-branch	Healthy-massive	Healthy-soft	Rubble	Sand
Algae	1							
Bleach-branch	0.980	1						
Bleach-massive	0.657	0.515	1					
Healthy-branch	0.777	0.676	0.962	1				
Healthy-massive	0.924	0.854	0.876	0.948	1			
Healthy-soft	0.973	0.983	0.591	0.756	0.894	1		
Rubble	0.991	0.995	0.569	0.711	0.880	0.984	1	
Sand	0.465	0.297	0.958	0.857	0.721	0.382	0.368	1

There is a strong correlation (0.98) between algae and bleached branching coral populations. This strong correlation is not surprising since it is probable that algae had already colonized the bleached coral surface, but it was not visibly apparent to the observer. The strong correlation may lead to confusion in classification of the separate populations, but since both bleached coral and algae-covered surfaces indicate vulnerable coral reef ecosystems, or ecosystems under stress, then this spectral confusion is not a major concern.

In fact, there are strong correlations between bleached branching coral and several other populations. Namely, bleached branching coral has a correlation coefficient of 0.995 with rubble, 0.983 with healthy soft coral, 0.854 with healthy massive coral and

0.676 with healthy branching coral. These strong correlations will undoubtedly lead to low classification accuracy and low confidence levels when identifying bleached branching coral and will cause confusion in classification of other populations. Curiously, while bleached branching coral spectra correlate strongly with the various populations above, they correlate only moderately with bleached massive corals. The uncertainty in the spectral reflectance characteristics of bleached branching corals may be a result of the small data set (n=15) or the specific qualities of the branches allowing the underlying substrate to influence measurements.

There are moderate correlations between bleached massive corals and both algae-covered surfaces (0.657) and bleached branching coral (0.515). The moderate correlation between bleached massive corals and algae-covered surfaces indicates, as above, that there may be confusion in classifying these separate populations. The spectral confusion is not as great between these two populations as with the two above possibly as a result of less algal colonization on the massive bleached corals. Massive corals are known to be more resilient, yet slower growing, than branching corals, so it is possible that algae does not colonize the surface of a bleached massive coral as readily as it does a bleached branching coral. It is surprising that bleached massive corals are not more strongly correlated with bleached branching corals, but this may be a result of the different morphologies and contribution from underlying substrates.

Healthy branching corals correlate highly with bleached massive corals (0.962), but only moderately with algae-covered surfaces (0.777) and bleached branching corals (0.676). The high correlation between healthy branching corals and bleached massive corals may result in classification errors. Branching corals, whether healthy or bleached, present complex problems with respect to spectral reflectance measurements due to varying densities of branches and variable reflectance properties of underlying substrates. For this reason, it is likely that a degree of uncertainty will be associated with the classification of branching corals, both healthy and bleached, for it is difficult to measure the pure spectral response of a branching coral.

Healthy massive corals are strongly correlated with algae (0.924), bleached branching corals (0.854), bleached massive corals (0.876) and healthy branching coral (0.948). It is not surprising that healthy massive corals are highly correlated with healthy branching corals, but it is worrisome that this population is also highly correlated with both forms of bleached corals. The results of this correlation analysis emphasize the complexity in discriminating between populations of a coral reef ecosystem, and underscore the need for a robust means of differentiation beyond basic spectral recognition.

Healthy soft corals are highly correlated with algae (0.973), bleached branching corals (0.983), and healthy massive corals (0.894). Healthy soft corals, however, are only moderately correlated with healthy branching corals (0.756), and weakly correlated to bleached massive corals (0.591). These correlation coefficients are encouraging with respect to the ability to differentiate between populations. Although there appear to be spectral similarities between healthy soft corals, algae and bleached branching corals, there are apparently differences between soft corals and healthy branching corals as well as bleached massive corals.

Rubble surfaces are highly correlated with algae (0.991), bleached branching corals (0.995), healthy massive corals (0.88) and healthy soft corals (0.984). Rubble surfaces, however, are only moderately correlated with bleached massive corals (0.569) and healthy branching corals (0.711). The spectral confusion between rubble and branching corals may be explained by the possibility that rubble substrate was underneath the branching corals, thus contributing to the reflectance signal. In other words, since rubble is an expected underlying substrate, branching coral reflectance curves may be influenced by the reflectance characteristics of rubble surfaces. Furthermore, it is not surprising that rubble surfaces and algae-covered surfaces are highly correlated since it is expected that rubble surfaces might be colonized by a certain amount of algae. If a rubble surface contained a high enough proportion of algal cover, then the algae would contribute to the spectral reflectance characteristics of the rubble surface.

Finally, sand surfaces are highly correlated to bleached massive corals (0.958) and healthy branching corals (0.857). Sand is moderately correlated with healthy massive corals (0.721), and weakly correlated with the remainder of the populations (<0.465). The weak correlation coefficients indicate that there may be higher confidence levels associated with discriminating sand from algae, bleached branching corals, healthy soft corals and rubble surfaces. There appears to be spectral confusion between sand and bleached massive corals as well as healthy branching corals. The confusion with branching corals may be related to the explanation for the confusion between rubble and branching corals: if sand is the underlying substrate, then it will contribute to the overall reflectance of a branching coral thus leading to spectral similarities.

In summary, several of the populations defined in this study appear to be highly correlated with one another, which may lead to classification errors. Some populations are not highly correlated, such as sand, algae, and rubble, which indicates that these populations should be accurately discriminated. There are several other populations with moderate correlations, which may result in variable confidence in classification procedure. Because of the strong correlations, healthy branching, massive and soft corals will be considered one population. Further analysis will be performed on representative spectra identified using principal components analysis determined in the following chapter.

6.6 SUMMARY

The spectra measured in Beqa Lagoon, Fiji in 1996, Manado, Indonesia in 1997 and Savusavu Bay, Fiji in 1998 were compared in order to examine the spectral differences of reflectance curves measured in different geographic locations. The 334 spectra considered were categorized into 8 broad populations and visually examined for within-population variability. Cluster and correlation analyses were used to further examine the within- and between-population variability. The within-population variability was found to be low, which indicates that spectral reflectance curves within a given population defined on the basis of feature type are spectrally similar regardless of geographic location. The between-population variability, however, was also found to be low, which suggests that the spectral differences in reflectance are subtle for the populations considered. On this basis, all healthy coral spectra in the 3 sub-populations of branching, massive and soft varieties will be amalgamated into one population in subsequent analysis.

CHAPTER 7

DEFINITION OF REPRESENTATIVE SPECTRA AND SPECTRAL DISCRIMINATION OF CORAL REEF FEATURES

7.1 INTRODUCTION

The first objective of this chapter is to identify spectra that are representative of populations or features commonly found in a coral reef ecosystem. Principal components analysis (PCA) will be used as a data reduction tool in an effort to identify the measured reflectance spectra that are most representative of the variance of each population. PCA is used to test the hypothesis that various visually similar coral reef features have distinct reflectance characteristics. This approach will have more rigour than the cluster analysis used as a data exploration tool in previous chapters. Six populations are investigated here. All healthy corals were amalgamated into one population due to the strong correlations between soft, branching and massive corals. Bleached massive corals, however, are considered a separate population from bleached branching corals for the purposes of this study. The remaining populations are rubble, sand and algae-covered surfaces.

The second objective of this chapter is to develop and test a procedure that would enable remote identification of coral reef ecosystem features. Since the reflectance values themselves do not appear to allow discrimination between populations, another method is needed. Inspection of the measured spectral reflectance curves reveals that within certain wavelength regions there are differences in the slope of the curves. Therefore, first derivatives can be calculated to examine the change in reflectance with respect to wavelength in an effort to differentiate between populations. Furthermore, second derivatives can be used to examine the change in slope with respect to wavelength to isolate more subtle differences.

Spectral derivative analysis is used to identify specific wavelength regions that would be ideal for discrimination. If the spectral distinction is present in the visible wavebands, which have the ability to penetrate water, then passive optical remote sensors with filters for these specific wavebands have potential to be used to identify populations present. It may therefore be possible to estimate the health or stress of a coral reef ecosystem in terms of the proportion of healthy corals, bleached corals and algae present.

7.2 PRINCIPAL COMPONENTS ANALYSIS

The purpose of the following principal components analysis (PCA) is to identify representative spectra of specific pre-identified populations. The data set has been divided into six populations representing substrate type based upon field identification: bleached branching coral (n=15), bleached massive coral (n=25), healthy coral (n=138), algae (n=94), rubble (n=28) and sand (n=34). Separate PCAs are performed on each of the populations in order to determine a representative spectral reflectance curve for each population based upon the variance distribution within the population.

Theoretically, the majority of the variance should be retained in the first component if the variance of all of the spectra within the dataset correspond to the same feature. This may be a more robust means of determining the most representative spectra corresponding to particular features than averaging or subjectively selecting representative spectra. No rotation techniques were applied to the data sets as proposed by Richman (1986) due to the likelihood of extracting the maximal variance from each data set without rotation. Richman (1986) also states that unrotated PCA solutions are ideal for situations where pure data reduction is sought, as in this case. This is indicative of the integrity of the population definition. The results of the 6 principal components analyses performed are summarized in Table 7.1. No less than 94% of the variance is explained by the first 2 components in all 6 cases, and the majority of the variance is explained by the first principal component (PC1) in all cases.

Table 7.1. The results of the 6 separate PCAs are summarized below.

Population	**n**	**Variance Explained by PC1**	**Variance xplained by PC2**	**Total Variance Explained by 1st 2 PCs**
Healthy coral	138	78.10%	18.16%	96.26%
Bleached massive coral	25	94.96%	3.82%	98.78%
Bleached branching coral	15	93.09%	6.20%	99.29%
Sand	34	84.94%	9.83%	94.77%
Rubble	28	89.68%	8.60%	98.28%
Algae	94	84.66%	13.92%	98.58%

A component loading, which ranges from –1.0 to 1.0, is calculated for each of the spectra included in the PCAs. A high positive loading indicates that the measured spectral reflectance curve is similar to the computed principal component spectrum. For each population, the 2 measured spectra with the highest loadings to the first 2 principal components were selected for comparison. The 2 measured spectra for each population are compared separately in Figures 7.1 through 7.6 with the loading indicated in brackets in the legends. Since the large majority of the variance is explained by the first principal component in all cases (ranging from 81.86% to 94.96%), the spectra with the highest loadings to the first component were selected as representative of each population.

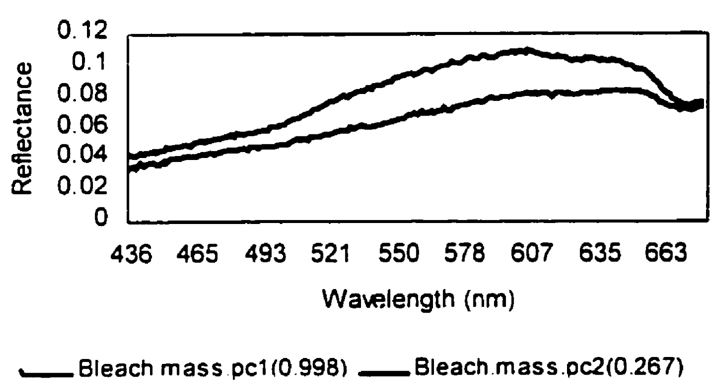

Figure 7.1. A comparison of the 2 measured spectra with the highest loadings for PC1 and 2.

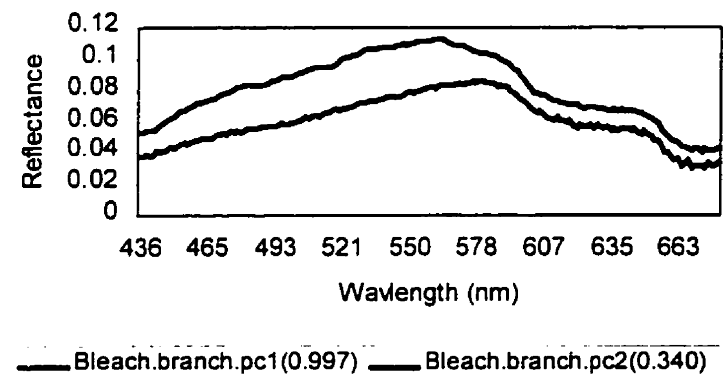

Figure 7.2. A comparison of the 2 measured spectra with the highest loadings for PC1 and 2.

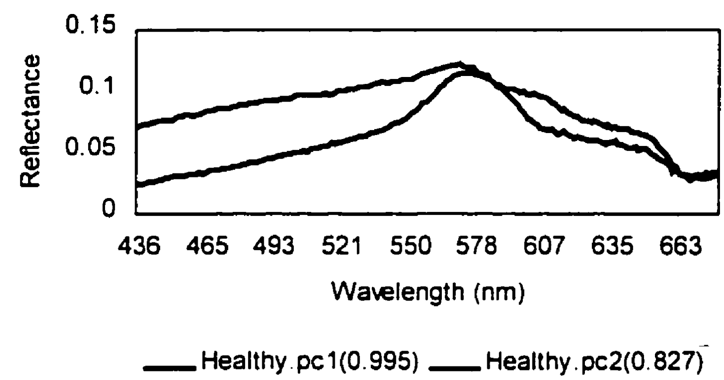

Figure 7.3. A comparison of the 2 measured spectra with the highest loadings for PC1 and 2.

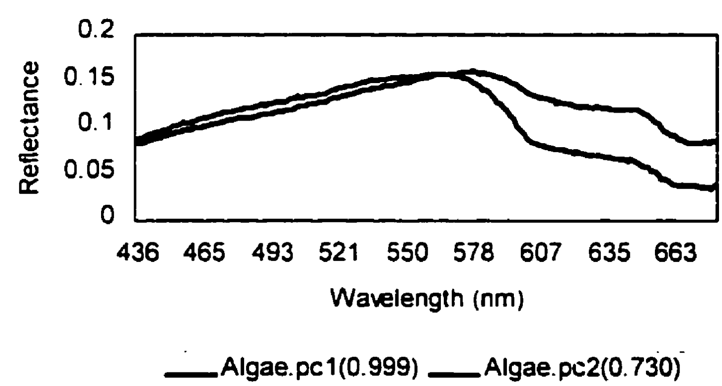

Figure 7.4. A comparison of the 2 measured spectra with the highest loadings for PC1 and 2.

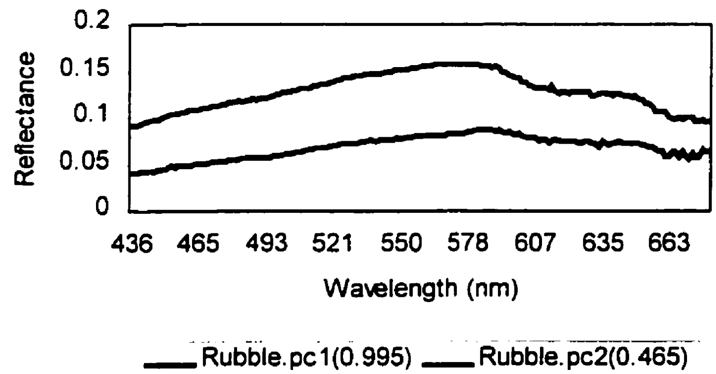

Figure 7.5. A comparison of the 2 measured spectra with the highest loadings for PC1 and 2.

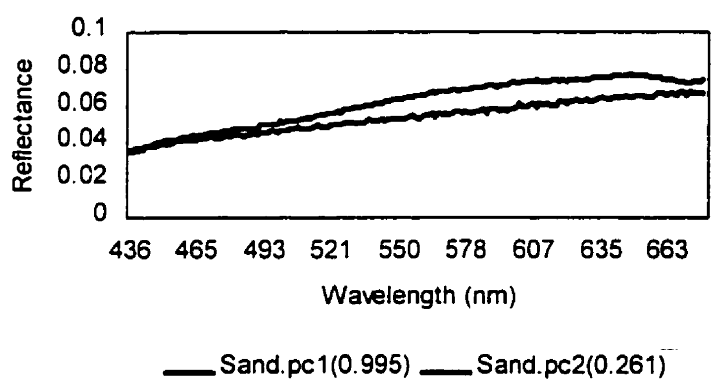

Figure 7.6. A comparison of the 2 measured spectra with the highest loadings for PC1 and 2.

The 6 measured spectra identified by the principal components analyses are considered to be representative of their respective populations. The loadings calculated for each of the 6 measured spectra identified with the PCA are all larger than 0.99, where a perfect match is 1.0, which indicates that the measured spectra are very similar to the computed first principal components.

It appears as though the representative spectra identified for rubble surfaces and algae-covered surfaces are very similar, so it is not expected that these two populations will be accurately discriminated. This is not a surprising similarity since varying degrees of macroalgae and dead coral debris commonly colonize rubble surfaces on the floor of a coral reef. If a coral reef ecosystem is under environmental stress to the extent that it becomes dominated by macroalgae, then it is not necessary to be able to differentiate between algae-covered dead coral and algae-covered rubble; therefore this spectral similarity may not be a limiting factor in classification. The actual measured spectra with the highest loading to the first principal component for each of the 6 populations are compared in Figure 7.7. Photographs of the features associated with these representative spectra are provided in Figure 7.8a through 7.8c.

The remaining spectra identified as representative of their populations appear to be spectrally different. The slope of the spectral reflectance curves appears to be a feasible characteristic to enable differentiation between populations. Therefore, in the next section, using the representative spectra identified here, first and second derivatives will be calculated in specific wavelength ranges in an attempt to discriminate between populations.


Figure 7.8a. An example of a healthy coral.

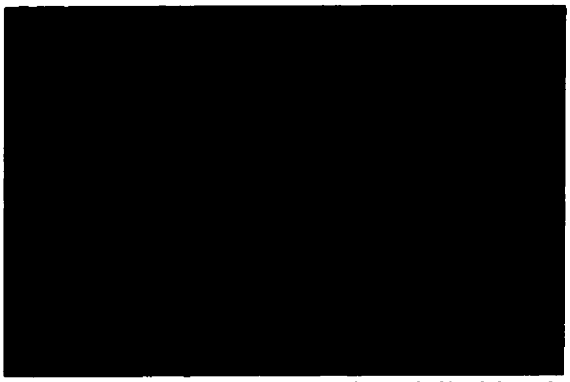

Figure 7.8b. An example of partially bleached (lower left) and partially algae-covered surface (upper right).

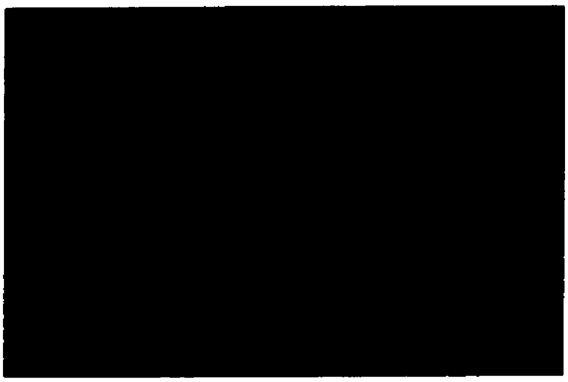

Figure 7.8c. An example of a debris/rubble surface.

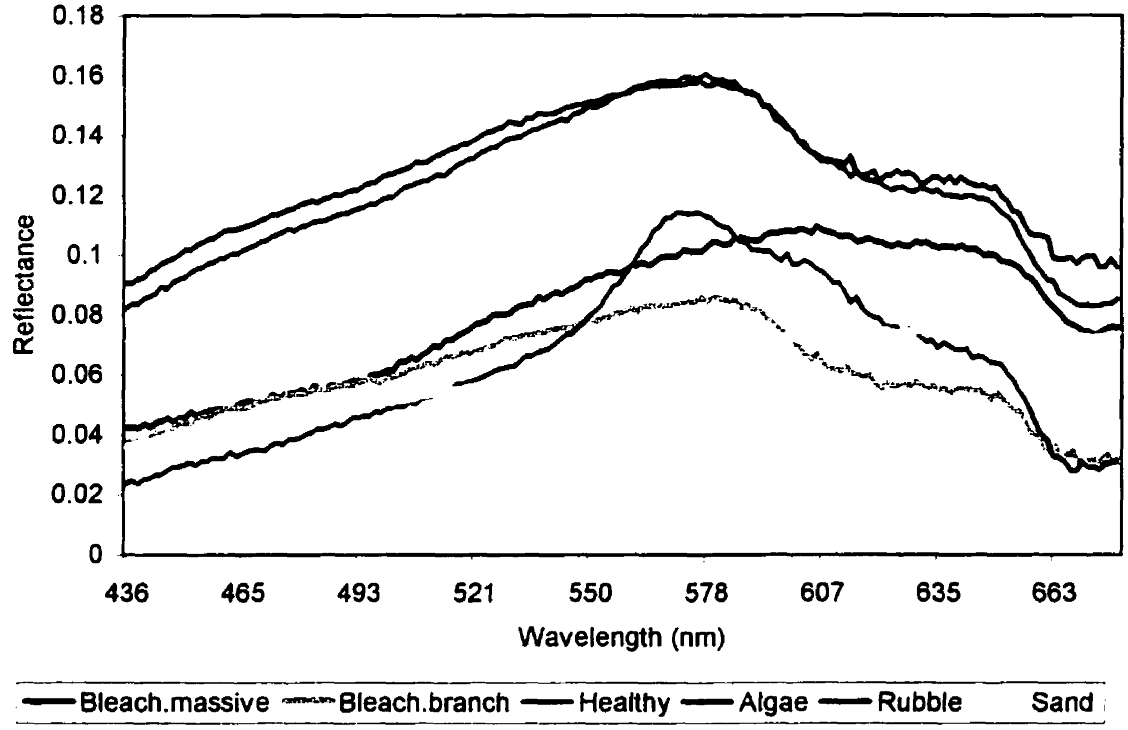

Figure 7.7. A comparison of the spectra with the highest loadings to PC1 for each population. (note: these are observed measured spectra, not PCA eigenvector count measures)

7.3 DERIVATIVE ANALYSIS OF REPRESENTATIVE SPECTRA

The slopes of the spectral reflectance curves are used as a means of discriminating between populations. The representative spectra identified with PCA are used in an effort to develop a procedure of discrimination and classification of populations based on slope of the reflectance curves. First derivatives are calculated by finding the difference in reflectance with respect to difference in wavelength. The second derivatives are calculated by finding the difference in slope with respect to difference in wavelength.

The representative spectra were inspected for wavelength regions that displayed different slopes or changes in slope. Small wavelength intervals are preferable in order to maintain the greatest amount of spectral information. Therefore, changes in reflectance and slope of the spectra that occurred over small wavelength ranges were investigated first. Through inspection, wavelength regions were identified as having potential to allow discrimination of the 6 representative spectra as illustrated in Figure 7.9. The process of finding the wavelength regions was iterative and subjective.

Two wavelength regions were identified as possibly enabling differentiation between populations based on change in reflectance (first derivative). Furthermore, one wavelength region was identified as possibly enabling differentiation based on change in slope (second derivative). The final stage of the classification involves calculation of the maximum magnitude of reflectance as a means of discrimination. The procedure identified involves 4 steps as described in the decision flow chart in Figure 7.10.

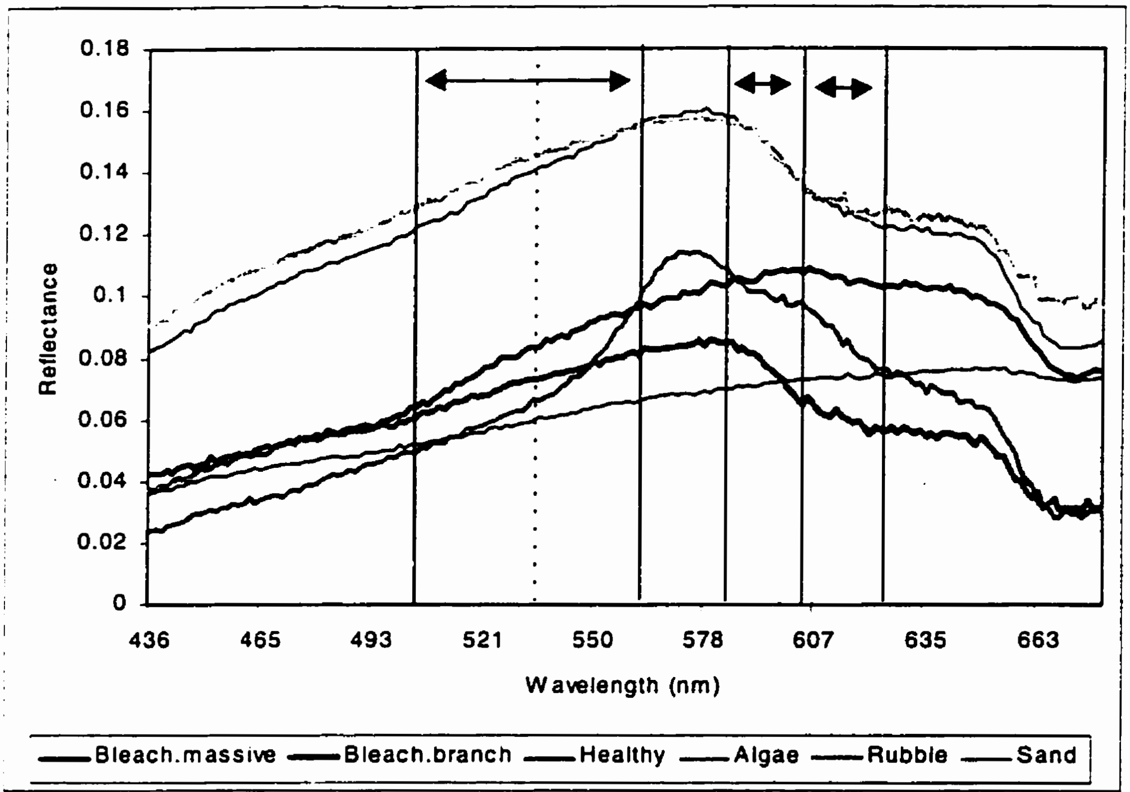

Figure 7.9. Spectral regions on the principal component spectra identified through inspection that enable discrimination.

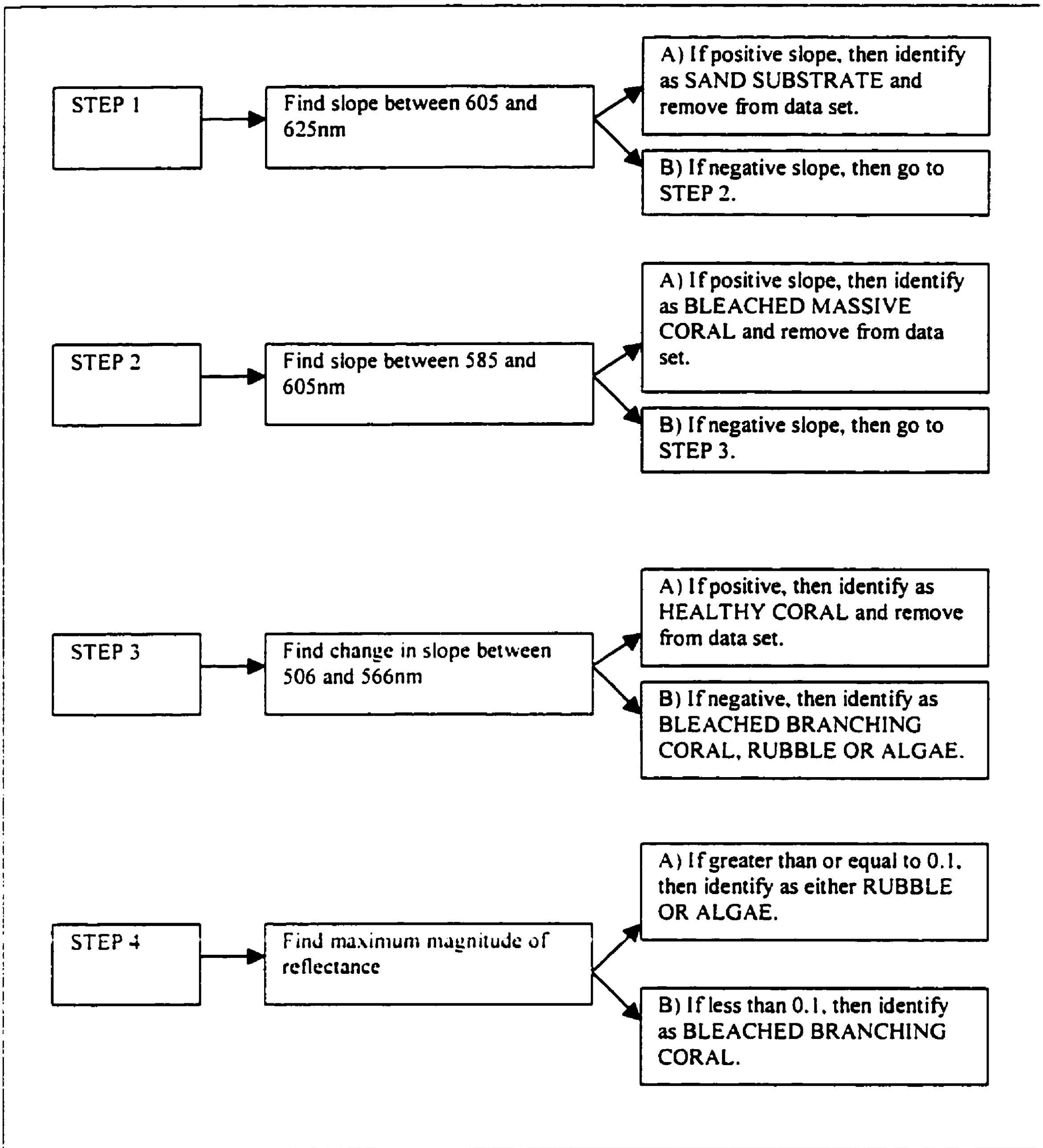

Figure 7.10. This decision flow chart is used to identify coral reef features based on first and second derivatives.

First, the slope between 605 and 625nm is found, and the spectra with positive slopes are identified as sand substrates based upon inspection of differences in slope. Secondly, the slope between 585 and 605nm is found, and the spectra with positive slopes are identified as bleached massive corals. Thirdly, the change in slope (second derivative) between 506 and 566nm is found, and spectra with positive changes in slope are identified as healthy coral, regardless of morphology. The remaining spectra are identified as bleached branching coral, algae or rubble substrates. To differentiate between these three final populations, the maximum magnitude of reflectance is determined for the entire spectrum. If the maximum magnitude of reflectance is greater than or equal to 0.1, then those spectra are identified as algae or rubble surfaces and the remaining are considered bleached branching coral spectra. The results of the derivative analysis based on the representative spectra are presented in Table 7.2. For interest, the first and second derivatives were calculated for all sub-populations of healthy coral.

Table 7.2. First and second derivatives are calculated on the representative spectra.

	Slope between 605-625nm	**Slope between 585-605nm**	**Change in Slope between 506 and 566nm**
	IF POSITIVE, THEN ID AS SAND	**IF POSITIVE, THEN ID AS BLEACHED MASSIVE CORAL**	**IF POSITIVE, THEN ID AS HEALTHY CORAL**
Bleached mass	-0.00029	0.00020 (ID as bleach mass)	
Bleached branch	-0.00053	-0.00090	-0.00001
Healthy mass	-0.00030	-0.00085	0.00003 (ID as healthy)
Healthy branch	-0.00038	-0.00040	0.00001 (ID as healthy)
Healthy soft	-0.000077	-0.00092	0.00002 (ID as healthy)
Algae	-0.00053	-0.00125	-0.00001
Rubble	-0.00027	-0.00110	-0.00001
Sand	0.00006 (ID as sand)		

The 3 healthy coral populations (massive, branching and soft corals) were considered as one population for the final classification scheme, as few spectral reflectance differences were discernable and the sub-populations correlate strongly with one another. There are distinct differences between the reflectance spectra of bleached branching coral spectra and bleached massive coral spectra, which may be a function of the small number of bleached branching corals available for sampling in the field. The fact that bleached branching coral spectra are (a) different than bleached massive coral spectra and (b) similar to healthy coral spectra results in great difficulty in identifying bleached branching coral.

Additionally, algae covered surfaces and rubble appear to have similar spectral reflectance curves. This is likely because the dead coral debris that constitutes a large portion of rubble surfaces is commonly colonized by algae thus contributing to spectral reflectance characteristics similar to algae-covered boulders. These two populations are considered to be one classification category in the following procedure as a result of the lack of unique spectral features enabling differentiation.

7.4 ACCURACY ASSESSMENT

To test the validity of this identification technique, the calculations proposed by the 4 step procedure (first and second derivatives, as well as maximum magnitude of reflectance) were performed on the remainder of the data. The spectra were identified based on the guidelines presented in Table 7.2 above, and thus classified as one of six populations. Therefore, the first derivative between 605 and 625nm of all spectra in the data set was calculated and all spectra with positive slopes were identified as sand substrates. These spectra were then removed from the data set, leaving 297 spectra and the first derivative between 585 and 540nm was calculated. All spectra with positive slopes in this wavelength range were identified as bleached massive coral, and subsequently removed from the data set.

Next, the second derivative between 506 and 566nm was calculated on the remaining 232 spectra, and those with positive change in slope in this wavelength range were identified as healthy coral (either branching, massive or soft), and removed from the data set. Finally, the maximum magnitude of reflectance was determined for the remaining 118 spectra and identified as either algae-covered or rubble surfaces if the magnitude was greater than or equal to 0.1. The remaining spectra were identified as bleached branching coral.

To determine the accuracy of this 4 step classification procedure using first and second derivatives and magnitude of reflectance, the number of spectra correctly and incorrectly identified was counted. At each step, the number of spectra correctly identified as well as the number of spectra incorrectly identified are counted. Regardless of whether the spectra were correctly or incorrectly identified, if the spectra met the criterion for the particular step, they were removed from the data set if it fit the hypothesis. Therefore, the total number of spectra in the data set is reduced at each step in the procedure.

Error matrices allow investigation of the relationship between what is known and what is classified in an effort to assess how well the classification procedure has categorized the spectra. An error matrix allows examination of the errors of omission (exclusion) and commission (inclusion) (Lillesand and Kiefer, 1994). The overall accuracy is computed by dividing the total number of correctly classified spectra by the total number of spectra in the entire data set. Similarly, the classification accuracies for each of the populations can be determined by dividing the number of correctly classified spectra in each population by the total number of spectra in the population (the column total). This is commonly called 'producer's accuracy'.

A third accuracy can be calculated by dividing the total number of correctly classified spectra for a population by the total number of spectra that were classified into that population (the row total). This figure is commonly called 'user's accuracy', and is a measurement of commission error, which indicates the probability that a spectra classified into a given population actually represents that population in reality.

An error matrix for the classification performed in this study is provided in Table 7.3. An overall accuracy of 80.1% was determined by dividing the total number of correctly classified spectra (the sum of the counts along the major diagonal) by the total number of spectra considered in this study [(117+16+5+100+31)/334=269/334=0.8054]. The producer's accuracy for each population can be found along the bottom of the matrix, and the user's accuracy can be found along the right side of the matrix.

Table 7.3. An error matrix for the classification procedure introduced here enables examination of errors of omission and commission.

	Healthy	Bleached massive	Bleached branching	Algae/ Rubble	Sand	**TOTAL**	User's
Healthy	**117**	1	9	7	0	134	117/134 **=87.3%**
Bleached massive	7	**16**	0	4	0	27	16/27 **=59.3%**
Bleached branching	2	1	**5**	9	0	17	5/17 **=29.4%**
Algae/ Rubble	4	3	1	**100**	3	111	100/111 **=90.1%**
Sand	8	4	0	2	**31**	45	31/45 **=68.9%**
TOTAL	138	25	15	122	34	**334**	
Producer's	117/138 **=84.8%**	16/25 **=64.0%**	5/15 **=33.3%**	100/122 **=82.0%**	31/34 **91.2**		

The producer's accuracy for healthy coral is 84.8%. In other words, 117 of the 138 healthy coral spectra that were considered in this study were classified correctly. Eight of the healthy coral spectra were erroneously classified as sand, 4 as algae or rubble, 2 as bleached branching coral and 7 as bleached massive coral. Therefore, there is still a small degree of spectral confusion between the populations. The user's accuracy for healthy coral is 87.3% since 117 healthy corals were correctly classified of the 134 spectra classified as healthy coral in total. This means that 17 (134-117) spectra in the data set were erroneously classified as healthy corals, which makes these errors of commission. This can be interpreted as an 87.3% chance that a spectral reflectance curve in the healthy coral category actually represents healthy coral measured spectra.

The producer's accuracy of bleached massive coral is 64.0% since 16 of the 25 bleached massive coral spectra considered in this study were correctly identified as bleached coral. Similarly, the producer's accuracy of bleached branching coral is 33.3%, since only 5 of the 15 bleached branching coral spectra were correctly classified. This is the lowest accuracy of all populations considered in this study. Both data sets are relatively small, so the spectral reflectance curves may not actually be representative of bleached coral. Alternatively, the bleached corals sampled were most likely in varying stages of bleaching, which is difficult to discern. A coral in the beginning stages of bleaching may have a larger proportion of healthy coral polyps present, which would confuse the spectral signature. Another contributing factor to the low accuracy of the bleached branching coral category is the variable effect of the underlying substrate on the measured reflectance. These factors may all contribute to the variability of bleached coral reflectance spectra, and the poor classification results.

The user's accuracy of the bleached massive coral category is 59.3%. This means that there is a 59.3% chance that a bleached massive coral will be correctly classified into the proper category. The user's accuracy for the bleached branching coral category is the lowest of all categories. The user's accuracy indicates that the probability of a spectrum in this category actually being a measured bleached coral spectrum is only 29.4%. This is a very low probability and will result in low confidence in classification results involving bleached coral.

The 82.0% producer's accuracy of the algae and rubble category is a result of 100 of the 122 algae and rubble spectra included in this study being correctly classified. Similarly, the user's accuracy of the algae and rubble category indicates that there is a 90.1% chance that a spectrum in this category actually is an algae or rubble reflectance spectrum. The high accuracies may be a result of combining the 2 populations into one. Had this not been done, there would have been great spectral confusion between the 2 resulting in an inability to discriminate. Inspection of the representative spectra reveals that algae and rubble spectra are nearly identical. This is most likely because the same algae that colonizes a dead coral massive will colonize a pile of dead coral branches that have broken off and gathered on the sea floor, for instance.

The producer's accuracy of the sand surface category is highest of all populations at 91.2% since 31 of the 34 sand spectra included in this study were correctly identified. The user's accuracy of the sand category is only 68.9% such that there is this amount of chance that a given spectrum of this category actually is a measured sand reflectance curve. The low user's accuracy is an indication that there is a relatively high probability that other features will be erroneously classified as sand.

The overall accuracy for the 4 step classification scheme proposed here is high compared to the results of the cluster analyses, and it may be acceptable for certain regional applications of coral reef ecosystem mapping and monitoring. Despite the inaccuracies due primarily to an inability to identify bleached branching corals, the overall accuracy is satisfactory, and it can be concluded that the procedure introduced here is an appropriate means of classifying populations commonly found in a coral reef ecosystem.

7.5 SUMMARY

The first objective of the chapter was to define representative spectra for the populations by using principal components analysis as a data reduction tool. Six separate principal components analyses were performed in order to identify one representative spectral reflectance curve for each population. This objective was met, and 6 representative spectra were defined.

Comparing the spectra revealed between-population differences in the slope and change in slope of the spectral reflectance curves, so spectral derivative analysis was investigated for its utility in discriminating populations. First derivatives (change in reflectance with respect to wavelength) and second derivatives (change in slope with respect to wavelength) were calculated for the 6 representative spectra to develop hypotheses for spectral discrimination of the populations. The first derivatives between 605 and 625nm as well as between 585 and 605nm enabled identification of sand substrates and bleached massive corals, respectively. The second derivative between 506 and 566nm enabled discrimination of healthy corals. Finally, the maximum magnitude of reflectance was used as a means of discriminating algae or rubble surfaces from bleached branching coral.

This 4 step procedure using first and second derivatives and magnitude of reflectance was tested on the remainder of the data set in order to test its accuracy. The overall accuracy of the classification was 80.1%, which is appropriate for many applications, such as coral reef ecosystem management on a regional scale. Furthermore, errors of omission (exclusion) and commission (inclusion) were investigated to determine which categories were contributing most to the overall accuracy results.

CHAPTER 8

SUMMARY AND CONCLUSIONS

8.1 SUMMARY

It is difficult to determine the exact cause of coral reef ecosystem decline, but it is probably due to the interaction of a combination of human-induced factors leaving coral communities less resistant to periodic natural disturbances. Although disease, temperature extremes, pest outbreaks, tropical cyclones, and other natural events periodically devastate coral reefs with widespread repercussions, healthy reefs are more resilient and will recover with time (Brown et al., 1997; Glynn, 1996).

There is thus a critical need for detailed monitoring and assessment of reef habitats in order to document how and where coral reefs are threatened and to understand what measures are needed to safeguard them. Scientists and managers have only a rudimentary, incomplete database on the status and health of coral reef ecosystems (Bryant et al., 1998). For instance, there is still a lack of an objective global map depicting reef location although subjective, survey-based maps covering non-continuous and small geographic areas are available from the International Center for Living Aquatic Resources Management (ICLARM) (Bryant et al., 1998). Qualitative, spatial information is essential for informed decision making by resource managers and agencies, fishers, tourism, and local industry. Moreover, the public, non-governmental organizations and scientists need such baseline data to better understand and advocate for protection of reefs.

A range of tools exist for assessing and monitoring reefs, each with advantages and limitations, as there is usually a trade-off between cost and detail (Green et al., 1996). For example, satellite imagery can be acquired at relatively low cost, but the spatial and spectral detail available is low, and conversely, underwater transects by ecologists are expensive, but provide great detail of ecosystem structure for small areas. The optimal approach might be multi-level sampling whereby information is extracted from limited, high-resolution sampling and extrapolated to a large area based on low-resolution data with regional coverage (Bryant et al., 1998).

Toward this end, the *in situ* spectral reflectance database used in this study is the first of its kind. The field data are difficult to collect and study areas are remote resulting in expensive and short field seasons. The sky conditions are often poor for radiometric measurements, as there is typically cloud cover in tropical coastal areas where coral reefs are commonly found. The water surface can be rough, also resulting in arduous circumstances for data collection based out of a small boat that is shallow enough to float over a coral reef. Furthermore, the environment is complex, so variables are difficult to control. These factors combine to create a challenging environment in which to develop a sampling strategy and methodology. Through trial and error and innovation, many of these fundamental data collection obstacles have been overcome and a methodology is now available for other researches to test, optimize and improve.

Mumby et al. (1998) present two basic advantages of the quantification of reef spectra such as in this study. The first is that prior knowledge of spectral responses allows users of hyperspectral imagery to make an informed selection of wavelength bands with which to operate. Secondly, spectral classification of hyperspectral imagery may become an automated procedure with access to spectral libraries. As a result, the use of a spectral library, such as collected for this thesis, could conceivably be used to the exclusion or reduction of fieldwork.

The work in this thesis is an important fundamental step in establishing consistent and quantitative international databases of accurate and replicable imagery delineating the extent of coral reef ecosystems, and spectral indexes or catalogues indicating the health of ecosystem components. Such a database could be augmented regularly to identify changes in coral health over time, and could serve as an integral source of information when relating coral bleaching to climatic anomalies or environmental changes, for example.

8.2 INTELLECTUAL CONTRIBUTIONS

The ultimate goal of this study was to use a unique data set of hyperspectral *in situ* reflectance measurements to determine the degree to which optically similar coral reef features could be discriminated. Meeting this goal required collection of the first *in situ* database of passive reflectance spectra in a submerged coral reef environment. Three field programs in Beqa Lagoon, Fiji; Manado, Indonesia; and Savusavu Bay, Fiji were designed to collect *in situ* reflectance measurements of a variety of features commonly found in a coral reef environment.

Field data collection was a significant challenge, and took many hours in the field to collect a relatively small amount of data. Limited resources necessitated small data collection teams, which resulted in physically demanding and challenging research. In addition, environmental limitations restricted the amount of data collected. For example, reflectance data should be collected when the sun is highest in the sky for greatest accuracy, so data collection times were limited to a few hours surrounding solar noon. Unfortunately, near the equator, this is a physically taxing time of day to be under the sun, especially on an exposed coral reef flat with no shade whatsoever. Additionally, overheating of the computer equipment was commonly an issue at this time of day.

Additional challenges to this field data collection are the physiological restrictions of scuba diving for extended periods of time. For safety reasons, measurements underwater while scuba diving were rarely taken for over an hour, and normally only twice per day. Furthermore, scuba diving tanks contain limited amounts of air, and the harder a scuba diver is working, the more quickly air is consumed.

The design of the field seasons changed slightly each year depending on the specific instrumentation, field assistants and time available. Furthermore, variable surface water conditions, coral reef structure, and boat characteristics demanded modification of field sampling designs. The establishment and documentation of sampling procedures in multiple environments with varying instrumentation and other resources is therefore a significant contribution that may aid scientists conducting similar field data collection in the future.

Additionally, similar features were measured in the three geographic locales to determine the degree to which reef location influences reflectance. While it is intuitive that similar coral reef ecosystem features would have similar spectral reflectance characteristics regardless of the geographic location of the reef, this had never before been investigated. Another contribution of this study, therefore, is the establishment of baseline information that geographic location does not appear to affect the spectral reflectance characteristics of the coral reef features.

Moreover, measurements of corals with different morphological characteristics and corals suffering from varying degrees of bleaching were collected to determine the spectral reflectance differences. Algae covered surfaces were also measured to examine the difference between pigments in macroalgae and those in zooxanthellae. The unique data set used in this thesis comprises a large array of features commonly found in a coral reef environment, and therefore allows comprehensive comparison of *in situ* spectra. Such baseline data is a necessity in accurate remote monitoring of coral reef environments, and may enable automated digital image analysis through reference to spectral libraries resulting in a reduction of expensive, time consuming and difficult field work (Mumby et al., 1998).

Since the data set used in this thesis was the first of its kind, the subsequent analysis was therefore also the first of its kind. The field data were first examined separately to investigate the between- and within-population variability. Average and standard deviation spectra were examined, and cluster and correlation analysis used to determine the spectral differences and similarities among spectra in a population and between spectra of different populations. After the three data sets were separately investigated, they were amalgamated and treated as one large spectral data set. Eight spectral populations were created and the between and within-population variability examined using cluster and correlation analysis. The purpose of comparing the amalgamated spectral data set was to examine the within-population variability that may be a result of geographic location of the spectral measurements.

Principal components analysis was then used to reduce the large amalgamated data set to representative spectra for each population. These representative spectra were used to develop a means of discriminating between populations based on the slopes and the changes in slope of the spectral curves. First and second derivatives were calculated in narrow wavelength ranges to retain the maximum value of the hyperspectral data. A 4 step procedure using first and second derivatives and magnitude of reflectance to eliminate identified spectra was developed based on the representative spectra and tested for accuracy on the remainder of the spectral data set. An accuracy assessment was performed to interpret the results of the spectral classification using the 4 step derivative procedure.

8.3 MAJOR FINDINGS

The spectral data set collected in Beqa Lagoon, Fiji in 1996 consists of 40 measurements of bleached massive coral, healthy massive coral and algae-covered surfaces. It was hypothesized that the within-population variability would be small such that all bleached massive coral spectra will be similar, for instance. Additionally, it was hypothesized that the between-population variability would be large as a result of wavelength-specific differences in reflectance. Initial inspection revealed that there are subtle differences in the shape and magnitude of the reflectance curves, which may enable discrimination between broad populations. Cluster analysis performed was able to discriminate between different spectra although there was a certain degree of misclassification. Additionally, correlation coefficients were calculated to examine the within-population variability of spectral reflectance measurements. This analysis revealed that, in all cases, a positive linear relationship exists between spectra within a given population. The relationship was strongest for the bleached massive coral group and weakest for the algae-covered coral group. The strong positive correlations between populations indicate that it will be difficult to differentiate these populations spectrally.

Secondly, average and standard deviation spectra were examined to visualize the within-population variability of the 5 populations defined for the data set collected in Manado, Indonesia in 1997. Cluster and correlation analyses were then performed to examine the within- and between-population variability. With the exception of the high variability among sand surface spectra, there was little within-population variability found. Correlation coefficients of average spectra were then examined to explore the between-population variability. The correlation coefficients were strongly positive for all spectral comparisons, which suggests that the average spectra are all similar. These results emphasize the difficulty in remotely identifying these spectrally similar features.

Third, the spectral data set collected in Savusavu Bay, Fiji in 1998 consisted of 215 reflectance curves separated into 6 populations: healthy branching corals, healthy massive corals, healthy soft corals, bleached branching corals, rubble surfaces and algae-covered surfaces. Initially, the average and standard deviation spectra were determined and examined in an effort to identify spectral differences in reflectance that might enable remote discrimination. Subtle differences in spectral shape and magnitude were identified. Cluster analysis was used to explore the within-population variability among spectra of a given population. In general, it was concluded that there is low within-population variability among spectra of the same population. Pearson correlation coefficients were also calculated to examine the relationships among spectra within a population. Overall, the relationships among spectra of a given population were strongly correlated, which reinforced the results of the cluster analysis. Finally, Pearson correlation coefficients were calculated to explore the relationships between average spectra for each predefined population. The results indicate that there is a strong positive correlation between populations, which reveals that there is low variability between spectra of different populations. This result suggests that it will be difficult tc distinguish between populations of a coral reef ecosystem. Visual analysis of the measured reflectance spectra, however, indicates that subtle spectral differences do in fact exist between populations, which is encouraging for further analysis.

In the next stage of analysis, the spectra measured in Beqa Lagoon, Fiji in 1996, Manado, Indonesia in 1997 and Savusavu Bay, Fiji in 1998 were compared in order to examine the spectral differences of reflectance curves measured in different geographic locations. The 334 spectra considered were categorized into 8 broad populations based on photographs and notes taken in the field, and visually examined for within-population variability. Cluster and correlation analyses were used to further examine the within- and between-population variability. The within-population variability was found to be low, which indicates that spectral reflectance curves within a given population defined based on feature type are spectrally similar regardless of geographic location. The between-population variability was also found to be low, which suggests that the spectral differences in reflectance are subtle for the populations considered. All healthy coral spectra in the 3 sub-populations of branching, massive and soft varieties were amalgamated into one population for further analysis since the high correlation coefficients revealed that there is little spectral difference attributable to coral morphology.

The first objective in the next stage of analysis was to define representative spectra for the populations by using principal components analysis as a data reduction tool. Six separate principal components analyses were performed in order to identify one representative spectral reflectance curve for each population: healthy coral, bleached massive coral, bleached branching coral, algae and rubble surfaces or sand surfaces. Comparing the spectra revealed between-population differences in the slope and change in slope of the spectral reflectance curves, so spectral derivative analysis was investigated for its utility in discriminating populations. First derivatives (change in reflectance with respect to wavelength) and second derivatives (change in slope with respect to wavelength) were calculated for the 6 representative spectra to develop hypotheses for spectral discrimination of the populations. The maximum magnitude of reflectance was used as the final discriminating factor. Through trial and error, it was discovered that the first derivatives between 605 and 625nm as well as between 585 and 605nm enabled identification of sand substrates and bleached massive corals, respectively. The second derivative between 506 and 566nm enabled discrimination of healthy corals. Finally, the maximum magnitude of reflectance was used as a means of discriminating algae or rubble surfaces. The remaining spectra were assumed to belong to the bleached branching coral population.

This 4 step procedure using first and second derivatives and magnitude of reflectance was tested on the remainder of the data set in order to test its accuracy. The overall accuracy of the classification was 80.1%, which is appropriate for many applications, such as coral reef ecosystem management on a regional scale. Furthermore, errors of omission (exclusion) and commission (inclusion) were investigated to determine which categories were contributing most to the overall accuracy results.

Bleached corals were the main source of error in this study. Since the classification of healthy corals and algae-covered dead corals appears to be accurate using this procedure, the inaccuracies in classifying bleached coral is less of a concern. Since bleaching is a temporary state of vulnerability, a bleached coral may not remain bleached for very long. The coral may die and be colonized by algae, or recover to healthy coral status in a very short time period, depending on the intensity and duration of the environmental stress. Therefore, it may be of greater utility to devise an accurate means of classifying algae-covered surfaces, so areas of change from healthy coral to algae-covered coral can be identified.

8.4 FUTURE RESEARCH

8.4.1 Improving Knowledge Base

Most data collection is focused on biological and physical dimensions of coral reef ecosystems such as the species found, location of habitats, and degree of degradation (Bryant et al., 1998). Socioeconomic and political information can help policy makers, managers, scientists and others better understand the direct and underlying factors that result in changes in reef condition such as subsidies and laws that result in over fishing. Information enabling the quantification of direct and indirect values resulting from coral reef ecosystems is important input for weighing development and management options. Collection of such policy-relevant data should be a priority in future monitoring and assessment efforts.

Pressure on coral reefs will grow as economies develop and coastal populations swell, so careful planning and management can assure healthy reefs while meeting the needs of local people. Increased concern and interest will hopefully lead to action at local, national and international levels in an effort to protect and conserve reef resources. Therefore, both physical and socioeconomic information must be considered in order to understand the workings of the system and successfully implement management and conservation schemes.

8.4.2 Hyperspectral Remote Sensing

The next stage of research following the development of this procedure for spectral identification should be to collect remotely sensed hyperspectral measurements of a coral reef ecosystem. The remotely sensed imagery should first be collected over a coral reef flat with little or no water cover to perform an analysis of the effects of mixing within one pixel. Secondly, remotely sensed imagery should be collected over a submerged coral reef to analyze the effect of the water column over the substrate. Energy is attenuated logarithmically through a water column of infinite depth or with a dark substrate. The bright and highly reflective substrates of a coral reef environment, however, present a complex radiative transfer problem due to multiple reflectance and/or solar-stimulated fluorescence off these substrate types. Considerable study is required to develop a means of correcting for the attenuating and augmenting effects of water columns of variable depth and quality over substrates of variable reflectance.

Airborne remote sensing, such as with the *casi* (Compact Airborne Spectrographic Imager) sensor, is presently the best source of high spatial and spectral resolution imagery. Additionally, future satellite missions, such as the Australian ARIES satellite or the American NEMO satellite, will offer high spectral resolution imagery with moderated spatial resolution within the next five years. Utilization of such hyperspectral imagery will allow identification of features that are spectrally similar, and will allow repetitive coverage over large geographic areas. The ability to perform change detection studies will improve with the use of hyperspectral imagery because subtle changes in spectral reflectance will be detectable.

8.4.3 Encompass Broad Coastal Zone

Finally, this field of study needs to be extended into the complicated yet highly related coastal environments of mangrove forests, seagrass beds and mudflats. Unique spectral reflectance properties are expected for components of these, and other, coastal ecosystems, which should allow for accurate identification on remotely sensed imagery. Submerged seagrass, however, has great potential to present an additional source of error due to the suspected spectral confusion between seagrass, coral and algae. If considering the broader coastal zone is a goal, then additional *in situ* measurements characterizing the spectral reflectance of seagrass, mangroves and mudflats, for instance, is a necessity. Such an approach to quantitatively mapping coastal ecosystems could be considered an essential component of a management plan, as it allows for consistent, repetitive and accurate monitoring of degradation and recovery of ecosystems.

Furthermore, even if not directly affected, coral reefs may be threatened by degradation of nearby mangroves, seagrass beds and associated habitats that serve as nurseries for many reef species. Mangroves play an important role in filtering out sediments washed into coastal areas from upstream runoff, and are unfortunately often cleared for wood fuel, creation of aquaculture ponds and for coastal development. Left unmonitored, unassessed and unplanned, the coastal zone, with increased economic development may face a devastating future.

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