

Jamaica as a Case Study of Human-Forest Interactions: An
Assessment of Forest Change and the Role of Scarcity in
Tropical Deforestation

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DECLARATION

I hereby declare that this thesis has been composed by me and that the work is my own, unless otherwise specified.

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PREFACE

This research was motivated by a concern for the fate of Jamaica's forests and a desire to draw the attention of scientists and policymakers to the serious deforestation problem the country faces. Tropical deforestation is widely recognized to be one of the most important environmental issues facing the developing world today. This recognition featured prominently in the United Nations Conference on Environment and Development (UNCED) held in Rio de Janeiro, Brazil (June 1992). Largely as a result of this conference, tropical deforestation is now perceived to be an important environmental issue having global repercussions. Indeed, together with biodiversity loss and global warming, tropical deforestation has rightly moved to occupy center-stage in the international arena of environmental concern.

This growing attention has also sparked a great deal of interest in the scientific monitoring and modelling of tropical deforestation worldwide. However — and perhaps due to tropical deforestation's new international stature — most of the focus of this scientific research has been on the large forest countries, namely Brazil, Nigeria, Thailand and Indonesia. This is hardly unexpected, as the loss of these forests threatens to have significant negative impacts for the global commons. Nevertheless, this should not blind us to the fact that there are many small countries of the world — of which Jamaica, perhaps, is the most extreme example — where forest cover is disappearing rapidly — indeed, even more rapidly — than in these high profile countries. There is no doubt that this relatively small loss from the global point of view will have more serious and immediate ecological and socio-economic consequences for these populations than will the loss of forest cover in the larger countries. Indeed, at current rates of deforestation, countries like Jamaica will lose their forests long before Brazil, which also has the economic potential to shift its economy more rapidly to less resource dependent activities.

It was in view of these basic facts that I was motivated to undertake research into Jamaica's disappearing forests. In a country burdened by debt and barely coping to provide basic welfare services to its largely poor population, I hope that this thesis in its own small way can provide Jamaica's scientists and government officials with a sense of the magnitude of the country's deforestation problem and its underlying driving forces. This information could constitute the first step in the development of more effective forest preservation and management programs for the island.

ABSTRACT

Using Jamaica as a case study, this thesis investigates the role played by poverty and population in driving deforestation in the tropics. It argues that Jamaica provides a good middle ground or 'meso-level' perspective from which to study these scarcity-forest interactions. Like many developing countries, Jamaica has suffered from economic problems since the 1970s that have constrained its capacity to develop. These problems have had an adverse impact on the welfare of its many poor residents, increasing their immediate dependency on the natural resource base.

One consequence of this dependency is an observable decline in the country's forests. Moreover, as a small island nation with an open economy and a fragile and limited resource base, deforestation threatens to generate serious socioeconomic and ecological externalities. Despite these pressures, however, the problem of Jamaican deforestation has received very little attention from the scientific community.

Forest data for the quantitative analysis of these interactions is derived from an analysis of Landsat MSS data from 1987 to 1992. Using a GIS (geographical information system) the study estimates that during this period, Jamaica experienced a national average deforestation rate of 3.9% per annum. Classification maps based on the original satellite images used to calculate this rate are combined with a political boundaries map of the island in a GIS to derive sub-national forest estimates at parish and constituency levels. The contributions of several scarcity-related land use and social variables to the calculated parish-level deforestation rates are presented and briefly discussed, before 'going one level down' to the constituency unit. At this level, forest constituency data is used to quantitatively assess a conceptual model of scarcity-driven land use for the island. The model includes a variety of population/poverty measures reflecting key socio-economic and land-related features of the island. Simple correlation and OLS regression results for both parish- and constituency levels support the importance of scarcity in driving the destruction of Jamaica's forests, and the relative contribution of its various population/poverty measures are noted and discussed.

The study's empirical analysis ends with a small simulation experiment that attempts to investigate future outcomes for Jamaica's forests under several different scenarios. The simulation experiment demonstrates that under either good or bad scenarios, the impacts of social and demographic changes on Jamaica's remaining forest cover may be substantial by the year 2010. The study concludes with a discussion of the implications of these findings for forest protection and management initiatives on the island, and, perhaps, for other Caribbean countries sharing similar social and economic characteristics

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I owe a special great debt of gratitude to David Strande at the USGS EROS Data Center for helping me through the data archive and for so untiringly answering my many questions about data format. I would also like to express my gratitude to the Jamaican Information Service (JIS) for providing me with the constituency map; to the Jamaican Planning Institute (JPI) for allowing me permission to use their LSMS data set; and to the Jamaican Statistical Institute (STATIN), for providing the Census data set. Despite a heavy workload and temporary computer malfunctions, Donneth Edmonson at STATIN was able to process the data expeditiously, and for this I am extremely grateful.

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TABLE OF CONTENTS

Declaration.....	i
Preface	ii
Abstract	iii
Acknowledgments	iv
Contents	v
List of Figures.....	ix
List of Tables	x
List of Photographs	xi
List of Appendices	xii
List of Data Sources.....	xiii
 Chapter 1: Introduction	
1.1 The Environment & Development.....	1
1.2 The Poverty/Population/Environment Nexus.....	2
1.2.1 A Scarcity-Informed Approach to the Study of Tropical Deforestation.....	2
1.2.2 Measuring the Social Process Behind Forest Clearance Activities.....	2
1.2.3 Micro- vs. Meso- vs. Macro-Level Analyses of Scarcity- Deforestation Interlinkages.....	3
1.3 Jamaica as a Case Study for the Analysis of Tropical Deforestation.....	4
1.4 Study Framework.....	5
 Chapter 2: Relevant Literature	
2.1 Population, Poverty and the Environment: Issues & Analyses.....	8
2.2 Theoretical Analyses & Case Studies	8
2.2.1 General Relationships & Themes	9
2.2.2 Prominent Scarcity-Related Factors Mediating Population/Poverty/Environmental Outcomes	9
2.3 Quantitative Studies.....	14
2.3.1 Population & Land Use Studies	14
2.3.2 Economic & Political Studies	18
2.3.3 Land Clearance Model Studies.....	22
2.4 The Poverty/Population/Environment Nexus: Issues & Analyses Summary	27
2.4.1 Concluding Remarks: Contextualizing the Present Study Within the Literature.....	32
 Chapter 3: The Social Context of Scarcity-Driven Forest Loss in Jamaica	
3.1 The Jamaican Economy: Overall Characteristics & Trends	33
3.2 Economic Spiral Downward: The "Lost Decades" of the 1970s and 1980s ..	34
3.2.1 Macroeconomic Shocks & Disequilibria	34
3.2.2 Retrenchment, Structural Adjustment & Debt	36
3.3 Uncertain Economic Prospects: The 1990s and Beyond.....	39
3.4 Social Repercussions of the Above Trends.....	45

3.4.1 Persistent Poverty & Inequality.....	45
3.4.2 Falling Real Wages & Rising Unemployment.....	47
3.4.3 The Special Case of Agricultural Employment.....	47
3.4.4 Performance on Other Welfare Indicators.....	49
3.5 Future Welfare Trends & Prospects.....	52
Chapter 4: Ecological Context: Forest Pressures & Consequences	
4.1 Biophysical Setting.....	53
4.1.1 Topography.....	53
4.1.2 Soils.....	54
4.1.3 Climate & Watersheds.....	55
4.1.4 Forest Classification.....	56
4.1.5 Biodiversity.....	57
4.2 Scarcity & Environmental Exploitation.....	58
4.2.1 Demographic Pressures & Trends.....	58
4.2.2 The Pressure of Production on the Land: The Plight of the Small Farmer.....	60
4.2.3 The Persistence of the Smallholder Sector & Constraints on Productivity.....	62
4.3 The Destruction of Jamaica's Forest Resources: Shifting Cultivation & Other Scarcity-Driven Forms of Exploitation.....	64
4.3.1 The Control of Squatters.....	67
4.3.2 Environmental Consequences of these Forest Pressures.....	69
Chapter 5: Measuring Jamaican Deforestation Using Landsat Images	
5.1 Satellite-Based Measures of Environmental Change.....	72
5.1.1 Some Basic Principles.....	73
5.1.2 Spectral Reflectance Curves for Vegetation.....	75
5.2 MSS Landsat Data.....	77
5.2.1 Satellite Data Source & Description.....	80
5.2.2 Considerations in the Selection of the Data.....	81
5.3 MSS Applications to Forest Resources in the Tropics.....	83
5.3.1 Strategy for Overcoming these Limitations.....	84
Chapter 6: Image Processing Methodology (A): Image Restoration & Enhancement	
6.1 Selection of Bands.....	86
6.1.1 Data Reduction.....	88
6.1.2 The Creation of a Vegetation Index.....	91
6.2 Image Rectification.....	92
6.2.1 Radiometric Restoration.....	92
6.2.2 Geometric Restoration.....	96
6.3 Image Enhancement.....	96
6.3.1 Contrast Stretch.....	96
6.3.2 The Creation of False Colour Composites.....	100
6.4 Image Resampling & Projection.....	100
6.4.1 The Process of Resampling.....	100
6.4.2 Image Projection.....	103

Chapter 7: Image Processing Methodology (B): Signature Development & Image Classification	
7.1 Classification: General Features	104
7.2 The Hybrid Unsupervised/Supervised Classification	106
7.2.1 Unsupervised Analysis	106
7.2.2 Supervised Analysis	108
7.3 Some Concluding Caveats	119
Chapter 8: Jamaican Forest Cover Extent & Change 1987-1992	
8.1 Integration of Classification and Constituency Maps	120
8.1.1 Mosaicking of Images	120
8.1.2 Creation of a Constituency Boundaries Map	121
8.2 Calculation of Forest Cover Extent & Deforestation	121
8.2.1 Forest Data: National- and Parish-Level	125
8.2.2 Comparison with Other National Estimates	125
8.3 Parish-Level Forest Loss & Some of its Possible Socio-economic Correlates	131
8.3.1 Representative Correlations	132
8.3.2 A Deeper Look at the Small Size Farm Category	139
Chapter 9: Regression Analysis	
9.1 Some Preliminary Remarks	144
9.2 A Conceptual Model of Scarcity-Driven Land Clearance	146
9.3 Description of Social and Physical Land Use Variables	147
9.3.1 General Description of Data Sources	147
9.3.2 Description of Independent Variables (Social)	149
9.3.3 Description of Independent Variables (Physical/Land Use)	153
9.4 Some Methodological & Data Notes	157
9.4.1 Data Explanation	157
9.4.2 Statistical Methodology	158
9.5 Constituency Level Analysis	159
9.5.1 Social Variables Descriptive Statistics	159
9.5.2 Regression Results Using Only Social Variables	163
9.5.3 Final Regression Results	167
9.5.4 A Closer Look at the Role of Social Scarcity in Deforestation	169
9.5.5 Regressions Including Physical Variables	173
9.6 Summary: Some Stylized Facts About Scarcity-Driven Forest Loss in Jamaica	176
Chapter 10: The Poverty/Population/Environment Nexus: Some Future Trends & Prospects for Jamaica's Forests	
10.1 A Simulation Experiment	182
10.1.1 General Remarks	182
10.1.2 Simulation #1	184
10.1.3 Results of Simulation #1	185
10.1.4 Simulation #2	187
10.1.5 Results of Simulation #2	189
10.2 Concluding Remarks	190

Chapter 11: Conclusions & Policy Implications	
11.1 General Findings & Discussion.....	192
11.2 Some Policy Directions for Conserving Forest Cover in Jamaica & Beyond	197
11.3 Final Remarks: Study Limitations & Future Research.....	205
 Appendices	 206
Bibliography	233

LIST OF FIGURES

Figure 2.1: Key Interlinkages in the Poverty/Population/Environment Nexus ..	29
Figure 3.1: Traditional Agriculture Export Earnings	48
Figure 4.1: Jamaica National Map	53
Figure 5.1: The Electromagnetic Spectrum	74
Figure 5.2: Major Remote Sensing Regions & Their Imaging Systems	75
Figure 5.3: Spectral Response Pattern of Green Vegetation.....	76
Figure 5.4: The Landsat MSS	79
Figure 5.5: The Nature & Structure of Landsat MSS Data	80
Figure 6.1: Horizontal Coordinates Relative to Sun Angle.....	95
Figure 6.2: Image Histogram, Original Band (Band 4, Jamaica 1987)	98
Figure 6.3: Image Histogram, Linear Stretch (Band 4, Jamaica 1987).....	98
Figure 6.4: Image Histogram, Special Contrast Stretch Jamaica 1987).....	99
Figure 6.5: The Concept of Resampling.....	101
Figure 7.1: Computer Random Generation of Field Sites	114
Figure 7.2: Actual Sites Field-Checked	115
Figure 8.1: Steps in the Calculation of Forest Cover Estimates	123
Figure 8.2: Steps in the Jamaican Forest Change Analysis	124
Figure 8.3: FAO Production Series Estimates of Forest Extent & Change.....	126
Figure 9.1: Locations of Major Tourist/Economic Centers.....	151
Figure 10.1: Simulation #1.....	186
Figure 10.2: Simulation #2.....	190

LIST OF TABLES

Table 2.1: Summary of Main Scarcity-Related Findings of Quantitative Studies	30
Table 3.1: Jamaica Economic Profile	38
Table 3.2: Jamaica Composition of Production, Trade & Employment	41
Table 3.3: Jamaica Productivity, Investment & Employment	43
Table 3.4: Jamaica Debt Profile	44
Table 3.5: Jamaica Welfare Profile	50
Table 3.6: Jamaican Government Expenditures on Health & Education	51
Table 6.1: PCA Results	89
Table 6.2: Band Correlation Matrix	90
Table 7.1: Error Matrix	117
Table 8.1: National Forest Estimates	125
Table 8.2: Parish Forest Estimates	132
Table 8.3: Parish Social Variables Deforestation Correlations	133
Table 8.4: Parish Agriculture/Land Use Variables Deforestation Correlations ..	135
Table 8.5: Parish Land Quality Variables Deforestation Correlations	138
Table 8.6: Parish Small Farm Variables Deforestation Correlations	140
Table 8.7: Parish Agricultural Activity Variables Deforestation Correlations ..	141
Table 8.8: Parish Small Farm Status Variables Deforestation Correlations	142
Table 9.1: Soil Variable Classification	156
Table 9.2: Constituency Social Level Variables Deforestation Correlations	160
Table 9.3: Constituency Social Change Variables Deforestation Correlations ..	161
Table 9.4: Correlation Matrix of Key Constituency Social Variables	165

LIST OF PHOTOGRAPHS

Photograph 4.1: Smallholder Coffee on Lower Slopes of the Blue Mountains . . .	62
Photograph 4.2: Small Domestic Farms near Christiana	63
Photograph 4.3: Slash & Burn Agriculture High in the Blue Mountains	65
Photograph 4.4: USAID/GOJ Agroforestry Project Near Spaldings	66
Photograph 4.5: Deforested & Eroded Slopes of the Blue Mountains	71
Photograph 4.6: Deforested & Eroded Slopes of the Blue Mountains	71

LIST OF APPENDICES

Appendix A: Landsat MSS Data	207
Appendix B: Colour Composite Images	212
Appendix C: Correspondence Files	212
Appendix D: Signature Profiles	216
Appendix E: Final Classification Maps	220
Appendix F: Constituency & Parish Maps	222
Appendix G: Constituency Deforestation Rates	225
Appendix H: Parish-Level Social Data	227
Appendix I: Parish-Level Soil Data	232

LIST OF DATA SOURCES

Forest Data

Forest data were derived from MSS Landsat images representing eastern and western portions of the island in 1987 and 1992 (4 images in total). Data were obtained from the USGS' EROS Data Center, Sioux Falls, Iowa. The eastern and western identification numbers for 1987 are: LM5011047048087252 (east) and LM5012047048087195 (west). For 1992 the identification numbers are: LM4011047048092082 (east) and LM4012047048092249 (west).

Socio-economic Data

Demographic, official unemployment, welfare and quality of life data were obtained from the Caribbean Commonwealth Housing and Population Census for 1992 and 1982. Data was purchased in digital form from STATIN (Statistical Institute of Jamaica).

Consumption and inequality data were obtained from the Jamaica Survey of Living Standards (JSLC). The data were purchased in digital form from the World Bank's Poverty and Human Resources Division.

An unofficial unemployment measure was created in a GIS by measuring the average distance locations of each constituency from an important economic center.

Descriptive data on the socio-economic conditions of the island since the early 1970s were obtained from a number of official sources, including the Inter-American Development Bank (1999), the World Bank's World Development Reports (1972, 1984, 1991, 19999) and the U.N. Food and Agriculture Organization (1999).

Physical & Land Use Data

The Jamaican Agricultural Census was the source of the study's agricultural land use and size of land holding data. Data were compiled by the Department of Statistics (DS, now STATIN). Data were available for the late 1970s (1978/9) and at the parish level only and each constituency was assigned its respective parish value.

Data on slope and soil quality were obtained from the FAO's Digital Soil Map of the World & Its Derived Properties (1996). The raster map version for Jamaica was extracted in 5 min x 5 min grids or roughly about 9 km x 9 km.

Political Boundaries Maps

The constituency boundaries map was obtained from the Jamaican Information Office and was created by the Jamaican Elections Office (1987) (scale: 1:250,000 lat/long reference system). The parish vector boundaries map was obtained from Arc-Info's *Digital Map of the World for Use with Arc-Info Software* and had an original mapping scale of 1:1 million and was extracted in 1 km x 1 km grids.

Chapter 1

Introduction

1.1 The Environment & Development

Increasingly, the development community is recognizing the intricate links that exist between poverty, overpopulation and environmental problems. Awareness is growing that environmental quality is an important factor in the development process and in whether countries will eventually be able to raise welfare levels and reduce population growth (Bienen & Leonard 1985; Leonard 1985 a,b).

One environmental problem that has elicited widespread concern is the growing destruction of forests in tropical developing countries. Due to the many functions and products that tropical forests provide, their widespread destruction directly affects a substantial portion of the developing world's poor. Forests provide a broad range of goods for these populations — from fuelwood and building supplies to food and medicines. In addition, forests provide a number of important ecological functions — preserving the integrity of soils and hydrological cycles and regulating climate. All these contributions are important as they sustain the economic base on which largely rural, subsistence-based populations depend for their survival (Myers 1993; Barraclough & Solon 1990; Dasgupta & Maler 1996).

1.2 The Poverty/Population/Environment Nexus

1.2.1 A Scarcity-Informed Approach to the Study of Tropical Deforestation

For the most part, existing research on the causes of tropical deforestation has tended to take the form of case studies of local areas. However, unlike quantitative analyses, these micro qualitative studies make it difficult to assess if causes identified in one locale also operate in another or what the relative contributions of each may be to the deforestation process (Southgate et al. 1991; Chomitz & Gray 1995; Heilig 1994).

Quantitative understanding is particularly weak for two key policy issues in development: population and poverty. It is generally believed that much of the deforestation in the tropics can be traced to its low level of development, which has been exacerbated by problems of overpopulation and poverty. However, little quantitative analyses of the contribution of these factors to deforestation or their interaction exists.

In this study, this lacunae is addressed in order to shed light on these facets of the deforestation process. Deforestation is conceptualized as the outcome of the activities of poor individuals clearing forested areas under such 'scarcity' constraints as: unequal access to and shortages of resources, a lack of sufficient employment opportunities, physical constraints of the land, a lack of productivity-enhancing inputs, and low levels of human capital formation due to inadequate provision of social welfare.

1.2.2 Measuring the Social Processes Behind Forest Clearance Activities

This study assumes that the scarcity factors driving individual land use responses are determined by an array of factors, many of them conditioned by factors quite far removed from the site of deforestation (Arizpe 1991; Schmink 1987). Of course, the complexity of these interactions means that any attempt, as in this study, to assess the contribution of social factors to deforestation is a partial one at best. This is because no study can possibly measure all the factors (micro, meso and macro) influencing land users to clear forest cover (Shaw 1994; Arizpe 1991; Lonergan 1993; Turner & Meyer 1994; Turner et al. 1994). Similarly, it should be recognized that no model (conceptual or mathematical), can fully capture the dynamic nature of these processes, with their

ever changing and complex interactions (Arizpe 1991; Schmink 1994; Lonergan 1993; Lonergan & Prudham 1994; Van den Oever 1994; Shaw 1994).

Accordingly, this study analyzes a mere subset of these processes here, and within this subset, considers only a few scarcity factors thought to determine the land clearance responses of the poor.¹ It recognizes that many social factors (e.g. macroeconomic policies, land management practices, investment policies) will also strongly determine these land use responses — but in no way does it attempt to measure them. It also recognizes that the linear statistical techniques it uses to measure them cannot fully capture their dynamic nature.

Despite these drawbacks, a quantitative analysis of human-forest interactions can provide useful information for understanding human-forest interactions. It is possible from such studies, in other words, to derive general empirical lessons or 'stylized facts' about scarcity-driven deforestation processes. Stylized facts are patterns or regularities observed to hold frequently in the data, and as such often constitute the first step toward a deeper understanding of the phenomenon in question. From the development perspective, such information is often useful as it serves to highlight potential and hitherto overlooked interactions for consideration in the development of more effective programs and policies.

1.2.3 Micro vs. Meso vs. Macro Level Analyses of Scarcity-Deforestation Interlinkages

This thesis takes the country as its unit of analysis. It conceptualizes deforestation as the outcome of the responses of poor land users at ground level, the collective result of which is a national and sub-national loss of forest cover. Thus, the focus is on conceptualizing and measuring the behaviour of the individual land clearer as this impacts on forest cover at the aggregate level.

This country level focus represents a middle-ground perspective between the fine detail of the micro or qualitative case study and the broad approach of the global study, which encompasses a wide variety of country characteristics (Bilsborrow 1994).

¹This emphasis on the poor land user is not to imply that other groups (e.g. wealthy landowners) do not also play an important role in this process. Much has also been written on the dependencies between these various groups or 'deforestation coalitions' in promoting tropical deforestation. See, for example, Rudel 1993 and Dorner & Thiesenushusen 1992.

As noted previously, and reviewed in detail in Chapter 2, the qualitative case study literature constitutes the principal form of social scientific discussion to date on the causes of tropical deforestation. At the other end of the spectrum lies a small but growing body of quantitative literature, largely dominated by regional or global cross-sectional analyses. These latter studies seek to find broad patterns or relationships in the data and are insensitive to individual characteristics or detail.

In contrast to both areal units of analysis, the meso or country level study provides a sufficiently detailed and varied unit of analysis to allow for the measurement of the contribution of a range of socioeconomic and land use indicators, while still retaining enough generality to provide empirical guidance for the design of effective policies at the national level (Bilsborrow 1994; Turner et al. 1994; McNeill et al. 1994; Rudel & Roper 1996). At the same time, a meso level perspective can provide potentially important information on human-forest interactions at the regional level of analysis since it is better suited to the extrapolation of deforestation results to other countries sharing similar histories and characteristics (Turner et al. 1994; McNeill et al. 1994). This country-level approach, advocated by researchers in the field of global environmental change, may eventually help to improve understanding of deforestation processes through the development of a series of regional forest scenarios or typologies (see, for example, Turner & Myer 1994; Lonergan & Prudam 1994; Bilsborrow 1994; Rudel & Roper 1996; 1997; McNeill et al. 1994)

1.3 Jamaica as a Case-Study for the Analysis of Tropical Deforestation

This thesis will attempt to empirically analyze the contributions of scarcity to deforestation in Jamaica, for the period 1987-1992. Although small — a mere 10,990 km² in total area — Jamaica provides a good case study for the analysis of human-forest interactions in the tropics. In addition, there are very good reasons, both environmental and social, for why Jamaica should itself be an object of scientific concern.

First, the island exemplifies many of the socio-economic pressures that have plagued developing countries to varying degrees since the early 1970s. During the period of this study, Jamaica experienced serious economic and social malaise that continues to this

day. External economic shocks coupled with endemic problems of low productivity, inflation and unemployment, have adversely affected the island's competitiveness and capacity to grow. These problems in turn have increased the vulnerability of the island's poor, many of whom have witnessed a substantial deterioration in their welfare.

Second, the island's forests are essential to its welfare, particularly its poor, who depend directly on them for a variety of essential building supplies, medicines, fruits, and wood-based fuels. At the same time the significant contribution that forests make to the aesthetic landscape of the island and to its environmental quality are critical to the island's tourism and agricultural industries. These industries provide a significant source of foreign exchange for the economy and employment for the island's many poor, low-skilled workers.

Third, Jamaican deforestation poses a serious threat to the island's biophysical diversity. Jamaica exhibits considerable diversity in its soils, topography, and vegetation. Highly interdependent links between these diverse features make the island particularly vulnerable to environmental degradation.

Fourth, the problem of deforestation in Jamaica has been essentially neglected by the scientific community. Interest in tropical deforestation has focused largely on a number of large forest countries, most notably Brazil. Jamaica, in contrast, is a small relict forest country which has seen its forest cover steadily disappear in recent decades. Depending on the estimate, Jamaica may have lost between 0.5% and 5.3% of its forest cover per annum during the 1980s (see Chapter 8). It is thought that less than 1/4 of the island is covered with some form of forest cover (see Chapter 8; NRCD 1987). Brazil, in contrast, registered an overall average annual deforestation rate of less than 1% for this decade (WRI 1994/5).

Fifth, Jamaica possesses relatively good quality data. Many social indicators of interest for this study have been consistently measured over time, and fairly timely land use and topographic data exists. A highly diverse country, Jamaica also provides a cohesive but varied unit of analysis for the derivation of meaningful statistical results.

1.4 Study Framework

The remaining chapters of this study use Jamaica as a case study in order to investigate the role of population and poverty in driving tropical deforestation. Specifically, to this

end the study seeks to: a) measure the extent and rate of forest cover loss on the island, for the period 1987-1992; and b) empirically assess a conceptual model of the scarcity-related processes thought to drive this change. Forest change data for the analysis is derived from country-level satellite data for this period. The resulting estimates are then used to empirically assess the relationship between deforestation and a range of cross-sectional data sets measuring scarcity factors of interest to this study.

The remaining chapters are organized as follows:

Chapter 2 reviews the existing literature on the relationships between social processes and forest depletion in tropical developing countries. In particular, it highlights the insights that can be derived from these studies for understanding the intertwined problems of deforestation, overpopulation, and poverty in tropical developing countries.

Chapter 3 moves away from the general descriptions provided in Chapter 2, to a consideration of the country unit of analysis. It provides a broad overview of the social context of the Jamaican deforestation study, paying particular attention to the ways in which economic circumstances and events of the period have impacted on the welfare of the poor in Jamaica. It also presents summary statistical data showing changes in relevant social and economic indicators for the period of study.

Chapter 4 describes the biophysical setting of Jamaica's forests, its main poverty-related pressures and some of the ecological consequences of its widespread destruction. It also attempts to show how the diminishment in welfare induced by the socio-economic trends described in the previous chapter may have increased the dependency of the island's poor on its natural resource base, with destructive consequences for its forests.

Chapters 5-10 constitute the empirical core of the thesis. Chapter 5 describes the satellite data set used to calculate forest cover and change estimates for the island between 1987 and 1992. This chapter begins with a discussion of the advantages of satellite data for the study of environmental change and outlines the basic principles underlying its use. This is followed by a detailed description of the thesis' MSS (multi-spectral scanner) data set — its mode of acquisition, format, and practical considerations surrounding the selection of the data. The chapter ends with a discussion of some of the limitations of MSS data for the analysis of deforestation in the tropics, and describes this study's strategy for overcoming these limitations.

Chapters 6 & 7 outline the various image processing steps involved in the prepa-

ration of the satellite images for the data extraction phase in a GIS (Geographical Information Systems). In particular, Chapter 6 is devoted to the enhancement and restoration techniques applied to the images, while Chapter 7 focuses on the development of land feature signatures and classification procedures used to interpret them.

Chapter 8 details the steps involved in the preparation of two land classification maps, and the subsequent extraction of the forest data from these maps using a GIS. In addition, it discusses how a GIS is used to integrate these classification maps to an administrative boundaries map of the island for the derivation of national and sub-national (i.e. parish and constituency) forest estimates. National forest cover and change estimates are then presented and compared to existing estimates, and some of their limitations briefly discussed. Parish level forest data are also presented and related to socio-economic and land use indicators for each of Jamaica's 14 parishes.

Chapter 9 carries this parish analysis one level down, to the constituency unit. The chapter briefly describes a conceptual model of scarcity-induced deforestation based on the discussion in Chapters 2, 3 and 4. Following this description, the model is then empirically assessed for 51 Jamaican constituencies, using both constituency-level socio-economic and land use data and the constituency forest estimates derived from Chapter 8. Simple correlation and OLS results are presented and discussed in view of their contribution to the formulation of a number of stylized facts about the scarcity-related processes driving deforestation in Jamaica. By way of shedding light on possible future human-forest scenarios for the island, Chapter 10 presents the results of a series of simulations based on findings for several key variables in the regression analysis of Chapter 9.

Finally, Chapter 11 summarizes the study's main findings and discusses their implications for the implementation of forest management and protection initiatives in Jamaica, and possibly, for other Caribbean countries of the region sharing similar environmental and social characteristics.

Chapter 2

Relevant Literature

2.1 Population, Poverty and the Environment: Analyses & Themes

Researchers have become increasingly aware of the environmental problems generated by poverty and overpopulation in the developing world. These issues were largely brought to worldwide attention by the influential (Bruntland) Report (WCED 1987) in such statements as:

“...Poverty is a major cause and effect of global environmental problems. Those who are poor and hungry will often destroy their immediate environment in order to survive; they will cut down forests; their livestock will overgraze grasslands; they will overuse marginal lands; and in growing numbers they will crowd into cities” (p. 28).

A growing body of research has sought to understand the nature of these processes. This literature ranges from theoretical discussions of the nature of these linkages to both case study and quantitative analyses of specific dimensions. The following discusses this literature within the context of these two broad categories: theoretical analyses/qualitative case studies and quantitative works. Space considerations preclude anything but a representative sampling of these works here. This literature has mushroomed considerably since the late 1980s, and is wide-ranging, both in the focus of its detail and scale of analysis. As a consequence, the next sections review only the most relevant studies, emphasizing their main contributions to understanding these interlinkages.

2.2 Theoretical Analyses & Case Studies

2.2.1 General Relationships & Themes

Theoretical and case study publications comprise part of a larger literature known as the 'political economy of the environment and development' or the 'social ecology of global environmental change'. This literature seeks to explain environmental problems in terms of the underlying or social processes that condition human-environment actions.¹ Many such works are devoted to understanding the complex ways in which poverty, overpopulation and environmental degradation interact and reinforce each other. Specifically, these studies show how population increases above the environmental carrying capacity eventually lead to declines in agricultural yields, shortages of fuelwood and other resources. These scarcities in turn generate ever greater levels of poverty, as populations increasingly attempt to meet their sustenance needs by mining soils, shortening fallows, and engaging in other unsustainable land use practices. Poverty in turn stimulates population growth, which in turn leads to greater environmental abuse (and thus greater impoverishment) as the poor desperately seek to maximize their output from a progressively diminishing resource base.

2.2.2 Prominent Scarcity-Related Factors Mediating Population/Poverty/Environmental Outcomes

Many factors are cited in the literature as determining the outcomes of these complex interactions. Prominent among them are: public policies biased against the poor; inequalitarian patterns of land ownership; tenure insecurity; insufficient investment in human capital formation; inappropriate land use practices; and an absence of sufficient technological inputs for raising productivity. Essentially, all these factors operate to constrain the opportunities available to the poor to increase their productivity and income, thereby preventing them from using land and other resources properly and lowering their fertility.

Many studies, for example, stress the role of government policies in this dynamic.²

¹See, for example, Barraclough & Ghimire 1990; Schmink & Wood 1987; Schmink 1994; Blaikie 1985; Blaikie & Brookfield 1987, Leonard 1985a,b, 1989; Durning 1991; Mink 1992; UNEP 1995; Biot et al. 1995; Redclift 1984; Blaikie & Brookfield 1987; Blaikie 1985.

²See, for example, Southgate & Whitaker 1992; Southgate et al. 1990; Repetto 1983; Repetto &

Price distortion in domestic food markets, for example, discriminate against small producers, thereby preventing them from making essential investments in their plots that would raise output and income. Low agricultural prices in turn have serious negative consequences for the productivity of rural areas, hindering the development of non-farm enterprises and viable markets. The consequence is that many poor farmers remain trapped at the subsistence level of existence.

Also significant is a general development bias against rural areas in many developing countries. Many works (e.g. Repetto & Gillis 1988; FAO 1986) highlight the environmental degradation resulting from the neglect of the rural economy, physical infrastructure and welfare (Leonard 1989; Mink 1992). One prominent aspect of this bias is the privileged position enjoyed by the export agricultural sector, which often receives the bulk of government technical, credit and other assistance. Also contributing to the chronic underproductivity of many rural areas is the concentration of government and private investment in urban infrastructure, industries and public services. Many of these works stress how, through the promotion of subsidies, tax breaks and other fiscal incentives to private investors, governments often channel substantive resources into urban development rather than rural areas, which often lag considerably behind in the level of services and employment opportunities (Leonard 1989; Mink 1992). All such policies in turn interact to maintain the high fertility rates, low skills formation and productivity levels that characterize life in many rural areas of the developing tropics today.

The environmental consequences of this distorted investment between urban and rural areas, smallholder and export agriculture sectors is well-documented in the literature. Collins (1986), for example, provides a fine case study of the environmental degradation that can occur as a result of such policies. She details how government neglect of smallholder agriculture in the Upper Ecuadorian Amazon is a central factor in the persistent poverty of the region. As a consequence of this neglect, smallholder farmers have been forced to seek off-farm employment elsewhere, a situation that has constrained their capacity to care properly for their plots. In addition, the need to meet debt obligations incurred in purchasing and working these plots often results in farmers adopting unsustainable land use practices (e.g. shortened fallows and monocropping)

Gillis 1988; Collins 1986; Binswanger 1991; Brothers 1997; Mahar 1988; Dasgupta and Maler 1996).

in order maximize output from the land. The consequence is that output begins to fall as the land becomes increasingly degraded, eventually forcing farmers to abandon their plots and clear land elsewhere. The author notes that the environmental externalities of these processes have been exacerbated by government pricing policies that discriminate against small producers, the extensive consolidation of surrounding agricultural areas in export agriculture and the small size of many peasant holdings.³

Another prominent factor cited in the literature for its role in exacerbating population/poverty pressures on the environment, is insecure tenure. Generally, when small farmers are assured of a relatively permanent presence on their plots (either through formal ownership or long-term leases) they tend to make essential investments in the land (e.g. planting appropriate crops, terracing, and tree planting). Stonich (1992), for example, demonstrates how short-term rental contracts in the southern Honduran highlands have generated poor land conservation practices among the region's landless farmers. In contrast, small landholders who owned their own plots were more likely to make essential labour investments in the land (e.g. tree planting, erosion control).

Many of these works also observe that if land is of sufficient size to support a household and tenure is secure, plots tend to be well-maintained if located in appropriate areas. However, the problem is that in most areas of the developing world, the poor lack secure tenure and plots are often situated in low resource potential areas where no amount of investment could significantly increase output (Leonard 1989).

Tenure insecurity, coupled with the marginal quality of smallholder plots are cited as key factors in the outmigration of the poor to frontier forest regions. Often migration to these new areas leads to as much if not more insecurity and poverty as in areas of outmigration. In many cases, gaining title to land and access to credit proves difficult for colonists, who often find themselves on plots that are incapable of producing a sufficient output to support them. Often title to land will depend on a certain amount being cleared. Coupled with the poor productivity of most of these areas, this requirement tends to promote extensive land clearance. As soils cleared of their vegetative cover in tropical regions often become infertile quickly, farmers are forced to abandon their

³Similar consequences have been documented in studies throughout the world, from Latin America (e.g. Schmink and Wood 1987; Rudel 1993; Colchester 1993; Cruz et al. 1992; Godoy 1984; Garland 1987; Utting 1993) to Asia (e.g. Anderson 1987; Cruz et. al. 1992; Hussain & Doane 1995; Belsky 1994) and Africa (e.g. Redclift 1984; Blaikie & Brookfield 1987).

plots, migrating to new areas which they then clear and eventually abandon after one or two seasons due to declining productivity.

One factor often closely related to tenure insecurity and affecting significantly the outcome of population/poverty pressures on the environment, is the pattern of land-holding. Dorner & Thiesenhusen 1992 and Thiesenhusen 1991, for example, highlight the complex linkages between land tenure regimes, population dynamics and land use practices. They note that the degree of equality in the distribution of land-holding is an important factor mediating the scale of environmental outcomes. For example, in areas where patterns of landholding are highly inequitable, as they are in Latin America, land tenure regimes will often “expel” people too rapidly from settled areas, which hastens the rate of land clearance in frontier areas. Alternatively, less inflexible, more egalitarian systems such as are found in many African countries, will “exaggeratedly” hold people in settled areas (and thereby slow the rate of environmental degradation) despite declining productivity. However, even these regimes will reach a point at which population pressures (and the poverty that they generate) become so acute as to overwhelm their ability to stabilize people on the land, thereby expelling them to other areas.

Chronic poverty and underproductivity in frontier areas is also exacerbated by the fact that migrants often lack the skills and capital resources to make proper investments in the land. Typically, many of these migrants will be from urban areas, and will have no farming experience. Environmental problems can also be magnified when settlers expropriate land from indigenous residents, who often have a knowledge of sustainable land use management practices (unlike the settlers). Often the original residents will find themselves displaced to areas where their land use practices are unsuited. This dynamic has been well-documented by Lopez 1987 in her case study of the Philippine island of Palawan. The author describes how increases in the number of small colonists and agroindustrial farmers to Palawan have progressively displaced the island’s indigenous people to marginal, steeply-sloped areas of the island where these conditions have forced them to abandon their sustainable land use practices for more intensive, highly destructive methods.

This breakdown in traditional sustainable land management regimes can also occur in the wake of the dissolution of common property arrangements following the commer-

cialization or privatization of public lands. In his study of 80 villages in Rajasthan India, Jodha 1985, for example, notes that rising population pressures cannot be blamed entirely for the resulting degradation in village common property resources. The real cause is the privatization of common property resources, which has left the remaining communal lands open to abuse and neglect, as farmers concentrate their resources exclusively on caring for their own plots. Note that this breakdown can also occur when the state takes control over and management of communal property resources. Typically, bureaucratic management will reduce the close involvement that rural residents once had in the care for these resources, with the consequence that they quickly become degraded (Colchester, 1993; Repetto & Gillis 1998; Vivian 1992).

A significant body of literature also emphasizes the role of technological factors in mediating population/poverty/environment interactions. Boserup 1981 and Bilsborrow 1987, for example, demonstrate how population pressures on the environment can be ameliorated to varying degrees by successive innovations in technology and land use methods. As they observe, in the initial stages of population growth, land is often used unsustainably in order to increase output. However, this temporary mining of soils and other destructive practices eventually generates sufficient gains in factor productivity to induce new technological solutions to the problem of increasing output under rising demographic pressures. Rising productivity, they argue, allows for new investments in land conservation and management to be made, with the resulting income gains in turn stimulating the growth of rural markets, capital, and infrastructure. Several studies appear to confirm this process (e.g. Downing et al. 1990; Tiffen & Mortimore 1994) while others suggest that in many places population pressures have increased too rapidly for technological innovations to ensure that productivity levels will rise as population pressures increase (e.g. Lele & Stone 1989; Cleaver and Schreiber 1994; Pingali 1990).

Finally, many studies stress the role of investment in human capital formation in mediating population/poverty impacts on the environment, arguing for its importance in inducing gains in factor productivity, technological innovation and income necessary for the generation of self-sustaining growth in the rural economy (e.g. Tiffen & Mortimore 1994; Cleaver & Schreiber 1994; Leonard 1989; Mink 1992; FAO 1986). They demonstrate how insufficient investment in poverty alleviation and capital formation

interact to depress the skills and productivity levels of the poor. Evidence suggests that if sufficient enough, such investments can have beneficial consequences, stimulating the growth of new remunerative opportunities, particularly in off-farm enterprises that would allow a large number of poor to move off the land into more productive pursuits.

2.3 Quantitative Studies

The above studies seek to elucidate, through conceptual analyses and case studies, the complex interlinkages between population growth, poverty and the environment. A small but growing body of literature seeks to analyze these insights within a quantitative context. The following reviews some of the more important of these studies, emphasizing their main contributions to understanding the relative roles played by these factors in driving deforestation in developing countries.

2.3.1 Population & Land Use Studies

Global or Cross-Country Studies

Palo 1994 examines the influence of population pressures on tropical deforestation. Using forest area as a percentage of total land area in 1980, the author finds population density (but not population growth) to be both significant at the 1% level of significance and negatively correlated with forest cover. Population is treated as a proxy for domestic demand for forest cover according to the assumption that demographic pressures increase the demand for fuelwood, infrastructure, and agricultural products. Other measures of population-induced effects, namely food production per capita and share of forest fallow, are also highly negatively correlated with forest loss.

Allen and Barnes 1985 find population change to be negative and significantly correlated with tropical forest cover for both Africa and Asia ($p \leq .01$) but less so for Latin America ($p \leq .05$). While change in forest area has no significant relation with cropland expansion, arable land is negative and significant, and changes in cropland and population growth, positive and significant, in the countries of their sample. This finding, they argue, suggests that population may exert its influence on forest cover in less direct ways, primarily through agricultural expansion, which in turn is driven by increases in

population.

Bilsborrow & Geores 1994 explicitly examine the linkages between demographic processes and deforestation in rural areas of the developing world. A wide variety of variables mediating potential human impacts on land use are measured for 68 developing countries using agricultural census data. Not surprisingly, the authors find a high correlation across countries between overall population density and the proportion of a country's land mass classified as having arable land; in other words, the more densely populated the country, the less per capita agricultural land available. There is also (albeit weak) evidence of an association between changes in population and changes in the amount of a country's land area in agriculture or land per agricultural worker (the study's two measures of land extensification).

The authors also test the possibility that outmigration to new areas may be driven by economic factors and the distribution of landholding in settled areas, leading migrants to clear land elsewhere. They find no evidence that such factors have influenced land clearance rates in the countries of their sample. The link between population changes and agricultural intensification (measured by changes in the intensity of fertilizer use) is also very weak and has no relation with either population density or land distribution variables.

Rudel 1994 finds similar strong and positive associations between forest depletion and population pressure for various periods and country data sets. In addition to using an aggregate population measure, the study includes a rural population growth measure designed to capture the effect of time lags on forest clearing on local population growth. The study finds that rural population growth explains a significant portion of tropical deforestation ($p \leq .001$) in the large number of countries comprising their sample. Surprisingly, agriculture and timber production variables have no significance in explaining variations in tropical deforestation. The strongly positive contribution of demographic factors in deforestation, however, suggests that these land use variables may influence forest cover loss through population effects. Demographic pressures, in other words, may stimulate the clearance of land for agriculture in rural areas, and thereby, demand for wood and food in the country as a whole.

In a later paper Rudel extends this research (Rudel & Roper 1997), using the most timely and reliable data (derived from FAO Tropical Forest Assessments and

country inventories) available on tropical rainforest deforestation in a large cross-section of countries. Two separate conceptual models are analyzed empirically in the study, labelled as: a) the frontier model; and b) the immiseration model. The first model hypothesizes that commercial developers and entrepreneurs are driving deforestation in the tropics, while the latter model explains deforestation largely in terms of population growth. The latter effect is hypothesized to depend on poor colonists who move into areas after they have been opened up by large-scale developers and entrepreneurs.

OLS regression analysis for the 1970s and 1980s suggests both models are correct: Significant findings for variables measuring hilly rainforest topography, high rural population growth and low GNP support the immiseration models for both periods, although high debt rather than GNP was a better explanation of deforestation in 1980. The frontier model was found to be significantly correlated with road-building in the 1970s. The same pattern held (albeit in attenuated form) for the 1980s.

It is worth noting that these findings were also robust to a separate analysis involving small and large rainforests. That is, the immiseration model was found to be a good predictor of forest loss in small forest countries; and the frontier model, in countries with large forests. These findings lead the authors to argue that policies designed to combat deforestation should be constructed in view of the differential nature of their underlying forces. That is, the protection of small remnant forests would be better served by “coercive” policies designed to control encroachment and delineate park boundaries. In contrast, integrated rural development of settled areas should be encouraged in large forest areas (e.g. through urbanization, the promotion of intensive agriculture, and an end to commercial subsidies).

Regional and Country-Level Studies

Population impacts are also a subject for quantitative investigation at the regional level for Latin America and the Caribbean basin (Lugo et al. 1981; Southgate 1994); and for countries as diverse as the Philippines (Kummer and Sham 1994); Thailand (Panayotou and Sungsuwan 1994); Indonesia (Osgood 1994); India (Chakraborty 1994); Brazil (Reis and Guzman 1994); and Ethiopia (Grepperud 1996).

Lugo et al. 1981 conduct a regression analysis of the effects of population and other variables on forest cover for the Caribbean basin. They find a positive and highly

significant relationship between population density and the proportion of land area under forest ($p \leq .001$). This was particularly the case for the island countries of the region, which, they note, have higher population densities and lower levels of forested area than do the mainland countries. They also find a highly significant but negative (inverse logarithmic) association ($p \leq .001$) between the log of energy consumption per unit of land area (the study's proxy for intensity of land use) and the proportion of total forested land as a percentage of total area. Overall, regression results suggest that, at least in the Greater Caribbean, high population densities and intensive fuel use are associated with low levels of forest cover. Deforestation also appears to be significantly lower in countries with steep topography.

Although its dependent variable is soil erosion rather than tropical deforestation, the interesting study by Grepperud 1996 should be noted for the contribution that it makes to the quantitative study of the population/poverty/environment nexus. The author constructs a soil erosion severity index (SESI) for 47 awrajas in Ethiopia, which he then regresses against a variety of relevant indicators: population and livestock pressure; susceptibility of crops to erosion; slope; rainfall intensity; soil type; and a language dummy variable designed to capture differences in tillage methods and land ownership. Regression results suggest that soil erosion is not so much due to the specific natural resource variables evaluated in the analysis as it is to human activities. Tree cover (a proxy for forest management practices), language group, and pressure variables — are all significant and strongly correlated with observed levels of soil erosion. The SESIs are significantly higher in regions where language groups suggest land use practices involving extensive farming and other practices (e.g. animal plowing and the cultivation of annual crops). Moreover, the author finds that the probability of soil erosion increases rapidly after a certain level with the increase in population and animal pressures on the land, but that below this level, the probability of one awraja suffering from soil erosion does not appear to be higher than in any other.

However, the study by Kummer & Sham 1994, for instance, suggests that demographic pressures are not a major driving force in deforestation, at least not in the Philippines, which has one of the highest population densities in the world. Rather, panel data analysis suggests that extensive forest loss in the country is associated with both logging and farmland expansion. As the authors note, these are not labour

intensive processes in the Philippines, which may be one reason why the results for population measures are not significant. However, they also argue that population may exert its effects on forest cover in less direct ways; that is, through land use activities that attract migrants to frontier areas.

The study by Walsh et al. 1999 should also be mentioned for its contribution to understanding the relationships between population and environmental change. The authors examine the general hypothesis that the relationship between demographic and environmental indicators will change according to the spatial scale at which they are measured. Various statistical methods and remotely sensed image data sets are used to measure the relationship between demographic factors (e.g. ratio of total land area under cultivation to total population, sex ratio, number of households, total population, and total land area under cultivation) and 4 biophysical/environmental variables (slope, angle, plant biomass, elevation and soil moisture potential) across 9 spatial scales. Data for these various measures is derived for 310 villages in the Nang Rong district of northeast Thailand.

Canonical correlation and OLS results suggest that, depending on the scale of resolution, some demographic variables are more significant than others in explaining the nature and concentration of population in an area. For example, at the 1050 m resolution, biomass is significantly related to both total population and the ratio of total land area under cultivation to total population; total population is significantly related to elevation; and slope is significantly related to the sex ratio. However, at finer resolutions (30 m), elevation is negatively and significantly related to both total population and the ratio of total land under cultivation to total population; biomass is significantly and positively related to total population; and soil moisture is significantly and positively related to the area under cultivation. This study suggests that the relationship between the environment and population is a complex one; that is, that different aspects of this relationship operate at different levels of analysis, and are significantly determined by individual features of the landscape.

2.3.2 Economic & Political Studies

Several quantitative studies measure the contributions of various global and macro-economic factors to forest cover loss. Although, as in the above, these studies do not

formally model population/poverty/forest interactions per se, they do consider factors that may relate directly to issues of interest to this study in the course of measuring other indicators.

For example, Capistrano 1994 examines the impacts of several scarcity-related variables on changes in forest cover: income, land availability, food self-sufficiency, debt, and population. The study's dependent variable, the area of closed broad-leaved forest industrially logged, is expressed in thousands of hectares for 45 countries comprising the regions of Asia, Africa, South America, Central America, and the Caribbean.

Regression results suggest that the causes of deforestation may vary with respect to changes in the overall macroeconomy for the 4 periods of the study: 1967-71; 1972-5; 1976-80; 1981-85. Significant variables of interest measured in the study include: per capita income, cereal self-sufficiency, population and debt service. All are significantly associated with tropical deforestation in Period 2, a period in which markets became increasingly unstable, food became more scarce and the price of oil increased. Results suggest that cereal self-sufficiency and income are positively associated with deforestation, while debt service ratio is negative in this period. However, with the exception of population growth, these findings do not suggest that growing scarcities may have induced tropical forest loss in this period. Thus, in the early 1970s, deforestation was not significantly correlated with a lack of essential investments in human capital formation arising from the need for countries to meet burdensome debt obligations.

Moreover, the reader can surmise from its poor significance levels that population growth does not appear to be a major factor driving the destruction of forest cover in any other period. Another potential scarcity measure, the ratio of arable land to agricultural population is significant but only in Period 4, a period which saw cutbacks in government spending, reduced investment and trade and rising debt for many tropical countries. However, as in the case of the cereal self-sufficiency and income per capita variables, its counter-intuitive (negative) sign suggests that scarcity-induced expansion of agricultural land cannot be implicated in forest depletion.

Contradictory and inconclusive findings also emerge from the study by Shafik 1994, which finds no statistically significant relationship between either income per capita or change in income per capita and deforestation. Another important variable having implications for poverty levels, the investment rate, also has no significant association

with forest depletion. A variable measuring the impact of energy pricing policies on forest cover loss is significant but opposite to the expected sign. Interestingly, higher energy prices are associated with higher rates of deforestation rather than, as expected, increased fuelwood dependency. Another key variable with implications for economic and social welfare — debt — also has no significance in explaining variations in forest cover in this study.

In contrast to both studies, Kahn and MacDonald 1994, Inman 1993 and Osgood 1994 find a highly significant relationship between debt and deforestation. Kahn and McDonald 1994 develop a conceptual model of the macroeconomy of tropical countries that assumes that economic scarcities will lead governments to exploit forests for short-term gain. Such scarcities will be magnified in the face of growing debt and unemployment, low rates of capital investment and high population levels.

The model is estimated for a series of regressions using cross-sectional data for 68 developing countries for 1981-85. Results suggest a strong positive relationship between debt (defined as total debt service divided by total exports) and deforestation ($p \leq .05$). Government spending, in contrast, has no significant relationship with deforestation, and its negative sign is contrary to expectations. According to the authors this finding may be due to this variable proxying some other variable associated with a higher GNP (e.g. infrastructure) or may already reflect a high consumption component in government spending. The coefficient on the study's labour force variable was opposite in sign to the model's assumption, suggesting that higher levels of employment lead to more deforestation⁴. The authors note that one reason for this counter-intuitive sign may be that this variable is actually measuring some other effect, which would have beneficial effects on forest cover (e.g. technology level).

Government policies are also central to the country-level deforestation studies by Chakraborty 1994 and Osgood 1994. As in the above, scarcity-related processes are not the focus of these works, but several factors (e.g. income per capita and fuelwood/charcoal use) of interest to the present study are analyzed.

In the Chakraborty study, for example, net national income per capita is negative and significantly related to deforestation, suggesting an adverse impact on forests of

⁴ Although insignificant, this predicted negative impact was also observed in the regressions unscaled by real U.S. dollar GNP.

rising prosperity. (For every Rs 1 per capita increase, the author estimates that forest cover decreases by 0.17 thousand square kilometers). The coefficient of fuelwood and charcoal production is significant at the 10% level, and bears the expected negative relationship to forest area. Investment in forest regeneration and afforestation appear to have a significantly positive relationship to reserve forest area. Surprisingly, there is no significant link between increases in the agricultural productivity index and forest cover. The author concludes that this latter finding may be due India's high level of urbanization and strong forest protection management initiatives, both of which would tend to discourage outmigration by agricultural colonists.

In contrast to the general macroeconomic focus of all these studies, Deacon 1994 provides an interesting analysis of the relationships between deforestation and political factors. A key hypothesis of interest in the study is the degree to which institutional factors may affect the rate of deforestation. The author reasons that the rate of forest depletion will be lower in countries in which property rights are governed by the "rule of law". Specifically, deforestation will be lower in countries characterized by the presence of "stable, fair and impartial institutions", as measured by a number of indicators of general lawlessness (i.e. the frequency of guerrilla warfare, armed revolt, changes in laws or constitutions) and democratic openness (i.e. government by popular representation, tolerance of political opposition, universal enfranchisement, the presence of a legislature).

Analysis of regression coefficients for these political attributes supports these hypotheses. For instance, those countries that experienced more revolutions, more guerrilla warfare and more constitutional changes between 1975-79 and 1970-74, also tended to experience less deforestation between 1980-85. The author also finds that the presence of guerrilla warfare in a country is associated with a 7% increase in deforestation over a 5 year period for all countries in the sample (an effect less acutely felt in countries heavily endowed with forest cover) whereas the presence of revolutionary activity in a country is associated with a decrease in forest cover of between a 6.8% to 10.5%. Results also suggest that deforestation rates are significantly higher in military regimes and lower in countries possessing parliamentary democracies.

These results, and the fact that political measures are also significant and negatively correlated with the investment variable, lead the author to conclude that political tur-

moil and political repression impact on deforestation rates through their depressive effects on investment. From the point of view of the current study, the depression of investment flows would undoubtedly adversely affect the number of economic opportunities available to the poor, and this in turn would increase human pressures on the forest base.

2.3.3 Land Clearance Model Studies

Several economic studies formally derive and statistically analyze models of land clearance and forest colonization for the developing tropics. In these models, the price of land determines the rate of forest clearance, which in turn is driven by various demand (e.g. agricultural prices) and supply (e.g. accessibility) factors. These models also assume that the market for new land reaches equilibrium at the point at which the marginal costs of bringing new land into production exceed the benefits to be derived from more clearance.

Pfaff 1999, constructs and empirically estimates an economic land use model for the Brazilian Amazon. The model assumes that land clearance at any point in time will be a function of farmer profit-maximizing behaviour; higher agricultural prices and lower input prices will raise the incentives to clear land among agriculturalists, while factors such as accessibility of the land will lower the rate of deforestation. The author finds that accessibility to roads and distance to markets are significant and positively related to deforestation. Surprisingly, population density is not significant; however, a quadratic specification for this measure suggests that deforestation is more acute in the initial stages of human settlement. In addition, areas with better soil and less vegetation will lower the costs of clearance and raise the output of small farmers. In cases where vegetation is minimal (e.g. grassland), the costs of clearance will be lower, which will also tend to alleviate pressures on forested areas.

Cropper et al. 1997, construct an equilibrium model to estimate the demand for land in Thailand in 1991. As in the above, the demand for land is assumed to depend on a number of factors (e.g. roads and population); and the supply of land, on factors that determine its suitability for agriculture. OLS regression results of the model suggest that both road density and number of agricultural households play a significant but small role in predicting the amount of land cleared in each province in the country. The

effect of population and road density on land clearance is also small but its magnitude varies with the region. Population density, for example has a larger impact on land clearance in the north, with its large numbers of small commercial and subsistence farmers and poor soils. Road density, however, is a more important determinant of land clearance in the south, where most of the country's large agricultural estates are located. Physical factors, such as slope, soil quality and distance to Bangkok also appear to influence the observed rate of land clearance. The better the soil, the less steep the topography, and the closer to Bangkok, the more land clearance. However, soil quality appears to be more of a determinant of land clearance in the south — a finding suggestive, perhaps, of the greater deprivation faced by farmers in the north.

In their study of land clearance in Belize, Chomitz and Gray 1996 also find that the impact of factors on land clearance vary according to type of agricultural land use. The authors find that overall, agricultural land clearance tends to decline with increasing distance from roads, on-road distance to market and slope of the land. However, these effects are more substantial for commercial than semi-subsistence farmers, who are not as integrated to markets and produce mostly for their own consumption. Moreover, while nitrogen content, wetness and acidity of soils are important disincentives to both commercial and semi-subsistence producers, their effects are stronger for the latter. Lacking sufficient inputs or equipment to improve these type of soils, small farmers will be more sensitive to the constraints that they impose on production.

Panayotou and Sungsuwan 1994, also develop and econometrically estimate a model of agricultural colonization for Northeast Thailand. Their model assumes that deforestation in this part of the world is driven by the demand for such factors as commercial timber, fuelwood and food. Other factors (e.g. accessibility, relative price of agricultural cash crops, and the price of agricultural inputs) will also affect this demand. So too will population pressures (which will tend to raise prices) and the availability of surplus labour (which will tend to lower the price of produce).

Findings indicate a strong significant impact on forest cover for many of the study's variables. Population density appears to be the most significant variable affecting the extent of forest cover (and thus, the rate of deforestation) in Northeast Thailand. Aggregate provincial income — a measure of overall wealth and employment opportunities — is also positively and significantly related to forest cover. The author calculates that

a 10% increase in income results in a 4.2% increase in forest cover. This suggests that as income rises subsistence pressures on the natural resource base will tend to decline. Higher rice yields also appear to provide protection for forests; however, the negative coefficient on the study's irrigation variable suggests that increasing output through the promotion of water-intensive technologies will actually lead to a loss of forest cover, perhaps due to displacement of farmers elsewhere. Similarly, an increase in the price of upland cash crops relative to lowland rice also suggests a negative impact on forests, since this would provide a strong incentive for farmers to clear more land.

In another study of Thailand, Lombardini 1994 finds no significant ameliorating effect on forest cover depletion for variables measuring agricultural productivity (i.e. cassava yield per cultivated hectare), which is assumed to decrease the need for extensive cultivation. The author also finds significant and positive ($p \leq .01$) findings for both GDP per capita and the % share of the labour force engaged in agriculture (the study's proxy for off-farm employment opportunities and urbanization). Since these findings are counter to expectations (i.e. poverty and lack of employment opportunities are assumed to drive forest depletion) the author re-estimates the model using urban population as a proxy for employment and an alternative measure of deforestation, and finds no essential difference in the results.

Southgate et al. 1991 investigate the linkages among land clearing, tenure security, demographic pressures and agriculture in eastern Ecuador in the early 1980s. According to the study's model, settlement in an area will depend upon such factors as the quality of the soil, road infrastructure and the level of development, which will in turn affect the demand for agricultural produce. The first stage of the model assumes that demographic pressures will increase with the prospect of capturing agricultural rents. These influences on agricultural rents are then regressed against the study's measure of rural population (i.e. agricultural labour force) for 20 cantons in eastern Ecuador. In the second stage of the model, agricultural labour force is regressed along with an index of relative tenure security against extent of land clearance or deforestation. Significant results for the study's variables suggest that agricultural colonization (and thus deforestation) is being driven in Eastern Ecuador by demand for agricultural produce, a situation made worse by the insecurity of tenure and delays that small settlers face in having their land claims recognized and by increasing population pressures in the

region.

Southgate 1994 examines the linkages between level of agricultural development and deforestation for 23 Latin American and Caribbean basin countries. According to the study's model, agricultural expansion depends on population growth and other factors such as the availability of essential inputs for raising agricultural yields. Regression results suggest that agricultural extensification (measured by changes in the proportion of land area in agriculture) is positively and significantly related to population growth and negatively and significantly related to higher yields. These results indirectly suggest a beneficial effect on forests of increasing agricultural yields. However, the author argues that simply increasing agricultural yields alone will not be enough to protect forests since governments must also address the institutional factors that prevent farmers from internalizing the costs of deforestation or caring for their plots properly.

Fearnside 1993 examines the effects of population pressures and land tenure on deforestation rates in Brazil. Quantitative analysis of the distribution of 1991 levels of clearance among the region's 9 states indicates that most land clearance is still occurring in areas dominated by large ranchers. Specifically, OLS regression results suggest that approximately 70% of the total deforestation activity in the Amazon can be accounted for by farms in the largest size classes. However, the author also presents evidence to suggest that the intensity of deforestation (forest impact per km²) is greater for small than for large and medium farms. This suggests that land reform efforts should focus on already cleared rather than forested areas, where much of the land is in large holdings.

Although not specifically concerned with measuring deforestation, Bilborrow and Winegarden 1985 develop and empirically assess the relationships between rural fertility and rural-urban migration. The study explicitly incorporates the effects of mediating factors on migration rates such as the pattern of landholding (e.g. size and nature of holdings). Results suggest strong relationships between outmigration and fertility: The higher the rate of outmigration the higher the fertility rate, and vice versa. Moreover, the higher the concentration of land ownership and the larger the size of holding, the lower the fertility rate (and thus the lower the rate of outmigration). However, simply owning land does not appear to be an incentive against outmigration.

Andersen et al. 1996 estimate a dynamic model of land use and urbanization for

the Brazilian Amazon. As in other similar models, deforestation is assumed to depend on the demand for agricultural land, the demand for which in turn will depend on the profitability of its various uses. Since it assumes that market forces largely drive the clearance of land, the study does not explicitly measure the constraints facing the poor, landless subsistence farmer, who is largely outside of the market. However, it does provide a number of indirect insights of interest to the present study.

Empirical results suggest that indirectly, poor farmers are more likely to benefit from deforestation in the initial stages of colonization, before agricultural output falls. However, evidence also suggests that the poor could benefit once development takes hold in the frontier, permanent agriculture replaces destructive methods and productivity and incomes rise. The authors provide detailed empirical evidence to suggest that, at least for the Amazon, there are clear advantages to investment in land clearance for the rural economy (and thus, for the poor) through its beneficial effects in promoting markets and economic development of the region. However, they also argue that greater economic benefits could be derived from the current value of the land through the promotion of more efficient use of resources, particularly land intensification.

Finally, Gunatilake 1998 measures the contributions of various social factors influencing dependency on forests in Sri Lanka (Sinharaja & Knuckles). Forest dependency is measured in terms of the total household income derived from this resource base. Although the study is not concerned with the analysis of deforestation *per se*, it does measure deprivation-related factors explicitly, unlike many studies. OLS regression results for a number of social indicators suggest that forest dependency is strongly determined by rural underdevelopment. In particular, the author finds that education, agricultural productivity and village involvement in off-farm pursuits play a negative and significant role in perpetuating dependency in Sinharaja. In Knuckles, income from agriculture rather than agricultural productivity is significantly negative, although educational level has no significant effect (possibly due to the higher unemployment levels of this region). Unemployment (measured as the overall availability of labour) is positive and significantly related to forest dependency in both communities, as are the number of shifting cultivators and the proximity of the communities to forests. In view of these findings, the author stresses the need for government to raise the productivity of these regions through tax incentives and subsidies that would encourage the development of

non-resource based industries.

2.4 The Poverty/Population/Environment Nexus: Analyses & Themes Summary

This chapter has reviewed a broad body of qualitative and quantitative studies on population/poverty/environmental interactions. A review of this literature yields a number of important insights for the present study. These can be summarized as follows:

*Scarcity-induced environmental outcomes depend on a wide range of micro, meso and macro level processes. Key factors noted in the literature as influencing the impact of poverty and population impacts on the environment include but are not restricted to: degree of economic dependency on the natural resource base; patterns of landholding and tenure security; fertility rates; level of welfare provision; physical features of the landscape; distance to markets; availability of income opportunities; and government spending priorities.

*Existing case study and theoretical discussions of scarcity-induced deforestation processes provide invaluable descriptions of the population/poverty/environment nexus. However, they do not lend themselves well to generalization and are unable to provide any sense of the impact on forest cover of one factor relative to another.

*The quantitative literature on human-forest interactions is modest but growing. However, many studies focus on measuring the contributions of proximate factors such as fuelwood collection or agricultural expansion.

*Most studies that consider underlying or social causes do so at the macroeconomic level. Although potentially important for what they may indirectly reveal about the poor, they do not explicitly model the factors that condition individual land clearance activities on the ground.

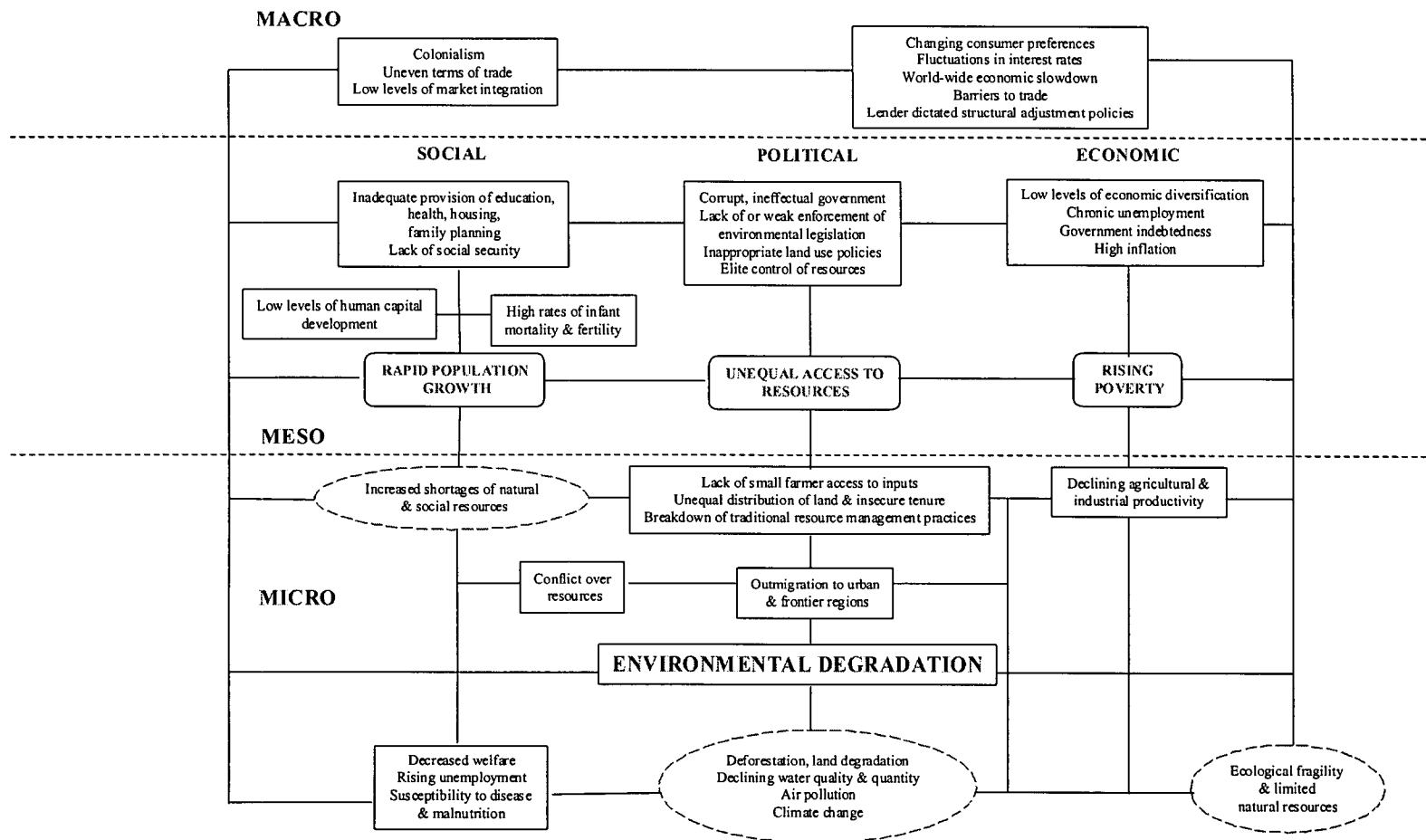
*Quantitative analyses bearing on scarcity-related issues in tropical deforestation largely measure demographic factors and rarely measure their effects on deforestation in relation to other scarcity indicators, such as welfare and poverty.

*Several country-level quantitative studies measure the determinants of colonization and land clearance. Several of these studies acknowledge explicitly the constraints that

drive poor farmers to engage in extensive land clearance. However, they do not model scarcity/forest interrelationships systematically. Relevant factors are considered in a few studies but are modelled only indirectly, and largely from the point of view of the commercial agricultural producer. Most of these studies are concerned with measuring the effects of relevant variables insofar as they affect the price of land (e.g. soil quality).

Figure 2.1 provides a summary of key interlinkages in the poverty/population/environment nexus. Table 2.1 provides a summary of the main findings of the quantitative literature as they bear on dimensions of the poverty/population/environment nexus.

Figure 2.1: Key Interlinkages in the Poverty/Population Environment Nexus



Adopted from deSherbinin 1996 and Leonard 1989.

Table 2.1: Summary of Main Scarcity-Related Findings of Quantitative Studies

<i>Variable</i>	<i>Study</i>
Population Growth/	Palo 1994* Burgess 1993*, Allen & Barnes 1985*,
Density/Rural/Urban	Grepperud 1996*, Inman 1993, Rudel 1994*, Capistrano 1994*,
Population/Household Size	Kahn & MacDonald 1994, Panayotou &
Dependency/Fertility	Sungsuwan 1994*, Cropper et al. 1997*
	Deacon 1994, Bilsborrow & Geores 1994*
	Rudel & Roper 1997*, Lugo et al. 1981*, Kummer
	& Sham 1994, Walsh et al. 1999,
	Cropper et al. 1997*, Lombardini 1994, Southgate et al. 1991*
	Southgate 1994*, Bilsborrow & Winegarden 1985*,
	Andersen et al. 1996*, Pfaff 1999*
Investment	Shafik 1994, Chakraborty 1994*, Deacon 1994*
	Andersen et. al 1996*
Debt	Capistrano 1994*, Shafik 1994, Kahn & McDonald 1994*,
	Inman 1993*, Rudel & Roper 1997*, Shafik 1994,
	Osgood 1994*, Gunatilake 1998
GNP/GDP	Palo 1994, Burgess 1993*, Rudel & Roper 1997*, Capistrano 1994*
Level/Growth/per capita	Shafik 1994, Deacon 1994, Allen & Barnes 1985,
	Chakraborty 1994*, Panayotou & Sungsuwan 1994*
	Lombardini 1994*, Kahn & McDonald 1994
	Andersen et al. 1996*, Gunatilake 1998*,
Food Production/Cropland/	Allen & Barnes 1985*, Rudel 1994, Bilsborrow
Food Self-sufficiency/	& Geores 1994*, Capistrano 1994*
Grazing Land	Lugo et al. 1981*, Grepperud 1996*,
	Walsh et al. 1996*, Chakraborty 1994*, Cropper et al. 1997*,
	Lombardini 1994, Southgate et al. 1991*,
	Panayotou & Sungsuwan 1994*,
	Andersen et al. 1996*, Fearnside 1993*

Table 2.1 (Cont'd): Summary of Main Scarcity-Related Findings of Quantitative Studies	
Labour Market/Distance	Panayotou & Sungsuwan 1994*, Lombardini 1994*,
	Southgate et al. 1991*, Andersen et al. 1996*,
	Chomitz & Gray 1995*, Gunatilake 1998*
Fuelwood/Energy /Dependency/Price	Lugo et al. 1981*, Capistrano 1994, Shafik 1994*,
	Panayotou & Sungsuwan 1994, Chakraborty 1994*,
Land/Soil Quality/Forest Extent	Palo et. al. 1987*, Palo 1994*, Rudel & Roper 1997*,
	Lugo et al. 1981*,
	Grepperud 1996*, Walsh et al. 1996*,
	Cropper et al. 1997*,
	Pfaff 1999*, Southgate et al. 1991*,
	Chomitz & Gray 1995*, Andersen et al. 1996*
Rural Infrastructure	Panayotou & Sungsuwan 1994*,
	Chomitz & Gray 1995*,
	Andersen et al. 1996*, Rudel & Roper 1997*
Land Availability/Prices	Bilsborrow & Geores 1994, Southgate 1994,
	Fearnside 1993*, Andersen et al. 1996*,
	Bilsborrow & Winegarden 1985*, Capistrano 1994,
Out-migration	Bilsborrow & Winegarden 1985*
Agricultural Inputs/	Southgate 1994*, Lombardini 1994*,
Productivity	Andersen et al. 1996* Gunatilake 1998*
	Bilsborrow & Winegarden 1985*
Agricultural Prices	Cropper et al. 1997*, Panayotou & Sungsuwan 1994*
Government Spending	Kahn & McDonald 1994
Political/Social Institutions	Deacon 1994*, Southgate et al. 1991*,
	Bilsborrow & Winegarden 1985*
Labour/Market Distance	Kahn & McDonald 1994*,
	Pfaff 1999*, Cropper et al. 1997*
Human Capital Formation	Gunatilake 1998*
*Denotes measure had significance in study.	

2.4.1 Concluding Remarks: Contextualizing the Present Study within the Literature

This chapter has highlighted the contributions of existing studies to understanding scarcity-induced deforestation processes, as well as noting an important lacunae in the literature. This thesis will attempt to build on these studies, using insights gained from both the quantitative and qualitative literature to derive and statistically analyze a conceptual model of scarcity-driven forest clearance for the tropics. It uses regression analysis to measure the relationships between the change in forest cover and selected variables reflecting aspects of scarcity likely to influence the actions of poor land users. However, unlike previous empirical studies, the model explicitly measures the impact of distributive, economic, and demographic factors on forest cover loss.

As noted in Chapter 1, the model is empirically analyzed for Jamaica between 1987 and 1992. Before formally introducing the data sets and methodologies used to measure these relationships, the next two chapters will attempt to give the reader a feel for the social and ecological context of Jamaican forest loss over this period. In particular, these chapters discuss how various socio-economic events of the period have affected the welfare prospects of the island's poor, examining how these in turn may have impacted on the island's forests.

Chapter 3

The Social Context of Scarcity-Driven Forest Loss in Jamaica

3.1 The Jamaican Economy: Overall Characteristics & Trends

Jamaica shares a number of characteristics with other island nations that are important for understanding its economic fortunes during the past several decades. These can be briefly summarized as follows:

*Jamaica's small size and poor endowment of natural resources have constrained its capacity to develop economically.

*Economic diversification is low and the economy depends heavily on a few products for the generation of foreign exchange. Little vertical integration exists.

*The country relies heavily on expensive imported goods to fill the gap in domestic production, particularly food and oil.

*A high import propensity coupled with a heavy reliance on a few exports makes Jamaica extremely vulnerable to global economic shocks.

*Economic production is tied significantly to the island's environmental resource base, increasing its susceptibility to natural disasters such as hurricanes and plant diseases.

(See Briguglio 1995; McAfee 1991; Kirton 1992 for more discussion of the constraints facing small open island economies).

During the period of this study, the Jamaican economy experienced significant decline, from which it has yet to recover. This malaise began with a series of negative shocks in the world economy in the 1970s. These shocks, in conjunction with deep-rooted structural problems in the economy — most notably, a low level of economic diversification and high dependence on exports — plunged the country into crisis. To this day, the country is plagued by problems of high unemployment, low investment and productivity, burdensome debt obligations, poor living standards and associated problems of violence and crime.

Moreover, since 1977 the country has concluded more than 10 IMF agreements and implemented several World Bank structural adjustment programs, most of them after 1989 (Handa & King 1997). Despite these measures, the economic trends suggest continued stagnation (Levitt 1991; *The Economist* 1999)¹. Real per capita GDP in 1997 was actually lower than at the beginning of the decade (IDB 1999). As in the previous two decades, economic growth in the 1990s has been sporadic, characterized by a good upturn in growth in the early part of the decade followed by shrinking output from the mid 1990s onwards (*The Economist* 1999).

3.2 Economic Spiral Downward: The ‘Lost Decades’ of the 1970s and 1980s

3.2.1 Macroeconomic Shocks & Disequilibria

Jamaica’s decline can be traced to the early 1970s, a period which brought sharp increases in the price of oil and rising inflationary pressures and deepening recession in the advanced industrial economies (Boyd 1988; Kirton 1992).² The economic shocks of

¹Between 1960 and 1970, the Jamaican economy grew on average by 4.5% per year, only to contract by -1.2% during the period 1970-1980 (Levitt 1991). Average annual growth in the 1980s was a mere 0.4%, with negative growth rates also recorded in some years. However, this performance is better than that achieved in later years. Between 1990 and 1997, for example, GDP grew on average each year by roughly 0.1% (ESBD 1999).

Such slow grow rates, accompanying population increases and inflation, have meant that GDP per capita has actually fallen since the 1970s.

²In the two decades prior to this period, Jamaica had experienced robust growth. Between the mid-1950s and early 1960s, for example, the economy grew by an average of 7.5% per annum (Kirton

this period resulted in large increases in prices for many of the country's imports (e.g. food and oil) and falling demand for its traditional exports (coffee, sugar, bananas and bauxite/alumina) (Stone & Wellisz 1993; Worrell 1987).

While these events were responsible for the deterioration in the country's terms of trade, the government in power at the time under Michael Manley must also be credited with contributing to the resulting economic crisis. As this section demonstrates, the expansionary fiscal and monetary policies pursued by this administration would eventually serve to depress any prospect for economic recovery, engendering extreme indebtedness in the process, as each successive government desperately attempted to shore up its faltering economy.

Elected on a platform of 'democratic socialism', the Manley administration sought to "recapture the commanding heights of the Jamaican economy" from foreign ownership and redress age-old inequalities through a series of expensive welfare, tax and income redistribution programs (Adam et al. 1992). One of the first policies implemented was the establishment of a new national minimum wage. To meet the costs of these and other redistributive programs, government spending rose dramatically, from 25% of GDP in 1972 to 46% just two years later. By 1976, the fiscal deficit had reached an unprecedented 19% of GDP (Looney 1987; Hope 1986).

At the same time, Manley's anti-free market rhetoric alienated foreign investors and middle class professionals, stimulating a flight of capital and skills away from the island. More than 100,000 skilled Jamaicans emigrated between 1975 and 1979, leaving the island poorer by an estimated US\$ 500 million (Gayle 1986). As a consequence, private investment, which had been as high as 32% of GDP in 1968 plummeted (Looney 1987; Stone & Wellisz 1993).

Declining demand for exports resulted in a serious shortage of foreign exchange revenues, increasing reliance on Central Bank credit creation and foreign borrowing to make up the gap. A growing fiscal deficit in turn stimulated inflationary pressures in the domestic economy (Anderson & Witter 1994; Worrell 1987). Widespread social unrest induced by the worsening economic climate resulted in a decline in tourism receipts between 1975-77, prompting disinvestment from the island by several hotel

1992). In 1973, GDP was an impressive \$2,376 (1980 \$U.S.) per capita. This impressive showing put Jamaica first among countries of the Commonwealth Caribbean in the level of its GNP (Levitt 1991).

chains (Boyd 1988; Worrell 1987; McAfee 1991).

In a bid to raise revenues, the Manley administration imposed a levy on the island's bauxite firms (Stone & Wellisz 1993). Most of the substantial revenues from the levy went for unproductive investments, such as balance of payments support and nationalization of private industries (World Bank 1993b; Stone & Wellisz 1993; Adam et al. 1992). In direct response to the perceived injustice of this tax burden, several multinationals immediately disinvested from the island (Stone & Wellisz 1993).

The worsening economic situation led the Manley administration to seek outside assistance, eventually accepting a US\$ 7.96 million loan over two years from the IMF in July 1977 (Stone & Wellisz 1993). After failing its December performance test, the agreement was abrogated. However, deepening economic crisis led the administration to accept a more austere package a year later in return for US\$ 240 million over three years (Mandle 1996). Measures included substantial reductions in public spending, the removal of subsidies on goods and services, tax increases, the implementation of a single exchange rate and the devaluation of the Jamaican dollar.

These and other loan agreements concluded shortly thereafter made Jamaica one of the largest per capita recipients of IMF resources in the world (Mandle 1996; Gayle 1986). Despite measures at reform and large amounts of external assistance, the economy continued on its downward spiral. Economic growth fell every year, declining by 21% between 1974 and 1980, the worst economic performance of the region (Adams et al. 1992). By 1980, GDP per capita in real terms was as high as it was in the mid-1960s and output had stagnated (Levitt 1991). The country's terms of trade continued to deteriorate, and international reserves fell to negative figures (Stone & Wellisz 1993). As economic crisis deepened, causing social hardship for the island's poor, discontent erupted into violence in the bloody general election of 1980.

3.2.2 Retrenchment, Structural Adjustment & Debt

The election brought major defeat to Manley's People's National Party (PNP) and ushered in a new administration under the Jamaican Labour Party (JLP) candidate, E. Seaga. In contrast to his predecessor, Seaga pursued a conservative economic agenda, one based on the promotion of private enterprise and foreign investment, deregulation of the economy and liberalization of trade. To assist in carrying out these reforms the

IMF and the World Bank approved an unprecedented US\$ 2.13 billion in bilateral and multilateral loans in the first few years of his administration (Worrell 1987; McKee & Tisdell 1990).

However, Seaga's economic reforms, buoyed by huge amounts of external assistance, failed to generate any significant change in the country's economic fortunes. With the exception of a small increase in growth in the early 1980s, the economy continued to stagnate. Export demand continued to remain soft and production suffered under government ownership (Stone & Wellisz 1993). The demand for exports also fell due to the imposition by Guyana and Trinidad and Tobago of unilateral import quotas, which saw the value of CARICOM trade plummet from J\$ 535 million in 1982 to J\$ 464 million by 1983 (Gayle 1986).

At the same time, falling exports and a removal of trade barriers under Seaga's reforms continued to exacerbate the balance of payments problem (Stone & Wellisz 1993; Kirton 1992). The budget deficit rose to 24% of GDP in 1983 (well above previous levels and the IMF's own guidelines) as spending increased to meet debt obligations and make up the shortfall in revenues (Stone & Wellisz 1993). Devaluation of the dollar also failed to make Jamaica's exports more attractive, with the consequence that the revenue crisis worsened.

Continued economic stagnation led to the negotiation of yet another IMF package in January 1984. Under this agreement, the Jamaican dollar was devalued, a unified exchange rate was introduced, interest rates and taxes rose, and user fees were introduced for many public services (Levitt 1991; Stone & Wellisz 1993; Kirton 1992). General subsidies also began to be gradually phased out (in a few cases, to be replaced with targeted subsidies). The reduction in certain subsidies saw a 20% increase in the price of gasoline and a 40% increase in transport fares as well as higher prices for other basic items (Stone & Wellisz 1993).³

Reforms in the tax and pension systems and a contraction in public sector employment resulted in a sharp decline in the public deficit from 15.3% in 1983/4 to 2.5% in 1986/7 (Stone & Wellisz 1993). The economy also began to improve at this time as a

³Incremental devaluations saw the Jamaican dollar fall from J \$1.80 to US \$1.00 in 1980 to J\$ 5.5 to US \$1.00 in 1988. With more devaluations, the dollar fell from J \$7.20 to US \$1.00 in 1990. In 1991 the Jamaican dollar was allowed to float freely against the U.S. dollar. In the spring of 1999, the Jamaican dollar was trading at roughly J \$38.00 to US \$1.00 (IDB 1999).

result of increased demand for traditional exports, trade liberalization and new textile and manufactures quotas introduced under the Caribbean Basin Initiative (Stone & Wellisz 1993).

However, while economic prospects showed improvement in the latter years of the 1980s, real GDP per capita was still below that at the start of the decade. Deficits in current account and trade balances also showed dramatic improvement but the overall government surplus remained in negative figures. Export demand showed only a modest increase (see Table 3.1).

	GDP per capita ¹	Current Account Balance ²	Trade Balance (U.S. million) ³	Exchange Rate JD/USD ⁴	Overall Deficit (-)/ Surplus (+) ⁵
1980	1571	-136.1	-75.5	1.8	-829.4
1982	1558	-378.2	-441.5	1.8	-868.6
1984	1508	-312.1	-334.7	3.9	-528.2
1986	1431	-16.1	-247.9	5.5	98.9
1988	1562	47.5	-356.2	5.5	-717.0
1990	1741	-312.1	-502.1	7.2	807.1
1992	1757	28.5	-424.6	23.0	3,171.5
1994	1772	93.2	-551.2	33.1	4,793.4
1996	1729	-111.6	-994.2	37.1	-14,966.1
1997	1672	-255.3	-1,132.3	35.4	-19,962.4
1998	—	-312.3	-1,096.7	36.6	-19,171.0

¹ 1990 US\$; Source: IDB 1999; ² Current US\$; Source: IDB 1999;
³ Current US\$; Source IDB 1999; ⁴ Market/par rate (period average);
Source IDB 1999; ⁵ Local Currency (current J\$); Source IDB 1999

Growth in the economy at the end of the 1980s was also well below that anticipated by the IMF, a mere 1.6% rather than the predicted 4.7% (Levitt 1991). In addition, revenues from manufactured exports declined dramatically due to extensive damage inflicted by Hurricane Hugo on the island's infrastructure (McKee & Tisdell 1990). New loan agreements were also signed at this time — predicated on the condition

that the government accelerate reforms aimed at liberalization and de-regulation of the economy (Levitt 1991).

In 1989 Manley regained power. Despite his previous socialist rhetoric, Manley continued Seaga's free-market focus, entering into new loan agreements with the IMF and the World Bank. As part of these new and previous agreements, all foreign exchange controls were removed and the Jamaican dollar was allowed to float freely (Levitt 1991).

3.3 Uncertain Economic Prospects: The 1990s and Beyond

Increasing demand for exports, a declining budget deficit, and new investment on the island resulted in a 3.8% growth in the economy in 1990 (PIJ 1990a; Gafar 1996). However, much of this growth can be attributed to an expansion of production in the wake of declining prices for most traditional exports rather than to a rise in world prices (PIJ 1990a).

Economic growth in the 1990s has been dismal, despite robust growth in the industrial economies. Jamaica's economic performance continues to lag behind other countries of the region (The Economist 1999). Despite some structural changes in the economy, manifested in a larger share of the country's GDP in tourism and manufacturing and a decline in agriculture and mining (NRCA 1995a), export earnings still depend on a few goods. Economic diversification, while it has occurred, has also been significantly slower than in other countries of the region. Furthermore, although GDP in 1995 was more than 10% above its 1980 level, the economy grew on average less than 1% between 1994 and 1995 (PIJ 1994a-1995a). GDP per person has fallen by 7% since 1991, and output is forecasted to continue to decline well into the year 2000 (The Economist 1999). Moreover, on-going problems of high inflation and poor terms of trade continue to require the imposition of stringent stabilization measures. As noted, real prices for the country's main exports are not much changed from the 1980s, and future projections are discouraging (World Bank 1993b; The Economist 1999).

There is also much uncertainty about the future for Jamaica's exports. Banana production, for example, is under threat from more efficient Central American producers and the probable cessation of EU import quotas soon. The World Trade Organization

(WTO) has recently ruled the quotas to be illegal, and has upheld Latin American producer claims for compensation. Similarly sugar quotas are set to end soon with the expiration of the Lomé Agreement in 2000, although world demand is expected to increase. Jamaica currently enjoys an export quota of 126,100 tons with the EU, but often fails to meet this quota or even domestic demand (Watson 1994; Gafar 1996). Although export demand for bauxite has strengthened in recent years, its value as a proportion of GDP has declined and demand for aluminium has shown erratic trends ⁴

Performance of the non-traditional exports sector has generally been disappointing (Levitt 1991; McKee & Tisdell 1990; Mandle 1996). Textiles, garments and light manufactures, which are governed under the Multi-Fibre Agreement and US 987 regulations, may enter the U.S. duty-free if constructed from American raw materials (McKee & Tisdell 1990). However, these preferential tariffs have been challenged in recent years from other Caribbean and Latin American producers demanding either similar arrangements or their elimination altogether. Most of these industries produce low-tech, inexpensive goods that can be produced more cheaply elsewhere in the world (especially in the wake of the decline in Asian currencies) (Mandle 1996). As is the case with traditional agricultural exports, many of these manufactures (e.g. textiles and footwear) are also in surplus supply. Markets are generally small and non-lucrative (Mandle 1996; Watson 1994; Thomas 1988). Moreover, labour productivity in this sector is low, and despite the island's chronically high unemployment rates, foreign workers have had to be recruited to replace the deficit in skills (The Economist 1998).

Liberalization of world trade and an end to preferential trade agreements leaves the future of many of Jamaica's exports (and thus employment prospects) in doubt. What is certain, however, is that performance will increasingly depend in coming years on Jamaica's position in respect to other producers. On the basis of current trends, however, there is every reason to question whether exports will be competitive with other countries of the region. Jamaica produces export goods at higher cost and less efficiently than do other countries, and world prices for many of its products are low (The Economist 1999).

⁴Coffee growing is one activity which has shown steady and sustained output since the 1970s. Most coffee Jamaica produces is destined for Japanese markets. However, Jamaica is not a major producer of this product, and since there are only a few areas of the island suited for it, the potential for expansion is limited.

<i>Table 3.2: Jamaica Composition of Production, Trade & Employment</i>					
<i>% GDP</i>	1950	1960	1970	1980	1990
Agriculture	31.0	13.4	7.1	8.2	7.8
Manufacturing	11.5	13.6	14.7	15.6	16.9
Mining	0.0	9.6	16.6	8.9	4.1
<i>% Exports</i>					
Agriculture	31.1	16.5 ¹	6.3	2.8	—
Manufacturing	4.4	—	8.4	11.4	28.2
Mining	0.0	49.3 ²	67.3	63.9	63.9
<i>% Employment</i>					
Agriculture	40.0	39.9	—	36.5	26.7
Manufacturing	—	—	—	10.5	15.2
Mining	—	—	—	1.1	0.8
<i>Tourist Arrivals ('000)</i>					
	74.9	226.9	414.7	543.1	1236.0
^{1,2} Estimates are for 1962; Source: Anderson & Witter 1994					

Increasingly, the government is looking to tourism as a means of quick-starting the economy and providing desperately needed foreign exchange earnings (NRCA 1995a). However, it is unclear that the tourism industry will be able to provide this economic stimulus. Like bauxite/alumina and the new export processing enclaves, tourism generates few linkages with the rest of the economy. Most goods it uses are imported rather than produced locally and leakage of foreign exchange is substantial (Beekhuis 1981). Some analysts believe that the demand for tourism may have reached saturation point, and concerns are also arising about its long-term environmental impacts (Beekhuis 1981; NRCD 1987; Floyd 1981; Berke & Beatley 1995). Competition from other regional tourism destinations and Jamaica's worsening problems of crime and violence also raise doubts about the potential for growth in this industry.

One vulnerability with important consequences for future productivity and competitiveness is Jamaica's relative deficiency in skills, technology and managerial know-how (Ramsaran 1988). This deficit makes it highly unlikely that the country will be able

to supply the investment and skills needed to ensure its economic competitiveness and promote on-going productivity gains (Gayle 1986; ECLAC 1996; Ramsaran 1988; World Bank 1993b). The absence of a strong entrepreneurial and professional class, in particular, remains a serious obstacle to future economic growth (Watson 1994).

Moreover, Adam et al. 1992 observe that, while Jamaica is distinguished by the unprecedented scope of its privatization program — selling off more state-owned enterprises than any other country in the region — domestic investment remains low. Moreover, many of these newly privatized services and manufacturing enterprises suffer from the same problems that plague the state owned enterprises — namely, inefficiency and unproductivity. In addition, the oligopolistic nature of the private sector continues to mitigate against the establishment of competitive industries (Adam et al. 1992).

Contributing to the economic uncertainty and raising questions about the island's future investment potential are deep social divisions and associated problems of crime and violence. These divisions have also made it difficult for successive administrations to achieve broad-based consensus on economic policy (Gayle 1986; Mandle 1996).

	Investment % GDP ¹	Capital Stock Per Worker ²	Unemployment Rate ³	Consumer Price Index ⁴
1966	27.5	3733	—	—
1968	32.2	4214	—	—
1970	31.0	5018	—	—
1972	22.8	5370	22.8	—
1974	23.6	5626	20.7	—
1976	18.7	5615	24.2	—
1978	15.1	5419	26.8	—
1980	12.0	4636	27.3	22.9
1982	15.0	4349	27.6	27.5
1984	14.0	3874	25.5	39.2
1986	12.2	3600	23.6	56.7
1988	16.1	3435	18.9	65.7
1990	17.2	3471	15.7	100.0
1992	—	—	15.7	252.6
1994	—	—	15.4	416.8
1996	—	—	16.0	606.2
1998	—	—	—	725.4
¹ Current international prices; Source: Penn World Tables ² 1985 international prices; Source: Penn World Tables ³ % of Economically Active Population; Source: Before 1980, Stone & Wellisz 1993; after 1980, IDB 1999; ⁴ 1990 Constant US\$; Source: IDB 1999				

Undoubtedly, the most serious threat to Jamaica's economy, is its high level of indebtedness (Levitt 1991). Jamaica's total debt burden has been reduced in recent years, partly due to rescheduling and a reduction in the level of new loans. Nevertheless, as Table 3.4 indicates, total outstanding public debt in 1997 was well over US\$ 3.0 billion, or just under 51% of GDP. In 1999, 41% of government revenues went solely to service the country's debt burden (The Economist 1999).

<i>Table 3.4: Jamaica Debt Profile</i>			
Year	Total External Public Debt (millions U.S. Dollars ¹)	External Public Debt Outstanding % GNP/GDP ²	Debt Service % Exports of Goods & Services
1970	154	11.5	2.5
1978	1,036	39.4	17.9
1980	1,299	54.1	12.8
1982	1,511	49.9	16.8
1984	2,175	104.9	21.0
1986	2,993	144.4	31.7
1988	4,002	117.4	38.8
1990	4,152	111.9	29.0
1992	3,678	115.4	27.1
1994	3,652	72.8	20.0
1996	3,232	56.0	18.0
1997	3,278	51.0	16.4
¹ Debt measure excludes private debt; ² Figures measured as a % of GNP up until 1986 and as a % of GDP from 1988 onwards Source: World Development Reports 1980-1989 & IDB 1999			

As Levitt 1991 observes, this debt poses serious problems for Jamaica's economic competitiveness. Moreover, it should be noted that most of this debt has accrued from loans disbursed to finance short-term balance of payments (stabilization) and structural adjustment programs rather than human resource development (Boyd 1988).⁵

To summarize, after years of stabilization and adjustment measures, the Jamaican economy continues to falter, and age-old structural disequilibria remain (Levitt 1991; Anderson & Witter 1994; Worrell 1987; Adam et al. 1992). Production remains geared around a few exports and consumption heavily dependent on foreign imports, technol-

⁵Levitt 1991 has characterized this ongoing situation as one in which the Jamaican government is effectively in "de facto receivership to the multilateral agencies which have monitored and supervised the affairs of the country throughout the 1980s — and are to a considerable measure responsible for the excessive level of official indebtedness contracted in the opening years of the decade" (p. 3).

ogy and investment. Very little diversification in the economy has taken place. Internationally, the liberalization of trade and financial regimes has intensified pressures on the economy (World Bank 1993b).

3.4 Social Repercussions of the Above Trends

3.4.1 Persistent Poverty & Inequality

The social consequences of the country's economic problems are also evident in the decline in welfare and income measures for various years for which data is available. Jamaica's poor have long been dependent on the provision of public welfare, and the decline in government spending has had negative repercussions for the quality of their lives (Levitt 1991).

According to Levitt 1991, statistics compiled by the Center for Nutrition provide a sense of the negative impact that these economic events had on the incomes of the poor during the 1980s. For example, the author calculates that a least cost basket of basic goods needed to feed a family of 5, required J\$ 24.27 in June 1979 when the minimum wage J\$ 26 per week. By 1986 the cost had risen to J\$ 165.88 (roughly three times the minimum wage) (Levitt 1991). Since then the number of poor has tended to fluctuate with economic trends (Adam et al. 1992). Statistics compiled in 1989, for example, estimated that 30% of the population lived in poverty. This figure rose to 41% in 1992, and fell dramatically to 29% in 1993, as economic prospects improved (Handa & King 1997).

A declining trend in real wages is also evident from 1977 to 1985 (Boyd 1988; Anderson & Witter 1994). According to one study by Anderson & Witter 1994, the number of workers reporting that their wages were insufficient to support a family, rose dramatically during this period. Labour force data for both periods suggest that in 1977, 35% of employed salaried workers reported income inadequacy in comparison to 61% in 1985 (Anderson & Witter 1994).

Although recent data are lacking, it is reasonable to assume that inflationary pressures, rising levels of unemployment, population growth and the progressive withdrawal of subsidies have all conspired to ensure that the number of workers suffering from income inadequacy has remained at a high level. No doubt, this inadequacy will be

greater for rural residents, who account for the majority of the country's poor. According to one estimate from 1989, 41% of the rural population lived in poverty in comparison to 10% in Kingston, and 36% in other built-up areas (Levitt 1991).

While income inequality may have improved slightly in the first years of the Manley administration, this improvement was not sustained, at least not for the poor (Boyd 1988).⁶ For example, in the early 1970s the income share of the poorest 20% of households was 2.2%, and that of the richest 20%, 61.5%. By 1991, the share of the poorest groups was essentially unchanged, with the bottom 20% holding 2.2% of income, as opposed to 47.5% for the richest 20% (World Bank 1972/3, 1991).⁷ Income inequalities are also greater in rural areas, largely due to large differences in wages between mining and agriculture.

However, it is possible that the decline in incomes that occurred in the mid-1980s was greater in urban than in rural areas. According to Anderson & Witter 1994, the proportion of urban wage earners reporting extreme income inadequacy (i.e. who could not afford to purchase more than half the minimum required family diet) rose five-fold between 1977 to 1985, a rate higher than in rural areas. This finding may also be attributed to the fact that the impact of structural adjustment was greater in urban areas, which are better serviced and receive the bulk of government spending (LeFranc 1994).

Rural income inequalities are largely rooted in the country's unequal distribution of agricultural land (Anderson & Witter 1994). For the most recent years for which figures are available, farms ≤ 5 acres account for 82% of all farm holdings while occupying only 26% of total farm acreage. By contrast, the largest 0.4% of farms (i.e. ≥ 100 acres) account for 32% of farm acreage (DS 1978/9). Although recent statistics are lacking, it is possible that inequalities in land ownership worsened during the 1980s with the rise in land prices and increasing fragmentation of small plots.

⁶Handa & King 1997 find evidence that inequality may have decreased slightly in 1989 before rising sharply in 1991 and 1992, before falling just as sharply again in 1993. The authors attribute the overall decline in inequality during this period to a resurgence in both domestic agriculture and an increase in remittances to the island. They argue that it had little to do with the implementation of market-friendly reforms or to the growth of non-traditional imports and export processing zones.

⁷The World Bank calculated Jamaica's gini coefficient to be 0.41 in 1991, which is high in comparison to many developing countries (World Bank 1999/2000).

3.4.2 Falling Real Wages & Rising Unemployment

The decline in real incomes of the poor since the 1980s is directly related to the country's endemic unemployment problem. During the 1980s, in particular, unemployment rose as high as 25% in some years (see Table 3.3)⁸. Unemployment rates for women were also more than twice as high in many years than for males; and three times as high for 15 -19 yr olds than for older workers (PIJ 1989a).

It is worth stressing that most of the jobs created in the formal sector in the 1990s have been in enterprises such as export-processing, light manufacturing, service and retail establishments. As Anderson & Witter 1994, observe, most of these jobs are low skilled and low wage, and hence essentially insecure (Anderson & Witter 1994). It is worth noting, too, that growth even in these low-skilled, low-productivity jobs has not been sufficient to match the decline in traditional formal employment (ECLAC 1996).

Another observable trend since the 1970s is the growing informalization of the labour market (Anderson & Witter 1994). During the 1980s, the percentage of informal sector workers in the economy was well above 40% (Anderson & Witter 1994; Boyd 1988; Bennett 1995). In Kingston and St. Andrew alone, informal sector employment during the 1980s accounted for nearly 30% of jobs in the urban sector (Anderson & Witter 1994). However, while informal sector activity did increase substantially during this period, it is unlikely that it helped the poor. Bennett 1995 presents evidence to suggest that the middle and upper-middle classes benefited more from cheaper prices for goods and services in this sector than did poor workers through increased production in the informal sector (Bennett 1995).

3.4.3 The Special Case of Agricultural Employment

Agriculture remains an important remunerative activity for the poor on the island, providing a livelihood for as much as 36% of the population in 1995 (NRCA 1995a).

As noted, export crops have performed inconsistently since this period, indicating uncertainty in the long-term prospects for employment in this sector (Newman & LeFranc 1994; NRI 1996). Sugar cane — still the island's most valuable agricultural

⁸Figures quoted here are based on an official measure of unemployment, which includes both those people seeking work and those "non-seekers" who make no attempt to find work during the period in question but who nevertheless state the desirability for work (World Bank 1998).

crop — and bananas have experienced dramatic fluctuations in revenue earnings. In contrast, export earnings from coffee have shown sustained increases, albeit starting from significantly lower levels than either sugar or bananas (see Figure 3.1).

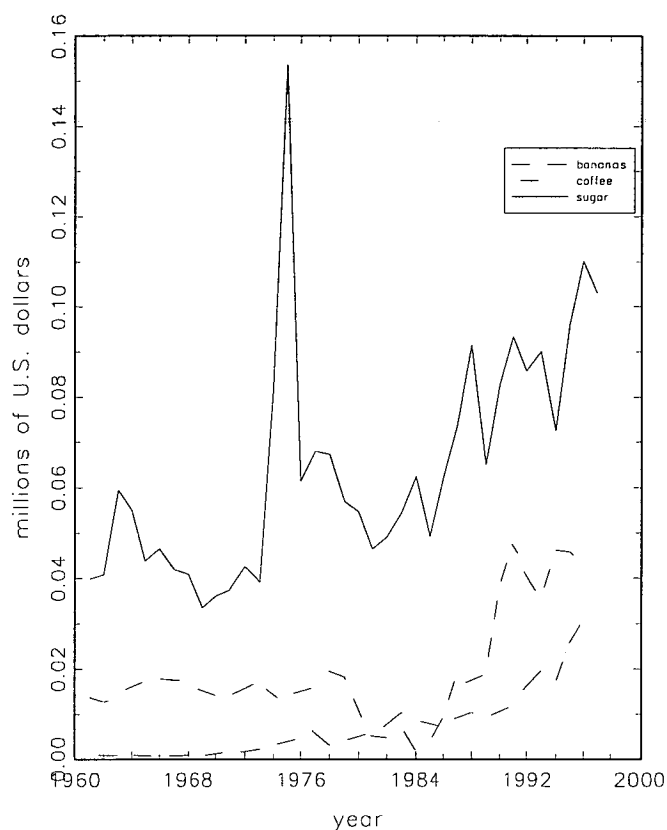


Figure 3.1: Traditional Agricultural Export Earnings (Source: FAO 1999)

Available evidence suggests a continuing downward trend in employment in the agricultural export sector in coming decades (Graham & Edwards 1984). Modernization and privatization initiatives will also likely lead to further contraction in employment (PIJ 1982a-1995a; Newman & LeFranc 1994). Evidence also suggests that both the number and proportion of self-employed farmers growing export crops has diminished since 1985 (Newman & LeFranc 1994). This possible decline in smallholder participation in export agriculture may have been associated with a rise in the size of large estates (Newman & LeFranc 1994).

3.4.4 Performance on Other Welfare Indicators

Successive economic crises, debt and structural adjustment initiatives have all seriously affected the quality of the country's infrastructure and public services. Not surprisingly, these developments have had serious negative impacts on the quality of life of the lowest income groups (Anderson & Witter 1994; Levitt 1991; Handa & King 1997). Despite this deterioration, structural adjustment and debt servicing imperatives will no doubt continue to require further expansion in user fees for many services and the elimination of basic subsidies. The hardship induced by these measures has sparked several violent protests in recent years, with negative repercussions for the tourist industry.

This deterioration in welfare is evident from an examination of Jamaica's performance in the areas of education and health. Per capita expenditure on health and education as a percentage of total expenditure fell sharply in the early to mid-1980s, after which it increased slightly (Behrman and Dolalika 1991; Levitt 1991). Although current data are lacking, the dismal performance of the economy in the 1990s would suggest that government spending on in these areas has probably fallen since then.

Declining real wages, devaluation and the introduction of user fees have also contributed to sharp increases in the cost of these services, both public and private (Boyd 1988). The provision of health and education has also been compromised by both a lack of essential supplies and equipment, and a dramatic decline in the number of trained professionals, many of whom have emigrated or gone into private practice (Levitt 1991; Boyd 1988; Kirton 1992).

Primary and secondary school education, in particular, has been adversely affected by this decline in spending, as evidenced by sharp declines in the number of trained teachers, deteriorating and inadequate facilities, overcrowding, shortages of basic instructional materials and poor pass rates (Levitt 1991; Boyd 1988). Handa & King 1997 note that a drop in the percentage of children passing the English proficiency portion of the Caribbean Examination Council exams also suggests a decline in basic literacy. Figures between 1989 and 1993, for example, reveal that the number of children passing the exam fell from 27% to 25%.

<i>Table 3.5: Jamaica Welfare Profile</i>		
<i>Welfare Indicator</i>	<i>Year</i>	
	<i>1982</i>	<i>1995</i>
% Population Access Safe Water ¹	96	93
% Population Access Sanitation ²	91	74
	<i>1980</i>	<i>1997</i>
Infant Mortality Rate ³	21	12
	<i>1979</i>	<i>1997</i>
Life Expectancy at Birth ⁴	71	75
	<i>1989</i>	<i>1993</i>
Hospital Beds per '000 inhabitants ⁵	2.4	2.1
	<i>1989</i>	<i>1991</i>
% Low birthweight Babies ⁶	7.0	7.3
	<i>1977</i>	<i>1984</i>
Population per physician ⁷	3,522	2,040
	<i>1979</i>	<i>1997</i>
Daily per capita Caloric Intake ⁸	2,597	2,553
Daily Protein Intake (gms) ⁹	63.8	62.5
	<i>1989</i>	<i>1992</i>
% Malnourished Children ¹⁰	2.9	5.1
	<i>1979/80</i>	<i>1992/3</i>
% Trained Teachers ¹¹	93	86
<p>1,2,3 Source: World Bank 1999; 4 1979 Estimate World Bank 1981; 1997 Estimate World Bank 1999/200; 5 IDB 1999; 6 Handa & King 1997</p> <p>7 1977 Estimate World Bank 1981; 1984 Estimate World Bank 1990</p> <p>8,9 FAO 1999; 10,11 PIJ 1992c, Handa & King 1997</p>		

Although progress in life expectancy and infant mortality appears to be unaffected so far, other health indicators have declined. Recent and comprehensive figures on a range of indicators are lacking, but there is evidence that childhood diseases increased in the 1980s, as did the percentage of low-birth weight children (LeFranc 1994; Handa & King 1997). Figures for the period 1975 to 1985 reported by the Bustamente Hospital

intake, for example, indicate a sharp increase in the number of children admitted for malnutrition, up from 3.5 per 1000 to 8.3 per 1000 (Levitt 1991).

As Melville 1998, notes, the deterioration in health may also be traceable to poor nutritional levels due to increases in the cost of food as a result of inflation, the phasing out of basic subsidies and price controls and successive devaluations of the Jamaican dollar.

	1979	1980	1981	1982	1983	1984	1985	1986	1987
<i>Health</i>	42.1	40.0	42.2	44.0	39.5	30.4	27.9	25.6	32.2
<i>Education</i>	80.2	82.4	84.7	83.5	75.6	62.8	64.4	57.8	63.6

Source: Levitt 1991; Based on 1987 US\$. Figures for later years unavailable.

Nutritional status has no doubt been affected by the removal of general food subsidies, beginning in the 1980s. In compliance with IMF mandates, general subsidies were phased out altogether in the early 1990s in favour of targeted programs (e.g. food stamps and school feeding programs), which now cover only the very poorest. In 1992, the food stamp program was redesigned, and eligibility restricted to 230,000 individuals and 70,000 households (Levitt 1991). However, this would have covered only 1/3rd the number of persons below the poverty line at the time (Boyd 1988; Kirton 1992).

Housing, water, and sanitation have also undergone serious deterioration. According to the government's *State of the Environment Report* (NRCA 1995a), population growth, inadequate investment and rising costs for materials have resulted in a serious shortage of housing on the island. According to a 1987 National Shelter Strategy Report, Jamaica needed to build 15,500 units and upgrade 9,700 units annually to the year 1990 just to satisfy short-term housing needs. To provide better housing and meet future demand, it estimated that an average of 4,009 new units needed to be built and 2,580 units upgraded annually to the year 2006. However, as of 1995, none of these targets was even close to having been met (NRCA 1995a).

While government-sponsored housing programs have been re-initiated in the 1990s, most poor cannot afford the cost of these homes. Another factor constraining the provision of housing is the high cost of land, magnified by inflationary pressures in the economy. Between 1983 and 1985, for example, rural housing prices jumped by 71%

(World Bank 1993b; Anderson & Witter 1994). One direct result of this increase is a rise in the number of housing built illegally on captured land (Kirton 1992; NRCD 1987).

In addition, only 25% of Jamaican households have sewage connections, and the rest must depend on unhygienic pits and latrines (World Bank 1993a). Although 93% of the population in 1995 had reasonable access to an adequate amount of safe drinking water (World Bank 1999), 30% of the population still drinks untreated water (World Bank 1993a). Moreover, the standard of basic facilities and quality of housing construction in rural areas is significantly below that of urban areas (PIJ 1992c).

3.5 Future Welfare Trends & Prospects

Continued government retrenchment suggests that the responsibility for job creation and the provision of basic services will have to fall on the private sector. However, economic prospects remain poor, and thus so does the potential for the poor to improve their living standards. Jamaica has lagged behind other Caribbean and Latin American countries in economic growth and development. Whether privatization and liberalization initiatives will result in an increase in competitiveness and efficiency and therefore growth is an open question.

There is little doubt that, in the absence of sufficient and adequate opportunities for the poor to better themselves, the country's development prospects remain gloomy. A poor, unskilled workforce will continue to undermine Jamaica's capacity to innovate, increase productivity and compete in the global market-place.

Chapter 4

Ecological Context: Forest Pressures & Consequences

4.1 Biophysical Setting

4.1.1 Topography

Jamaica is a medium-sized (10,940 km²) Caribbean island, approximately 236 km long and 35 to 82 km wide (NRI 1996).

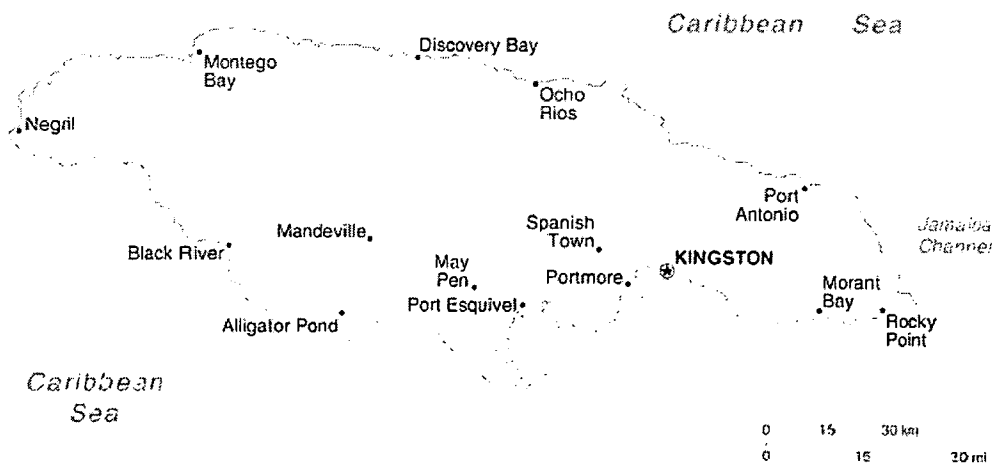


Figure 4.1: Jamaica National Map (Source: CIA 1999)

Most of the island's interior is characterized by mountainous or hilly formations, that plateau out toward a coastal plains region. Eighty-percent of the land surface is either hilly or mountainous (NRCD 1987). More than 50% of the island has slopes

greater than 20°, making the island vulnerable to land and watershed degradation (World Bank 1993a). Biogeographically, the island is characterized by a diversity of landforms and associated ecosystems (NRI 1996; World Bank 1993a; NRCD 1987).

Mountains in the eastern portion of the island are extremely steep and can reach as high as 2,260 m in the Blue Mountains. Less steep than the mountainous zone, the upland plateaux/hills zone is interspersed by many valleys and is roughly found at 300-600 m in height (NRI 1996; Floyd 1981). This limestone interior is characterized by many karst formations, or small round hills containing pock-marked depressions (cockpits). These formations characterize the area known as the Cockpit Country and parts of the John Crow Mountains (Floyd 1981; NRI 1996; NRCD 1987).

The coastline spans a length of 885 km and varies in length, but is widest on the southern, eastern and western sides of the island (Floyd 1981; NRI 1996; NRCD 1987).

4.1.2 Soils

A general soil classification has been made on the basis of the island's three main landform types: a) soils of the interior mountain ranges; b) upland/plateaux limestone soils; and c) alluvial soils of the coastal plains, inland basins and valley areas (Floyd 1981; NRI 1981). The fair to low productivity of much of the island's soils, particularly their high degradability and poor drainage, place considerable constraints on use (FAO/UNESCO 1975; Gumbs 1981).

Soil quality tends to decline with elevation. The reddish brown loams or clay soils (acrisols and lithosols) of the highland area comprise about 10% of the country's land area (FAO/UNESCO 1975). These soils are acidic, poorly drained and particularly susceptible to erosion. (NRI 1996; FAO/UNESCO 1975). In the Blue Mountains, and surrounding Yallahs Valley poor land use practices have resulted in considerable erosion of these soils (Berke & Beatley 1994;

Upland/plateaux soils comprise approximately 64% of the island's land area and consist mainly of cambisols, nitosols and rendzinas. These soils support the vast proportion of the island's small-holder producers (FAO/UNESCO 1975). Cambisols are high in ferrous iron and aluminum, and hence require regular applications of phosphate and nitrogen (FAO/UNESCO 1975). They are found predominately in the Rio Cobre, Rio Minho and Upper Yallahs watershed regions, where much of the island's domestic

agriculture is situated. Under traditional systems, the yields on these soils are generally fair to poor for most crops (e.g. maize and beans, bananas, plantations and root vegetables) but under better management they may be induced to support tree crops and coffee (FAO/UNESCO 1975). In contrast, the nitosols and rendzina soils generally have fair to good agricultural potential and can support fairly intensive mixed cropping systems if fertilizers are applied (FAO/UNESCO 1975). However soil erosion, extensive gullying and even desertification are common in many interior areas of the island where these soils are farmed by smallholder agriculturalists.

The island's most fertile soils, the alluvial soils (fluvisols), are largely found in the low-lying coastal plains areas and in the interior valleys and floodplains (NRCD 1987; Floyd 1981; NRI 1996). These soils are extremely fertile and well-drained, and account for approximately 10% of the island's soils. Fluvisols also support the vast majority of the island's export agriculture. Luvisols, which comprise about 12% of the island's soils, also tend to be good soils and in some areas, are extremely fertile (FAO/UNESCO 1975).

4.1.3 Climate & Watersheds

Jamaica exhibits a wide diversity in precipitation patterns. Rainfall increases with the decrease in temperature and from south to north (NRCD 1987). It averages over 3,300 mm per annum in the northeastern mountain zone to less than 1,500 mm per annum in the south central plains region (NRI 1996). The island also receives over 50% of its rainfall between May and September (NRCD 1987). Total precipitation is approximately 2,000 mm per annum on average (NRI 1996), but on occasion Jamaica has suffered from serious droughts. It is also vulnerable to hurricanes and tropical storms (NRCD 1987; Floyd 1981). Temperatures vary according to elevation and local climate, and can be quite considerable in the interior of the country (NRI 1996).

Main watersheds on the island by location include: (East) the Yallahs, Black Rio Grande, Wagwater, Hope, Buff Bay, Negro and Plantain Garden Rivers; (West) the Rio Minho, Rio Cobre, Great, Cabarita, Negril and Orange Rivers; (North) the Martha Brae, Montego, and Hector Rivers; and (South) the Rio Cobre, Rio Minho, and Milk Rivers. The Rio Cobre and Rio Minho Basins, in particular, are important for their contribution to agriculture, accounting for 64% of the island's irrigable area of 187,744

acres (NRCD 1987).

4.1.4 Forest Classification

Jamaica's forests have been classified according to three types: a) natural forests; b) ruinate forests; and c) man-made or plantation forests. Natural forests are further classified into 5 groups based on elevation, temperature and rainfall: 1) dry limestone forest; 2) wet limestone forest; 3) lower montane rainforest; 4) upper montane rainforest; and 5) marsh forest and mangrove woodland (Symes 1970; NRCD 1987; NRI 1996).

Dry limestone forests are associated with the southern hills and plains regions of the island, where rainfall can range from 1,530 mm to under 1,020 mm per year. No primary limestone forest exists, and most trees of this classification are heavily exploited for fuelwood/charcoal (Symes 1970; Floyd 1981). Trees in these areas (e.g. the Hellshire Hills of St Catherine, the plains areas of Clarendon and St. Elizabeth) are largely designated as scrub woodland or thorny bush (Symes 1970; NRCD 1987; NRI 1996).

Wet limestone forests can be found in the Cockpit Country, Mount Diablo and Dolphin Head Mountains. These were once prominent in the coastal lowlands and foothills of Portland, St. Mary, Trelawny, northern St. James, and Hanover, but have long since been cleared for agriculture (Floyd 1981; NRCD 1987; Symes 1970). Trees in this classification are better developed than are their wet counterparts. Typical species include the Jamaican Mahogany, Mosquito Wood, Shadbark, and Silk Cotton trees. However, these tree types are quite rare and have been extensively logged (Symes 1970; Floyd 1981). These forests are also being heavily encroached upon by shifting cultivators, fuelwood collectors and squatter settlements.

The lower montane forest is found on the northern slopes of the Blue Mountains and John Crow Mountains up to 1,220 m (Symes 1970; Floyd 1981; NRCD 1987). Blue Mahoe, Ironwood and Cedar are representative trees of this forest type, which are also quite rare. Forests in this classification are now being cleared by small-scale agriculturalists in search of land. In addition, government reforestation efforts have resulted in the planting of large areas with non-indigenous Caribbean Pine and Eucalyptus. Bamboo has also established itself in regenerated areas (NRCD 1987; Symes 1970; Floyd 1981).

Upper montane forests are located only in the Blue Mountains, above 1,220 m.

Trees in these areas are small (no higher than 15 m) due to the high humidity of the region. Trees in this classification include the Blue Mountain Yacca, Juniper Bloodwood, Soapwood and Bilberry. The steepness and inaccessibility of the region have largely protected them from human exploitation (Floyd 1981; NRCD 1987; NRI 1996). However, increasingly even these forests are under threat from encroachment from small agriculturalists and large-scale illegal drug cultivation.

Marsh forests and mangrove woodlands are situated in low-lying coastal areas, and have been exploited heavily in recent years for the production of charcoal. Many of these coastal woodlands are also being destroyed by pollution from built-up areas, sediment from soil erosion and harbour dredging (NRCD 1987; NRCA 1995a).

The remainder of the island's forests — approximately 51,890 acres — are classified as plantation. These are largely Caribbean pine, although small areas of hardwood (e.g. Eucalyptus, Blue Mahoe, Honduras Mahogany) have been planted in the central and western portions of the island. At least 1,236 acres have been planted in private land owned by the bauxite companies that operate on the island (NRCD 1987; NRI 1996).

It is probable that undisturbed natural forest exists only in the Blue Mountains and the Cockpit Country (Floyd 1981; Symes 1970; NRCD 1987). Despite the diversity of forest ecosystems, the predominant forest type on the island is 'ruinate'; that is, comprised of relict areas of secondary forest and herbaceous shrub and woodland (NRCA 1995a; NRCD 1987).

Approximately half of Jamaica's land area has been classified as unsuitable for anything but forest, but most areas have suffered from some form of human encroachment (World Bank 1993a; NRCA 1995a).

4.1.5 Biodiversity

Jamaica's variegated topography, island remoteness, and tropical situation are associated with a diverse, and in many cases, unique biodiversity. Many species of plant and animal are endemic to Jamaica. Jamaica ranks 5th among island nations in the number of its unique plant species (USAID 1989). More than 40% of its unique flora are found only in the Blue Mountains and John Crow Mountains Forest Reserves in the eastern portion of the island (Berke & Beatley 1995). Many unique species of bird, lizard, frog,

toad and bat are now either endangered or extinct (Ansine 1999). Indigenous flora and fauna are found only in the Blue Mountains and John Crow Mountains, the Hellshire and Portland ridge in the southeast (NRCD 1987; Berke & Beatley 1995).

The destruction of habitat is the principal cause of the loss of biodiversity (Ansine 1999). This destruction is the result of the clearance of forests, swamps and mangroves, both for subsistence and commercial uses (NRCA 1995a).

4.2 Scarcity & Environmental Exploitation

4.2.1 Demographic Pressures & Trends

Population Distribution

Population at the end of 1998 was 2.6 million, an increase of just over 20,000 people from the year before (IDB 1999). Jamaica is one of the most densely populated countries in Latin America and the Caribbean Basin, with an average density of 230 persons per km² in 1998 (IDB 1999). This figure is at least eight times the average for comparable middle-income countries (NRCD 1987).

Jamaica's variegated landscape has also determined the distribution of population (Floyd 1981). Population densities are considerably lower, for example, in very steep and extremely dry areas (e.g. the Hellshire Hills), swampland regions and along parts of the coast (NRCD 1987; Floyd 1981). Population is concentrated in and around Kingston and Montego Bay, Spanish Town, Ocho Rios, and Mandeville. Population densities in the urban sprawl areas of Montego Bay and Kingston can exceed 9,500 people per km² (Floyd 1981). In contrast, in the more inhospitable regions of the island (e.g. the Cockpit Country), densities can be as low as 1 person per km² (Floyd 1981).

Trends in Population Growth

At current annual average growth rates of 0.8% since 1989, Jamaica's population growth is classified as 'moderate'. The annual rate of growth for the period of this study, 1987-1992, was significantly higher, at 1.5% (World Bank 1998).

Although not as high as some neighbouring countries, Jamaica's growth rate must be placed within the socio-economic and biophysical constraints facing the island (Boyd

1988). It is worth remembering, too, that demographic pressures would be higher if not for high levels of emigration, particularly in the 1980s.

The government has long given priority to family planning and prenatal health care programs in the provision of basic health care. However, it is unclear whether advances in fertility reduction in the 1970s were sustained in the 1980s and 1990s due to a lacking of adequate funding for the collection of vital statistics (NRCD 1987; Newman & LeFranc 1994). Moreover, factors implicated in lowering fertility rates — health care, education and employment opportunities for women — have all been affected adversely by the economic crisis of this period. Thus, it is plausible that these figures are indeed too optimistic. These uncertainties notwithstanding, however, projections are that fertility rates will continue to decline, reaching replacement level by the year 2000 (under the moderate growth scenario) (PIJ 1992b).

However, even under a moderate scenario, Jamaica's population will contain large numbers of young persons in years to come. In 1992, the dependency ratio (i.e. the ratio of non-working population to working population) was 0.79 (STATIN 1992). Coupled with the higher fertility rates of the poor, this concentration will invariably lead to an intensification of pressures on the island's already limited resources even if population falls to replacement levels soon.

Likewise, a declining population growth rate still implies a large number of new entrants into the labour force each year. It is worthwhile noting that growth in the labour force has averaged about 2% each year and is projected to remain so into the 21st century (World Bank 1987). However, on the basis of past and current levels of employment it is unlikely that all those seeking work will be gainfully employed. That this is the case becomes clear if one considers that even in 1990 — a year in which the economy registered a 3.8% growth rate and average employment was 2.8% higher than in the year before — the jobless rate was still as high as 15.3%. Young persons also had higher levels of unemployment than did older workers: More than half of the persons unemployed in 1990, for example, were under 25 years of age (PIJa 1990).

4.2.2 The Pressure of Production on the Land: The Plight of the Small Farmer

Patterns of Agrarian Landholding & Use

Jamaica's Census of Agriculture divides farms into several distinct categories according to size. These range from landless farmers (< 1 acre) to large estate holdings (100+ acres). Farms \leq 5 acres constitute the overwhelming proportion of farms on the island. These small farms, in particular, are distinguished by the variety of arrangements under which they are held and worked (DS 1978/9).

For example, it is not unusual for small farmers at the higher end of the size category, to hire labourers. Similarly, it is not uncommon for farmers who own their own plots to farm other land in order to supplement their income or grow food, or simply to keep their land idle for one or more seasons as a means of boosting productivity (Newman & LeFranc 1994). This land may be acquired illegally by squatting, be owned or rented, or given to use by another farmer or emigrant under informal customary arrangements (Newman & LeFranc 1994). Many small farmers who live close to urban areas or large estates will tend to supplement their livelihoods by engaging in informal sector activities or casual labour. Landless agricultural labourers may also lease and/or illegally capture land by encroaching upon rinate or protected areas. These plots may be planted with some form of cash crop, such as ganja (marijuana) or trees, the profits from which may eventually be invested in purchasing a new plot of land (Newman & LeFranc 1994). Still, other, typically older farmers, will engage in market gardening to supplement an already established household income or pension (Floyd 1981).

All these examples demonstrate a fundamental fact about Jamaica's small farmer sector. That is, while it is comprised of a relatively large number of farmers and landless labourers who engage in farming on a full-time and permanent basis, it also is characterized by a large number of part-time agricultural wage-workers and 'market gardeners'. These latter groups will often resort to farming during bad economic times, or simply farm to make up shortfalls in household income and/or food (Newman & LeFranc 1994).

Although current data are lacking, there is good reason to believe that inequalities in land ownership have widened since the last agricultural census. Some research suggests

a trend toward the concentration of holdings in larger size classes and a concomitant increase in small farms as a result of the fragmentation of plots (Gajraj 1996; Newman & LeFranc 1994). The effect of these possible trends on small farmers is not known. However, it is not unreasonable to assume that many farmers have ended up illegally squatting on marginal land elsewhere (Gajraj 1996). Furthermore, the impact of these trends would most certainly have been greatest among those small farmers who depend solely on farming for a living. Chaney 1988, for example, reports a substantial decline in farm housing, crop production and food marketability during the 1980s for the 1500 small farmers interviewed in her study.

Very small farmers grow most of the domestic food produced on the island. According to the most recent census available, 86% of domestic crops are grown on farms ≤ 5 acres. Collectively, domestic farms account for a mere 20% of all farm acreage. In contrast, 50% of export crops are grown on farms ≥ 500 acres, and account for 43% of total farmland production (DS 1978/9).

Most small farmers eke out a living in hilly or mountainous regions of the island. As noted, these tend to be low-productivity areas that lack irrigation and must therefore depend on rainfall.¹ The small size of these plots, coupled with their low productivity mean that they are often insufficient to support a household (McKee & Tisdell 1990). It is worth stressing that while they mostly grow food for the domestic market, many small farmers will also grow crops for commercial purposes. However, given that farmers often do not have access to transportation or distribution networks, they often rely on middle-men or higglers to market their produce and therefore often receive very little for their endeavours.

The vast majority of small farms employ traditional methods of cultivation (NRCD 1987). The use of fertilizers and other chemical inputs is rare. Forks and hoes are primarily used for cultivation, and harvesting is often done by hand as many farms do not have access to mechanical equipment (NRCD 1987). Land is typically cleared using cutlasses, machetes or fire, resulting in considerable destruction and stimulating

¹An inventory of costs highlights the low profitability of farming under these constraints, even for the island's better-off small farmers. One farmer the author spoke to in a farming community near Alexandria (St. Ann parish) provided an explicit economic calculus of the problem: "I have 25 acres of land. On it I plant yams, cabbage, Irish potato, and banana. I own 8 goats (two died this winter) and I cow. I employ 5 people on my farm. It costs me J\$ 28,000 to operate this farm. Once I have met costs (e.g. for fertilizer, feed, labour, seed) I have made J\$ 4,000 (US\$ 105.00). I get no loans; the government has abandoned me and farmers like me. At least the fuelwood is free".

excessive clearance (NRCD 1987). Intercropping is widespread since it allows farmers to maximize output and to minimize the risk of crop failure (World Bank 1993a). Coffee is especially favoured by small farmers because it is profitable, easy to grow and transport and helps to maintain soil fertility.



Photo 4.1: Smallholder Coffee on Lower Slopes of the Blue Mountains (Portland Parish; Source Author)

4.2.3 The Persistence of the Smallholder Sector & Constraints on Productivity

The large number of small cultivators engaged in low productivity agriculture in marginal conditions across the island has been described by one observer as a “disquieting reality of contemporary Jamaican agriculture” (Floyd 1981, p. 87). Chronic underproductivity in the domestic agricultural sector has been blamed in turn for reinforcing the island’s heavy dependency on expensive food imports (Thomas 1988; McKee & Tisdell 1990; Gumbs 1981). Moreover, the low prices domestic farmers receive for their produce prevents them from making the necessary investments in their plots that would raise output and lead to sustainable land use practices (Beckford 1975). In addition, small farmer productivity remains constrained by the lack of adequate access to markets and transportation and poor distribution networks (McKee & Tisdell 1990; Gumbs 1981; Beckford 1975). Compounding problems of market accessibility are the scattered and inaccessible nature of many of the plots.

Small farmer attempts at raising self-sufficiency have suffered from the successive withdrawal of government support for the smallholder farmer since the early 1980s. As Newman & LeFranc 1980 note, the two agencies responsible for farmer assistance (the Jamaican Agricultural Society, and the government's own Rural Agricultural Development Authority) have seen their budgets cut drastically in recent years and are essentially unable to provide any type of assistance to small farmers (Newman & LeFranc 1994; World Bank 1993a). Government initiatives are now restricted to stimulating private sector involvement and eliminating market distortions (Newman & LeFranc 1994; Anderson & Witter 1994). To what extent these measures will help the smallholder is difficult to ascertain. One study (Newman & LeFranc 1994) has suggested that small farmers are no better off, and may be even worse off than they were before. It is not unreasonable to think that structural adjustment initiatives have mainly benefited large commercial producers, who are in a better position to exploit opportunities arising from trade liberalization and the rationalization of production structures (Anderson & Witter 1994).



Photo 4.2: Small Domestic Farms near Christiania (Manchester Parish; Source: Author)

In the continued absence of appropriate means to raise output and self-sufficiency, small farmers will remain poor, and hence rural areas will be incapable of generating the kind of effective demand that would enable a large number to improve their living standards and move off the land. Moreover, it is worth stressing that much of the investment on the island in recent years has been directed toward manufacturing and tourism industries situated in built-up areas. This bias, coupled with the chronic un-

derproductivity of the domestic agricultural sector, will no doubt further depress the potential for the creation of self-sustaining, off-farm rural enterprises. Indeed, there is a real fear that the exclusive direction of investment in one or two sectors will widen the already deep divisions that exist between urban and rural areas (World Bank 1993b), placing greater pressure on residents to seek a livelihood in forest destructive activities.

4.3 The Destruction of Jamaica's Forest Resources: Shifting Cultivation & Other Scarcity-Driven Forms of Exploitation

A lack of alternative remunerative opportunities, homelessness and insufficient plot size are just several factors prompting encroachment by rural inhabitants into forested areas. No doubt the stimulus for colonization among some of these residents has fluctuated with the economic fortunes of the island. However, as noted, the permanent full-time farmer must also be implicated in this destruction. The poor quality of most smallholder plots means that output is often insufficient to produce either a continuous stream of income or an adequate household food supply, with the consequence that more land is continually being brought into production.

Many areas being deforested are within protected or national parks. This is particularly the case in the Blue Mountains and John Crow Mountains where squatters are progressively moving up hillsides and clearing new land for the cultivation of root crops — and increasingly — coffee and ganja. The high market value of the latter two crops has resulted in extensive destruction of forests in the park in recent years.



Photo 4.3: Slash & Burn Agriculture High in the Blue Mountains (Portland Parish; Source: Author)

Some of this destruction must be attributable to government programs designed to encourage private landowners in the area to grow coffee. Large subsidies to farmers from CIDCO, the government-owned coffee monopoly, have resulted in large areas being stripped of their vegetative cover (Berke & Beatley 1994; World Bank 1995a). Many small farmers have benefited from these programs, but for the most part areas planted in coffee have proved unsuited for it, with the consequence that yields are low and the soil is quickly eroded (World Bank 1995a). Likewise, the expansion of tourism, bauxite/alumina production and government reforestation efforts in various parts of the island have also led to farmers being displaced to forested areas but the extent of this expansion or the effect it has had on subsistence farmers is unknown.



Photo 4.4: USAID/GOJ Agroforestry Project Near Spaldings (Manchester Parish; Source: Author)

Fuelwood collection is also another cause of the destruction of the island's forests, which has been exacerbated by the increasing use of charcoal (NRCA 1995a). One estimate suggests that 84% of the wood taken from Jamaica's forests is consumed as charcoal and fuelwood (Berke & Beatley 1995). One factor in the growing appeal of charcoal is its low production and transportation costs. Since most of it is produced in small holes dug into the ground, it provides one means of livelihood for a poor squatter with few resources (NRCD 1987).

The impact that the removal of fuel subsidies has had on Jamaica's forests is unknown. Approximately 37% of households depend exclusively on fuelwood/charcoal for their heating and cooking needs (NRCA 1995a). It is likely that the demand for wood based fuels will rise in the future, particularly in view of the poor economic forecast, which will make imported fuels expensive (Graham & Edwards 1984).

Another source of deforestation on the island is encroachment by homeless squatters, particularly in built-up and tourist areas. It is not uncommon, for example, for rural dwellers close to these areas to clear a small patch of land simply to construct

a house and grow a few crops while remaining employed in off-farm pursuits. Problems of homelessness and encroachment are particularly severe around the Kingston Metropolitan Area (KMA) and the prime tourist resort of Ocho Rios. However, housing shortages are also driving the clearance of forested land in interior regions, which suffer from problems of inadequate housing and homelessness.

4.3.1 The Control of Squatters

In recent years, the Jamaican government has attempted to control encroachment, particularly in the Blue Mountains and Jim Crow Mountains, where it is most extensive. In 1992, the government of Jamaica established a 193,000 acre park with assistance from USAID, and the Jamaica Conservation and Development Trust (Berke & Beatley 1995; NRCA 1995c). In addition, several hillside agriculture and watershed management projects have been established to encourage farmers in the park to adopt sustainable farming practices. One such program, which has had some success, is a collaborative partnership between the Forestry Department, the park and local farmers. Under this program, 600 acres of government-owned land have been allotted to landless squatters, who have been given legal title to their plots (Berke & Beatley 1995). Other initiatives involve ecotourism and related sustainable enterprises aimed at enjoining the participation of local residents (Berke & Beatley 1995).

In 1990, the Jamaican government established its National Forestry Action Plan (NFAP), which gives priority to the establishment of agroforestry programs in key watersheds on the island (NRCA 1995b). As of 1995, the NFAP had not been implemented due to budgetary shortfalls, but several outside NGOs have been closely involved in parts of the plan. One is the IDB (International Development Bank) funded afforestation project, which targets 6 of the country's main watersheds: Yallahs, Rio Minho, Black River, Cave River and Rio Grande (NRCA 1995b). Another project, CIDA's (Canadian International Development Agency) "Trees for Tomorrow", aims to introduce soil and water conservation measures in the Buff Bay region of the northern part of the island (Brand et al. 1993).

Project Feasibility

Although many of these programs are still in their initial stages, their long-term viability remains uncertain. One problem mitigating against the success of these projects is their cost. The initial impetus for the establishment of the Blue Mountains John Crow Mountains Park came from USAID and various NGOs, but finding adequate funds for park maintenance has proved problematic (Berke & Beatley 1995). In view of the island's on-going economic problems, it is certainly going to be difficult for the government of Jamaica to meet even a small portion of the finances required to ensure the park's integrity. One study has estimated that 25 wardens are required to monitor the entire area of the park, requiring a budgetary commitment that was not feasible with current levels of spending (NRCD 1987).

There is also concern that areas outside and within the park have been neglected by the projects, and thus, are being used more intensively than before (Berke & Beatley 1995). Moreover, ecologists have charged that areas designated for protection have been circumscribed too narrowly to maintain the ecological viability of the park (Berke & Beatley 1995). Furthermore, enforcement of park rules is weak and encroachment is widespread. A recent trip to the park by this author found extensive evidence of deforestation throughout the area. Upper reaches of the park were not immune to encroachment. Many deforested areas were also close to key tourist centers and trails, detracting considerably from the aesthetic landscape that visitors expected to see.

Farmer assistance programs face similar problems. As noted in the country's *State of the Environment Report* (NRCA 1995a), programs aimed at encouraging sustainable land use practices have been in place for the past 40 years. However, many of these programs have been costly failures, as evidenced by the island's serious and worsening problems of soil erosion and deforestation (NRCA 1995a). As Blustain 1982 notes, the reasons for the failure rest in low farmer adoptability arising from a neglect of such issues as tenure insecurity, suitability of crops and technology, the marginal nature of most small plots, debt and a lack of smallholder access to credit and markets (Blustain 1982). The high costs of the programs and considerable resources required for their on-going maintenance have also been cited as reasons for their low success rate (Blustain 1982). The USAID funded Hillside Agricultural project (HAP), for example, has found that the benefits for farmers of soil conservation measures were only realizable after a

long period (World Bank 1993a).

4.3.2 Environmental Consequences of these Forest Pressures

Very little scientific information exists on the ecological implications of the island's deforestation problem. However, observations are that the problem is engendering serious externalities. The adverse impacts of deforestation that have been noted in the literature range from the destruction of watersheds, changes in stream flows and microclimate, soil erosion and land degradation (NRCD 1987; World Bank 1993a; NRCA 1995a). What impact these changes will have on the productivity of the land is unknown, but there is little doubt that they pose a serious threat to the livelihood of many of the island's residents who depend directly on the resource base for their livelihood.

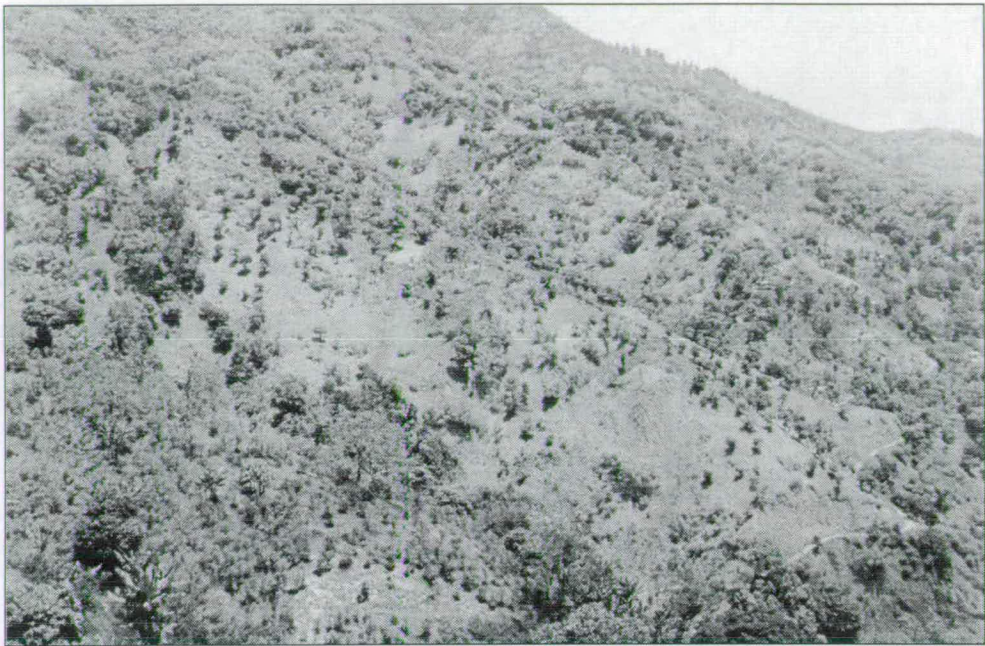
The most visible and immediate effects of the island's extensive loss of forest cover are widespread soil erosion and land degradation. One recent study has estimated that Jamaica loses 40 to 50 tons of topsoil per acre per year due to erosion, and that currently 400,000 acres are seriously eroded (Lane 1989, cited in Berke & Beatley 1995). This is a considerable amount in view of the fact that the sustainable annual rate of erosion is estimated to be much lower, at around 1-3 tons per ha (Lugo et al. 1981). The effect of this rate of soil loss on agricultural productivity and other resource-based enterprises such as fisheries has not been quantified.

Watershed destruction is also a serious problem throughout the island. The build-up of sediment and vegetative debris in rivers and streams has reduced the quantity and quality of water flow in many areas (NRCA 1995a; Eyre 1989/90). 19 of the 26 identified Watershed Management Units on the island are now deemed to be in critical condition (NRCA 1995a) and 60 named rivers no longer flow annually (World Bank 1993a). One problem area with serious implications for tourism, is the Ocho Rios sub-basin. According to a study by Eyre 1989/90, the rivers in this prime tourist area are being adversely affected by turbidity and altered stream flow due to the build-up of sediment and vegetative debris from upstream deforestation.

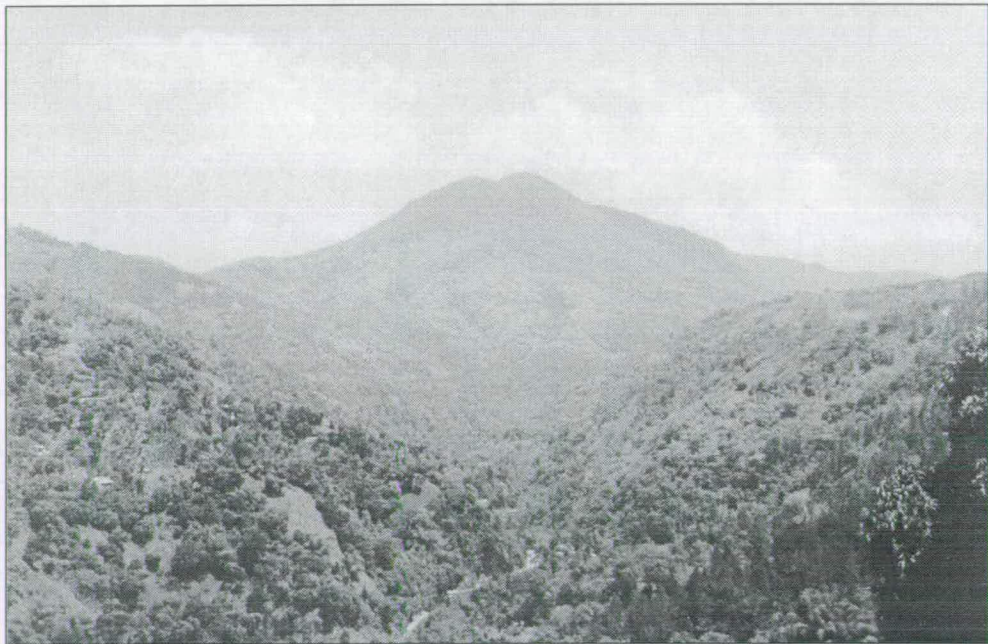
Changes in evapotranspiration rates and albedo due to extensive forest loss have also been blamed for recorded declines in precipitation on the island in recent years (Eyre 1989/90). These changes, in conjunction with the destruction of the island's watersheds, have been implicated in growing water shortages (particularly around the

Kingston Metropolitan Area (KMA) where several underground springs have now dried up) and in several serious flooding incidents in recent years.

It is unclear to what extent heavily deforested and degraded areas will ever sufficiently regenerate to produce a viable forest ecosystem again. In many instances, regenerated areas have been observed to be accompanied by tree formation that is poor and quite diminished (Eyre 1987; personal observation).



Photographs 4.5 & 4.6: Deforested & Eroded Slopes of the Blue Mountains (Portland Parish)



Chapter 5

Measuring Jamaican Deforestation Using Landsat Images

Despite the evident social and ecological externalities it is generating, the problem of deforestation in Jamaica has been largely neglected by scientific researchers. One reason may be due to a basic lack of data. What few forest estimates exist for the island are partial and contradictory in nature, and forestry inventory data have not been collected since the early 1970s (Gray & Symes 1972; NRCD 1987).

The next several chapters attempt to derive an estimate of forest loss for Jamaica, for part of the period surveyed in Chapters 3 and 4: 1987-1992. This estimate is derived from satellite data, and then compared with estimates of the few published deforestation figures that exist for the island. These latter estimates are based largely on land survey data from various periods and locations which have then been extrapolated to provide an island-wide estimate. However, before presenting and discussing the thesis' satellite-based forest estimates, this chapter and the next two chapters will outline the data used and methodological steps followed to obtain this estimate.

In particular, this chapter provides a brief background to the use of remotely sensed data in studies of land cover change and introduces some basic concepts in remote sensing. It follows with a description of the satellite image data set and discusses issues involved in its selection and methodology. A crucial step in a remote sensing study of environmental change is the integration of image data with other forms of

data in a geographical information system (GIS). This information is used in Chapter 8 to calculate forest estimates for use in the empirical analysis of key socio-economic indicators at the national and sub-national (i.e. parish and constituency) levels.

5.1 Satellite-Based Measures of Environmental Change

Earth observation satellites have been in operation since the early 1970s, providing a large number of images at a variety of spectral and spatial resolutions, from the global level (AVHRR) to the local level (SPOT or Landsat TM data) (Downtown 1995; Sabins 1997). Because remote sensing systems have a short revisit period (e.g. twice daily in the case of AVHRR data and every 26 days in the case of SPOT data) a substantial volume of information can be theoretically acquired continuously for the same location over time (Downtown 1995). The cost of these images is also proportionately lower per unit area than are aerial photographs, the traditional medium for studying environmental change (Howard 1991). The digital nature of the images also makes it possible to process images cheaply and efficiently; unlike the interpretation of photogrammetric data, which requires a high level of expertise and time (Sabins 1997; Lillesand & Kiefer 1979).

5.1.1 Some Basic Principles

Remote sensing systems exploit the properties of matter to reflect and radiate electromagnetic radiation (EMR) (Sabins 1997). Natural phenomena (e.g. trees, rocks, water, ice) will reflect, absorb and/or transmit radiation in different portions of the electromagnetic spectrum according to their unique physical and molecular properties.

Energy can take many forms: visible light, ultraviolet light, radio waves, x-rays. What identifies it as such is its location in the electromagnetic spectrum. Despite the length of this spectrum and the differences in the behaviour of objects both within and between its various bandwidths, only a small portion of this spectrum has viability from the perspective of a remote sensing study (Sabins 1997).

Most remote sensing applications, including this study, focus on the reflected portion of the electromagnetic spectrum. This spectrum ranges from the visible to the infrared regions (0.4 μm to 3.0 μm). Visible light is composed of blue (0.4 μm to 0.5 μm), green

(0.5 μm to 0.6 μm), and red (0.6 μm to 0.7 μm) portions of the spectrum. Reflected energy peaks in the green wavelength band of the visible spectrum at 0.5 μm . The infrared region is comprised of a reflected IR band (0.7 μm to 3.0 μm) and a thermal IR band (Sabins 1997).

Figure 5.1 provides a pictorial representation of the electromagnetic spectrum, which is further divided into bands in Figure 5.2.

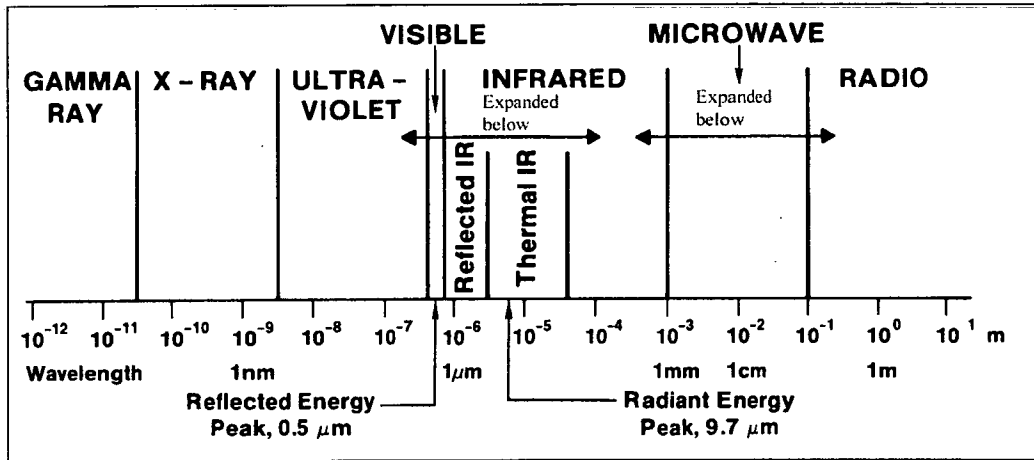


Figure 5.1: The Electromagnetic Spectrum (Source: Sabins 1997)

Note that the intensity of the electromagnetic response, i.e. the amount reflected, absorbed or transmitted, will differ from one wavelength band to another. More sensitive remote sensing systems will be able to pick up more information about this variability (i.e. by recording in a number of bandwidths) and thus will have a higher spectral resolution.

The nature of the spectral responses elicited by an object throughout various portions of the EMR is known as a 'signature'. When these spectral responses are graphed as a function of wavelength, the resulting curve or 'spectral signature' can help to determine what band is most appropriate for the study (Lillesand & Kiefer 1979).

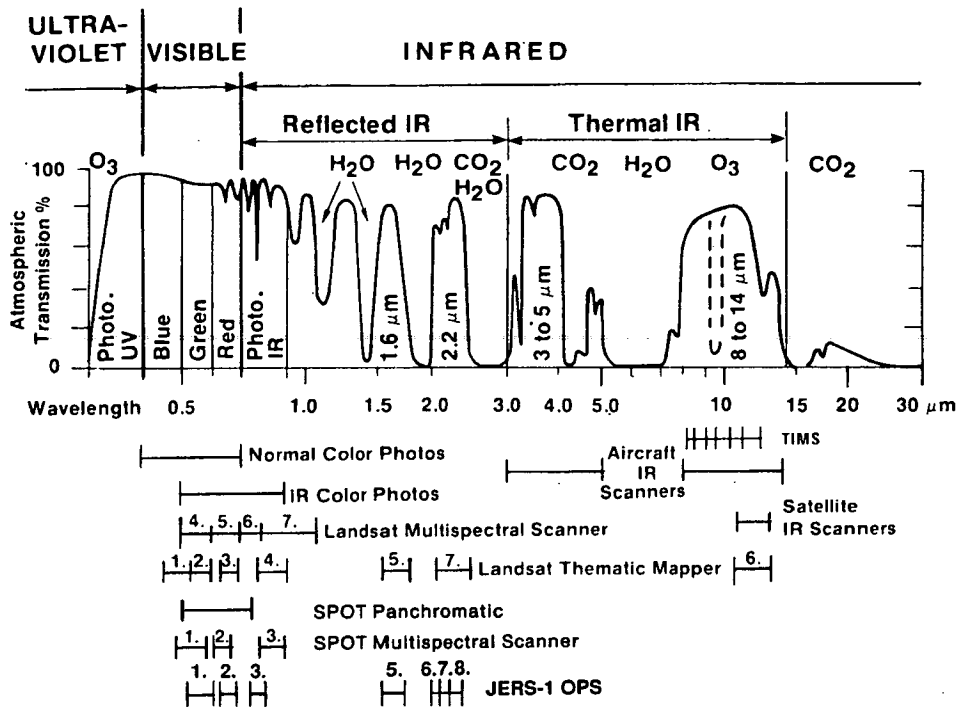


Figure 5.2: Major Remote Sensing Regions & Their Imaging Systems (Source: Sabins 1997)

5.1.2 Spectral Reflectance Curves for Vegetation

Spectral reflectance curves vary from one landscape feature (e.g. trees, water, cloud) to another. Within these various feature groups, member types (e.g. deciduous vs. coniferous trees) will also evince distinctive responses that will make them identifiable as such (Lillesand & Kiefer 1979; Howard 1991; Swain 1978). These feature types in turn will contain specific groups (e.g. oak vs. pine) identifiable by their spectral response, and so on (Lillesand & Kiefer 1979).

However, it should be stressed that many factors can affect these highly stylized spectral response patterns. In the first instance, different object groups and feature types will share similar reflectance properties in one bandwidth and/or under certain conditions but not another (Lillesand & Kiefer 1979). Similarly, the environmental conditions (spatial, temporal and atmospheric) at the time of data acquisition can also affect the resulting spectral response patterns observed for individual object groups and their species types. However, if data is chosen carefully in view of the goals of the study, in most remote sensing studies there will be enough conditions represented and bandwidths available in an image archive to identify features of interest (Landgrebe

1978a; Lillesand & Kiefer 1979).

The above points can be highlighted by a consideration of Figure 5.3, which depicts the spectral reflectance curve for healthy vegetation with its distinctive ‘peak and valley’ configuration. This distinctive response pattern arises from the differential reflectance and absorption of light by vegetation in the visible, near-infrared, and middle-infrared portions of the spectrum (Landgrebe 1978a; Howard 1991; Lillesand & Kiefer 1979).

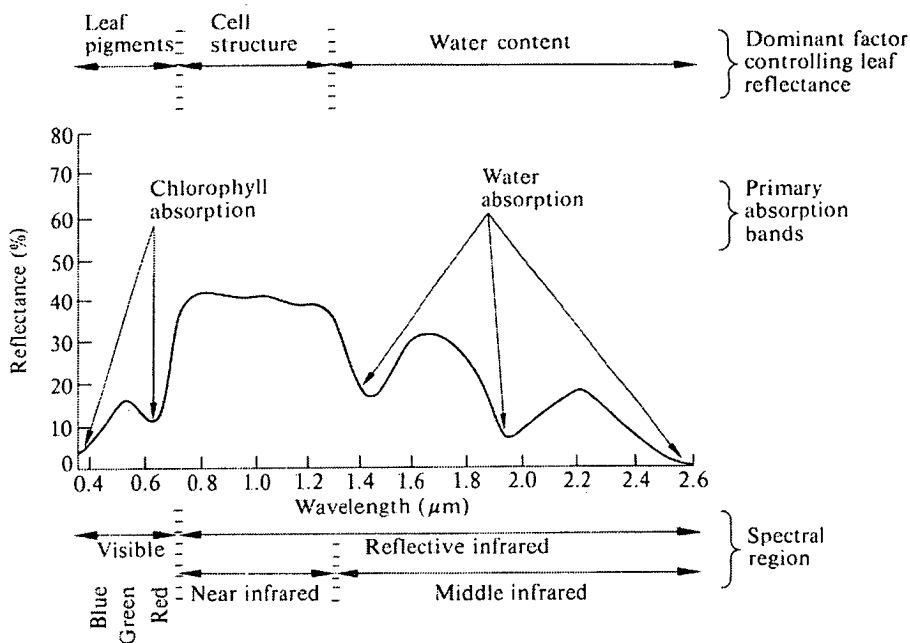


Figure 5.3: Spectral Response Pattern of Green Vegetation (Source: Hoffer 1978)

In the visible portion of the spectrum, peaks and valleys can be attributed to the strong reflection by plant pigments of green light ($0.54 \mu m$) and their strong absorption of red and blue light ($0.45 \mu m$ to $0.65 \mu m$). This reflectance by chlorophyll of green light lends to vegetation its green appearance. However, if chlorophyll production is affected in some way due to disease or stress, there will be less green reflectance and proportionately greater absorption of red and blue light, with the consequence that vegetation will appear yellow. Healthy vegetation reflects light strongly in the near-infrared portion of the spectrum, between $0.7 \mu m$ and $1.3 \mu m$ (Landgrebe 1978a; Howard 1991; Lillesand & Kiefer 1979). Given the high variability that exists in plant structure, the reflected IR portion of the spectrum can reveal important information about vegetative species and condition (e.g. senescence and stress). Appropriately, this region of the EM spectrum is often used for forest classification and stress detection

studies (Howard 1991).

After 1.3 μm , the spectral reflectance of vegetation varies according to the amount of water contained in the leaves. The higher the water content, the thicker the leaf, and the less reflection and more absorption of EMR. Reflectance peaks around 1.6 μm and 2.2 μm . Absorption is greatest in the region known as the 'water absorption bands', lying between 1.4 μm and 1.9 μm , and further, at 2.7 μm . Mature and diseased trees will reflect more EMR in these regions than will younger vegetation due to their lower leaf water content. This middle infrared portion is also useful for detecting the age and stress of vegetation (Landgrebe 1978a; Howard 1991).

As noted, within this overall response pattern characteristic of healthy vegetation, individual species or vegetative conditions will elicit distinctive response patterns that will identify them as such. However, in practice, the differentiation of such fine classifications of vegetation can be difficult. Factors affecting vegetative reflectance include but are not limited to: geographical area, weather conditions at the time of recording, soil texture and composition, density of canopy, size and age class of tree, angle of incident radiation, precipitation patterns, seasonal factors and farming practices (Landgrebe 1978a; Garcia & Alvarez 1994). These variations often make it difficult to identify forest species (e.g. deciduous vs. coniferous trees) and condition (e.g. diseased vs. healthy trees) on images. For this reason, extensive knowledge of the study area is usually necessary if species are to be identified accurately and their conditions assessed (Lillesand & Kiefer 1979).

5.2 MSS Landsat Data

Most remote sensing systems in use today are satellite scanner systems. At their most basic level, these scanners work by moving across the landscape in a series of parallel lines across, recording the intensity of the electromagnetic radiation they receive (Sabins 1997; Lillesand & Kiefer 1979).

The data for this study, which is discussed in greater detail in the next section, were acquired by the Landsat program, an unmanned satellite system launched by NASA in the early 1970s. These satellites carried an imaging scanner known as the Multispectral Scanner System (MSS). This scanner was capable of recording energy simultaneously in the bandwidths, 0.3 μm to 0.14 μm (Sabins 1997; USGS 1998).

Initially named ERTS-A, Landsat 1 was launched in 1972 and ceased functioning 5 years later. Landsat 2 was launched in 1978 and decommissioned in 1982. Landsat 3 had a slightly longer life-span, operating from 1978 to 1983. The second generation of satellites, Landsats 4 and 5, were launched in 1982 and 1984, respectively. In addition to the Multispectral Scanner, these satellites also carried the Thematic Mapper (TM), a higher resolution scanner. Landsat 4 is no longer in operation, and Landsat 5 will be decommissioned in the near future. Landsat 6 failed to achieve orbit in 1993, and Landsat 7 was launched in 1998. MSS data were collected up until 1992 (USGS 1998).

NASA relinquished responsibility for operating the Landsat program in 1983, when it was transferred to EOSAT (Earth Observation Satellite Co.). TM data more than 10 years old and all MSS data up to 1992 are housed at the U.S. Department of the Interior's USGS (U.S. Geological Services). Responsibility for management and dissemination of the data rests with the EROS (Earth Resources Observation Service) Data Center at the USGS (USGS 1998).

All the Landsat satellites have followed the same orbital or sun-synchronous path.¹ Consistent with all Landsat platforms, the MSS, which is no longer functioning, operated at an altitude of 705 km and made 14.5 orbits a day, recording data over a 185 km swath. It covered the earth in 233 orbits, and had a repeat cycle of every 16 days (USGS 1998).

The satellite has a spatial resolution of 82 m x 82 m. However, information is recorded in a series of 68 m x 82 m cells, resulting in a nominal pixel spacing of 68 m x 82 m. (Note, however, that each pixel value is based on the average of brightness values in an 82 m x 82 m area on the ground) (Lillesand & Kiefer 1979; USGS 1998).

As it moved along the landscape, the scanner recorded the amount of energy detected in each part of the electromagnetic spectrum in 4 bandwidths. The four EMR bands, which comprise the spectral range of the MSS data set are:

- a) Band 1 (Green): 0.50-0.60 μm

¹A sun-synchronous orbit means that the satellite follows the sun's westward path as the earth rotates each day. Accordingly, the satellite always crosses the equator at the same local sun time each day. This orbital pattern facilitates the comparison of images between different time periods since it means that similar illumination conditions will exist when the satellite passes over the same location at the same time in the future. Note, however, that it cannot adjust for changes in solar altitude, azimuth or intensity, which are not constant and change from one location and season to the next (Lillesand & Kieffer).

- b) Band 2 (Red): 0.60-0.70 μm
- c) Band 3 (Reflective Infrared): 0.70-0.80 μm
- d) Band 4 (Reflective Infrared): 0.80-1.10 μm

As the satellite moved along its north-south trajectory, the scanner moved in a west-east direction, recording information in each of these 4 bandwidths. The resulting four images consists of approximately 3,250 scan lines (rows) with about 3,800 pixels per line (columns). Thus, each image data set contains over 12 million pixels per band for each of 4 spectral bands, or more than 48 million pixels. Figure 5.4 depicts a typical MSS scanning arrangement.

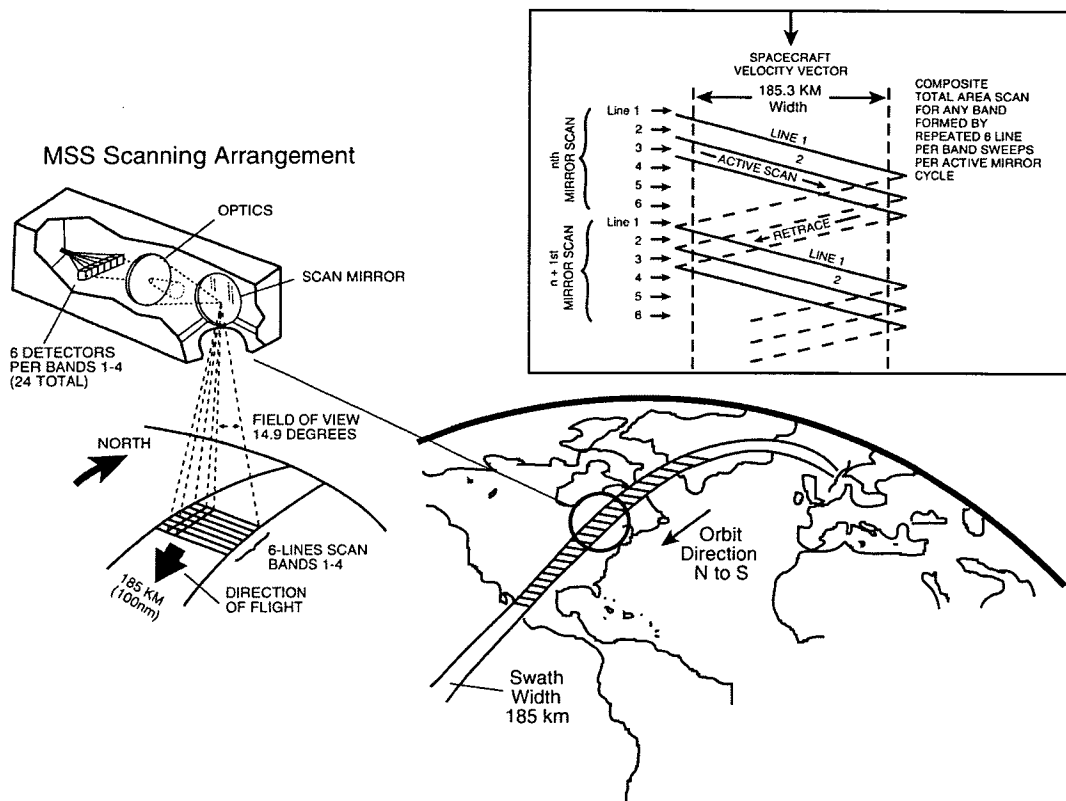


Figure 5.4: The Landsat MSS (Source: USGS 1998)

Pixels in each image are identified by their geographical (x,y) coordinates. In addition, each pixel records spectral information about the physical terrain (z-axis). These digital numbers (DNs) are represented on a computer display defined by a bit range (e.g. 0-255 for 8-bit data). The higher the DN, the stronger reflection (intensity) of energy recorded in that band (ERDAS 1995).

Resolution of the image data can be expressed in terms of the: bandwidth range

(spectral resolution); ground measure to which each pixel corresponds (spatial resolution); and brightness value range (radiometric resolution) (ERDAS 1995).

Figure 5.5 provides pictorial meaning to these concepts as they relate to MSS data:

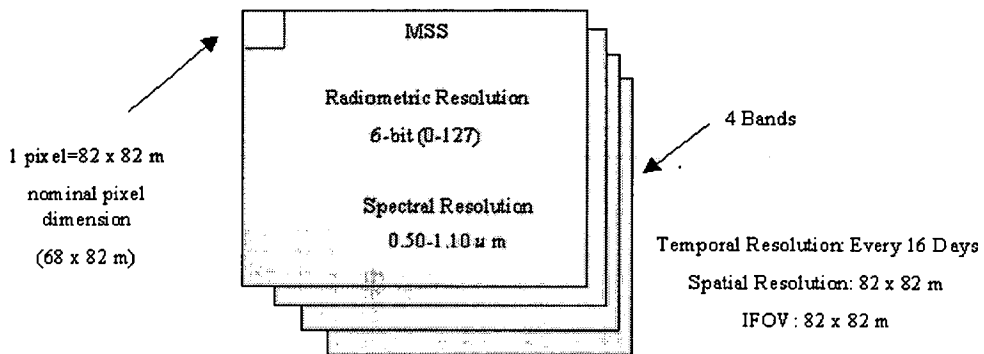


Figure 5.5: The Nature & Structure of Landsat MSS Data (Adopted from ERDAS 1995)

5.2.1 Satellite Data Source & Description

Data was purchased from the USGS' EROS Data Center for two years, 1987 and 1992. Two scenes in each time period make up the island. Full coverage of the island in each year was originally spread over four separate images which overlapped quite considerably between consecutive centerpoints on the same path. Images for 1987 and 1992 were acquired by Landsats 5 and 4, respectively.

Images are referenced according to satellite path (southbound portion of the orbital path) and row (the latitudinal center of the scene) (USGS 1998). It is possible to shift parts of images with the same centerpoint, path and acquisition date (after 1981 only) along the path to incorporate portions of adjacent scenes. In this study, northern centerpoints for each set of image scenes were shifted southward by 50% for both periods. Thus, it was possible to purchase two scene-shift products at half the price of a standard scene, thereby reducing the original set of images required for both periods from 8 to 4. The total price for the two standard scenes and their corresponding scene-shift products was US\$ 800.00 (i.e. 2(\$200) + 2(\$200)).

Image data are stored in CD-ROM and are in BSQ (Band Sequential Format). Each CD-ROM consists of a header file and four consecutive image files followed by a trailer file (8 image files (4 x 2 CD-ROMs) make up an entire island scene for each year)). Data are stored in left to right, top to bottom row order (USGS 1998).

5.2.2 Considerations in the Selection of the Data

Ideally, a forest change study should employ as long a temporal window as possible. What may amount to an imperceptible 'nibbling away' of vegetation at the forest margin in one year will eventually manifest itself in a wholesale loss of forest cover in X years time. Even when the loss is more dramatic, increasing the number of years in a study will increase the reliability of estimates.

However, the real world constraints of empirical research often necessitate that researchers make trade-offs, and this study is no exception. There is little doubt that satellite remote sensing imagery provides an important development in the monitoring of tropical deforestation. However, the use of such imagery is not without its drawbacks.

A significant drawback is the prohibitive cost of the data. As mentioned, EOSAT holds exclusive rights to sell all Landsat data less than 10 years old. Prices for 1997 TM data, with its higher ground resolution, were US\$ 4,400 per scene for system-corrected digital data. Obtaining TM data for two points in time between 1982 and 1998 (the longest period for which data are available) would have raised the cost of the study to a minimum, US\$ 17,600 (assuming a similar scene-shift product was available).

Another alternative would have been to combine the MSS data with the more recent TM data, but this too proved to be too expensive. A third route would have been to purchase archived TM data at US\$ 440.00 per scene (slight more than double the price of the MSS archival data). However, older TM data (10 years or more) is available only at archival prices, and its use would have reduced the study's temporal window from 6 to 4 years. Other data, for example, SPOT and aerial photographs would have cost even more than the full-priced TM data.

The least expensive satellite data, AVHRR data, has also been used for monitoring forest cover change in tropical areas (Mayaux et al. 1998). It has the advantage of a short revisit period (twice daily), which increases the likelihood of obtaining good quality, cloud-free images. However, the sensor's 4 km (and more recently, 1 km) resolution makes it unsuitable for deriving forest estimates for an island as small as Jamaica.

Another important factor affecting choice of data set was quality. Atmospheric problems are particularly prevalent in remote sensing studies of the tropics where cloud-cover and smoke often occlude the atmosphere. This reduces the availability of good

quality images.

Although Landsat MSS images are available for as far back as 1972, the quality of most of them is poor. Good quality scenes for a part of the island were often available in one year but not another. For these early images, there was not enough repetitive coverage to avoid defects. Luckily for this study, however, improvements in Landsat scanners over the years have resulted in the production of successively better images.

Yet, the quality of even these later MSS images is also highly variable, with cloud cover being the main problem in most years. Despite the substantial number of images in the USGS archives, finding relatively cloud-free images proved to be difficult. Heavy clouds not only reduced the period of coverage *across* the years but *within* each year as well, with the consequence that there are gaps in monthly coverage between each image representing either side of the island. The need to ensure a minimum level of cloud cover necessitated choosing images within each year that were acquired 2 months apart in the case of the 1987 image set and 6 months apart in the case of the 1992 image data set. (Recall that it requires two images in each year to form one complete picture of the island).²

However, this monthly or seasonal variation poses less of a problem for an analysis of forest change in Jamaica than for a study in the temperate zone further north. The main reason is that factors affecting leaf abscission and senescence in tropical forests do not vary significantly from season to season (Longman & Jenik 1987). Thus, while drier regions of scrub forest and the wetter montane forest regions of the island will have completely different microclimates and soil characteristics, these will tend to remain fairly constant.

Another critical issue in the selection of the data was whether to focus on the entire island or just a small part of it. Certainly, it would have been cheaper to measure only one scene for two corresponding points in time (i.e. to study only one part of the island), thereby extending the analysis by several years. However, this route was rejected since it would have resulted in the loss of potentially important island-wide forest cover variation and would have reduced the overall number of sample points for the statistical analysis accordingly. Thus, the choice of data set reduced to one of

²The earliest image of the eastern portion of the island was acquired in 09/09/87, and the latest, in 03/22/92. The earliest western portion of the island was acquired in 07/14/87 and the latest in 09/05/92.

obtaining the best quality data at the lowest price for as many years and as much of the island as possible. Working within these parameters meant trading off resolution and coverage to a certain extent against cost and quality.

In light of the above constraints, only MSS data for which a scene-shift product was available and for which the classifications 'defect free', best quality (1) and cloud cover 0 (0-10%) were applicable were chosen. The higher quality of the data meant that the lower spectral resolution of the MSS data could be compensated for partly by the better clarity of the images. Likewise, the purchase of a scene-shift product circumvented cost constraints imposed by the full set of standard images while allowing for the broadest possible geographical coverage.

5.3 MSS Applications to Forest Resources in the Tropics

Landsat MSS data have been used extensively for monitoring forest cover in the tropics (see, for example, Williams & Miller 1979; Adenyi 1985; Fearnside 1986; Nelson et al. 1987; Gilruth et al. 1990; Skole & Tucker 1993; Jha and Unni 1994; Tuomisto et al. 1994; Garcia & Alvarez 1994; Laba et al. 1997). The use of MSS data to study forest change has proved particularly useful when simple classifications of forest vs. non-forest are made (Tuomisto et al. 1994; Williams & Miller 1979). Generally, the discernment of fine detail required for such studies is only possible when forests cover extensive areas.

Furthermore, MSS data can provide an invaluable 'snapshot' of the extent and process of forest change in an area, prior to carrying out more intensive field surveys and detailed classifications (Howard 1991). In this respect, it has proved particularly useful for detecting forest patterns in relatively large and/or unsurveyed areas and for calibrating existing data (Tuomisto et al. 1994). Results from a variety of studies suggest that MSS provides a good national level resolution (e.g. scales of 1:200,000-250,000) (Sader et al. 1990; Sabins 1997). The use of MSS data has also provided fruitful results in assessments of carbon dioxide, temperature flux, and biodiversity (Foody and Hill 1996).

However, due to its limited spectral and spatial range MSS data has had less success in fine classification assessments (Tuomisto et al. 1994). Its limited resolution, in particular, makes it difficult to pick up slight reflectance differences, which is necessary

for determining species type and condition.

5.3.1 Strategy for Overcoming MSS Data Limitations

Since this study is concerned with deforestation rather than the discrimination of forest classes *per se*, it follows other remote sensing investigations in subsuming all forest species and conditions under one single class: forest. Where timely inventory data are unavailable as they are in Jamaica, this is a justifiable strategy. In Jamaica, where the last comprehensive forest inventory was undertaken more than 25 years ago, current information on the island's remaining forest species is non-existent.³

It is also justifiable when one considers the size of Jamaica and the largely relict nature of its forest cover. In comparison to broad classifications (e.g. forest vs. water), the identification of species depends to a far greater extent on the existence of strong contrasts between one species and another (Tuomisto et al. 1994). Likewise, accurate species identification depends significantly on the diversity of factors that can affect forest spectral response patterns (e.g. seasonal differences, topography, soil class, etc.). This information is particularly difficult to discern on images representing small tropical islands, with their complex, highly interdependent and heterogeneous landscapes (Laba et al. 1997). Not surprisingly, in these kind of classifications, ground knowledge becomes exceedingly important, but is difficult to achieve at the country level and/or when appropriate biogeographical data are lacking. Generally, classification accuracy declines as more classes are included in an analysis or as finer gradations in object features are made, since the probability that pixels may be misclassified increases as the differences between classes decreases (Tuomisto et al. 1994).

In short, the level of detail required to discern even a few species — as opposed to simply standing forest — is very high and dependent on prior knowledge of the study site. This knowledge was not available in this study and could not be obtained from any existing sources. Extensive, time-consuming and expensive field survey work would have been required to obtain such information for even a small part of the island. By restricting itself to a simple forest/non-forest discrimination, the study has purposely kept the required level of classification detail low so as to raise the probability of

³To quote one forestry official, who wishes to remain anonymous, "We have no idea of what's growing where, anywhere on the island" (personal communication, February 1997).

obtaining greater accuracy in the classification.

Forest cover is broadly interpreted in this study to mean any type of woody cover and includes closed and open forests and plantations. This general definition is well-suited for the purposes of the socio-economic analysis of this thesis (see Chapters 8, 9 and 10). Indeed, as Allen & Barnes 1985 observe, all such forests (and the land beneath them) have value from the point of view of the poor.

Chapter 6

Image Processing Methodology

(A): Image Restoration & Enhancement

This chapter and the next are devoted to what is commonly referred to as the image processing portion of an environmental change analysis. Both chapters provide detailed descriptions of the methodology used to prepare the images for the data extraction stage, which is commonly handled in a GIS (geographical information system). This chapter details the steps involved in the restoration and enhancement of the images. Chapter 7 describes the selection of signatures and classification of images. Once the data has been extracted, the extent of and change in forest cover can be calculated, as in Chapter 8.

Image display, choice of band selection and processing of the bands were all accomplished in IDRISI (Version 2), a combined image processing and GIS software program.

6.1 Selection of Bands

As discussed previously, every land cover feature will elicit distinctive responses in each portion of the electromagnetic spectrum. Differences in feature intensity response both within and between wavelength bands provide useful information about the characteristics of the remotely sensed area. For example, water (e.g. clouds and lakes) elicits high reflectance in Band 1 but considerably less reflectance in Band 4, whereas vegeta-

tion elicits the opposite pattern. Thus, a study wishing to delineate forests from water should not discard Band 4 in favour of Band 1. Moreover, careful choice of bands also helps to minimize the effects on landscape features of interest from reflectance by other objects (e.g. the effects of soil reflection on forest cover) and ensures that a full range of feature spectral responses is included in the study. (Hoffer 1978; Curran 1985).

Typically, then, the unique spectral responses of features in various spectra and under various conditions (e.g. forests in wet dark soils) will dictate that more than one band be used in an analysis. However, it is worth stressing that increasing the number of bands in a study will not necessarily increase the amount of meaningful information available to the researcher. Indeed, the greater the number of bands, the greater the possibility that important information will be lost to the analysis due to its being obscured by information contained in other bands (Lillesand & Kiefer 1979). At the same time, however, parsimonious use of computing time and resources usually dictates that as few bands as possible be used, preferably weakly correlated bands (Curran 1985).

In light of the above remarks, the question in band selection thus becomes one of: a) carefully selecting the right bands so as to maximize the information available in the study; and b) using the minimum number of bands necessary to achieve this goal (Lillesand & Kiefer 1979; Landgrebe 1978a).

With respect to point a) above, MSS-based investigations of tropical forest change have had good success with Bands 2 and 4 (see, for instance, Sader et al 1990; Boonyobhas et al. 1977). This finding is not surprising in view of the distinctive reflectance properties of forest vegetation described earlier. This information (together with the results from the correlation matrix described in this chapter) suggests that for a forest change analysis such as this one, bands 2 and 4 are good choices.

The suitability of bands 2 and 4 for this study was also reinforced by experimentation with a large number of band combinations in the hybrid unsupervised/supervised classification (described in Chapter 7). That is, bands 2 and 4 (and a vegetative index based on these bands discussed in 6.1.2) consistently provided the most spectral variability and classification meaning, based on personal knowledge of the island, detailed ordnance survey maps and scientific and documentary reports. This combination of 2,4-bands was used at all stages of the image processing and GIS portions of the study,

from image rectification to classification.¹

Black and white images of bands 2 and 4 for both eastern and western sections of the island are presented in Appendix A for both years of the study, 1987 and 1992.

6.1.1 Data Reduction

Data reduction, or point b) above, can be achieved by the use of a linear transformation procedure which is common in remote sensing studies, known as principal components analysis (PCA). PCA analysis is a multivariate statistical technique that reduces the complexity of a large data set to its various components (in the remote sensing context, new images) and then orders them according to the degree of variance explained by each. Typically, the first two to three components will explain the largest amount of the variance in the data and each successive component (which tends to be noise) progressively less of the variance.

¹Experimentation with a large combination of bands and their transformations (i.e. reverse transformed bands, ratioed bands and vegetative indices) consistently demonstrated that neither of these options performed as well as the 2, 4 bands and the normalized differenced vegetation index based on these bands. Results for these other band combinations, however, are available on request.

<i>Table 6.1: PCA Results</i>				
<i>Component</i>	<i>C1</i>	<i>C2</i>	<i>C3</i>	<i>C4</i>
<i>Loading</i>				
Eastern Jamaica 1992 Band 1	0.91	-0.41	-0.10	0.02
Eastern Jamaica 1992 Band 2	0.94	-0.31	0.14	0.00
Eastern Jamaica 1992 Band 3	0.98	0.19	-0.02	-0.07
Eastern Jamaica 1992 Band 4	0.96	0.29	0.00	0.08
<i>% Variance Explained</i>	90.48	8.53	0.62	0.37
<i>Loading</i>				
Western Jamaica 1992 Band 1	0.93	-0.36	0.01	-0.09
Western Jamaica 1992 Band 2	0.93	-0.36	0.01	0.09
Western Jamaica 1992 Band 3	0.98	0.20	-0.07	0.00
Western Jamaica 1992 Band 4	0.94	0.33	0.08	0.00
<i>% Variance Explained</i>	89.88	9.47	0.34	0.32
<i>Loading</i>				
Eastern Jamaica 1987 Band 1	0.96	-0.24	0.07	0.00
Eastern Jamaica 1987 Band 2	0.97	-0.24	-0.07	0.00
Eastern Jamaica 1987 Band 3	0.98	0.18	0.00	-0.06
Eastern Jamaica 1987 Band 4	0.96	0.28	-0.00	0.06
<i>% Variance Explained</i>	93.96	5.62	0.24	0.19
<i>Loading</i>				
Western Jamaica 1987 Band 1	0.89	-0.44	-0.08	0.08
Western Jamaica 1987 Band 2	0.89	-0.44	0.08	0.01
Western Jamaica 1987 Band 3	0.98	0.18	-0.00	-0.05
Western Jamaica 1987 Band 4	0.96	0.28	0.00	0.04
<i>% Variance Explained</i>	88.76	10.88	0.22	0.14

In Table 6.1, for example, C1, C2, C3 and C4 refer to the new component files produced by this transformation. The loadings refer to the degree of correlation between the new component (columns) and the original band (rows). The row labelled, *% Variance Explained* refers to eigenvalues expressing the variance explained by each component. In the case of Band 1 for Eastern Jamaica in 1992, for example, C1

(component 1) explains 90.48% of the variance in the original band.

<i>Table 6.2: Band Correlation Matrix</i>				
<i>Correlation Matrix: Eastern Jamaica 1992</i>	<i>Band 1</i>	<i>Band 2</i>	<i>Band 3</i>	<i>Band 4</i>
Band 1	1.00	0.96	0.81	0.75
Band 2	0.96	1.00	0.86	0.81
Band 3	0.82	0.86	1.00	0.98
Band 4	0.75	0.81	0.98	1.00
<i>Correlation Matrix: Western Jamaica 1992</i>	<i>Band 1</i>	<i>Band 2</i>	<i>Band 3</i>	<i>Band 4</i>
Band 1	1.00	0.98	0.84	0.75
Band 2	0.98	1.00	0.84	0.76
Band 3	0.84	0.84	1.00	0.98
Band 4	0.75	0.76	0.99	1.00
<i>Correlation Matrix: Eastern Jamaica 1987</i>	<i>Band 1</i>	<i>Band 2</i>	<i>Band 3</i>	<i>Band 4</i>
Band 1	1.00	0.99	0.90	0.85
Band 2	0.99	1.00	0.91	0.86
Band 3	0.90	0.91	1.00	0.99
Band 4	0.85	0.86	0.99	1.00
<i>Correlation Matrix: Western Jamaica 1987</i>	<i>Band 1</i>	<i>Band 2</i>	<i>Band 3</i>	<i>Band 4</i>
Band 1	1.00	0.99	0.79	0.72
Band 2	0.99	1.00	0.80	0.73
Band 3	0.79	0.80	1.00	0.99
Band 4	0.72	0.73	0.99	1.00

PCA also produces a correlation matrix for the original bands as part of its output, presented in Table 6.2. This matrix gives an indication of the degree of intra-band correlation present in the image data set and thus can be used to determine which bands to drop from the analysis (Eastman 1997). Correlation results in Table 6.2. for each of the four bands comprising each of the 4 image data sets, suggest that

Bands 1 and 2 are highly correlated with each other (i.e. represent essentially the same information), as are Bands 3 and 4.

It is not uncommon for researchers to work principally from the components themselves (e.g. C1 and C2) since the first one or two contain most of the information in the data set minus the noise. However, this study chose to work from the original bands for two reasons: Since the classification of land use features is based on the development of signatures for each land use class, it was necessary to ensure that these individual properties were not lost. (Principal component bands explain the varying patterns in the band, and each original band contains the original reflectance data). Second, the cluster module in IDRISI, which is required for the unsupervised classification (described in Chapter 7), uses a 3-colour composite image. However, as Table 6.1 indicates, the third component band of the PCA analysis performed on each of the 4 original images explains less than .05% of the variance in the original bands. Since the cluster module weights the three bands comprising the false colour composite equally, it is possible that essential information contained in the other components will be ‘drowned out’ by the noise largely comprising this third component (Eastman 1997).

6.1.2 The Creation of a Vegetation Index

A number of vegetation indices (VI models) have been developed in the remote sensing literature. These models exploit the properties of healthy vegetation to absorb and reflect low amounts of electromagnetic radiation in the red and high amounts in the infrared portions of the spectrum. They can be created by either: ratioing the bands, linearly transforming the bands, or calculating the difference of pixel values from a soil line (Eastman 1996). Despite their different approaches, all these procedures work by differentiating vegetation from background noise (e.g. soil reflectance) in these bands (Eastman 1997).

Results from the hybrid unsupervised/supervised classification indicate that of all the methods tested, the normalized difference vegetation index (NDVI) performed best. This index, in other words, had the highest overall accuracy and spectral variability of any index in comparison to the reference data.

The normalized difference vegetation index (NDVI) is given by:

$$\frac{NIR - RED}{NIR + RED}$$

As is clear from this expression, the index is obtained by dividing the difference between the NIR (Band 4) and RED (Band 2) bands by the normalized sum of those bands:

$$\frac{\textit{Band 4} - \textit{Band 2}}{\textit{Band 4} + \textit{Band 2}}$$

Ratioing of the red and near-infrared bands negates the multiplicative errors that act uniformly in all bands but not the additive or random errors (Singh 1989). To avoid division by zero and limit the value range, the bands are normalized (Eastman 1997). The concept of band ratioing is elaborated in greater detail in the context of the discussion on topographic effects in Section 6.2.1.

6.2 Image Rectification

After the data have been imported and the number and type of bands have been selected, a typical satellite image processing project will follow several steps: a) image restoration (rectification); b) image enhancement; d) image interpretation; and e) image resampling (Sabins 1997). The extraction and manipulation of the resulting image data is treated in detail in Chapter 7, in the context of the use of GIS in the analysis.

Rectification constitutes an important initial stage in any image processing project. Image rectification involves the removal of distortions caused by such factors as: the curvature and rotation of the earth in relation to the sensor platform, atmospheric scattering and random perturbations in the sensor (Curran 1985; Sabins 1997). This stage ensures that the images reflect (as much as possible) the original spectral and geometric properties of the landscape (Sabins 1997).

Two types of distortions that the researcher must address at this stage are: a) radiometric distortions and b) geometric distortions. Radiometric distortions express themselves as changes to the original scene pixel values. Geometric distortions introduce spatial irregularities into the data such that the images do not geographically describe the landscape that they depict (Sabins 1997; Lillesand & Kiefer 1979).

6.2.1 Radiometric Restoration

Many nonrandom radiometric distortions are typically corrected for prior to the release of the data. Radiometric distortions can arise when one of the scanner's detectors

fails completely or is disproportionately brighter or darker than the others, resulting in large alternating stripes or bands across the images (Sabins 1997). Essentially, these are corrected for by replacing the values of the affected lines with those of adjacent good lines or by calculating average brightness values for affected areas (Sabins 1997). Fortunately, radiometric distortions of this kind were not a problem with this study's images since only the highest quality data were purchased.

Other radiometric distortions, which are not related to intrinsic failures in the scanner and therefore are non-systematic and non-uniform, are not regularly corrected for prior to the release of data (Sabins 1997; Lillesand & Kiefer 1979). One common radiometric problem that can affect images is the scattering of light from atmospheric haze, which lends to images an opaque quality that makes it difficult to discern landscape features or derive meaningful information from the images (Sabins 1997). Haze was not a problem with the images in this study; however, another atmospheric problem — cloud cover — does obscure parts of the island in all years. One procedure often used for the reduction of haze on images — known as 'reverse transformation' — has shown some success in reducing peripheral cloud cover in images (Eastman 1997). Essentially this procedure involves taking the first two to three components in a principal components analysis and 're-assembling' them to produce the original bands minus the haze and other types of noise such as cloud cover (Eastman 1997).

In an attempt to reduce cloud cover, this study used the row eigenvectors reported in Table 6.1 to transform the first two component images produced through PCA of Bands 2 and 4 back into their corresponding bands. In the case of Band 2, for instance, this meant multiplying the 1st component image by 0.94 and the 2nd component image by -0.31 and then summing the weighted components together using IDRISI's image calculator. Like most transformation procedures, the success of the reverse transformation procedure for cloud reduction can only be determined on a 'try it and see' basis. In this study, the procedure had no effect in reducing cloud cover as hoped.

Dealing with Cloud Cover and Topographic Differences

Unfortunately, cloud cover is a problem that plagues most satellite images of the tropics and is not unique to this study despite the fact that only high quality data with a minimum of cloud cover was purchased. Cloud cover is a particular problem on the

images representing the eastern portion of the island in 1987 and 1992 (see Appendix A). This study treats cloud cover as a given feature of the landscape. It assumes that deforestation patterns in clouded areas are the same as in non-clouded areas. Thus, if it is calculated that a constituency has 70% of its unclouded areas in forest, this figure is assigned as the forest cover estimate for that particular constituency.

Topographic features of the landscape will naturally reflect sunlight in different ways, thereby creating differences in light and shadow across the landscape that can artificially affect brightness values (Eastman 1997). These differences can be particularly acute in very mountainous areas, such as the eastern portion of Jamaica, and will vary according to the time of day.

One common way of compensating for differential illumination of the landscape is to ratio bands. This ratioing effect was described in the context of the creation of a vegetation index above, for which it is also commonly used. As discussed, the basic idea behind band ratioing is that every image will contain multiplicative errors (in this case, solar angle effects arising from topographic differences in the landscape) that can be negated by dividing one band by another. More formally,

If

a) O_1 and O_2 = Observed spectral values of the landscape (i.e. Bands 1 and 2), respectively

and

b) T_1 and T_2 = True spectral values of the landscape in Bands 1 and 2, respectively

and

c) e = the error (in this case, sun angular effects),

Then

$$O_1 = T_1 e$$

$$O_2 = T_2 e$$

Hence

$$\frac{O_1 - O_2}{O_1 + O_2} = \frac{T_1 e - T_2 e}{T_1 e + T_2 e} = \frac{T_1 - T_2}{T_1 + T_2}$$

Adjustment for Solar Angle Illumination

One radiometric problem with important implications for this study, is the radiometric differences introduced into images as a result of differences in the angle of the sun relative to the earth at different times of the year. Differences in solar illumination posed a potential problem in this study since the images acquired within each year were obtained at slightly different times and thus different solar angles. This difference was particularly great in the case of the 1987 data set. Accordingly, corrections for solar angle illumination were made for each image by following the procedure outlined in Eastman 1997. Specifically, this involved dividing each pixel by the cosine of the sun's elevation from the zenith or solar angle (θ_0). The solar angle for each image was calculated by subtracting 90° from the sun's elevation. The latter figure was obtained from each image file.

The concept of solar angle is illustrated in Figure 6.1. In this figure solar angle is measured as the angle from z to the position of the sun on the horizon (sun). The more light striking the landscape and the less light scattered and absorbed by the atmosphere the longer this angle, which obviously has implications for the discernment of landscape features.

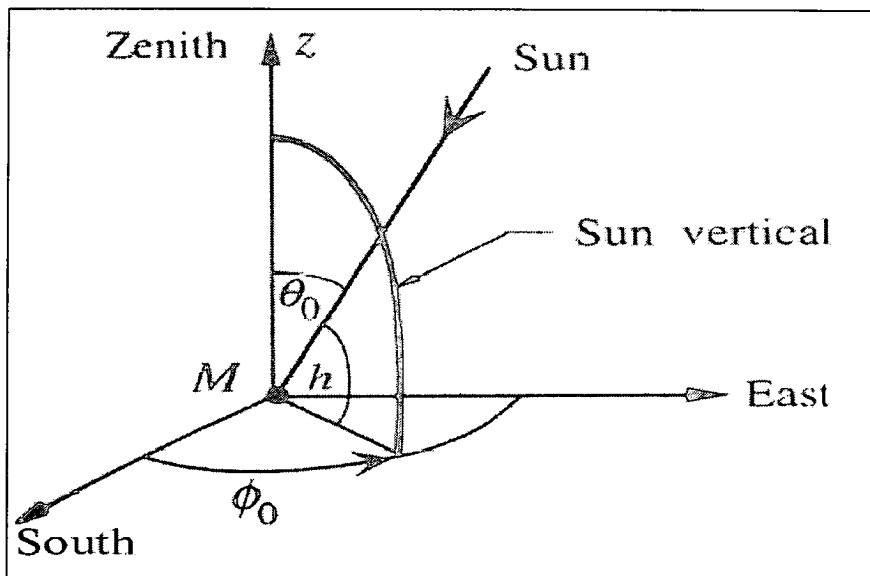


Figure 6.1: Horizontal Coordinates Relative to Sun Angle (Source: Seinfeld & Pandis 1998)

6.2.2 Geometric Restoration

Geometric distortions associated with the collection of data can also be random or systematic (Sabins 1997; Lillesand & Kiefer 1979). As in the case of their radiometric counterparts, system-related distortions are typically corrected for prior to the release of the data. Two of the most important corrections are for ‘scan skew’ and ‘cross-track’ distortions. Scan skew is created by the movement of the scanner mirror as the satellite moves on its orbit. This movement introduces spatial distortions into the images (Sabins 1997). These variations can be easily adjusted for by calculating the deviation in the movement of the scanner mirror from the velocity of the satellite (Sabins 1997). Cross-track distortion lends to images a warped appearance, and arises from differences in the angle at which the scanner records information as it moves along the landscape (Sabins 1997). This distortion can be corrected for by increasing the width of pixels along the margins of the image (Sabins 1997).

Non-systematic distortions are not uniformly corrected for prior to the release of data. Generally these problems arise from differences in the variation and altitude of the scanner (Sabins 1997; Eastman 1997). Their correction requires the identification of ground control points and the calculation of a transformation equation linking these locational points to the image pixel values (Lillesand & Kiefer 1979). Fortunately, these non-systematic geometric differences were not a problem for this study since only data of the highest level of geometric processing was purchased (Level 8).

More information on the processing steps, both radiometric and geometric, for MSS data can be obtained from the USGS’ EROS Data Center web site at *http://edcwww.cr.usgs.gov/glis/hyper/guide/landsat*.

6.3 Image Enhancement

6.3.1 Contrast Stretch & Other Procedures

Enhancement procedures increase the visual contrastability and variation in the image, thereby facilitating the identification of landscape features. Visual enhancement is especially important in this study due to the low contrastability of the original images. Whereas the grey palette in which these images are displayed ranges from 0 (black) to

255 (white)², the minimum and maximum file pixel values of the images themselves range from 0 to 126. Hence since only low end values are used to display these images they look rather dark, making it difficult to discern features.³

Contrast was increased in these images by applying two enhancement processes. The first one, a simple linear stretch, allowed the pixel file values in the images to be displayed using the entire value range of the computer display. More specifically, enhancement was accomplished by a simple linear stretch on Bands 2 and 4 and the NDVI band for both sides of the island for both years. New images were created by linearly scaling values between the 0 and 255 limit. In this enhancement procedure, all pixels with value 0 were assigned the lowest output class (0) while all those equal to 126 were assigned the highest output class (255). All other values were scaled in between (Eastman 1997).

An enhancement of this stretched image was then performed that enabled land cover features to stand out in greater contrast. Examining the tabular output of the histograms for each stretched image band concurrently with the flash freeze option in IDRISI facilitated the identification of minimum/maximum value cut-off points for each image. These cut-off points were chosen individually for each image, and defined the upper and lower pixel image values for all land cover features in the image while excluding those defining cloud and water, which were concentrated at the lowest and the highest portions of the scale.

²The 24-bit computer display used in this study has the capability to display 24 bits per pixel (i.e. 8 bits per each of the three colour guns (RGB) per pixel). Thus, each colour gun has 256 possible brightness values (i.e. 2^8), and each pixel, 2^{24} (16,777,216) possible colours.

³This low contrast is evident to a certain extent in the images presented in Appendix A. However, it should be stressed that the images in this appendix have been "stretched" to varying levels purely for presentational purposes. The original images were significantly darker than these images, and would not have provided the reader with any sense of the landscape scene that they depict.

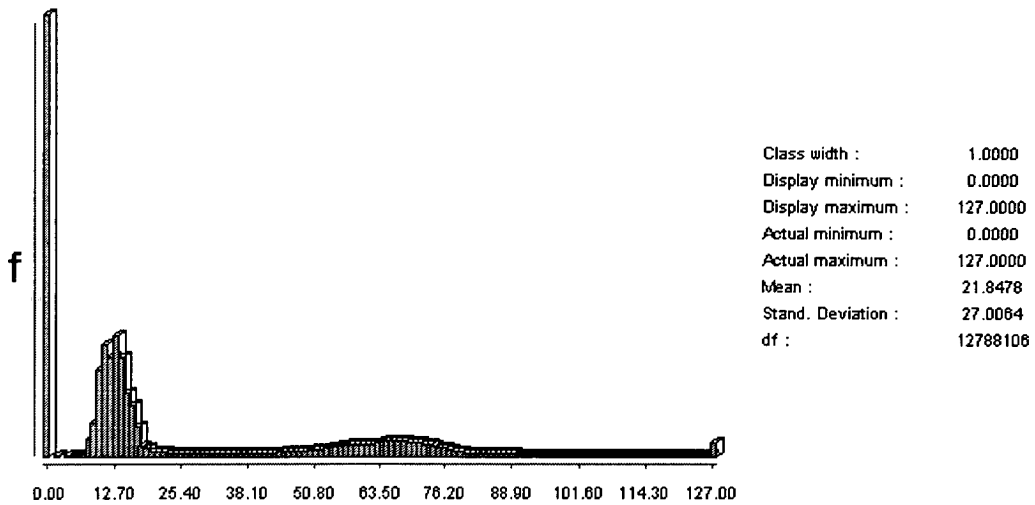


Figure 6.2: Image Histogram, Original Band (Band 4, Jamaica 1987)

Figure 6.2 is a histogram of the original unstretched image of western Jamaica in 1987 (Band 4), which depicts scene values in the range of 0-126, the original radiometric range of values for these images.

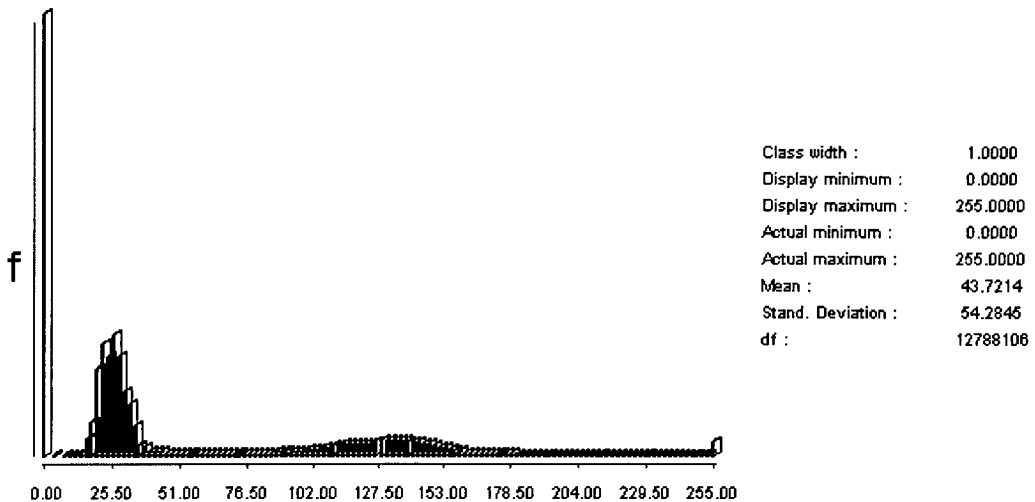


Figure 6.3: Image Histogram, Linear Stretch (Band 4, Jamaica 1987)

Figure 6.3 is a histogram of this image linearly stretched with its pixel values filling all the display values of the computer (0 to 255). However, a large portion of pixels in the image are cloud and water, and are concentrated in the highest and lowest portions of the display range, while landscape features occupy a small clump in the middle portion.

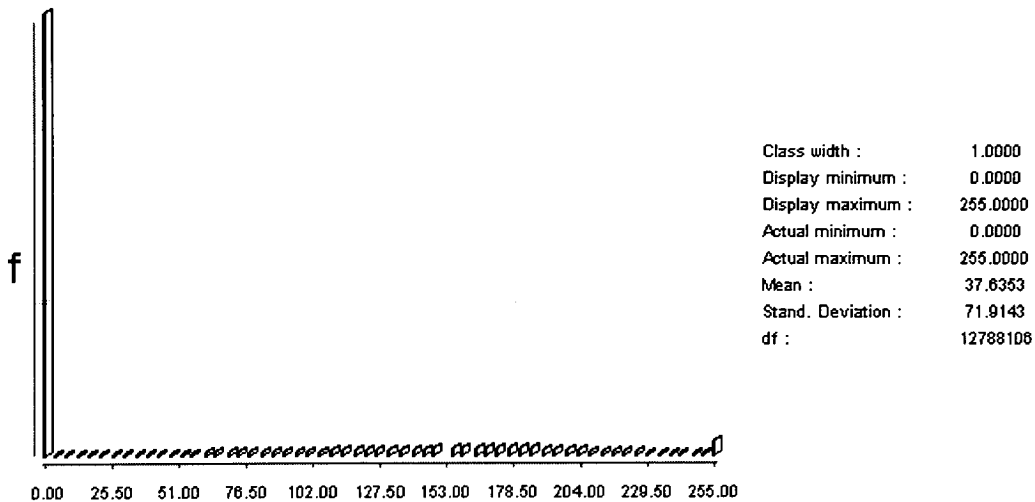


Figure 6.4: Image Histogram, Special Contrast Stretch (Band 4, Jamaica 1987)

Figure 6.4 is a histogram of the above represented image in 6.3, and demonstrates how a special stretch enables the spectral information associated with landscape features to be accentuated at the expense of the cloud/water categories. Specifically, the range of values in-between the minimum and maximum cutoff points (in this case, 58-175) were enhanced by stretching the image out to fill the interval *between but not including* 0 and 255. All values below the 58 cut-off point were assigned the number 0 while values above 175 were assigned the value 255. Thus, the big cluster of pixels in the original stretched image around the interval of 6 to 25, for example, were all assigned the value 0. This clump was identified as deep water, and putting it along with pixels above 175, which also represented various types of water and cloud, is appropriate for a study interested only in landscape features.

Experimentation with other common enhancement techniques did not selectively improve brightness differences in the images to any great degree, and were therefore rejected. Two alternate methods were applied but their results were subsequently discarded: a) a high-pass filter; and b) the transformation of the image bands into their intensity, hue and saturation (IHS) component.⁴

⁴The high pass filter is a local operation that accentuates changes in the landscape by modifying the values of a predetermined set of pixels so as to increase their brightness and darkness values vis-a-vis one another.

The other technique involved the transformation of each band from a BGR into an IHS (intensity, hue and saturation) system. Once the saturation component for each band is obtained, it can be stretched, and recombined with the other components to form a colour composite. This method is useful for

6.3.2 The Creation of False Colour Composites

When more than one band is used it is common practice to combine them to create a colour composite image. In this study, false colour composites for each of the four images in each year were created by assigning the colour blue to Band 2 (the visible green band); the colour green to the NDVI image (difference ratioed bands 2 and 4); and the colour red to Band 4 (the infrared band). When these images are combined together, a new colour image is produced using the red, green and blue colour guns of the display screen. The resulting image is referred to as a 'false' colour composite since it includes portions of the spectrum that lie outside the range of human vision (i.e. visible colour). Appendix B contains a copy of the colour composite image created using the above band combinations (enhanced and adjusted for solar angle) for eastern and western portions of Jamaica in 1987.

6.4 Image Resampling & Projection

6.4.1 The Process of Resampling

Resampling allows two separate images, often acquired by different satellites and on different dates, to share the same column and row number and geographical reference system. Without this essential step, the images remain mismatched, making it impossible to make meaningful geographical comparisons between them (Eastman 1997). Essentially, the resampling process involves the calculation of coefficients that relate one image to another in a transformation equation that describes the relationship between the two images (Lillesand & Kiefer 1979).

Specifically, ground control points (GCPs) are chosen in both images. One image is arbitrarily assigned as the 'master' image to which the other or 'slave' image is georeferenced. GCPs are geographical coordinates that can be discerned quite easily on both images (e.g. airport runways). A correspondence file containing image ground control points or geographical (x,y) coordinates for each image is constructed, and these points then used to calculate coefficients for transformation equations that compute new pixel values for the old or slave image (Lillesand & Kiefer 1979). Several orders of

increasing the saturation in images (Sabins 1997).

transformation equations or mapping functions are possible, but all can be thought of as describing a set of 'directions' about how to move from one image to another. The end result is a new image sharing the same geographical reference system as the one to which it has been resampled. Figure 6.5 provides a pictorial representation of the resampling process. In this figure, the geographical coordinates or reference grid of the old and new images are represented by dotted and solid squares, respectively.

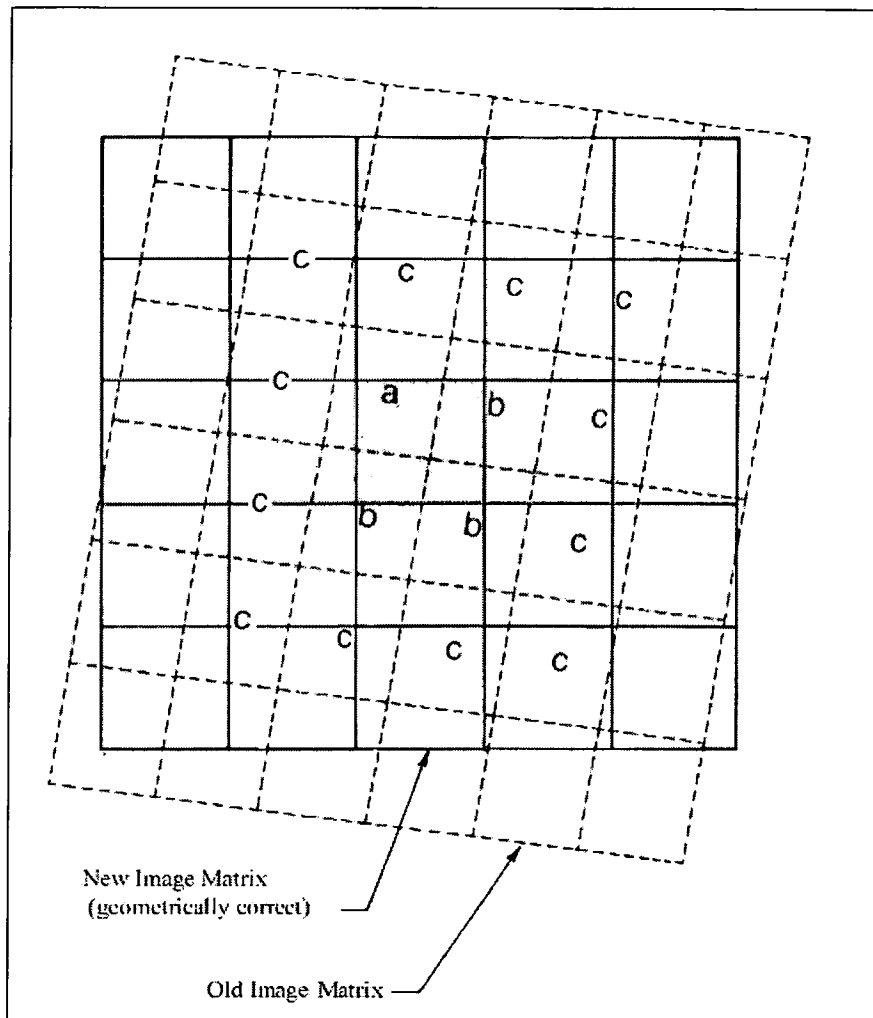


Figure 6.5: The Concept of Resampling (Adopted From Lillesand & Kieffer 1979)

In the above figure, the differences between the old and new pixel values are expressed by the mismatched squares. In the new image coordinate system, pixels may not match up exactly, and the computer must therefore make a decision about which value it should assign to the pixel (Lillesand & Kieffer 1979). These various decisions are expressed by the letters, 'a', 'b', and 'c', above. The simplest way to resample the pixel values is represented by 'a', and is known as nearest-neighbour resampling. This

procedure assigns the pixel the value of the pixel closest to it. The bilinear method, averages the pixel values over a slightly larger area, or 'a', 'b', 'b' and 'b' above. The cubic convolution resampling method averages pixel values over an even greater area, represented as bounded by the 'c's above.

In this study the estimation of pixel values was carried out using the simplest procedure, or nearest neighbour resampling method. Although this method does not produce as smooth an image as higher order transformation methods, it has the advantage over them in that it does not alter the original pixel values (Lillesand & Kiefer 1979). In addition, a linear or first order mapping function was used to calculate the pixel values for the new image. Data used for the resampling procedure were stored in correspondence files containing GCPs for both 1987 and 1992 images. The 1992 slave images were then resampled to the 1987 image coordinates. This process created two new images with the same geographical coordinates and row and column numbers as their respective 1987 images. Despite the fact that a nearest neighbour resampling method was chosen, both of the georeferenced 1992 images were distinguished by their relative smoothness and clarity of appearance.

Although the use of a linear transformation equation requires the least number of control points of the three techniques, far more ground control points were chosen in this study to assure that a good fit was obtained between images. Goodness of fit is expressed by the Root Mean Squared (RMS) error for each transformation (Eastman 1997). These are residuals for each ground control point that express the difference between the slave image GCPs and the master GCPs. In addition, a total RMS error is given for all the points comprising the correspondence file.

Resampling, as it was in this study, is a painstaking procedure; one requiring a large number of iterations before a good RMS is obtained. For most applications, a raster mapping accuracy or RMS of $1/2$ a pixel or less is considered to be an acceptable standard (in this study, $1/2 \times 82 \text{ m} = 41$) (Eastman 1997). This standard was eventually achieved in this study by iterative selection and discarding of ground control points. For the 1992 eastern image, the total RMS eventually achieved was 27.54 meters; and for the 1992 western image, which had less cloud cover overall and was larger and therefore allowed for more opportunities to observe features, the total RMS was 16.31 meters. Correspondence files and residuals for individual ground control points for all

resampling carried out in this study are available in Appendix C.

6.4.2 Image Projection

Resampling produced 2 new georeferenced images with the same ground coordinates and row and column numbers as the 1987 images. However, it did not change the underlying datum of the images. Simply put, a datum refers to the particular reference ellipsoid that is used to describe the shape of the earth at a particular location and relates this smooth ellipsoid to the uneven configuration of the earth. The representation in turn of these three-dimensional, spheroidal coordinates on a one-dimensional image or map, is known as a map projection. All projections of this kind introduce distortion into the map, but the mercator projections, of which the most common is the UTM (Universal Transverse Mercator) are conformal. This means that the distortion is more true to scale and shape of this ellipsoid than others (Sabins 1997).

Images for this study were purchased in the WGS (World Geodetic Survey) datum, which is a global reference surface. However, this datum was different from that of the Jamaica ordnance survey maps used in this study, which were in a North American datum, known as NAD27. Since these maps were an important reference source for the analysis, the datums of the images were changed from WGS84 to NAD27, using the PROJECT module in IDRISI.

The PROJECT module uses well-known ellipsoidal formulas and constants (in this case Molodensky constants) to change from one datum to another. Unlike the resampling procedure described above, a bilinear option was chosen in this study. In addition, the projection was achieved using transformation equations rather than calculating a 'best-fit' formulae (Eastman 1997).

Chapter 7

Image Processing Methodology (B): Signature Development & Image Classification

7.1 Unsupervised & Supervised Classification Procedures: General Remarks

Classification of remotely sensed images marks the stage at which image data recognition takes place (Lillesand & Kiefer 1979; Sabins 1997; Eastman 1997; Swain 1978). At its most basic level, classification is a process of dividing up pixels into various groups or classes according to some information class or other criterion.

Classification procedures fall into two groups: unsupervised and supervised. In the unsupervised classification, the computer unearths the main spectral similarities in the data and groups them accordingly (Lillesand & Kiefer 1979; Eastman 1997). Spectral similarity expresses itself in the measurement space as areas where pixels are densest or occur most frequently.

In contrast, in the supervised classification, the analyst guides (or 'supervises') the classification of pixel values into groups through the use of carefully chosen sample sites that inform the computer what to look for (Lillesand & Kiefer 1979; Swain 1978). Note that unlike the unsupervised classification procedure, which simply groups data according to similar reflectance patterns, the supervised classification produces meaningful categories based on the information that the analyst provides (Eastman 1997).

This information comprises 'training sites' or representative samples of landscape features of interest that are vectorized on screen.

Once these training classes have been selected and vectorized, they are stored in a special file containing their respective pixel values or DNs, and geographical locations. The computer then analyzes these files to develop a statistical characterization (i.e. the mean of reflectance values for each band and the variance/covariance over all the bands) of the pixels in each class (Lillesand & Kiefer 1979). The resulting signature files are then used to classify all the remaining pixels in the image.

Ideally, training sites should be selected from areas of the image known to represent as pure or homogeneous examples of the feature in question as possible (Eastman 1997; Lillesand & Kiefer 1979). In other words, they should represent clearly separable information classes.

In the supervised classification, the analyst can use one of several different procedures for classifying the data. Known as 'classifiers', all these algorithms make a decision about which group a pixel should be assigned to. Weaknesses with these two classifiers (i.e. their insensitivity to variance and correlation)¹ dictated the use of the normal maximum likelihood classifier in this study. This classifier is described in Section 7.2.2 in the context of the discussion of the hybrid unsupervised/supervised classification procedure. (See Lillesand & Kiefer 1979; Eastman 1997; and Swain 1978 for more information on these various classifiers).

Finally, it is worth noting that most classifiers used in environmental changes studies are 'hard' classifiers in that their decision logic categorically specifies whether a given pixel should or should not be included in a particular class (Eastman 1997). In contrast, 'soft' classifiers calculate the probability of a pixel belonging in each particular class

¹The simplest of these classifiers, the Minimum Distance to Means, calculates the distance of each unknown pixel from the calculated mean pixel value for each signature class. The unknown pixel is then assigned to the class that is closest to it in the measurement space. However, this classifier is insensitive to differences in the degree of variance among classes since it characterizes each class in terms of its proximity to this mean spectral value.

The Parallelepiped classifier, in contrast incorporates a sensitivity to differences in variation among classes (usually defined in terms of the highest and lowest DN values in the signature class). However, this classifier, while taking into consideration the variance in pixel values, encounters problems when categories overlap (i.e. the range of one category values extends to the range of another). Overlap in the decision space between information classes arises from the presence of correlation in spectral values between bands, lending to information classes an elongated circular shape. Because this shape is poorly explained by this classifier's rectangular decision space, unknown pixels in the overlap areas will remain unclassified or will be arbitrarily located in either category (Lillesand & Kiefer 1979, ERDAS 1995).

relative to all others, producing not just one image as do the hard classifiers, but a series of images one for each information class with degrees of membership in each class indicated on the image (Eastman 1997).²

7.2 The Hybrid Unsupervised/Supervised Classification

7.2.1 Unsupervised Classification

This study followed a common procedure in many remote sensing applications known as a hybrid unsupervised/supervised classification.

In the first stage of the classification analysis, an unsupervised classification was carried out on the 4 colour composite images using the CLUSTER module in IDRISI. This module uses a “histogram peak cluster technique” to identify areas where pixels are densest (properly speaking the values at the center of a probability density function) (Eastman 1997). After these ‘peaks’ or centers of frequently occurring pixels have been located, the computer iteratively assigns all remaining pixels to their closest group. Each of these group assignments is known as a ‘cluster’. In IDRISI, clusters can be defined by either a fine or a broad clustering rule. The fine cluster option allows for the determination of smaller peaks (and thus, allows for a more detailed segmentation of the data) within larger areas of frequently occurring pixels. The cluster module also allows the analyst to specify the number of clusters and hence the number of peaks to look for. Obviously, the more clusters specified, the more clusters the algorithm will search for (Eastman 1997).

The cluster module often provides valuable information about spectral groupings in the data (Lillesand & Kiefer 1979). Indeed, it was precisely its suitability for unearthing basic land cover features as the first step toward the delineation of informational classes in the supervised classification that motivated the classifier’s use in this study.

A standard cluster routine was followed, as outlined in Eastman (1997):

- 1) The composite image was analyzed using the ‘fine generalization’ and ‘all clusters’ operation.

²Soft classifiers were not an option for this classification. These newly developed algorithms are still in the experimental stage in IDRISI, which may be one reason for why they did not perform well with this data set.

2) A histogram was produced for each image displaying the number or frequency of pixels in each bin.

3) 38 clusters were located in all with the exception of the eastern image of the island in 1987, for which 36 clusters were located.

4) Examination of the histograms for each image indicated that about 1/2 of the clusters contained less than 1% of all pixels. In addition, several large clusters, clearly representing various types of water and cloud, dominated the images.

5) These clusters would be unidentifiable in a study of such broad coverage. The histograms for all four images suggested that the first 20-22 clusters in the image could be retained and the rest discarded.

6) Accordingly, the cluster module was re-run and the first 20-22 clusters in each image extracted.

7) The resulting classified images were displayed and general land cover classes identified by locating their positions using established sources, including a full set of ordnance survey maps of the island produced in the early 1980s, the original black and white colour composite images, and other sources (e.g. written descriptions and personal knowledge of the island). After comparing the classified images with these sources, many land category-type clusters (e.g. cloud) were aggregated into single categories.

Once a broad overview of major land use features was obtained, the identified clusters were used to guide the selection of training sites for the supervised classification, detailed in the next section.

Since the unsupervised classification was designed to facilitate the location of training sites for the supervised classification only, in the interests of brevity the classification maps from this portion of the analysis are not presented here but they are available on request.

It is sufficient to note, however, that these images revealed several basic informational classes (e.g. water, cloud, agriculture, built-up areas, forest) evident in other sources. However, the cluster procedure was less successful than was the maximum likelihood classifier (described below) in separating out vegetative classes (e.g. forest from agriculture). In particular, areas in both images representing the western portion of the island that were known to be either agriculture or ruinate land were erroneously

classified as scrub forest regardless of the number of clusters specified in the cluster analysis. This provided additional justification for using the normal maximum likelihood classifier (described in the next section).

7.2.2 Supervised Analysis

Classification Scheme

In this stage of the classification process, the classification maps (i.e. the aggregated cluster based maps) produced from the unsupervised cluster procedure helped to guide the selection of training sites for the supervised classification. Between 16 and 20 representative homogenous training sites for each image scene were vectorized from the original 4 colour composite images. Training sites for each land use type were taken from various locations throughout each image scene rather than from one single location in order to ensure a good representation of spectral values for each identified class. Forested areas were digitized in places on the image where the purest samples of the information class were found, based on a wide variety of reference material (e.g. ordnance survey maps, scientific reports, personal knowledge of the island). These were mainly areas where spectral reflectances for tree cover, in particular, were less likely to be 'sullied' by soil background or understorey vegetation.

As in the unsupervised classification, a Level I classification was followed based on the scheme laid down by Anderson et al. 1976. This is the most basic of land cover classifications, Level III being the most detailed. This multilevel classification system provides definitions of various land use and land cover features. Level I definitions are based on 9 different categories: i) Urban or built-up; ii) agriculture; iii) range land; iv) forest land; v) water; vi) wet land; vii) barren land; viii) tundra; and ix) perennial snow/ice (Anderson et al. 1976). Levels II and III provide further classifications for these most basic land cover/use categories. For example, a Level II classification would differentiate between mixed, evergreen and deciduous forest. A Level III classification would break these forest categories down further by species (e.g. oak vs. pine).

It should be stressed that, while clear-cut and straightforward on paper, this multi-level classification often presents problems for the classification in practice (Sabins 1997). Separating one feature from another can be difficult if not impossible. However this is far less of a problem with the Level I classification scheme since it employs

only broad category types. For lower resolution data such as MSS images, Level I classification schemes are the most appropriate. This is particularly the case when images cover large areas and the information needed to carry out a more detailed classification cannot be discerned on this lower resolution data. For use with country maps or broad geographical areas as in this study, the Level I classification scale of 1:250,000 and smaller is suitable and realistic (Sabins 1997).

As mentioned previously, the goal of this remote sensing study is a restricted one; that is, to calculate island-wide forest extent and change estimates. It does not carry out a full scale Level I classification of the data and is concerned with the identification of land use categories other than forest cover only insofar as these can help to delineate the latter.

Thus, while it is of general interest that the unsupervised classification was able to differentiate between several different types of agriculture (e.g. sugar cane vs. pasture vs. banana), for the sake of the delineation of training sites in the unsupervised classification, these were simply referred to in the study as agriculture 1, agriculture 2, and so on. The same schema guided the development of training sites for all other land use and land cover categories, including forests. Other land cover categories identified included: built-up areas, water, cloud, wet land, and forest.

It is interesting to note that the unsupervised classification identified two kinds of forest cover quite clearly in the images. These were areas where forests were: i) largely deciduous scrub, closer to built-up areas and receive average to less than average precipitation; ii) more expansive, receive higher than average precipitation and located predominantly in higher altitude areas.

The Selection of Training Sites

The number of pixels included in each training class varied according to the availability of clearly digitizable pixels; however, in all cases, a common digitizing rule in remote sensing applications was followed: the minimum number of pixels in each training class was always at least 10 times the number of bands (n) in the image to classify (Eastman 1997). In this study, a minimum would be 30 pixels or 10×3 bands. However, in order to ensure a full sampling of pixel observations, every training class contained far more pixels than this minimum number (i.e. over 30000 per band or 90000 pixels in

total). This was particularly the case for the forest and agriculture classes, since the unsupervised clustering procedure had highlighted possible problems in separating the two vegetative classes in some locations. From a statistical standpoint, greater accuracy in profiling signatures can be achieved by choosing a wide range of sample points.

After the training sites were digitized their geographical locations and DNs were stored in a vector file sharing the same name. Signature files were then created by assigning each classification name an identifier number and evaluating a statistical characterization of each training site.

This statistical information (mean, variance/covariance) can be displayed in graphical format. Graphical representation provides a good means for the evaluation of the statistical normality and separability of the training classes (Lillesand & Kiefer 1979).

Histograms are the most common way of expressing the degree of normality in the spectral response distribution. For the reasons discussed later in the context of the normal maximum likelihood classifier, normality is an important criterion of the data. The presence of a normal or bell-shaped distribution indicates the sample classes are homogenous and thus good representations of features of interest (Eastman 1997). Due to the differential reflectance properties of objects and their interactions in various portions of the spectrum, signatures should be examined in more than one bandwidth (Lillesand & Kiefer 1979).

Histograms for each signature for each image scene were evaluated for their normality in each of the 3 bands comprising the colour composite images. Signature distributions revealed evidence of extreme bimodality in only a few cases, and these were restricted to the water/cloud categories, perhaps due to the inclusion of sand/reef in the training sites. However, bimodality was not a problem in any of the other land cover categories, especially the all-important vegetative classes (forest and agriculture). Due to the large number of signatures in each image band scene (16-20 signatures per 3 bands per 4 scenes), not all signature histograms are presented in this study, but they are available on request. Appendix D presents histograms for the dominant forest signature class in the images, derived from Band 4 of the composite images.

Although the histograms visually depict the distribution of signature classes *within* each spectral band, they can reveal nothing about the degree of spectral separation existing *between* classes (i.e. the multivariate distribution of the data) (Lillesand &

Kiefer 1979). This information can be represented more clearly by creating spectral plots for each separate signature class. These signature scatter plots compare signatures in different bands, representing the mean spectral response of each category and the variance of the distribution (Lillesand & Kiefer 1979).

In IDRISI, the degree of spectral separability between bands is expressed in terms of a box with its midpoint at the mean for each band and its border encompassing ± 2 standard deviations for each (Eastman 1997). Note that only two bands and a maximum of 9 signatures only can be displayed on one scatterplot. Due to the large number of signature classes and IDRISI's graphical restrictions, only selected signature scatterplots of significance for the study are presented in Appendix D. Looking at these scatter plots, the strong spectral separability between three wholly different classes (e.g. forest (FOR), urban (URB) and agriculture (AG) (which includes ruinate land) for both eastern (e) and western (w) portions of the island becomes evident.

Note that spectral separability is (as expected) less extreme in the case of the agriculture and forest classes, whose signatures are closer together in the measurement space (although they are clearly demarcated as separate classes). Water and cloud categories are also clearly demarcated, but are not presented on these signature scatterplots since they lie largely outside the measurement space that can be viewed in these plots.

Moreover, while there is good spectral separability between these training classes, there is some spectral mixing of signatures *within* forest and *within* agriculture classes in the image bands. However, given the broad classification aims of the study (i.e. the focus on differentiating forest cover from other land cover features rather than the identification of forest species *per se*) this is not a problem for the reasons discussed. A more detailed classification would dictate that these categories be broken down (if possible) into separate subclasses.

The Normal Maximum Likelihood Classifier

The information contained in these individual signature files enables the classifier to assign all remaining, non-polygonized pixels to an appropriate information class based on the mean/variance and covariance data of the signatures (Lillesand & Kiefer 1979). In this study, a maximum likelihood classifier was used to assign all remaining pixels

to their most similar information class.

The normal maximum likelihood classifier is the most commonly used classifier in remote sensing classification studies, producing an accurate classification if training sites are homogenous and well-defined (i.e. normally distributed) (Eastman 1997). Moreover, unlike the minimum distance to means and parallelepiped classifiers, this classifier is sensitive to both the variance and correlation between bands, and thus avoids the problems noted earlier associated with the use of these classifiers. One drawback of the classifier is that it is very slow, since it computes the probability of each pixel's belonging in each category and thus requires a large number of computations (Eastman 1997).

It should be noted that the exact location and shape of a normal distribution depends on two parameters — its mean and variance; the mean indicates where this 3-dimensional bell-shaped curve is located, and the variance indicates how spread out the distribution is. This information is calculated in the signature creation stage of the analysis, discussed earlier. Hence the normal maximum likelihood classifier will use this information in determining to which class an unknown pixel should be assigned.

Specifically, the mean and covariance of the signature files are used to calculate probability values for each remaining unclassified or unknown pixel (Lillesand & Kiefer 1979). Each of these unknown pixels is then assigned to the most likely class based on these probability values for each information class (Lillesand & Kiefer 1979). Appropriately, the probability of an unknown pixel belonging to a given class will be highest at the mean point of the distribution and will then taper off from this point in the measurement space.

To facilitate the classification, signature group files were created from each individual signature file for each image scene. IDRISI's MAXLIKE module was used to classify the remainder of the pixels in the four composite images. The resulting information classes were then conflated into three broad overall classes and given new attribute assignments. Specifically, the various classes of agriculture, urban/built-up areas, forest, water, and cloud were reduced to 3 broad information categories: Forest (F), Land not Forest (LNF), and Cloud/Water (CW).

These reclassified (mosaicked, according to the procedure described in Chapter 8) maps from which forest change statistics are calculated in the next chapter are presented

in Appendix E. In the interests of brevity, the original classification images are not presented here but they are available on request to the interested reader.

Accuracy Assessment

The last stage in a classification typically involves some sort of error assessment, although it is not uncommon for many studies to exclude it (e.g. Haack & English 1996; Gilruth et al. 1990; Brondizio et al. 1994). The assessment of error depends on the availability of appropriate and accurate reference data (Lillesand & Kiefer 1979). The process of comparing classified images against various reference sources is referred to as 'ground-truthing' and need not actually involve a visit to the field (Lillesand & Kiefer 1979).

Typically, however, field visits provide an excellent source of reference data if the area to be covered on the ground is not too large or visibility is good. On-site assessment can be as informal and unsystematic as that of making 'eye-ball' comparisons between the classified image maps and the field. Or it can be a more formal comparison, involving the generation of a random set of locations on the computer and then comparing observations in the field at various sites with those on the map. A statistical assessment of error can then be computed by comparing the information collected in the field against the classified image or map (Eastman 1997).

The substantial financial and labour demands imposed by the study's island-wide focus meant that it was impossible to carry out extensive field-checking. Most studies that undertake field assessments can do so because they are restricted to small areas that can be easily checked. Thus, unlike in a traditional accuracy assessment, the site visits in this study were not randomly generated by the computer. The resources (both time and financial) were simply not available to visit all parts of the island. Another important factor against the adoption of such an approach was that the image sets used in this study are not recent data. Hence random generation of site locations for verification would provide problematic results in those areas where forest cover has since disappeared. This would also apply to those cases where cloud cover in the images occludes the ground below. Accessibility and personal safety were also factors mitigating against the selection of sample sites in this manner.

However, despite the fact that it was not possible to visit sites chosen at random

(and thus, a true statistical assessment of error could not be carried out), it is nonetheless worthwhile to compare the sites that were actually visited with those randomly generated by the computer.

Computer Random Generation of Field Sites

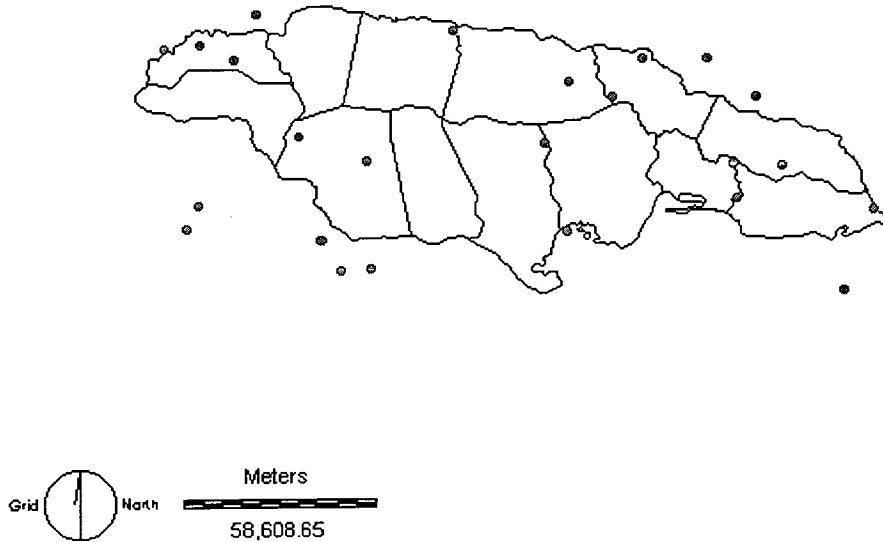


Figure 7.1

Rather than intensively ground-truth in one small area of the island, the tactic taken was to follow the logic of computer generated selection, and cover as much of the island as possible, in view of the constraints above. In practice, this meant restricting the ground-truthing to parts of the northeastern and northwestern coast, the interior eastern highlands (e.g. the Blue Mountains) and the interior central highlands. Although the southern and western regions were not visited, these parts of the island, with the exception of the forested areas of the Hellshire Hills and the Santa Cruz and Nassau Mountains, are largely dominated by agriculture and built-up areas, and thus, were not as important as the former regions for this study.

As indicated by Figure 7.2, a fairly comprehensive number of field sites were ground-truthed on the island, and several are in the same general locale as the computer-generated sites depicted in Figure 7.1. Altogether, 35 sites were inspected in the field. These sites were largely vegetation (either agriculture/ruinate land or forest) but built-up areas were also recorded. Note that in the computer generated sample of random

sites, it is possible to specify the number of sites to be visited. The sample size is determined by the following equation, given in Eastman 1997:

$$n = z^2 pq / e^2$$

where

- z is the standard score for the desired level of confidence
- e is the desired confidence interval
- p is the a priori estimated proportional error, and
- $q = 1 - p$

If a 10% level of confidence is assumed (i.e. $z = 1.64$ and $e = .10$) and if the not unreasonable assumption is made that 10% of the pixels may be mislabelled (i.e. $p = .10$) then the number of sample points randomly selected should be 24, which is considerably less than the number actually visited (see Figure 7.2).

Actual Sites Field-Checked, April 1999

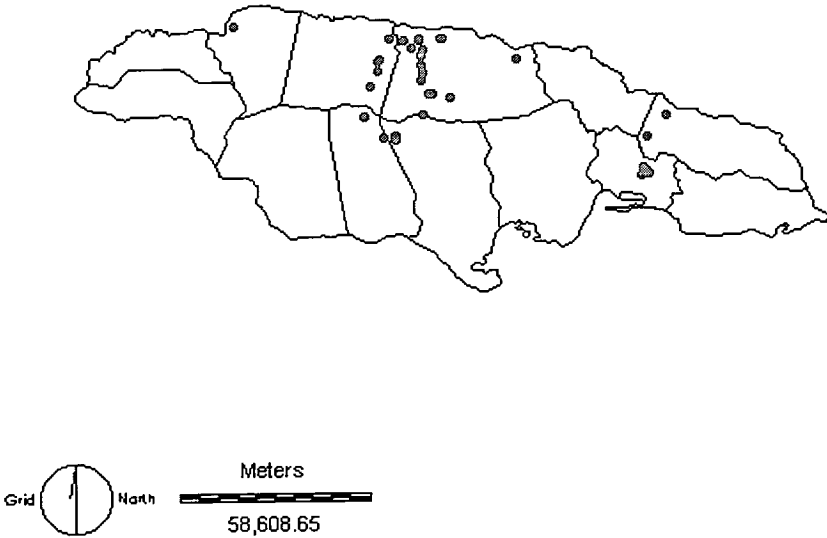


Figure 7.2

The assumption of an estimated proportional error of 10% is not unjustifiable given that a wide variety of reference data was used in the initial selection of training sites for the classified images. Thus, training sites were chosen only from locations known to

have standing forest, situated largely in inhospitable or remote areas (e.g. the Cockpit Country, Hellshire Hills and Dry Harbour Mountains). It is also justifiable in view of the broad classificatory aims of the study. That is, the only real class of importance is forest cover, broadly defined, which obviously reduces the level of discrimination required for delineating training sites (and, thereby, the overall level of error).

Figure 7.2 was created by recording the UTM coordinates at each sample site visited on the ground using a GPS (global positioning system). These points were then used to create a vector point file (expressed by the dots in the maps above). This is essentially the same procedure as that followed by the computer generated version, except that the latter's vector points were chosen at random.

Since the data were from several years back, its use obviously undermines the capacity of field checks to provide information about the accuracy of a classification, particularly in areas observed to be secondary scrub or where land is largely ruinated or given over to subsistence agriculture. In other words, there was no way of being entirely sure of whether the land in these areas was covered in forest in 1987 and 1992 or not. However, as the following explains, this was not as much of a problem as it would appear on face value to be.

Training sites were selected from areas of the island that were forested in 1987 and 1992, and remain so to this day, in addition to being of sufficient geographic area to allow for spatial error in image resolution and GPS recording. One of the last remaining areas of the island containing primary forest — the Cockpit Country, located largely in the parish of Trelawny — and the dry secondary scrub forests of the Dry Harbour Mountains in the north, were two areas of relatively significant forest cover in which training sites were identified and subsequently visited on the ground.

Thus, while other reference sources closer in time to the images themselves were relied upon heavily for information in the classification process, on-site observation provided a follow-up check of the training classes selected, and a good overall view of the 'larger picture'. Specifically, it allowed for the verification of forest cover in areas from which training classes had been drawn but had not undergone any significant change. (In addition, it provided verification of non-forest areas insofar as these helped to identify the forest classification, namely those designated in the classification as LNF (e.g. built-up and well-established agricultural areas, such as plantation agriculture))

and areas occluded by cloud cover in the images (CW)).

However, while the training classes for forest cover were chosen from the purest and largest samples on the island and these sites were visited in the field, a true accuracy assessment of the classification was still not possible due to the problems noted above (i.e. the lack of randomly generated sites and the fact that the calculation of error would also have had to include those regions of the island where forest had no doubt undergone change but in which way is unclear). There were several such sites observed in the field; that is, areas where trees were either dead or dying, with plenty of new growth under them, but growth that would not have been there in 1987 or even 1992. As noted, whether forest was the original land feature in these areas or whether it was abandoned subsistence agriculture, for example, could not be ascertained.

Table 7.1: ERROR MATRIX

<i>Field Map</i>						
<i>Classification Map</i>		0	1	2	Total	ErrorC
	0	–	2	2	4	–
	1	–	7	4	11	36%
	2	–	4	14	18	22%
	Total	–	13	20	33	–
	Error0	–	36%	22%	–	–

Despite these drawbacks, it is possible to see what kind of information an error matrix can reveal about the comparison between forest cover in the most recent image (1992) and on-site observation of land features at specific locations. After a point vector file was created from the GPS-recorded coordinates and their respective land feature class recorded in a values file, a raster image of the ‘true’ classes was created. This image was then compared to the 3-category classification map.

In IDRISI, an error matrix is produced in which each observed sample point is compared with the classified image; it records the proportional error in respect to both errors of commission (i.e. areas that were mapped as one category but were found to be different in the field) and errors of omission (i.e. areas observed to be different on the ground from what they had been mapped). For the land features mapped and observed in this study, a matrix can be constructed for LNF and F classes, as in Table 7.1.

In this matrix, rows are represented by the 1992 3-category classification map, and columns by the on-site map created from the rasterized point file of vector locations. Since cloud/water (0) represents a feature category on the classified map but no examples were observed in the field, only the rows contain values for this category; nonetheless, it is still useful to see from this matrix what field-checking can reveal about what is underneath the clouds on the classified image. In addition, while 35 observation sites were field-checked, two were too close to other sites to be separated clearly on the classification map, so that the actual number for which comparisons can be made is 33.

As is evident from this matrix, 2 of the on-site sample points field-checked as forest (1) were cloud in the original classified image, 7 were forest, and 4 were LNF (2). Similarly, 2 of the sample points registered as LNF in the field were classified as cloud cover in the classification map, 4 were forest, and 14 were LNF. It is common to use the error of omission (ErrorO) figure as a means of judging the adequacy of the classification map. If the category for WC (0) is dropped from the estimation of this error, it can be seen that of the areas of the island field-checked as forest, 64% of them were classified correctly; and of those field-checked as agriculture (including ruinate and pasture land), 78% of them were classified as such on the map. (In this example, the errors of commission are the same).

These accuracy figures should be interpreted in view of the drawbacks discussed above, namely, the untimely nature of the images, the non-random way in which sites were chosen, the problem of cloud cover, inherent geometric inaccuracies in the GPS (approximately 50 m) and in the satellite measurements (unknown). In addition, in several "fuzzy" cases, decisions made about forest cover on the ground may or may not coincide with the decision logic of the supervised classification.

For example, most areas recorded on-site as F (and, for that matter, LNF) were observed to have wide geographic coverage (e.g. larger than the 82 m x 82 m resolution of each pixel image grid). However, in some cases the field of vision was obscured at this distance, and land features within the line of sight appeared to be mixed (e.g. pasture/ruinate land and scrub forest). In these instances, it was unclear what the dominant class would be in a corresponding 82 m x 82 m area. For instance, if an area was observed to have roughly 70% forest and 30% ruinate land, it was recorded as forest; in other areas, where forest cover was roughly 50% and pasture 50%, the area

was classified as LNF. In these obscured areas, on-site observation would obviously have yielded less information than in an 82 m x 82 m image grid cell. If forest actually covered the remaining area of the corresponding grid size, then the average values of pixels would have been classified as forest in the supervised analysis (assuming normal environmental conditions at the time of satellite recording). Thus, in addition to the natural process of change from the 1992 image to the present day, differences between on-site observation and classification can be explained by the inherent problem of resolution.

However, as noted, most sample field sites visited and training sites chosen represented the purest sample forest classes available on the island, and were predominately in areas with well-established forest cover; usually quite dense by Jamaican standards, and remote. Viewed in this light (and in light of the drawbacks noted above), the 68% accuracy in the forest classification suggests that this strategy for the selection of training classes was an appropriate one and that the classifier performed well.

7.3 Some Concluding Caveats

First, the large amount of and complex nature of the data comprising a scene mean that errors in analysis and interpretation are inevitable. However, as noted, this study has attempted to minimize error in two ways: i) It uses only high quality data with a minimum of cloud cover (i.e. 10% or less); ii) It subsumes the complexity of forests and other features in each scene under broad categories (e.g. forest, land not forest, cloud/water). The latter strategy, in particular, reduces the potential for error associated with the delineation of closely related classes such as forest species.

Second, the definition of forest cover adopted in this study is a rather broad and arbitrary one in that all forest conditions and types are included as one class. Field observations at selected training sites around the island identified vegetation classified as forest in the analysis in areas characterized as containing a minimum of 10% or more of crown cover of leaves; however, many of these areas could in no way be considered to constitute expansive areas of dense, lush forest. Yet, as indicated in Chapter 4, Jamaica possesses only a few areas of natural forest of this kind. Given the scattered and sparse nature of most of the country's largely ruinate forest, this definition is a realistic one despite the fact that it may be considered inaccurate according to some forestry definitions.

Chapter 8

Jamaican Forest Cover Exent and Change 1987-1992

8.1 Integration of Classification and Constituency Maps in GIS

8.1.1 Mosaicking of Images

Before forest loss statistics for the island in both years could be calculated, eastern and western scenes had to be mosaicked together to produce a single image of the island for each year. The mosaicked 3-category classification maps for both years are presented in Appendix E. Included in Appendix E is a classification map of a section of the Hellshire Hills, located in the southeastern portion of the island (St. Catherine parish). This map was extracted from the 3-category national map and displays the three main categories of land cover class for this part of the images. Note, in particular, the large amount of forest cover lost (approximately 40%) between 1987 and 1992 for the area depicted here.

Mosaicking of images was achieved in IDRISI by matching coordinate points for both eastern and western images. However, due to the satellite overshooting its orbital path after each rotation of the earth, part of the images overlap. This overlap can be dealt with by specifying a 'transparent overlay' procedure in IDRISI, in which images are joined together at their coordinate points and the pixel values of the overlaid image allowed to show through while occluding those in the reference image (Eastman 1997).

Typically overlaying will be done in a way that minimizes unwanted features of interest (e.g. cloud cover). For both years, minimizing cloud cover meant that the image representing the eastern side of the island covered the western side.

8.1.2 Creation of a Constituency Boundaries Map

Since the main socio-economic unit of the analysis in this study is the constituency and the classification maps are at the national level, there is obviously a natural disjunction in scale between the two forms of data. It is possible, however, to integrate maps of varying scale to each other in a geographical information system (GIS).

In order to obtain forest data at the constituency level, it was first necessary to create an appropriate digital map (in this case, from an existing paper map). Accordingly, a vector paper map representing the division of electoral units by constituency in 1987 was digitally scanned in the university's graphics laboratory and a rasterized map of the constituency boundaries created in which each constituency was assigned a different colour.¹ The resulting raster image was then resampled to the georeferenced satellite images, the island's coastline providing a large number of easily recognizable GCPs in both map images. Unsurprisingly, given its simplicity, it was a considerably easier task to obtain a low total RMS (0.019 m) for the political boundaries map than for the satellite images, with their complex and often difficult to discriminate features. Correspondence files for this resampling exercise are located in Appendix C.

The end result of all these mapping and image processing steps was the creation of two distinct data layers — the political boundaries map and the two 3-category (F, LNF, and CW) land information maps created from the earlier supervised classification. Both constituency and parish boundaries maps (with accompanying identifiers) are presented in Appendix F.

¹This map was created by the Jamaican Office of Elections. It had a mapping scale of 1:250,000 and a lat/longitude reference system.

8.2 Calculation of Forest Cover Extent & Deforestation Rates

Once the constituency boundaries map was created and the constituency map georeferenced to the other images, the cumulative proportions of LNF, CW and F for each image scene were calculated at the constituency level using the EXTRACT module in IDRISI.

The constituency-level data were then used to calculate the proportion of forest cover per total land area (as opposed to the proportion of the image scene which also includes water/cloud). To this end, it was first necessary to calculate: the proportion of forest cover (F) and the proportion of LNF (land not forest) per 3-category image scene. This step involved the creation of two Boolean images for both years: a) one in which forest cover was assigned the attribute value 1 and CW (cloud/water) and LNF the value 0; b) one in which LNF was assigned the attribute value 1 and CW and F the value 0. The AVERAGE module in IDRISI was then used to calculate a figure for the island-wide proportion of F and LNF, respectively, for both years. Constituency-level data for the proportion of F and LNF in each image scene were then calculated using the EXTRACT module in IDRISI. Once these figures were obtained it was a simple matter to isolate the proportion of F and LNF as a proportion of each 3-category image scene (i.e. $\frac{F}{LNF + F + CW}$ and $\frac{LNF}{LNF + F + CW}$) for both years. The ratio of F to LNF for each constituency was then calculated (i.e. $\frac{F}{LNF}$).

This ratio was then used to calculate the proportion of F in total land area (excluding clouded/water areas) (i.e. $\frac{F}{LNF + F}$) for each constituency by dividing $\frac{F}{LNF}$ by $1 + \frac{F}{LNF}$.

Once this information was obtained, a constituency-wide deforestation rate was calculated by taking a simple percentage change in the proportion of forest cover on the island between 1987 and 1992 for each constituency. These steps are summarized diagrammatically in Figure 8.1.

Figure 8.2 is a flow chart summarizing the remote sensing and GIS steps involved in the forest change analysis of this study. The dotted lines represent techniques tested in earlier computer runs but were later rejected since they performed poorly or produced inefficacious results.

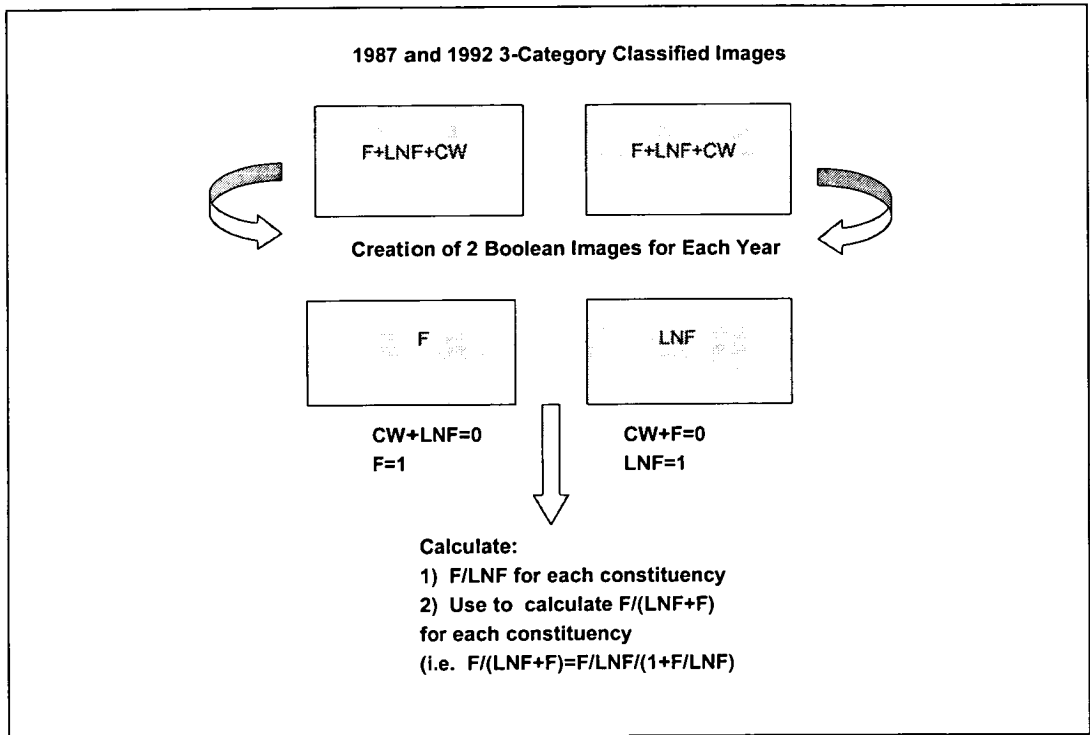
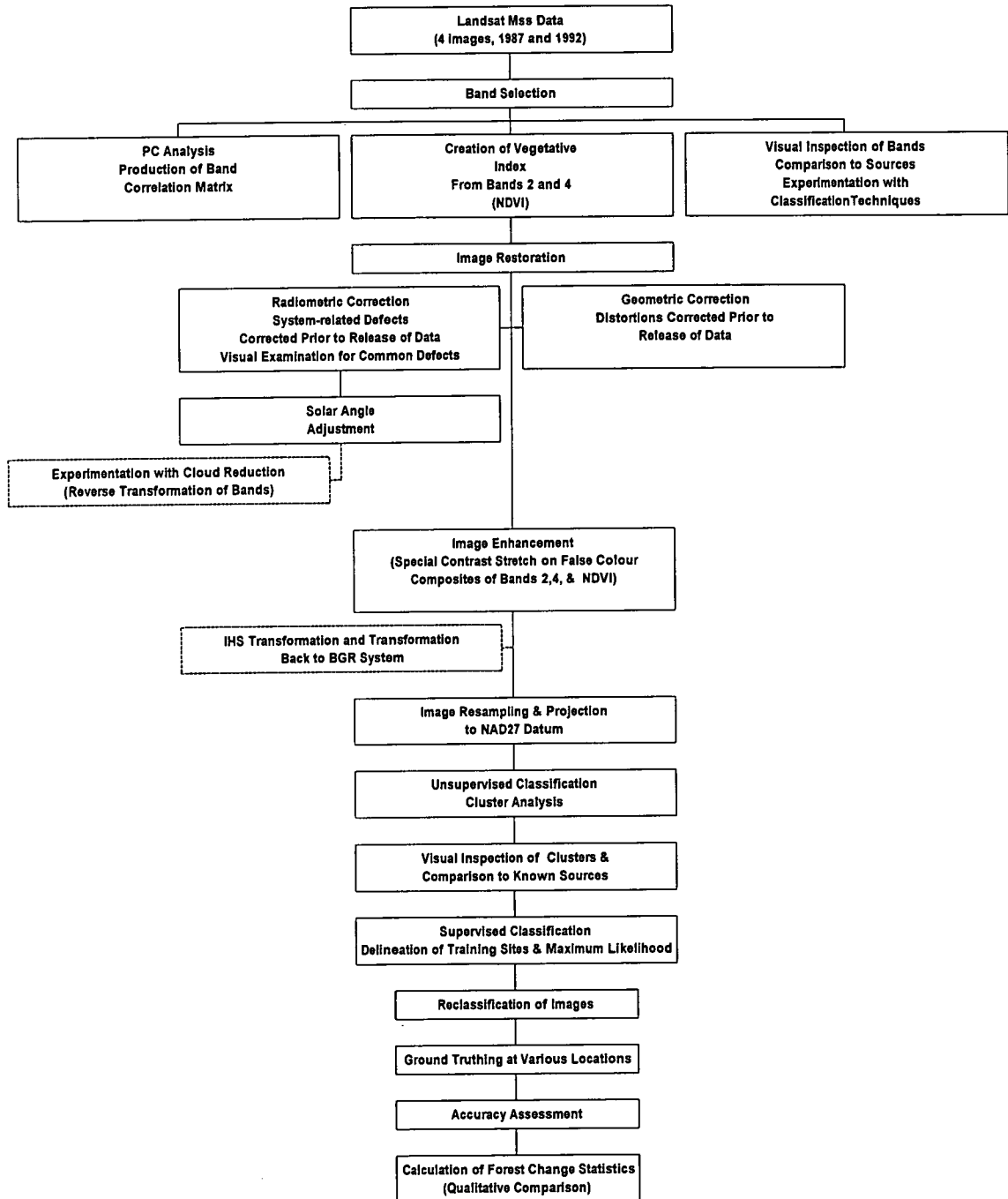


Figure 8.1: Steps in the Calculation of Forest Extent Estimates

Figure 8.2: Steps in the Jamaican Forest Change Analysis



8.2.1 Forest Data: National- and Parish-Level

Prior to the extraction of the constituency forest data, an island-wide estimate of the proportion of the island's land area in forest was estimated for 1987 and 1992, and both overall percentage and average annual percentage rates of national forest loss calculated. Table 8.1 presents these figures:

<i>Forest Indicator</i>	<i>1987</i>	<i>1992</i>	<i>1987-1992</i>
Percentage of Forest Cover	24.75	20.32	
Overall Percentage Forest Loss			17.90
Average Annual Percentage Forest Loss			3.87

As this table indicates, Jamaica lost 17.90% of its forest cover between 1987 and 1992, or 3.87% per annum. In 1987, in other words, 24.75% of island was covered in forest; by 1992 this figure had shrunk to 20.32%. This amounts to a loss of 39,020 hectares for the period.

8.2.2 Comparison with Other National Estimates

As noted previously, the problem of deforestation in Jamaica has received very little attention from the scientific community. Some of this neglect must surely be attributed to a lack of basic forest data for the country. Indeed, the last wide-scale forest inventory was carried out in the late 1960s, and few estimates — either of the proportion of land area in forest or the change in forest cover over time — exist.

Undoubtedly the most comprehensive statistics on the state of Jamaica's forests are the FAO's *Production Statistics*. The FAO has been collecting forest data on countries for the past three and a half decades, as part of its global inventory of land use and agricultural production. These statistics measure the area of land under forest and woodland, and like this study, adopt a broad definition of forest cover. This deforestation measure is based on a definition of forest cover that includes all woody vegetation. Forests and woodland refer to all land under natural or planted stands of trees, regardless of its productivity. However, unlike this study, the FAO data also includes land that has been cleared of forests but will be reforested in the near future. Thus, all types

of forest cover and condition are included, the definition of deforestation being based more on the use to which land is put than on the actual state of the forest.

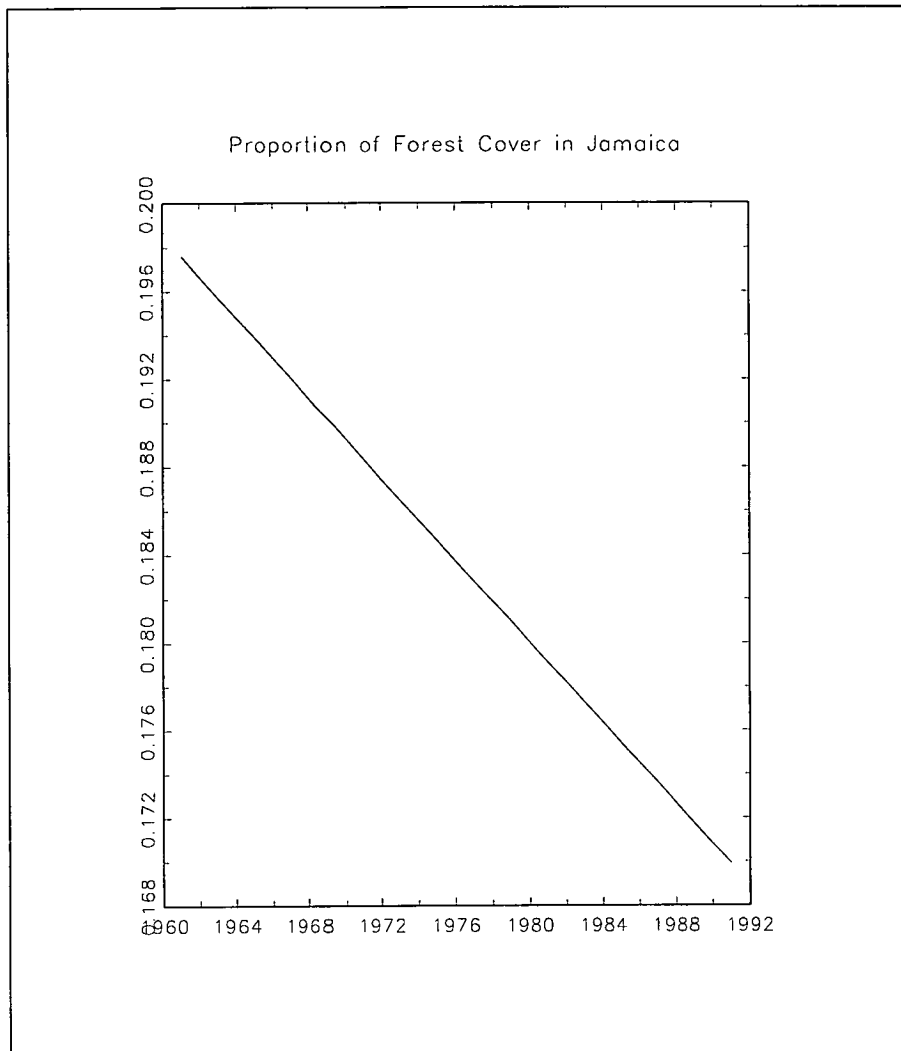


Figure 8.3: FAO Production Series Estimates of Forest Extent & Change

One drawback of the *FAO Production* data is that it is based on limited ground surveys carried out in selected years by the Jamaican forestry department. For those years in which there are no formal surveys, figures on land area under forest for each year are simply extrapolated on the basis of years for which survey data is available. If these values are plotted as in Figure 8.3, it can be seen that between 1960 and 1992, Jamaica lost nearly 14.02% of its forests. This amounts to an average annual forest loss rate of 0.5% per year or 20,000 hectares. To relate this loss to this study, this is a deforestation rate of roughly 0.5% each year on average between 1987 and 1992. Note, however, that the uniform shape of this line makes this estimate highly suspect.

Although the general downward sloping nature of the line no doubt reflects an accurate deforestation trend, it is highly unlikely that Jamaica lost *exactly* 0.5% of its forest cover each year.

Another recent attempt to derive a deforestation estimate for Jamaica is the study by Gray & Symes 1972. Using data from two different sources — the 1970 Jamaica Forest Inventory and CRIES 1982 (Comprehensive Resource Inventory and Evaluation System) — the author, the managing director of FIDCO, estimated that between 1970 and 1980, Jamaican forest cover actually *expanded* by 94%. However, this study has been attacked by scientific experts, and is not regarded as valid outside of government circles. Eyre 1987, for example, has criticized the estimate for combining both incompatible forest definitions and data sources (i.e. the forest inventory survey based on a compilation of Ministry of Forestry and other agency estimates and the CRIES photogrammetric survey).

In addition to providing its own photogrammetric survey, the CRIES 1982 study compared early photogrammetric-based ordnance survey maps from 1954 with 1980 photogrammetric-based maps and estimated an increase of 59% in forest cover for this period. Although these ordnance survey maps are considered to be more accurate than is the Gray and Symes data (i.e. they were compiled using similar methods, survey scale and land classification categories), this study has also been faulted for serious interpretative differences in the classification of forests, particularly secondary forest land (Eyre 1987).

Two other forest change detection studies, that by Eyre 1987 and that by the FAO/UNEP, deserve mention, not the least of which because they are generally considered to provide a more accurate picture of the extent and rate of change in Jamaica's forest cover.

Using the 1982 CRIES survey as a base-line, Eyre 1987 combined on-the-ground and aerial surveys in 1986 for selected areas of the island that were designated as forest in 1980. Although the definition of forest cover adopted in the study was different from the original CRIES definition (i.e. restricted to areas of the island where forests constituted 10% or more crown cover of trees), there was a certain degree of definitional overlap in the choice of sample areas, particularly in areas above 1000 meters. In respect to the total area of 687 km² (6% of land area) surveyed, the author estimated

the average annual rate of deforestation to be 3.3% between 1980 and 1986. The overwhelming number of sample sites in this study were recorded as having relatively small to extensive loss of forest cover. Only a few districts registered an increase in forest cover during this period. Given the wide divergence in deforestation rates across sample areas, it would be hazardous to extrapolate this 3.3% figure to the entire island. Moreover, since the selection of areas for analysis was based on subjective criteria (i.e. areas do not correspond to recognizable administrative or other formal units), it is difficult to compare these findings to area deforestation rates calculated in this study.

The final estimate worth mentioning is that of the FAO's *1990 Tropical Forest Resources Assessment* (FAO 1993). This study estimates Jamaica's deforestation rate to be considerably higher than any of the above. According to this estimate, between 1981 and 1990, Jamaica's average rate of deforestation was 5.3% per annum. (Note that the assessment reports an even higher figure of 7.2%. The 5.3% figure is derived from the summary reports sent by the FAO to the World Resources Institute, and is the figure which is commonly cited). Since this estimate forms part of a worldwide data base of tropical forest resources that will be updated regularly, it is perhaps useful to examine how this estimate was obtained in greater detail.

As is clear from the above, the FAO *Assessment* is much higher than are the figures reported annually in its *Production Yearbooks*. This is not surprising, given that the FAO *Assessment's* explicit goal is to "provide reliable and globally consistent information" (p. ix) on the state of the world's tropical forests. Thus, to a greater degree, perhaps, than with the *Production Series* data, forest definitions have been standardized from year to year. In addition, whereas the *Production Series* data uses a broader definition of land use, the FAO *Forest Assessment* adopts a narrower definition of forest cover and deforestation. Forests are defined as "ecosystems with a minimum of 10% of crown cover of trees and/or bamboos, generally associated with wild flora, fauna and natural soil conditions, and not subject to agricultural practices" (p. 10). Similarly, deforestation refers to the "change of land use with depletion of tree crown cover to less than 10%" (p. 10).

Note that, while the 1990 FAO *Assessment* uses FAO *Production* figures in its determination of forest extent and change estimates, the latter ground inventory is only one of a number of sources (e.g. maps, satellite images, aerial photographs) comprising

the 1990 *Assessment* database.

In Jamaica's case, forest data are given a reliability indicator of "2" This ranking means that Jamaica's forest archive includes data derived from medium resolution satellite data (typically Landsat MSS), with limited ground truthing. Likewise, change estimates are given a reliability rating of "average". This classification is assigned to countries for which some "partially reliable observations" are available for more than one date, but does not mean that satellite data were necessarily available for both dates.

Forest and other types of data (e.g. population and ecological factors) were used in a regression analysis of countries elsewhere in the tropics known to have highly reliable data, and the resulting regression fitted values then used to obtain an estimated relationship between these factors and deforestation. This model was then applied to Jamaica, using original base-line forest data and population data for both points in time. For Jamaica, baseline forest data was available for 1985 and was used to standardize the forest data to the common years of the *Assessment* (i.e. 1980 and 1990).

It is unclear in the case of Jamaica whether the 1985 baseline data used was MSS or coarser resolution (e.g. AVHRR) data, since the report does not provide details about individual country data sets.² Moreover, it is also uncertain to what extent this remotely sensed data covers the entire island or simply a portion of it. Similarly, the definition of "reliable" in the *Assessment* need only refer to remotely sensed data for at least one point in time; and in addition, does not need to be comprehensive in geographical area. However, if one assumes for the moment that a similar MSS image as in this study was used to calculate baseline forest data in 1985, how can the difference in estimates between this study (3.9%) and the FAO *Assessment* (5.3%) be explained?

As noted, this study adopts the older FAO *Production Series* definition of forest cover, and includes areas of scrub vegetation that would not be classified as deciduous forest in the FAO *Assessment*. Unlike the FAO *Assessment*, it also includes areas having less than 10% crown cover of trees. In other words, the FAO *Assessment* of the deforestation rate is restricted to large pristine "natural" forest areas rather than to other types of forest cover (e.g. secondary growth). Hence it may be the case that in these areas, deforestation rates really were as high as 5.3% for the period 1981-1990.

²Extensive inquiries with the FAO's Forestry division also failed to produce this information.

In addition, some areas covered by cloud in the images were observed in field checks to have undergone deforestation in recent years; if these areas were cloud-free in the FAO MSS images, it may explain the higher estimate.

Another explanation no doubt lies in the type of model used by the FAO to derive the forest estimates. The *Assessment* uses a deforestation model to extrapolate forest data using population density and ecological factors as explanatory variables. This model was derived from relationships observed in a wide range of countries comprising the *Assessment's* FORIS data base, and as noted, forest data were all standardized to the same years. The degree to which these global relationships hold within individual countries is unclear. Indeed, the FAO *Assessment* implicitly recognizes this problem, acknowledging that individual country data provide a unique source of information. It is quite possible that in Jamaica's case socio-economic factors have played a greater role than has population density in driving deforestation. Even if population density had increased to a significant degree in Jamaica during this period (and in comparison to many tropical developing countries it did not), the estimated rate of deforestation, according to this regression model, will likewise increase irrespective of whether population density/growth is actually correlated with forest loss on the ground.

Other potential discrepancies between the two studies may be explained by the fact that the *Assessment* baseline data for dry forests are less reliable than for other forest ecosystems; the issue of cloud cover is not addressed in the data; and state and change data are extrapolated from baseline data rather than from actual data for each respective year. These criticisms notwithstanding, however, the explicit global perspective of the FAO *Assessment* means that the data are largely inappropriate for anything but global or cross-country comparisons. Likewise, the use of forest estimates based on this model is contraindicated in studies such as this one, which seek to unearth the population-driven subsistence factors underlying deforestation.

8.3 Parish-Level Forest Loss & Some of its Possible Socio-economic Correlates

Constituencies comprise the areal units of analysis in the study's regression analysis (see Chapter 9) and sub-divide the island's 14 parishes. The parish is the largest official areal unit into which the island can be sub-divided. Since the constituency-level forest data permits fine variations in geographic areas and their corresponding socio-economic characteristics to be made, it is suitable for the kind of regression analysis carried out in the next chapter. Overall percentage forest loss rates for each constituency used in the regression analysis are presented in Appendix G.

At this stage, it is nonetheless worthwhile to link these parish-level forest loss figures to some general physical and social indicators of scarcity, before going 'one level down' to the constituency unit. Although coarse, the resolution afforded by a parish level analysis provides a convenient vantage point from which to view forest change at the macro level and highlight individual deforestation 'hotspots' on the island. Moreover, the presentation of simple correlation results for parish socio-economic data and their respective deforestation rates will also serve to indicate potentially significant human-forest interlinkages for examination in greater detail at the constituency level.

A weighted average of forest cover for each constituency within each parish can be taken to give a deforestation rate for the parish level, as in Table 8.2. Figures are given for the percentage of forest cover in each parish for each year, as well as for both the overall percentage change and average annual percentage change in forest cover between 1987 and 1992.

PARISH	% Forest '87	% Forest '92	Overall % Forest Loss	Average Annual % Forest Loss
St. Andrew	17.10	15.89	33.26	7.78
St. Thomas	29.57	23.09	23.39	5.19
Portland	26.70	23.09	13.23	2.80
St. Mary	8.00	8.20	-29.49	-5.30
St. Ann	28.23	26.62	3.15	0.64
Trelawny	54.87	41.27	21.60	4.75
St. James	24.46	21.72	-45.57	-7.80
Hanover	7.96	11.62	-49.96	-8.44
Westmoreland	10.11	11.36	-15.44	-2.91
St. Elizabeth	21.41	16.51	21.63	4.76
Manchester	26.26	18.30	30.86	7.11
Clarendon	8.43	10.91	-28.79	-5.19
St. Catherine	21.84	15.71	24.07	5.36
Kingston	33.25	49.85	-49.91	-8.43

An examination of this table reveals that of Jamaica's 14 parishes, 6 registered a negative forest loss rate; that is, actually saw their forest cover increase during this period: St. Mary, St. James, Hanover, Westmoreland, Clarendon and Kingston. The highest rate of forest loss was recorded for St. Andrew (33.26%); however, by any measure (i.e. average annual or overall % change) the loss of forest cover experienced by the other parishes is nothing short of extreme.

8.3.1 Representative Correlations

What scarcity characteristics, if any, do those parishes registering forest loss have in common? And by implication, what do those parishes that saw forest cover increase over this period, lack to varying degrees?

Table 8.3 presents correlation results for parish-level deforestation rates and scarcity factors of interest in this study. Some parish socio-economic measures, which are described in greater detail in the regression analysis of the next chapter, are given in

Appendix H for each parish. These parish values have been derived from the constituency data, by taking the average of each parish's respective constituency figures. Farm data for 13 of Jamaica's parishes (i.e. excluding Kingston) are also included in this appendix.

Table 8.3 indicates that, at least at the parish level, population density in 1982 (the year closest to 1987 for which population census data is available), the change in population density between 1982 and 1992, and the proportion of household income spent on food in 1988, are both unexpectedly negative albeit not significant. However, the dependency ratio is of the expected positive sign, but once again is not significant. Most of the remaining variables have intuitively correct signs but none are significant. The only exception is the proportion of land area in forest in 1987, which is marginally significant ($p \leq .20$).

<i>Table 8.3: Parish Social Variables</i>	
<i>Deforestation Correlations</i>	
<i>Key Social Indicators</i>	<i>Correlation with % Forest Loss</i>
Population Density 1982	-0.01
Change in Population Density 1982-1992	-0.05
Fuelwood Use	0.19
Access to Piped Water	-0.23
Proportion of Income Spent on Food	-0.16
Proportion of Land Area in Forest 1987	0.43*
Dependency Ratio	0.19
*Significant at 20% level	

It is expected, for example, that poorer households, being deprived, would spend a greater share of their income on food as opposed to non-basic goods. However, the negative sign of this relationship suggests the counter-intuitive result that greater poverty (i.e. the more income spent on food) is linked with less deforestation. One explanation for this finding may be that the food variable is not an accurate reflection of the sort of poverty that is driving deforestation on the island. That is, the negative correlation with deforestation may suggest that those individuals who are cutting down forests fastest on the island are precisely those who must grow their own food because

they lack the income to purchase it.

In addition, the counter-intuitive signs of the two demographic variables cannot be explained by the possibility that more densely populated areas initially had less forest cover (and therefore less deforestation), since the correlation between the proportion of forest cover in 1987 and both population variables is extremely low ($r^2 = 0.07$).

The lack of significance for these variables, while disappointing, may perhaps be explained by the low number of data points, and (with the exception of fuelwood) the indirect nature of these variables. Both of these characteristics make it difficult to statistically ascertain underlying threads of causality.

Table 8.4: Parish Agriculture/Land Use

Variables Deforestation Correlations

<i>General Land Use Indicators by Size, Type & Status</i>	<i>Correlation with Overall % Forest Loss</i>
% of Farms	0.14
% Landless Farms	0.24
% Farms ≤ 1 acre	-0.17
% Farms $\geq 1 \leq 5$ acres	0.37 ¹
% Farms ≤ 5 acres	0.16
% Farms $\geq 5 \leq 50$ acres	-0.16
% Farms ≥ 50 acres ≤ 100	-0.33
% Farms 100+	-0.69***
% Farms Domestic Crop	0.42*
% Farms Export Crop	-0.57***
% Farms Mixed Crop	0.19
% Farms Livestock/Poultry	0.19
% Farms Other	-0.07
% Farms None	-0.05
% Farms Full-time	0.25
% Farms Part-time	-0.10
% Farms Agricultural Employment	-0.37
% Farms Non-Agricultural Employment	0.01
% Farms Female-Headed	0.26
% Farms ≤ 20 years Holder	0.44*
% Farms ≥ 20 years ≤ 29 years Holder	0.50**
% Farms ≥ 30 years ≤ 39 years Holder	0.51**
% Farms ≥ 39 years ≤ 49 years Holder	-0.27
% Farms ≥ 50 years ≤ 59 years Holder	-0.41*
% Farms 60+ years Holder	-0.45* ²
***Significant at 5% level; ** Significant at 10% level; *Significant at the 20% level.	
¹ Nearly significant at 20% level; ² Nearly significant at 10% level.	

Table 8.4 provides correlation results for general agricultural indicators by size, type, activity and status of farm for each parish.³ Unfortunately, land use data are available from the mid to late 1970s only, the period of the last island-wide agricultural census. This drawback notwithstanding, the data nevertheless provide a general picture of the overall farm and land quality characteristics of each parish. It is worth noting that virtually all the correlations for these variables have the expected sign and in several cases are significant. This suggests a possible role at the parish level for physical and land use factors related to deprivation in this key economic sector.

Specifically, as Table 8.4 indicates, deforestation rates are correlated positively with areas in which agriculture dominates, as measured by the percentage distribution of farms in each parish; however, this relationship is not significant. This finding may reflect the fact that predominately agricultural parishes have more trees, and heavily urbanized parishes have less agricultural land (and therefore less forest cover to lose). However, the extremely low correlation between the proportion of forest in 1987 and population density in 1982 ($r^2 = 0.07$), and between the percentage distribution of farms in each parish and the proportion of forest cover in 1987 ($r^2 = -0.14$) suggest that there is more to the positive relationship between deforestation and agriculture

³Note that, since these land use variables are measured at the parish level only, a greater number of indicators are presented here than are actually used in the regression analysis in Chapter 9. Land use variables which are not included in the regression analysis and therefore not defined formally in the next chapter are as follows:

a) A farm is defined as all land forming a holding or part of a holding (i.e. land used for agricultural purposes as defined by minimum criteria of enterprise; for instance, more than one square of cultivation and 12 or more economic trees) and which is situated in a single parish.

Note that farms are single holder farms (i.e. those in which the holder is the sole operator of a farming enterprise, which comprise approximately 98% of all farms in Jamaica).

b) Landless Farm: Farm involved in the keeping of livestock (e.g. defined as one head of cattle or two heads of pig or goat) but where less than one square of cultivation criterion or twelve economic trees criterion is owned and/or operated.

c) Agricultural Employment: Employment, paid or unpaid, provided by operators of farming enterprises.

d) Non-Agricultural Employment: Employment provided in non-farming enterprises.

e) Export Crops: Farms in which the major output is exported (e.g. sugar cane, bananas, coffee, cocoa, citrus, pimento).

f) Domestic Crops: Crops produced mainly for local consumption and all crops not classified as export crops.

g) Mixed Crops: Two or more crops planted and grown together within the same area of land.

h) Livestock/Poultry: Farms in which the main enterprise is the keeping of livestock/poultry (defined as holding one or more of: cattle, pig, goat sheep, ducks, turkeys, rabbits and bee hive cultures) for agricultural purposes.

These definitions are derived from the Jamaican *Census of Agriculture* (DS 1978/9). "None" and "Other" agricultural activities are not defined in this census, but presumably would include fallow farms and farms that would not fit any of the above activities, respectively.

than simply the relative extent of forest cover in one area versus another.

Surprisingly, the percentage figure for number of farms ≤ 1 acre (which includes landless farms), is negative (albeit not significant). This pattern of negativity for this size class was repeated throughout the parish correlation analysis, regardless of which land use indicator (i.e. size, type and status of farm) was included. However, it was not a pattern found for the landless farm category, which was always consistently positive (albeit not significant). Although it is difficult to make inferences given the size of the data set and the presence of possible intermediary factors affecting this pattern, this consistent result suggests that farmers owning parcels of land comprising the very smallest acre size class may be dependent on sources of support not available to the next highest size group (i.e. ≥ 1 acre ≤ 5 acres). The latter class, having a little more land, may thus be slightly better placed to choose farming as a livelihood. Moreover, while neither is significant, the correlation for the proportion of income spent on food and the proportion of farms ≤ 1 acre ($r^2 = 0.10$) is positive, but negative for the proportion of farms ≥ 1 acre ≤ 5 acres. That is, it may be that the smallest land class, while very poor, is more likely to spend a greater proportion of its income on food than is the next highest size class, which is more likely to grow food (and thereby destroy forest cover).

The contribution of this size group (i.e. ≥ 1 acre ≤ 5 acres) to deforestation is indicated by its positive and marginally significant correlation ($p \leq .20$) with deforestation. As the farm class progressively increases, the positively significant relationship between deforestation and the second largest size class breaks down, as evidenced by the negative (albeit not significant) correlations for farms ≥ 5 acres ≤ 50 acres, and for farms ≥ 50 acres ≤ 100 acres ($r^2 = -0.16$, and $r^2 = -0.33$, respectively.) In other words, the correlations become increasingly close to being significant with each successive increase in the farm size category, eventually becoming highly significant at the level of the largest farm class: farms over 100 acres ($p \leq .05$).⁴

It is also interesting to note the marginally significant and positive correlations between the % of farms growing domestic crops ($p \leq .20$), and the % of farmers in each parish headed by the young to middle age categories (i.e. less than 39 years).

⁴ Although results are not reported here, this pattern of correlation for farms falling between ≥ 5 acres ≤ 100 acres size group was also evident for the medium to large size groups comprising this amalgamated class (i.e. farms ≥ 5 acres ≤ 10 acres; ≥ 10 acres ≤ 25 acres; ≥ 25 acres ≤ 50 acres).

This pattern of results, however, completely reverses itself for the variable measuring farms whose major activity is the production of export crops (which is highly significantly correlated with deforestation ($p \leq .05$)), and farms in the older age categories, particularly the over 50 acre size class ($p \leq .20$).

Moreover, while not significant, there is also a positive relationship between deforestation and the % of farms in each parish that are: female-headed, devoted mainly to the production of mixed crops or livestock/poultry, and not employing labour. Similarly, farms in the main agricultural activity 'other' (i.e. not defined by these other enterprises) and "none" (i.e. dormant land) categories, part-time farms and farms that employ labour, are also negatively correlated with the overall % rate of forest loss in each parish.

<i>Table 8.5: Parish Land Quality</i>	
<i>Variables Deforestation Correlations</i>	
<i>Land Quality</i>	<i>Correlation with % Forest Change</i>
Good Capability	-0.65***
Average/Fair Capability	0.38*
Poor Capability	0.54***
***Significant at 5% level; *Significant at 20% level.	

Finally, Table 8.5 presents correlation results for deforestation and land capability indicators based on slope and soil characteristics. There are negative and significant correlations between deforestation and the island's best agricultural land, and positively significant correlations for those areas with average/fair ($r^2 = 0.38, p \leq .20$) and poor capability ($r^2 = 0.54, p \leq .05$). These findings indicate, rather plausibly, that most of the deforestation on the island has occurred in areas where the land is generally not very good, and places quite severe restrictions on use. Likewise, the marginally strong correlation between forest loss and the proportion of land area in forest in 1987 presented earlier also suggests that those areas that experienced the worst rates of deforestation also contained most of the island's remaining large tracts of standing forests. Furthermore, the significantly strong correlation ($r^2 = .60, p \leq .05$), between the proportion of land area in forest and areas with poor land quality suggests that those areas that are the least likely to support human populations, and should therefore

remain in forest, are precisely those losing their vegetative cover the fastest.

8.3.2 A Deeper Look at the Small Size Farm Category

While farms ≥ 1 acre ≤ 5 acres are not the very smallest size class, they comprise a size of class that is nevertheless quite marginal. Moreover, it is a size class that is quite pervasive in Jamaica, one accounting for approximately half of all farm sizes in each parish (see Appendix H). As noted in Chapter 4, and evidenced by its highly significant correlation with the % of full time farms variable ($r^2 = 0.88$, $p \leq .05$), this size of farm class comprises the core of the small farming sector. The part-time farmer, in contrast, is more likely to have only a little land available for farming, and to supplement his or her garden with income earned elsewhere; for example, from employment on large farm estates or higglering in the informal sector.

A more detailed examination of the characteristics of this small farm class reveals some interesting findings of relevance to this study. Tables 8.6, 8.7 and 8.8 provide correlations between the overall % forest loss rate and the ≥ 1 acre ≤ 5 acres size class. Note the significant positive correlations between deforestation and farms of this size class: a) growing domestic crops ($p \leq .10$); b) farming full-time ($p \leq .20$); c) held by the under age 30 group, particularly the under 29 age group ($p \leq .05$); and d) headed by a female ($p \leq .20$).

Note, also the strongly negative correlation between this size category and export crop production ($p \leq .05$), suggesting that even at the level of this very small size class, there are potentially positive benefits for forests from farmers growing food for the export market. Unfortunately, comprehensive statistics on agricultural inputs (e.g. extension services, access to inputs, financial investment) and so on, is lacking but it may be that either one or a combination of higher incomes and/or access to sophisticated farming inputs in the export sector has helped to stabilize even very small farmers in one location, thereby eliminating the need for expansion into forested areas.

<i>Table 8.6: Parish Small</i>	
<i>Farm Variables Deforestation Correlations</i>	
<i>Land Use Indicators by Small Size Group of Farms</i> <i>Type of Agricultural Produce</i>	<i>Correlation with Overall</i> <i>% Forest Loss</i>
% Farms < 1acre Domestic Crop	-0.06
% Farms $\geq 1 \leq 5$ acres Domestic Crop	0.49**
% Farms ≤ 5 acres Domestic Crop	0.28
% Farms < 1 acres Export Crop	0.06
% Farms $\geq 1 \leq 5$ acres Export Crop	-0.63***
% Farms ≤ 5 acres Export Crop	-0.63***
% Farms < 1 acre Mixed Crop	-0.03
% Farms $\geq 1 \leq 5$ acres Mixed Crop	0.37 ¹
% Farms ≤ 5 acres Mixed Crop	0.16
% Farms < 1 acre Livestock/Poultry	0.28
% Farms $\geq 1 \leq 5$ acres Livestock/Poultry	0.10
% Farms ≤ 5 acres Livestock/Poultry	0.31
% Farms < 1 acre Other	-0.12
% Farms $\geq 1 \leq 5$ acres Other	-0.12
% Farms ≤ 5 acres Other	-0.13
% Farms None < 1 acres None	0.03
% Farms None $\geq 1 \leq 5$ acres None	-0.12
% Farms None ≥ 5 acres None	-0.03
***Significant at 10% level; ***Significant at 5% level; *Significant at 20% level	
¹ Nearly significant at 20% level	

Moreover, the strongly positive and highly significant correlation between the % of farms ≥ 1 acre ≤ 5 acres and the proportion of land with average/fair/poor capability is 0.60 ($p \leq .05$). This finding supports the notion that much of the forest cleared on the island has occurred mainly in areas where farms of this second smallest size group dominate. By contrast, the correlation of this small size group of farms with the proportion of land having good soils and slope quality is highly strongly negative ($r^2 = -0.66$, $p \leq .05$).

*Table 8.7: Parish Agricultural Activity
Variables Deforestation Correlations*

<i>Land Use Indicators by Small Size Group of Farms Income Earning Activity</i>	<i>Correlation with Overall % Forest Loss</i>
% Farms \leq 1 acre Full-Time	-0.0
% Farms \geq 1 acre \leq 5 acres Full-time	0.41*
% Farms \leq 5 acres Full-time	0.26
% Farms Landless Farms Part-time	0.33
% Farms \leq 1 acre Part-time	-0.26
% Farms \geq 1 acre \leq 5 acres Part-time	0.03
% Farms \leq 5 acres Part-time	-0.08
% Farms $<$ 1 acre Agricultural Employment	-0.27
% Farms \geq 1 acre \leq 5 acres Agricultural Employment	-0.43*
% Farms \leq 5 acres Agricultural Employment	-0.35
% Farms Landless Farms Non-agricultural Employment	0.21
% Farms $<$ 1 acre Non-agricultural Employment	-0.07
% Farms \geq 1 acre \leq 5 acres Non-agricultural Employment	0.03
% Farms \leq 5 acres Non-agricultural Employment	0.03
% Farms Landless Other Employment	0.13
% Farms $<$ 1 acre Other Employment	-0.04
% Farms \geq 1 acre \leq 5 acres Other Employment	-0.23
% Farms \leq 5 acres Other Employment	-0.09
***Significant at 5% level; **Significant at 10% level; *Significant at 20% level.	

Alternatively, the highly negative and significant correlation between deforestation and farms of the 100+ category, suggests that areas of good land capability have a low deforestation rate because large farms — which are highly significantly correlated with these areas ($r^2 = 0.66$, $p. \leq 05$) — are not clearing more land due to poor productivity (as is the case with the $\geq 1 \text{ acre} \leq 5 \text{ acres}$ size group). (Note that the correlation between the change in forest cover and the proportion of land area of good quality is -0.18, which suggests that the strongly significant inverse relationship of large farms with deforestation cannot be attributed to their being situated in areas where agriculture is

well-established (and, thus, have less forest cover)).

<i>Table 8.8: Parish Small Farm Status</i>	
<i>Variables Deforestation Correlations</i>	
<i>Land Use Indicators by Small Size Group of Farms</i> <i>Landholder Status (Sex and Age Group)</i>	<i>Correlation with</i> <i>Overall % Forest Loss</i>
% Female Landless Farms	0.30
% Female <1 acres	-0.04
% Female ≥ 1 acre ≤ 5 acres	0.45* ¹
% Female ≤ 5 acres	0.33
% Farms ≤ 1 acre ≤ 20 years	0.29
% Farms ≤ 1 acre 20-29 years	0.33
% Farms ≤ 1 acre 30-39 years	0.19
% Farms ≥ 1 acre ≤ 5 acres ≤ 20 years	0.60***
% Farms ≥ 1 acre ≤ 5 acres 20-29 years	0.50**
% Farms ≥ 1 acre ≤ 5 acres 30-39 years	0.38*
% Farms ≤ 5 acres ≤ 29 years	0.53** ²
% Farms ≤ 5 acres 30-49 years	0.11
***Significant at 5% level; **Significant at 10% level; *Significant at 20% level	
¹ Nearly significant at 10% level; ² Nearly significant at 5% level.	

The highly significant correlations between deforestation and farms of the ≥ 1 acre ≤ 5 acres class, can be coupled with the strongly negative correlations between deforestation and export-oriented farms of this size class (noted above) and the marginally significant negative correlation of this size class that hire labour ($r^2 = -.045$, $p \leq .20$). Together these findings give weight to the inference that deforestation may be attributable to the low incomes of these farms rather than simply to their small size alone (and, ultimately, to bad land management practices, which low incomes and small farm size would imply). (Note, in addition, the significantly negative finding for small farms that grow export crops cannot be attributed entirely to the fact that these farms are situated on better soils, since the correlation between the latter and areas of the island with good capability is fairly weak (i.e. $r^2 = .027$)). In other words, export crops generate higher incomes, and the capacity to hire labour implies the presence of a sufficient

income beyond what is needed merely to survive.

In summary, the picture of the land clearer that begins to emerge from these simple correlation results is one of a very small farmer, occupying a marginal sized plot of land, but neither landless nor near-landless, farming full-time, on land of low productivity, growing domestic foodstuffs, slightly more likely to be a female and to be of a very young age (under 30).

The next chapter will examine some of these relationships in more detail in a regression analysis including a range of physical and social measures, in an attempt to shed greater light on the role of scarcity in driving deforestation on the island.

Chapter 9

Regression Analysis

9.1 Some Preliminary Remarks

This chapter describes the regression model and data set used to analyze the relative contributions of some key scarcity-related factors – discussed in Chapters 2 and 3 – to the rate of forest loss calculated in Chapter 8. Previous discussion highlighted the myriad of factors thought to drive forest clearance by the poor in the tropics, particularly in Jamaica. Earlier chapters indicated that scarcity can impact on forest cover through a host of mediating factors. Among the key factors noted were: population density and growth, inequitable social conditions, shortages of land and other resources, inappropriate land use technologies, insufficient and low quality employment prospects for the mass of the population, market distortions, misguided policies and failings in political institutions. Broader level factors, for example, Jamaica's economic dependency on and poor integration into world markets, were also noted for the crucial role that they played in deforestation.

As noted previously, the aim of the socio-economic portion of this study is to measure the contributions of a few key variables to deforestation in Jamaica. These are the factors identified earlier in the review of the environment/population/poverty literature as being potentially important for their role in structuring the land use decisions of a particular social group: the poor. Thus, it does not attempt to provide a comprehensive analysis of all the variables driving deforestation in Jamaica. Nor does it model all those factors (direct or indirect) that are thought to condition the behaviour of the poor individual land clearer. Data limitations, coupled with the complexities

and uncertainties involved in modelling to any degree of accuracy the dynamic inter-relationships among all the factors responsible for driving this process, mean that no model or analysis will ever be complete. Thus, only a highly simplified depiction of reality can be conceptualized and measured.

It should be stressed that this study's depiction of the poor individual land clearer is not a formal or mathematical one in the tradition, for instance, of the equilibrium land clearance models discussed in Chapter 2. As noted, these models assume that the amount of land cleared is determined by the individual farmer's profit-maximizing decisions in relation to the supply of cleared land, which depends on the marginal costs of clearance. In the first instance, these models are themselves highly stylized despite their formal economic derivation and econometric implementation. But even if one assumes for the moment that these models are indeed accurate descriptions of land clearance in Jamaica (i.e. are equally applicable, for example, to rent-seeking farmers who sell their produce in markets, to subsistence farmers unintegrated to markets, and to homeless individuals who clear land for shelter), their estimation nevertheless depends on the availability of suitable data (e.g. agricultural output prices, wage rates, land prices). Such data were unavailable for this study. Moreover, some of the data (e.g. farm-gate prices) required to model this behaviour do not vary across constituency to any significant degree.

In short, like most social scientific models of these relationships, the study's conceptual model is informal and incomplete. Moreover, its empirical measurement can provide an understanding of suggestive patterns only in the data. Due to the fact that many relationships cannot be observed, the model is aptly referred to in the economic literature as a reduced-form model. This model is used in the study to determine whether empirical findings are consistent with the qualitative literature, its conceptual models, and the few quantitative studies that have measured similar variables of interest. This approach will hopefully yield stylized facts that can provide the basis for more formal theorizing and model development in future work. However even these latter or 'structural' models should be recognized for what they are, namely, simplifications of the underlying, dynamic relations and interrelationships in the deforestation process.

9.2 A Conceptual Model of Scarcity-Driven Land Clearance

The conceptual model underlying the statistical analysis of this chapter is based on the assumption that the scarcity-induced demand for cleared land (and thus, deforestation) is determined largely by the economic and welfare prospects of a given individual. Land clearance, in other words, is hypothesized to be an activity of last resort for individuals in the absence of sufficient remunerative and welfare-related opportunities elsewhere. In such circumstances, individuals will clear land for any number of purposes: to supplement income earned from work in low-wage service or agricultural sectors, to provide shelter, grow food or raise forest produce (e.g. fuelwood) on a full-time basis, as a temporary 'stop-gap' measure to meet income and consumption needs during times of unemployment, and so on..

As discussed in Chapter 2, many factors can mediate the relationship between poor individuals and the land. Low levels of human capital development, for example, can impair the ability of individuals to find suitable employment, exacerbating poverty levels and increasing their dependency on the land. Inadequate provision of social infrastructure (e.g. housing, hygiene) contributes to rural underproductivity and poverty, leading poor individuals to colonize forested areas. Similarly, low levels of agricultural productivity arising from insufficient support for small farmers contributes to extensive agricultural land practices that degrade these ecologically fragile areas further.

Likewise, poverty and inequalities in the distribution of land and income mean that fewer resources are available for the poor to make a living or meet basic needs. Low incomes and productivity in turn will suppress the growth of employment opportunities in off-farm enterprises or in built-up areas. Shortages of good quality accessible land will also stimulate excessive land clearance in other areas. Demographic pressures will exacerbate these relationships in turn by increasing the demand for cleared land and for forest produce, particularly fuelwood. However, as discussed in Chapter 2, the environmental consequences of this pressure can be ameliorated to varying degrees according to the level and/or rate of change in these and other variables.

All these scarcity-related influences on forest cover can be expressed in terms of the regression equations presented below. Some of these equations capture indirect

influences on deforestation related to the remunerative opportunities and life chances open to individuals, using variables measuring individual household income, poverty, employment, welfare provision and human capital development. As the opportunities for earning alternative income become scarce and poverty levels rise, the demand for remunerative and other welfare benefits achieved through forest invasive activities increases, which is hypothesized to lead to greater levels of deforestation.

In addition, it is also hypothesized that the rate of forest loss will be affected by such land use factors as size of farmer holding, and overall availability of good accessible land, as measured by soil quality and slope.

Finally, these regression equations also measure demographic-induced scarcity, i.e. the hypothesis that forest clearance is also a function of the sheer absolute number of individuals lacking sufficient off-farm remunerative opportunities, welfare and physical assets (e.g. fuelwood, suitable farmland, and adequate housing).

9.3 Description of Social and Physical Land Use Variables

9.3.1 General Description of Data Sources

Independent variable data were obtained for both years of the study from several Jamaican government and international sources. The Jamaican government's statistical agency, STATIN (formerly the Department of Statistics (DS)) has collected data on several economic, demographic and agriculture-related indicators over time.

Most socio-economic and demographic data were derived from the *Caribbean Commonwealth Population and Housing Census* for 1992 and 1982, the years closest to the period of interest to this study (1987-1992). This census is conducted once every ten years. The latest census is the 12th such census, the previous one having been completed in 1982. The census uses consistent definitions and concepts to track a wide variety of population characteristics (e.g. age, sex, fertility, economic activity, educational attainment, housing quality and household composition).

The Census divides the island into over 5,000 geographic units or enumeration districts for both years. Each enumeration district constitutes an independent unit which shares contiguous boundaries with other enumeration districts. The size of the enumeration district is determined by the number of households (approximately 100 in

rural and 150 in urban areas) that can be manageably contained within it. Enumeration districts can be reconstituted to form larger political units such as the constituency. The constituency is a legally defined parliamentary unit which encompasses all enumeration districts and does not violate parish boundary lines. In 1982 there were 51 and in 1991, 60 constituencies. Constituencies can be reconstituted to form broader legal divisions or parishes. Each parish has a minimum of 2 constituencies and upwards of 140 enumeration districts. The parish is the largest unit in terms of which all other legal and census units can be reconstituted. Since the number of constituencies in some parishes was greater in 1992 than in 1982, it was necessary in cases where new constituencies had been created in 1992 to conflate each one into the respective 1982 constituency from whence it came, so as to ensure data comparability between the two years. (See Appendix F for constituency and parish boundary maps and their respective identifiers).

In addition, the World Bank, Poverty and Human Resources Division, has conducted a survey of living standards (LSMS) for the island since 1988. As with the other 21 countries comprising the data base, the purpose of the Jamaican study is to gather information on living conditions on the island as a means of determining baseline indicators for evaluating the effect of various government policies on the welfare of the population. The survey is implemented on a nationwide basis at the household level, and is also linked to the country's on-going quarterly labour force survey. Each JSLC (Jamaica Survey of Living Conditions) survey has included module questionnaires on health, education, nutrition, consumption and housing — and in recent years (97-99) — migration and agricultural household activities (World Bank 1998).

The other major data source for the study's independent variables is the Jamaican government's *Agricultural Census*. Published in 1976, it is the most recent completed census to date.¹ The agricultural census is compiled in collaboration with the FAO's World Agricultural Census program. This census was conducted in two parts: a census of farms and farm operators, their structure, content and characteristics; and a sample survey of selected areas of crop, livestock production and inputs (DS 1978/9). The census covers all agricultural activities in non-urban areas and hence excludes Kingston,

¹ Jamaica is now in the process of collecting data for its 1996 agricultural census. None of this data has yet been made available to researchers.

parish capitals and towns (with the exception of those farms listed on the Land Valuation List identified as holding 50 acres or more). The survey is based on a total of 3,600 enumeration districts; however, data for this study were available only at the parish level.

The study's physical land use indicators — soil and slope data — were obtained from the FAO's *Digital Soil Map of the World & Derived Soil Properties* (1998). This digital map is based on the original 1961 FAO/UNESCO paper soil map of Mexico and Central America, which includes the Caribbean islands. The map unit consists of a soil unit or association of soil units along with accompanying data on soil texture, slope class and phases. The soil map for this region of the world was digitized from the original soil map (which has a scale of 1:5 million).

For the most part, variables were extracted directly from each of these established data sets but in some cases variables had to be constructed from existing socio-economic data. In addition, several variables were constructed from the study's satellite-derived data and maps using a GIS. Each of these variables, and where applicable, their method of construction, is described in detail below.

9.3.2 Description of Independent Variables (Social)

Population

Population measures are derived from the population and housing census for both 1982 and 1992. This series contains total population measures for each constituency as well as useful information about the age and sex composition of the population. A population density variable (**POPDEN**) was created by dividing the total population (male & female) for each constituency over the total land area of each constituency in hectares. Area data were derived from the study's constituency boundaries map, using the **EXTRACT** function in IDRISI.

Age composition figures in this series were used to derive a dependency ratio variable for each constituency (**DEPRAT**). This variable was created by dividing the number of residents in each constituency aged 0-14 and over 64 years (non-working age population) by the number of residents 15-64 years (working-age population).

Employment

The population and housing census contains data on the economic situation of households surveyed for all residents 14 years and over. The census recognizes a number of categories of economically active persons, defined by the ILO as “all persons of either sex involved in the production of goods and services”. Included in this definition are “the usually active population” and the “currently active population”. These two categories comprise all those persons who have worked for either a long (e.g. ≥ 1 year) or a short reference period preceding the census. These would be all persons working, actively seeking work, employed but not working and unemployed but not actively seeking work (although would take a job if offered one).

An unemployment measure for each sex (**UNMALE**, **UNFEM**) was constructed as follows:

$$Unmale/Unfem = \frac{\text{No. of Males/Females Seeking Work}}{\text{No. of Males/Females Seeking Work} + \text{No. Males/Females Working} + \text{No. Males/Females Employed but Not Working}}$$

Access to Off-farm Economic Opportunities

The study’s unemployment variables measure the overall availability of job opportunities (both farm and non-farm) in each constituency; however, accessibility to economic opportunities is also an important factor ameliorating the pressures of population and poverty on the land.

The study’s variable measuring distance to major economic centers attempts to capture positive forest spill-over effects from the proximity of poor individuals to areas of relative prosperity. Whereas the unemployment variable largely measures levels of economic activity in the formal sector, a large portion of the impoverished population of Jamaica labours in the informal sector. In this study, **DIST** measures the average Euclidean distance (i.e. ‘as the crow flies’) of each constituency to the major resorts/cities: Kingston, Negril, Ocho Rios, Montego Bay & Port Antonio. It is designed to capture access to both formal and informal economic activities that act as pull factors attracting poor migrants from the surrounding countryside.

DIST was created in a GIS by: a) creating a point vector file of coordinate locations; b) rasterizing the resulting image; c) calculating the average distance of each pixel to each measured location using the **DISTANCE** function in IDRISI; and d) Extracting average distances for each location for each constituency. Figure 9.1 defines each one of these geographical points with their corresponding identifier names.

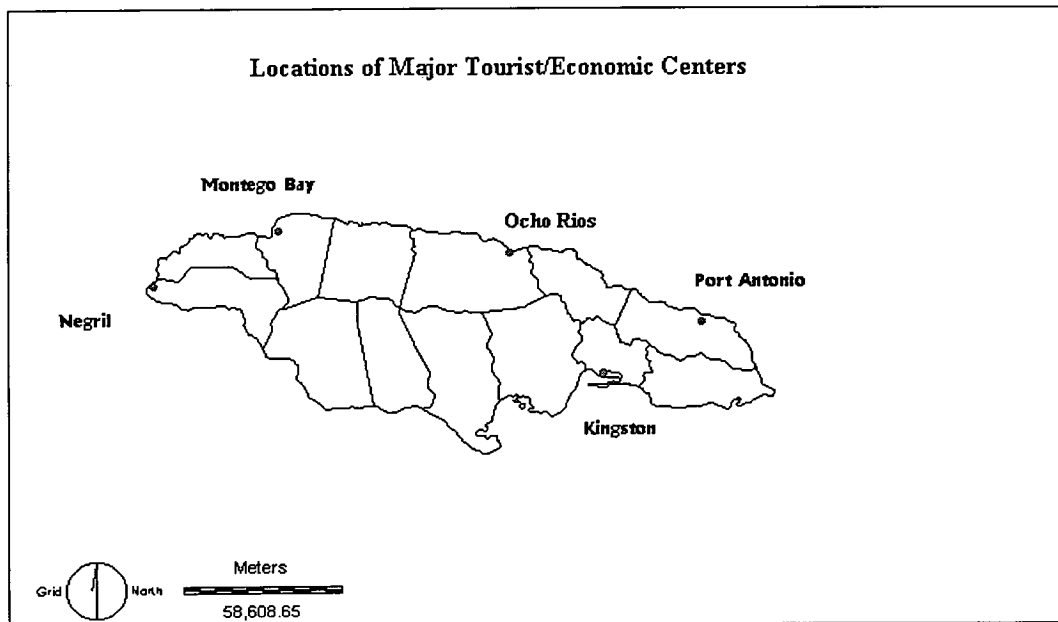


Figure 9.1

Welfare, Consumption & Quality of Life

Income is a key indicator of welfare, but other measures are equally important (e.g. health, housing, sanitation). This information is often difficult to obtain for developing countries, but Jamaica is fortunate in that it has consistently measured key dimensions of the welfare of its population over time.

a) Housing One of the most basic measures of welfare provision is access to piped water, which often serves as a good proxy for overall level of public services provision. Another quality of life indicator for which Jamaican data is available is housing. The *Census* provides a range of information relating to the composition, type, and age of housing on the island.

Data were obtained from this series on the percentage of houses lacking piped water and the size of housing units within each constituency. The *Census* defines households as consisting of one or a group of persons who may or may not be related but who

jointly occupy whole or part of a dwelling unit and share common arrangements for housekeeping. A housing unit is defined as a building or set of buildings used for living purposes at the time of the census.

The first variable (**WATER**) measures the number of households in each constituency with access to piped water, either public or private, in the yard or in the home, as a proportion of the total number of households in each constituency. The second variable was created by dividing the number of households in each constituency with one room (**ROOM**) only by the total number of households in each constituency. The latter variable was also derived from the *Census*' housing series.

b) **Fuelwood** Another important infrastructure and quality of life indicator, particularly for this study, is fuelwood dependency. As noted, the poor are heavy users of fuelwood, in Jamaica. The census monitors energy use per household by a variety of fuel types and is the source for the study's fuelwood dependency variable. This variable (**FUEL**) measures the proportion of all households that use wood/charcoal as their main source of fuel for cooking.

c) **Education** The Jamaican census is also the source for the study's human capital development measure. The attainment of basic literacy and numeracy is an important indicator of level of welfare achieved by a country, and has important implications for a number of other indicators, particularly fertility and employment. In this study, educational attainment is measured by the number of males and the number of females (**ATTAINM**; **ATTAINF**) over 14 years of age with primary school education or less, as a proportion of the total population in each constituency. This total population variable was derived from the Census' demographic series, described earlier.

d) **Consumption & Income Inequality** The study also contains variables on income levels and on variance in household income. The variable **FOOD**, for example, measures annual household expenditure in the last twelve months on 43 categories of food items as a proportion of total consumption. (Note that for the 1992 expenditure measure, the value of home production and gift food is also included). **FOOD** was created by dividing the amount spent by each household on food by total household consumption (defined as the amount spent on food, non-food, housing and other items

and measured by the *JSLC Survey*'s consumption series). Thus, higher values of this variable are associated with higher levels of poverty.

The study also includes a measure of the degree of variation in incomes across households. This income inequality variable (**STEDEX**) was derived by taking the standard deviation of the total annual household consumption variable is was also derived from the *JSLC Survey*.

9.3.3 Description of Independent Variables (Physical & Land Use)

Land Poverty

The Jamaican *Agricultural Census* provided data on the ownership of land and size of holdings in each parish. In view of the fairly strong significance of many scarcity-related agricultural variables in the previous chapter and their overall importance in the deforestation literature in general, a farm variable was included in the constituency-level regression analysis.

Although the data were collected at least 10 years before the satellite imagery and are available only at the parish level, two points in defence of the inclusion of a variable from this data set can be made. First, the overall pattern of land distribution does not typically change too much over time. If anything, land inequality and size of land holding have worsened from the point of view of the small farmer, so that results should be interpreted as providing a more extreme reflection of the situation as it existed during the 1980s and after. Second, with regard to the strategy of assigning parish values to each constituency, it can be noted that the variation (i.e. in respect to both geography and administration) within a parish is small relative to the variation across parishes. Hence it is not entirely unjustifiable to suggest that some of this similarity may be captured in a very general way at the constituency level.

Given the way in which the data had to be constructed, the decision was made to include only one agricultural variable of interest. Appropriately, the study's land distribution variable, **SMLFARM**, was derived by calculating the number of farms in each parish in the size class ≤ 5 acres, as a proportion of total farms. A constituency variable for this measure was subsequently created by ascribing to each constituency its respective parish value. Due to its consistently strong associations in the parish level deforestation correlations presented earlier, only this size class is included in the

regression analysis. The variable provides a good measure of the predominance of small farmers in each constituency, and in view of the constraints facing these farmers, represents a good measure of the degree of 'land poverty'.

Soil & Topography Data on slope and soil quality were obtained from the FAO's *Digital Soil Map of the World & Its Derived Properties* (FAO-UNESCO 1993). This land information archive identifies 129 categories of soil type. As mentioned previously, the original mapping scale was 1:5 million. The raster map version for Jamaica was extracted in 5 min x 5 min grids, or roughly about 9 km x 9 km. Due to this coarse resolution, relatively few soil mapping units exist for Jamaica. Likewise, the extremely small size of the raster map and resulting resampling problems meant that subnational level data could only be extracted at the parish level. As in the agricultural variables above, each constituency was assigned the same value as its corresponding parish.

Each map unit is a soil association represented by: a) the dominant soil unit; b) a number for the composition of the soil association; c) a number representing textural classes coarse, medium, fine (i.e. 1,2,3); and d) letters representing the slope classes: level to gently undulating, rolling to hilly and strongly dissected to mountainous (i.e. a, b, c).

In total, 9 soil units were included in the study from the original national scale raster map. Parish level land data were derived from the national map by first rasterizing and then resampling (RMS = .04 m) the vector parish boundaries map in Appendix F to the 1987 3-category classification map (see Appendix C for correspondence file). The vector map was obtained from Arc-Info's *Digital Chart of the World* (ESRI 1993) and had an original mapping scale of 1:1 million and was extracted in roughly 1 km x 1 km grids). Area data for each of the 9 soil units for each parish were derived by using the EXTRACT function in IDRISI. In order to reduce the number of variables in the regression analysis, the 9 soil units were subsequently conflated into 3 land quality categories designated as: good, average/fair, and poor. These broad categories were based on the FAO's own assessment of the restrictions imposed by these soils on traditional agricultural land use practices (i.e. those lacking farming inputs, mechanized equipment, irrigation, etc.). Specifically, restrictions are based on a combination of the dominant association, texture and slope for each soil unit. This classification was designed strictly for the purposes of this study, and is intended to provide only broad

groupings based on the general characteristics associated with these soil units.

The first soil group, 'good' (measured by variable, **SOILG**) comprises the island's best soils, and these possess few if any restrictions on land use. The second category, of soils 'average/fair' (measured by variable, **SOILA**) comprises soils that place varying restrictions on subsistence agriculture but are generally of moderate to fair quality. Soil group, 'poor' (measured by variable, **SOILP**) comprises the worst soils on the island. All these soils place severe restrictions on any type of land use and are highly unproductive.

Table 9.1 provides a breakdown of the 3 soil groups with a description of their respective soil units, slope and phases. Appendix I provides area statistics extracted for the three soil groups for each parish.

Table 9.1: Soil Variable Classification

Classification	FAO Unit	Association	Texture	Slope	Capability
Good	LC30-3ab	Chromic Luvisols	Fine	Gentle to Hilly	Fertile, little difficulty
	JE44-2a	Eutric Fluvisols	Medium	Gentle to Undulating	Fertile, some flooding, but otherwise good
Average	ND36-3bc	Dystric Nitisols	Fine	Rolling to Mountainous	Deep, fairly good yields, esp. coffee
	E6-3bc	Rendzinas	Fine	Rolling to Mountainous	Partially rocky, but generally good, fertile, well-drained
	BC4-3bc	Chromic Cambisols	Fine	Rolling to Mountainous	Generally good to fair, depending on management
	LC27-3bc	Chromic Luvisols	Fine	Rolling to Mountainous	Moderately good, care to avoid erosion, yields not high
Poor	AO56-2bc	Orthic Acrisols	Medium	Rolling/Hilly	Fertility, drainage & erosion problems, fair to poor yields
	I-BE-c	Lithosols/ Eutric Cambisols	None given	None given	Generally extremely thin, stoney; infertile
	I-NE-c	Lithosols /Eutric Nitisols	None given	Steeply Dissected to Mountainous	Generally very thin, stoney; infertile

Proportion of Forest Cover

It is not unreasonable to assume that deforestation may be higher in areas with more forest cover; after all deforestation presupposes the existence of a standing forest which is being destroyed. Yet, it is often the case in the tropics that areas with the largest amount of forest cover are also the least accessible.

The use of a percentage change as the dependent variable partly measures this effect, since a 10% loss in forest cover, for example, will be treated in the same way in the analysis regardless of whether 10% of a large forested area in a densely forested constituency or 10% of the last remaining relict area of forest in an otherwise deforested constituency is measured. However, to capture fully the possible impact of the standing forest effect on deforestation rates, the study also includes the variable **PROPFOR**, measured as the amount of forest cover in hectares as a proportion of total land area for each constituency in 1987. This variable is based on the study's satellite-derived measures of forest cover for each constituency in 1987.

9.4 Some Methodological & Data Notes

9.4.1 Data Explanation

The dependent variable in the regression analysis is the percentage change (i.e. decrease) in forest cover between 1987 and 1992. As noted previously, constituency level forest data, which were extracted from the 3-category classified images according to the procedures outlined in Chapters 6-8, are the same data set from which forest cover and loss estimates were calculated for the parish analysis in Chapter 8. Note, moreover, that deforestation in this constituency level regression analysis is measured over 5 years rather than as the average annual percentage change rate, for which figures were also presented in the national level analysis.²

For the purposes of description and analysis of the statistical results, the explanatory variables described above are classified into three categories: a) Social; b) Land

²Thus, the dependent variable in the constituency level regression analysis should be taken to mean, for example, that a constituency such as St. Ann NW, which has a value of 15.02, lost 15.02% of its forest cover between 1987 and 1992. Conversely, a constituency like St. Andrew E Rural, which had a negative percentage change of -6.05%, saw its forest cover increase by this amount between 1987 and 1992.

Use/Farm; and c) Physical/Topographical. Unfortunately, as noted, only data for variables in the first group are available at the constituency level. For variables in the other two groups, all constituencies comprising the parish were assigned the same value. Such a strategy enables data for the latter two groups to be included in the regression analysis. As noted previously, while far from ideal, this strategy will nonetheless give a rough indication of cross-constituency variation in respect to these variables. However, it is recognized that the use of parish level data in a constituency level analysis can introduce a fair degree of measurement error into the explanatory variables.

For this reason, there are two general parts to the regression analysis. In the first, the study's social variables are presented and discussed, with all other variables omitted. The second part determines how the key regressions from this part of the analysis are modified by the inclusion of variables from the other two groups (i.e. land use/farm and physical/topographical). Although the problem of error associated with the use of these parish-level variables should always be kept in mind when interpreting results, this strategy of separating constituency level social variables from land use and topographical variables is justifiable. In other words, since the direct effect of farm and physical land variables was investigated in the previous chapter, this chapter will emphasize their possible indirect effects in a regression context in order to determine how these variables affect the social relationships of most importance to this study, namely those bearing on the poverty/population/deforestation nexus.

It should also be noted that both the levels of and change in the study's social variables are analyzed here. Levels variables are based on respective values for the earlier year, 1987, rather than for 1992, according to the assumption that conditions at the beginning of the period affected what went on in later years. Change variables can be identified by the prefix **CH** (i.e. **CHDEPRAT**) in the variables above. All change measures were constructed by taking the percentage change in the levels variables for their respective dates.

9.4.2 Statistical Methodology

OLS estimates of regression coefficients are presented in the standard way. As a measure of the uncertainty in these estimates, either standard errors, t-stats, or p-values can be presented. Of the three, p-values are the most informative about whether a

correlation/regression coefficient is significant, and are used in this study. Variables significant at the standard 5% and 10% levels are presented (i.e. $p\text{-value} \leq .05$ or $.10$, respectively). In some instances, variables significant at the 20% level (i.e. $p\text{-value} \leq .20$) are noted. As in the parish correlation results, these are referred to as being ‘marginally significant’.

It should be stressed that all data contain measurement error, but that this is a particular problem for data from developing countries, which typically lack the resources to survey the welfare characteristics of their populations on a wide scale. Moreover, due to the subsistence nature of the poverty in these countries, adequate data on characteristics pertaining to the lowest income groups can be difficult to obtain. In this study, in particular, measurement error also arises from the untimely nature of the agriculture data and from the fact that farm and soil data have been constructed from the parish average.

Measurement error will tend to reduce the significance of coefficients (i.e. a variable observed to be significant at the 20% level may, in actuality, be significant at the 10% level had it only been measured better). Of course, readers are free to downweight the evidence placed on such marginally significant results.

9.5 Constituency Level Analysis

9.5.1 Social Variables Descriptive Statistics

Tables 9.2 and 9.3 present correlation results and accompanying p -values for the % change in forest cover and each social variable, measured in terms of both its levels and change. Variables are described by their individual acronyms as noted above.

Although not many correlation results are significant, virtually all are of the expected sign. This finding is suggestive. That is, if it were truly the case that all statistically insignificant variables had no effect on deforestation in the 51 constituencies measured here, then a random pattern of signs would obtain, with statistical theory predicting roughly half the variables having the expected sign and half having the opposite sign.

<i>Table 9.2: Constituency Social Level Variables Deforestation Correlations</i>		
<i>Social Level Variable</i>	<i>Correlation</i>	<i>P-Value</i>
WAT	-0.19	0.19*
ROOM	-0.07	0.64
FUEL	0.23	0.10**
ATTM	0.18	0.20*
ATTF	0.21	0.14*
POPDEN	0.11	0.45
DEPRAT	0.30	0.04**
UNMALE	-0.10	0.50
UNFEM	-0.05	0.74
HSIZE	0.05	0.72
FOOD	0.14	0.33
EXP	-0.14	0.34
STDEX	-0.08	0.56
DIST	0.23	0.10**
***Significant at 5% level; **Significant at 10% level; *Significant at 20% level		

The finding that almost all are intuitively of the right sign indicates that the general assumptions about the contribution of these variables to deforestation is essentially correct, but that the statistical evidence in support of them is not strong enough to come through overwhelmingly in the analysis. Classical statistical hypothesis testing involves tests of a null hypothesis, as embodied in statements of the type: 'variable X has no effect on deforestation'. The null hypothesis is rejected only if there is overwhelming evidence against it. Needless to say, such 'overwhelming evidence' is difficult to find in data with more than its share of measurement error.

<i>Social Change Variable</i>	<i>Correlation</i>	<i>P-Value</i>
CHWAT	0.22	0.12*
CHROOM	0.11	0.46
CHFUEL	0.27	0.06**
CHATTM	-0.08	0.58
CHATTF	-0.07	0.62
CHPOPDEN	-0.01	0.93
CHDEPRAT	-0.27	0.05***
CHUNMALE	0.06	0.67
CHUNFEM	0.13	0.36
CHHSIZE	0.07	0.64
CHFOOD	-0.16	0.25
CHEXP	0.03	0.83
CHSTDEX	0.06	0.67

***Significant at 5% level; **Significant at 10% level; *Significant at 20% level .

The only counter-intuitive results in the tables are the negative correlations with deforestation of **CHDEPRAT**, **CHFOOD**, **CHWAT**, **CHPOPDEN**, **UNMALE** and **UNFEM**. According to the assumptions of both the literature and the conceptual model, higher unemployment levels should be positively rather than negatively correlated with deforestation rates across constituencies. However, the correlation between deforestation and the change in both of these variables (**CHUNMALE**, **CHUNFEM**) is, as expected, positive (i.e. the more unemployment grew between 1987 and 1992 the higher the constituency deforestation rate).

Similarly, the greater the change in the average food share of each household in total consumption (**CHFOOD**) the less deforestation, which is counter-intuitive to the expectations of the model, and opposite to that obtained for the levels variable (**FOOD**). A similar pattern can be observed for the variable, **CHWAT**, which measures the change in the proportion of households in each constituency with access to piped water. Where this number increased between 1987 and 1992, the deforestation

rate also tended to increase. As expected, the levels variable **WAT**, is negative, suggesting, perhaps, that constituencies with higher human welfare — as measured by access to proper sanitation and drinking water — experienced lower deforestation rates than otherwise.

The study's demographic change variables also demonstrate this pattern of reversed sign for change and levels measures. The result for **POPDEN** accords with the assumptions of the model that areas with greater numbers of people will have greater demands on forested areas than will less densely populated constituencies. However, as the numbers of people per hectare rose between the two periods in each constituency, the deforestation rate tended to fall, which is counter to the expectations of both the model and the literature.

At first glance, these counterintuitive results are difficult to account for, particularly since their levels measures are of the correct sign. The effects of these and the other social variables are explored in more detail in the regression analysis proper, where correlations among explanatory variables are also presented. In combination with a careful analysis of the relationships among explanatory variables, regression analysis will allow for the measurement of the relative effects of each variable on constituency deforestation rates.

For now, however, it is worth noting that, of the strongly significant variables, **FUEL**, **DEPRAT**, **DIST**, **CHFUEL** and **CHDEPRAT**, only the latter's correlation with deforestation has a counterintuitive (negative) sign. Marginally significant variables are: **CHWAT**, **WAT**, **ATTM** and **ATTF**. Of these variables, only **CHWAT** has an unexpected sign, as discussed above. Overall, these correlation results suggest the predicted pattern: a wide variety of variables reflecting social conditions and various aspects of deprivation appear to drive deforestation at the constituency level. Variables **DEPRAT**, **WAT**, **ATTM** and **ATTF** reflect more indirect scarcity influences on deforestation rates related to social welfare, demography and human capital development, while **FUEL** represents more direct impacts arising from poverty and a subsistence life-style. Surprisingly, none of the consumption and income variables is significant. As noted, **DIST** captures the possible special tourist and manufacturing pull effects that may ameliorate deforestation rates by drawing people away from the land. As expected, **DIST** is of the correct sign: The greater the average distance of

each constituency from a major tourist site or Kingston, the higher the constituency deforestation rate.

9.5.2 Regression Results Using Only Social Variables

Overview of Regression Strategy & Preliminary Results

There are 29 explanatory variables in the social group regression analysis: 15 levels variables and 14 change variables plus an intercept (the variable **DIST** has no change measure, which is why there is one more level than change variable).

With just 51 data points, it is impossible to obtain a great deal of accuracy in estimating 30 coefficients. Furthermore, regressors reflect different processes (both proximate and indirect), which may drive or influence observed rates of deforestation across constituencies. For example, it can be said that fuelwood use is a direct cause of deforestation, whereas low levels of social welfare are indirect contributors. (The latter, for example, may increase poverty, which may in turn increase dependency on the land and on fuelwood and thereby generate deforestation). As a consequence, indirect poverty measures may be overwhelmed by the fuelwood variable if included in a regression. Furthermore, as the correlation matrix of social variables in Table 9.3 indicates, quite a few social variables are also fairly highly correlated with one another so that including all of them in one regression is problematic.

Given the nature of these social variables and associated problems of multicollinearity, the regression analysis must choose variables with care. In this study, variable selection was guided by recognition of the importance of the variables in the literature and to the conceptual model, their degree of correlation with other explanatory variables, and the results of the preliminary regression runs.

The following strategy was adhered to in determining the sequence of regression runs: A large number of regressions including different subsets of the explanatory social variables were run and the dominant patterns across them noted. (These general patterns are discussed in the context of the preliminary regression results below). b) Observed patterns were then used to determine which variables should be omitted or included in the final regression runs. This strategy of running a large number of regressions, each one containing different sets of explanatory variables, is defensible as a statistically sound one. Indeed, a variable observed to be significant across a wide

range of regressions is more likely to have an explanatory role than one that holds in just one or two regressions.

An alternative strategy — common in regression studies — would have been to first run one large regression containing all the variables in the study, and then to run a series of regressions, successively dropping out insignificant variables until one regression was obtained in which all results were significant. In contrast to this ‘step-wise’, approach, this study adopted a less mechanical, more intuitive strategy. This was one that allowed the model, the correlations and regression results themselves to guide the choice of which variables to include and which to subsequently exclude from the analysis. Rather than choose variables according to overt statistical criteria, then, theoretical considerations and the pattern of results successively guided the selection of variables and regression runs.

Note that an approach that successively drops out insignificant variables in the regression runs risks obscuring the contribution of important variables in certain subsets of important variables. Since this mechanical approach is dependent on which variables are found initially to be insignificant (and thus, are dropped from the regression model), it can arbitrarily lead the analysis one way as opposed to another. The consequence is that results will be different depending on the sequence in which variables are excluded. By including both significant and insignificant variables in a large number of regression runs, however, the effects (both significant and insignificant) of a variety of variables are allowed to come through in the analysis (especially in respect to less direct measures).³

Of course, the strategy adopted here is a ‘messier’ one in that it involves running literally hundreds of regressions, all of which cannot possibly be presented here. It should be stressed that these representative regressions are precisely what their label implies; namely, examples of the consistent patterns noted in these variables across a wide variety of regressions. *They are not simply regressions chosen to support the assumptions of the model or the findings of other studies.* These preliminary regressions are not presented here but they are available on request to the interested (or skeptical) reader.

³Yet, there is also a sense in which a statistical ‘step-wise’ regression strategy is followed, since a regression containing all the study’s significant and conceptually important variables is also included in the analysis.

*Table 9.4: Correlation Matrix
of Key Constituency Social Variables*

	FUEL	ATTM	POPDEN	DEPRAT	CHFUEL	CHATTM	CHPOPDEN	CHDEPRAT	DIST
FUEL	1.00								
ATTM	0.91	1.00							
POPDEN	-0.62	-0.50	1.00						
DEPRAT	0.91	0.90	-0.39	1.00					
CHFUEL	-0.40	-0.34	0.71	-0.14	1.00				
CHATTM	-0.40	-0.44	0.32	-0.37	0.43	1.00			
CHPOPDEN	-0.03	0.054	0.22	0.11	0.31	-0.18	1.00		
CHDEPRAT	-0.24	-0.35	0.082	-0.28	0.29	0.57	-0.01	1.00	
DIST	0.61	0.49	0.43	0.48	-0.17	-0.21	-0.05	-0.09	1.00

Overall, the patterns of preliminary regressions tend to support the assumptions of the model and of the literature. The strongest results obtained were for the variables **FUEL**, **CHFUEL**, and **DEPRAT**, all of which were significant and positive in virtually every regression run. **POPDEN** was also significantly positive in most regressions. These relationships will be discussed further in the context of the presentation of the final regression runs in the next section.

To reduce the number of variables in the final runs, several of the study's variables that were never or almost never significant in the preliminary runs of various subsets of variables were dropped from the study:

UNMALE, UNFEM, CHUNMALE, CHUNFEM, HSIZE, CHHSIZE, FOOD, CHFOOD, EXP, CHEXP, STDEX, CHSTDEX.

Furthermore, **ROOM** and **CHROOM** were almost never significant in the preliminary regression runs, regardless of the variable combination, and for this reason were excluded from the final regression analysis. Educational attainment for both men and women (**ATTM** and **ATTF**) and their changes (**CHATTM** and **CHATTF**) were highly correlated with each other; hence, there was no real gain in including both variables in the final regression analysis. For this reason, and in view of the slightly more significant findings for the male measures of these variables than for the female, both **ATTF** and **CHATTF** were dropped from the final runs.

Furthermore, **WAT** and **CHWAT** came through as significant in some regressions, (and of the expected sign) but given that they are strongly correlated with **FUEL** and **ATTM**, they were omitted from the final regression runs. However, it should be stressed that the significant findings for the **WAT** variable in some regressions suggests that it does play a role (albeit a weak one) in explaining the variation in deforestation rates across constituencies, and that as an overall measure of poverty and living conditions, it is stronger than variables measuring more traditional indicators (e.g. food consumption, or level of income and income inequality).

The disappointing finding of non-significance for the study's consumption and income inequality variables is difficult to explain. In no regression were these variables significant. As argued in the parish correlation analysis, it could be said that these variables do not adequately capture the income and consumption characteristics of the lowest social groups. By its very nature, a subsistence life-style is difficult to monitor,

particularly in respect to the island's many shifting cultivators, who will not be 'stabilized' in the same place from year to year. In the case of the variable **FOOD**, it can be argued that, while poorer households will spend a greater proportion of their income vis-a-vis wealthier groups on food, they are not significant players in deforestation since they at least have the money to purchase food. In other words, those who depend entirely on growing their own food (as opposed to purchasing it) may be unaccounted for by such a variable.

Likewise, the unemployment variable for both men and women had no significant effect in explaining deforestation rates across constituencies. This finding, too, may be due to measurement error. Given the informal nature of much economic activity in developing countries, it is hardly surprising that unemployment figures are often notoriously unreliable. Thus, it is possible that 'work seekers', who form the basis of the unemployment measure in both groups, are measured primarily by individuals seeking formal sector, largely urban or resort-based jobs. Consequently, they may not be a sufficient measure of individuals living at or near the subsistence level. However, it is also possible, as in the consumption and income inequality variables above, that unemployment plays no role in deforestation at the constituency level or that the connection, if it exists, is too indirect and tenuous to be measured.

The omission of these remaining variables from the analysis, reduces the number of explanatory variables to 9. Table 9.3 provides a correlation matrix of these 9 explanatory variables. Correlation results for all other explanatory variables that were included in the preliminary regression runs but subsequently dropped from the analysis are not presented here in the interests of brevity but are available on request.

9.5.3 Final Regression Results

This section begins with the presentation of regression results for the 9 explanatory social variables. As discussed in the previous section, the strategy followed was to begin with this 9 variable explanatory model and then take various routes to simplify it.

$$DEFOR = 133.44 + 356.22 \times FUEL^{***} - 368.44 \times ATTM^*$$

$$\begin{aligned}
& +0.60 \times POPDEN - 161.82 \times DEPRAT + \\
& 0.15 \times 10^{-3} \times DIST + 265.13 \times CHFUEL^{***} \\
& -49.85 \times CHATTM - 86.51 \times CHPOPDEN \\
& -7.17.87 \times CHDEPRAT^{***}
\end{aligned} \tag{1}$$

$$N = 51 \quad R^2 = .40$$

(Denotes ***Significant at 5% level; **Significant at 10% level; * Significant at 20% level for all regressions presented in this chapter).

Many of the results in this regression are quite strong and of the expected sign. In particular, **FUEL** and **CHFUEL** are both positive and strongly significant, a pattern that repeated itself throughout the regression runs. Given the consistently strong and positive results for these variables in the analysis, the contribution of fuelwood dependency to deforestation in Jamaica can be said to be well-established in this analysis, and the findings are in line with the expectations of the conceptual model and the literature. Moreover, the impact of fuelwood/charcoal consumption on forest cover is quite substantial, as this regression implies. For instance, holding all other explanatory variables constant, a 0.01 unit increase in this variable is associated with a 3.56% increase in deforestation. That is, if the proportion of these households consuming fuelwood/charcoal as their main energy source, rose from 0.52 to 0.53, deforestation would increase by 3.56%, *ceteris paribus*. Moreover, given the direct impact that fuelwood collection has on forest cover, this consistently strong pattern is not surprising relative to the weaker showing of the welfare, consumption and income variables, whose effects are less direct and more difficult to disentangle.

As the correlation analysis of these variables indicates, **FUEL** is also strongly (positively) correlated with educational attainment for both men and women and the study's dependency ratio variable. It is also negatively correlated with **WAT**. Thus, while **FUEL**, is in one sense, a direct cause of deforestation, it also appears to be a good proxy for several other measures of social welfare.

Both educational attainment and its change have a negative effect (i.e. the greater the proportion of the population with primary schooling or less the less deforestation). Although these findings are counter-intuitive and opposite in sign to the simple correlation results, they are not significant (albeit **ATTM** is marginally significant).

DIST is positive, as it was in the simple correlation results presented earlier; however, it is no longer significant.

The study's demographic variables present a similar picture to the simple correlation analysis in that the levels measures all have the expected positive sign but are not significant and the change measures are unexpectedly negative (although only **CHDEPRAT** is significant). The unexpected negative finding for these variables is difficult to explain given that their corresponding levels variables are positive. These relationships are investigated in further detail later.

Thus, in comparison to the simple correlation results, this regression model suggests that most of the social variables are of the expected sign and several are quite significant; but a few have counterintuitive signs and/or are no longer significant. The next section investigates these relationships in more detail; in particular, it seeks to determine whether the results are being affected by certain variables 'swamping' the influence of others and/or by multicollinearity between certain explanatory variables.

9.5.4 A Closer Look at the Role of Social Scarcity in Deforestation

Fuelwood Use

The regression below re-confirms the strong importance of **FUEL** and **CHFUEL** in driving deforestation. **POPDEN**, which measures less direct pressures on the land (e.g. through its effects on the demand for resources and on poverty) is once again of the expected positive sign but not significant.

$$\begin{aligned}
 DEFOR &= -93.43 + 155.90 \times FUEL^{***} + 142.74 \times CHFUEL^{**} \\
 &\quad + 1.22 \times POPDEN \\
 N &= 51 \quad R^2 = .22
 \end{aligned}
 \tag{2}$$

Demographic Factors

Could it be possible that **FUEL** and **CHFUEL** are overwhelming the effects of this important demographic variable **POPDEN**? If both **FUEL** and **CHFUEL** are dropped from the analysis, the following results obtain:

$$\begin{aligned}
DEFOR &= -189.41 - 317.68 \times ATTM + 2.11 \times POPDEN^* + 362.23 \\
&\quad \times DEPRAT^{***} + 0.11 \times 10^{-2} \times DIST^* + 118.77 \times \\
&\quad CHATTM - 53.88 \times CHPOPDEN \\
&\quad -498.17 \times CHDEPRAT^{**} \\
N &= 51 \quad R^2 = 0.27 \quad (3)
\end{aligned}$$

The key difference between this model and Regression 1 is that now all levels measures of the study's demographic variables are positive and significant. **POPDEN** is positive and marginally significant, **DEPRAT** is positive and very significant. However, **CHPOPDEN**, while positive, is not significant and **CHDEPRAT** is still negatively significant. It is clear that the effects of the levels of these demographic variables in Regression 1 were being swamped by the fuelwood variables. Regression 3 now suggests a strong role for demographic factors in driving constituency deforestation rates. A similar finding holds for **DIST**, which is now significant and retains its expected positive sign.

When the levels of these variables are run in a regression together the following results obtain:

$$\begin{aligned}
DEFOR &= -177.40 - 211.40 \times ATTM + 2.22 \times POPDEN^{**} \\
&\quad + 320.77 \times DEPRAT^{**} + 0.11 \times 10^{-2} \times DIST^* \\
N &= 51 \quad R^2 = 0.19 \quad (4)
\end{aligned}$$

Note that results are similar to the previous regression, except that now **POPDEN** is significant at the 10% level.

Educational Attainment

Since **CHATTM** was rarely significant in the regression runs, the focus in this subset of variables is on **ATTM**. Recall that **ATTM** was positively correlated with deforestation in the simple correlation analysis and was marginally significant. This result

was as expected, since **ATTM** is an educational level measure. As such, less education would imply more deforestation (i.e. if **ATTM** is high, then the level of education is low; consequently, a positive correlation between **ATTM** and deforestation means that constituencies with large numbers of poorly educated males tend to have higher rates of deforestation). In contrast, it appears to have a negative coefficient in the above regressions, although it is never significant.

Note that the correlation matrix indicates that **ATTM** is strongly correlated with the other explanatory variables. In particular, the correlation between **ATTM** and **FUEL** is 0.91, and between **ATTM** and **DEPRAT** is 0.90. Obviously there is strong multicollinearity between these variables, which may be affecting the result for **ATTM**. If **FUEL** and **DEPRAT** are dropped from the regression the following obtains:

$$\begin{aligned}
 DEFOR &= -192.89 + 2.10 \times POPDEN^{**} + 251.32 \times ATTM^{**} \\
 N &= 51 \quad R^2 = 0.09
 \end{aligned}
 \tag{5}$$

Now **ATTM** is positively significant, as is **POPDEN**. Thus, if the regressions are simplified slightly so as to avoid conflating **ATTM** with other variables, its positive contribution to deforestation comes through as expected and also quite strongly.

Note that there is a strong 'social welfare component' to deforestation beginning to emerge here of which **DEPRAT**, **FUEL** and **ATTM** are different measures. All these variables *individually* are both strongly and positively correlated with deforestation (i.e. as long as these variables are not being measured in the same regression reasonable results arise). This regression model implies that a 0.01 unit increase in population density is associated with a 2.1% change in forest cover, *ceteris paribus*. Thus if population density were to increase by 0.01 people per hectare, forest cover would tend to decline by 2.1%, *ceteris paribus*. Similarly, a 0.01 increase in the proportion of males with only primary schooling or less would translate into a 2.5% increase in deforestation in constituencies with comparable population densities.

The Dependency Ratio Re-visited

As noted above, **FUEL** and **ATTM** are both very strongly correlated with **DEPRAT**. However, if **ATTM** and **FUEL** together with the insignificant variables from the original 9-explanatory variable regression model are dropped from the analysis, the following results obtain:

$$\begin{aligned} \text{DEFOR} &= -213.50 + 2.58 \times \text{POPDEN}^{***} + 190.67 \\ &\quad \times \text{DEPRAT}^{***} + 0.11 \times 10^{-2} \times \text{DIST}^* \\ N &= 51 \quad R^2 = 0.18 \end{aligned} \tag{6}$$

Given the strong correlation between **ATTM** and **DEPRAT** it is not surprising that results are quite similar to the previous regression (i.e. **ATTM** and **DEPRAT**, in a sense, are measuring the same phenomenon — human capital formation — and therefore yield similar results). Note that both **DEPRAT** and **POPDEN** are now both positive and quite significant.

Distance

In the previous regression, **DIST** is once again positive and marginally significant. Although this result is as expected, it is not particularly strong, and the above regression is representative of the results found for this variable in most regression runs. In the simple correlation results presented earlier, the variable was positive and quite significant ($p \leq 0.10$). However, in virtually every regression run, **DIST**, while still positive, was slightly less significant. In a few regressions it was positive but not significant.

Social Levels vs. Social Change

The stronger results for the levels as opposed to the change variables in previous regressions were also repeated throughout the regression analysis. In all regressions run, **CHFUEL** and **CHDEPRAT** were the only change variables of significance, and often only marginally so. **CHDEPRAT**, while often significant, had a counterintuitive sign. While not significant, **CHPOPDEN** was always of the opposite expected sign. In

particular, it is difficult to explain these findings for the demographic change variables, especially in view of the fact that **CHDEPRAT** and **POPDEN** were consistently significant and almost always positive. As with any variable, these counterintuitive findings may simply reflect measurement error in the data. Alternatively, it may be that the greatest increases in the dependency ratio and in population densities occurred in those constituencies which had less tree cover to begin with (i.e. cities and towns). The fairly strong correlation between **CHPOPDEN** and **PROP** ($r^2 = -0.37$) would tend to lend weight to this contention for demographic measures pertaining to density but not to dependency, for which the correlation between **DEPRAT** and **PROP** is positive ($r^2 = 0.23$). Moreover, the former relationship (i.e. **CHPOPDEN** and **PROP**) cannot shed light on why **POPDEN** is positively significantly correlated with the deforestation variable. Indeed, constituencies with more built-up areas would naturally have higher population densities than would largely rural constituencies. (However, it may be that the latter variable is capturing some other phenomenon closely associated with high population densities but which also impacts adversely on forest cover, such as poverty).

9.5.5 Regressions Including Physical Variables

Proportion of Forest

The above regressions measure only social factors identified for their possible role in driving deforestation on the island. However, the study also included several ‘physical’ factors related to aspects of the Jamaican environment that are hypothesized to influence the rate of forest loss. The first variable, **PROP**, measures the proportion of forest cover in 1987. To capture the effects of forest cover on deforestation rates, Regression 7 below includes the proportion of forest cover measure along with the 9 social variables from Regression 1:

$$\begin{aligned}
 DEFOR = & 184.67 + 428.02 \times FUEL^{***} - 430.76 \times ATTM^* \\
 & + 1.42 \times POPDEN - 261.23 \times DEPRAT + 0.52 \times 10^{-4} \\
 & \times DIST + 225.96 \times CHFUEL^{***} - 71.65 \times CHATTM \\
 & - 20.87 \times CHPOPDEN - 711.94 \times CHDEPRAT^{***}
 \end{aligned}$$

$$+145.87 \times \text{PROPFOR}^{**}$$

$$N = 51 \quad R^2 = 0.44 \quad (7)$$

A comparison of this regression output with Regression 1 indicates that the impacts of the social variables are essentially the same. **FUEL**, **CHFUEL**, and **CHDEPRAT** are still highly significant and **ATTM** is marginally significant of the wrong sign. Thus, controlling for **PROPFOR** in the regression analysis does not alter the basic results so far. Furthermore, **PROPFOR** is statistically significant and positive, indicating that constituencies with more forest cover also tended to have higher deforestation rates during the period of this study. It is worth noting that **PROPFOR** was consistently positive and significant in all the regressions run, and that its inclusion did not alter the effects of the other variables.

This regression (Regression 7) gives some indication of the relative effects of these individual explanatory variables on deforestation, controlling for all other explanatory variables. For example, for constituencies comparable in all respects — with the exception of the proportion of their households consuming fuelwood/charcoal — a 0.01 difference in fuelwood/charcoal consumption is associated with a 4.28% higher deforestation rate. Likewise, for constituencies equal in all measures except in respect to the proportion of their land area in forest in 1987, a 0.01 unit increase in this value is associated with a 1.46% decrease in forest cover. In other words, if one were to compare two equal constituencies, one in which the proportion of land area covered in forest was 0.47, and the other in which it was 0.46, the deforestation rate in the former would also tend to be higher than in the latter by 1.46%. For the variables, **CHDEPRAT** and **CHFUEL** a 0.01 increase in these values is associated with an increase in forest cover of 7.12% and a decrease in forest cover of 2.26%, respectively, *ceteris paribus*.

Soil

As indicated earlier, the assignment of parish values to every constituency comprising each parish is far from ideal. However, such a strategy will give a very rough indication of cross-constituency variation for these physical factors. As with the social variables, the physical variables were included in a variety of regressions, and not all results are reported here but they are available on request.

In the case of the study's soil variables, the strongest results obtained were for the variable, **SOILG**. Since the inclusion of all the soil variables in a regression is redundant (i.e. constituencies with a lot of good soil are also those that equally have little bad and average soil, and vice versa), only results for the **SOILG** variable are presented here. The following regression includes the study's 9 social variables and the variable **PROPFOR**:

$$\begin{aligned}
 DEFOR = & 236.59 + 474.21 \times FUEL^{***} - 337.45 \times ATTM + 1.06 \\
 & \times POPDEN - 390.28 \times DEPRAT^* - 0.33 \times 10^{-3} \\
 & + 254.16 \times CHFUEL^{***} - 147.36 \times CHATTM \\
 & - 7.82 \times CHPOPDEN - 699.14 \times CHDEPRAT^{***} \\
 & + 150.76 \times PROPFOR^{**} - 105.83 \times SOILG^{**} \\
 N = & 51 \quad R^2 = .48 \quad (8)
 \end{aligned}$$

SOILG is negative and significant at the 10% level, a finding that mimics the parish correlation result except that in this regression analysis, it can now be said that constituencies with higher soil quality tend to experience less deforestation, *ceteris paribus*. That is, even when a wide variety of social factors are controlled for, constituencies with good land capability are still associated with lower deforestation rates.

Small Farms

As in the case of **SOILG**, very few results are reported for **SMLFARM** in view of the problems associated with using parish level data in a constituency level regression. Thus, this variable is mainly included to see how it affects the other regression results.

For example, when added to the regression of the 9 social variables (Regression 1) and the physical variables presented so far, the following results obtain:

$$\begin{aligned}
 DEFOR = & 110.86 + 404.88 \times FUEL^{***} - 364.99 \times ATTM^* + 0.86 \\
 & \times POPDEN - 297.50 \times DEPRAT - 0.34 \times 10^{-4} \times DIST \\
 & + 269.68 \times CHFUEL^{***} - 178.90 \times CHATTM - 19.22
 \end{aligned}$$

$$\begin{aligned}
& \times CHPOPDEN - 700.03 \times CHDEPRAT^{***} \\
& + 156.08 \times PROPFOR^{**} + 107.16 \times SMLFARM \\
N = 51 \quad R^2 = 0.46
\end{aligned} \tag{9}$$

This regression demonstrates a pattern observed consistently for **SMLFARM** throughout the regression analysis. As expected, **SMLFARM** has a positive coefficient, suggesting that constituencies with a higher proportion of very small farms tend to experience more forest loss, *ceteris paribus*. This result was robust (i.e. occurred in most regressions). Furthermore, the inclusion of this variable in this large regression (and others not reported here) did not alter the basic qualitative effects of the other variables noted so far. Disappointingly, however, **SMLFARM** was rarely significant in any regression run. When significant, it was only marginally so, as the following regression demonstrates:

$$\begin{aligned}
DEFOR = & -226.80 + 93.19 \times FUEL^{***} + 207.65 \times CHFUEL^{***} \\
& -602.82 \times CHDEPRAT^{***} + 132.64 \times PROPFOR^{**} \\
& + 117.77 \times SMLFARM^* \\
N = 51 \quad R^2 = 0.19
\end{aligned} \tag{10}$$

Note that **SMLFARM** now has a p-value ≤ 0.20 . This suggests that constituencies with large numbers of small and landless farms have higher rates of deforestation, *ceteris paribus*, than do those having fewer farms of this size class. However, as in the case of **SOILG**, the meaning of these findings must be treated with caution in view of the way in which this data was constructed.

9.6 Summary: Some Stylized Facts About Scarcity-Driven Forest Loss in Jamaica

The above regression findings and the previous correlation analyses suggest a number of general patterns, or stylized facts, about the contribution of scarcity-driven processes to deforestation of Jamaica. There appears to be consistent and strong evidence to

suggest, in other words, that both poverty and population are driving the destruction of the island's forest cover. It should also be noted that, for reasons that are not entirely clear, the levels of these variables in 1987 were consistently more significant than was the change in these variables from 1987-1992.

In the majority of cases where results did not suggest a significant role for variables reflecting various dimensions of scarcity (e.g. income measures), both correlation and regression coefficients were of the expected sign. This consistency in sign across numerous regressions provides support for the contention that scarcity factors are driving the destruction of forests on the island, despite the fact that statistical evidence for their contribution to deforestation did not come through overwhelmingly in the data. Moreover, given that the study has only 51 data points (and therefore it is impossible to expect high levels of accuracy in estimating the coefficients), this consistency in sign, coupled with the consistency in significance for several of the study's variables throughout a wide variety of regression runs, should itself be considered an important finding of the study.

Following the strategy outlined earlier, a number of statistical results were reported for a wide variety of variable combinations. The empirical analysis of scarcity-deforestation interactions yielded the following stylized findings for the period, 1987-1992.

a) Demographic pressures were a strong contributor to deforestation on the island. Constituencies with higher numbers of both young/old dependents and higher population densities had significantly higher rates of deforestation, *ceteris paribus*, than did less densely populated constituencies characterized by lower dependency ratios and population densities. These results point to the pressures being placed on the land base by sheer numbers of people, many of whom are of a young age and will no doubt exacerbate the pressures for physical space, food and forest produce in years to come (particularly as they approach adulthood and their childbearing years). Furthermore, it should be noted that demographic indicators may be measuring other, poverty-related aspects of human-forest interactions. Indeed, large dependency ratios and population densities in developing countries are often highly correlated with deprivation.

b) Household demand for fuelwood/charcoal consumption was a significant contributor to forest loss on the island. In addition, its correlation with several of the study's

welfare variables, notably educational attainment, piped water provision, and household dependency suggests that this variable may be capturing aspects of scarcity other than just reliance on forests for basic energy supplies.

c) The study's variables measuring aspects of absolute and relative differences in income and consumption, household size, nutritional status and unemployment rates were all consistently insignificant in every preliminary regression run, regardless of the subset of variable combinations chosen. In certain cases — for example, income spent on food or female/male unemployment rates — it was noted that this lack of significance may be attributable to these variables being inadequate measures of the conditions of the island's poor, since they do presuppose a certain level of income exists to buy food, or that jobs will be sought after in the formal sector. The study's measure of the proportion of houses in each constituency containing only one room was occasionally significant and positive, suggesting some role for inadequate shelter in driving deforestation. However, it may be the case that this variable is also acting as a proxy for some other dimension of poverty (e.g. lack of adequate income). Note, too, that this variable was dropped from the final regression runs in favour of stronger welfare indicators.

d) Employment prospects, especially in the informal sector, were additionally measured by the average distance of each constituency from a major tourist/economic center. This variable was found to be significantly positive throughout virtually every regression run, suggesting that there may indeed be beneficial spin-offs for forest cover from their proximity to these centers. Evidence presented also suggested that this proximity effect cannot be attributed simply to rural areas having more forest cover, since the correlation between proportion of forest cover and population density was not particularly high nor significant.

e) Some variables were found to be significantly related to the deforestation measure but were omitted from final regression runs due to their strong correlation with other key measures of significance. The study's indicator for household availability of piped water in each constituency was consistently significant in most preliminary regression runs, and always of the expected sign. However, it was also consistently strongly correlated with the study's fuelwood, dependency ratio and educational attainment indicators and therefore was dropped from the final regression analysis. Nevertheless,

the significant finding for this variable provides more evidence for the assumptions of the conceptual model; namely, that deforestation on the island can be explained in part by social deprivation, since the availability of clean water is considered to be an important indicator of the provision of basic welfare provision.

f) The proportion of men and women with an elementary education or less also appears to be significantly related to the loss of forest cover in each constituency. However, this significance was largely noticeable in regressions that excluded variables with which they were highly correlated (e.g. fuelwood/charcoal consumption, the dependency ratio, and availability of piped water). Note that this pattern of significance was consistently higher for the male measure of this indicator than for the female measure. Note, too, that female unemployment was dropped from the final regression runs due to its high correlation with male unemployment.

g) The proportion of constituency forest cover was also found to be significantly positively related to forest loss, suggesting that constituencies with higher levels of forest cover deforested at a faster rate during this period, *ceteris paribus*, than did constituencies with little forest cover.

h) At the constituency level, a consistently significant finding for the variable measuring areas of good farming capability was found. Areas of the island with a combination of the best soils and gentle slopes were found to be negatively associated with the loss of forest cover and marginally significant in most regressions run. However, as noted, this finding should be interpreted with caution, given the rather artificial way in which this constituency data were constructed from parish measures.

In contrast, correlation analysis of parish level land capability measures were highly significant and of the expected signs. These findings indicate that, at least at the parish level, areas of the country with the worst soils and slopes — areas which have been designated by the FAO as placing serious limitations on land use — are losing more forest cover than are areas with fair to average capability (also positive but less significant) and considerably more so than are areas with the best land capability (highly negatively significantly correlated with forest loss in each parish). Additionally, the significantly positive correlations between farms of the larger size classes, and good capability areas and the significantly positive correlations between farms of the small size class (≥ 1 acre ≤ 5 acres) and areas with either a fair/average or severe land

capability classification, suggests indirectly, that they are also areas in which higher numbers of small farms are located.

i) In respect to agricultural land use, the small farm variable was marginally significant in only a few regression runs. This finding must be interpreted with caution in view of the way in which the variable was constructed, but it would suggest that deforestation is higher in constituencies having predominately small farms.

In contrast, the parish level values of the study's agricultural land use indicators suggest that many are strongly correlated with forest loss. At the parish level of analysis, small farms were found to be positively correlated (and almost marginally significant with forest loss, with the exception of the smallest farm size class (≤ 1 acre). For the next largest size classification, and increasingly, up to the ≤ 50 acre size class, the relationship was also positive. Above this size class, the relationship was negative and became increasingly significant, with the 100+ size class demonstrating the highest level of significance.

The proportion of farms growing domestic crops was strongly significantly related to deforestation at the parish level. This finding was taken to reflect the essential resource poverty of these farms, a condition related to the fact that domestic crops are far less lucrative than are export crops. Conversely, coefficients for farms growing export crops were found to be significantly negatively related to the loss of forest cover at the parish level, irrespective of their size. As indicated, the latter finding suggests the presence of possible income benefits for forests to be derived from growing food in this sector; in particular, better land management practices that would obviate the need for extensive farming practices. There also appear to be some marginal positive benefits for forests for small farms that hire labour (which may indicate a higher household income or perhaps better land use practices (e.g. the adoption of labour-intensive farming methods)).

Deforestation from agricultural activities also appears to be related quite significantly at the parish level to the age of farmers. The young to middle age categories, particularly the ≤ 40 age class, show positive and highly significant associations with deforestation; and older age groups, negative (and for the ≥ 50 years group significant) correlations. For farms of the small size class (e.g. ≥ 1 acre ≤ 5 acres), however, the youngest age classes dominate. The concentration of young age groups in this farm size

classification suggests that these groups lack few alternatives to farming; they are obviously at a time in life when resource demands and pressures on the land to meet basic sustenance needs can only increase with time. Moreover, farms of this size class which engaged in farming full-time were marginally more likely to be situated in parishes with higher rates of deforestation than otherwise. This gives additional weight to the hypothesis that farming at this level is linked to the activity of individuals, who, for want of alternative off-farm opportunities, must depend on forest destructive activities for their livelihood. At the same time, the marginally significant correlation with parish forest loss rates of female-headed farms of the ≥ 1 acre ≤ 5 acres size class may be indicative of the greater deprivation faced by women overall. Being poorer in general than men, women tend to have fewer resources with which to maintain a household and therefore may be more dependent on farming for a living and/or less likely to maintain their plots properly.

In conclusion, the quantitative results suggest that there is strong evidence for the contribution of scarcity in driving deforestation in Jamaica; in particular, many poverty and population-related indicators were found to be significantly correlated with forest loss at the constituency areal unit of analysis, where the effects of other mediating factors could be controlled for in a regression model. Strong evidence also exists for the contribution to deforestation of several important factors, notably land quality and agricultural land use measures, albeit these results did not control for the effects of other variables. However, two variables from this data set were found to be marginally significant when included in regressions containing important socio-economic measures of scarcity.

On a statistical level, the regression results seem quite good, given the problems noted with both types of data analysis (e.g. satellite and socio-economic) and with linking the two. An examination of the large regression (Regression 9) containing many of the study's key variables, indicates that the $R^2 = 0.46$, suggesting that these variables together explain 46% of the cross-constituency variation in deforestation rates.

Chapter 10

The

Poverty/Population/Environment

Nexus: Some Future Trends &

Prospects for Jamaica's Forests

10.1 A Simulation Experiment

10.1.1 General Remarks

The regression analysis aimed to unearth general patterns in the data in order to establish 'stylized facts' about the role of scarcity in the deforestation of Jamaica. However, it is also useful to draw out the implications of these patterns in an intuitively simple way. This is the aim of the simulation analysis discussed in this section.

It should be stressed from the outset that for simulations to provide policy guidelines for what 'might happen', it must be assumed that the model on which the simulation is based is the 'correct' one. That is, that the model reflects causality in the sense that the explanatory variables are causing the dependent variable — and equally so, that patterns observed to hold in one period (in this case, 1987-1992) will continue to do so into the future. Of course due to the fact that simulations are based on events that have, for the most part, not yet occurred, it is impossible to verify that conditions operating in the present will indeed hold in the future. Hence while it is common-place

to talk about ‘scenarios’ of change, this should always be done on the understanding that the results of such simulations are suggestive rather than definitive about future deforestation outcomes.

This study’s use of a cross-sectional regression model for the simulation experiment involves consideration of several points:

a) Choice of regression to use.

b) Choice of values of the explanatory variables, a process commonly referred to as choosing ‘scenarios’.

c) The latter or b) is a very difficult exercise, particularly when many explanatory variables exist, as in this study. That is, the researcher must choose values for all explanatory variables to be included in the simulation but the choice of values is often an open question. This exercise can be complicated by the inclusion of ever more variables in the regression simulation, thereby increasing the likelihood of choosing meaningless scenarios.

Furthermore, explanatory variables of the type used in this study can often be correlated with each other; in some cases, quite strongly. As noted, the correlation between **FUEL** and **ATTM** is 0.91. This result can be interpreted as meaning that constituencies with high numbers of poorly educated males will also tend to have high levels of fuelwood consumption. This high level of correlation may reflect the existence of an indirect causality between the two (i.e. a poor education may lead to poverty and thus dependency on fuelwood, which in turn may cause deforestation). If the Jamaican government were today to make concerted efforts to improve the level of education of its male population, then this causal relationship would imply that fuelwood consumption should drop in the future, thereby causing deforestation rates to fall. Thus, in practice, a scenario involving both explanatory variables would have to be constructed with a great deal of understanding of what the true relationship between these variables was. Values for one variable (e.g. **FUEL**) would have to be chosen in view of the values of the other variable (e.g. **ATTM**), and this would require a model linking or describing the relationship between the two. If this model is incorrect, then the simulations would have little predictive meaning. (In other words, they would attempt to show what would happen if bizarre and irrelevant scenarios unfolded).

Moreover, the above discussion relates to the issue of the effects of multicollinearity

in regression analysis, a topic discussed previously. As noted, the conceptual model described earlier assumes that many indirect causes (e.g. social deprivation) prompt individuals to engage in specific land use practices (e.g. shifting cultivation), resulting in a loss of forest cover. However, as was noted in the previous regression runs, the inclusion of both indirect and direct causes in a regression simulation may cause the latter (i.e. agricultural land use variables) to swamp the former, less immediate or ‘ultimate’ causes. In such cases, the effects of certain variables will be unobservable in the simulation analysis — variables that may actually play an important role in determining a likely deforestation outcome.

Given these problems (i.e. the uncertainty about choice of variables, their values and the exact nature of their interaction), this study restricts itself to simulating some very simple regressions, containing at most two explanatory variables. Moreover, only those variables that were found to be consistently strongly significant in the previous regressions are used. This strategy increases the likelihood of choosing more meaningful scenarios. It also makes it easier in practice to both implement and present results in an intuitive and straightforward fashion than if values for all the study’s explanatory variables had been chosen.

Specifically, the strategy is to choose results in view of what could possibly happen to forest cover on the island as a whole, under different scenarios. To this end, the study uses 1992 values for both the proportion of national land area under forest cover and the explanatory variables chosen as representative of key population-poverty dimensions. It begins with the 1992 average figures for these variables and then asks what would happen if the explanatory variables increased/decreased by X% per year until the year 2010. Each simulation exercise includes a ‘good’ and a ‘bad’ scenario, and a ‘base’ case against which the two are compared, as described.

10.1.2 Simulation #1

The first deforestation regression in the simulation exercise includes one social welfare indicator, **ATTM** (proportion of males with a primary education or less) and a demographic variable, **POPDEN** (number of people per hectare). These are two representative explanatory variables which were also significant throughout most of the regression runs. The base case against which the two scenarios are set assumes that

the 1992 values for these variables holds across time (i.e. the explanatory variables are unchanging). The regression estimated in Chapter 9 (Regression 5) is the model relating deforestation to **POPDEN** and **ATTM**, and is given by:

$$DEFOR = -192.89 + 2.10 \times POPDEN^{***} + 251.32 \times ATTM^{***}$$

The Good Scenario

In this scenario both **ATTM** and **POPDEN** are assumed to decrease from their respective 1992 Jamaica-wide figure by 1% per year. Although unlikely (given that these figures rose prior to and during the period of this study), this scenario is not that inconceivable if emigration rates were to increase dramatically and fertility rates were to fall, and if concerted improvements were made in education. (Note that **ATTM** measures the proportion of all men on the island with primary schooling or less, such that if this variable decreases by 1% per year the proportion of men on the island with an inadequate or barely adequate education would concomitantly decrease).

The Bad Scenario

In this scenario both **ATTM** and **POPDEN** increase from their 1992 Jamaica-wide figure (base case) by 1% per year until the year 2010. This scenario is not inconceivable, given that the population density growth rate on the island for this study averaged approximately 1.6% per annum during 1987-92. It is possible that the proportion of the population with inadequate education will continue to increase in view of the retrenchment in government spending in public education coupled with the introduction of private user fees.

10.1.3 Results of Simulation #1

Figure 10.1 plots the results of the first simulation analysis. The X-axis describes the year of the forecast; and the Y-axis, the proportion of forest *relative to the base case*.

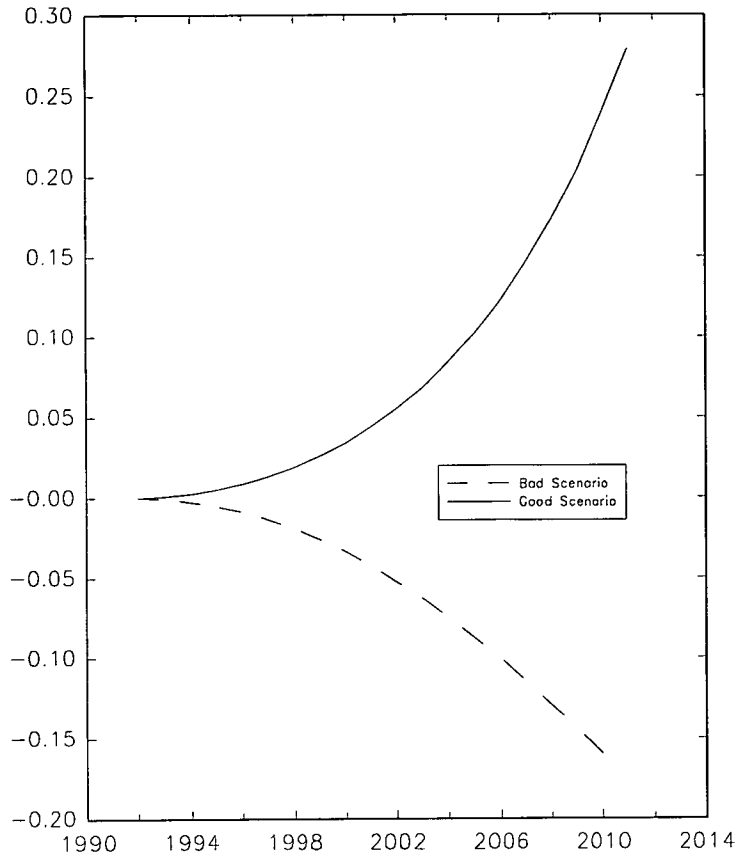


Figure 10.1: Simulation #1

Specifically, Figure 10.1 plots the proportion of forest cover relative to the base case where population density and educational attainment do not change from their 1992 levels over time. Since good and bad scenarios start at the 1992 base case, the difference between both scenarios is 0 in 1992. However, they quickly diverge thereafter. As expected, the good scenario shows forest cover rising relative to the base case, while the bad scenario shows it falling.

The striking point about these numbers is their magnitude. These numbers can be interpreted thus: in 2008 the lines indicate that the proportion of forest cover in 2008 is approximately 0.15 more than the base case for the good scenario and approximately

0.12 less than the base case for the bad scenario. These numbers must be added to the original 0.23 figure (the proportion of forest cover in 1992) to determine what the proportion of forest cover will be under the two scenarios. Accordingly, under the good scenario depicted here, the proportion of forest cover will expand until it reaches roughly 38% of total land area in 2008 $((0.23+0.15) \times 100)$ and 50% $((0.23+0.27) \times 100)$ in 2010. Under the bad scenario, the proportion of forest cover will decline to approximately 11% of land area in 2008 $((0.23+(-0.12)) \times 100)$ and 8% $((0.23+(-0.15)) \times 100)$ by 2010.

Of course, these numbers should not be taken to imply the truth about what will happen, for the reasons outlined earlier. In particular, the pattern of causality between **ATTM** and forest cover implicitly assumed in the regression model may not necessarily hold in the future. Indeed, it is not unreasonable to expect that if forest cover actually approached this 8% level that the government of Jamaica would implement draconian measures to avert such an extreme loss. Likewise, some areas may remain in forest simply because they are inaccessible to humans, no matter how quickly the population density rises or the educational system deteriorates. In short, a regression model that appears to describe a relationship well when the proportion of forest cover is at 23% may be wholly inappropriate as a predictor of this relationship when the proportion of forest is very much lower/higher.

With these qualifications in mind, the figures can be interpreted to illustrate one important finding: slight changes in scarcity-related variables may have an enormous effect on Jamaica's forests in the future. The good and bad scenarios may initially not look too dissimilar — after all, a mere 1% increase/decrease in population and in the numbers of poorly educated males may not seem that large; however, over time these changes will have a substantial impact.

10.1.4 Simulation #2

Despite the inherent difficulties in such an exercise, the previous simulation is nevertheless very informative, and is illustrative of the type of information these regressions can provide. The next simulation is also noteworthy for what it reveals.

This simulation includes, in addition to **POPDEN**, the variable **FUEL** (fuel-wood/charcoal consumption), which was found to be highly significant throughout the regression analysis. Indeed, it was also found to be highly correlated with several mea-

asures of social welfare, for which it may also be acting as a proxy. The following model relates deforestation to **POPDEN** and **FUEL**:

$$DEFOR = -116.01 + 3.23 \times POPDEN^{***} + 162.75 \times FUEL^{***}$$

As before, the simulation begins with the establishment of a base case defined using the Jamaica-wide 1992 values for these variables, and subsequently allows for the values of the two explanatory variables to change by a specified amount over time. However, to demonstrate the implications of changing these variables, the scenarios have been altered slightly. In the above simulation, the base case against which the two scenarios were initially set involved no change in the explanatory variables over time. Admittedly, this assumption is probably unrealistic. After all, population continues to grow on the island, and even were the Jamaican government to institute Chinese-style birth control policies today, some time would have to elapse before the population stopped growing and began to decline. Accordingly, the assumption that **POPDEN** remains constant in the base case is perhaps unreasonable. In contrast, the base case for fuelwood/charcoal consumption will be set at its 1992 level.

Thus, the base case has **FUEL** remaining at its 1992 level over time and **POPDEN** increasing by 1% each year.

The two new scenarios are defined as follows:

The Good Scenario

Under this scenario **POPDEN** remains constant (i.e. is set to 0%, with the number of deaths/emigration equal to the number of births), and **FUEL** decreases by 1% per year. As discussed earlier, the former assumption is possibly too optimistic. The latter scenario is perhaps more conceivable, given that fuelwood/charcoal consumption did decline *overall* during the period, 1987-1992. Whether it has continued to decline and will do so in the future is unclear.

The Bad Scenario

Under this scenario **POPDEN** grows by 2% per year, and **FUEL** increases by 1% year. The former scenario is quite conceivable, particularly if the deterioration in

government support for basic family planning programs continues and emigration (a traditional outlet for demographic pressures) ceases. In reality, population density increased on the island overall by 1.6% a year in the 1987-92 period. The scenario for **FUEL** may be a little less reasonable given that during this period, fuelwood/charcoal consumption decreased. However, if the price of alternative fuels were to rise (as it has since the mid-1990s) it is not inconceivable that fuelwood use would rise even beyond the 1% level.

10.1.5 Results of Simulation #2

Figure 10.2 plots the proportion of forest cover relative to the base case in which **FUEL** remains constant over time and **POPDEN** increases by 1% per year. As in the first simulation, the magnitude of the impact on forest cover of these incremental changes is quite dramatic with the passing of time.

For instance, under the good scenario, forests will expand to cover approximately 32% of total land area $((0.23+0.09)\times 100)$ in 2008 and approximately 43% in 2010 $((0.23+0.20)\times 100)$. Under the bad scenario forest cover will decline to 11% $((0.23+(-0.12))\times 100)$ of land area in 2008, and to 6% in 2010. The results of this simulation confirm those of the previous one in that even relatively small changes in the social welfare of the population threaten to have grave impacts for the country's forest cover in the coming years.

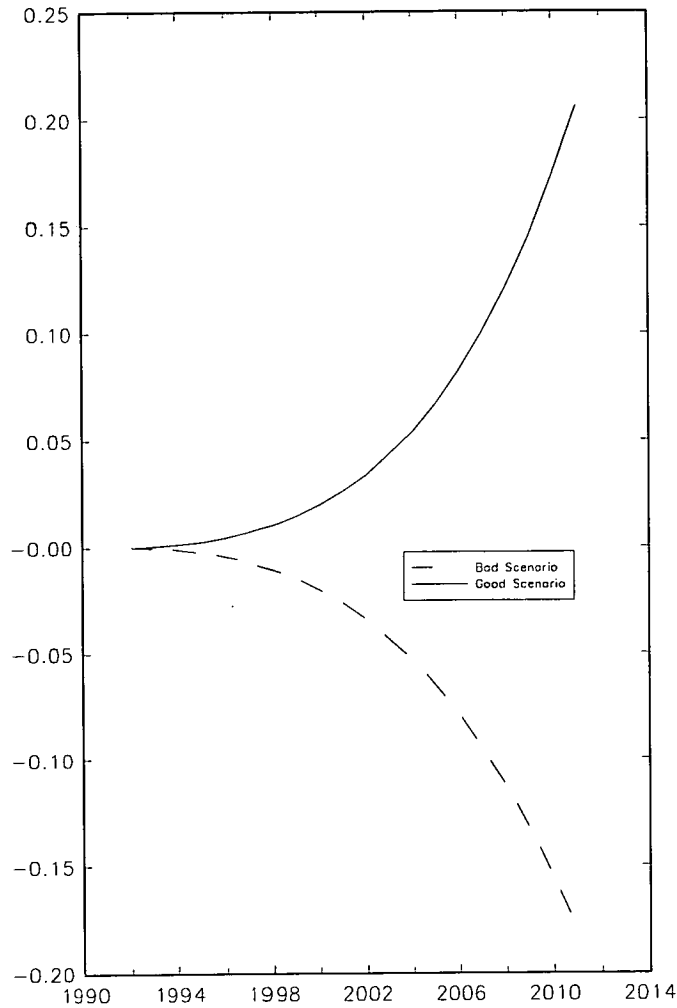


Figure 10.2: Simulation #2

10.2 Concluding Remarks

As stressed, the assumption underlying these simulations is that the same relationships observed to hold between the variables in the period 1987-92 will continue to do so into the future. However, as stressed in Chapters 1 and 2, human-forest interactions are complex and dynamic. The scarcity factors conditioning, for example, large numbers of fuelwood users and poorly educated men are subject to change from one period to the

next, and their effects may be mediated by other changing variables. Nevertheless, the scenarios depicted here can give a general if impartial picture of future forest conditions if 1992 values of these social indicators were to either stay the same, worsen or improve over the next decade.

Chapter 11

Conclusions & Policy

Implications

11.1 General Findings & Discussion

In the past decade, the interlinkages between poverty, overpopulation and environmental quality have become increasingly recognized. This study has attempted to go beyond existing qualitative case studies and conceptualizations of poverty/population interlinkages and empirically analyze the influence of scarcity factors on one environmental problem: deforestation. For this purpose, a simple conceptual model, based on the literature was elaborated that attempted to relate deforestation to several key factors measuring aspects of the poverty/population/environment nexus.

At the country or meso level of analysis, the study provided quantitative information on the nature of these interlinkages for Jamaica. This country was chosen for the reason that it exemplified many of the socio-economic and environmental problems now facing developing countries to varying degrees. In addition, the study estimated national and subnational measures of forest extent and change for the country for 1987-1992, a period characterized by extreme economic disequilibria and adjustment, high levels of unemployment and inflation, and significant declines in social welfare, particularly for the island's many poor residents.

The study used a variety of data sources for its measures of social scarcity, and its findings should always be interpreted in view of the inherent difficulties in carrying out socio-economic surveys in developing countries, especially on marginal populations.

Moreover, it should be remembered that there are intrinsic problems associated with any satellite remote sensing study of environmental change that also introduce error and uncertainty into the analysis. These problems notwithstanding, however, the study has produced a number of relevant findings. These findings have importance not only for understanding environment/population/deforestation interactions in general but for the specific case of Jamaica and, possibly, other countries of the region.

In contrast to the few existing analyses of Jamaican forest cover extent and change, this study has estimated an average annual deforestation rate of 3.9% for the island between 1987 and 1992. This figure is higher than existing forest inventory-based estimates, but is significantly lower than the FAO's own *Tropical Forest Assessment*, which is the most frequently quoted estimate. The weakness of the latter study was noted, particularly its use of a regression model based on other countries and time periods to estimate rates of deforestation for Jamaica. Furthermore, the present study has the advantage over the FAO analysis and others in that it calculates sub-national forest estimates for the island as a whole, thereby allowing forest data to be integrated with relevant socio-economic indicators collected at different areal units of analysis. On a general level, the remote sensing portion of this study has demonstrated how MSS data can provide an invaluable resource for monitoring tropical forest change when a simple classification of forest vs. non-forest is made. This kind of broad snapshot constitutes a relatively inexpensive and efficient way for policymakers to obtain benchmark estimates of deforestation at the national level, as a first step in the production of more detailed forest classification and change studies. Moreover, such benchmark information may prove to be useful for monitoring forest cover change globally, with an eye to the eventual construction of a number of deforestation typologies at the regional level.

The contribution of scarcity to deforestation on the island is confirmed in the study by the significant results for a number of socio-economic and land use/quality indicators designed to tap various dimensions of the poverty/population/forest nexus. In this general respect, the study has provided solid empirical evidence for the qualitative literature on these relationships. Much has been written and hypothesized about the role of scarcity in driving deforestation in the tropics, but so far little empirical research on the relative contributions of its many processes and factors has been carried out. This study constitutes the first systematic attempt to formally model their contribu-

tion. Moreover, the quantitative evidence based on the measurement of a wide range of variables in this study suggests that deprivation in both human and environmental resources is a significant driving force in the destruction of Jamaica's forests. This information can suggest valuable areas for social policy intervention and the development of forest protection and management efforts at the national level.

More specifically, the study has found that demographic pressures have played an important role in this destruction. Results for demographic indicators were not only robust across a wide variety of regression models — but, with the exception of one variable (the change in the dependency ratio) — were consistently of the expected sign, as predicted by the study's conceptual model. The conceptual model hypothesized that demographic pressures would impact negatively on forests in one or both ways: a) Through their direct effects in creating shortages of essential resources; b) Through their indirect effects in generating poverty and deprivation and restricting the life chances open to individuals to better themselves.

These destructive practices may in turn result in greater impoverishment of the population, inducing high fertility rates in the face of growing resource scarcities. Moreover, lacking sufficient off-land opportunities, growing numbers of poor will increasingly come to depend on the environmental resource base for their sustenance, with the consequence that ever more forest cover will be destroyed.

Significant findings for many of the study's measures of 'welfare poverty', also provide weight to these hypotheses. In particular, the study has found that deprivation in several key indicators of human development — notably those measuring standards of education, housing, drinking water and fuelwood dependency — were significant determinants of the level of forest cover on the island during the period of this study. These variables were also found to be strongly correlated with several other welfare variables, for which it was suggested that they may also be acting as proxies. In particular, the study found that deforestation is significantly associated with dependency on fuelwood/charcoal, a resource that is disproportionately consumed by the poor.

Although of the expected sign, the coefficient measuring the contribution to deforestation of the study's official government measure of unemployment was consistently insignificant. However, as an official measure of joblessness in the formal sector, it was argued that it is probably an inadequate indicator of the economic activity of poor

unskilled workers, since the bulk of the jobs open to them are in the informal sector.

In contrast, the study's proxy measure for economic opportunities in formal and informal sectors was found to be consistently significant throughout the empirical analysis. That is, there appear to be fairly strong protective benefits for forests situated in and near major economic centers. No doubt this effect is due to the higher proportion of off-farm opportunities provided by these centers, which may help to alleviate resource dependencies both within and near them.

In contrast to this indirect spatial effect, the study's direct measures of income adequacy and inequality had no significant determinative effect on rates of forest loss on the island. As noted, this finding was contrary to the hypotheses of the study's conceptual model and the vast amount of qualitative literature. However, it was argued that these measures may not be capturing scarcity-driven deforestation effects adequately, for the simple reason that they presume that individuals have an income with which to purchase food and other household items. For groups living at the subsistence level, this assumption of an annual income may be unreasonable.

The study also found that several measures of land use and land quality were consistently significantly related to the loss of forest cover. Simple correlation results at the parish level indicated a consistently strong contribution to deforestation by small agriculturalists, and this finding carried over (albeit less strongly) to the constituency level. There also appear to be strong negative associations between export agriculture and forest cover loss at the parish areal unit of analysis. Although unobserved in the study, it was hypothesized that the higher incomes earned by these export enterprises in comparison to domestic farms would allow small farmers to make key investments in resource husbandry and farming inputs. These in turn would obviate the need for extensive agricultural practices, and thereby, encroachment into forested areas. This beneficial effect was found to hold regardless of farm size or land capability.

Moreover, further evidence for a possible investment/conservation effect for forests on the island was supported in the study by the significantly negative correlation between deforestation and small farms that hired labour. It was argued that the latter measure may be proxying the presence of surplus income or labour, which would be needed to raise productivity. Conversely, the strong positive correlation between forest loss and small farms that grow domestic crops (either for their own consumption or

for the home market) suggested that both the poor prices fetched for these crops and the subsistence nature of many of these farms preclude farmers from making essential investments in the land. As discussed, such investments would ameliorate the need for extensive forest clearance in the first place, eventually allowing farmers to shift into non-agricultural livelihoods. Indirect support for this hypothesis was also noted in the significantly negative association of farms of the smallest size class (i.e. ≤ 1 acre) and forest loss. It was suggested that this result may imply that there is a point below which farming is never a viable option for a land-poor individual, such that he or she is naturally drawn to earn an income elsewhere. For those farmers with a bit more land, however, an important factor in the association of small farming and deforestation may be a fundamental lack of productivity-enhancing assets; that is, the ability to make investments in land intensification and conservation.¹

The deforestation induced by these small farms is no doubt compounded by the poor resource capabilities of the land on which many of them are situated. The strong positive correlations between small farms and these areas (and conversely, the strong negative correlation between large farms and areas with good land capability) suggest that small farmers are concentrated on the island's most unproductive land, which is also deforesting faster than are good quality areas. Indeed, those parts of the island having the classifications average/fair and poor in respect to their capacity to support traditional farming methods (i.e. rain-fed agriculture largely unassisted by chemical inputs), were found to be losing more forest cover than were other parts of the island.

Moreover, areas undergoing rapid deforestation were also marginally more likely to have large numbers of young agriculturalists and female-headed farms. It was noted that not only are young farmers destroying forests faster than their older counterparts, they also place disproportionately more pressure on the land to produce food and other basic necessities. The higher deforestation rate for this group may reflect this basic demographic difference, or it may simply be a sign of higher youth unemployment in comparison to other groups. To what extent these young groups would have remained in farming had other opportunities arisen can only be conjectured. In any event, the significant correlation with deforestation of farms of the small size group farming full-time, suggests that had they chosen farming as a sole source of livelihood, they would have

¹For a discussion of the concept of 'investment poverty' see Reardon & Vosti 1995.

caused significantly more damage to forests than would have part-time agriculturalists.

Deforestation was also found to be significantly higher in areas with large initial amounts of standing forest. This suggests that large, hitherto immune areas of forest cover have undergone faster rates of deforestation than have areas characterized by small amounts of relict forest. Moreover, these former areas tend to have the worst soils and the steepest topography on the island, as evidenced by the strong correlation between variables measuring the proportion of land area in forest and the proportion of land area placing severe restrictions on traditional agriculture.

It is worth stressing that in many cases, the relative impacts on forest cover of several of the study's scarcity-related measures were shown to be quite considerable, particularly fuelwood dependency and demographic pressures. From a statistical point of view, this finding was not surprising given that these variables measure more immediate impacts on forests than do other aspects of human-forest interactions empirically analyzed here; however, several of the study's less proximate scarcity indicators were also found to have large absolute impacts. Moreover, two simulation experiments involving these variables in conjunction with one key indicator of human capital formation (male educational achievement) suggest that even relatively small (negative or positive) changes in these variables will have substantial impacts on Jamaica's forest cover now and into the next century.

11.2 Some Policy Directions for Conserving Forest Cover in Jamaica & Beyond

This study has argued that the complexity of the scarcity related processes underlying deforestation makes it impossible to ever measure these relationships precisely or entirely. Furthermore, the measurement error inherent in the use of both satellite and socio-economic survey data in the tropics must always be kept in mind when drawing policy conclusions. However, this study has argued that quantitative analyses such as this one can provide useful empirical generalizations to guide policy makers in developing forest protection and management initiatives. In particular, the study's quantitative emphasis on the contribution of scarcity-driven processes to the destruction of Jamaica's forests suggests important areas for policy intervention.

Keeping in view the above caveats concerning the inherent difficulties and limitations in carrying out research on human-forest interactions, the following paragraphs conclude with a number of general policy implications for forest protection and management initiatives in Jamaica. Beyond the country level, the study's findings and policy implications may also have relevance for several English-speaking islands of the region. Notable examples include: Trinidad & Tobago, Antigua, Barbuda, and Grenada. Not only have these countries experienced varying levels of forest loss in recent decades, they also share similar demographic, economic and ecological constraints. It should be stressed from the outside that none of these policy suggestions can in any way be said to be innovative. All the strategies outlined here are clearly laid down in other policy documents, particularly several recent World Bank policy papers on Jamaica and the Caribbean region. If anything, this study provides empirical support for the policy recommendations that have long been promulgated by the development community and are contained in these and similar documents.

Of course, it is recognized that realizing these policy suggestions is not going to be easy in the present economic climate. However, there is much scope for collaboration between foreign NGOs, and governments in helping Jamaica to achieve these goals. It should also be stressed that each of these policy directions will depend on concerted efforts being made in all other areas; however, achieving success in one sphere will certainly have positive spin-offs in others.

- *CONTROL POPULATION GROWTH RATES*

The Jamaican population has exhibited growth rates of between roughly 1.0% and 1.5% per annum between 1988 and 1998 (PIJ 1992a-1995a). While not high by the standards of some Caribbean nations, these rates of increase are nevertheless substantial in view of the serious resource constraints facing the island. Note, however, that this rate of increase would have been higher had it not been for external migration. For instance, between 1994 and 1995, the natural increase in the population was 1.8%. This increase would have added another 44,800 people to the island over the previous year had it not been for a net external migration of 17,700 people, which lowered the growth rate to 1.1% (PIJ 1995a).

However, even this 1.1% increase translates into a substantial number of people — 27,100 in just one year. Moreover to a significant degree, slowing population growth

rates will continue to depend on the availability of emigration routes, which cannot be guaranteed. It will also depend on further reductions in the fertility rate. However, as noted, recent government estimates of the extent of the decline in fertility rates have been disputed by some demographers due to the deterioration in record-keeping in vital statistics which occurred during the 1980s.

In any event, the study's simulations have suggested that even a 1.0% per annum rise in population will have substantial negative effects on forest cover in years to come. This figure is below the government's own medium population projection of 0.8% per annum (PIJ 1992b). Under this projection the population in the labour force age group is also expected to increase substantially, particularly the 30-64 age group. In the absence of adequate planning for education and training, job creation and infrastructural development, it is not inconceivable that a good proportion of these people will be relegated to a life at the margins, either higgling in the streets or growing food at increasingly higher elevations along mountainsides.

Given that population will continue to increase into the next decade, the government must act now to aggressively minimize its welfare and environmental impacts by expanding family planning programs and improving basic health care services. The National Family Planning Board identified several key areas for health care intervention if replacement level fertility is to be reached and population is not to exceed 3.0 million by the year 2020, based on a 0.8% per annum increase during this period (PIJ 1992b). Success in this area will also depend on the promotion of better education and income opportunities for women and on further reductions in infant mortality.

- *REDUCE DEPENDENCY ON FUELWOOD*

In the absence of strong economic growth in coming decades, Jamaica's dependency on non-imported sources of energy will deepen. This dependency will no doubt be magnified by population increases, particularly among the poor, who have a higher fertility rate and are heavy users of fuelwood (Graham & Edwards 1984).

In view of these trends, immediate measures must be taken now to alleviate these pressures on the forests. One way would be to raise subsidies on petroleum-based fuels (e.g. kerosene) through targeted schemes similar to the country's food stamp program. Ensuring that subsidies are well-targeted is essential if these programs are not to end up simply subsidizing energy consumption of the well-to-do. Targeted programs will

also be less likely to discourage efficiency in kerosene use and abuses of the system, such as the mixing of commercial petroleum fuels with kerosene.

Additionally, demand reduction could be achieved by promoting alternative energy sources through programs such as the World Bank/UNDP sponsored, Improved Charcoal and Kerosene Stoves Project (World Bank 1993a). However, it is important that such programs do not discourage energy efficiency or lower the price of charcoal to the point that petroleum-based fuels become prohibitively expensive, causing people to switch to charcoal. Supply side measures could involve the establishment of more plantations on degraded lands and — once current deficiencies in tenure and extension are addressed — expanding agroforestry programs. For the poorest areas, such programs could include the subsidization of tree-planting programs and the establishment of large-scale fuelwood plantations, village wood-lots and natural forest groves. Another supply-side measure, little tried in Jamaica, is the development of biomass-based fuels from agricultural waste such as sugar cane, which is plentiful in many rural areas. Similarly, price distortions in fuelwood markets could be addressed by raising stumpage fees, which are currently well below the replacement value of the forest stands (World Bank 1993a).

Of course, supply-side measures will be ineffectual if fuelwood can still be collected easily in open-access reserves, and fuelwood markets remain distorted. In rural areas, fuelwood is a free good that can be collected in the vicinity of the household, with the only real opportunity cost being the time involved in its collection. Hence success in these programs will ultimately depend on addressing the problem of encroachment onto both public and private lands.

- *PROVIDE SUPPORT FOR THE DOMESTIC FARMER & OTHER RURAL ENTERPRISES*

Poverty is a persistent fact of life for many residents in Jamaica, and certainly a condition responsible for the underproductivity and low incomes of rural areas in general. Although the export agricultural sector no longer enjoys the level of support it once received, it remains the primary focus of liberalization and market-oriented reforms in agriculture, being the main beneficiary of structural adjustment loans and private investment.

Government and private funding should be immediately directed to helping the smallholder farmer raise productivity, even if this means substantially shifting resources (e.g. tax breaks and other subsidies) away from the export sector (World Bank 1993a). Specifically, this should involve the provision of extension, credit and technological assistance to smallholder farmers. Intersectoral cooperation between relevant departments (e.g. forestry, agriculture) should be encouraged so as to ensure that these smallholder programs are implemented in view of the overall sustainability of land resources (World Bank 1993a; NRCA 1995b; Berke & Beatley 1995). In addition, priority should be given to raising smallholder output through the promotion of more intensive farming techniques and suitable crop varieties (World Bank 1993a; Blustain 1982). The problem of insecure tenure should also be addressed through land distribution programs of the type successfully implemented in parts of the Blue Mountains and John Crow Mountains Park. Temporary leases should also be abandoned and family-owned land granted legal recognition in order to strengthen individual property rights and encourage sustainable investments in the land (World Bank 1993a). In conjunction with substantial credit and extension assistance to small farmers (e.g. through Grammeen Banks, which have been quite successful in India), these measures should lead to greater domestic food production and rural employment. Furthermore, the stimulation of domestic production will reduce the need for imported foodstuffs, which should help in turn to rectify Jamaica's chronic balance of payments problems, with beneficial consequences for the economy as a whole.

Additionally, government policies should promote private investment in rural areas as part of a larger program of integrated development for the countryside. Such enterprises should be encouraged particularly in areas which are unsuited for agricultural production, are densely populated and/or highly degraded (Leonard 1989). Tax breaks, labour market deregulation, and the removal of bureaucratic barriers to entry, could be used to encourage both domestic and foreign investment in unskilled enterprises such as agricultural processing, light-manufacturing, and eco-tourism. Remaining distortions in product, factor and trade regimes, which have depressed domestic agricultural production in the past, should also be eliminated (World Bank 1993a). The government of Jamaica should also direct resources to the rehabilitation of heavily exploited forest areas and degraded lands, and to the improvement of rural infrastructure, including

housing.

- *PROMOTE ECONOMIC OPPORTUNITIES IN BUILT-UP AREAS*

Priority should also be given to the stimulation of jobs in built-up areas as a means of providing additional sources of income for the rural poor and absorbing the surplus labour of the countryside (Leonard 1989; World Bank 1993a). If problems of labour inefficiencies, lack of skills and shortages of raw materials could be addressed, there may be potential for greater expansion in manufacturing and processing industries, particularly in the production of domestically consumed goods in the special export processing zones and in tourism-related enterprises (World Bank 1993b). Built-up areas have the advantage over the countryside of better infrastructure, more developed markets and higher incomes, and hence will naturally be more attractive to private investors in large-scale projects. However, large-scale investment of this type will require that the government of Jamaica nurture an environment conducive to foreign and domestic investment through the promotion of greater competitive markets and openness to trade (ECLAC 1996; World Bank 1993b). Informal sector activities should also be encouraged by easing bureaucratic restrictions on trading (World Bank 1993a).

In addition, the government of Jamaica must also address issues of urban sprawl into rural areas, which will naturally increase as impoverished rural residents are attracted to cities in search of employment (Leonard 1989; World Bank 1993a). This will necessitate that improvements be made in water and sanitation in built-up areas, and that existing housing be upgraded (World Bank 1993a).

- *INVEST IN THE HUMAN CAPITAL OF THE POOR*

Achieving the above goals and ensuring that economic growth is sustainable will require that the Jamaican government make substantial investments in raising the skills level and productivity of the poor. Such investments will have positive spin-offs for both the economy and the environment, since higher productivity is associated with higher economic growth and incomes and greater efficiency in the use of resources (World Bank 1993b; ECLAC 1996).

In order to facilitate the process of economic development, particularly the growth of employment in non-traditional enterprises, short-term priority should be given to

extending assistance (in the form of targeted programs and subsidies) to the very poorest groups (World Bank 1993a). However, long-term investments should also be made, perhaps in conjunction with external funding agencies, in projects and policies that will have eventually lead to an improvement in the health, education, and nutrition of the poor beyond this level (Leonard 1989). These programs and policies could eventually enable the poor to take advantage of new remunerative opportunities as the economy expands (ECLAC 1996; World Bank 1993a,b). Rising incomes and investments induced by the transition to a more capital-intensive, skills-based economy open up the possibility in turn of some revenues from this economic growth being invested in forest management and protection.

- *STRENGTHEN ENFORCEMENT OF FOREST RESERVES & PROMULGATE SUSTAINABLE LAND USE PRACTICES IN & AROUND THEM*

In the first instance, clearer delineation of both public and private lands would protect and allow for better land use planning in these areas (Berke & Beatley 1995; NRCA 1995b). Since the pressures in these areas are driven by deprivation, any boundary delineation must be implemented in the context of a larger economic strategy; for example, as laid down in rudimentary form in the National Environmental Action Plan (NRCA 1995b; Berke & Beatley 1995). Identification of appropriate land uses and management of these areas will also depend on the development of an effective land use planning system, which Jamaica currently lacks (Berke & Beatley 1995). Second, enforcement of park boundaries and monitoring of change within them should be strengthened. This could be achieved by raising the number of enforcement agents and technical staff (Berke & Beatley 1995).

One way to ensure sustainable use of these lands while maximizing scarce resources would be to enlist the help of staff in other agencies and departments. Cross-sectoral coordination would make it easier to establish priority programs (e.g. watershed maintenance, reforestation) and ensure their success (World Bank 1993a; Berke & Beatley 1995). The NRCA — the government's umbrella environmental body — could coordinate these efforts in conjunction with forestry, agriculture and other government departments, the private sector, NGOs and foreign donors (NRCA 1995b; Berke & Beatley 1995; World Bank 1993a). Another cost-effective way to protect forests and encourage rural employment would be to enlist the support of local communities, both

within and outside of forest reserves and parks. However, it must also be realized that any planning and management efforts in forested areas will only be successful if local residents derive clear economic benefits from them.

Better protection and management of parks and protected areas could be realized through the creation of proper economic incentive structures, so that the prices of land and other resources within them reflect their true scarcity value (World Bank 1993a). Measures could include: charging entrance fees for parks; changing property taxes to encourage individuals to grow ecologically sound crops; and price increases for the use of resources (e.g. timber) by commercial users (World Bank 1993a; Berke & Beatley 1995). Moreover, there is some potential for raising revenues for such programs and for forest friendly initiatives in general through the implementation of debt-for-nature swaps (Berke & Beatley 1995). Admittedly, the latitude for relief is small, given that only a mere fraction of the country's debt is owed to commercial banks. Nevertheless, given the chronic shortage of funds for forest protection and management efforts, even small-scale swaps could have far-reaching environmental and economic benefits.

To summarize: The above policy recommendations for reversing the decline in Jamaica's forests imply a three-fold strategy based on: a) improving the lives of the poor; b) encouraging economic growth; and c) maximizing sustainability in the use of resources and care of the environment. Tackling the problem of scarcity-driven forest loss will require wide-ranging and coordinated initiatives in both private and public sectors, as well as a clear assessment of the trade-offs involved within each of these target areas.

Achieving these goals will not be easy, and the Jamaican government must in all cases resist the temptation to accept the *status quo*, hoping for an eventual economic upturn to ease scarcity pressures on the forest base. Indeed, the condition of the country's forests can no longer be separated from the social and environmental welfare of the island. Not only are the forces driving forest loss in Jamaica largely economic, widespread deforestation and the resulting environmental problems and resource scarcities it is generating now threaten the potential for future gains in productivity and human welfare. Such gains are essential in the long-term for promoting economic growth and development. They depend in turn on the presence of a natural resource base that is capable of regenerating and sustaining a growing economy.

11.3 Final Remarks: Study Limitations & Future Research

The study has a number of limitations related primarily to: a) the quality and availability of data sets; b) statistical technique; and c) model construction.

a) *Data*. One possible way to improve the analysis would have been to use higher resolution satellite data, preferably radar data. This type of data has the advantage that it does not suffer from cloud coverage; its finer resolution means that potentially more landscape information is available to the researcher. However, the issue of atmospheric occlusion notwithstanding, the use of radar data, like all fine resolution data, does not imply that resulting estimates will be more accurate since a number of factors can affect the quality of the interpretation. For example, finer resolution data can make it difficult to discern landscape features, such that the researcher has trouble 'seeing the forest for the trees'. In any event, the unavailability of appropriate social variables at anything other than the constituency level outweighs the advantages of using finer resolution data in a study such as this one.

A higher temporal resolution (e.g. 5 year data for 20 years up to the present) would have increased the number of years for which forest estimates were available, thereby offering a more comprehensive picture of forest cover on the island and the social factors driving its change. However, as noted, the financial and labour costs involved in such an analysis are immense, and would have far exceeded the resources available in this study.

b) *Statistical Technique*. Correlation and regression are powerful tools that can extract most of the information in any data set. Indeed, the large number of regressions in this study can confidently be said to provide a general picture of the relationships of interest. Nevertheless, more sophisticated econometric techniques could have been used to measure other dimensions of these relationships. For instance, it is quite conceivable that socially deprived farmers in one constituency are migrating to adjacent constituencies where they are clearing land of its vegetative cover. Such 'spillover effects' are not captured in the study's regression analysis, and this fact may be one reason for why results are not stronger. Techniques for measuring these effects can be found in the newly emerging field of spatial econometrics. Although they require considerable data

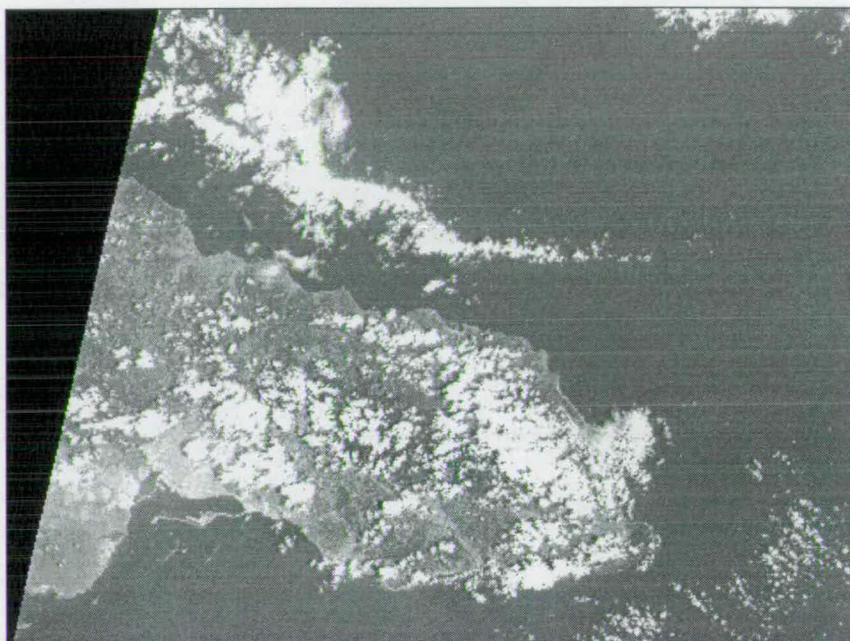
and are typically quite computer-intensive, one topic for future research would be to apply these techniques to an analysis of such interactions.

c) *Model Construction*. Rather than hypothesize about human-forest relationships in the form of simple verbal descriptions as in this study, an alternative approach would have been to specify and empirically estimate a formal model of land clearance. As the review of the literature indicated, several quantitative studies have developed formal structural models of land clearance. Typically, these begin with a mathematical consideration of the problem of how a landowner decides whether to clear a parcel of land. The decision is shown to depend on many variables for which economic data are collected and econometrically analyzed (e.g. the price of agricultural crops on cleared land, benefits from produce sold now as opposed to in the future, the nature and quantity of produce grown, the price received for selling forest produce vs. crops, household labour supply and so on). In comparison to the reduced form regression model approach of this study, which produced largely stylized or informal facts about the clearance process, the econometric versions of these models are rooted firmly in economic theory and their coefficients have explicit economic interpretations.

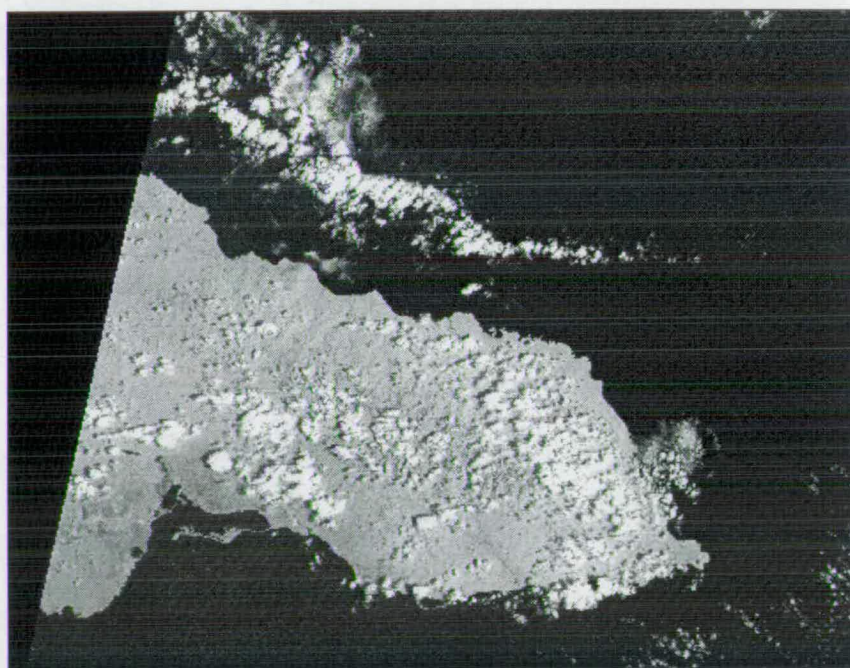
Such a model could be developed for Jamaica, and is an interesting topic for future research. However, it should also be recognized that the data required for estimation of these models is typically very difficult (and often impossible) to obtain. Ideally, the estimation of such a model requires that data be available on each variable for each individual land clearer of economic interest, including measures for how much forest cover has been cleared by each. However, even if such data could be obtained, possibly through extensive surveys of farmers, it would shed light on the contributions to deforestation of this *particular group of land clearers only*. In reality, there are many other types of individuals whose behaviour does not conform to these agricultural models of land clearance but who are nonetheless potentially important for understanding the deforestation process. Modelling the contribution of even a small handful of these agents would be an extremely difficult exercise. Finally, and most importantly, existing land clearance models of this kind are poorly equipped to incorporate social deprivation factors, which form the heart of this study.

APPENDICES

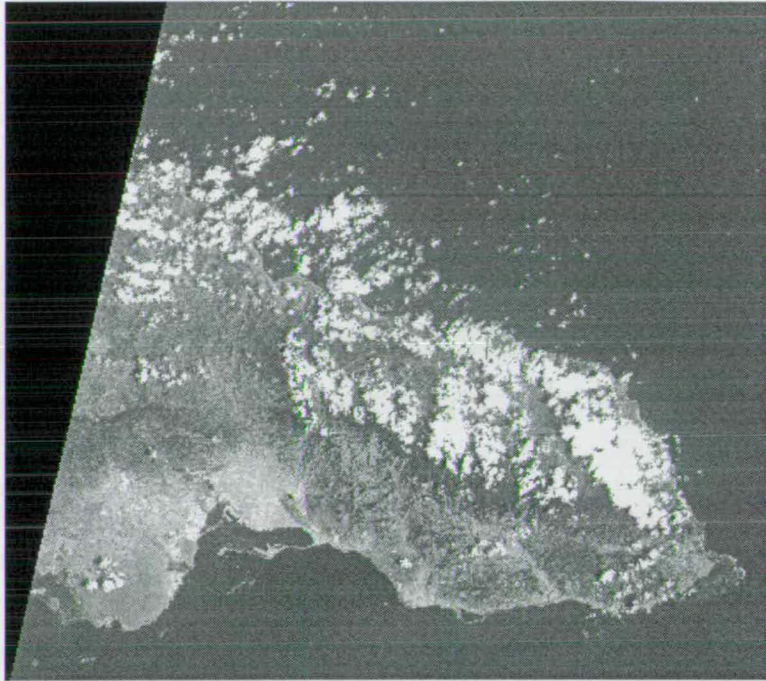
Appendix A: Landsat MSS Data



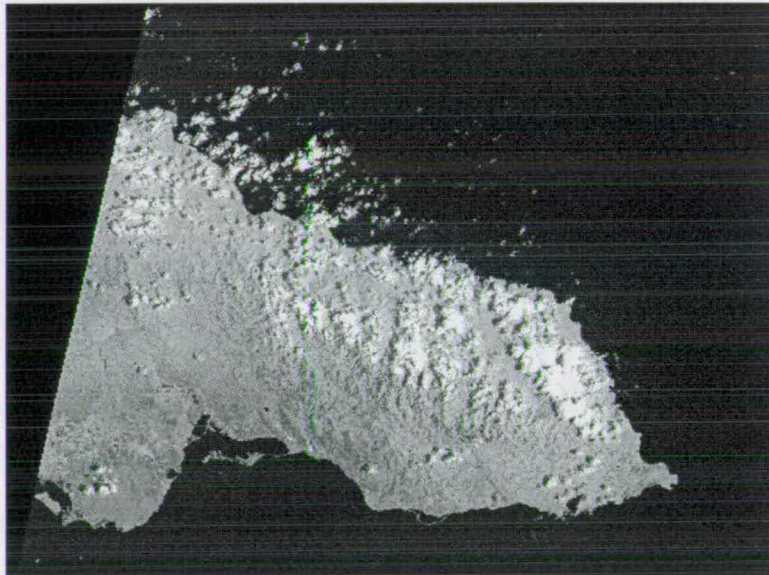
Landsat MSS Band 2: Eastern Jamaica 1987



Landsat MSS Band 4: Eastern Jamaica 1987



Landsat MSS Band 2: Eastern Jamaica 1992



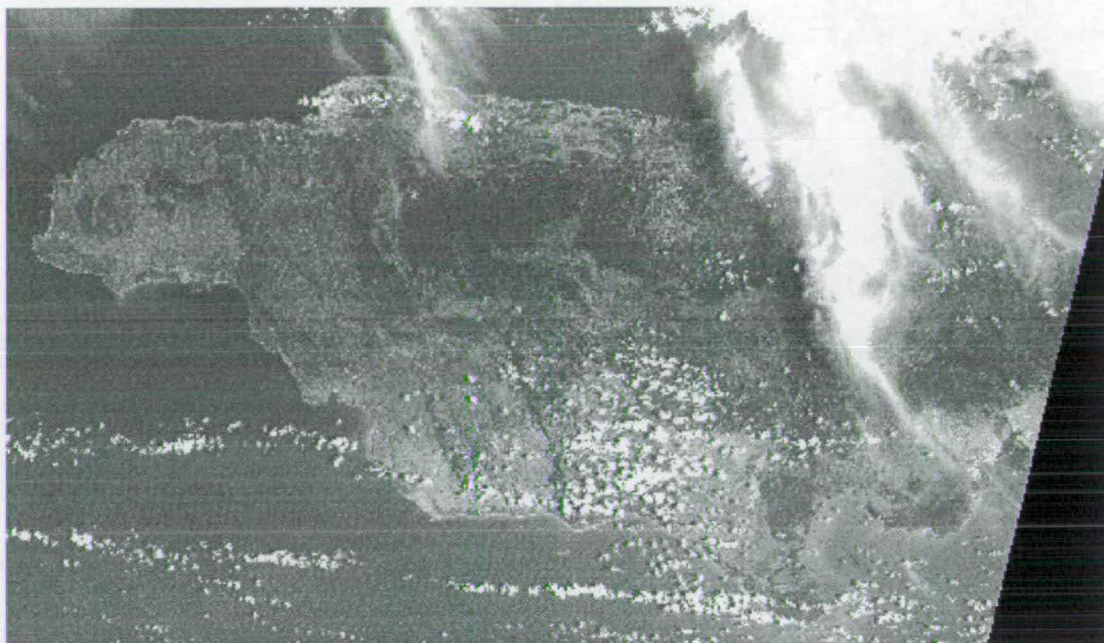
Landsat MSS Band 4: Eastern Jamaica 1992



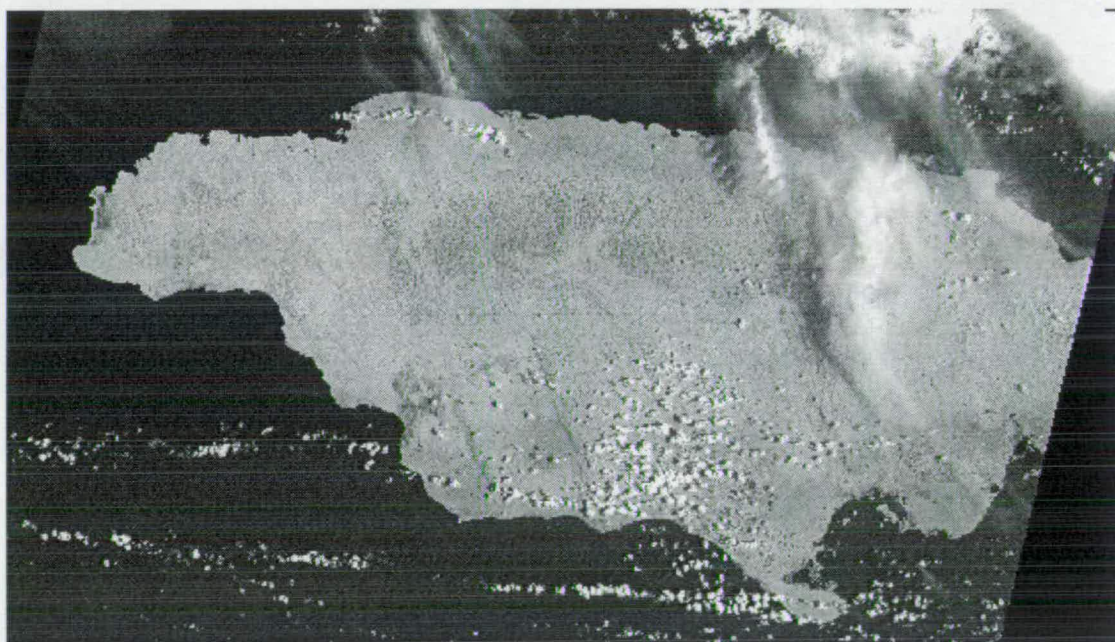
Landsat MSS Band 2: Western Jamaica 1987



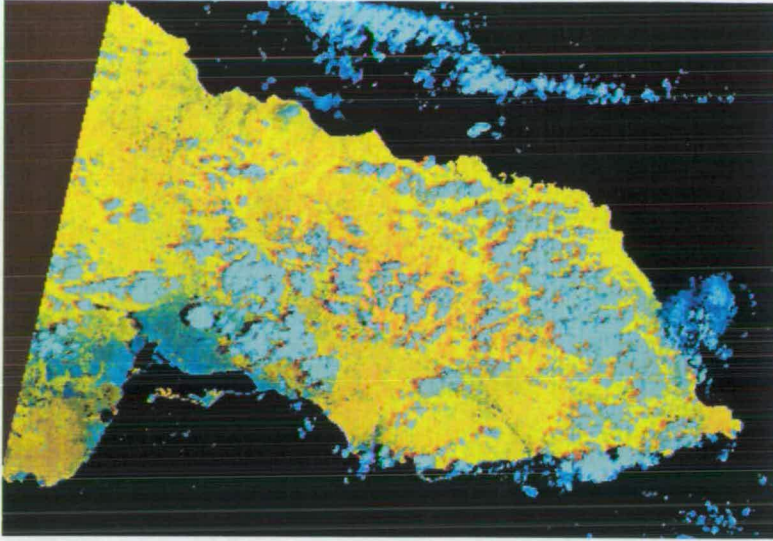
Landsat MSS Band 4: Western Jamaica 1987



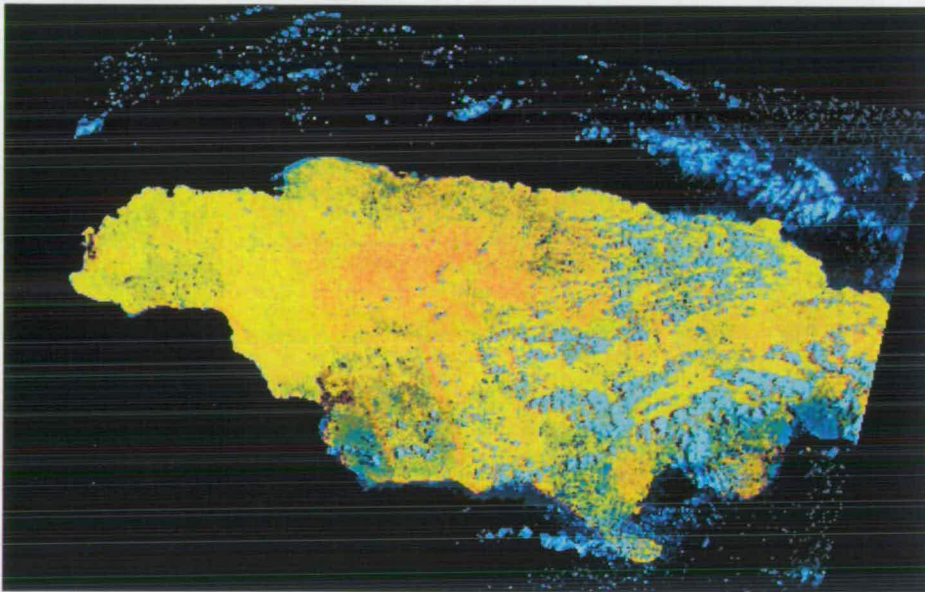
Landsat MSS Band 2: Western Jamaica 1992



Landsat MSS Band 4: Western Jamaica 1992



False Colour Composite Bands: Eastern Jamaica 1987 (Bands 2, NDVI, 4)



False Colour Composite: Western Jamaica 1987 (Bands 2, NDVI, 4)

Appendix C: Correspondence Files

Eastern Jamaica 1992 Correspondence File

Computed Polynomial Surface: Linear

Lineage : Old X Old Y New X New Y Residual

Lineage : 349524.000000 2010675.000000 350037.000000 2012385.000000 26.095439
Lineage : 360525.000000 2001726.000000 361095.000000 2003379.000000 20.041326
Lineage : 296856.000000 1979154.000000 297426.000000 1980864.000000 20.368793
Lineage : 331756.700000 1983738.000000 332324.500000 1985392.000000 18.501027
Lineage : 359580.000000 2004949.000000 360147.800000 2006602.000000 28.087979
Lineage : 331756.700000 1983738.000000 332324.500000 1985392.000000 18.501027
Lineage : 359580.000000 2004949.000000 360147.800000 2006602.000000 28.087979
Lineage : 345192.000000 2004006.000000 345762.000000 2005716.000000 29.859216
Lineage : 314310.100000 2022054.000000 314811.000000 2023842.000000 21.426004
Lineage : 373557.300000 1982072.300000 374150.000000 1983717.000000 29.219963
Lineage : 372745.200000 1983126.000000 373352.200000 1984781.000000 37.191172
Lineage : 368277.000000 1985595.000000 368847.000000 1987191.000000 38.988744
Lineage : 364800.000000 1977729.000000 365370.000000 1979268.000000 omitted
Lineage : 310764.000000 2021676.000000 311220.000000 2023443.000000 37.271238
Lineage : 307059.000000 2016831.000000 307686.000000 2018370.000000 omitted
Lineage : 303183.000000 1992663.000000 303867.000000 1994316.000000 omitted
Lineage : 303240.000000 1994031.000000 303696.000000 1995684.000000 omitted
Lineage : 293774.700000 1974555.000000 294317.200000 1976207.000000 omitted
Lineage : 291779.900000 1974241.000000 292322.500000 1975951.000000 12.067225
Lineage : 344964.000000 2003892.000000 345534.000000 2005602.000000 29.804271
Lineage : 359123.800000 1984536.000000 360147.800000 1986190.000000 omitted
Lineage : 373535.700000 1982106.000000 374106.800000 1983730.000000 28.993884
Lineage : 319336.300000 2023060.000000 319211.100000 2023023.000000 omitted

Overall RMS = 27.535682

RMS Error is expressed in input image units.

Appendix C (Continued)

Western Jamaica 1992 Correspondence File

Computed Polynomial Surface: Linear

Old X Old Y New X New Y Residual

Lineage : 178331.300000 2009625.000000 178908.300000 2011444.000000 5.6756420
Lineage : 297218.700000 1978672.000000 297399.600000 1980492.000000 7.6935540
Lineage : 273035.900000 1962843.000000 273314.800000 1964667.000000 5.7458230
Lineage : 297218.700000 1978672.000000 297399.600000 1980492.000000 7.6935540
Lineage : 178331.300000 2009625.000000 178908.300000 2011444.000000 5.6756420
Lineage : 183297.200000 2041182.000000 183854.400000 2042991.000000 27.341037
Lineage : 259152.600000 1970610.000000 259458.100000 1972433.000000 17.656283
Lineage : 273239.800000 1978510.000000 273512.200000 1980348.000000 12.483804
Lineage : 309869.300000 2023758.000000 309982.600000 2025586.000000 12.174550
Lineage : 187849.200000 2042615.000000 188367.000000 2044439.000000 11.658890
Lineage : 270030.600000 1971556.000000 270317.500000 1973380.000000 4.6577560
Lineage : 183867.000000 2042407.000000 184369.300000 2044214.000000 25.955543
Lineage : 232237.500000 1974406.000000 232638.300000 1976252.000000 22.195276
Lineage : 304048.800000 1991334.000000 304169.600000 1993152.000000 31.762543
Lineage : 289407.900000 1973658.000000 289641.500000 1975487.000000 17.950371
Lineage : 273239.800000 1978510.000000 273512.200000 1980348.000000 12.483804
Lineage : 183867.000000 2042407.000000 184369.300000 2044214.000000 25.955543
Lineage : 188234.400000 2042969.000000 188760.700000 2044780.000000 14.566550
Lineage : 301080.000000 1986028.000000 301256.300000 1987851.000000 10.379980
Lineage : 301421.900000 1985863.000000 301595.200000 1987686.000000 8.4802420
Lineage : 273903.300000 1962723.000000 274189.500000 1964545.000000 11.520811

Overall RMS = 16.312851

RMS Error is expressed in input image units.

Appendix C (Continued)

Jamaica Constituency Boundaries Map Correspondence File

Computed Polynomial Surface: Linear

Old X Old Y New X New Y Residual

lineage : 0.247163 0.368447 357405.300000 1995399.000000 0.01121
lineage : 0.251010 0.281078 360141.800000 1986159.000000 0.00503
lineage : 0.171187 0.892661 343380.600000 2043992.000000 0.00992
lineage : 0.181766 0.882676 345262.000000 2042281.000000 0.00167
lineage : 0.201962 0.882676 350906.000000 2041768.000000 0.00363
lineage : 0.266397 0.256116 364729.100000 1982958.000000 0.01392
lineage : 0.294287 0.178732 370146.700000 1976109.000000 0.00831
lineage : 0.394307 0.161258 394383.600000 1974112.000000 0.00247
lineage : 0.454895 0.188717 405142.600000 1976714.000000 0.01515
lineage : 0.574149 0.051423 435714.200000 1962529.000000 0.00470
lineage : 0.033058 0.752865 310423.300000 2033173.000000 0.01695
lineage : 0.037478 0.779273 312247.400000 2034883.000000 0.01226
lineage : 0.020373 0.723966 305749.100000 2024050.200000 0.05695
lineage : 0.051336 0.587032 314236.800000 2017857.000000 0.01662
lineage : 0.068064 0.552618 318245.100000 2014653.000000 0.01778
lineage : 0.143626 0.585536 335807.000000 2016251.000000 0.00974
lineage : 0.162661 0.515212 340140.500000 2009633.000000 0.00947
lineage : 0.216388 0.375936 352787.400000 1995570.000000 0.00334
lineage : 0.227928 0.383425 355181.800000 1995741.000000 0.00488
lineage : 0.750144 0.323515 478667.200000 1985475.000000 0.00565
lineage : 0.807848 0.675487 492349.800000 2016787.000000 0.01159
lineage : 0.850164 0.643036 502611.800000 2013878.000000 0.00968
lineage : 0.930948 0.548178 521767.400000 2004638.000000 0.00973
lineage : 0.989613 0.323515 534252.800000 1983422.000000 0.01313
lineage : 0.994422 0.278582 555107.900000 1979658.000000 0.07058
lineage : 0.804963 0.231154 491469.900000 1976087.000000 0.00882

lineage : 0.719369 0.335996 470258.700000 1987497.000000 0.01043
lineage : 0.533757 0.088867 426023.800000 1966178.000000 0.00563
lineage : 0.640508 0.188717 452696.700000 1975288.000000 0.00972
lineage : 0.639546 0.875187 454749.400000 2035762.000000 0.01356
lineage : 0.672245 0.880180 461363.700000 2036675.000000 0.00865
lineage : 0.697250 0.375936 465925.200000 1991262.000000 0.00693
lineage : 0.720331 0.715427 473194.200000 2021235.000000 0.00573

Overall RMS = 0.018622

RMS Error is expressed in input image units.

FAO Soil Map Correspondence File

Computed Polynomial Surface: Linear Coefficient

b0 -1.7704837912730227 -1.1040276719967999

b1 1.0331436215319751 -0.0292685834631121

b2 0.2388308621274433 0.9397311956671501

Old X Old Y New X New Y Residual

Lineage : -77.956090 18.440530 -77.915790 18.499280 0.012210

Lineage : -76.190650 17.915930 -76.169870 18.001080 0.054157

Lineage : -76.606410 17.866750 -76.667470 17.917570 0.021444

Lineage : -78.371860 18.270440 -78.338620 18.418650 0.070477

Lineage : -78.044160 18.186430 -78.085500 18.251620 0.033538

Lineage : -76.903380 18.399550 -76.834300 18.418650 0.019728

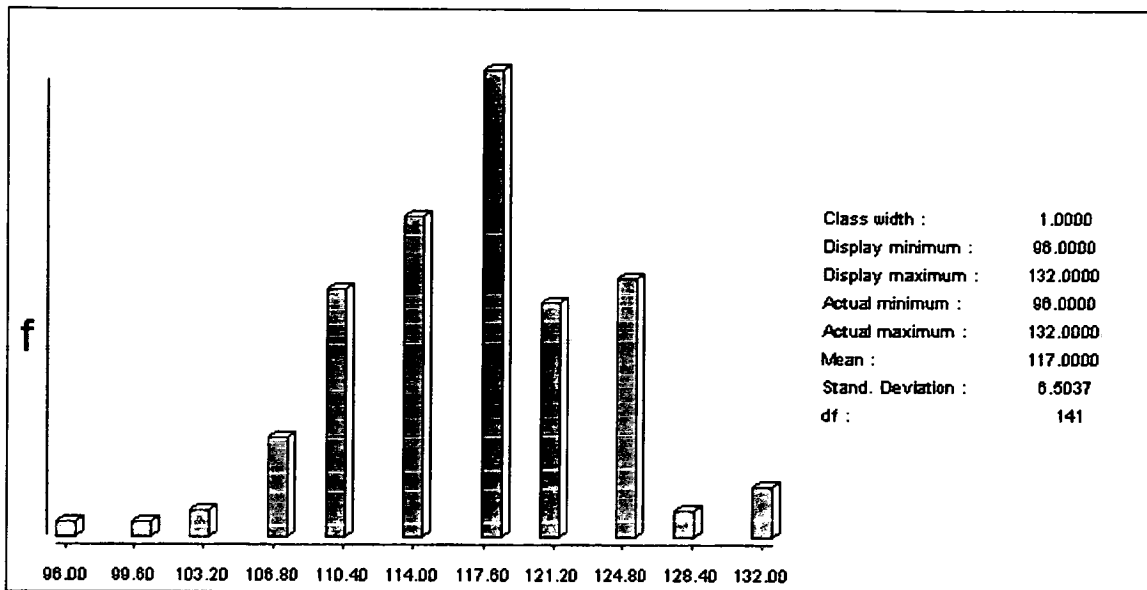
Lineage : -76.608460 17.864700 -76.667470 17.917570 0.018259

Lineage : -77.954050 18.030680 -77.999210 18.087470 0.034208

Overall RMS = 0.037958

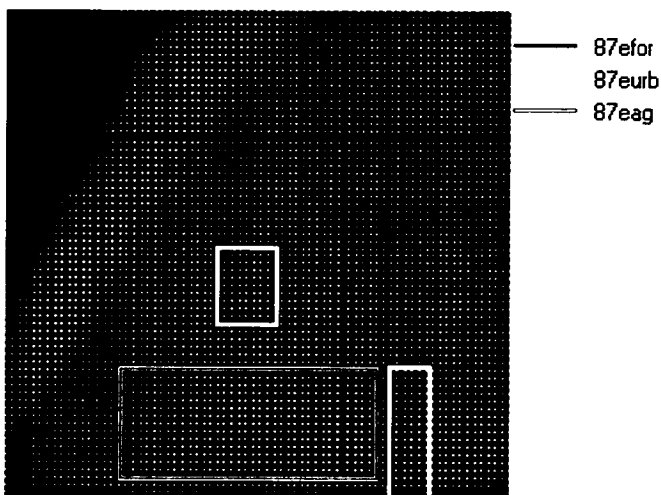
Note: RMS Error is expressed in output map units.

Appendix D: Signature Profiles



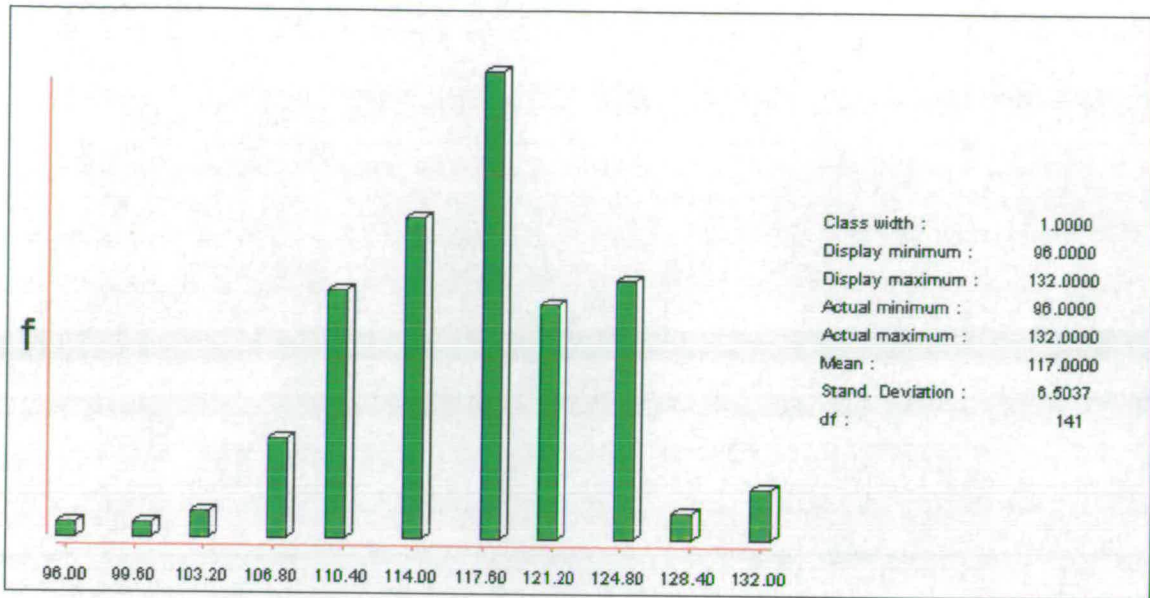
Forest Signature Histogram: Eastern Jamaica 1987 (Band 4)

Signature Scatterplot Band 2 (Y-axis) and Band 4 (X-axis)



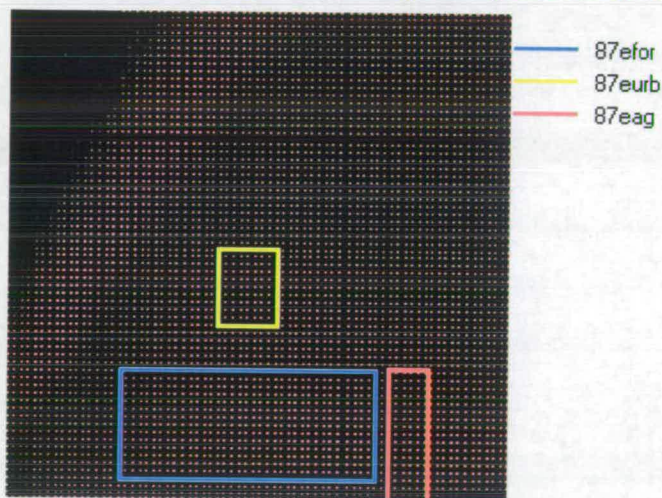
From FCC Eastern Jamaica 1987: Bands 2,4, NDVI

Appendix D: Signature Profiles

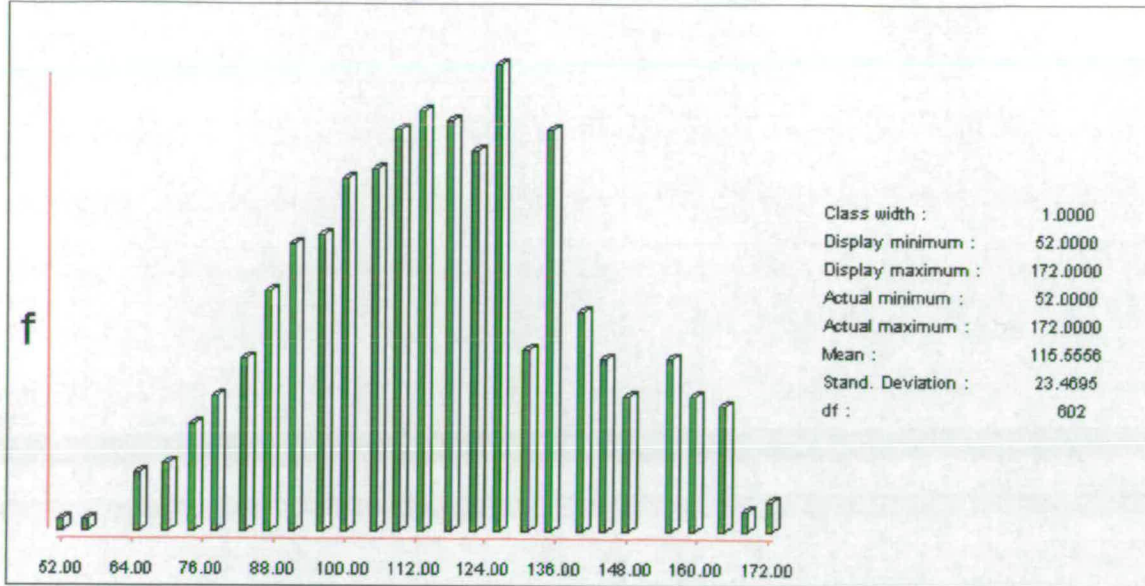


Forest Signature Histogram: Eastern Jamaica 1987 (Band 4)

Signature Scatterplot Band 2 (Y-axis) and Band 4 (X-axis)

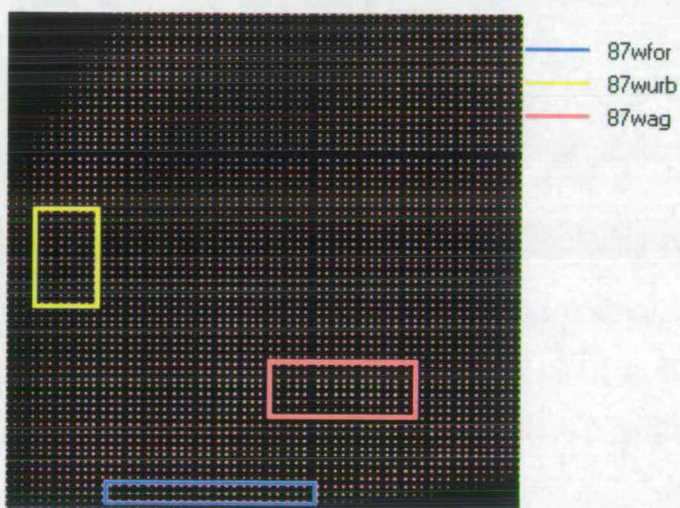


From FCC Eastern Jamaica 1987: Bands 2,4, NDVI

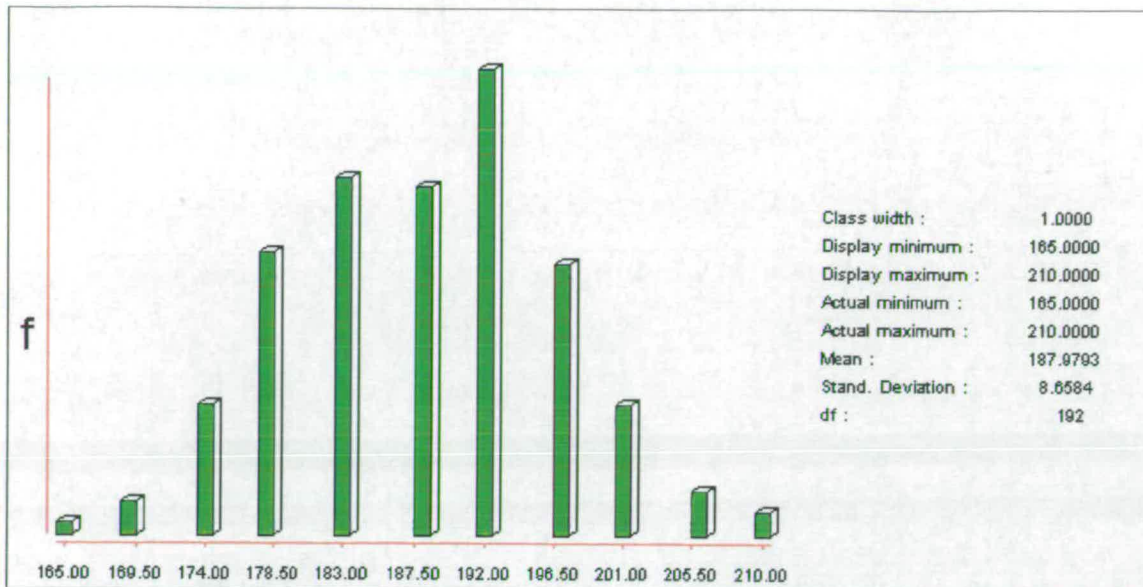


Forest Histogram Signature: Western Jamaica 1987 (Band 4)

Signature Scatterplot Band 2 (Y-axis) and Band 4 (X-axis)

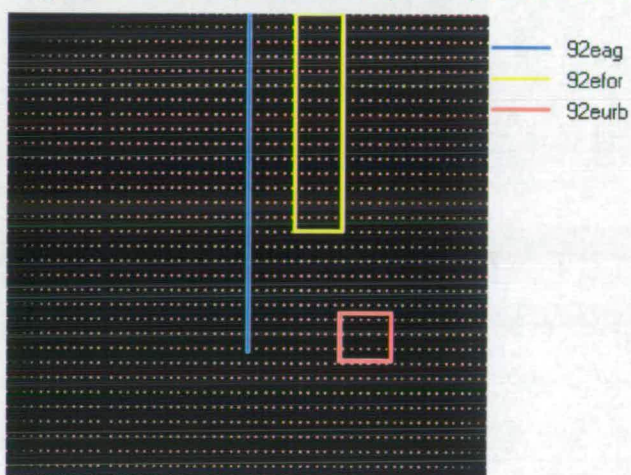


From FCC Western Jamaica 1987: Bands 2,4, NDVI

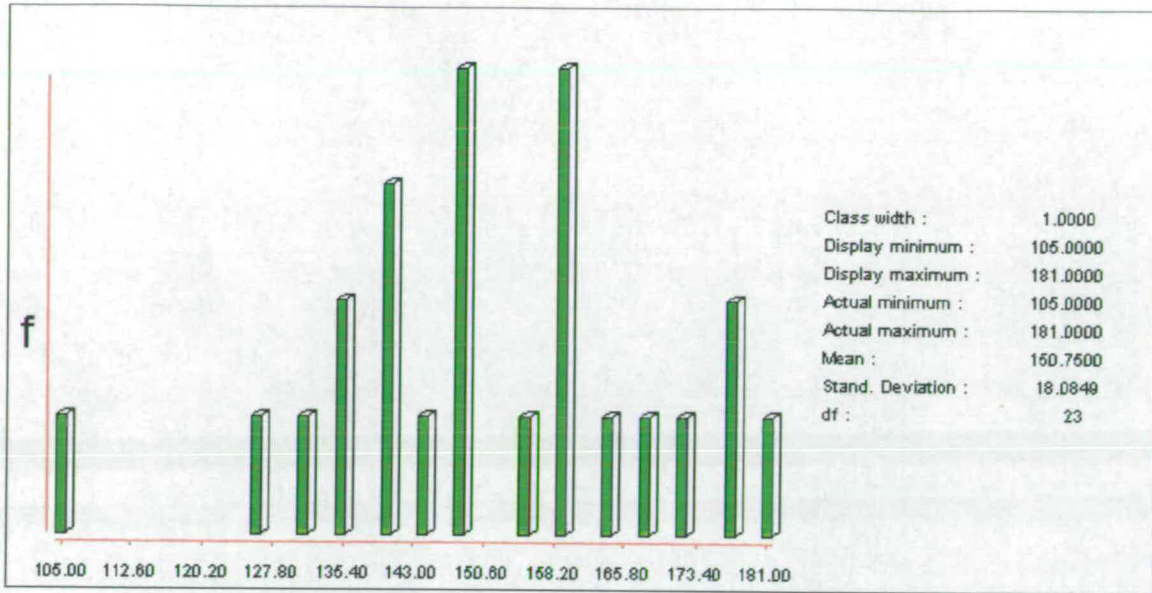


Forest Signature Histogram: Eastern Jamaica 1992 (Band 4)

Signature Scatterplot Band 2 (Y-axis) and Band 4 (X-axis)

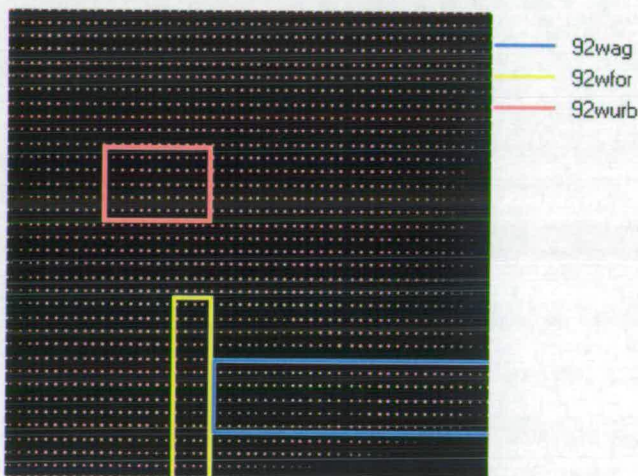


From FCC Eastern Jamaica 1992: Bands 2,4, NDVI



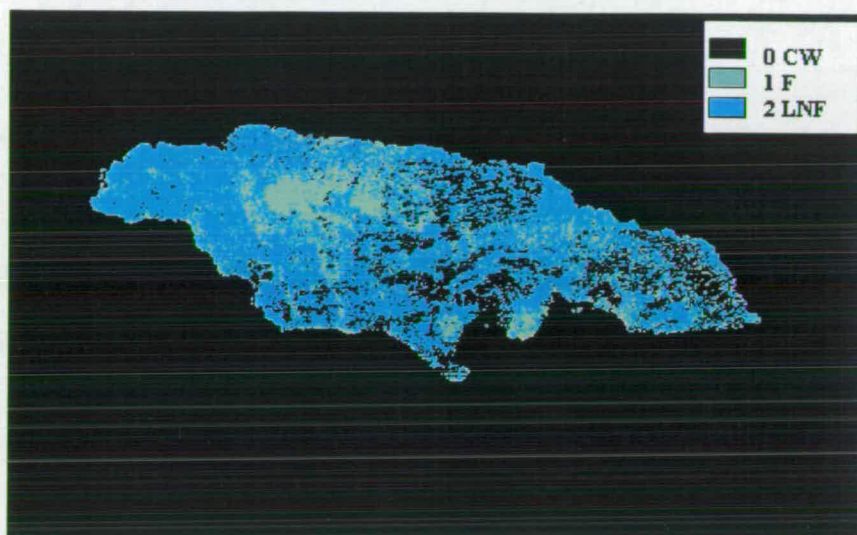
Forest Signature Histogram: Western Jamaica 1992 (Band 4)

Signature Scatterplot Band 2 (Y-axis) and Band 4 (X-axis)



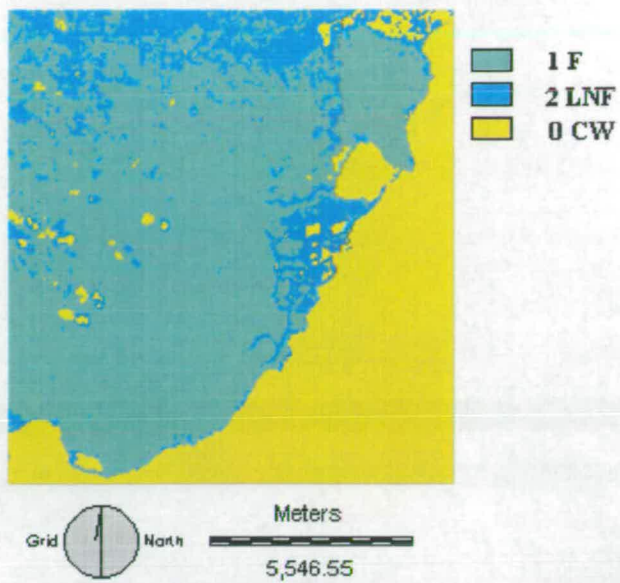
From FCC Western Jamaica 1992: Bands 2,4, NDVI

Final Classification Image: Jamaica 1987

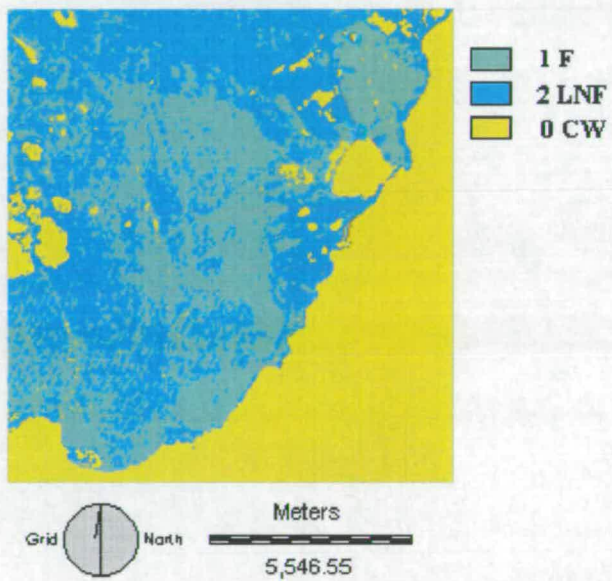


Final Classification Image: Jamaica 1992



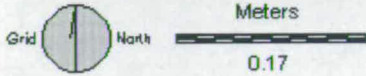
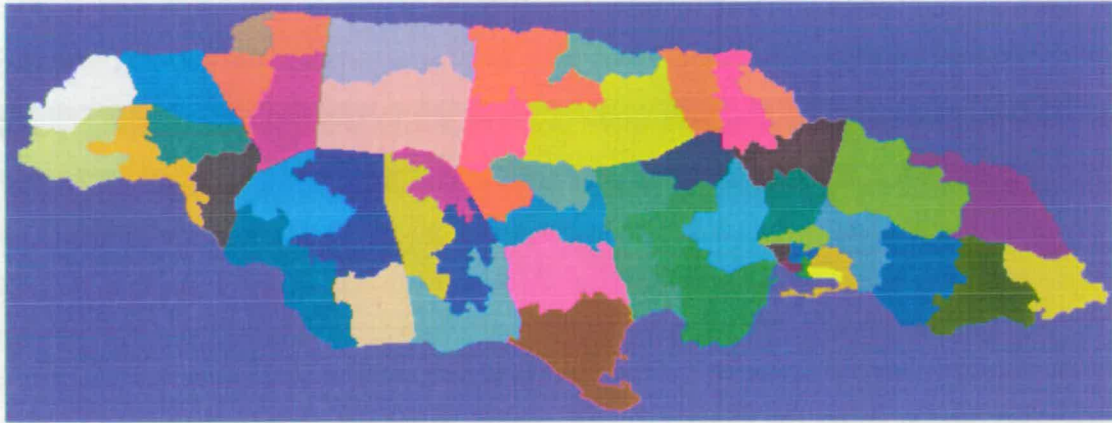






















































Hellshire Hills Region of Jamaica 1987



Hellshire Hills Area of Jamaica 1992

Jamaica Constituency Boundaries



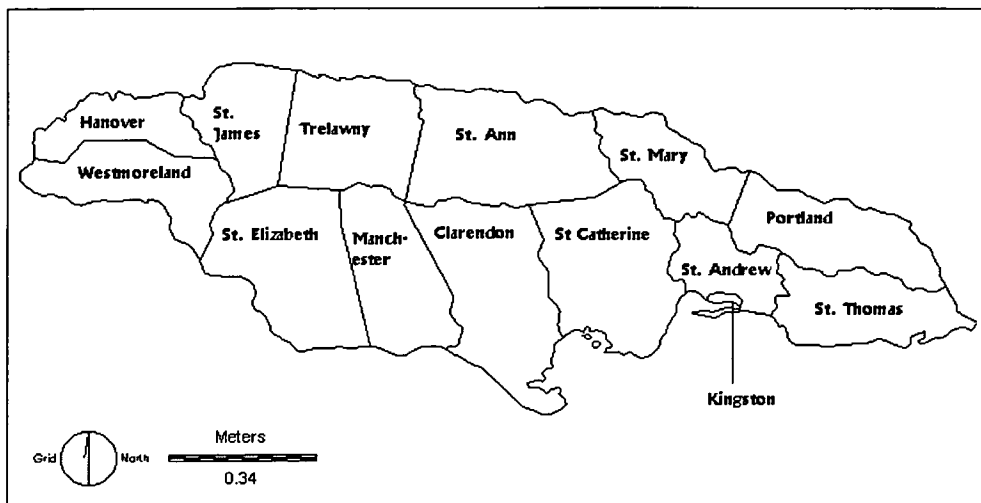
	1		18		35		52
	2		19		36		
	3		20		37		
	4		21		38		
	5		22		39		
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	7		24		41		
	8		25		42		
	9		26		43		
	10		27		44		
	11		28		45		
	12		29		46		
	13		30		47		
	14		31		48		
	15		32		49		
	16		33		50		
	17		34		51		

Jamaica Constituency Boundary Colour Key

Appendix F (Continued)

Identifier Number	Constituency	Identifier Number	Constituency	Identifier Number	Constituency
1	Clarendon N	18	St. Catherine N	35	Kingston
2	Hanover E	19	St. Andrew E Rural	36	St. Andrew SW
3	St. Thomas E	20	Westmoreland C	37	Westmoreland NE
4	St. Ann NW	21	Portland W	38	St. Elizabeth NW
5	St. Thomas W	22	St. Ann SW	39	Manchester C
6	St. Andrew S	23	St. Elizabeth NE	40	Clarendon SC
7	Westmoreland W	24	St. James SE	41	St. Andrew WC
8	St. Mary N	25	Trelawny N	42	Water
9	Manchester S	26	St. Andrew W Rural	43	St. James NW
10	St. Mary C	27	Westmoreland SE	44	St. Ann NE
11	St. Thomas C	28	St. Elizabeth SE	45	St. Mary W
12	St. Andrew SE	29	St. Catherine E	46	Manchester NW
13	St. Catherine W	30	Clarendon S	47	St Catherine C
14	Portland E	31	Hanover W	48	Clarendon NW
15	Trelawny S	32	Manchester NE	49	St. Andrew N
16	St. Ann SE	33	St. Elizabeth SW	50	St. Mary SE
17	St. James Central	34	St. Catherine S	51	Clarendon NC
				52	St. Andrews EC

Appendix F (Continued)



Jamaica Parish Boundaries

Appendix G: Constituency Deforestation Rates

<i>CONSTITUENCY</i>	<i>% CHANGE IN FOREST COVER 1987-1992</i>
Clarendon North	-12.19
Hanover East	-51.54
St. Thomas East	41.18
St. Ann NW	15.02
St. Thomas W	0.96
St. Andrew S	76.69
Westmoreland W	-25.87
St. Mary N	25.93
Manchester S	41.84
St. Mary C	-56.25
St. Thomas C	33.79
St. Andrew SE	-16.13
St. Catherine W	-9.19
Portland E	10.07
Trelawny S	28.30
St. Ann SE	-26.46
St. James Central	-27.03
St. Catherine N	86.67
St. Andrew E Rural	-6.39
Westmoreland C	-27.58
Portland W	15.80
St. Ann SW	23.93
St. Elizabeth NE	26.39
St. James SE	30.34

Appendix G (Continued)

<i>CONSTITUENCY</i>	<i>% CHANGE IN FOREST COVER 1987-1992</i>
Trelawny N	11.48
St. Andrew W Rural	-30.92
Westmoreland SE	26.83
St. Elizabeth SE	9.91
St. Catherine E	-5.47
Clarendon S	-0.82
Hanover W	-41.49
Manchester NE	26.77
St. Elizabeth SW	23.10
St. Catherine S	44.26
Kingston	-49.91
St. Andrew SW	94.72
Westmoreland NE	-31.36
St. Elizabeth NW	22.56
Manchester C	20.99
Clarendon SC	-64.52
St. Andrew WC	-24.84
St. James NW	-470.92
St. Ann NE	55.84
St. Mary W	-61.03
Manchester NW	27.74
St. Catherine C	39.66
Clarendon NW	-17.98
St. Andrew N	-39.73
St. Mary SE	43.27
Clarendon NC	-32.45
St. Andrews EC	17.61

Appendix H: Parish-Level Socio-economic & Land Use Data

PARISH	Population	% Change	% Population Using	Income on Food	Proportion of Forest	Dependency
	Density 1982	Population Density 1982-92	Fuelwood/Charcoal	as % Total	1987	Ratio
St. Andrew	20.54	0.04	0.20	0.40	0.20	0.71
St. Thomas	1.59	0.05	0.67	0.54	0.30	0.93
Portland	0.92	0.04	0.69	0.55	0.26	0.94
St. Mary	1.74	0.34	0.64	0.45	0.11	0.93
St. Ann	1.48	0.06	0.64	0.45	0.29	0.93
Trelawny	0.83	0.01	0.74	0.53	0.50	0.98
St. James	3.00	0.09	0.48	0.46	0.18	0.82
Hanover	1.34	0.04	0.70	0.55	0.08	0.91
Westmoreland	1.52	0.04	0.70	0.53	0.10	0.89
St. Elizabeth	1.17	0.06	0.80	0.46	0.21	0.94
Manchester	1.85	0.08	0.67	0.45	0.27	0.92
Clarendon	1.79	0.03	0.75	0.49	0.14	0.98
St. Catherine	1.78	0.08	0.62	0.49	0.21	0.90
Kingston	15.13	0.25	0.20	0.43	0.33	0.73

Appendix H (Continued)

PARISH	Total # Farms	% Landless Farms	% Farms ≥ 1 acre ≤ 5 acres	% Farms ≤ 5 acres	% Farms 100+
St. Andrew	8967	5	52	86	0
St. Thomas	11569	7	50	84	1
Portland	8740	4	50	73	1
St. Mary	1278	3	51	79	1
St. Ann	15075	3	47	79	1
Trelawny	10666	3	48	88	1
St. James	8643	4	48	83	1
Hanover	7742	1	47	81	1
Westmoreland	17534	2	43	84	1
St. Elizabeth	19174	3	49	82	1
Manchester	18296	1	52	81	1
Clarendon	24113	7	51	81	0
St. Catherine	20957	8	49	82	0
Kingston	NA	NA	NA	0	1

Appendix H (Continued)

PARISH	% Farms Domestic	% Farms Domestic ≥ 1 acre ≤ 5 acres	% Farms Export ≥ 1 acre ≤ 5 acres	% Farms Mixed ≥ 1 acre ≤ 5 acres
St. Andrew	40	15	15	11
St. Thomas	39	17	17	8
Portland	31	17	25	6
St. Mary	24	12	25	10
St. Ann	89	32	8	4
Trelawny	68	34	12	2
St. James	28	11	70	3
Hanover	49	23	45	3
Westmoreland	54	23	27	3
St. Elizabeth	64	34	16	3
Manchester	74	41	15	2
Clarendon	34	18	58	4
St. Catherine	32	25	57	6
Kingston	NA	NA	NA	NA

Appendix H (Continued)

Parish	% Farms Full	% Farms Full ≥ 1 acre ≤ 5 acres	% Farms Part	% Farms Part ≥ 1 acre ≤ 5 acres
St. Andrew	5	11	20	10
St. Thomas	6	8	16	8
Portland	3	6	17	9
St. Mary	4	10	24	13
St. Ann	4	4	22	10
Trelawny	3	2	15	6
St. James	3	3	13	5
Hanover	3	3	21	9
Westmoreland	5	3	16	6
St. Elizabeth	4	3	14	7
Manchester	3	2	18	9
Clarendon	5	4	17	8
St. Catherine	7	6	19	9
Kingston	NA	NA	NA	NA

Appendix H (Continued)

Parish	% Farms Female \geq 1 acre \leq 5 acres
St. Andrew	19
St. Thomas	20
Portland	16
St. Mary	17
St. Ann	15
Trelawny	20
St. James	17
Hanover	20
Westmoreland	20
St. Elizabeth	22
Manchester	22
Clarendon	19
St. Catherine	18
Kingston	NA

Appendix I: Parish-Level Soil Data

Parish	Proportion of Land Area Good Capability	Proportion of Land Area Average-Fair Capability	Proportion of Land Area Poor Capability	Proportion Land Area Capability Unknown
St. Andrew	0.00	0.50	0.50	0.00
St. Thomas	0.14	0.67	0.14	0.05
Portland	0.10	0.71	0.10	0.09
St. Mary	0.13	0.60	0.00	0.21
St. Ann	0.23	0.66	0.03	0.08
Trelawny	0.08	0.31	0.50	0.11
St. James	0.28	0.44	0.28	0.00
Hanover	0.42	0.42	0.00	0.16
Westmoreland	0.28	0.56	0.06	0.10
St. Elizabeth	0.29	0.42	0.23	0.06
Manchester	0.00	0.73	0.27	0.00
Clarendon	0.09	0.88	0.00	0.03
St. Catherine	0.09	0.88	0.03	0.00
Kingston	1.00	0.00	0.00	0.00

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